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Personality-based Recommendation: Human Curiosity Applied to Recommendation Systems Using Implicit Information from Social Networks

Author: Alan Menk
Supervisor: Dra. Laura Sebastia

DSIC
DEPARTAMENTO DE SISTEMAS INFORMÁTICOS Y COMPUTACIÓN

Universitat Politècnica de València

DSIC - Departamento de Sistemas Informáticos y Computación

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Are you Curious?

À minha amada esposa Rebeca.
E à minha família...

Acknowledgements

Nobody told me it was impossible, so I did it! I saw this phrase of Jean Cocteau during my master in Campinas, São Paulo; with so many difficulties I was facing at that time, such a simple message made me reflect on that moment lived. Today, after almost five years of PhD, many obstacles of all orders have been overcome, from technical questions or even psychological and personal issues. I dedicate to each one of you, who have helped me in those years, each line of this thesis, without you I would not have arrived here and I would not have achieved all the objectives set forth in this thesis.

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The supervisor to whom I refer is the professor Laura Sebastiá. It is really hard to describe in a single paragraph all the gratitude I have for her, the doors of her office were always open to me. In moments of uncertainty, there she was with a small flashlight illuminating the direction I should follow. We shared not only pain but also happiness; every positive result, every lecture presented, every published work or even every corrected comma (yes, why not? Is there a more genuine happiness as an unnecessary one?). In summary, thank you, professor Laura, for making these last five years worthwhile, I will always remember these moments with immense joy!

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The thanks also go to those who are approximately 9 thousand kilometres

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Alan Menk

Abstract

In daily life, people usually rely on recommendations, traditionally given by other people (family, friends, etc.) for their most varied decisions. In the digital world, this is not different, given that recommender systems are present everywhere in such a way that we no longer realize. The main goal of these systems is to assist users in the decision-making process, generating recommendations that are of their interest and based on their tastes. These recommendations range from products in e-commerce websites, like books to read or places to visit to what to eat or how long one should walk a day to have a healthy life, who to date or who one should follow on social networks.

And this is an increasing area. On the one hand, we have more and more users on the internet whose life is somewhat digitized, given than what one does in the "real world" is represented in a certain way in the "digital world". On the other hand, we suffer from information overload, which can be mitigated by the use of recommendation systems. However, these systems also face some problems, such as the cold start problem and their need to be more and more "human", "personalised" and "precise" in order to meet the yearning of users and companies.

In this challenging scenario, personality-based recommender systems are being increasingly studied, since they are able to face these problems. Some recent projects have proposed the use of the human personality in recommenders, whether as a whole or individually by facet in order to meet those demands. Therefore, this thesis is devoted to this new area of personality-based recommendation, focusing on one of its most important traits, the curiosity. Additionally, in order to exploit the information already present on the internet, we will implicitly obtain information from social networks.

Thus, this work aims to build a better experience for the end user through a new approach that offers an option for some of the gaps identified in personality-based recommendation systems. Among these gap improvements, the use of social networks to feed the recommender systems soften the cold start problem and, at the same time, it provides valuable data for the prediction of the human personality. Another found gap is that the curiosity was not used by any of the studied recommender systems; almost all of them have used the overall personality of an individual through the Big Five personality traits. However, psychological studies confirm that the curiosity is a relevant trait in the process of choosing an item, which is directly related to recommendation systems.

In summary, we believe that a recommendation system that implicitly measures the curiosity and uses it in the process of recommending new items, especially in the tourism sector, could clearly improve the capacity of these systems in terms of accuracy, serendipity and novelty, allowing users to obtain positive levels of satisfaction with the recommendations.

This thesis begins with an exhaustive study of the state of the art, where we highlight works about recommender systems, the human personality from the point of view of traditional and positive psychology and how these aspects are combined. Then, we develop an online application capable of implicitly extracting information from the user profile in a social network, thus generating predictions of one or more personality traits. Finally, we develop the CURUMIM system, able to generate online recommendations with different properties, combining the curiosity and some sociodemographic characteristics (such as level of education) extracted from Facebook. The system is tested and assessed within the tourism context by real users. The results demonstrate its ability to generate novel and serendipitous recommendations, while maintaining a good level of accuracy, independently of the degree of curiosity of the users.

Keywords

Recommender Systems, Personality, Curiosity, Serendipity, Novelty, Diversity

Resumen

En el día a día, las personas suelen confiar en recomendaciones, tradicionalmente aportadas por otras personas (familia, amigos, etc.) para sus decisiones más variadas. En el mundo digital esto no es diferente, dado que los sistemas de recomendación están presentes en todas partes y de modo transparente. El principal objetivo de estos sistemas es el de ayudar en el proceso de toma de decisiones, generando recomendaciones de su interés y basadas en sus gustos. Dichas recomendaciones van desde productos en sitios web de comercio electrónico, como libros o lugares a visitar, además de qué comer o cuánto tiempo uno debe caminar al día para tener una vida sana, con quién salir o a quién seguir en las redes sociales.

Esta es un área en ascensión. Por un lado, tenemos cada vez más usuarios en internet cuya vida está digitalizada, dado que lo que se hace en el "mundo real" está representado en cierto modo en el "mundo digital". Por otro lado, sufrimos una sobrecarga de información, que puede mitigarse mediante el uso de un sistema de recomendación. Sin embargo, estos sistemas también enfrentan algunos problemas, como el problema del arranque en frío y su necesidad de ser cada vez más "humanos", "personalizados" y "precisos" para satisfacer las exigencias de usuarios y empresas.

En este desafiante escenario, los sistemas de recomendación basados en la personalidad se están estudiando cada vez más, ya que son capaces de enfrentar esos problemas. Algunos proyectos recientes proponen el uso de la personalidad humana en los recomendadores, ya sea en su conjunto o individualmente por rasgos. Esta tesis está dedicada a este nuevo área de recomendación basada en la personalidad, centrándose en uno de sus rasgos más importantes, la curiosidad. Además, para explotar la información ya existente en internet, obtendremos de forma implícita información de las redes sociales.

Por lo tanto, este trabajo tiene como objetivo proporcionar una mejor experiencia al usuario final a través de un nuevo enfoque que ofrece una alternativa a algunos de los retos identificados en los sistemas de recomendación basados en la personalidad. Entre estas mejoras, el uso de las redes sociales para alimentar los sistemas de recomendación reduce el problema del arranque en frío y, al mismo tiempo, proporciona datos valiosos para la predicción de la personalidad humana. Por otro lado, la curiosidad no ha sido utilizada por ninguno de los sistemas de recomendación estudiados; casi todos han usado la personalidad general de un individuo a través de los Cinco Grandes rasgos de la personalidad. Sin embargo, los estudios psicológicos confirman que la curiosidad es un rasgo relevante en el proceso de elegir un item, cuestión directamente relacionada con los sistemas de recomendación.

En resumen, creemos que un sistema de recomendación que mida implícitamente la curiosidad y la utilice en el proceso de recomendar nuevos ítems, especialmente en el sector turístico, podría claramente mejorar la capacidad de estos sistemas en términos de precisión, serendipidad y novedad, permitiendo a los usuarios obtener niveles positivos de satisfacción con las recomendaciones.

Esta tesis realiza un estudio exhaustivo del estado del arte, donde destacamos trabajos sobre sistemas de recomendación, la personalidad humana desde el punto de vista de la psicología tradicional y positiva y finalmente cómo se combinan ambos aspectos. Luego, desarrollamos una aplicación en línea capaz de extraer implícitamente información del perfil de usuario en una red social, generando predicciones de uno o más rasgos de su personalidad. Finalmente, desarrollamos el sistema CURUMIM, capaz de generar recomendaciones en línea con diferentes propiedades, combinando la curiosidad y algunas características sociodemográficas (como el nivel de educación) extraídas de Facebook. El sistema ha sido probado y evaluado en el contexto turístico por usuarios reales. Los resultados demuestran su capacidad para generar recomendaciones novedosas y sorprendentes, manteniendo al mismo tiempo un buen nivel de precisión, independientemente del grado de curiosidad de los usuarios.

Palabras Clave

Sistemas de Recomendación, Personalidad, Curiosidad, Serendipidad, Novedad, Diversidad

Resum

En el dia a dia, les persones solen confiar en recomanacions, tradicionalment aportades per altres persones (família, amics, etc.) per a les seues decisions més variades. En el món digital això no és diferent, atès que els sistemes de recomanació estan presents a tot arreu i de manera transparent. El principal objectiu d'aquests sistemes és el d'ajudar en el procés de presa de decisions, generant recomanacions del seu interès i basades en els seus gustos. Aquestes recomanacions van des de productes en pàgines web de comerç electrònic, com a llibres o llocs a visitar, a més de què menjar o quant temps una persona ha de caminar al dia per a tindre una vida sana, amb qui eixir o a qui seguir en les xarxes socials.

Aquesta és una àrea en ascensió. D'una banda, tenim cada vegada més usuaris en internet la vida de les quals està digitalitzada, atès que el que es fa en el "món real" està representat en certa manera en el "món digital". D'altra banda, patim una sobrecàrrega d'informació, que pot mitigar-se mitjançant l'ús d'un sistema de recomanació. No obstant això, aquests sistemes també enfronten alguns problemes, com el problema de l'arrencada en fred i la seua necessitat de ser cada vegada més "humans", "personalitzats" i "precisos" per a satisfer les exigències d'usuaris i empreses.

En aquest desafiador escenari, els sistemes de recomanació basats en la personalitat s'estan estudiant cada vegada més, ja que són capaços d'enfrontar eixos problemes. Alguns projectes recents proposen l'ús de la personalitat humana en els recomendadors, ja siga en el seu conjunt o individualment per trets. Aquesta tesi està dedicada a aquest nou àrea de recomanació basada en la personalitat, centrant-se en un dels seus trets més importants, la curiositat. A més, per a explotar la informació ja existent en internet, obtindrem de forma implícita informació de les xarxes socials.

Per tant, aquest treball té com a objectiu proporcionar una millor experiència a l'usuari final a través d'un nou enfocament que ofereix una alternativa a alguns dels reptes identificats en els sistemes de recomanació basats en la personalitat. Entre aquestes millores, l'ús de les xarxes socials per a alimentar els sistemes de recomanació redueix el problema de l'arrencada en fred i, al mateix temps, proporciona dades valuoses per a la predicció de la personalitat humana. D'altra banda, la curiositat no ha sigut utilitzada per cap dels sistemes de recomanació estudiats; quasi tots han usat la personalitat general d'un individu a través dels Cinc Grans trets de la personalitat. No obstant això, els estudis psicològics confirmen que la curiositat és un tret rellevant en el procés de triar un item, qüestió directament relacionada amb els sistemes de recomanació.

En resum, creiem que un sistema de recomanació que mesure implícitament la curiositat i la utilitze en el procés de recomanar nous ítems, especialment en el sector turístic, podria clarament millorar la capacitat d'aquests sistemes en termes de precisió, sorpresa i novetat, permetent als usuaris obtindre nivells positius de satisfacció amb les recomanacions.

Aquesta tesi realitza un estudi exhaustiu de l'estat de l'art, on destaquem treballs sobre sistemes de recomanació, la personalitat humana des del punt de vista de la psicologia tradicional i positiva i finalment com es combinen tots dos aspectes. Després, desenvolupem una aplicació en línia capaç d'extraure implícitament informació del perfil d'usuari en una xarxa social, generant prediccions d'un o més trets de la seua personalitat. Finalment, desenvolupem el sistema CURUMIM, capaç de generar recomanacions en línia amb diferents propietats, combinant la curiositat i algunes característiques sociodemogràfiques (com el nivell d'educació) extretes de Facebook. El sistema ha sigut provat i avaluat en el context turístic per usuaris reals. Els resultats demostren la seua capacitat per a generar recomanacions noves i sorprenents, mantenint al mateix temps un bon nivell de precisió, independentment del grau de curiositat dels usuaris.

Paraules Clau

Sistemes de Recomanació, Personalitat, Curiositat, Sorpresa, Novetat,

Diversitat

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I

Introduction and State of the Art

Chapter 1: Introduction

Contents

Recommender Systems (RSs) are software tools and techniques providing suggestions for items to be of use to a user [9]. In order to do so, RSs collect information on the preferences of the users for a set of items, which can be acquired explicitly or implicitly. They also can use users' demographic features and/or social information [10]. In other words, the task of RSs is to turn data on users and their preferences into predictions of users' possible future likes and interests [11]. The suggestions provided by an RS are aimed at supporting their users in various decision-making processes, besides being a valuable means to cope with information overload. From the second generation of World Wide Web (WWW) [12], also called Web 2.0 [13] started in mid-2004, diverse techniques for recommendation generation have been proposed. Many of them have also been successfully deployed in commercial environments.

Development of RSs is a multi-disciplinary effort which involves professionals from different fields, such as artificial intelligence, human-computer interaction, data mining, statistics, decision support systems, marketing, consumer behaviour and psychology [9]. As a consequence, they can be used in different contexts and, by collecting information available on the web, the user's recommendation becomes personalised. To do this, the process builds an internal representation of a user based on the data gathered about the users' characteristics such as age, gender, interests, preferences, likes and dislikes, etc. Various levels of personalisation could exist within a system using explicit user characteristics (e.g. age, gender, demographics) or implicit user behaviour pattern (web browsing history, click pattern).

Nowadays, we have an amount of data never seen before, that comes mainly from Social Networks (SNs), and also a diversification and data specialisation in all areas of our daily lives (Internet of Things). The SNs have provided a unique opportunity for RSs to use other aspects of user behaviour. Besides users' structured information contained in their profiles (e.g. demographics), users produce large amounts of data about themselves in a variety of ways including textual information (e.g., likes, dislikes, comments, shares, friends). Thus, RSs are being able to extrapolate the boundaries of basic recommendations based on a user's history or similar profiles, and now they are able to generate recommendations that are increasingly "personalised", "human", and closer to the profile of the recipient.

Many latent variables such as personalities, emotions and moods which, typically, are not explicitly given by users can be extracted from user-generated content [14]. Having the ability to predict and use one or more personality traits from SNs is truly valuable for many applications, and RSs are one of them.

This new generation of "human" recommenders, also called personality-based recommender systems [15, 16, 17, 18], should consider the "character" of users as something more than simply individual behaviour, but a broad and complex group of thoughts, feelings, and behaviours. That is, "character" in recommenders must reflect the user's desires considering who she is, what and when she wants. Thus, to make recommenders even more successful, we must integrate technical designs for recommender applications with a deep knowledge about human decision-making processes [19].

Several authors have been studying ways to measure and interpret the characteristics of personality, so various approaches have been created over the years. Personality assessment studies have revealed that responses to a relatively short personality questionnaire can predict human behaviour in many different aspects of life [20]. Decades of psychology research suggest that individuals' behaviour and preferences can be accurately explained by psychological constructs called personality traits [21]. This is important, since it implies that knowledge of an individual's personality enables prediction of both behaviour and preferences across different contexts. Thus, they could be used as a "human" property of the existing RSs, since according to some psychological theories, cognitive and decision psychological phenomena have a major impact on the outcome of the decision processes [19].

One of the most popular models in psychology to define personality traits is the Big Five Factor (BFF) [22], which defines five traits: openness to experience, conscientiousness, extroversion, agreeableness and neuroticism.

In relation to e-commerce, curiosity has proven to play a key role, as described by [23] in a Groupon[1] scenario, where individual's curiosity can stimulate consumers to actively explore online group-buying websites and propel them to perceive enjoyment, excitement, and playfulness. That is, the participation in e-commerce may be influenced more by motivations such as fun, convenience and mainly the curiosity [24]. Korper and Ellis [25] describe a classic example of the impact of curiosity on business.

Briefly, the curiosity can be in three main theories. The first, almost biological in nature, is that curiosity is a human drive, much like hunger or thirst, which is satisfied by the acquisition of knowledge; the second, more cognitive in nature, is that curiosity is evoked by incongruity between something and a person's existing world view; and third, building on incongruity theories, but slightly more emotional in nature, frames curiosity as the desire to close an information gap between a given reference point and a person's existing information set [26].

In summary, this doctoral thesis has used one personality trait, specifically *human curiosity*, in a recommender system because, as stated above, it has a great relevance in the individual's decision making when choosing an item. The state of the art of recommender systems and human personality in the psychology field, identified a relevant gap in personality-based recommender systems.

Firstly, we observed that the use of data from SNs to feed the recommenders can make the "cold start" problem smoother [27, 28, 29, 30, 31] and, at the same time, it can provide valuable data for the prediction of human personality [32, 33]. Secondly, we noticed that the curiosity has been scrutinized in psychological studies in the last 100 years, and it has occupied a pivotal position in the study of motivation, emotion, and cognition since the origins of psychology; however, it was not used in RSs. The immense part of the sought to use the general personality of an individual, that is, they used the Big Five personality traits as a whole and not specific personality traits.

[1] www.groupon.com

Therefore, we identified a scenario in which we have (1) the ability to predict, in an implicit way, traits of the human personality using data available in social networks [34, 35, 36]; (2) that curiosity is indispensable for an individual in the psychological process of choosing an item [37, 38]; and (3) a gap in the use of curiosity in recommending systems [38].

Thus, this thesis aims to offer a new approach to computational recommender systems that considers the user personality. To achieve this goal, we propose the use of the curiosity, a human trait of personality according to the psychology, which is the kernel of the process of decision-making. We believe that it could clearly improve the capacity of the recommender systems in terms of accuracy, serendipity and novelty, allowing users to obtain positive levels of satisfaction with the recommendations.

1.1 Objectives

As explained above, the main goal of this thesis is to present a new recommender system based on the use of the human curiosity to provide accurate, novel and serendipitious recommendations. In order to test our system, we will focus on the tourism domain. This goal requires us to overcome some challenges such as:

1. *To review the state of the art in recommendation systems:*

    1.1. To study existing approaches of personality-based recommendation systems.

    1.2. To analyse which properties (novelty, diversity, serendipity, etc.) are adequate to consider in a recommender system that makes use of the human curiosity.

    1.3. To analyse the existing approaches that use information from social networks to generate the recommendations focusing in recommendation in the tourism domain.

2. *To identify which psychological models are used to measure a person's curiosity. As sub-objectives, we have:*
   - 2.1. To analyse some psychological models form the point of view of traditional as well as positive psychology.
   - 2.2. To identify which personality traits and sociodemographic characteristics are relevant in a tourism context.
3. *To analyse the data available in social networks to predict a person's curiosity, considering the psychological models. This implies:*
   - 3.1. To study privacy and limitation issues, besides the opportunities of social networks on the future of recommendation systems.
   - 3.2. To develop an online application capable of implicitly extract information from the user profile in a social network.
   - 3.3. To generate a model to predict the human curiosity.
4. *To develop a recommender system that considers the user's degree of curiosity to provide accurate, novel and serendipitous recommendations. This objective is divided into the following sub-objectives:*
   - 4.1. Design of a model of a recommendation system to fulfill this goal.
   - 4.2. Implementation of this model.
   - 4.3. Setting up of the framework to test the system. This includes to create a database with tourist places around the world and to implement the interface to collect the users' feedback.
   - 4.4. Evaluation of the system with the help of real users to measure the quality of the recommendations generated.

1.2 Contributions

The first contribution of this thesis is a comprehensive and thorough literature review of tourism recommender systems that use social networks, reported in journals and conferences since 2004. Moreover, we analyse the data extracted in those publications, besides properties, techniques, evaluation methods, interface, among other characteristics.

The second point is related to the development of a model for the prediction of curiosity based on data from social networks. On the one hand, an analysis of what data from these social networks are pertinent in a process of prediction of human curiosity is performed and, on the other hand, we study whether these data correlate or not with human curiosity. We also define a first model to infer curiosity from data retrieved from SNs.

Thirdly, the development of the CURUMIM system demonstrates, in a practical way, that the curiosity can play a key role in a recommendation system. We define a complete model, which is tested with several cases of study. In addition, this system is evaluated by more than 100 real users. These experiments show its ability to generate positively surprisingly recommendations of tourist places around the world using the human curiosity factor, obtaining at the same time a satisfactory level of accuracy.

In general, we understand that future recommender systems will have to deal with the challenge of recommending items as if they were recommended by a person's "best friend". In this sense, this thesis is a step forward in this new kind of computational recommendation systems based on the traits of human personality, offering a contribution in the context of one of its main traits, curiosity.

1.3 Structure of the Thesis

This PhD thesis is organized as a compendium of published research articles that compile and synthesize the results of this work. The remainder of this document is organized in three parts as follows:

1. Part I. Introduction, that gives the objectives, contributions and the list of publications. Moreover, the state of the art of the different aspects related to this thesis is included;

2. Part II. Selected Papers, which presents the articles supporting this thesis which were published in different conferences and journals.

3. Part III. Discussion, which summarises the results obtained in the published works, and it also presents some concluding remarks, some identified limitations and possible paths for future work.

1.4 Publication List

In this section, all publications related to this thesis are listed. They have been classified according to their type (conferences or journals) and the local of publication (national or international). The publications that are submitted but not published are marked with (*).

Conferences:

National

- Alan Menk and Laura Sebastia. Predicting the Human Curiosity from Users' Profiles on Facebook. In Proceedings of the 4th Spanish Conference on Information Retrieval (CERI '16). ACM, New York, NY, USA, Article 13, 8 pages. June, 2016. DOI: 10.1145/2934732.2934743 [39].

International

- Alan Menk. A Hybrid Recommendation System Based on Human Curiosity. Doctoral Consortium. In Proceedings of the 9th ACM Conference on Recommender Systems (RecSys '15). ACM, New York, NY, USA, (pp. 367-370). September, 2015. DOI: 10.1145/2792838.2796545 [40]. (**Core2017 Rank: B**).

- Alan Menk, Laura Sebastia and Rebeca Ferreira. CURUMIM: A Serendipitous Recommender System based on Human Curiosity. In Proceedings

of the International Conference on Knowledge Based and Intelligent Information and Engineering Systems (KES2017). Procedia Computer Science, 112, pp.484-493. September, 2017. DOI: https://doi.org/10.1016/j.procs.2017.08.098 [41].
(**Core2017 Rank: B**).

- Alan Menk, Laura Sebastia and Rebeca Ferreira. CURUMIM: A Serendipitous Recommender System for Tourism Based on Human Curiosity. IEEE 28th International Conference on In Tools with Artificial Intelligence (ICTAI), IEEE Computer Society. pp. 788-795, November 2017. DOI: 10.1109/ICTAI.2017.00124 [42].
(**Core2017 Rank: B**).

Journals:

- (*) Alan Menk, Laura Sebastia and Rebeca Ferreira. Recommendation systems for tourism based on social networks: a survey. Artificial Intelligence Review (AIR), ISSN: 0269-2821. Springer Netherlands Publisher [43].
(**JCR-SCI: Q2 - Categories: Computer Science, Artificial Intelligence, Impact Factor: 2.63**).

- Alan Menk and Laura Sebastia. Are you Curious? Predicting the Human Curiosity from Facebook. International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems (IJUFKS), ISSN: 0218-4885. World Scientific Publishing Company, 2017. Vol. 25, No. Suppl. 2, pp. 79-95. DOI: 10.1142/S0218488517400128 [44].
(**JCR-SCI 2016: Q3 - Categories: Computer Science, Artificial Intelligence, Impact Factor: 1.21**).

The papers included in Part II of this thesis reflect the results of this research over the last four years (2015-2018), in the context of the objectives set out in Section 1.1. However, they are pieces of a larger project that sought to introduce traits of the human personality through data from the social networks applied in computational recommendation systems.

Chapter 3 (submission currently under review) reviews and analyses publications focusing on tourism recommender systems that use social networks. This paper details the benefits and which the most used social networks in the projects about tourism recommendation are, also analysing the common extracted data, the recommendation techniques applied, the methods of evaluation, and type of recommendation generated. Through a comprehensive literature review, suggesting that research on social networks applied to recommender systems in the tourism sector is on solid and continuous growth since 2004, we sought to collaborate with the future recommender systems, by supporting researchers and practical professionals in their understanding of development in recommender system applications.

Chapter 4 (previously published in Menk and Sebastia [40]) presents our first architecture, a hybrid human curiosity-based recommendation system, which is able to measure the degree of curiosity of users and to provide recommendations in form of sites of South America based on it. To prove the efficiency of our hybrid system in contrast to traditional RSs, as well as to measure the satisfaction of users about the recommendations, we performed some experiments with the participation of 105 volunteers to predict the curiosity, and 26 volunteers to evaluate the recommendations generated by this system.

Chapter 5 (previously published in Menk and Sebastia [39]) is focused on predicting just one of the human personality traits, the curiosity. We counted with the collaboration of 105 Facebook users, that granted access to their profiles and filled in a questionnaire to calculate their degree of curiosity. We analyse the information that can be extracted from the users' profile on Facebook. We present our methodology for extracting, analysing and classifying the Facebook profile information and we determine the set of features that can be used to describe their degree of curiosity. Then we present some results about the correlations between some features extracted from the Facebook profile and the curiosity degree, in order to determine which features are more relevant. Finally, we generate a prediction model in the form of a decision tree.

Chapter 6 (previously published in Menk and Sebastia [44]) presents a new approach for predicting the human curiosity built on the work developed in Menk and Sebastia [39]. In this paper, we relied on greater participation of volunteers (176 users), and generate several new prediction models of the human curiosity, with the support of supervised machine learning models. In addition, this new experiment with 176 users found new correlations not previously identified.

Chapter 7 (previously published in Menk et al. [41]) describes an important part of our project, the CURUMIM system. From data available on social networks, it is able to predict the level of curiosity of a user to then generate novel and serendipitous recommendations of tourist places (cities) around the world. First, an overview of the state-of-the-art in serendipity, novelty and psychology in RS is provided. Then, we present CURUMIM, including its architecture, the necessary input data, and the developed techniques to then detail two complete use cases which show the main aspects of the RS.

Combining all the papers listed here, Chapter 8 (published in Menk et al. [42]) presents the final version of CURUMIM, an online tourism recommender system, able to generate serendipitous recommendations of places around the world. In summary, from data available on social networks, it predicts the degree of curiosity of a user, which is then used, along with the user history and her level of education, to select the most appropriate recommendations. We have performed an experiment with 74 real users who reported positive levels of satisfaction with the recommendations in terms of accuracy, serendipity and novelty.

Chapter 2: State of the Art

Contents

This chapter focuses on the state of the art of the three aspects on which this thesis relies. The first section provides an overview of state of the art in recommender systems, their properties and the details of some relevant works about recommendation systems.

The second one summarises general ways to measure human personality, either in general or focused on some specific traits. Thus, first we analyse the state of the art in the field of psychology, that developed psychological techniques for measuring personality. Then, we describe the state of the art in relation to the computational projects that have made use of these psychological techniques for the measurement of the human personality through the use of social networks; that is, using data available on social networks, they predict some traits or the personality as a whole of a given person.

Finally, the third focuses on recommender systems that use human personality to improve their recommendations. Thus, we check which traits of human personality have been investigated in the context of recommender systems, how human personality has been employed, and what the gains and goals that this adoption brought to these recommenders have been.

2.1 Recommender Systems

Sielis et al. [45] defined a Recommender System (RS) as a software tool in applications or websites that suggests information (e.g. items, people, news articles) that might be of interest to the end user, taking into account various types of knowledge and data, such as the user's preferences, actions, tasks and contextual information. Ricci et al. [9] presents a complete definition, saying that the RSs are software tools and techniques providing suggestions for items to be of use to a user. The suggestions provided by a recommender system are aimed at supporting the users in various decision-making processes, such as what items to buy, what music to listen, or what news to read. RSs are valuable means for online users to cope with information overload and help them make better choices.

Recommender systems are no longer novelties. If in the past we had, for instance, a friend or relative who recommended us a film, a restaurant, or even a job, today with the digitization of everything, recommender systems play a fundamental role in this scenario. Adomavicius et al. [46] in 2005 already pointed out that RSs had become an important research area, since the appearance of the first papers on collaborative filtering in the mid-1990s.

In addition, Ricci et al. [47] mention five responsibilities that are business-oriented: (1) Increase the number of items sold; (2) Diversify sales; (3) Increase user satisfaction; (4) Increase user loyalty; (5) Understand user needs. In this sense, to give an state of the art on RSs, this subsection briefly summarises some important aspects. Some definitions have been presented previously and, in the following subsections, the main properties (e.g. diversity, serendipity, utility, etc) are defined; then, we also describe the main techniques used in the development of RSs, such as collaborative filtering, content-based, and others. We finish with the description of online and offline evaluation techniques used in RSs.

2.1.1 Properties

This subsection presents a range of *properties* introduced by Ricci et al. [9] that are commonly considered when deciding which recommendation approach to select. Aggarwal defines some of them such as diversity, novelty, relevance and serendipity, as *operational* and *technical* goals of recommender systems, stating that, when considering them, higher sales of products and/or services are achieved, thus fulfilling the most common central purpose of a recommender system: increasing sales. The *properties* alphabetically ordered are listed bellow:

Accuracy is considered one of the most fundamental measures through which RSs are evaluated. A basic assumption in an RS is that a system that provides more accurate predictions will be preferred by the user. This way, many projects try to find algorithms that improve the predictions, assuring accurate and consistent user ratings for items.

Adaptivity means that an RS may operate in a setting where the item collection changes rapidly, or where trends in interest over items may shift.

Confidence in the recommendation context can be defined as the system's trust in its recommendations or predictions. That is, Collaborative Filtering (CF) recommenders tend to improve their accuracy as the amount of data over items grows. So, the confidence in the predicted property typically also grows with the amount of data.

Coverage is referred to the degree to which recommendations cover the set of available items and the degree to which recommendations can be generated to all potential users.

Diversity is the average pairwise dissimilarity between recommended items [48], and implies that the set of proposed recommendations within a single recommended list should be as diverse as possible [49]; generally, diversity is defined as the opposite of similarity. In some cases, suggesting a set of similar items may not be as useful for the user because it may take longer to explore the range of items. On the other hand, if there are not any similarities among the items recommended, users' satisfaction with the system could be affected too [50, 51, 52].

Novelty is an important metric of customer satisfaction [53], which is able to measure how different an item is with respect to "what has been previously seen" by a user [54] (e.g. popular films of a preferred genre would rarely be novel to the user). According to Zhang [53], novelty should have three characteristics: the item is unknown by the user; the item is satisfactory to the user; and, the item is dissimilar to items in the profile of the user. The RSs are truly helpful when the recommended item is something that the user has not seen in the past [49].

Privacy is related to the user preferences, which he willingly discloses to get useful recommendations, to be protected of a third party knowledge.

Relevance is the most obvious operational goal of an RS, it refers to recommend items to be relevant to the user at hand.

Risk is the effect of uncertainty on objectives, where an uncertainty includes events which may happen or not. In some cases, a recommendation may be associated with a potential risk. For instance, in a stock recommendation for purchase, users may wish to be risk-averse, preferring stocks that have a lower expected growth with a lower risk of collapsing, while others prefer stocks that have a potentially high, even if less likely, profit (risk-seeking) [9, 55].

Robustness is the stability of the recommendation in the presence of "fake" information, normally inserted on intentional in order to influence the recommendations. For instance, an owner of a Point of Interest (POI) may wish to increase the rating for his POI. This can be done by injecting fake user profiles that rate the POI positively, or by injecting fake users that rate the competitors negatively.

Scalability in RSs is related to its ability to provide rapid results even for huge datasets. Usually, it is measured by experimenting with growing datasets and monitoring how the speed and resource consumption behave as the task scales up.

Serendipity has been recognized as one of the most untranslatable words. Serendipity is "the faculty of making fortunate discoveries by accident", where "discovery" means the novelty of serendipitous encounters, while "fortunate" indicates that the discovery must be relevant and unexpected. Kaminskas and Bridgek [56] define serendipity in one word, surprise. In the RSs context, it is a measure of how positively surprising the recommendations are, in other words, wherein the items recommended are somewhat unexpected, and therefore there is a modest element of lucky discovery, as opposed to obvious recommendations. It is a difficult concept to study, as it includes an emotional dimension, besides to be challenging to define serendipity in recommender systems as well as what kind of items are serendipitous and why, since generally serendipitous encounters are very rare [57].

Trust refers to the user's trust in the system recommendation. For instance, it may be beneficial for a recommender generate a few items that the user already knows and likes. Thus, even though the user gains no value from this recommendation, she observes that the system provides reasonable recommendations, which may improve her trust in this RS for unknown items.

Utility refers to cases where the recommendation engine can be judged by the revenue that it generates for the website. In general, different types of utility functions that the recommender tries to optimize are defined. In many cases, measuring the utility, or the expected utility of the recommendations may be more significant than measuring the accuracy of recommendations.

Novelty vs Serendipity

While the definitions may overlap, several authors distinguish novelty from serendipity [56]. As explained by Herlocker et al. [58], novelty occurs when the system suggests to the user an unknown item that she might have autonomously discovered. A serendipitous recommendation helps the user to find a surprisingly interesting item that she might not have otherwise discovered (or it would have been really hard to discover).

To provide a clear example of the difference between novelty and serendipity, consider an RS that simply recommends a film that was directed by the user's favourite director. If the system recommends a film that the user was not aware of, the film will be novel, but probably not serendipitous. On the other hand, a recommender that suggests a film by a new director is more likely to provide serendipitous recommendations.

The subjective nature of serendipity is certainly quite a problem when trying to conceptualize, analyze and implement it, because it is by definition not particularly susceptible to systematic control and prediction [59]. Andel [60] even claimed that we cannot program serendipity because of its nature. However, research and projects have relativized Andel's assertion and have since been developing projects and research that apply serendipity.

2.1.2 Techniques

Recommender systems should propose items of potential interest to a user or, alternatively, compare the utility of some items, and then decide which items to recommend based on this comparison. An RS can be applied in different item domains such as books, websites, financial service, and software artefacts [61].

In the subsequent, we present an initial overview of the different types of RSs, distinguishing between five different basic classes of recommendation approaches [61, 49, 9, 62]: Content-Based (CB), Collaborative Filtering (CF), Knowledge-Based (KB), Demographic (DF) and Hybrid (HY).

Content-Based (CB)

Essentially, a CB learns to recommend items that are similar to those the user has liked in the past. The similarity of items is calculated based on the features associated with the compared items. The main advantage of this technique is the "user independence", given that it depends only on the user's own data; in other words, it identifies the common characteristics of items that have received a favourable rating from a user u, and then it recommends to u new items that share those characteristics [63, 64, 65]. For example, when a user rated (positively) a POI, the system can recommend similar POIs by calculating how similar these two POIs are, according to their features.

Commonly, the input in CB systems is a set of item content descriptions, such as the genre, director and actors, in the context of films. With respect to the user profile, Candillier et al. [66] distinguishes three approaches:

1. Profiling information can be obtained from users explicitly, through questionnaires about their preferences for the item descriptions;

2. User profiles may be built implicitly from user preferences for items, by searching for commonalities in liked and disliked item descriptions;

3. User models may be learned implicitly by an automatic learning method, using item descriptions as input to a supervised learning algorithm, and producing user appreciations of items as output.

The profiles of users are interpreted as vectors of weights on item descriptions. Any other user model may be considered if an automatic learning method is used. That is, the items that have a high degree of proximity to a given user's preferences would be recommended.

Aggarwal et al. [49] describe some advantages and disadvantages of the CB method. An advantage that it is capable of making recommendations for new items when sufficient rating data are not available for that item, given that other items with similar attributes might have been rated by the active user. This way, CB will be able to leverage these ratings in conjunction with the item attributes to make recommendations. On the other hand, some disadvantages also exist. For example, when the content does not have enough information to discriminate the items precisely, the recommendation will be not accurate at the end. Another one is the over-specialization problem, that is, the CB method provides a limited degree of novelty, since it has to match up the features of the user profile and items. Another drawback is the new user problem, that is, when there is not enough information to build a solid profile for a user, the recommendation could not be provided correctly. In other words, to be efficient, a CB system needs rich and complete descriptions of items and well-constructed user profiles [66].

Collaborative Filtering (CF)

Emerged in the mid-90s [67] and considered the most popular and widely implemented technique in RS [47], the fundamental idea of CF approaches is to exploit information about the past behaviour or the opinions of an existing user community for predicting which items the current user of the system will most probably like or be interested in [68]. Schafer et al. [69] define CF as the process of filtering or evaluating items using the opinions of other people. These opinions can be obtained explicitly from users through form responding, or by using some implicit measures, such as records of the previous purchasing. That is, CF is an algorithm for matching people with similar interests for the purpose of making recommendations [47]. For instance, a system may recommend a customer who travelled to Madrid and Lisbon, to travel to Rome, because other users that travelled to Madrid and/or Lisbon, travelled to Rome as well.

In general, the stages that the CF algorithms have in common in the generation of the recommendations are three:

1. the calculation of neighbors, that is, users with tastes or needs more similar to the active user.
2. the prediction of the preference evaluation, that is, once the neighbors are obtained, a prediction is made that estimates the preference value that the active user would give to each of the products that he has not evaluated.
3. the best-rated top-N recommendation, where the list of recommended products is ordered by their predicted preference value in descending order and the first N products on the list are recommended.

Generally, two types of methods are used, the *memory-based* and *model-based* methods. The *memory-based* method was the earliest CF algorithm in which the ratings of user-item combinations are predicted on the basis of their neighbourhoods; it can be user-oriented or item-oriented. The *model-based* method refers to the machine learning and data mining methods used in the context of predictive models; in cases where the model is parameterised, these are learnt within the context of an optimization framework. John et al. [70] present a summary of basic techniques applied to CF: clustering [71], algorithms based on association rules [72], Bayesian networks [73], reduction of dimensionality [74] and singular value decomposition [75].

As other recommendation methods, CF has advantages and disadvantages. The main positive points are related to the no necessity to have information about the products that are going to be recommended. This is because CF RSs treat the products as a "black box", of which only the preference ratings that the different users of the system have given on them are known. Another advantage is that CF improves accuracy over time, in other words, the more users and the greater number of shared ratings, the better the recommendation will be.

On the other hand, the disadvantages of CF are: they need a large amount of data to function, they suffer from scalability problems, and from the cold start problem. The cold start problem can be viewed from two perspectives: the user perspective, because a user may not have a sufficient number of preference ratings so that the neighbourhood cannot be calculated correctly; and the item perspective, when a new product is introduced in the system and it cannot be recommended until there is a sufficient number of ratings about it.

Knowledge-Based (KB)

This technique works by recommending items based on specific domain knowledge about how certain item features meet users' needs and preferences and, ultimately, how the item is useful for the user [47]. In other words, it generates recommendations to the user based on the knowledge about his needs towards a particular item. These recommendations are performed under measures of utility, derived from the knowledge of the relationship between a specific user and item. For this reason some authors call it "utility recommendation" [76].

An interesting point about KB RS is that it avoids some drawbacks such as it does not have a ramp-up problem since its recommendations do not depend on a base of user ratings. It does not have to gather information about a particular user because its judgements are independent of individual tastes. These characteristics make KB not only valuable systems on their own, but also highly complementary to other types of RSs [77].

For example, a knowledge-based system that recommends travels can take advantage not only of what is known about the user's experience on previous visited places, but also what is known about the characteristics of the places already visited and the locations available to be recommended.

Demographic Filtering (DF)

Essentially, DF is based on the idea that individuals with certain common personal attributes (sex, age, country, etc.) will also have common preferences

[10]. That is, this algorithm recommends items based on the demographic profile of the user, providing different recommendations for different demographic niches and/or combining the ratings of users in these niches [47, 78, 79].

One of the problems with this approach is that the recommendations are very generic, failing to capture the specific tastes of people, since it is assumed that people grouped in the same demographic profile tend to have an interest in similar content, regardless of the prior navigation of each individual.

Hybrid approaches (HY)

Finally, hybrid RSs are based on the combination of the above-mentioned techniques [47] (or some others, because this is not an exhaustive list). A hybrid RS combines techniques "X" and "Y" trying to enhance the advantages of "X" to mitigate the disadvantages of "Y" (and vice versa).

Burke et al. [80] presents some common strategies used in hybrid recommendation projects such as:

- Alternation of techniques (Switching), where the system chooses, among several recommendation methods, the one that best suits each situation.
- Cascade techniques, where different techniques are used hierarchically, giving priority to each one, and then systems with lower priorities are used to break ties in the results of the highest priority.
- Combination of weights, which consists of numerically combining the score that different hybridized systems give to a specific item. One way of doing this could be the linear combination or a convex combination of the scores.
- Feature Augmentation (Magnification), which is used to calculate a set of features that are then used as input to the next technique.
- Feature combination, derived from different knowledge sources are combined together and given to a single recommendation algorithm.

- Meta-Levels, where a technique produces a model that will then be delivered to the next technique.

- Mixed of results, which means that recommendations of different types are delivered jointly to the user, that is, several lists of recommendations where each one is calculated with a different technique are presented to the user. This leaves the user the decision of which list of recommendations is more convenient at each moment.

2.1.3 Evaluation

Developers and researchers have been trying to improve RSs more and more. In the search for a suitable recommendation algorithm, a question is raised: how good an RS is? In order to answer this question, it is necessary to understand the evaluation methodology of a recommendation system. That will help us understand why and how we should evaluate, and what should be evaluated in those systems.

Due to the complexity and variety of today's RSs, their use in different areas, and the similarity of intentions and functionalities of some of them [81], their evaluation is key to keep enhancing those systems in order to achieve better results towards the customer. Evaluation of RSs implies assessing how much of these properties have been achieved [82, 49].

Typically, evaluations are based on experiments, which must be well designed, since an incorrect design of the experimental evaluation can lead to either gross underestimation or overestimation of the true accuracy of a particular algorithm/model. By analysing its results, the researcher can then select the best performing algorithm, given structural constraints such as the type, timelines and reliability of available data, allowable memory and CPU footprints. Furthermore, most researchers who suggest new recommendation algorithms also compare the performance of their new algorithm to a set of existing approaches. Such evaluations are typically performed by applying some evaluation metric that provides a ranking of the candidate algorithms (usually using numeric scores) [9].

As mentioned before, an RS may have different goals. Therefore, a single evaluation criterion cannot capture many of the goals of the designer, so evaluation is often multifaceted. With the evaluations, researchers are able to measure some important properties, such as accuracy, satisfaction, profit generated by the system, user-changing behaviour, algorithm enhancement.

Recently, researchers have been attempting to solve this problem by evaluating different concepts of evaluation, rather than simply using predictive accuracy [58]. There are many properties (concepts) regarding the evaluation of recommendations; in subsection 2.1.1 presented above we described twelve of them: accuracy, adaptivity, confidence, coverage, diversity, novelty, risk, robustness, scalability, serendipity, trust and utility.

Although some authors, for instance, Ricci et al. [9] and Robillard et al. [81], describe three different types of experiments (*offline*, user studies and *online*), Silveira et al. [83] describe that historically, the evaluations of these properties have been performed in *offline* or *online* protocols. So, we are going to direct our effort in these two evaluation methods.

In summary, online experiments involve issuing recommendations and then querying the users about how they rate an item. Instead, *offline* experiments do not require real users, as they use part of the data to train the algorithm and part to test the predictions regarding the users' tastes [83]. From all the projects analysed, the number of projects[1] that opted for an *offline* evaluation is considerably higher in relation to those that perform an *online* evaluation, due to different reasons. On the one hand, *offline* evaluation has an enormous amount of data available, lower costs, independence in relation to the availability of users, and well-defined standardisation in relation to the experiments; on the other hand, the *online* evaluation is the most desired, since it can provide accurate results on how good a system is, though these experiments with real users are usually costly. As the number of *offline* works is immense, we will highlight some RSs in different application scenarios, besides considering

[1] from a search of scientific papers performed by means of a filtering process in some databases (e.g. ACM Digital Library, IEEE Xplore, Springer) selecting articles of RSs, searched as "recommend*", "offline" OR "online"

the number of citations according to Google Citations[2]. They will be further detailed in the next subsections.

Offline Evaluation

The *offline* evaluation is based on the idea of estimating the prediction quality of an algorithm using datasets that include user-item evaluations (ratings). That is, a dataset is divided into training and test sets (e.g. we can use 80% of data for training and 20% for test) [9]. Such settings are used for the evaluation of a recommendation algorithm in the light of given evaluation metrics on the basis of repeated sampling and cross-validation.

We can mention Yang et al. [84], who constructed a location-aware RS that combines the information abundance of the Internet with the tangible richness of physical shopping, in terms of location. This system is designed to recommend vendors' webpages (including offers and promotions) to interested customers. To do so, the interest of the customer is first estimated based on the history of web browsing behaviour. Then, the recommendation list of possible webpages is generated based on the estimated customer's interest and also taking into account the physical distance between customer and vendor. The system is evaluated by means of synthetic and empirical data, to evaluate its *online* workload and its effectiveness, respectively.

In addition, Levandoski et al. [85] propose LARS, a location-aware RS that uses location-based ratings to produce recommendations. It addresses a problem that most RSs do not consider, by dealing with three types of location-based ratings: spatial ratings for non-spatial items, non-spatial ratings for spatial items, and spatial ratings for spatial items. This triple taxonomy of location-based ratings is supported by its RS and can be applied separated or jointly. By using datasets from MovieLens and Foursquare, and also a synthetic dataset generated randomly, they developed experiments comparing several variations of their system with the standard item-based collaborative filtering technique in terms of recommendation quality, scalability, and query

[2]scholar.google.com

processing performance, among others, achieving better results compared with the traditional RSs.

Using a Chinese social platform for sharing reviews and recommendations for books, film and music called Douban, Liu and Aberer [86] propose SoCo, an RS that combines contextual information and social network information to improve the quality of recommendations. To do this, some steps were performed: (1) diverse contextual information are extracted, which is expected to be associated with user preference; (2) a random decision trees algorithm is applied to partition the given user-item-rating matrix, considering some contextual information; (3) a matrix factorization model is employed to predict missing preferences of a user, and on the basis of this, an additional social regularization term was introduced to improve recommendation quality (considering the influence of a user's friends from an SN); (4) a context-aware Pearson Correlation Coefficient was also proposed to measure user similarity. With this, they conducted some experiments on two real datasets to demonstrate the performance of the system from the root mean square error showing that SoCo outperforms the state of the art context-aware and social recommendation models.

When we analyse the technical bias of these projects, we are faced with works like Zheng et al. [87], who presented a novel serendipity-oriented recommendation mechanism combining the concepts of item rareness and dissimilarity. The less popular is an item and the further is its distance from a user's profile, the more unexpected it is assumed to be. In relation to the usefulness, the author adopts PureSVD latent factor model, whose effectiveness in capturing user interests has been demonstrated. Also, in order to take serendipity into account, they employed a weight for penalising items that are popular and similar to the user's profile. Their evaluation was performed comparing two representative serendipitous algorithms and two popular latent factor models using popular benchmark datasets. Their results suggested the algorithm not only achieved the best performance in terms of serendipity, but it also performed well in terms of precision and diversity.

Online Evaluation

The *online* evaluation is based on the idea of using user study techniques to evaluate an algorithm, a user interface, or a whole system *online*. In one hand, nowadays, the major challenge of this approach is to define a standardised evaluation framework. On the other hand, *online* evaluation is often very expensive and involves the recruitment of study participants who are then engaged in tasks. To avoid this limitation, as an alternative to lab studies, recent research in recommender systems started to use crowd-sourcing platforms as a source of user feedback [61].

As an example of *online* evaluation, we can highlight Woerndl et al. [88], that used only 7 users in their experiments, to develop an application to recommend mobile applications for individuals. Or, a recommender that compared two approaches for presenting information in a spoken dialogue system generating flight recommendations, called *wizard-of-Oz (WoZ) study* by Winterboear and Moore [89]; this project counted on the participation of 34 participants, mostly students of the University of Edinburgh.

Another one, developed by Ducheneaut et al. [90], presents the results of an experiment assessing user satisfaction with recommendations for leisure activities. These recommendations are generated by an RS called Magitti, which takes into consideration user's contextual data and tastes. Such recommendations are obtained from different combinations between a CF technique and the user's context plus preferences; the main goal of this experiment is to find the best combination of techniques in order to achieve the most effective recommendations. The results of this qualitative evaluation are in terms of usefulness and serendipity, and show that a hybrid approach may produce too exotic or too familiar recommendations. Also, it is highly user-dependent and, for systems addressed to users highly familiar with the recommended item, the CF approach is not enough.

Called MMedia2U, Lemos et al. [91] presented a prototype of a mobile photo RS that exploits the user's context and the context when the photo was taken as a means to improve the recommendation. That is, the system generates recommendations of photos created in contexts similar to current users' context (a similarity measure is used). This similarity is computed from three contextual dimensions (spatial, social, and temporal). MMedia2U has two types of users as target, those who are in an unusual context (e.g., visiting a tourist sight for the first time) and those who have already been in this similar context and that the recommended photos may give a new vision and perspective of the situation they find themselves. In order to measure the satisfaction in relation to MMedia2U recommendations, a group of 13 users evaluated photos from 8 different contexts. Their results showed that the system can bring gains in the photo recommendation compared to a random list. Farther, Durao and Dolog [92] presented a tag-based RS which suggests similar Web pages based on the similarity of their tags from a Web 2.0 tagging application. The *online* evaluation was aimed at measuring the "acceptance" of the recommendations; in other words, the author opted to measure the degree of satisfaction of users about the received recommendations. This evaluation involved 38 participants from 12 countries.

Another interesting project is Auralist [93], a framework that generates recommendations focused on diversity, novelty and serendipity, but limiting the impact on accuracy. To aid the quantitative analysis, the authors described a series of metrics designed to assess both accuracy and the three additional properties. In relation to the database, this experiment was conduced over a 360k Last.fm user dataset and involved 21 participants. Each participant was asked to name six pre-2008 artists that represented his/her music tastes, which were used as "seed" histories for the recommendation. This project concludes that the serendipity enhancing techniques improve overall user satisfaction.

Finally, Bostandjiev et al. [94] presents TasteWeights, an interactive hybrid RS that generates item predictions from multiple social and semantic web social networks. In this evaluation, accuracy, utility and the role of the interface as an explanatory mechanism for the underlying algorithms was measured, using to each social network a different core recommender system technique such as: content-based/semantic (Wikipedia), collaborative/social (Facebook), and expert-based (Twitter), through 32 participants ranging in age from 19 to 35.

Most of the projects presented previously developed their experiments with the participation of few volunteers. Unfortunately, it is not easy to find a wide group of users willing to participate in this kind of evaluations. In summary, table 2.1 presents a general overview of these works describing experiments and evaluations with the number of users and citations[3]. Even in the face of this fact of limitation of volunteers, the relevance of the projects is remarkable when we observe the number of citations of these works.

Table 2.1: *Some relevant works related to RSs ordered by the number of participants.*

References	Title	Participants	Citations
[88]	A hybrid recommender system for context-aware recommendations of mobile applications recommendation	7	142
[91]	Towards a Context-Aware Photo Recommender System	13	12
[90]	Collaborative Filtering Is Not Enough? Experiments with a Mixed-Model Recommender for Leisure Activities	16	23
[93]	Auralist: introducing serendipity into music recommendation	21	193
[94]	TasteWeights: a visual interactive hybrid recommender system	32	145
[89]	Evaluating Information Presentation Strategies for Spoken Recommendations	34	15
[92]	A Personalised Tag-Based Recommendation in Social Web Systems	38	50

2.1.4 Tourism Recommender Systems

As the tourism industry grows around the world, technological challenges in this industry follow the same trend. Different approaches, solutions and innovations have been developed in this area. Computational recommender systems have emerged as a means of selecting and recommending items from a wide range of alternatives becoming like a human aid [95].

[3]The number of citations was obtained in January 2018 from Google Scholar, in order to show the level of relevance of these works.

They range from approaches that seek to solve the difficulties encountered by tourists, from when they plan the trip until arriving in an unknown city. Some systems seek to help users through recommendations of places, routes or points of interest, through traditional approaches of recommendations such as content-based [96, 97], collaborative filtering [98, 99] and hybrid approaches [100, 101]. In the technological current context, the massive use of social networks made the role assigned to recommender systems change from simply filtering tasks and selecting of items through traditional techniques, to a growing need to bring “what really matters to each individual” based on the personality, tastes and wishes of each individuals with the items that have not been discovered by him.

Therefore, when we filter our searches only in projects of recommenders in the tourism sector, that is, that make recommendations of places, POIs, photos, routes, or tourist destinations, which is the focus of this thesis, different projects with different approaches arise.

Roes et al. [102] introduce a new version of a personalised museum guide (including museum tours) offered on a mobile device in the physical museum space, but that can also be used online; in this way, personalised interaction both online and in the museum are supported. Moreover, a dynamic user model is used to ensure high relevance of recommended artworks. Finally, semantic web technologies to enrich the museum collection and guarantee serendipity, novelty and relevance of the recommendations are applied. Also, the authors proved that the system helps users, especially novice users, to quickly elicit their art interests in the museum collection and it recommends artworks suiting different user’s preferences.

De et al. [103] proposed an RS that offers personalised recommendations for travel destinations to individuals and groups. This hybrid system considered recommendations based on the users’ rating profile, personal interests, and specific demands for their next destination combining content-based, collaborative filtering, and knowledge-based solution. For groups of users, individual recommendations are aggregated into group recommendations, with an additional opportunity for users to give feedback on these group recommendations. About the databases, Wikivoyage and Wikipedia were used. In relation to the evaluation, the system developed was submitted for 16 users, who are representative of the target market of a travel service. These volunteers were asked to experiment with the recommender system and evaluate the different recommendation lists (CB, CF, KB and HY). As a result, the authors conclude that travel destinations are a complex domain for recommendations, characterized by personal preferences, user constraints, and the typical group activity.

Another interesting paper was presented by Moreno et al. [104] describing the development of the SigTur/E-Destination, a complete web-based system that provides personalised recommendations of touristic activities in the region of Tarragona. In comparison with other similar works, the SigTur/E-Destination system presents some novel characteristics, such as, the integration of several types of information and recommendation techniques. It employs many recommendation techniques, from the use of stereotypes (standard tourist segments) to content-based and collaborative filtering techniques. The use of a domain ontology to guide the recommendation process permits to make inferences about the correspondence between the characteristics of an activity and a certain user profile. It also includes GIS tools to store the main tourism and leisure resources with geospatial information, which is used to recommend the activities and to show the results in a user-friendly map-based Web application. It is also worth noting that their project also relies on real users in their experiments. Their results, in brief, meant that the final recommendations had a good diversity and match quite nicely with the main motivations of the user.

In summary, there is a great variety of techniques, models, algorithms, etc. that are used in different RSs. For example, the context-aware RSs, that characterise the situation of an entity (person, place or object) that is considered relevant to the interaction between a user and an application, including the user and the application itself [105]. For instance, in a tourism RS, the context referring to the season in which a person is going to travel is important because recommendations of destinations in winter should be very different from those provided in summer [65].

2.2 Obtaining the Human Personality

The psychology through human personality, on the one hand, is widely used to identify psychology and behavioural disorders and diseases, or for us to better know ourselves, how, why we act this or that way. On the other hand, it also can be used to aid and improving a huge amount of technology to what we are exposed to. Especially because the technology exists to make our lives better and easier.

A psychometric test is one of the most common and easy ways that people can use to find out their personality, and there are several different tests that can be taken, according to different authors and approaches. Subsection 2.2.1 focuses on some of the most well-known models in psychology for personality measurement through forms that can be found and a comparison between them. Then, Subsection 2.2.2 presents some projects capable of measure the human personality using only data available on social networks. Subsection 2.2.3 presents the positive psychology, their virtues and strengths, and their characteristics in relation to strength of curiosity.Finally, Subsection 2.2.4 presents some aspects of personality and sociodemographics in the environment in travel choices.

2.2.1 The Personality Through the Forms

Our personality is constantly expressed in our daily activities, in our social relations, but these footprints can also be measured by means of questionnaires.

Different personality traits are associated with different psychological dimensions [32], that is, the number of psychological models to measure different personality traits and dimensions is numerous. For example, the *Affect scales*, through a 20-item form, are referred to as measures of affect or measures of emotion[106]; the *Well-being scales* [107] using a five-item form is capable of measure tendencies of feeling good about oneself and the future and general joyfulness; the *Appetitive motivation scales* [108] is able to measure three factors: reward responsiveness or reactivity to rewarding opportunities; reward-seeking efforts, and the propensity to be spontaneous. Another one is the *social desirability scales* [109], a 40-item which assesses the impression management (e.g. presenting oneself in an unrealistically favourable light) and self-deception (e.g. denying universally true but potentially threatening self-descriptions). The *state trait personality inventory* consists of eight 10-item scales for measuring emotional states and the traits anxiety, anger, depression, and curiosity [110]. The *sensation seeking scale* [111] is used to assess individual differences in the tendency to seek novel sensory stimulation by engaging in social exploratory behaviour; the *novelty experiencing scale* [112] measures individual differences in the tendency to approach or avoid novel stimuli that activate sensory and cognitive processes.

We focus here on the most well-known models in psychology for the measurement of human personality, especially curiosity. First, we present the details of Big Five Factor (BFF), a model able to measure the complete personality of a person. Then, Curiosity and Exploration Inventory (CEI-II) is presented, a model focused on a specific human personality trait, curiosity, which is the trait this thesis focus on. And finally, we compare both.

Big Five personality traits

The article presented by Johan and Srivastava [8] defined one of the most used and known models, the Big Five Factor (BFF), which aims to "categorise" the personality into five dimensions derived from the analysis of the natural-language terms people use to describe themselves and others. Those five factors (fig. 2.1) are the following personality dimensions: openness, conscientiousness, extraversion, agreeableness, and neuroticism. They summarise several more specific facets that comprise a person's personality, and are described bellow.

Openness is highly compatible with the motivational goals of self-direction (autonomy of thought and action and openness to new ideas and experiences)

Figure 2.1: *The Big Five Factor Personality Traits Illustration by Carter [1]*

and universalism (understanding and tolerance for all people and ideas and appreciation of beauty and nature). It is also compatible with the motivational goals of stimulation values (novelty and excitement) [113]. People who rate high on openness tend to be very creative, open to trying new things, focused on tackling new challenges. That is, people incompatible with openness dislike change, do not enjoy new things, and are not very imaginative [1].

Conscientiousness is a tendency to show self-discipline, act dutifully, and aim for achievement. McCrae and John [114] identify two distinct aspects of conscientiousness, a proactive aspect (will to achieve) and an inhibitive aspect (holding impulsive behaviour in check) [113]. In summary, those who are high on the conscientiousness also tend to finish important tasks right away, pay attention to details or also, enjoy having a set schedule. On the other hand, people who are low in this trait tend to dislike structure and schedules, make messes and not take care of things or also procrastinate and fail to complete the things they are supposed to do [1].

Extraversion is compatible with pursuing excitement, novelty, and challenge, i.e. the goals of stimulation values. Moreover, the active and assertive aspects of extraversion facilitate the goal of achievement values, success through demonstrating competence according to social standards. Extroverted behaviour is also likely to facilitate the pursuit of pleasurable experience, i.e. the goal of hedonism values [113]. People who rate high on extraversion tend to enjoy being the centre of attention, like to start conversations, enjoy meeting new people, feel energized when they are around other people. In contrast, people who rate low on extraversion tend to prefer solitude, feel exhausted when they have to socialize a lot, dislike making small talk, carefully think things through before they speak, dislike being the centre of attention [1].

Agreeableness is highly compatible with the motivational goal of benevolence values-concern for the welfare of people with whom one has personal contact. Agreeableness is also quite compatible with the motivational goals of conformity values (not violating norms or upsetting others) and of traditional values (accepting and complying with cultural and religious norms). In contrast, agreeableness conflicts with pursuing dominance and control over others, the goal of power values. In summary, Cherry [1] said that people who are high in this trait, in one hand, tend to have a great deal of interest in other people, feel empathy and concern for other people or also, enjoy helping and contributing to the happiness of other people; on the other hand, people who are low tend to take little interest in others, have little interest in other people's problems or also, insult and belittle others.

Neuroticism (sometimes reversed and called Emotional Stability) describes vulnerability to unpleasant emotions such as anger, anxiety, or depression [20]. Those who are high on the neuroticism tend to experience a lot of stress, worry about many different things, get upset easily and, feel anxious. Those who are low in this trait are typically emotionally stable, deal well with stress, rarely feel sad or depressed and also are very relaxed [1].

Table 2.2 presents the complete taxonomy of BFF from the analysis of 112 terms. These terms clearly define the five factors (cited previously), and each term loads only on its respective factor [8].

Regarding the measurement approaches of the BFF, we can mention the NEO Personality Inventory-Revised (NEO-PI), considered the most comprehensive inventory. It contains 240 items and permits the measurement of the

Table 2.2: *Based on the paper presented by John and Srivastava [8].*

Openness		**Conscientiousness**		**Extraversion**	
Low	High	Low	High	Low	High
-.74 Commonplace	.76 Wide Interests	-.58 Careless	.80 Organized	-.83 Quiet	.85 Talkative
-.73 Narrow Interests	.76 Imaginative	-.53 Disorderly	.80 Thorough	-.80 Reserved	.83 Assertive
-.67 Simple	.72 Intelligent	-.50 Frivolous	.78 Planful	-.75 Shy	.82 Active
-.55 Shadow	.73 Original	-.49 Irresposible	.78 Efficient	-.71 Silent	.82 Energetic
-.47 Unintelligent	.68 Insightful	-.40 Slipshot	.73 Responsible	-.67 Withdrawn	.82 Outgoing
	.64 Curious	-.39 Undependable	.72 Reliable	-.66 Retiring	.80 Outspoken
	.59 Sophisticated	-.37 Forgetful	.70 Dependable		.70 Dominant
	.59 Artistic		.68 Conscientious		.73 Forceful
	.59 Clever		.66 Precise		.73 Enthusiastic
	.58 Inventive		.66 Practical		.68 Show-off
	.56 Sharp-Witted		.65 Deliberate		.68 Sociable
	.55 Ingenious		.46 Painstaking		.64 Spunky
	.45 Witty		.26 Cautious		.64 Adventurous
	.45 Resourceful				.62 Noisy
	.37 Wise				.58 Bossy

Agreableness		**Neuroticism**	
Low	High	Low	High
-.52 Fault-fiding	.87 Sympathetic	-.39 Stable	.73 Tense
-.48 Cold	.85 Kind	-.35 Calm	.72 Anxious
-.45 Unfriendly	.85 Appreciative	-.21 Contented	.72 Nervous
-.45 Quarrelsome	.84 Affectionate		.71 Moody
-.45 Hard-hearted	.84 Soft-hearted		.71 Worrying
-.38 Unkind	.82 Warm		.68 Touchy
-.33 Cruel	.81 Generous		.64 Fearful
-.31 Stern	.78 Trusting		.63 High-strung
-.28 Thankless	.77 Helpful		.60 Temperamental
-.24 Stingy	.77 Forgiving		.59 Unstable
	.74 Pleasant		.58 Self-punishing
	.73 Good-natured		.54 Despondent
	.73 Friendly		.51 Emotional
	.72 Cooperative		
	.67 Gentle		
	.66 Uselfish		
	.56 Praising		
	.51 Sensitive		

Five Factor Model (FFM) of a person, provides a systematic assessment of emotional, interpersonal, experiential, attitudinal, and motivational styles, a detailed personality description that can be a valuable resource for a variety of professionals [115]. Given its considerable length and time spent to complete it, a number of shorter questionnaires arose. We can mention the 100 Trait Descriptive Adjectives (TDA) developed by Goldberg et al. [95] that selects only adjectives that uniquely defined each trait; or also, the NEO-Five Factor Inventory (NEO-FFI), composed of 60 items [115], which consists of items that loaded highly on one of the five factors; and the Big Five Inventory (BFI) [8], which includes 44 items and, instead of using adjectives in the questionnaires, uses short phrases based on the trait adjectives.

Curiosity and Exploration Inventory II

Figure 2.2: *Curiosity and Exploration Inventory II (CEI-II), a form to measure the human curiosity though of two factors, the stretching and embracing*

However, although most people intuitively know what it is to be curious, an exact definition of curiosity is difficult to pinpoint. In academic literature, we can interpret curiosity as interest, novelty-seeking, and openness to experience, which represents one's intrinsic desire for experience and knowledge [116, 4], for an appetitive state involving the recognition, pursuit, and intense desire to investigate novel information and experiences that demand one's attention. It can be also defined as the desire to explore novel, uncertain, complex, and ambiguous events [117]. People with greater trait curiosity experience curiosity states more frequently, intensely, and for a longer duration than less trait curious peers [118].

With the proliferation of theoretical models [4], a number of self-report questionnaires have been developed to measure individual differences in curiosity (e.g. state-trait curiosity inventory [110], sensation-seeking scale-form [119], need for cognition scale [120], openness to experience scale of the NEO-PI-R [115]) and, given the relevance of curiosity and the use made of it in this investigation, it is of great importance that the model to measure the curiosity to be used in this project is reliable and also easy to use. In this sense, different models to measure the curiosity (presented previously) were investigated.

One of the simplest, modern and reliable forms is the Curiosity and Exploration Inventory-II (CEI-II) form [2], a 10-item scale (Fig. 2.3). It includes two specific factors, the *stretching* and *embracing* (Fig. 2.2). The first one assesses broad dimensions of curiosity, being motivated to seek knowledge and new experiences (e.g. I am at my best when I am doing something that is complex or challenging), while the second focus on a general willingness to embrace the novel, uncertain, and unpredictable nature of everyday life (e.g., I am the type of person who really enjoys the uncertainty of everyday life).

Items are scored on a 1 (very slightly or not at all) to 5 (extremely) Likert scale as shown in fig. 2.3. Kashdan et al. [2], in their experiments, were able to demonstrate that this model had a strong reliability.

The more curious a person is, the more receptive to the experiences of the world around, flexible to everything that is new, different, unusual, this a person tends to be. That is, in this aspect, curiosity tends to minimize the preconception, be it aesthetic, intellectual, cultural, etc. Curious people are willing to explore the unknown before judging it. Thus the curious do not settle for certainty or old ideas. In the face of the unexpected and the "not known" the curious are stimulated to seek, to unravel, to know. As a manifest behaviour, curiosity can be directed to a specific object, as an interest in astronomy, for example. Or it may be of a generic order, characterizing a form of personal functioning aimed at the exploration of all that is new and unknown. So curiosity and novelty usually go hand in hand [121]. Knowing this, and being able to measure the level of curiosity by computer means, RSs can take advantage of this important personality trait.

Curiosity and Exploration Inventory (CEI-II) Instructions: Rate the statements below for how accurately they reflect the way you generally feel and behave. Do not rate what you think you should do, or wish you do, or things you no longer do. Please be as honest as possible.		Very Slightly	A Little	Moderately	Quite a Bit	Extremely
1	I actively seek as much information as I can in new situations.	1	2	3	4	5
2	I am the type of person who really enjoys the uncertainty of everyday life.	1	2	3	4	5
3	I am at my best when doing something that is complex or challenging.	1	2	3	4	5
4	Everywhere I go, I am out looking for new things or experiences.	1	2	3	4	5
5	I view challenging situations as an opportunity to grow and learn.	1	2	3	4	5
6	I like to do things that are a little frightening.	1	2	3	4	5
7	I am always looking for experiences that challenge how I think about myself and the world.	1	2	3	4	5
8	I prefer jobs that are excitingly unpredictable.	1	2	3	4	5
9	I frequently seek out opportunities to challenge myself and glow as a person.	1	2	3	4	5
10	I am the king of person who embraces unfamiliar people, events, and places.	1	2	3	4	5

Figure 2.3: *The CEI-II form with 10-item scale and 7-point Likert-type scale, composed of two factors, the stretching and embracing.*

Comparison between the Big Five Model and the Curiosity Exploration Inventory

The main difference between those two widely known models is that the BFF measures human personality as a whole, while the CEI-II model focuses only on the measurement of curiosity. In this sense, we found a project developed by Kashdan et al. [2] that, in one of the experiments, the factor structure and validity of the CEI-II was examined, comparing it, among others, with the NEO-FFI.

The correlation results of this study are presented in Figure 2.4, indicating that the CEI-II has acceptable internal reliability ($\alpha = .85$). As it might be expected due to their conceptual overlap, the strongest correlation with the CEI-II appear with the openness to experience (r =.51), that is, in the BFF, curiosity is considered a lower order trait belonging to the central facet of openness to experience. Also, curiosity had a large positive correlation with extraversion (r = .42), often considered to be a reflection of positive affectivity and reward sensitivity. In summary, Kashdan et al. showed that the CEI-II, in addition to measure curiosity with greater objectivity, also provides good evidence for the psychometric properties of the 10-item test. For the purposes of our research, the CEI-II becomes more practical and easy to use, since it is comprised by only 10 items, against the 60 items of the BFF model.

	CEI-II-total	CEI-II-stretching	CEI-II-embracing
Mean (*SD*)	32.90 (7.48)	17.08 (3.88)	15.82 (4.37)
α	.85	.78	.75
Big Five			
Openness to experience	.51**	.50**	.43**
Conscientiousness	.20*	.31*	.07
Extraversion	.42**	.29*	.46**
Agreeableness	−.04	.03	−.09
Neuroticism	−.27*	−.30*	−.20*
Mindfulness	−.14	−.02	−.22*
Conservative political views	−.26*	−.28*	−.19*

Lower scores reflect greater mindfulness.
* $p < .05$.
** $p < .001$.

Figure 2.4: *Means, standard deviations, and Pearson correlations between Big Five Factor and CEI-II according to [2]*

2.2.2 The Personality Through the Social Networks

As mentioned, a means of measuring the human personality are forms such as BFF, CEI-II, and others. However, with the continuous increase of the data accessible on the internet, especially in social networks, a new window of opportunities is available in the scenario of the prediction of the human personality. Consequently, researchers have begun to be interested in trying to predict the user personality from the information shared in these social networks, that is, to infer personality in an implicit way, without forms [122].

Nowadays, our personality can be expressed by deliberate attempts to make statements to others. However, other forms of expression may simply be individual's inadvertent actions. This is known as *behavioral residue* [123], which can be found in personal websites [124] and in social networks such as Facebook [125]. This is due, in large part, because the data available online include very "intimate" information (that includes food, politics, travel, friendship, dating, preferences, etc). The tendency is that such online behavioural residues will increase, which could aid in the task of inferring personality through this data.

In spite of the many limitations or even prohibitions imposed by the great social networks, like Facebook in 2015 [126], or also by the creation of laws that regulate the issue such as in UK and EU [127], the access to data of social networks is provided by application programming interfaces (API). Every social network offers a specific API with more or fewer restrictions.

Over the last few years, many works have been developed using the most varied data from the most varied social networks. In summary, we can quote some papers that used social networks, for instance, Facebook[4] [128, 129, 32, 130, 33], Foursquare[5] [131], the professional network Xing[6] [3] and also Sina[7], the largest Chinese web portal on information and entertainment [36].

In short, Buettner [3] counted on the participation of 395 users of the social network Xing to compare their profiles with the five personality traits BFF. This correlation is shown in Figure 2.5.

Another paper that we can highlight was developed by Segalin et al. [128], that explored how self-assessed personality profiles can be inferred by looking at the Facebook profile pictures. They could demonstrate a positive and significant

[4] www.facebook.com
[5] www.foursquare.com
[6] www.xing.com
[7] www.sina.com

Indicator / Features	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
static profile (node) information					
no. of interests	+				
no. of groups / categories					+
no. of profile pictures			++	+	−
dynamic profile (node) information					
no. of profile picture changes	+		+		+
no. of general picture adds	+		+	+	
usage intensity / frequency					
no. of logins			+	−	+
time spent on OSN		−−	++		++
no. of other pages / profiles viewed		−	++	+	
messages / communication					
no. of messages sent			++	+	−
no. of wall postings (on own and other walls)			++	+	+
no. of wall postings by other			+	+	
no. of faux pas (dirty words)		−−		−	
no. of blog entries	+				
intensity of emotional content					+
network properties					
no. of contacts			++	+	−
network centrality	+			+	

Figure 2.5: *Stable and substantial relationships between online social networks indicators and big five traits. (+)+ (very) positive correlation, (-)- (very) negative correlation presented by Buettner [3].*

correlation between the profile pictures and Extroversion and Neuroticism, the two traits that obtained better scores.

Bachrach et al. [129] demonstrated correlations between some traits of personality measured by the Big Five and some features from Facebook profiles. By using data from 180.000 users from the project MyPersonality, they analysed the following Facebook features: friends, groups, likes, photos, status and tags. Their results showed some correlations, such as positive correlation between Openness and number of users' likes; a negative correlation between

Agreeableness and number of likes. Then, they selected a subset 5.000 individuals and used their Facebook profiles to predict their personality traits, using a multivariate linear regression with 10-fold cross-validation. The best accuracy for the prediction was found in Extraversion and Neuroticism traits, and the lower in Agreeableness.

Another study developed by Golbeck et al. [32], with 279 users from different countries, took into account linguistic features (by applying analysis methods), in addition to personal information, the number of friends and activities and preferences from Facebook. They had to complete a personality test (a 44-question version of the BFI) and then, they analysed the correlations between those features and the Big Five personality traits. They found that Conscientiousness is negatively correlated to swear words, but positively correlated with words surrounding social processes. After that, they predicted the score of the personality traits by means of a regression analysis. Their results showed strong correlations on Openness, Conscientiousness, Extraversion and Neuroticism.

In the same research line, also using the BFI, Gao et al. [36] demonstrated that Big Five personality traits can also be extracted from other data sources and languages. By collecting status text from 1766 users of the Chinese micro-blog Sina[8], having those users responded to the BFI questionnaire, the authors first performed a feature extraction of the statuses, and then, built a prediction model using Gaussian process, M5'Rules and Pace Regression algorithms, finding significant correlations for Conscientiousness, Extroversion, and Openness.

Solinger et al. [130] obtained a positive prediction accuracy in all traits of Big Five, achieving 65% for Extraversion and Agreeableness, 55% for Neuroticism, 50% for Openness and 40% for Conscientiousness. They used data collected from Facebook such as profile bios, status updates, photos, and the number of friends. To achieve these results, they included additional cognitive psychology metrics in a multidisciplinary approach to increase Facebook

[8] www.sina.com.cn

personality prediction accuracies.

Ortigosa et al. [33] developed TP2010, a Facebook application, working with data of 20.988 users. Through it, the users filled in a questionnaire based on ZKPQ-50-cc, corresponding to the five traits of the alternative five model. The authors were able to get the users' personality; then, they tried to infer personality from interactions of the users on the social network. They performed a prediction with 3-class and 5-class model. The results showed that the classifiers obtained a level of accuracy higher than 70% for all personality traits.

There are also works that predict the personality traits from Big Five with less known social networks, such as Foursquare. Chorley et al. [131] created an online personality experiment examining the relationship between Big Five traits and the number and types of places visited by Foursquare users. The authors found a positive correlation between Conscientiousness and the number of places visited, possibly due to the organized routine required to consistently check in at places. On the other hand, they also identified a negative correlation between Neuroticism and the number of places visited.

2.2.3 The Positive Psychology

Differently from the approach of the traditional psychology, focused on treating abnormal behaviour and their consequent mental illnesses [132], the positive psychology represents a change in the way of thinking, by also building the best qualities in life. Positive psychology is a recent movement whose aim is that contemporaneous professionals adopt a wider vision of the potentials, motivations and human skills [133], focusing on the search for happiness instead of devote efforts to healing.

Since the ancient times, happiness has been subject of debates and philosophical and religious reflections. Similarly, relevant names in psychology ([134, 135, 136]) have studied the positive emotions. But, what positive psychology is? Nothing more than the scientific study of ordinary human strengths and virtues that enable people, groups and society to live healthfully [137], based on the belief that it is possible to identify, understand, develop, and foment the needed mechanisms to live in a meaningful and satisfactory way.

In order to include happiness in the field of science, the positive psychology has been using traditional methods but also advanced techniques in the field of neuroscience to study the emotions and the human behaviour. This way, positive psychology tends to the empirical research, respecting the rigours of the scientific research and basing its analysis in concrete data.

The approach of positive psychology developed by Peterson and Seligman [4] summarises more than 200 positive attributes into six virtues, namely humanity, justice, temperance, transcendence, courage, and wisdom and knowledge. These virtues are subdivided in twenty-four more concrete and measurable character strengths, as shown in Figure 2.6. What follows is a brief summary of each one of these virtues and strengths.

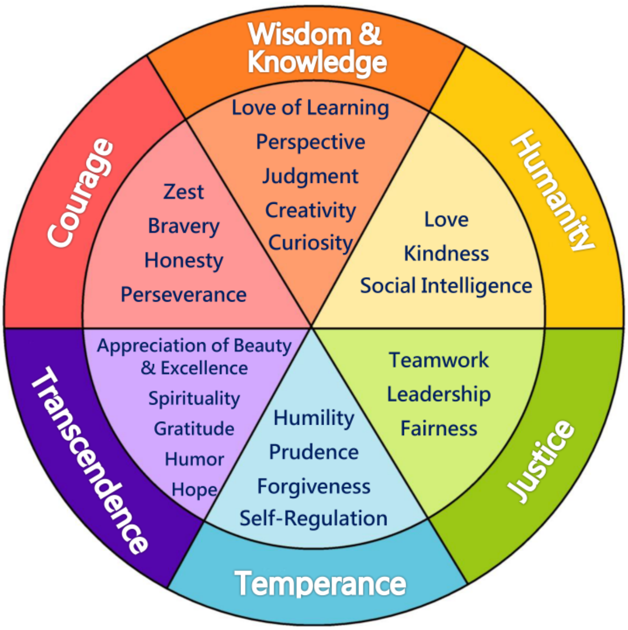

Figure 2.6: *The six groups of virtues and twenty four character strengths developed by Peterson and Seligman [4], illustrated by University of Hong Kong [5]*

The first one, **Humanity**, refers to interpersonal strengths that involve tending and befriending others. The next one is the **Justice**, that means civic strengths that underlie healthy community life. The **Temperance** strengths are related to protection against excess. **Transcendence** are strengths that forge connections to the larger universe and provide meaning. **Courage** is related to emotional strengths that involve the exercise of will to accomplish goals in the face of opposition, external or internal. And last but not least, **Wisdom and Knowledge** refers to cognitive strengths that entail the acquisition and use of knowledge. Among its character strengths, we highlight the curiosity, a powerful facet of human motivation [138], along with creativity, judgement, perspective and love of learning. Given its importance, curiosity is the most endorsed of the 24 fundamental strengths mentioned above [2].

According to the positive psychology, a more curious person tends to be more receptive to new experiences and is more flexible regarding the new, different, and unusual. In this aspect, curiosity tends to minimise preconceived concepts, be it aesthetic, intellectual, cultural, etc. Curious people are willing to explore the unknown instead of judging it. Thus, they do not accommodate to the uncertain or to old ideas; when facing the unexpectedness, curious people feel stimulated to search, to unveil, to know. As an apparent behaviour, curiosity can be driven by a specific subject (e.g. interest in astronomy); as a generic behaviour, it is oriented to the exploration of the new and the unknown [139, 140]. Thus, many authors describe ways and methods that can be applied in the daily routine of any person who wants to develop or strengthen her degree of curiosity [141, 142, 26], such as:

- To change the path and the means of transport used everyday to go to work or to school;
- To try doing something never done before, such as learn how to dance, to sail, to sing, to climb, to sing at a karaoke, to try new food;
- To learn new languages, a musical instrument, doing handicraft, to collecting something;

- To visit new places, and get to know the history of those places.

By knowing which habits and behaviours a person needs to increase her curiosity according to positive psychology, we can interpret that people who have such behaviours are more curious that those who do not have them. In addition, by being able to retrieve and correctly interpret what people say (explicitly or implicitly) about themselves from SNs, it would be possible to develop curiosity-based recommendation systems. For instance, by retrieving the travel history of a person by analysing her pictures' labels and its details, such as diversity of places and characteristics, it would enable the measurement of her curiosity and allow the recommendation of places based on this factor.

2.2.4 Aspects of Personality and Sociodemographics in the Environment in Travel Choices

The personality is a fundamental differentiating factor of human behavior. Literature suggests that, among other individual factors, it could be a plausible predictor of tourists' behaviours, since it tends to be enduring throughout one's course of life [143]. According to McCrae and John [114][1992] personality tries to explain the individual differences in emotive reactions to common stimuli. So personality does affect the emotive response of users when receiving the recommendations.

In the tourism context, curiosity has direct implications. According to Nada and Kenneth [144], the motivations for travel stem from the human desire for fun, recreation and the undefined motive to seek and explore the unknown and unseen. The wanderlust travellers are those who travel to seek and explore other cultures and places, motivated by the basic human characteristic of curiosity. In addition, Werthner and Ricci [145] describe that the e-commerce in the tourism sector falls short to ignore the fact that the web is also a medium of curiosity, of creating communities, or just having fun. The tourism has to do with emotional experiences. In such a scenario, the tourism-recommendations should consider the personalisation through an extensive exploitation of user modelling, taking into consideration user behaviour and cognition as well as emotional aspects.

Despite these findings confirming the influence of personality on information search behaviour, few have examined its influence in tourism settings [38], and the psychological issues (e.g the personality) are ignored [37] in many RSs. In this sense, researchers have dedicated their efforts to identify which personality factors influence tourists' behaviour in travel choices [146, 147]. Some of these aspects are already well defined [148], such as personal restrictions (income and number of children), sociodemographic characteristics (e.g. size of the city of residence and age), trip characteristics related to the individual (use of intermediaries and transport mode), tourist behaviour variables (psychographic factor and variety seeking), and motivations when choosing a destination (search for relaxation and climate, curiosity, and visiting friends and relatives). We briefly describe these ideas below.

Personal restrictions

Regarding the *level of income* (personal budget), Nicolau [148] concludes that the distance exerts a different influence on individuals depending on their income; people with high salaries can have easier access to long-distance destinations, which generally cost more money. Therefore, the negative effect of distance, at least in terms of money, should be lower for them. In fact, income has been proved to be highly explicative of tourist behaviour [149].

Additionally, the *number of children* may limit the destination choice, since it reduces individuals' freedom of movement. It means that vacations with children tend to be associated to closer destinations. Therefore, the family size can restrict vacation spending [150, 148].

Sociodemographic characteristics

In this category, the sociological and demographic characteristics that can influence the choice of a destination are included. In plain terms, it looks at the life around individuals and their characteristics such as age, gender, religion, size of the city of residence and level of education. The *age*, although not unanimous among researchers, is considered one of the most important demographic characteristics that influence vacation demand [151].

Another relevant topic is the *size of the city of residence*, which could affect the sensitivity to distance. At an empirical level, it was identified that the proportion of the population that get involved in tourist activities reaches the lowest levels in towns with lower populations. This is because inhabitants of cities with high population density have a greater need to escape in search of "relaxation", which consequently brings about greater propensity to travel further distances, allowing them to go away from home [152].

Stumm et al. [153] have shown that curiosity makes our brains more receptive for learning, and that as we learn, we enjoy the sensation of learning. Instilling students with a strong desire to know or learn something is what every teacher lives for, and research has even shown that curiosity is just as important as intelligence in determining how well students do in school. In other words, the curiosity prepares the brain for learning at the same time, makes subsequent learning more rewarding.

Trip characteristics related to the individual

The vacation products can be purchased by means of different *intermediaries*, such as apps, travel agencies, news portals, etc. Generally, an individual is more likely to use the internet to book a flight rather than an all-inclusive vacation. However, the purchase of vacation products from travel agents is associated with more complex products, such as long-distance vacations, due to the reduced uncertainty intermediaries bring and the time saved in the organisation of multicomponent trips. Thus, the purchase of vacation products through intermediaries should be associated with long-distance destinations. That is, the identification of the intermediary can give us clues about how far the individual is willing to travel.

Another important characteristic is the *transport mode*, individuals' willingness to travel farther is also contingent on the transport mode selected for the trip, as the physical, temporal, and financial efforts change according to the mode used. Therefore, the destination depends on the transport mode that the individual has chosen.

Tourist behaviour

We can highlight two characteristics, the *psychographic factor* (interest of the traveller in discovering new places) and the *variety-seeking behaviour*. The first is about the internal aspects of the individual, that is, the psychological aspects, that have a special relevance in the planning of vacations, through which people feel a deep need to explore the unknown. Although the previous characteristics are of great use in explaining tourist behaviour, Plog [154] suggests incorporating dimensions that allow representation of other internal aspects of the individual, such as the influence exerted by predominate psychographic groups in the fluctuation of the popularity of places.

Other researchers, for instance, Gonzalez and Bello [155], have demonstrated that psychographic variables have a strong explanatory power on the tourist choice behaviour, such as the time spent per square kilometre or the visiting of multiple attractions. Called as the Ulysses factor, Pearce [156] describes another psychological aspect of special relevance in the planning of vacations, through which people feel a deep need to explore and to discover what lies beyond the known horizon. Mayo [157] suggests that this "need to explore" is determinant in the explanation of travel because "travel allows one to satisfy the intellectual need to know". Finally, we highlight Harrison-Hill [158] who states that novelty facilitates the choice for faraway destinations. Bearing this in mind, it can be assumed that this yearning to explore, manifested by an interest in discovering new places, is associated with a greater willingness to travel farther.

The *variety-seeking behaviour* is a characteristic that, according to Mokhtarian and Salomon [159], can influence the effect of distance, as it can increase the utility of more distant destinations. In other words, it shows that an individual has a greater willingness to travel long distances if the destination was not previously visited by her; thus, the additional effort implied in the long distance will depend on whether the individual is a first-time or a recurrent visitor [160]. Kemperman et al. [161] distinguish two ways of diversifying behaviour: the first one derived, in which a tourist changes the chosen destination because of external reasons, and the second one intentional, in which the constant change of destination is the goal in itself.

Motivations for choosing a destination

The reasons for deciding to go on vacation may influence the chosen destination. Thus, the characteristics of individuals act as push factors leading to the realisation of tourist travel. Three points are worth mentioning. The first one is the search for a place due to is *climate* and/or *relaxation*; we can expect that people who choose a destination for those reasons have a greater propensity to travel farther if they receive these attributes in return. Secondly, visit *friends*, considering that the interpersonal motivation of socialising through visiting friends and relatives leads many individuals to this type of tourism. Finally, the *degree of curiosity*, that is indeed the core pillar of many tourism products and services. A tourism product can be almost anything that provokes human curiosity and as long as that "anything" is named, described, priced, and offered. Even with this fundamental role, there has been a relatively little contribution by tourism literature to the area of product development in assisting existing and new tourism businesses to create their competitive position in such a volatile market.

The factors described above are able to show that the relation between psychology (mainly the curiosity), budget, distance and implicitly level of education, have a strong influence on the tourism choices. In accordance with the aforementioned Ulysses factor, we can consider curiosity because travel allows a person curious about a destination to satisfy his or her intellectual need to know [148]. Therefore, the curiosity factor plays a key role in recommendation systems of tourist places; moreover, it is a fundamental part in the process of serendipity, since the characteristics that describe the curiosity may be strongly related to the definition and requirements presented in serendipity.

2.3 Recommender Systems Based on Personality

The recommendation systems are, by definition, personalization systems. The personalization is about building customer loyalty by building a meaningful one-to-one relationship; by understanding the needs of each individual and helping satisfy a goal that efficiently and knowledgeably addresses each individual's need in a given context [162]. According to Dyche [163] personalization is the capability to customize customer communication based on knowledge preferences and behaviours at the time of interaction. When we are dealing with the digital universe like a Web site, a personalization is a process of tailoring pages to individual users' characteristics or preferences.

Adomavicius and Tuzhilin [46] said that the implementation of a recommendation is more effective to create "personalization" in the digital scenario than in the "real world". The reason for this is that personalization technologies, in general, are information-intensive; that is, they require the speedy collection and processing of large volumes of data about consumers, providers, and markets, as well as a quick response to the results of this analysis. For example, imagine a travel agent trying to sell a personalised package tour for a customer.

That is, RSs play a key role in this scenario by combining various computational techniques to select personalised items based on the interests of users and the context in which they are inserted. Such items can take a variety of forms, such as books, films, news, music, videos, advertisements, sponsored links, web pages, virtual store products, etc.

In this continuous pursuing for "personalisation", the RSs seek to adopt new approaches in their systems, and the use of human personality is one of them, given that considering its traces could to improve the effectiveness of these recommenders. Thus, researchers and developers have sought to create new technologies, understand personalisation from a business perspective, and develop novel applications [38].

In this section, we present some projects that consider the user personality in their recommendation techniques.

The paper developed by Huang and Bian [164] presents a recommendation system that offers personalised recommendations of tourist attractions at a given destination. With respect to the psychological part, the author interpreted the personality as the reflection of a person's enduring and unique characteristics that urge him or her to respond in persistent ways to recurring environmental stimuli, converting this variable in three common labels: *allocentricism* (prefer exotic and unfamiliar activities), *mid-centricism* (mixture between allocentricism and psychocentricism preferences), and *psychocentricism* (prefer to visit familiar activities). The recommendation is performed using the Bayes theorem, that is, the probability distribution of the preferred activities is updated involving two steps: (1) the traveller type is updated given some variables (age, occupation and personality); (2) the preferred activity is updated given the last variable (tour motivation) with the updated traveller type. Huang and Bian also present an example of estimation result of the preferred activity given a person (age between 18 and 34, student, personality = allocentrism, tour motivation = learning something new). That is, this person with allocentric personality prefer exotic and unfamiliar activities, while psychocentrics tend to visit familiar activities.

Another project that uses *Big Five Factor* is presented by Wu and Chen [165]. They focus their efforts on deriving users' personality from their implicit behaviour in the film domain and, furthermore, used the derived personality to augment online movie recommendations. To do this, first, they validated the significant correlations between multiple features and users' personality traits through a user survey. Second, three regression models were compared in terms of their ability to unify these significant features into automatically inferring a user's personality. Here the Gaussian Process showed better performance than Pace Regression and M5 Rules. And finally, they implemented three variations of CF method which are all based on the implicitly acquired personality;

one based on the inferred personality to enhance user-user similarity in CF process and the other two combine the personality with users' ratings in either generating the final item prediction score or computing user-user similarity. The results indicated that the algorithms incorporated with both implicit personality and ratings significantly outperform, not only the non-personality approach, but also the pure personality-based approach, in terms of both rating prediction and ranking accuracy.

Following this same bias in using the *Big Five Factor* personality model, Tkalcic et al. [15] proposed a novel approach for calculating the user similarity for a CF RS. Unlike the projects mentioned previously, this used an offline experiment of a memory-based CF RS that relies on end-users' personality parameters to determine the nearest neighbours, which is a crucial step of the recommending procedure. In addition, Roshchina et al. [34] developed a project that also used the *Big Five Factor*, whose target was to recommended items chosen by like-minded (or "twin") people with similar personality types which are estimated from their writings.

Wu et al. [166] also propose to use the *Big Five Factor*; however, their strategy explicitly embeds personality, as a moderating factor, to adjust the diversity degree within multiple recommendations. Her results demonstrated an effective solution to generate personality-based diversity in recommender systems. To do this, an RS that explicitly adopts personality for adjusting diversity degree within the set of N recommendations was developed. Also, a user evaluation to compare the system to a variant that used personality in a contrary way was conducted. The experiments demonstrated that this project can significantly increase users' perceptions of system competence and recommendation accuracy. This way the results showed that the satisfaction of users with such personality-based recommendations was improved.

Hu and Pu [30] project focuses on a well-known problem in RSs, the cold-start problem. The paper aims at addressing this problem by incorporating human personality into the collaborative filtering framework, through three approaches: the first is a recommendation method based on users' personality information alone; the second is based on a linear combination of both personality and rating information; and finally, it uses a cascade mechanism to leverage both resources. To evaluate their effectiveness, they conducted an experimental study comparing the proposed approaches with the traditional rating-based CF in both cold-start scenarios: sparse data sets and new users. They results indicated that the proposed CF variations significantly outperform the traditional rating-based CF as measured by MAE and ROC sensitivity, especially the cascade hybrid approach.

While the projects presented above generate recommendations for individuals, Recio-Garcia et al. [167] presents a project that makes recommendations only for groups based on existing techniques of CF and taking into account the group personality composition. This project was tested in a film recommendation domain and evaluated under heterogeneous groups according to the group personality composition. Masthoff [168] describes three algorithms to model and predict the *satisfaction* experienced by individuals using a group recommender system which recommends sequences of items. In other words, the project modelled satisfaction as a mood, drawing on the mood literature for inspiration. It models the wearing off of emotion over time and assimilation effects, where the effective state produced by previous items influences the impact on the satisfaction of the next item. Also, the author compares the algorithms with each other, and investigates the effect of parameter values by comparing the algorithms' predictions with the results of an earlier empirical study, showing a way in which the affective state can be used in RSs.

II

Selected Papers

In this chapter, we present a selection of the main works we have published or submitted to magazines and national and international conferences, that have been developed over 4 years of research 2.7. The order in which the papers are presented follows a parallel order to the investigation, that is, from an outline of our general idea in early 2014 to the final results generated in 2017.

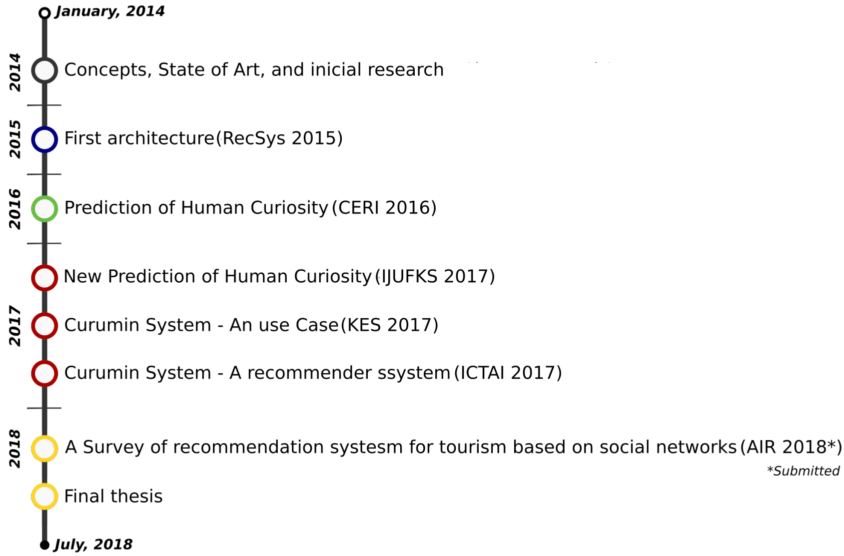

Figure 2.7: *Evolution of the work from the developed works.*

The first year of our research (2014) was a period to define the research line, followed by the development of a robust state of the art. After gathering information to define the state of the art, we identified that the field of human psychology applied to recommendation systems for the tourism sector was a relevant, consistent, and novel subject. This whole study on the state of the art has based on about 31 papers of the more than 312 analysed, focusing on RSs that use SNs in their projects detailing the benefits, and which are the most used social networks in the projects about tourism recommendation. We also try to analyse some technical aspects of these projects to develop our research, such as: the most common extracted data, the recommendations applied, the evaluation methods, and the type of recommendation generated by each system analysed. It is worth mentioning that the analysis of the state of art has lasted throughout the entire development of our research. Therefore, references were updated until the middle of 2018. As a result we developed a paper called "Recommendation Systems for Tourism Based on Social Networks: A Survey" that is shown in Chapter 3.

With the experience acquired in the analysis process for the development of the survey presented previously, at the end of 2014 we could develop an overview of the project, presenting the technical and methodological characteristics of a hybrid recommendation system called "A Hybrid Recommendation System Based on Human Curiosity", that can be found in Chapter 4. There, we present the complete architecture of a hybrid recommendation system that considers the curiosity level of each individual as a decisive factor to recommend places of South America; we also performed some preliminary experiments with the participation of 105 Brazilian volunteers. Considering that it was the first year of research, and because it was a general idea at that time, the project needed to mature, that is, to be reviewed and criticised by RS specialists, to identify points of improvement, so we submit an article as an extended abstract format in the section of Doctoral Symposium Papers, which was one of the seven papers approved for presentation at the international conference RecSys, 2015.

The contribution generated with the opinion received in the previous work was crucial to show us that we were the right way, and that the chosen subject would be a relevant contribution to the state of the art proposed here, that's not counting the interest that the work has generated on the listeners and professors at the conference. From this point on, in the middle of 2016, we divided the research project into three stages: 1. Prediction of the curiosity level from data available on social networks; 2. Analysis of the relationship between novelty, serendipity and diversity with human curiosity in the recommendation systems; and 3. Development of a complete architecture that aggregates the previous steps into a single recommendation system evaluated by real users, based on the recommendation of tourist places around the world.

The first step, completed in the first half of 2016, resulted in the article "Predicting the Human Curiosity from Users' Profiles on Facebook" (Chapter 5), presented to CERI (Spanish Conference on Information Retrieval); we focused our efforts on predicting just one of the human personality traits, the Curiosity, from data that can be extracted from the users' profile on Facebook and the set of features that can be used to describe their curiosity level and finally, we generated a prediction model in the form of a decision tree. For that, we had the participation of 105 Brazilian users.

In the same year, and deriving from the work mentioned in the previous paragraph, we received an invitation to submit a new article in a special issue on new trends in information of the journal IJUFKS; this new article should contain more than 50% of new material and contribution with respect to the paper accepted in CERI 2016. This gave us the opportunity to mature the previous project, adding a greater amount of experiments and users, showing the details of a method for the extraction, processing and prediction of the curiosity using data from Facebook. We also analysed additional features from Facebook that were not used in the previous project. We increased from 105 to 176 users in the new experiment. We have identified new positive correlations as: degree of curiosity and number of visited places, cities or countries and level of education. More than 10 different algorithms were tested. The result can be seen in Chapter 6, called "Are you Curious? Predicting the Human Curiosity from Facebook".

In the second stage, carried out during 2017, we aimed to congregate the papers altogether in order to generate a tangible result, a unique recommendation system, combining the prediction techniques achieved, the hybrid recommendation system, and some properties such as: accuracy, novelty, serendipity and diversity. The prototype of this complete system is called CURUMIM. Its name comes from two ideas combined; the first one sought to combine "CUR" CURiosity "CURiosidade" in Portuguese, and I "MIM" in Portuguese, that is, a recommendation system that uses "My Curiosity". The second explanation is due to the fact that the word Curumim, in Tupi language, generally designates indigenous children, that is, our project is still a Curumim, is in the stage of growth and maturation.

Throughout the year 2017, Curumim provided two important articles. The first one, published at KES 2017 conference, can be found in Chapter 7 and it is called "Curumim: A Serendipitous Recommender System based on Human Curiosity". Its architecture was completely adapted to a novel and serendipitous recommendation of tourist places around the world for people of different degrees of curiosity, depicting it in two use cases. We sought to build a better experience for the tourist through the fusion of three axes: human psychology, namely curiosity, technological innovation and social networks. In summary, we wanted to demonstrate that it is possible to generate accurate and adapted recommendations to the degree of curiosity of a given user on one hand, and on the other, they will positively surprise the users.

The second article was presented at ICTAI conference and it is called "CURUMIM: The Serendipitous Recommender System for Tourism Based on Human Curiosity" and is located in the Section 8. It addresses in a practical way all presented in the previous article, that is, its development process, operation, implementation, the experiments carried out, and finally the analysis of the results obtained with 74 real users.

To conclude, we hope that this small introduction could be able to demonstrate the stages of a research project over 4 years (2014 to 2017), beginning with a small initial idea, going through a deep analysis of the state of the art, reappraisal of the project on the basis of constructive criticisms, and which resulted in the subsequent development of a new recommendation approach from the use of a characteristic of human personality, curiosity, here called CURUMIM.

Chapter 3: Recommendation Systems for Tourism Based on Social Networks: A Survey

Contents

Recommendation Systems for Tourism Based on Social Networks: A Survey

Authors: **Alan Menk, Laura Sebastia, Rebeca Ferreira**

{amenkdossantos, lsebastia, redelferrer}@dsic.upv.es

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Abstract

Nowadays, recommender systems are present in many daily activities such as online shopping, browsing social networks, etc. Given the rising demand for reinvigoration of the tourist industry through information technology, recommenders have been included into tourism websites such as Expedia, Booking or Tripadvisor, among others. Furthermore, the amount of scientific papers related to recommender systems for tourism is on solid and continuous growth since 2004. Much of this growth is due to social networks that, besides to offer researchers the possibility of using a great mass of available and constantly updated data, they also enable the recommendation systems to become more personalised, effective and natural. This paper reviews and analyses many research publications focusing on tourism recommender systems that use social networks in their projects. We detail their main characteristics, like which social networks are exploited, which data is extracted, the applied recommendation techniques, the methods of evaluation, etc. Through a comprehensive literature review, we aim to collaborate with the future recommender systems, by giving some clear classifications and descriptions of the current tourism recommender systems.

3.1 Introduction

The expansion of the use of Social Networks (SNs) has become clear when looking at the increase in the number of users and the data volume in these networks. In 2016, 79% of U.S. adults that accessed the internet used the SN Facebook [169]. As a result, the amount of data available for several purposes (marketing, investigation, analysis, etc.) is vast. The Digital Universe study from the International Data Corporation (IDC) found that, back in 2012, about 68% of data was created and consumed by users watching digital TV, interacting with the social networks, sending images and videos taken with the phone camera between devices and around the internet. Their prediction is that, in 15 years, the world's data will grow by a factor of 300 [170].

The continuous changes in the consumption behaviour of the individuals in the internet or in the way we communicate with family and friends are evident. Companies of products and services spend increasing amounts of money in marketing and advertising with the focus on the web, in detriment of traditional physical means of communication, like newspapers and flyers. Therefore, Recommendation Systems (RSs) are becoming more present in many websites and applications, such as SNs (e.g. Facebook), e-commerces (e.g. Amazon), so that we are recommended where to travel to (e.g. Expedia), what music to listen (e.g. Spotify), what films to watch (e.g. Netflix), what to eat (e.g. Ifood) or even who date with (e.g. Tinder) [171, 172, 173].

The main input that allow RSs to work is data about user tastes and preferences. How to access these data was one of the main bottlenecks of RSs some time ago. Now, a relevant amount of the population is connected to SNs and, therefore, data about users (usually highly intimate and personal) can be accessed more easily. With the use of these data, an RS can "learn" about what a particular user likes, but more than this, it can analyse intrinsic and personal information such as his psychological profile, context issues, a profile of his circle of friends, etc. The current RSs are becoming more accurate, and they can be integrated with target platforms to obtain data in an implicit way, so it is possible to replace data acquisition through lengthy forms, annoying questions, etc. Consequently, the cold-start problem, a well-known and discussed issue in RSs, can be mitigated when users connect to a new platform by using a pre-existent account in another platform, thus enabling it to have access to the data available in the first one. In brief, what we highlight here is the importance that SNs can have in RSs.

In parallel, the area of tourism is an important source of income of countries and regions. Nowadays 10% of GDP corresponds to a direct, indirect or induced effect on tourism, creating 1 out of 11 jobs in a country. In 1950, the number of international tourists in the world was 25 million whereas, in 2015, it jumped to 1186 million and the predictions for 2030 are 1800 million, an annual growth of 3.3% [174]. Tourism is the first or second source of income in the economy in 20 of the 48 least developed countries. In European countries like Spain, the activity reached numbers like 10.9% of GDP in 2014, that is 12.7% of the jobs in this country was possible thanks to tourism. This favourable scenario, where users and data in SNs are massive, made many important projects arose [175] in order to build more efficient and customised systems in the tourism sector.

In this work, we present a review of existing tourism RSs that use data from SNs and discuss some research directions following the same ideas. The motivations of this work are diverse:

- SNs have been a *popular research* area, not only regarding data and web mining but also with respect to SN analysis. Many of these works are devoted to develop new techniques and algorithms or to improve traditional mining techniques for SN analysis, decision support and RSs [175]. In fact, very profitable knowledge for RSs can be obtained from SNs due to the rising amount of data available online, and from the analysis of social relations existing in the web, that mainly reflect the behaviour of the real world [176], providing an opportunity to study them through computational algorithms.

- SNs can help to *improve the prediction accuracy* of RSs in two ways. First of all, the quality of the available data can offer detailed information about the users, including their preferences, tastes, and social or geographical context. The second point is related to the possibility of predicting the user personality from data available in SNs, which could be specially valuable for particular market niches and recommendation systems. Moreover, in both cases, data are obtained implicitly, thus avoiding the use of long forms or tests.

- By reviewing the existing studies, it is possible to get to know the *approaches and methods* used by the researchers when introducing/combining data from SNs into RSs, thus gathering the best practices and using them as a starting point to keep improving the items to recommend, consequently increasing the satisfaction of the individuals.

- A *classification* of tourism RSs that use SNs can help developers and researchers gain a quick understanding of which kind of data can be retrieved from SNs and are the most used to generate recommendations.

This paper is organised as follows. First, the basic techniques used in RSs are described; then, we give a brief overview on SNs and their types (Section 2). Section 3 describes the methodology used for selecting the papers reviewed in this work. In Section 4, we present an analysis of the selected papers, with a general classification of them and a temporal evolution of SNs, comparing with the amount of papers related to them. We also try to answer some questions using the analysed projects such as what data are extracted from SNs, which the main used recommendation techniques are, which type of recommendations are generated and how they are presented to the user and which evaluation methods are used. Finally, we present the discussions (Section 5) and conclusions, research challenges and future prospects (Section 6).

3.2 Background

3.2.1 Techniques for recommender systems

RSs are software tools and techniques that provide suggestions of items that are most likely of interest to a particular user [177]. Studies about recommendations, suggestions or content filtering for the tourism sector are not that new. In 1986, [178] proposed that travellers construct their preferences for alternative destinations from their awareness and effectiveness; in 1989, [179] proposed a path model of direct and indirect relationships leading to destination choice. In the mid-1990's, [180] presented a framework of routes selection in Prince Edward Island region (Canada). The authors developed propositions suitable for empirical testing by using eight leisure traveller choice subsystems:

destinations, accommodations, activities, visiting attractions, travel modes, eating options, destination areas, and routes. However, it is worth mentioning that they reported the data collection as their biggest limitation, which was made entirely manually, but also the amount of available personal data about travellers, actually hardly null. From this century on, with continuously increasing rates of new users on the web, surrounded by the beginning of the mobile age, the problem of lack of data faced in the 90's in the projects about the recommendation in the tourism sector is not a problem anymore. This section describes a summary of the main techniques used in RSs.

Content-Based (CB): Essentially, a CB RS learns to recommend items that are similar to those the user has liked in the past. The similarity of items is calculated based on the features associated to the compared items. The main advantage of this technique is the "user independence", given that it depends only on the user's own data; in other words, it identifies the common characteristics of items that have received a favourable rating from a user u, and then it recommends to u new items that share those characteristics [63, 64, 65]. For example, when a user rated (positively) a point of interest (POI), the system can recommend similar POIs by calculating how similar these two POIs are according to their features.

Collaborative Filtering (CF): It is the process of filtering or evaluating items using the opinions of other people [69]. These opinions can be obtained explicitly from users through form responding, or by using some implicit measures, such as records of previous purchasing. That is, CF is an algorithm for matching people with similar interests for the purpose of making recommendations [47]. For instance, a system may recommend a customer who travelled to Paris and Barcelona, to travel to Rome, because other users that travelled to Paris and/or Barcelona, travelled to Rome as well. Two types of CF algorithms can be found: (1) memory-based CF, where user rating data is used to compute the similarity between users or items and (2) model-based CF, where models are developed using different data mining and machine learning algorithms to predict users' rating of unrated items.

Knowledge-Based (KB): This technique works by recommending items based on specific domain knowledge about how certain item features meet users' needs and preferences and, ultimately, how the item is useful for the user [47]. In other words, it generates recommendations to the user based on the knowledge about his needs towards a particular item. These recommendations are performed under measures of utility, derived from the knowledge of the relationship between a specific user and item. For instance, a KB tourism RS will generate recommendations not only based on the past travel experience of the user, but also based on what are the characteristics of the places/cities visited and the places available to recommend, that is, a KB RS exploits knowledge to map a user to the products he likes. They can use a wide range of techniques and, at the same time, they require a big effort in terms of knowledge extraction, representation and system design.

Demographic Filtering (DF): Essentially, this algorithm recommends items based on the demographic profile of the user [10]. In other words, this technique provides different recommendations for different demographic niches, combining the ratings of users in these niches [47, 78, 79].

Finally, we also find hybrid RSs which are based on the combination of the above mentioned techniques [47] (or some others, because this is not an exhaustive list). A hybrid RS combines techniques "X" and "Y" trying to enhance the advantages of "X" to mitigate the disadvantages of "Y" (and vice versa).

Nowadays, there is a great variety of techniques, models, algorithms, etc. that are used in different RSs. For example, the context-aware RSs, that characterise the situation of an entity (person, place or object) that is considered relevant to the interaction between a user and an application, including the user and the application itself [105]. For instance, in a tourism RS, the context referring to the season in which a person is going to travel is important because recommendations of destinations in winter should be very different from those provided in summer [65].

3.2.2 Social Networks

SNs are means of electronic communication through which users create online communities to share information, ideas, personal messages, and other content (as videos) [181]. To define a web page as a SN, it must cover three essential characteristics: to offer services that allow individuals to construct a public or semi-public profile within a bounded system, to articulate a list of other users with whom they share a connection, and to offer the opportunity of viewing and traversing their list of connections and those made by others within the system [182].

There are further definitions, such as from [183], who define it as a group of internet-based applications that build on the ideological and technological foundations of Web 2.0, and allow the creation and exchange of user-generated content. Also, for the authors, the SNs are applications that enable users to connect by creating personal information profiles, inviting friends and colleagues to have access to their profiles, and sending e-mails and instant messages between each other. In brief, a SN is a structure composed of people or organisations that share values and common goals. Figure 3.1 represents, on the one hand, the individual means of communication *(1 to 1)*, like, for example, phones and internet telephony service providers (such as Skype); and, on the other hand, the mass media *(1 to n)* like TV, radio, printed or online newspapers and magazines. Finally, if these two scenarios are combined, SNs *(n to n)* emerge, as we know them today.

Since their creation, SNs have been producing an astonishing amount of data, as previously mentioned. Such growth is not merely regarding the available content, but also the growing use of internet and consequently of SNs. For instance, in the middle of 2015, Facebook reached a 1.5 billion of users who have used it at least once in a month; this means that one in seven people in the world connected to Facebook in 2015.

Nowadays, even with increasingly restrictive policies, it is possible to obtain not only standard data widely used in traditional forms (i.e. name, age, gender, marital status) but also information extremely "intimate" about users, as

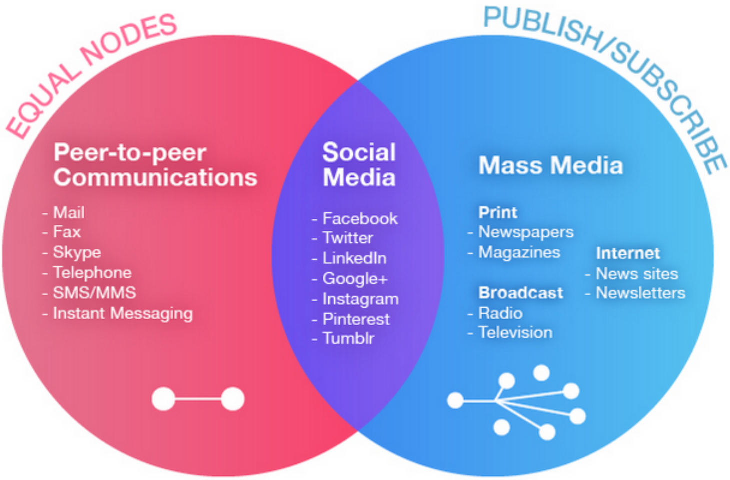

Figure 3.1: *Relation between peer-to-peer communication and mass network generating the SN by [6]*

personal preferences, likes, past trips or even where the person wants to travel to. With such valuable information available in SNs, we understand they can enrich and improve the predictions of RSs in the tourism sector.

3.3 Methodology

As explained above, our aim in this survey is to analyse existing works on tourism RSs that use data from SNs. Our search of scientific papers was performed by means of a filtering process in several databases such as: ACM Digital Library, IEEE Xplore, dblp, Emerald, Springer Link, Science Direct, Web of Science, Scopus, Dialnet plus, among other open source databases like DOAJ. Only articles and e-books were selected as document types, and we only selected RSs, searched as "recommend*", oriented/aimed to the tourism sector ("touris*") that used some type of data from SN in their model ("social network*").

Figure 3.2 shows a summary of the result of this search. Here, we can

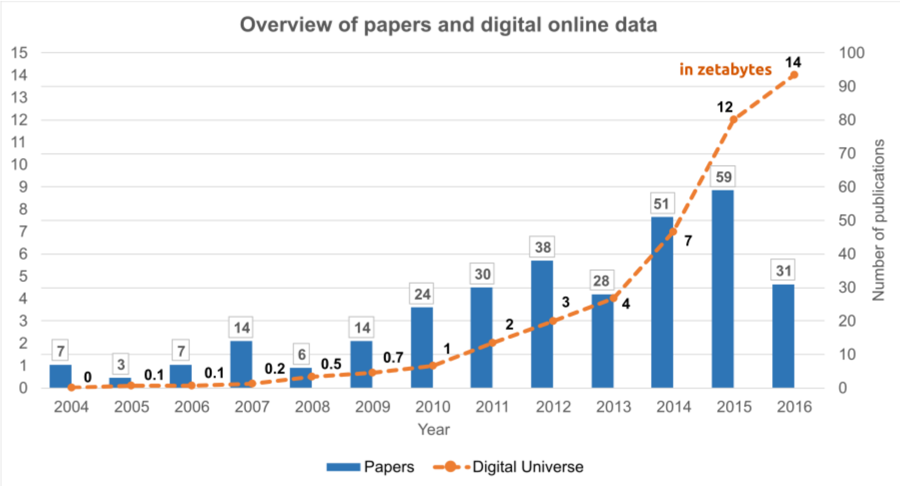

Figure 3.2: *The growth of online data [7] and tourism RSs research based on SNs.*

observe the relation between the number of scientific papers found in our search, as well as the amount of online available data. The number of publications was insignificant until the year 2004, so they are not depicted in Figure 3.2. However, with the expansion of the use of SNs in 2004, data (text, video, audio and other files) started to increase, albeit the amount of related papers oscillated between 3 and 14 in the subsequent 5 years. From 2009 onwards, the growth in the research represented in Figure 3.2 is clear, which can be associated to the growth in the volume of data available online in zetabytes (thanks to the inclusion of new devices such as tablets and the increasing of the number of smartphones), in addition to the launching/release of APIs for the main SNs. In 2009 and 2010, the scientific papers found rised from 14 to 24 and kept growing until reaching the peak of 59 papers in 2015. In the following year, though, only 31 projects were found, which could be related to the limitation on the access to the main SNs' data through their APIs. An example of this data limitation is Facebook, that limited the access to users' data in 2015 [126]. Other SNs such as Twitter and Linkedin are also putting restrictions in the data accessible through their APIs. In parallel, we should not be disregarded that we can see an increase in the volume of data (text, video, audio and others files) from 2004 to 2016, when we reached 14 zettabytes of data generated on the internet [184].

From the 312 papers that fulfilled our search parameters, we selected 31 papers to be deeply analysed, following three criteria: those which used the most known SNs (based on the number of users); those focused on the development of a practical application, that is, real RSs; and those with a relevant number of citations. Tables 3.1 and 3.2 show the list of selected papers descendingly ordered by the year of publication.

Once defined the target work to be studied, we classified these papers by the different aspects that we wanted to analyse, which are shown in the columns of Tables 3.1 and 3.2. Specifically, these aspects are:

1. SNs, that is, from which SN data is extracted.
2. Other data sources, that is, additional data sources used in these papers (if any).
3. Extracted items, that is, which type of information is extracted from SNs.
4. Recommendation technique, which indicates the several recommendation techniques used in each system.
5. Evaluation, indicating whether the evaluation of the system was performed using synthetic data or real users.
6. Recommendation system properties, describing which desirable properties are pursued in each system, such as accuracy, serendipity, etc.
7. Output, regarding whether the RS shows a list of POI recommendations, a route or a guide.
8. Interface used by the user to interact with the RS.

We also discuss the relevance of each aspect and the positives of the main systems, which will be detailed in the next sections.

General Information		Social Networks						Other Data Sources								Items Extracted						
Authors	**Title**	**Facebook**	**Flickr**	**Foursquare**	**Panoramio**	**Twitter**	**Others SN**	**Yahoo Maps**	**Geonames**	**Google Maps**	**Tripadvisor**	**Wikitravel**	**Wikipedia**	**OpenStreetmap**	**Others DB**	**Comments**	**Geotag Photos**	**Geotag Labels**	**Geotag Weather**	**Rating itens**	**Tweets**	**Geotag Timestamp**
Vakeel *et al.* (2016)	A Motivation-Aware Approach for Point of Interest Recommendations			✓													✓					
Memon *et al.* (2015)	Travel Recommendation Using Geo-tagged Photos in Social Media for Tourist		✓												✓		✓	✓	✓			
Han *et al.* (2015)	Adaptive landmark recommendations for travel planning: Personalizing and clustering landmarks using Geo-tagged social media		✓														✓	✓				✓
Fang *et al.* (2015)	How to Extract Seasonal Features of Sightseeing Spots from Twitter and Wikipedia					✓							✓					✓			✓	
Shen *et al.* (2015)	Attraction recommendation: Towards personalized tourism via collective intelligence		✓								✓	✓					✓	✓		✓		✓
Lim *et al.* (2015)	Recommending Tours and Places of Interest based on User Interests from Geo-tagged Photos		✓										✓				✓					✓
Phan *et al.* (2014)	Collaborative Recommendation of Photo-Taking Geolocations		✓														✓	✓				✓
Oku *et al.* (2014)	Mapping Geotagged Tweets to Tourist Spots for Recommender Systems			✓	✓	✓											✓	✓			✓	✓
Meehan *et al.* (2013)	VISIT: Context-Aware Intelligent Recommendation System for Tourism					✓															✓	
Sun *et al.* (2013)	Road-based travel recommendation using Geo-tagged images		✓								✓			✓			✓	✓				✓
Smirnov *et al.* (2013)	TAIS: Mobile Application for Guiding Tourist Activities: Tourist Assistant		✓		✓									✓	✓			✓				✓
Chang *et al.* (2013)	A Recommender System Combining Social Networks for Tourist Attractions	✓														✓		✓		✓		
Chatcharaporn *et al.* (2013)	Improving Performance of a Mobile Personalized Recommendation Engine using Multithreading	✓															✓	✓				✓
Chen *et al.* (2013)	A context-aware personalized travel recommendation system based on geotagged social media data mining		✓												✓		✓	✓	✓			✓
Lucchese *et al.* (2012)	How Random Walks Can Help Tourism		✓										✓				✓	✓				
Okuyama *et al.* (2012)	A travel Planning System Based on Travel Trajectories Extracted from a Large Number of Geotagged Photos on the Web		✓					✓		✓							✓	✓				✓
Yin *et al.* (2012)	Trip Mining and Recommendation from Geotagged Photos				✓												✓	✓				✓
Lemos *et al.* (2012)	MMedia2U: Towards a Context-Aware Photo Recommender System				✓		✓		✓						✓		✓	✓				
Mahmood *et al.* (2012)	A conceptual framework for personalized location-based Services tourism mobile application leveraging semantic web to enhance tourism experience				✓				✓							✓	✓					
Baraglia *et al.* (2012)	A Trajectory-Based Recommender System for Tourism				✓								✓				✓					
Petrevska *et al.* (2012)	Tourism Recommendation System: Empirical Investigation	✓								✓							✓					
Canneyt *et al.* (2012)	Time-Dependent Recommendation of Tourist Attractions using Flickr		✓				✓										✓	✓				✓
Popescu *et al.* (2011)	Mining Social Media to Create Personalized Recommendations for Tourist Visits		✓										✓			✓	✓	✓				
Kofler *et al.* (2011)	Near2me: An Authentic and Personalized Social Media-Based Recommender for Travel Destinations		✓														✓	✓				✓
Jiang *et al.* (2011)	ContextRank: Personalized Tourism Recommendation by Exploiting Context Information of Geotagged Web Photos				✓												✓	✓				✓
Choudhury *et al.* (2010)	Automatic Construction of Travel Itineraries using Social Breadcrumbs		✓					✓								✓	✓	✓				
Kurashima *et al.* (2010)	Travel Route Recommendation Using Geotags in Photo Sharing Sites		✓														✓					
Cao *et al.* (2010)	A Worldwide tourism recommendation system based on geotagged web photos		✓							✓							✓					
Tintarev *et al.* (2010)	Off the beaten track: a mobile field study exploring the long tail of tourist recommendations		✓										✓				✓					
Mamei *et al.* (2010)	Automatic Analysis of Geotagged Photos for Intelligent Tourist Services		✓							✓							✓	✓				
García-Crespo *et al.* (2009)	SPETA: Social pervasive e-Tourism advisor						✓						✓	✓		✓	✓	✓				
	Total of items:	3	18	2	7	3	3	2	2	4	2	1	7	3	4	5	27	22	2	2	3	14

Table 3.1: *Overview of classified projects and their characteristics sorted by date of publication, showing the SNs used and items extracted.*

3.4 Analysis of Tourism Recommender Systems using Social Networks

3.4.1 Which social networks and additional data sources are used?

This section gives a brief review of the main SNs employed in tourism RSs in the last years, which are summarised in the second column of Table 3.1. We found projects that work with widely used SNs such as Facebook and Twitter, and others focused on a more specialised audience such as Flickr[1], that allows the user to store, search, sell and share photos or videos; Foursquare[2], a local search-and-discovery service mobile app which provides personalised recommendations of places to go to near a user's current location based on users' previous browsing history, purchases, or check-in history and Traveleye[3], focused on trips organisation, that allows users to write posts with travel experiences, to follow other travellers' journeys, to share travels with friends, to search tourist attractions and travel guides, etc. We also have found works that used no longer available SNs, such as Picasa [91] and Panoramio, which was a was a geo-located tagging, photo sharing mashup, acquired by Google in 2007.

In relation to the analysed projects, we can observe that Flickr was the most used, with 58% of the projects [185, 96, 186], among others; then, Panoramio with 23% [187, 188]. The advantage of these SNs is that they enable the collection of "Coordinates", some "Geotag Labels" and even data about the person who took the photo, providing researchers with interesting data for RSs.

Facebook and Twitter (1st and 5th most used in the world [189]) are used only in the 10% of the analysed works. This low rate can be explained with the fact that both are generalist SNs and, therefore, data related to tourism is

[1] www.flickr.com
[2] www.foursquare.com
[3] www.traveleye.com

more difficult to obtain. Several works [190, 191, 192] have used Facebook to obtain numbers of likes, groups, friends, comments or geotags of check-ins.

With regard to Twitter, the core data are the user tweets, retrieved with different goals. For instance, [193] considered the concept of sightseeing spots for different seasons, thus generating seasonal feature vectors for each sightseeing spot, which could support context-aware recommendation of tourist spots depending on the time of the year. Tweets also can be used to characterise the tourist spots [194], or be combined with sentiment analysis to determine the current "mood" of each tourist [195]. [196] opted to work with Twitter and Traveleye in their project. The first was employed for inferring the sentiment analysis merged with context-aware (location, weather and time) data, while Traveleye was used to extract the moment when the user visited a given city.

Figure 3.3 shows the temporal evolution of some of the SNs that stand out in the recommendation projects oriented to the tourism sector since 2006, relating their appearance with the number of papers found in our search. In the middle of 2006, Twitter released an Application Programming Interface (API) for easing the access to data. Nowadays, all the major SNs have their own APIs, which allow to obtain data in an organised and automated way, by means of function calls. Combined with OAuth[4], released in 2008, APIs enable wider approaches of user integration, besides to add value to the user, the developer and the application. We observe that a number of projects, independent from the SN used, started to appear in 2008 and kept growing until 2015. Specifically, Facebook was used in 16 papers in 2015, followed by Flickr and Twitter, with 12 and 8 papers, respectively. One of the components that boosted such growth could be the ripeness of the available technologies with the definition of new standards, protocols and the documentation for their platforms. This opened an opportunity, even for non-IT researchers, to have access to data, integrate systems and develop new tools in a quick and simplified way. The reduction in the publications registered in 2016 seems to be related to the limitation on the access to users' data imposed by the

[4] An open standard for access delegation, which allows an end user's account information to be used by third-party services, such as Facebook, without exposing the user's password.

main SNs, as explained previously. In summary, Figure 3.3 shows the relation between the ease to access data from SNs after the standardization of access and authentication (APIs, OAuth, etc.) and the volume of published papers that use these SNs.

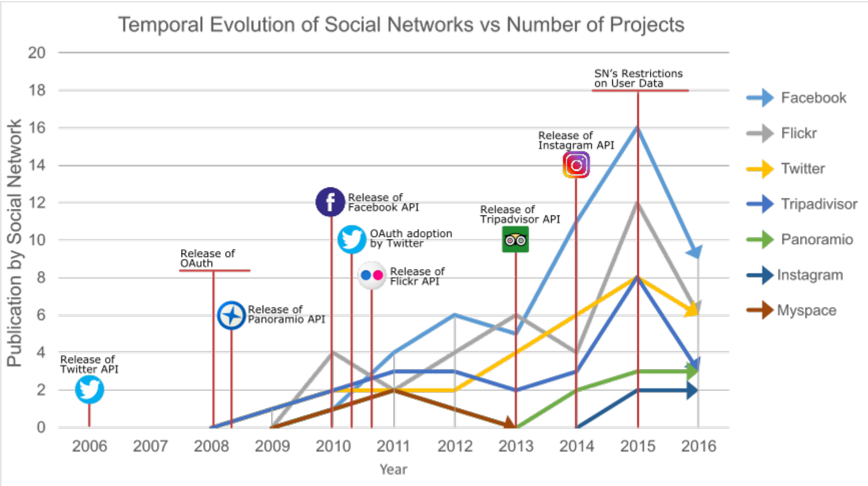

Figure 3.3: *Temporal evolution depicting the papers of fig. 3.2 classified by SN and the year of appearance of their APIs and protocols.*

On the other hand, Table 3.1 shows, in the third column, other data sources used in the analysed papers, as a complementary source. Most of the analysed projects used these additional data sources for showing the recommendations on a map. For example, [197, 192, 198] used Yahoo Maps, Google Maps and OpenstreetMaps, respectively. Others, such as [97] used Wikipedia to extract the list of POIs, latitude/longitude coordinates, and interest categories. [199] considered that the advantage of using Wikipedia is twofold. They used it, in one hand, to identify a large number of POIs in every city (even the less popular ones) and, on the other hand, to provide additional structured information about the POI (e.g. a subdivision of categories). [198] have chosen to use TripAdvisor to obtain a dictionary of landmarks. In this same scenario, [185] have used Tripadvisor to retrieve user comments about candidate attractions, besides the user rating about each attraction. [187], in addition to Wikipedia and Panoramio, have also used another data source, the Wikivoyage, to obtain detailed information about the attraction.

3.4.2 What data are extracted from social networks?

Recommender Systems mainly need two types of information: information about user tastes and preferences and information about the items to recommend. In our analysis, we have noted that SNs are used for retrieving both. Regarding items, SNs can be used for discovering new items or for adding additional characteristics to existing items in the RS database.

In the last column of Table 3.1, we can see that, regardless the type of SN used in the reviewed projects, the collected data are quite similar: 87% of them use an SN for obtaining "Geotag Photos", that is, labels that contain the geographical identification metadata, such as latitude and longitude coordinates, though they can also include altitude, bearing and distance, accuracy data, like [200, 186], among others; 71% extract "Geotag Labels", which are labels indicating the name of the city, country, address or labels that describe the photo, fundamental in projects such as [186, 96]; and, finally, the "Geotag Timestamp", which indicates when a photo (for example) was taken, is used in 45% of the projects [197, 201].

Less used, but also important, is textual information such as "Comments" and "Tweets", which are used to extract keywords/labels commonly exploited in projects of text mining and sentiment analysis. "Comments" were used in 16% of projects, like [202, 188] or [190], which extracted items shared by the user in Facebook along with likes, comments and ratings. On the other hand, [193, 195, 194] worked with tweets in their projects.

Only 6% of papers used a "Geotag Weather", tags that contain weather information for a particular location, which helps the development of context-aware systems [97, 194, 200]; the same figure has the "Rating Items" [185, 190], that means, the extraction of ratings such as online evaluations made by the users, which indicates their level of satisfaction (e.g. stars, ranking, likes) regarding restaurants, hotels, cities, POIs, routes, etc.

Table 3.1 shows that many projects combine several of these data. For instance, [185] collected heterogeneous data source using Flickr, Tripadvisor and Wikitravel: from Flickr, photos with metadata (time, location, attraction, and User ID); from Tripadvisor, user comments about the candidate attractions and user rating about each attraction; and from Wikitravel, official travelogues. Such heterogeneity reflects in the system a performance gain in terms of effectiveness as well as efficiency; an example is the "coordinates" of POIs, which is combined with "comments" and "rating items" from TripAdvisor, with the aim of learning from the experience of tourists who already visited the POI. In this case, collective intelligence is first gathered from a large amount of user-generated content in social media. Also, different aspects of knowledge can be mined from collective intelligence for denoising data and structuring heterogeneous information. In [194], three different data sources were used: Foursquare, to obtain POI names, coordinates and category; Twitter, for the date, hour and coordinates of the visit; and Panoramio to obtain a POI photo with the title, coordinates and owner. In other words, three types of datasets were used: tourist spots, geotagged tweets, and geotagged photographs to generate a method for mapping geotagged tweets to tourist spots on the basis of the substantial activity regions of the spots and also for extracting temporal features and phrasal features based on the mapped tweets, with a positive level of effectiveness according to experiments developed.

The second target when obtaining data from SN is focused on the discovery of behavioural patterns, preferences, and personal characteristics of users. In this case, it is valuable the extraction of user profiles, friends, and comments, which are the three key components of SNs [203]. For example, [204] recommend attractions that are likely to fit the current user expectations by exploiting the information exposed by user preferences; here, they based on the current user profile of the SN OpenSocial[5], which determines the common characteristics of the previously visited places and the user behaviour. Within this project, several elements were extracted from the SN: (1) Coordinates, which means

[5] http://code.google.com:80/apis/opensocial/

knowing the user's location, allowing the offering of a set of places, but also the detection of contacts or friends in the surrounding areas; (2) Time and weather, to recommend indoor locations when the weather does not give any other possibility, also taking into consideration timetable restrictions of attractions; (3) The users' profile through the explicit interaction of the user, determining what their interests are, what kind of places they prefer to visit, and the ratings given to attractions; but also through the implicit data retrieval, collecting information regarding favourite painters, writers, or music preferences, for instance.

In this same line, the VISIT project [195] used five types of contextual data, which are location, time, weather, social media sentiment and personalisation. The location is extracted from three main location sensing techniques used outdoors: GPS, GSM and WiFi; time, calculated from the amount of time that a user stays at each attraction; weather, extracted from the WorldWeatherOnline; social media sentiment, performed on Twitter messages (tweets) in real time to determine to current "mood" of each tourist attraction; and personalisation, by using the user profile data to describe a person in terms of age, gender, relationship status and the number of children, which can be used as a starting point for the application when first launched with no previous history.

As we can see, data extraction can be performed over a unique or multiple SNs, and in each case, one or more pieces of information about items that can be extracted. In addition, generally the use of data from SNs have some interesting advantages, such as the fact of counting on real data, the chance to later make tests with the users and also the availability of well-defined APIs provided by the most important SNs, thus making the development of their projects easier. However, we observe that regardless the SN, researchers face the same problem: irrelevant or false data, not only in case of users that insert or dismiss such information, but also with respect to those responsible for the development of SNs, who sometimes do not specify well the categories or standards neither establish required fields.

General Information		Recommendation Technique					Evaluation		Recommendation System Properties										Output			Interface	
Authors	**Title**	**Col. Filtering**	**Content Based**	**Knowledge-Based**	**Hybrid**	**Context-Aware**	**Online Method**	**Offline Method**	**Accuracy**	**Coverage**	**Confidence**	**Trust**	**Novelty**	**Serendipity**	**Diversity**	**Utility**	**Robustness**	**Scalability**	**Route**	**POIs**	**Guide**	**Mobile**	**Online**
Vakeel *et al.* (2016)	A Motivation-Aware Approach for Point of Interest Recommendations	✓				✓		✓				✓								✓			
Memon *et al.* (2015)	Travel Recommendation Using Geo-tagged Photos in Social Media for Tourist	✓						✓	✓									✓		✓			
Han *et al.* (2015)	Adaptive landmark recommendations for travel planning: Personalizing and clustering landmarks using Geo-tagged social media		✓				✓		✓												✓		✓
Fang *et al.* (2015)	How to Extract Seasonal Features of Sightseeing Spots from Twitter and Wikipedia		✓					✓	✓											✓			
Shen *et al.* (2015)	Attraction recommendation: Towards personalized tourism via collective intelligence				✓			✓	✓				✓	✓			✓			✓			✓
Lim *et al.* (2015)	Recommending Tours and Places of Interest based on User Interests from Geo-tagged Photos		✓					✓	✓										✓	✓			
Phan *et al.* (2014)	Collaborative Recommendation of Photo-Taking Geolocations	✓						✓	✓											✓			✓
Oku *et al.* (2014)	Mapping Geotagged Tweets to Tourist Spots for Recommender Systems		✓					✓			✓									✓			
Meehan *et al.* (2013)	VISIT: Context-Aware Intelligent Recommendation System for Tourism				✓			✓	✓											✓		✓	
Sun *et al.* (2013)	Road-based travel recommendation using Geo-tagged images	✓						✓	✓										✓				
Smirnov *et al.* (2013)	TAIS: Mobile Application for Guiding Tourist Activities: Tourist Assistant				✓	✓		✓										✓			✓	✓	
Chang *et al.* (2013)	A Recommender System Combining Social Networks for Tourist Attractions	✓						✓	✓		✓	✓								✓			
Chatcharaporn *et al.* (2013)	Improving Performance of a Mobile Personalized Recommendation Engine using Multithreading	✓						✓									✓			✓		✓	
Chen *et al.* (2013)	A context-aware personalized travel recommendation system based on geotagged social media data mining				✓			✓	✓											✓			
Lucchese *et al.* (2012)	How Random Walks Can Help Tourism			✓				✓	✓		✓									✓			
Okuyama *et al.* (2012)	A travel Planning System Based on Travel Trajectories Extracted from a Large Number of Geotagged Photos on the Web	✓						✓	✓										✓				
Yin *et al.* (2012)	Trip Mining and Recommendation from Geotagged Photos	✓						✓	✓				✓						✓				
Lemos *et al.* (2012)	MMedia2U: Towards a Context-Aware Photo Recommender System				✓		✓		✓		✓									✓		✓	
Mahmood *et al.* (2012)	A conceptual framework for personalized location-based Services tourism mobile application leveraging semantic web to enhance tourism experience				✓			✓	✓												✓	✓	
Baraglia *et al.* (2012)	A Trajectory-Based Recommender System for Tourism			✓				✓	✓	✓	✓					✓		✓		✓			
Petrevska *et al.* (2012)	Tourism Recommendation System: Empirical Investigation	✓						✓	✓		✓									✓			
Canneyt *et al.* (2012)	Time-Dependent Recommendation of Tourist Attractions using Flickr				✓	✓		✓	✓		✓									✓			
Popescu *et al.* (2011)	Mining Social Media to Create Personalized Recommendations for Tourist Visits	✓						✓	✓	✓	✓										✓		
Kofler *et al.* (2011)	Near2me: An Authentic and Personalized Social Media-Based Recommender for Travel Destinations		✓			✓	✓								✓	✓			✓				✓
Jiang *et al.* (2011)	ContextRank: Personalized Tourism Recommendation by Exploiting Context Information of Geotagged Web Photos	✓						✓	✓											✓			
Choudhury *et al.* (2010)	Automatic Construction of Travel Itineraries using Social Breadcrumbs	✓					✓		✓	✓									✓				✓
Kurashima *et al.* (2010)	Travel Route Recommendation Using Geotags in Photo Sharing Sites	✓						✓	✓		✓								✓				
Cao *et al.* (2010)	A Worldwide tourism recommendation system based on geotagged web photos	✓						✓	✓								✓			✓			✓
Tintarev *et al.* (2010)	Off the beaten track: a mobile field study exploring the long tail of tourist recommendations			✓			✓				✓		✓	✓						✓		✓	
Mamei *et al.* (2010)	Automatic Analysis of Geotagged Photos for Intelligent Tourist Services	✓						✓			✓									✓			
García-Crespo *et al.* (2009)	SPETA: Social pervasive e-Tourism advisor			✓	✓	✓		✓	✓										✓				
	Total of items:	15	5	4	8	5	5	26	24	3	11	2	3	2	1	2	3	3	8	20	4	6	6

Table 3.2: *Overview of classified projects and their characteristics sorted by date of publication, showing the evaluation, technique used, output, architecture and interface.*

3.4.3 What recommendation techniques are used?

With respect to the recommendation techniques used in the papers that we have analysed, we distinguish between those using the more traditional techniques, such as content-based, collaborative filtering and knowledge-based techniques and those combining these techniques in hybrid approaches or with context-aware information. The details of each paper are shown in the first column of Table 3.2, where we can observe that traditional techniques represent 48%, 16% and 13% of the works, respectively for CF, CB and KB, hybrid approaches and context-aware RSs represent 25% and 16%, respectively.

Regarding the content-based technique, [202] developed a prototype called "Near2me" integrating multimedia content items, user-generated metadata as their context to convey authenticity, and personalisation to the user.

We can highlight some projects that worked with collaborative filtering methods, like [192], which developed the national tourism web portal in Macedonia, adopting the cloud-model CF to reduce the dimensionality of data and avoid the strict matching of attributes in similarity computation. [188] presented a method named ContextRank, that calculates personalised interests for a specific user from different aspects, namely visual similarity score, textual tags similarity score and collaborative filtering score, which exploits different context information of geotagged web photos to perform personalised tourism recommendation. [190] calculated the similarity among users and users' network, combining collaborative filtering techniques, based on users appraisal and trustability evaluations, and social recommendations based on users' activities on SNs. Finally, other relevant models for collaborative filtering include the use of data mining models such as clustering, classification or association pattern mining, like in [198] and [205].

The Knowledge-Based technique was used in three projects. For example, [199] proposed an algorithm for the interactive generation of personalised recommendations of POIs based on the knowledge mined from Flickr photos and Wikipedia. [200] created, on one hand, a knowledge model, used for calculating suggestions, and used, on the other hand, information of the path of a current user during a visit, that combined with the first one, allowed the system to produce a list of suggestions as possible locations to visit.

In addition to these traditional techniques, we highlight hybrid RSs. For instance, [185] used techniques such as content-based, semantic-based and social-based knowledge; [195] in their hybrid project use collaborative filtering, content-based recommendation and demographic profiling. [206] introduced a hybrid RSs combining the Markov Model (using a probabilistic model that can handle sequential information) and topic models, also known as a hierarchical probabilistic model, in which a user is modelled as a mixture of topics, and a topic is modelled as a probabilistic distribution over landmarks.

Regarding context-aware systems, we can mention [207] who proposed an algorithm approach that applies a post-filtering contextual approach on a list of recommendations generated by traditional RS algorithms. Also, [187] developed TAIS, a mobile application that used an attraction information service, a recommendation service, a region context service, a ride-sharing service, and a public transport service. Another interesting work is the SPETA project [204] that makes use of a variety of techniques which include context-aware, knowledge-based and social-based methods to retrieve the most suitable services. Finally, we highlight [196] who explored the possibility of using temporal context factors to better predict which POIs might be interesting to a given user.

3.4.4 What properties of recommender systems are used?

We surveyed a range of properties that are commonly considered when deciding which recommendation approach to select. As different applications have different needs, it must be decided which properties are important to pursue the specific application at hand. In this survey, we have identified the following properties: accuracy, coverage, confidence, trust, novelty, serendipity, diversity, utility, robustness and scalability, as defined by [47] and shown in the third column of Table 3.2.

As expected, accuracy, which is one of the most fundamental measures through which RSs are evaluated. The main components of accuracy evaluation are: designing the accuracy evaluation; and accuracy metrics (accuracy of estimating ratings and accuracy of estimating rankings). In summary, accuracy is able to tell if the RS is able to predict those items that you have already rated or interacted with, thus RSs which optimize accuracy will naturally place those items at the top of a user's list, is found in almost all the projects analysed (77% of them). The second most-seeked property is confidence, that can stem from available numerical values that describe the frequency of actions, i.e. how much time the user watched a certain show or how frequently a user bought a certain item. These numerical values indicate the confidence in each observation. Various factors that have nothing to do with user preferences might cause a one-time event; however, a recurring event is more likely to reflect user opinion [58]. That is, a confidence measure is important as it can help users decide which movies to watch, products to buy, and also help an e-commerce site in making a decision on which recommendations should not be displayed, because an erratic recommendation can diminish the trust of users in the system [208].

In contrast, some projects concentrated in developing a recommender with the focus on a less "popular" property, such as [186], oriented in improving scalability, that can be understood as the ability of the system to process an increasing amount of work with respect to a desirable performance metric, for example the predictive accuracy of the system [209]. The importance of scalability has become particularly great in recent years because of the increasing importance of the "big-data" paradigm. A variety of measures are used for determining the scalability of a system: training time (Most RSs require a training phase, which is separate from the testing phase), prediction time (Once a model has been trained, it is used to determine the top recommendations for a particular customer), memory requirements (When the rating matrices are large, it is sometimes a challenge to hold the entire matrix in the main memory) [47]. Or [187], centred in guaranteeing robustness that means, an RS is stable and robust when the recommendations are not significantly affected in the presence of attacks such as fake ratings or when the patterns in the data evolve significantly over time. In general, significant profit-driven motivations exist for some users to enter fake ratings, for instance, the author or publisher of a book might enter fake positive ratings about a book at Amazon.com, or they might enter fake negative ratings about the books of a rival.

In many cases, several properties are pursued. For instance, [91] tried to improve both accuracy and confidence, to make satisfactory recommendations of georeferenced photos without prior knowledge of the user profile, considering only its current context; Also to analyse, the context in which the photos were taken is relevant in making recommendations; and the usage of a context model considering various contextual dimensions may lead to an improved recommendation comparing to the result of one which uses only one context attribute (e.g., location). Others combined accuracy with coverage [200, 210, 211], that is, even when an RSs is highly accurate, it may often not be able to ever recommend a certain proportion of the items, or it may not be able to ever recommend to a certain proportion of the users (this measure is referred to as coverage). Due to this limitation the trade-off between accuracy and coverage always needs to be incorporated into the evaluation process. There are two types of coverage, which are referred to as user-space coverage and item-space coverage, respectively.

Some of the properties can be traded-off, for instance, perhaps the decline in accuracy may imply that other properties (e.g. diversity) are improved. Besides, while we can certainly speculate that users would like diverse recommendations or reported confidence bounds, it is essential to show that this property important in practice. In other words, when suggesting a method that improves one of this properties, one should also evaluate how changes in this property affects the user experience, either through a user study or through online experimentation [212].

Overall, independently of the property (or properties) seeked in the several RS that we have reviewed, it is clear that the diversity and quantity of the properties used in the scientific researches is increasing, which demonstrates that those features can improve even more the recommenders, when they are well applied.

3.4.5 Which type of recommendation is generated?

In this survey, we have found that RSs mainly generate three types of outputs: places/points of interest (*POIs*) such as monuments, churches, museums, etc.; tourist routes inside or outside the cities (*route*); and basic information or instructions of a tour, mountain walks, schedules (*guide*). The output of each analysed project can be observed in the fifth column of Table 3.2.

Firstly, the most common output are *POIs*, which represent 61% of the projects analysed. [188] for instance, proposed a new method called ContextRank, which exploits different context information of photos to recommend personalised tourism POIs. Their architecture first detects landmarks from geotagged photos and estimates their popularity; then, by analysing the photos and their textual tags, only the representative ones are extracted for each landmark. It calculates user similarity from users' travel histories with all this contextual information, predicts a user's preference score in a landmark from different aspects, and combines these scores to give the final recommendation of POIs with their proposed algorithm, called ContexRank. Another example of POIs recommendation is [205], whose project generates recommendations based on visual matching and minimal user input, by creating clusters of geotagged images and then recommending those POIs matching a query input by the user describing her preferred destinations. Another one is presented by [194], that proposed a method for mapping geotagged tweets to POIs on the basis of the substantial activity regions of the POIs as learned using one-class support vector machine. We also highlight [99], that applies collaborative recommendation algorithms to geotagged photos in order to produce personalised suggestions for POIs in the geocoordinate space. They used a collection of 3 million Flickr geotagged photos on which a series of steps was applied: first, unique locations were identified by discretizing the continuous geocoordinates into geographic virtual bins; second, implicit feedback was calculated in a user/location matrix using normalised frequency; and third, missing feedback values were imputed through four different algorithms.

Secondly, we find that 26% of projects recommend *routes*, among which we highlight three works. The first one is presented by [198], who developed a travel recommendation approach integrating landmark and routing. The routing is generated based on the Dijkstra algorithm, combined with spatial clustering of images. The second one is presented by [197], which proposes a travel route RS based on sequences of geotagged photos. The authors explain that the online processing of the system consists of the following steps: selection of tourist places that a user would like to visit; presentation of travel route candidates; and presentation of the selected travel route on a map. The third one, unlike the two projects previously mentioned, [201], developed not a recommendation of routes, but of pedestrian tracks of paths (remind that a path can be, for instance, "pedestrian path" in open areas without pre-established paths, such as a large garden), in this case for the *Forbidden City* in China, helping users to plan trips. As an output, their recommender also shows some features like the distribution of the visit duration along with the path. Another feature is the popularity of a destination by the total number of paths of the destination; with this popularity, the system can recommend what the hottest destinations are, in terms of seasons or months, thus being able to tell users whether March or October is the best travel time, for instance.

Finally, we found systems recommending *guide* in 13% of projects. An example was the project developed by [210]; according to the authors, classical tourist guides are usually organised around landmark popularity and fail to account for each visitor's preferences. Considering this issue, this project introduced techniques like collaborative filtering for personalising the visit guides, based on one's tagging record and on the discovery of users with similar preferences.

3.4.6 Which evaluation methods are used?

In this section we classify the projects analysed in two possible evaluation methods, online or offline, presented by [213, 214, 215]. On the one hand, the *online* evaluations, recommendations are shown to real users of the system during their section, that is, the process of evaluating a system is generated with the active and direct participation of the users, where the investigator obtains real feedback from them. On the other hand, *offline* evaluations use pre-compiled offline datasets from which some information has been removed, in other words, the process of evaluating a system is not developed with the active and direct participation of users, but rather, they can use data from users (real data), or not (synthetic data). Subsequently, the recommender algorithms are analysed on their ability to recommend the missing information [213].

According to [216], although the number of studies that use users has increased, the conducting such studies on real-world remains time-consuming and expensive, particularly for academic researchers. Consequently, relatively few studies measuring aspects related to user satisfaction have been published [47].

In one hand, from all the papers analysed in this research (column 3 in Table 3.2), 84% have evaluated their systems using the *offline* method, such as [186]. They used a sample of a dataset from Flickr with 1,376,886 photographs with their spatial and temporal context, and cleaned these photos' data, removing two types of photos from dataset: photos that were collected in the result of search based on text containing name of a city in their metadata and photos with incorrect temporal context. Then, they applied the density-based clustering algorithm to geo-tags associated with photos. This way, they compared some methods like, popularity rank, collaborative filtering rank, classic rank and, recommend popular places, to show the effectiveness of context ranking, which is his propose. With this method of evaluation, Memon demonstrated that his project is able to predict tourist's preferences in a new city more precisely and generate better recommendations as compared to other recommendation methods.

Using no one, but three different datasets, tourist spots (Foursquare), geotagged tweets (Twitter), and geotagged photographs (Panoramio), [194] conducted qualitative analyses in order to evaluate the effectiveness of the proposed methods (mapping geotagged tweets to tourist spot and extracts features of the tourist spot). Thus, he showed the effectiveness of the methods through qualitative analyses.

Another example was proposed by [188], a method named ContextRank that used a dataset from Panoramio, containing approximately 15 million of geotagged photos. For each landmark, he choose 10 representative photos by clustering. In his offline evaluation, he compared his method to scale space representation of all the geotags proposed in [217]. His results showed that different kinds of context information can help to enhance the recommendation performance when a user is lack of travel history.

Unlike previous works, [200], to build a knowledge model, chose to measure the effectiveness and the efficiency of the proposed solution using two trajectory sets: synthetic and real data. In relation to the offline real dataset, it was made up of data coming from Flickr, where the trajectories are built using users' photos. On the other hand, the offline synthetic dataset was generated using a trajectory generator for a specific geographic area. It takes as input a dataset of POIs, which are combined in sequences that form trajectories. In this way, this project was able to perform two evaluations: (1) the quality of the trajectory set, adopting spatial coverage, data coverage, region separation and rate; and (2) the effectiveness and efficiency adopting the prediction rate, accuracy, average error and omega. The results showed that this project is able to generate suggestions of potential POIs, depending on the current position of a tourist, and a set of trajectories describing the paths previously made by other tourists.

On the other hand, only 16% of the projects have submitted their projects to an assessment by real users. Even those counted on a very low amount of users. Using 21 participants represented in 8 different countries, [218] developed an online evaluation to see the effect of personalisation on the behaviour of participants. Besides to use a questionnaire to get travel habits of the participants who started travelling in the past, they had also completed parallel data collection tasks. Then, a list of recommendations of POIs was generated. These lists were either personalised or based on popularity, but both consisted of precisely five POIs given the limited time available for sightseeing. These participants received a list of recommended points of interest to say how much they liked of each POI on a scale from 1 to 7 (1=not at all, 7=a lot). Although some participants did not follow many of the recommendations in the personalised lists, the author found that personalised recommendations enabled a "discovery mode", that is, participants visited more POIs than in the popular condition, and these POIs were also rarer than POIs visited by participants in the popular condition. Thus, this project showed that personalised recommendations may increase serendipity since users are more likely to discover sites that surpass their a priori assessment.

In the project called MMedia2U developed by [91], a group of 13 users evaluated photos from 8 different contexts, each one consisting of a stage of evaluation. Lemos pointed out in his project that an online evaluation of an RS is a hard task, due to the fact that item's relevancy has a strongly personal nature and it is complex to be measured. This difficulty is enhanced when existing a lack of historical evaluation data, which makes large-scale studies very costly and difficult to be run. In his case, the complexity is even bigger, since his project needs to range the possible contexts of real situations. In each stage of his evaluation, one context (approximately 100 photos, 20 were taken in similar contexts to the one showed to the user and 80 were different in some dimensions of the context) was presented to the user. The volunteers had to visualize a set of photos and choose those that seemed to be more appealing to him/her, taking into consideration the context he/she suggested. And then, the degree of success on recommendations was then evaluated by the ratio of chosen photos. In general, the results of this project concluded that, for the data used, context-awareness can bring gains in the photo recommendation compared to a random list.

In the case of [202], 12 volunteers participated in the user-oriented evaluation of the prototypical implementation of Near2me. This project focused in discovering: how Near2me is perceived by users in general and how users interact with the system; how are the individual components used to contribute to the users' satisfaction with the system; and finally, how the interplay of the components used convey authenticity and personalisation to the user. The evaluation consisted of a task-directed walkthrough of the interface carried out on the working prototype. During the evaluation, the subjects were asked to use the Near2me prototype to plan a possible trip to Paris and were left free to interact with the prototype for a maximum time of 30 minutes. While performing the task, the participants were asked to speak aloud, giving insights about the motivations behind each action, the possible expectations about the foreseen outputs, and the satisfaction towards the actual recommendation and interaction paradigm. The subjects were observed, most relevant comments and behaviours were noted, and each session was recorded using both a video camera and screencast software. After the walkthrough, information was obtained from the participants through semistructured interviews. A question framework based on the research questions guided the interviews. This framework was adapted for each participant according to her vocabulary and the notes were taken during observation allowed for exploring and confirming the participant's feedback. This evaluation showed that the participants are interested in three perspectives: locations, topics, and experts.

3.4.7 What type of interface is used?

In our survey, we have found projects that use an interface based on mobile phones, based on web or without any interface at all. Specifically, from 18 papers that provided an interface, 12 of them (67%) were web-oriented and the remaining (33%) were mobile-oriented. These are detailed in column 7 (Table 3.2). We did not find any desktop-oriented application.

An example of an RS with an interface for Android mobile phones is the app

TAIS (Tourist Assistant) developed by [187]. The main application screen is shown in Figure 3.4 (left). The tourist can see images extracted from accessible internet sources, a clickable map with his/her location, current weather, and the attractions around ranked by the recommendation service. When the tourist clicks on an attraction, a context menu shows detailed information about the chosen attraction (Figure 3.4 right).

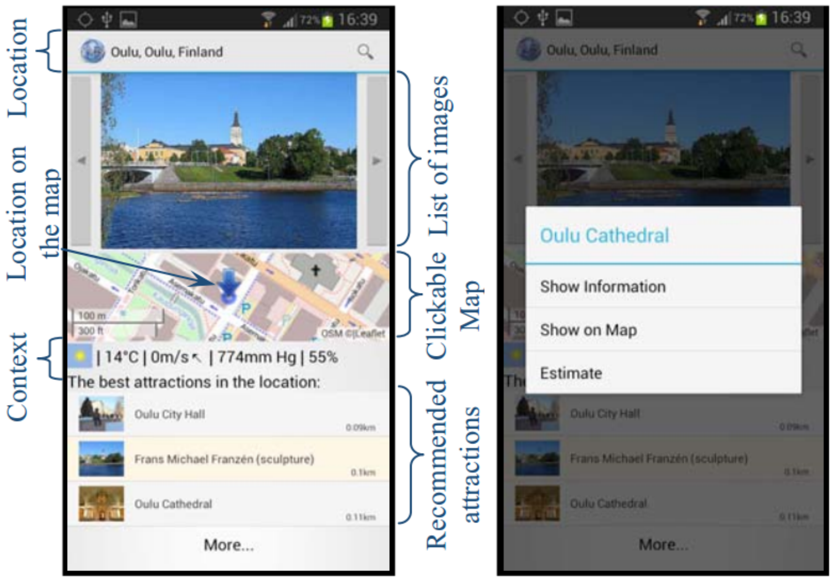

Figure 3.4: *Mobile interface of TAIS: main screen, context menu with actions*

We also show some details of the web-oriented project presented by [201], which, unlike the other projects, makes a recommendation of not only where to visit but also how to visit, that is, it makes a recommendation of "path" alongside with high-quality photos taken in this destination. In Figure 3.5, we see an example of the results obtained after a user inputs a destination name and then get the recommended paths within the query destination, in this case "the Forbidden City".

A web-oriented project was introduced in [185]. Figure 3.6 shows a visual example of the personalised travel recommendation. The system can collect

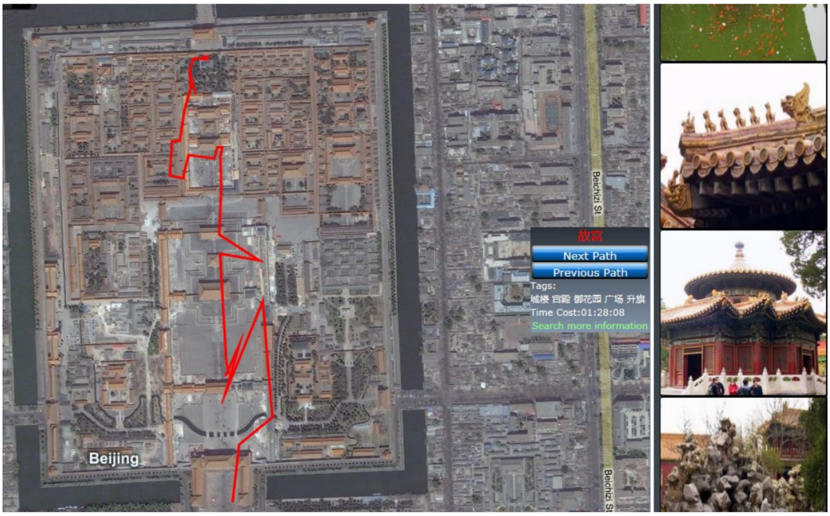

Figure 3.5: *An interface of path recommendation of user-specified places.*

the current location and show the located city on the map with high-quality photos taked in that destination are also shown to users. Also, the user can input their favourite and non-favourite attractions on the right side of the interface. If the user does not wish to interact with the system, the system will show them the results which are ranked by popularity, to avoid the cold-start problem.

3.5 Discussion

As we showed in this article, the combination of RSs and SNs is obtaining better results and, indirectly, enhancing the tourism sector's economy [219]. It is crucial, since the application of RSs in such a customer sensitive sector has become a necessity, not a luxury; moreover, RSs have great value because they assist all parts of the tourism value chain. On one side, they support better and faster decisions when the customer is choosing a destination, and help them to plan holidays according to their needs, improving the overall service offered. On the other side, they also offer considerable benefits for service providers

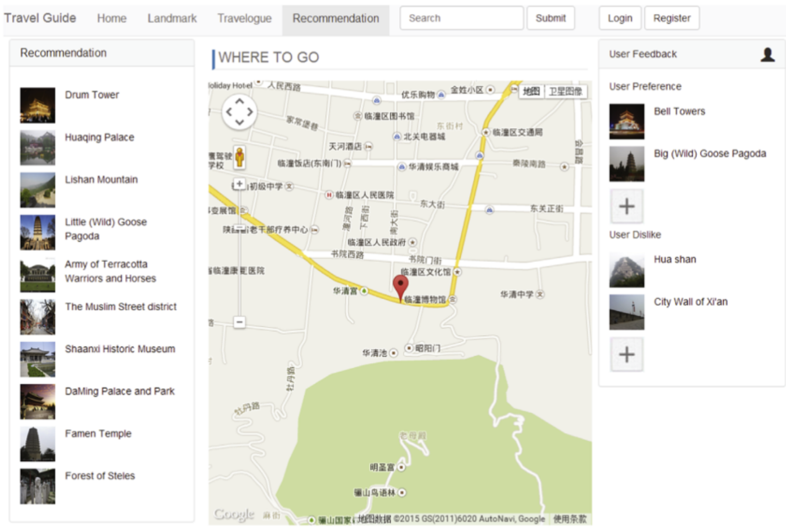

Figure 3.6: *User's interface is shown a visual examples in Xi'an, China.*

such as hotels, restaurants or cultural event organisers, improving their online presence, increasing sales, and reducing costs for advertising activities [220].

This way, the extent of projects that use SNs in their RSs keeps growing, as well as the volume of data generated in those environments, as shown in Fig. 3.2, thus progressively influencing tourists around the world. The RSs are deeply changing the way tourists search, find, read and trust when choosing a destination. On the other hand, people through SNs create and share content related to everything, from travel agencies to relevant information about a certain POI. However, the increment in the academic research production can be affected by some relevant challenges, from which the main is to get access to the data from SNs.

In 2018, Facebook, for instance, announced dramatic data access restrictions on its app and website in response to the public outcry following the Cambridge Analytica scandal [221]. This decision made it virtually impossible to carry out large-scale research on Facebook. The changes make extinct software and libraries dedicated to academic research on Facebook, including Netvizz, NodeXL, SocialMediaLab, fb_scrape_public and Rfacebook, all of which relied on Facebook's APIs to collect data. In the case of Twitter, it operates three well documented public APIs, in addition to its premium and enterprise offerings. Twitter's relative accessibility leads it to be vastly overrepresented in social media research. But public and open APIs are an exception in the social media ecosystem. Facebook's Public Feed API, for example, is restricted to a limited set of media publishers.

Due to the increasing data restriction on the part of the large companies such as Twitter [222], Instagram [223], and Facebook [126], some campaigns and initiatives pro data sharing have gaining adepts in the scientific environment. The idea of one of those projects, known as "Open Data"[6] is that the data be available for everyone, without restrictions, and can be freely used, reused and redistributed by anyone, meeting the requirement of mentioning the original source and sharing under the same licenses in which that information was collected. In other words, the goal of the open data movement is similar to others such as open source, open content and open access.

We believe that data sharing, whether from SNs, public or private bodies, is extremely relevant for the researchers in all areas of knowledge. In the case of public bodies, the Ministers of Science of all nations belonging to the Organisation for Economic Co-operation and Development (OECD[7]) signed a statement in 2004 saying that, basically, all archive data publicly funded must be accessible for the public. With respect to the data available online like in SNs, future researches would have to deal with an increasingly sensitive and troubling phenomenon, the privacy and the use of the data, among other reasons because they have stored very intimate data. Recently, we can observe two simultaneous scenarios: the SNs that provide APIs to the data access and analysis; and the SNs that suppress it, such as Facebook as we have already mentioned.

According to [224], the aforementioned data restriction, which causes a differentiation between public and "premium" versions, will widen the gap

[6] http://www.opendatafoundation.org/

[7] http://www.oecd.org

between industry researchers hired by SNs and researchers working outside of corporations.

In spite of such restrictions, there are large databases available for research purposes, which could be used on projects that seek an offline evaluation to measure their accuracy, for instance. Some examples of those databases are Open Data, Stanford Large Network Dataset Collection, UCI Network Data Repository, Interesting Social Media Datasets, Network data, and Kevin Chai's.

Throughout this paper, we tried to disclose and clarify some theoretical and technical topics in the development of a recommender, by analysing the projects of recommendation systems since mid-2004. We presented a summary of the basic recommendation techniques, an overview of what SNs are about, their benefits, and their importance to the recommendations projects. Then, we ordered (by date of publication) the main works of the last 10 years about RSs in the tourism sector that make use of SNs and classify them into categories such as: SNs and online databases used, items extracted from these sites, evaluation techniques applied, general goals in evaluating, display and interface.

Overall, we observed that RSs are diversifying their data source, consequently adding more complexity in its ability to interpret and predict the customer interests. There are still many researches that use a single data source (e.g. Flickr), which retrieve data considered basic (e.g. age, gender, marital status, number of children, etc.), and seek only the accuracy improvement by means of basic techniques such as CB and CF to generate POIs recommendations. But then, recent investigations started to use more complex data (e.g. correlations between network contacts in a SN, behaviour, texts, photos, etc.) from multi data sources (e.g. Facebook + Wikipedia + TripAdvisor) and different properties (e.g. novelty, serendipity, diversity), increasing the variety of assessments, mainly thanks to machine learning.

We also consider that the use of SNs (also known social-based RSs) can indirectly solve or at least mitigate some well-known issues of recommenders, such as the problem of (1) the new user/item, known as the cold start problem;

(2) sparsity or ratio diffusion; (3) compilation of demographic information; (4) Portfolio effect; (5) recommendations with excessive results; (6) serendipity [49, 9, 225],as well as, to improve the quality of recommendations in the tourism context [37].

The cold start problem (1) appears with new users/items, i.e., a system is not capable of recommending an item with an acceptable accuracy until the user has rated enough items. By using SNs, this problem can be mitigated, since it is possible to retrieve "likes", comments, and reviews made by the user in one or more SN. Similarly, there is the new element problem, in which a new item is not recommended until a considerable number of users have rated it, so the probability of the system recommending such item is low. To get around this problem, first, the POIs ratings could be retrieved from different SNs such as Facebook, Flickr, TripAdvisor or Google Maps. Secondly, those POIs with no enough reviews or comments can be of interest for people who like exotic, isolated or less known places; thus, if the system is able to detect those profiles, it would be able to recommend them those places.

The sparsity or ratio diffusion problem (2) occurs when there are few or no user ratios that match each other, thus there would be few users to compare with or few similar elements to look for. This problem is commonly found in CB and CF RSs. In this context, SNs play a crucial role due to its large extent of user profiles available, which could minimise or even neutralise such problem.

The compilation of demographic information (3) refers to the lack of information related to where people reside or is currently located. Sometimes, a user can be reticent in providing information to a new system, whether due to their privacy concerning, whether due to lack of trust in the service. The use of data already shared on SNs, also used to retrieve such kind of information in a non-intrusive way, could solve this problem.

Portfolio effect (4) is regarding the recommendation of an item very similar to another item that the user already has in her history. In the case of tourism, an RS that previously knows the places the user has visited through information posted on their SN could then avoid recommending places of similar categories and locations.

The recommendations with poor or excessive results (5) can overwhelm the user. In order to reduce or specialise the items recommended, additional properties could be applied to the RSs, such as novelty, diversity, serendipity, utility, etc. A good number of those properties could be based on the personality predicted using data available on SNs, following some already existent psychological theories. For instance, the system could recommend useful POIs in a reduced quantity when considering the curiosity, that means, the higher the degree of curiosity, the lower the popularity of the POI, and vice-versa [42].

One of the keys of the serendipity (6) may be the prediction of an individual's personality. By using data from SNs, such prediction could be easily achieved, thus the RSs would be able to positively surprise the user by recommending items that really match the user's interests. Regarding the adoption of real users to assess the recommenders developed, it is worthwhile stressing its importance when measuring the quality of a system. It is highly abstract to build a system that generates positive surprisingly (serendipitous) recommendations without the cooperation of a human being since each has unique tastes, and the same item may be relevant for one individual but not for another. In short, the researcher needs to understand the response of the user to the delimited parameter, which is not feasible in an offline environment.

In spite of the advantages and facilities that offline tests offer to the researcher, we believe that a recommendation system shall be submitted to field experimentation, where the data are recorded from reactions resulting of the variables the researcher enter in the experiment; as previously stated, the variables are not controlled, because the RSs are developed for human beings, whose tastes, situations and profiles are different. To strengthen this point of view, we must also analyse the psychological relationships between tourism and psychology [38] or recommendation projects that use psychology to improve their recommendations [226, 34, 33]. We believe that the RSs cannot lose their target, which is the human being and the context in which it is presented.

That is, the individual plays an extremely important role in this process.

Nevertheless, projects counting on the participation of volunteers to assess their systems, thus seeking an online evaluation, have as possibilities the Open Source Social Network (OSSN), a rapid development social networking software, but then it would be needed to recruit volunteers to feed those OSSNs, which is laborious. Another option for projects that need user interaction is Diaspora[8], an SN launched in 2010 that already has 600 thousand users, where the user "owns" his data and has the power to share it as he wants. Therefore, with the request and acceptance, these data could be used.

Although further studies are needed to assess the benefits of the online evaluation, it is vital to encourage the forthcoming projects to ask for feedback from the users, who are the main beneficiaries of the recommenders. This way, it would be possible to widely explore the influence and the impact of SNs in all the aspects of the RSs in the tourism sector.

We expect that the clarification of which SNs were used in the recommendation projects may contribute in encouraging the use of SNs as a method of nourishing their RSs in new projects, since nowadays its use is simple and accessible to any researcher. In general words, we hope to contribute to make an approach about the recommendation systems and SNs to cover existing definition in the literature, their types and characteristics; we also hope that the state-of-the-art knowledge here generated can support researchers and practical professionals in their understanding of developments in RS applications.

With regard to the challenges of future investigations, it is important to emphasise that we did not find works of RSs for the sector of tourism that use human personality to enrich the user profile so that different aspects can be taken into account [227, 228]. Also, we consider that the generation of recommendation in the tourism sector based on SNs and that somehow consider the human personality will have a start of importance. In this sense, the first steps have already been taken in other areas of knowledge in the industry, and this will not be different.

[8] https://diasporafoundation.org/

Chapter 4: A Hybrid Recommendation System Based on Human Curiosity

Contents

A Hybrid Recommendation System Based on Human Curiosity

Authors: **Alan Menk**

amenkdossantos@dsic.upv.es

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Abstract

Traditional recommendation systems use multiple computational techniques to perform personalized recommendations, and can consider the interests of users and even the context in which they live. However, they usually ignore each individual's personality factors, and hence, the recommendations generated overwhelmingly consider that all the users are identical psychologically. They ignore, for example, the curiosity level of each user, which may indicate that individuals with a high level of curiosity seek visit exotic locations and/or not yet visited by them, or even individuals with a low curiosity level tend to do the same things they did in the past, uninterested in new or different areas. Our paper presents a complete hybrid recommendation system considering the curiosity level of each individual as a decisive factor to recommend sites of South America. In order to prove the efficiency of our system in contrast to traditional recommendation systems, as well as to measure the satisfaction of users about the recommendations, we performed some preliminary experiments with the participation of 105 Brazilian volunteers. The first results indicate that considering the level of curiosity of a user increases the satisfaction with the recommendations.

4.1 Introduction and Motivations

Nowadays, recommendation systems are facing challenges to generate recommendation of contents with low rejection rates and high performance, besides to overcome already known obstacles in the area of content recommendation, for example: limited content analysis, super-specialization and cold start problem [46]. Hence, in these last few years, several lines of study have been developed, in order to consider the psychological characteristics of users, giving a greater weight to what people feel and think, instead of simply consider their previous purchases or people with similar profiles.

In the literature we can find a wide variety of academic papers related to recommendation systems for individuals and groups, using both traditional methods and hybrid applications. However, papers that use psychology in recommendation systems are still rarely found.

We can highlight the work in [168]. It describes three algorithms to model and predict the satisfaction experienced by individuals using a recommender system for groups, which recommends sequences of items. By analysing the impact on satisfaction of the following item after visualize the previous one, they could model the wearing-off effect and the assimilation effect, in order to select the next item. Another research presented in [230], proposes a new method of performing recommendations for groups bearing in mind the personality of the group members and how they deal with conflicts.

This work introduces a complete recommendation system that combines theoretical psychological models with the contemporary idea of positive psychology to enhance the performance of traditional recommendation systems for tourist domains. This system presents two important features. First, data collected from a social network is analysed in order to calculate the level of curiosity of a given user. Then, through an online recommendation system, we show the user the recommended sites of South America, in order to assess the level of satisfaction of volunteers and, consequently, analyse the efficiency/accuracy of our technique.

This way, we aim to demonstrate that the combination of traditional recommendation techniques by taking into account psychological characteristics of individuals can improve the user satisfaction with respect to the recommendation. It is expected that this way, we can generate a more "humanized" recommendation, according to the psychological characteristics of the individual, being able to positively surprise the users.

This paper is organized as follows. First, we introduce the definition of curiosity and how it can be measured, after we present the architecture of our system and we describe the different modules that compose our system. Next, we detail the performed experiments and the feedback obtained from the volunteers when the recommendations were presented. We finish with some conclusions and further work.

4.2 Curiosity

Why some people tend to always travel to the same places while others do not? Why do individuals explore the unknown? What makes people curious? From the publication of the paper “A theory of human curiosity” by Berlyne in 1954 [116] the word “curiosity” starts to gain a higher visibility in psychology, and a number of researches have been developed since then, so questions like those can be measured and answered. Curiosity is defined as a desire for acquiring new knowledge and new sensory experience which motivates exploratory behavior [231]. Recent studies have introduced different scales to measure the curiosity of an individual, and one of those is the model Curiosity and Exploration Inventory (CEI-II) by Kashdan et al. [2], which we have adopted in this project.

This scale is considered one of the most reliable and practical today, consisting by only 10 items (Figure 4.1). It offers empirical support for two curiosity dimensions: motivation to seek out knowledge and new experiences (Stretching; five items) and a willingness to embrace the novel, uncertain, and unpredictable nature of everyday life (Embracing; five items).

4.3 The Hybrid Recommender Based on Curiosity

This section describes the main aspects of our recommendation system. We formulate three hypothesis: (H1) The level of curiosity of a given user may influence his decisions about what places to visit; (H2) It is possible to use data available on social networks like Facebook[1] to measure the level of curiosity; And (H3) the level of curiosity of an individual may play a crucial role in the choice of the recommendation technique.

[1] Facebook <https://www.facebook.com/>.

Curiosity and Exploration Inventory (CEI-II) Instructions: Rate the statements below for how accurately they reflect the way you generally feel and behave. Do not rate what you think you should do, or wish you do, or things you no longer do. Please be as honest as possible.		Very Slightly	A Little	Moderately	Quite a Bit	Extremely
1	I actively seek as much information as I can in new situations.	1	2	3	4	5
2	I am the type of person who really enjoys the uncertainty of everyday life.	1	2	3	4	5
3	I am at my best when doing something that is complex or challenging.	1	2	3	4	5
4	Everywhere I go, I am out looking for new things or experiences.	1	2	3	4	5
5	I view challenging situations as an opportunity to grow and learn.	1	2	3	4	5
6	I like to do things that are a little frightening.	1	2	3	4	5
7	I am always looking for experiences that challenge how I think about myself and the world.	1	2	3	4	5
8	I prefer jobs that are excitingly unpredictable.	1	2	3	4	5
9	I frequently seek out opportunities to challenge myself and glow as a person.	1	2	3	4	5
10	I am the king of person who embraces unfamiliar people, events, and places.	1	2	3	4	5

Figure 4.1: *CEI-II Form applied to the participants*

To prove our hypothesis, we have developed a hybrid recommendation system based on human curiosity. Figure 4.2 shows the architecture of our system which was divided into two main parts: The first one, “Model Generation”, is devoted to generate a model of curiosity by using information available in Facebook and the CEI-II psychological test and, the second one, the “Model Execution” applies this model to new users to measure the curiosity level and it is also responsible for the recommendation itself.

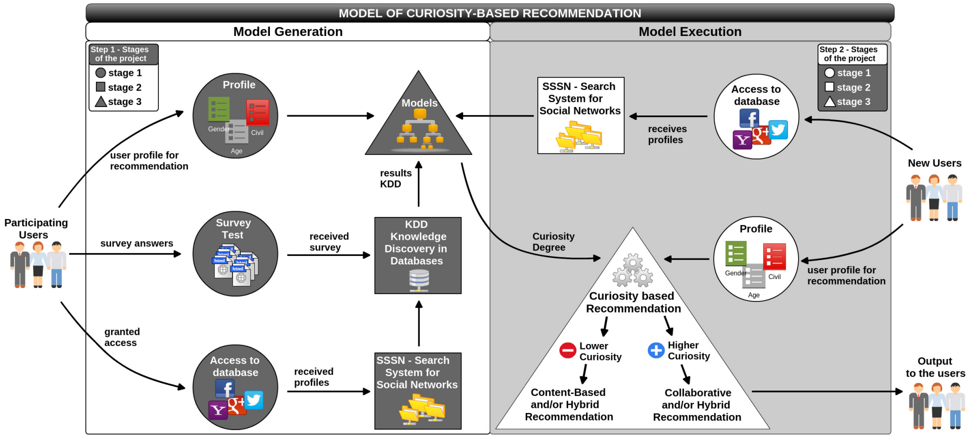

Figure 4.2: *Architecture of our Recommendation System Based on Curiosity*

4.3.1 Model Generation

The "Model Generation" phase works in 3 stages, with the aim of generating a curiosity model. For this purpose, we recruited 105 Brazilian volunteers that participated in the project. This set of volunteers is composed by 50% of men and 50% women, from different regions of Brazil, between ages from 18 to 56, whose level of study is: 60% Postgraduate, 31% Graduate, 3% High School and 6% Basic Level.

At the first stage (represented by circles in Figure 4.2) we obtained three types of different information. The first one (Profile) obtains basic data from Facebook in an implicit way (age, gender, marital status, etc). The second one (Survey test) calculates the level of curiosity of each volunteer through the CEI-II questionnaire. And the third type of information (Access to database) consists in implicitly obtaining Facebook data as likes, groups, visited places, photo tagging etc.

The second stage (represented by squares in Figure 4.2) comprises Search System for Social Network (SSSN) and Knowledge Discovery in Databases (KDD) modules. The SSSN (square in Figure 4.2) aims "to clean" data obtained in the previous process, i.e remove repeated, incomplete or inconsistent data, but also SSSN is responsible for classifying the "likes" of a given user, in order to better capture his interests. This is performed by selecting the "name" field in table "likes". In Table 1, we can observe an example of the results obtained with the fan pages classification and groupings performed by category and subcategory.

Table 4.1: *Sample of Fan Pages classification grouping by category and subcategory*

Like Name	Category	Subcategory	Method
Gloria Alegria	Temple	Religion	Deduction
Assassin's Creed	Game	Fiction	Wikipedia
Bar do Ze	Place	Bar	Deduction
Caetano Veloso	Music	MPB	Wikipedia
Gigante acordou	Forum	Politic	Deduction

In the KDD module (square in Figure 4.2), we receive the data from the survey test and the data previously processed by SSSN, in order to generate the curiosity model through the application of a data mining algorithm. We have performed some experiments with three different algorithms: Apriori, J48 and K-means [232].

In our simulations, we obtained better reliability values with the J48 algorithm, the results were: 32.24% for Extremely curious, 64.57% for Moderately curious, 91.03% for Quite a Bit curious and 38.56% for A Little curious. In other words, when introducing a new user (Model Execution) to our system without answering the Survey test, we can infer his curiosity level with the values of reliability mentioned above. Although we think that these values are not good enough, they are promising with respect to the Moderately and Quite a Bit curious users.

4.3.2 Model Execution

The "Model Execution" is also divided in 3 stages. At stage 1, the system analyses the Facebook data of the user to infer, through the generated model, his level of curiosity (stage 2).

The stage 3, called "Curiosity-based recommendation", consists in our hybrid recommendation system. It uses two basic recommendation techniques: content-based (CB) and collaborative filtering (CF). Then, two lists of recommendations are computed. The first list corresponds to the CB recommendation technique, which uses travelling history to make a list of sites with similar features to those that the user visited in the past. The second list is generated by means of the CF recommendation technique, which makes a new list of sites from similar profiles to the user. The final list of recommendations is obtained by combining both lists in a weighted way, which depends on the level of curiosity of the user.

Specifically, for users with a lower level of curiosity a higher percentage of items from the CB recommendation list is used, and for those who have a higher level of curiosity a higher percentage of items from recommendation lists based on CF is used.

Table 2 shows the relationship between the level of curiosity and the percentage of items of each list that is used in the hybrid system to build the final lists of recommendations. Let's consider for instance a user with a level of curiosity "1 - A Little"; the hybrid algorithm will create a new list with 80% of recommendation items from the CB list and 20% from the CF list, whose results will be ordered according to their estimated rating.

To derive the values presented in Table 2, we consider the premise of positive psychology stated by [4], which says that curious people are willing to explore the unknown before judge it. Thus, curious people are not apathetic to uncertain things or new ideas. Face to unexpected or unknown, the curious feel excited to seek, unveil, know. Therefore, curiosity and novelty often go hand in hand.

By applying this theory in recommendation systems, we realized that, the more curious an individual, the more will be his seek for sites different of those he already knows so the recommendation based on CF fits optimally in this situation. On the contrary, little curious people tend to visit the same or

Table 4.2: *Weights Hybrid Recommendation System based on Curiosity*

	Degree of Curiosity	% CB	% CF
1	A Little	80%	20%
2	Moderately	60%	40%
3	Quite a Bit	40%	60%
4	Extremely	20%	80%

similar places, so the CB recommendation becomes the best option to those individuals.

4.4 Evaluations

This section summarizes the experiments we have performed in order to test our hybrid recommendation system. Given that we were interested in making some preliminary tests, only 26 out of 105 volunteers were asked to participate.

They received a recommendation of sites of South America through photos, allowing us to meet two objectives: first, analysing the level of the satisfaction of volunteers regarding to the recommendation and second, comparing possible gains of the hybrid system we developed to traditional recommendation systems. For this purpose, we developed an online system (Figure 4.3) called “Points of Interest in Latin America” which, integrated to the Flickr[2] platform, shows photos of sites of South America corresponding to the recommended places.

By accessing the online system (through a web page), the three recommendation lists were presented to the users, with 3 photos of sites in each page (10 pages in total), and they could rate each sight as: Little Interesting, Moderately Interesting and Extremely Interesting, according to their tastes. The system generates three lists of 10 recommendations for each volunteer, and the level of curiosity that we have considered is the one obtained by the CEI-II questionnaire.

[2] Flickr <https://www.flickr.com/>.

Figure 4.3: *Main page online system Points of Interest in Latin America*

The first results we have obtained with real users are shown in Figure 4.4. It can be observed that both CB and CF techniques had 86 and 81 votes, respectively, of "uninteresting" recommendations, whereas the recommendation based on curiosity obtained only 76 votes, which represents a reduction in the rejection rate of approximately a 18%. When analysing the second aspect, "Moderately Interesting", we can see that the curiosity-based recommended achieved a gain in relation to the CB technique of 20% and 25% compared to the CF technique, so an average gain of about 23% in relation to traditional recommendation systems. Finally the number of sites that the volunteers found "Extremely Interesting" remains stable regardless the recommendation system.

Therefore, we can conclude that the use of our hybrid recommender is able to increase the user satisfaction. In other words, the use of curiosity can aid recommendation systems to achieve better prediction rates and also decrease rejection rate if compared to traditional recommendation systems.

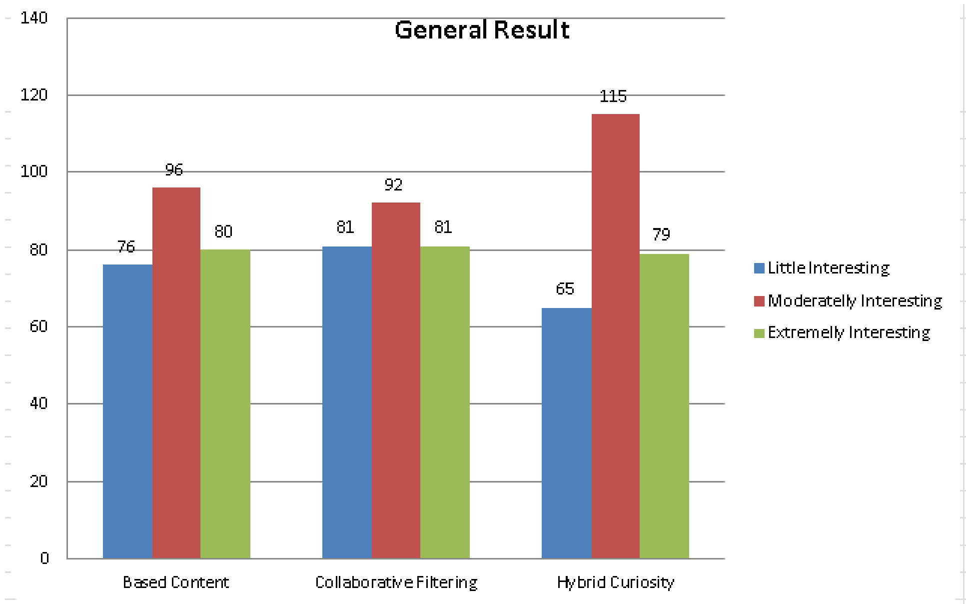

Figure 4.4: *Comparison of traditional and hybrid recommendation systems.*

4.5 Conclusions and Future Work

In this work, we have presented a curiosity-based recommendation system. By means of the data available in the social network Facebook, our system is able to measure the curiosity level of a given user and to provide recommendations based on this level. In the experiments we performed, we proved that human curiosity defined in Psychology can aid recommendation systems to be more efficient.

Regarding to future researches, we intend to use a larger amount of personal characteristics by means of other data sources like the social networks Linkedin and Twitter, thus getting data like: history of previous jobs, skills, certifications, courses, content of tweets, etc., always looking for variables which can identify the personal characteristics of the individuals.

We also intend to use the database from MyPersonality[3] project, which

[3]Mypersonality <http://mypersonality.org/>.

currently has approximately 4,000,000 individual Facebook profiles, so we could test the curiosity generated models here. Finally, we will perform new experiments with a bigger amount of volunteers. We will also generate lists with different weights between the content-based and collaborative-filtering lists and, moreover, we will present the results (photos) in a scrambled way, so that the user is not influenced by the order in which they are shown.

Chapter 5: Predicting the Human Curiosity from Users' Profiles on Facebook

Contents

Predicting the Human Curiosity from Users' Profiles on Facebook

Authors: **Alan Menk, Laura Sebastia**

{amenkdossantos, lsebastia}@dsic.upv.es

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Abstract

Nowadays, social networks store a massive amount of data, which can say a lot about our personality. Given the ease to access the internet everywhere at any time, many people use social networks in daily life, reflecting in a certain way their behaviour from the "real world" to the "virtual world", by storing in social networks what they like, hate, feel, where they travel to, their relationships, opinions, etc. Once obtained the access to this data, some authors have tried to infer the personality of the individual without the use of long questionnaires, only working with data in an implicit way, that is, transparently to user. In this scenario, our work is focused on predicting just one of the human personality traits, the Curiosity. In this paper, we analyse the information that can be extracted from the users' profile on Facebook and the set of features that can be used to describe their degree of curiosity. Finally, we generate a prediction model in the form of a decision tree.

5.1 Introduction

In the literature we can find a wide variety of academic papers related to recommendation systems to individuals and groups, by using both traditional methods and hybrid approaches. However, projects that make use of the information from social networks to improve the performance of recommendation systems started to gain strength from 2004. The main reason for this is the huge amount of people's data available on social networks. This data tend to increasingly grow since nowadays there are still about 4.4 billion people worldwide without access to the internet [233]. In this propitious scenario, social networks are one of the big beneficiaries. Companies like Facebook[1] have already exceeded the mark of one billion active users, who share photos, opinions, feelings and places visited, among other information.

In previous works, it is stated that the information in users' Facebook

[1] Facebook http://www.facebook.com/

profiles is reflective of their current personalities, not an “idealized” version of themselves [234]. This factor, added to the great amount of users, makes this social network an ideal platform for studying the connection between the information shared on Facebook and the personality of the users. In this context, we can find a popular project called myPersonality[235], which is a Facebook application that allowed users to take psychometric personality tests (Big Five Personality Inventory [236]), thus recording their psychological and Facebook profile. It is considered the most complete database for researches in this field, with about 4.000.000 individual Facebook profiles. More than 200 researchers are currently working with myPersonality data. This paper aims to provide a more targeted approach in relation to personality, putting as central research question only a specific point of the human personality: Curiosity. Our focus is on trying to find a link between the use of social networks and the respective degree of curiosity of its users.

In the literature, it is usually considered that a recommender system should provide diverse recommendations [212]. However, some authors [237] think that the satisfaction of the user with respect to diversity in the recommendktion depends on their own personality. One of the personality factors that may determine how diverse should be a recommendation, is the degree of curiosity of the user [40]. According to positive psychology, curious individuals are more open to novelty, the new, the unknown, like to learn new things [238, 4]. That is, the little curious individuals prefer to visit places already known or places with the same thematic. For instance, a little curious person who went to the beach in the past tends to go to that or to a different beach in future trips, but they would maintain a pattern, leaving aside mountains or cities. Therefore, once we ascertain the curiosity degree of a person, we can recommend tourist places to them, based on her degree of curiosity.

The aim of our work is to determine whether the degree of curiosity of a given user can be derived from the information that this user shares on Facebook. Therefore, our objective is to develop a model to predict this degree of curiosity. In order to do so, we contacted with more than one hundred users who filled in a psychological questionnaire to calculate their actual degree of curiosity and who also granted access to their profiles on Facebook. This data was analysed and, as the results will show, we were finally able to develop a model to predict the degree of curiosity with a satisfactory confidence level.

This paper is organized as follows. First, we give a quick summary about the prediction of personality traits from the information in social networks. Then, we describe what curiosity is according to psychology and how we can measure it. Section 6.3 presents our methodology for extracting, analysing and classifying the Facebook profile information. Next, we present some results about the correlations between some features extracted from the Facebook profile and the curiosity degree of a given user, in order to determine which features are more relevant. We also describe the data mining techniques we used and we show the model that we obtained for predicting the degree of curiosity from the data in Facebook. Finally, we conclude with a discussion of the results and the implications that this work may have in using the degree of curiosity to determine the degree of diversity that should be included in a recommendation, seeking to improve the user satisfaction with this recommendation.

5.2 Related Work

With the increasing information available on social networks, many authors are now interested in trying to predict the user personality from the information shared in these social networks. The growth of this interest is reported in [122], which shows an average of 20 projects between 2000 and 2004, and about 120 projects between 2010 and 2012. This research considered only the number of papers per year with the word "personality" in their title (sum over IEEE Xplore and the ACM Digital Library). Below we present some projects that made use of social networks to predict personality.

The work described in [32] is considered the first research about prediction of personality with social media. The authors presented a method by which the personality of the users can be accurately predicted through the public information available on their Facebook profiles. To do this, they used the big five personality inventory, a self-report inventory designed to measure the Big Five dimensions (extraversion, agreeableness, conscientiousness, neuroticism and the openness to experience). It is a multidimensional personality inventory with 44 items [236]. They collected information about the users such as: list of friends (to calculate the density of network), features like date of birth, relationship status, religion, education history, gender and home-town, personal activities, favourite things and other information. The authors analysed the user personality and their Facebook profile, and were able to find correlations in the data; by using the profile data as a feature set, they trained two machine learning algorithms (m5sup/Rules and Gaussian Processes) to predict each of the five personality traits to within 11% of its actual value. In their conclusions, the authors considered that the ability to guess the personality traits of a user creates many opportunities for personalising interfaces and information.

In [35], the authors investigated the relationship between user popularity in Facebook (number of contacts) and personality traits on a large number of subjects. They analysed if the popular users are the ones whose personality traits either predict many offline "real world" friends or predict propensity to maintain superficial relationships. By using the Big Five model through the MyPersonality database, the authors reached some conclusions such as, for instance, that popular Facebook users tend to have the same personality as popular people in the real world, suggesting that the nature of online interactions does not significantly differ from those of real world.

The work in [239] shows that computer-based models are significantly more accurate than humans in the personality judgement task. Using several criteria, they show that computers' judgements of people's personalities based on their digital footprints in Facebook are more accurate and valid than judgements made by their close others or acquaintances (friends, family, spouse, colleagues, etc.).

In the literature, we can find some other similar works trying to measure the personality from the social network data. We highlight the work described in [33], that developed a system called TP2010, a Facebook application able to collect information about the personality traits of more than 20.000 users, along with their interactions within Facebook. Based on all the collected data, automatic classifiers were trained by using different machine-learning techniques, with the purpose of looking for interaction patterns that provide information about the personality traits of the users. In summary, the authors used total values to predict user personality, such as the number of friends or the number of wall posts, etc. In this same train of thought, we can also mention the works described in [240, 21, 241, 36] that sought to examine other characteristics of social networks in order to try to infer personality.

As indicated above, our work is centered on the human curiosity, which is closely related to the "openness to experience" trait in the Big Five. Some works have investigated the correlations between the Facebook profiles and openness. For example, [176] showed that individuals who scored higher on the trait of openness to experience used more features from the personal information section in Facebook. Moreover, [123] reported that openness was related to adding and replacing photographs, which may reflect the fact that individuals high on this trait tend to engage in a wide range of activities and it also was correlated with the number of overall friends, the number of friends in the local network, and the number of networks. Finally, [129] showed that openness is positively correlated with number of users' likes, group associations and status updates.

5.3 The Human Curiosity

Human curiosity in the purview of psychology is defined as the desire for new knowledge or new experiences. It is considered one of the fundamental strengths and personality traits studied by psychologists [116, 139, 242] and it is widely recognized as an important antecedent of exploration [243, 244]. According to Berlyne [116], curiosity is classified into two types, namely: Perceptual Curiosity, which leads to increased perception of stimuli, that is, the desire of discover new things, more instinctive; and Epistemic Curiosity, characterised by the desire of learning new things with the aim of acquiring new information and knowledge, more intellectual. Curiosity is a human strength with relevance to domains ranging from creativity, leisure and social relationships to applications in educational, sport, organizational, and clinical psychology [245]. The existing surveys show that curiosity has an approximate weight of 10% in variations of performance results and 36% in career choice [246]. In relation to behavior at work, curiosity can define how well individuals would adapt to new occupations [247], to work-related changes or it even would influence learning and performance at the workplace [248, 249, 247]. Consequently, we can consider that curiosity, in any of its dimensions, has an important contribution in defining the personality of individuals and acts directly in their decisions; in this sense, we consider that it is a key element in the predictions of recommender systems.

From the 50s, many new scales have been and continue to be presented in order to expand research in curiosity, and also to provide effective means and methods of curiosity measurement. In this regard, we can highlight three studies. The first [139] presents a new research field called positive psychology, becoming a reference for many contemporary researches; in this field, personality is divided into 6 virtues which in turn contain a set of 24 strengths, including curiosity, but it also includes related strengths like creativity, open-mindedness, love for learning and perspective [4]. Another remarkable scale in psychology is the questionnaire called EPCQ - Experimental Perceptual Curiosity Questionnaire [250], which contains simple questions like "discover new places to go", "travel to places never been to", where they seek to determine if Perceptual Curiosity could be identified as a meaningful personality construct.

Finally, we have a large psychological study described in [2], where the CEI-II form is introduced. This scale is considered one of the most reliable and practical questionnaires today, consisting by only 10 items. The CEI-II form (Figure 5.1) offers empirical support for two curiosity dimensions:

Curiosity and Exploration Inventory (CEI-II) Instructions: Rate the statements below for how accurately they reflect the way you generally feel and behave. Do not rate what you think you should do, or wish you do, or things you no longer do. Please be as honest as possible.		Very Slightly	A Little	Moderately	Quite a Bit	Extremely
1	I actively seek as much information as I can in new situations.	1	2	3	4	5
2	I am the type of person who really enjoys the uncertainty of everyday life.	1	2	3	4	5
3	I am at my best when doing something that is complex or challenging.	1	2	3	4	5
4	Everywhere I go, I am out looking for new things or experiences.	1	2	3	4	5
5	I view challenging situations as an opportunity to grow and learn.	1	2	3	4	5
6	I like to do things that are a little frightening.	1	2	3	4	5
7	I am always looking for experiences that challenge how I think about myself and the world.	1	2	3	4	5
8	I prefer jobs that are excitingly unpredictable.	1	2	3	4	5
9	I frequently seek out opportunities to challenge myself and glow as a person.	1	2	3	4	5
10	I am the king of person who embraces unfamiliar people, events, and places.	1	2	3	4	5

Figure 5.1: *CEI-II Form applied to the participants*

motivation to seek out knowledge and new experiences (Stretching; five items) and willingness to embrace the novel, uncertain and unpredictable nature of everyday life (Embracing; five items). This paper uses the CEI-II scale, due to the fact that it has been subjected to a psychometric examination, ensuring greater reliability in its use.

5.4 Methodology

This section describes the main aspects of our architecture (Figure 8.1). As stated above, our aim is to generate a model to predict the degree of curiosity of a user given their Facebook profile.

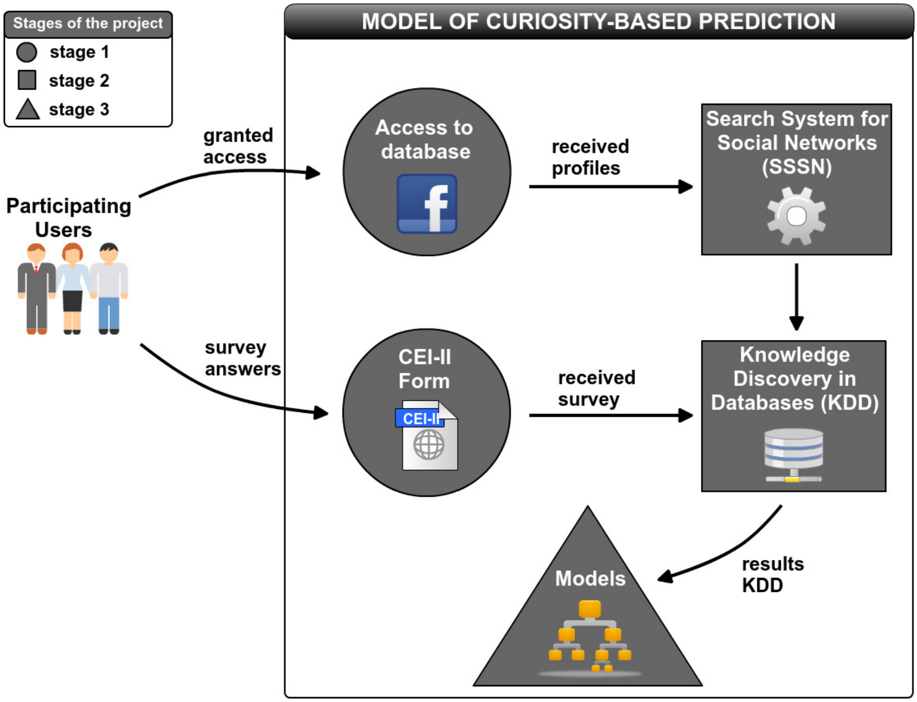

Figure 5.2: *Architecture of our system*

In order to do this, we implemented a system that first extracts the data from Facebook and analyses and classifies the data from the profile of the users; then, it determines which information is correlated with the degree of curiosity obtained from the CEI-II form; only the correlated information will be finally used to generate the prediction models.

Our architecture is basically divided in three stages. First of all, our system asked a given user to fill in the CEI-II form (Figure 5.1) and, at the same time, it also collected all the information from the Facebook profile of the user (after authorization). In the second stage, by means of our Search System for Social Networks (SSSN), the Facebook profiles of the volunteers were processed. In other words, the data was cleaned up, we suppressed noise and duplicated or empty records, obtaining this way a set of reliable values to be used as input to the next step, which consisted on the process of knowledge discovery in databases (KDD). The result of this KDD process was a model to predict the degree of curiosity of users from their Facebook profile.

5.4.1 Data Extraction

In order to generate the models to predict curiosity, we need real users that fill in the CEI-II form (Figure 5.1 adapted to online platform) and give us access to their Facebook profiles (Figure 6.3). It is important to note that these profiles are language–dependent, which may lead to problems in language processing [251], where non-compositional idiomatic expressions represent a significant problem in computational linguistics in the context of translation and understanding of texts. For this reason, we decided to work only with Brazilian users. Formal invitations were emailed to participants in different discussion groups, forums, etc., containing the details of the project, terms of use, privacy of personal information and authorization to its use for scientific purposes. We obtained the voluntary participation of 105 users, consisting of 55% male and 45% female, from different regions, age groups, gender, marital status and educational level.

The data in the Facebook profile that we initially took into account was (Figure 6.3):

A) Information from followed groups

B) Timeline

C) Profile data

D) Information from uploaded photos

E) Information from friends

F) Information from likes

Figure 5.3: *Example of a profile from the social network Facebook containing the fields to be analysed.*

5.4.2 Pre-Processing

The common problems found in the pre-processing step were described in [252], such as data with inconsistent values, in addition to distorted or incomplete information, or even with little relevance to the task of data mining and prediction. To avoid this issue, we analysed the structure, organization and consistency of the data we extracted from Facebook (A to F). In the remainder of this section, we present our experience and the challenges we faced to analyse the data.

In Groups (A) we can find consistent information, with name and description. However, we found an obstacle related to the data volume, because users tend to follow very few groups (none in some cases) in social networks; in average, our volunteers follow only 8 groups, making the knowledge discovery infeasible. Because of this, we only used the total of followed groups per volunteer.

In timeline (B), we observed that our volunteers usually share a big amount of videos, photos, news from mass media and activities of their friends, and add short texts in most cases. In conclusion, their timeline contains a big amount of irrelevant data to our research because it provides more information about their friends than about the individual itself. For this reason, we do not consider this in our analysis.

The basic profile information (C) was clearly stored in Facebook in tables for each data profile, so there was no trouble to obtain them. With respect to the information about uploaded photos (D) and friends (E), we only considered the total of photos and friends, in the same way than previous works [36, 33, 21, 32, 35].

The "likes" (F) became the best field to be used, because it contains one of the largest databases of personal data from Facebook, with an average of approximately 214 "likes" per individual. Facebook defines two types of likes: "likes" related to pages and "likes" related to posts from a friend, and we used the first one. In addition to "likes" and its sum, the item (F) also includes the places visited and their total, which are relevant to our research, since they are well defined, having the name of the place visited, latitude, longitude and other information.

Some "likes" are classified into pre-existing Facebook categories such as: places, sports, music, movies, TV shows, books, apps and games, whilst other "likes" are not classified and can be found in the "all likes" section, which contains approximately 80% of all "likes". The fact that only the field "name" is required at the creation of such pages could be the reason behind that; sometimes, even when the other fields are not empty, we find incorrect information, for example they are written in languages that do not fit with the country of origin or have spelling mistakes. So, Facebook cannot classify such pages and, therefore, it is not possible to classify the "likes" into the categories generated by Facebook.

To make possible the use of the "likes" table (F), we needed to solve two crucial problems. The first was to identify a consistent field, in Portuguese language, that represented clearly the subject of that fan page; this was solved by using the "name" field, which expresses clearly and objectively the meaning and the overall theme of the pages, in addition to be filled in all the pages (it is a required field). The second problem was to categorize such "likes", seeking to obtain a reliable classification, because as previously stated, Facebook does not categorize all the created fan pages. This issue was solved by means of a manual classification of each page through researches in Wikipedia[2] and other websites; we also performed a manual deductive method when a direct classification could be used. Table 5.1 presents an example of the results obtained within this classification, grouped by category (further called *label features* in Table 5.2). That is, we grouped each fan page in its respective category, which allowed us to count the number of "likes" by category for each user. In summary, the data extracted from the Facebook profiles that have been used to generate the prediction models are the following:

- (A): Total Groups, calculated as the number of different group id;
- (C): Basic profile data, such as id, gender, age, marital status, current city and also the educational level. For instance, we considered that a person with university studies has a level of 3 (primary, high school and graduate degrees);
- (D): Total of photos using the field "total count";
- (E): Total of friends, using the field "total count";
- (F): Total Likes, sum of "likes" using the field "total count" and the total multimedia items and also the total of visited places, recently visited

[2]Wikipedia https://www.wikipedia.org/

places, visited cities, visited countries, visited states of South America, based on performed check-ins;

It is noteworthy that although we obtain all the data mentioned above, it is necessary to analyse these data to decide which are relevant for the generation of models to predict the curiosity.

Table 5.1: *Sample of classification of Fan Pages grouping by category and subcategory*

"Like" field name	**Category**	**Method**
Gloria Alegria	Communities	Deduction
Assassin's Creed	Game	Wikipedia
Bar do Zé	Restaurant	Deduction
Caetano Veloso	Music	Wikipedia
O Gigante Acordou	Politics	Deduction

5.5 Predicting Curiosity

Data mining is a process of exploration and analysis, in an automatic or semi-automatic way, of large amounts of data, in order to detect patterns and rules [253]. To perform these processes, data mining combines methodologies and tools from many knowledge areas like: machine learning, statistics, databases, expert systems, etc. [254]. There are two ways of applying it: as a verification process, where the user suggests a hypothesis about the relationship between the data and seeks to validate it by using techniques such as statistical and multidimensional analysis; or as a discovering process, where there is not any prior assumption, and a model or pattern of the data is found by using techniques like association rules discovering, decision trees, genetic algorithms and neural networks [255].

Our goal is to obtain a model to predict curiosity from the data extracted from Facebook. In order to do so, first we analysed the correlation between these data and the degree of curiosity obtained from the CEI-II form. Then, once the most relevant features were identified, they were used to generate the prediction model.

By using the open source software Weka[3], we tested some data mining techniques in order to find the better model to this project, such as association rules discovering (APRIORI algorithm), clustering (K-means algorithm), decision tree (J48 algorithm). To validate our choice, we also submitted our database to Auto-Weka algorithm [256], which seeks to find the best algorithm considering the wide range of feature selection techniques (combining 3 search and 8 evaluator methods) and all classification approaches implemented in Weka standard distribution.

5.5.1 Curiosity and Profile Correlations

Once executed the KDD process presented in the previous section, our system was able to generate a consistent database that made possible an analysis of correlation between the data extracted from Facebook and the degree of curiosity. We recluted 105 subjects who completed the CEI-II form, but we only used data from 75 subjects who granted access to their data on Facebook.

Table 5.2 shows the results of our analysis. It shows three groups of features: label features, features related to check-ins and other totals. For each feature, three Pearson correlation values have been calculated. As stated above, the CEI-II form distinguishes two aspects of curiosity: stretching and embracing. Therefore, our analysis shows the correlation value for stretching (Strech.), embracing (Embr.) and the total degree of curiosity (Total). First, in general we can observe weak correlations between the labels and curiosity, except with respect to the technology label (with significance $p = 0.00201$ for stretching, $p = 0.00024$ for embracing and $p = 0.00009$ for total). In other words, we can say that individuals with a high number of "likes" on items related to technology are likely to be more curious. In relation to other items such as sports and movies (stretching) and games (embracing), although its p-values

[3]Weka http://www.cs.waikato.ac.nz/ml/weka/

were outstanding, the correlation with respect to the total degree of curiosity did not reach a significant value.

Then, we analysed the correlation values of performed check-ins (places) and we found positive results, since in all features of this group the values demonstrated a significant correlation. For instance, the total number of visited states in South America achieved the best ratio p (p = 0.0000006, p = 0.00006 and p = 0.0000001 for stretching, embracing and total curiosity respectively). Positive results can also be observed in the total of places, cities, places and recently visited countries with minor variations, but within our significance level of p<0.05. Finally, in the third group we have the correlation of the total sums of the features; items such as likes, groups, music and friends showed no satisfactory correlation between them and curiosity. The exception was the "total education", where p-value were respectively p = 0.00014, p = 0.00128 and p = 0.00004.

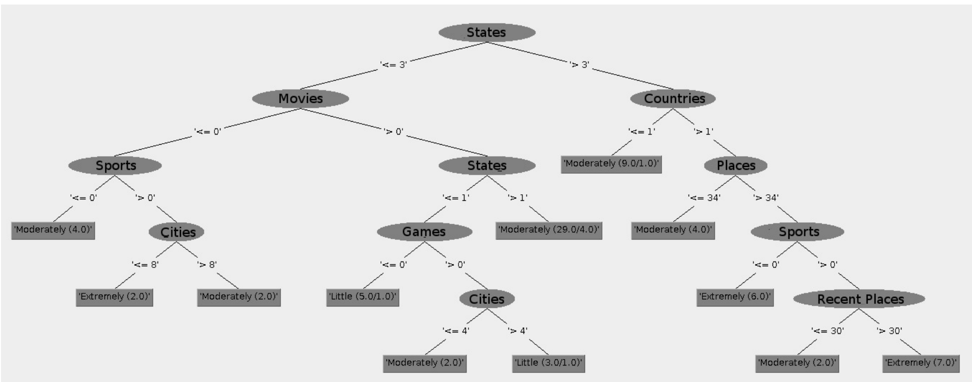

Figure 5.4: *Decision tree generated of stretching curiosity.*

In the Figure 5.5 we can observe some linear trends, such as the relationship between technology and curiosity (Figure 5.5A), where we interpret that individuals with more than 30 "likes" related to technology are extremely curious. The relation between visited states of South America and curiosity (Figure 5.5B) proves what we saw in Table 5.2: the more places visited (places, cities, states or countries), the more will be the degree of curiosity.

Table 5.2: *Pearson correlation values between feature scores and curiosity scores. Significant correlations are shown in bold for $p < 0.05$.*

	Stret.	Embr.	Total
Label Features			
Nature (e.g. animals, associations, parks)	-0.111	-0.021	-0.078
Business (e.g. mall, marks, stores)	-0.155	0.048	-0.066
Heath (e.g. diseases, medicine)	-0.177	-0.027	-0.120
Automotive(e.g. marks, cars, motorcycles, communities)	-0.002	-0.010	-0.007
Education (e.g. universities, marks, courses, schools)	0.116	0.150	0.152
Sports (e.g. soccer, teams, others sports)	**-0.255**	-0.019	-0.162
Musics (e.g. musics, rhythms, singers)	-0.035	0.084	0.026
Politics (e.g. communities, politicians, political parties)	-0.088	-0.106	-0.111
Religious (e.g. groups, communities, dogmas)	0.004	0.045	0.027
Technology (e.g. marks, books, software, programming)	**0.351**	**0.412**	**0.437**
Tourism (e.g. travel agencies, airlines, transports)	-0.126	-0.026	-0.089
Books (e.g. Authors, Books, Communities)	0.012	0.157	0.095
Drinks and Foods (e.g. marks, recipe, beers, wines)	-0.112	0.016	-0.058
Movies (e.g. actors, movies)	**-0.243**	-0.077	-0.187
Relationship Family (e.g.communities, family groups)	-0.087	0.058	-0.020
Games (e.g. equipments, games, brands, tips)	0.064	**0.237**	0.169
POIs(e.g. tourist places, museums, exhibitions)	-0.023	0.124	0.055
Restaurants (e.g. restaurants,bars)	-0.045	0.143	0.052
TV Cinema(e.g. movies, artists, series, tv channels)	-0.045	0.143	0.052
Check-in (total)			
Places Visited	**0.293**	**0.388**	**0.389**
Cities Visited	**0.318**	**0.467**	**0.448**
Recent Places Visited	**0.256**	**0.389**	**0.368**
Countries Visited	**0.429**	**0.418**	**0.487**
States of South America Visited	**0.446**	**0.537**	**0.563**
Other Totals			
Total Likes (sum of likes)	-0.041	0.094	0.028
Total Groups (sum of groups)	**0.250**	-0.030	0.132
Total Music/Movies (sum of musics)	-0.084	**0.226**	0.076
Total Education (level of study)	**0.425**	**0.365**	**0.455**
Total Friends (sum of friends)	**0.282**	0.079	0.212

Finally, we performed some other analysis in order to find out whether other elements had influence in the relationship between visiting different places and curiosity. In Figure 5.5C we can see a relationship between the educational level and curiosity, as well as the total visited places and education.

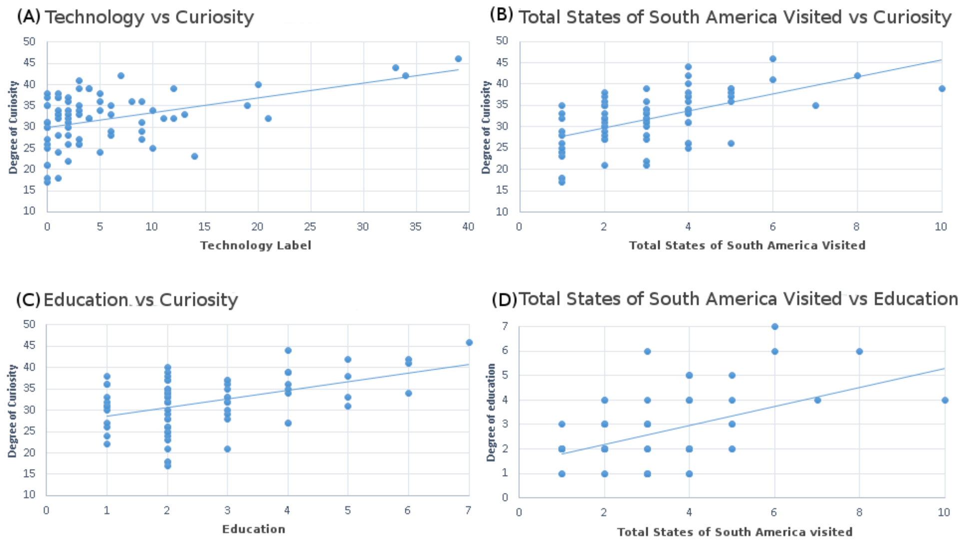

Figure 5.5: *Graphs containing trend lines between label technology (A), education (B),states visited in South America (C), with the degree of curiosity, and also visited states of South America and education (D).*

Thus, it is possible to interpret that the relation between visited places and the degree of curiosity could reflect an indirect relation through the educational level, that is, the relationship between high educational level and high income may lead to a greater amount of trips. Nevertheless, it would be necessary obtaining these data to assure such assumptions. We can only say that there is a relationship between curiosity and amount of places visited, as well as educational level and curiosity. We also studied the potential relationships between the basic information extracted from Facebook and the curiosity, such as religion, gender, marital status and age. However the predictions demonstrated that the correlations between them are weak or null.

5.5.2 Predicting Curiosity

Starting from the Pearson correlation (Table 5.2), we took into account any feature with a significant correlation with at least one of the components of curiosity (stretching and embracing) and the total degree of curiosity. This led us to 13 features apart from curiosity, which are:

1) Stretching: Sports, Movies, Total Groups and Total Friends;

2) Embracing: Games and Total Music/Movies;

3) Total: Technology, Visited Places, Visited Cities, Recently Visited Places, Visited Countries, Visited States of South America and Total Education;

Then we carried out the Auto-Weka, that tested, selected and verified the best algorithm to be used in Weka according to our database, given that it usually provides a classification performance better than using standard selection / hyperparameter optimization methods [256]. As a result, J48 proved to be the best option regarding other algorithms, such as SimpleCart and BFThree classifiers or clustering algorithms like SimpleKMeans. So, we used J48 with a 10-fold cross-validation, generating a decision tree (Figure 6.7) made up of 12 leaves with 63% of correctly classified instances and 38% of incorrectly classified instances.

We can extract several interesting classification rules that are relevant to our research. From the root of the tree, we can say that individuals who visited more than 3 states of South America, more than 1 country and more than 34 places tend to be extremely curious. Another example is that individuals who visited less than 4 states of South America, have more than 1 "like" related with movies, have visited 1 state of South America and do not have any "like" related to games, tend to be little curious.

5.6 Conclusions and Future Works

In this paper, we have shown that the degree of curiosity of an individual can be predicted by taking data from the social network Facebook. Our volunteers answered the CEI-II form through an online application, which was also responsible for collecting the data from their profiles on Facebook. After applying the steps we had defined in the KDD process, we were able to identify labels with little or no correlation, but also relevant relationships to predict the curiosity. With a well defined set of features, we trained the J48 algorithm to generate a decision tree, which presents classification rules for the prediction of curiosity.

Although we did found satisfactory results in the group of items "places", the prediction of the curiosity degree of an individual needs improvements, given that our scenario was limited to Brazilian users and had a small number of participants. Thus, further works comprising more users and from different countries are necessary to improve our models. Moreover, it would be very interesting to use information from different sources, like other social networks (for example, Linkedin[4]), which could give us data such as salary range, employment history, etc., and may allow the generation of more complete prediction models.

Against the global trend of the growth in data generation, since 2015 Facebook have limited the access to users data, affecting many researchers that were developing new projects [126]. Other social networks such as Twitter[5] and Linkedin are also putting restrictions in the data accessible through their APIs. Thus, the way to obtain data is an important issue to be considered in future projects. Our work began in 2014, which allowed us to obtain the needed data for the predictions. Nowadays, this would be no longer possible.

In the context of recommendation systems, the issue raised from works like this, whose aim is inferring personality from data in social networks [257, 16, 228, 15], is how this inference could be used to improve the satisfaction of users with a given recommendation. Specifically, with respect to curiosity, there is a prior work which studied, that the degree of curiosity of user could influence in his satisfaction with a recommendation [40]. This paper showed that, in general, extremely curious users were more satisfied with recommendations that introduced more novelty, whereas little curious users preferred recommendations closer to their already rated items. Therefore, the

[4]Linkedin http://www.linkedin.com/
[5]Twitter http://www.twitter.com/

information inferred about the degree of curiosity of a given user could be used to adapt their recommendation in this approach.

Chapter 6: Are you Curious? Predicting the Human Curiosity from Facebook

Contents

Are you Curious?

Predicting the Human Curiosity from Facebook

Authors: **Alan Menk, Laura Sebastia**

{amenkdossantos, lsebastia}@dsic.upv.es

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Abstract

Nowadays, social networks are daily used to share what people like, feel, where they travel to, etc. This huge amount of data can say a lot about their personality because it may reflect their behaviour from the "real world" to the "virtual world". Once obtained the access to this data, some authors have tried to infer the personality of the individual without the use of long questionnaires, only working with data in an implicit way, that is, transparently to the user. In this scenario, our work is focused on predicting one of the human personality traits, the Curiosity. In this paper, we analyse the information that can be extracted from the users' profile on Facebook and the set of features that can be used to describe their degree of curiosity. Finally, we use these data to generate several prediction models. The best generated model is able to predict the degree of curiosity with an accuracy of 87%.

6.1 Introduction

Online recommendation systems (RS) are very powerful personalization tools whose main goal is to improve a visitor's experience by offering relevant items.[258] Two examples of companies that are successfully using RS are Netflix and Amazon. In the case of Amazon, the company reports that 35% of all sales are estimated to be generated by the RS[a], whereas according to Gomez-Uribe *et al.*,[259] the RS saves Netflix more than $1B per year thanks to the reduction of monthly churn.

Despite these benefits, there is still work to do. For example, Netflix reports the member coldstarting problem as one of the main current open issues[259] and Amazon states that one of the major difficulties in the RS is how to show a diverse selection of items in the recommendation. In the literature, we can find works that address these problems from different points of view. One of the most novel approaches aims to mitigate them by exploiting user personality information. For example, both Tkalcic *et al.*[260] and Hu *et al.*[30] address the cold start problem, the former by using a personality-based user similarity measure and the latter by using a personality-based collaborative filtering approach.

With respect to diversity, it is usually considered that a recommender system should provide diverse recommendations.[47] However, some authors[237] think that the satisfaction of the user with respect to diversity in the recommendation depends on their own personality. One of the personality factors that may determine how diverse should be a recommendation, is the degree of curiosity of the user. According to positive psychology, curious individuals are more open to novelty, the new, the unknown, and like to learn new things.[4] On the contrary, the slightly curious individuals prefer to visit places already known or places with the same thematic. In fact Menk (2015),[40] shows that the degree of curiosity of an user could influence her satisfaction with a recommendation; this study concluded that, in general, extremely curious users were more satisfied with recommendations that introduced more novelty, whereas slightly curious users preferred recommendations closer to their already rated items. Therefore, the information inferred about the degree of curiosity of a given user could be used to adapt the diversity of the recommendation.

With the popularisation of smartphones and similar devices, the generated amount of information (texts, videos, music, etc), especially in social networks, grows vertiginously. Companies like Facebook have already exceeded the mark of one billion active users, who share information, opinions, feelings and visited places, among other possibilities. In 2025, this amount will be about 180 zettabytes compared to 4.4 zettabytes in 2013.[184] With such growth, the opportunities in using this scenario for the benefit of users are many; only in the health and psychology area we can highlight some studies such as the identification of pedophiles on social networks using the sentimental analysis[261] or the analysis of correlations between social networks and obesity,[262] social isolation[263] and suicide.[264]

Following these ideas, the aim of our work is to determine whether the degree of curiosity of a given user can be derived from information she shares on Facebook. Therefore, our objective is to develop a model to predict this degree of curiosity. In order to do so, we recruited 225 users that participated in our experiment. First, we obtained their degree of curiosity by means of a (well-known in Psychology) questionnaire. Then, they granted access to their Facebook profile. However, some users were discarded due to their incomplete profiles, thus the final experiment counted on 176 users. These data were analysed and, as the results will show, we were finally able to develop a model to predict the degree of curiosity with a satisfactory confidence level.

This paper is organised as follows. First, we give a quick summary of the background for this work (Section 6.2). Section 6.3 presents our methodology for extracting, analysing and classifying the Facebook profile information. In Section 6.4 we present some results about the correlations between some features extracted from the Facebook profile and the curiosity degree, in order to determine which features are more relevant. As a result, we present several prediction models to infer the degree of curiosity. Finally, we present our conclusions and future works (Section 10.1).

6.2 Background

With the increasing information available on social networks, many authors are now interested in trying to predict the user personality from the information shared in these social networks.[122] We summarize here a few of them that specifically use information from Facebook profiles.

In Quercia *et al.*[35] the authors investigated the relationship between user popularity in Facebook (number of contacts) and personality traits on a large number of subjects from MyPersonality database.[265] The authors reached some conclusions such as, for instance, that popular Facebook users tend to have the same personality as popular people in the real world, suggesting that the nature of online interactions does not significantly differ from those of real world. Similarly, the work in Youyou *et al.*[239] shows that computers' judgements of people's personalities based on their digital footprints in Facebook are more accurate and valid than judgements made by their close others or acquaintances (friends, family, spouse, colleagues, etc.). Ortigosa *et al.*[33] introduces TP2010, a Facebook application used to collect information about the personality traits and the interactions in Facebook of more than 20.000 users. Based on information such as number of friends, number of posts in his wall per month, or number of "active friends", among others, the accuracy of the classifiers built for each personality trait in this model is higher than 70% for all personality traits.

In Golbeck *et al.*[32] the authors presented a method by which the personality of the users can be accurately predicted from the public information available on their Facebook profiles. To do this, they used the *Big Five personality inventory*,[236] a self-report inventory designed to measure five personality dimensions: extraversion, agreeableness, conscientiousness, neuroticism and the openness to experience. Additionally, information about the users such as the list of friends, features like date of birth, relationship status, religion, education history, gender and hometown, personal activities, favourite things, etc. were also collected. The authors analysed the user personality and their Facebook profile, and were able to predict each of the five personality traits to within 11% of its actual value.

As indicated above, our work is centred on the human curiosity, which is closely related to the *openness to experience* trait in the Big Five. Some works have investigated the correlations between the Facebook profiles and openness. For example, Amichai-Hamburger *et al.*[176] showed that individuals who scored higher on the trait of openness to experience used more features from the personal information section on Facebook. Moreover Gosling *et al.*[123] reported that openness was related to adding and replacing photographs, which may reflect the fact that individuals high on this trait tend to engage in a wide range of activities and it also was correlated with the number of overall friends, the number of friends in the local network, and the number of networks. Finally, Kosinski *et al.*[129] showed that openness is positively correlated with a number of users' likes, group associations and status updates and Gao *et* *al.*[36] showed correlations with the number of friends, joined groups, likes, uploaded photos, times others tagged user in photos as well as with the network density.

The remaining of this section is devoted to the definition and measurement of curiosity. **Human curiosity** in the purview of psychology is defined as the desire for new knowledge or new experiences.[116, 266] Curiosity is a human strength with relevance to domains ranging from creativity, leisure and social relationships to applications in educational, sport, organisational, and clinical psychology.[245] Consequently, we can consider that curiosity, in any of its dimensions, has an important contribution in defining the personality of individuals and acts directly in their decisions; in this sense, we consider that it is a key element in the predictions of recommender systems. From the 50s, many new scales have been presented in order to provide effective means and methods of curiosity measurement. For example, the questionnaire called Experimental Perceptual Curiosity Questionnaire (EPCQ)[250] or the Curiosity and Exploration Inventory (CEI-II),[2] which is considered one of the most reliable and pcactical questionnaires today, consisting of only 10 items. The CEI-II offers empirical support for two curiosity dimensions: the Stretching dimension (five items), the motivation to seek out knowledge and new experiences; and the Embracing dimension (five items), a general willingness to embrace the novel, uncertain, and unpredictable nature of everyday life. This paper uses the CEI-II scale, due to the fact that it has been subjected to a psychometric examination, ensuring greater reliability in its use.

6.3 Methodology

The architecture of the system to build the curiosity model is shown in Figure 8.1, and it mainly consists of a **Facebook application** in charge of obtaining access to the users' Facebook profiles and collecting their answers to the CEI-II questionnaire. After completing the data acquisition step, the module **Search System for Social Networks (SSSN)** processes the collected Facebook profiles to remove noise, duplicated or empty records, so that this information can be used as input to the next step. The process of **Knowledge Discovery in Database (KDD)** analyses the data and the last step (**Models and Predictions**) generates the model to predict the degree of curiosity of users from their Facebook profile.

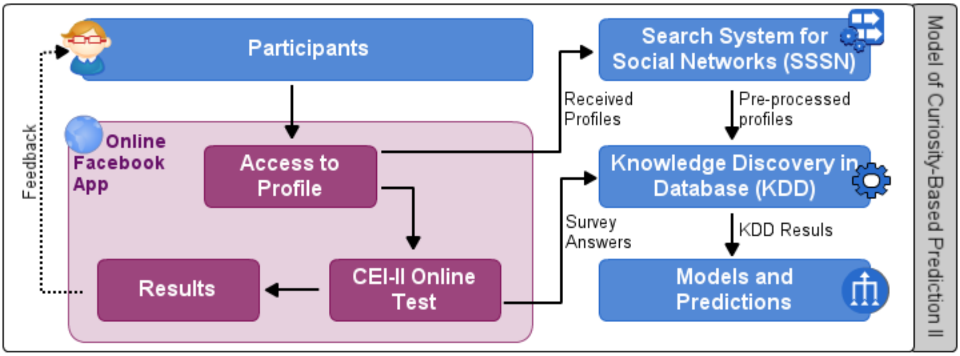


Figure 6.1: *Architecture of our system*

6.3.1 Facebook Application

We have developed an application[1] integrated in the social network Facebook. Given that Facebook profiles are language-dependent, which may lead to problems in language processing, [251] we decided to work only with Brazilian users and, for this reason, this application is written in Portuguese[2]. First, the users are shown some useful information about curiosity, human personality, besides tips on how to become a more curious person, as well as the link to access the experiment (Fig. 6.2A). The online page informs about the average time to perform the experiment (approximately 3 minutes), the privacy policy, and allows the user to login to Facebook to access her profile (Fig. 6.2B); then, the application asks the user to fill in the CEI-II form (Fig. 6.2C). By finishing the test, the online system analyses the entered data and then displays a

[1]Test of Curiosity: https://www.facebook.com/testedacuriosidade/
[2]For the sake of understanding, we show here the English version.

feedback into three graphs, which are, respectively, the scores of stretching and embracing facets, ranging from 5 to 25, and finally the sum of them, ranging from 10 to 50. It can be easily interpreted that, the higher the score, the higher the curiosity of the individual, and vice-versa (Fig. 6.2D).

Figure 6.2: *Interface of the Facebook application.*

6.3.2 Search System for Social Networks

The common problems found in the pre-processing step were described in Tan *et al.*[252] such as data with inconsistent values, distorted or incomplete information, or even with little relevance to the task of data mining and prediction. To avoid this issue, we analysed the structure, organisation and consistency of the data we extracted from Facebook. In the remainder of this section, we summarize our experience and the challenges we faced to analyse the data (more details can be found in Menk (2016) *et al.*[39]).

The data in the Facebook profile (Fig. 6.3) that we initially took into account was: (A) Followed groups, (B) Timeline, (C) Profile data, (D) Information from uploaded photos, (E) Item Information from friends and (F) Information from "likes". In *Followed groups* (A) we found consistent information, with name and description. However, users tend to follow very few groups (none in some cases), which difficulties extracting conclusions about the particular interests of a given user. For this reason, we only used the total of followed groups per participant. In *Timeline* (B), we observed that our participants usually share a big amount of videos, photos, news from mass media and activities previously shared by their friends. We do not consider this in our analysis because it provides more information about their friends than about the individual itself. The basic *Profile data* (C) was clearly stored in Facebook in tables for each data profile, so there was no trouble to obtain them. With respect to the information about uploaded photos (D) and friends (E), we only considered the total of photos and friends, in the same way than previous works. [36, 33, 32, 35]

The "likes" (F) became the best field to analyze, because it contains one of the largest databases of personal data from Facebook; the average "likes" per individual of our participants was approximately 225. Facebook defines two types of "likes": related to pages and related to posts from a friend, and we used the first one. In addition to "likes", and its sum, the item (F) also includes the visited places and their total, which are relevant to our research, since they are well defined, having the name, latitude, longitude and other information about the visited place. Some "likes" are classified into pre-existing Facebook categories such as places, sports, music, movies, TV shows, books, apps and games, whilst other "likes" are not classified and can be found in the "all likes" section, which contains approximately 80% of all "likes". To make possible the use of this information, we (manually) grouped each fan page in its respective category according to the "name" field, which allowed us to count the number of "likes" by category for each user.

In summary, the data extracted from the Facebook profiles that have been used to generate the prediction models are the following:

- (A): Total Groups, calculated as the number of different group id;
- (C): Basic profile data, such as id, gender, age, marital status, hometown and also the educational level, from 1 to the lowest level (No study / Elementary) to 7 for the highest level (PhD);
- (D): Total of photos, using the field "total count";
- (E): Total of friends, using the field "total count";
- (F): Total likes, amount of "likes" using the field "total count" and the total of some sections such as films, TV programs, music, books, sports teams, sports people, restaurants and reviews; finally, the total of visited places, cities and countries, based on performed check-ins.

Figure 6.3: *Example of a Facebook profile.*

6.4 Predicting Curiosity

Our goal is to obtain a model to predict curiosity from the data extracted from Facebook. In order to do so, first, we analysed the correlation between these data and the degree of curiosity obtained from the CEI-II form. Then, these features were used to generate the prediction model.

6.4.1 Analysis of the participants

In order to generate these models, we need real users that interact with our Facebook application. Formal invitations were emailed to participants in different discussion groups, forums, etc., containing the details of the project, terms of use, the privacy of personal information and authorization to its use for scientific purposes. In our experiment, the users are consisted of 47% male and 53% female, from different regions, age groups, gender, marital status. Their levels of study are also heterogeneous, being 4% with a primary level, 10% intermediate, 23% secondary, 30% graduate, 16% postgraduate (MBA or Master) and also 16% PhD or Postdoctorate level.

Fig. 6.4 shows the value of the total curiosity and the value for each facet (stretching and embracing) per user (ordered by total curiosity) and the average score for these values reported in Kashdan *et al.*.[2] The value of total curiosity of our participants varies from 14 to 47, where the stretching facet (blue bar) is more remarkable that the embracing facet (orange bar). This is clearly observed in Table 6.1, which shows a comparison of the scores obtained by our participants with the average scores.[2] The total value is similar in all cases; however, our participants seem to be more stretching than the average, which means that are more motivated to seek out knowledge and new experiences but less willing to embrace the novel, uncertain and unpredictable nature of everyday life. With respect the value per gender, our results are similar, so there is not a bias in this case.

Fig. 6.5 shows the relationship between the degree of curiosity vs. the level of education (Fig. 6.5a) and the age (Fig. 6.5b) of the participants, classified

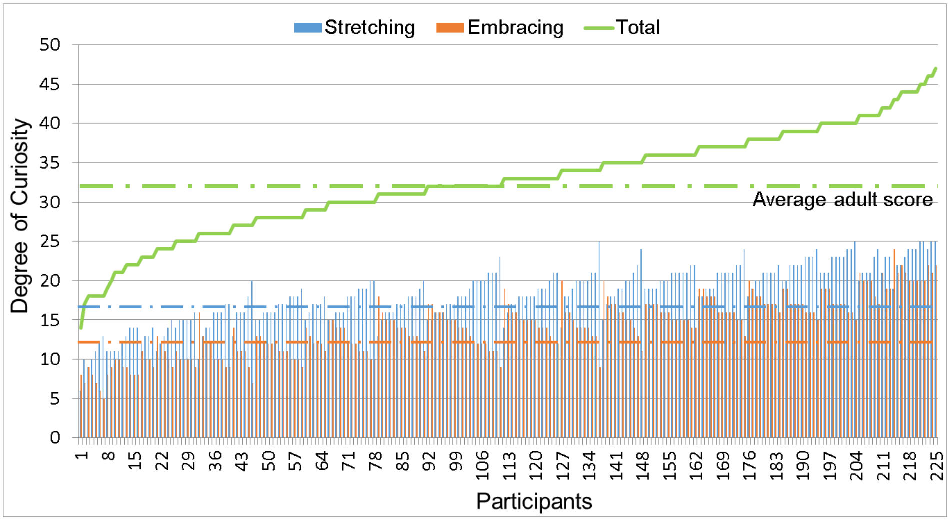


Figure 6.4: *Individual degree of curiosity of our participants*

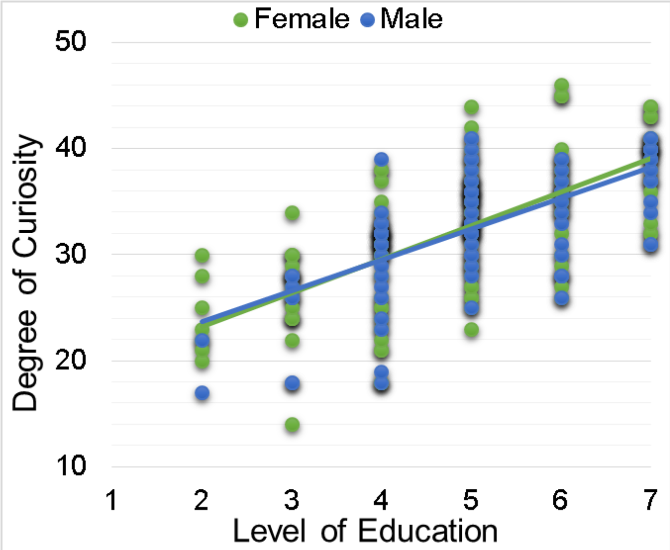
Table 6.1: *Average of scores in total curiosity and stretching and embracing facets.*

	Stretching	Embracing	Total
Female	17.83	14.13	32
Male	18.83	14.3	33.13
Total	18.31	14.21	32.52
Kashdan[2]	17.3	15.62	33

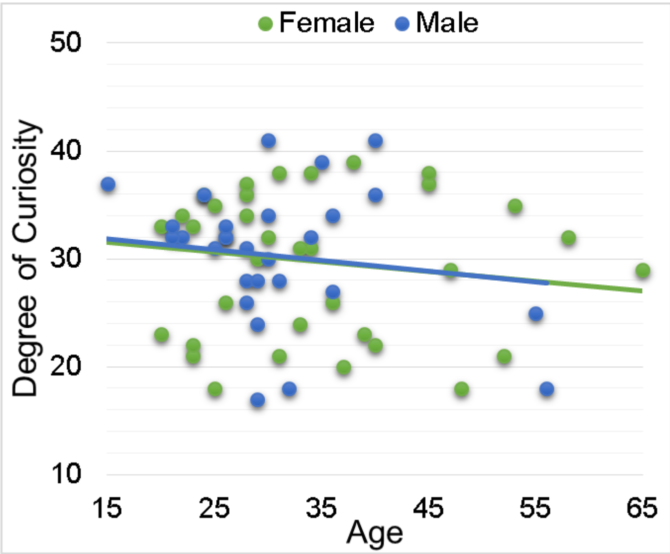
by gender. In the first case, we can observe that there is a clear positive correlation of the degree of curiosity and the level of education, whereas there is a slightly negative correlation with respect to the age. It is also remarkable the fact that again there is not a difference in the degree of curiosity regarding the gender of the participants.

We also studied the potential relationships between the basic information extracted from the Facebook profile and the curiosity, such as religion or marital status. Nonetheless, the correlations between them were weak or null.

In order to clarify some analysis, we have classified the users into three categories regarding their degree of curiosity: *slightly*, *moderately* and *extremely*



(a) *Degree of curiosity vs. Level of education*



(b) *Degree of curiosity vs. Age*

Figure 6.5: *Correlations between degree of curiosity vs. level of education and age, per gender.*

curious users if the degree of curiosity belongs to the interval [10,26], [27,36] and [37,50], respectively. Regarding our participants, 40 (17.8%) users were slightly curious, 124 (55.1%) users were moderately curious and 61 (27.1%) users were extremely curious.

6.4.2 Curiosity and Facebook profile Correlations

In our first experiment[39] (with 105 users), we found a positive correlation between some data extracted from Facebook and the degree of curiosity. The most relevant correlation was established with respect to the performed check-ins (places, cities, recent places, countries and states of South America visited), where we found moderately positive correlation results in all of these features.

In this new experiment, we have more than double the number of users in relation to the first experiment, reaching 176 users, and our goal is to confirm the conclusions of our first study, as well as to perform new analysis. Due to access restrictions imposed by Facebook in its new policy of sharing data, only part of the labels were tested in this second experiment, namely movies, TV programs, music, books, sport teams, sport people and restaurants. Moreover, we also used check-ins (countries, cities and places), and totals (reviews, groups, "likes", and level of education).

Table 6.2 shows the results obtained in relation to the correlation of the degree of curiosity with the labels indicated above; once again the generated correlations were positively low or zero. We also performed the same correlation analysis grouping the users in slightly, moderately and extremely curious users, but we did not find any difference. In relation to check-ins, again the correlations were positively satisfactory and higher to the results obtained during the first experiment. Visited places obtained .49 for the total curiosity, .40 for the stretching facet and .47 for the embracing facet compared to .39, .29 and .39 obtained in the first experiment, respectively. The total of cities (.44 for the total of curiosity) and countries (.45 for the total of curiosity) obtained satisfactory results similar to the first experiment. For the total of groups and likes, the results showed a low or no correlation, whereas the level of education

Table 6.2: *Pearson correlation values between label scores and curiosity scores.*

	Total Countries	Total Places	Total Cities	Total Reviews	Total Groups	Total Likes	Label Movies	Label TV Programs	Label Musics	Label Books	Label Sport Teams	Label Sport People	Label Restaurants	Level Education
Total Curiosity	**.45**	**.49**	**.44**	.20	.05	.02	.09	.01	.02	.14	.04	.11	-.02	**.68**
p-value	***.00***	***.00***	***.00***	*.01*	*.52*	*.79*	*.25*	*.93*	*.83*	*.06*	*.56*	*.14*	*.80*	***.00***
Stretching	**.35**	**.40**	**.33**	.14	.07	-.03	.06	-.04	-.04	.14	-.02	.05	-.01	**.62**
p-value	***.00***	***.00***	***.00***	*.06*	*.35*	*.72*	*.45*	*.60*	*.61*	*.06*	*.77*	*.55*	*.89*	***.00***
Embracing	**.42**	**.47**	**.45**	.21	.01	.06	.09	.05	.07	.10	.10	.15	-.02	**.57**
p-value	***.00***	***.00***	***.00***	*.01*	*.85*	*.42*	*.21*	*.50*	*.38*	*.17*	*.20*	*.05*	*.76*	***.00***
Total Education	**.65**	**.45**	**.49**	.11	.05	-.10	.13	-.02	-.02	.17	-.10	-.07	.01	
p-value	***.00***	***.00***	***.00***	*.14*	*.51*	*.20*	*.08*	*.82*	*.82*	*.02*	*.20*	*.35*	*.93*	

Note. $p<0.05$ *(p-value)*

showed a high correlation (.68 for the total curiosity, .62 for the stretching facet and .57 for the embracing facet versus .45, .42 and .36 in the first experiment, respectively).

Regarding the new labels, we identified a weak correlation with the total of reviews (.20, .14 and .21). However, the correlations between the level of education and data extracted from Facebook were positively high for total of countries (.65) and positively moderate for cities (.49) and places (.45). This correlation shows us that, in addition to the degree of curiosity, the level of education can also show us the willingness of a user to visit new places and, given the higher correlation with the total of countries, we can interpret that the higher the level of education, the greater will be the international travels.

Given that the highest correlations are found with respect to the check-ins, we have analysed this aspect in depth. First, we classified the places in our database (nearly 60000) into three groups according to their popularity (weight). We used the K-means algorithm with Euclidean distance to determine the best division in three clusters: the first one represents low popular places (low weights), the second represents moderately popular places (medium weights) and the third represents the very popular places (high weights). The result

Table 6.3: *Average of visited places (by popularity) per degree of curiosity*

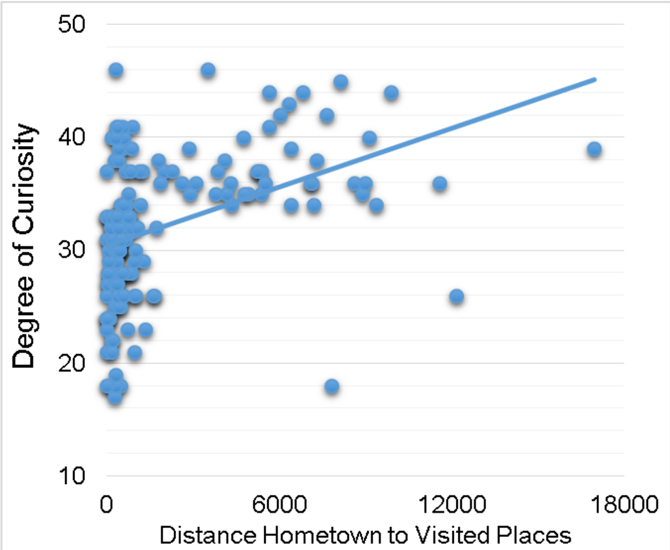
	Low Weight	Medium Weight	High Weight
Slightly Curious	2.00	1.45	2.86
Moderately Curious	1.59	1.18	2.24
Extremely Curious	3.20	1.68	3.07

was that 93% of places were classified as low popular places, 6% as medium popular and only 1% as very popular places.

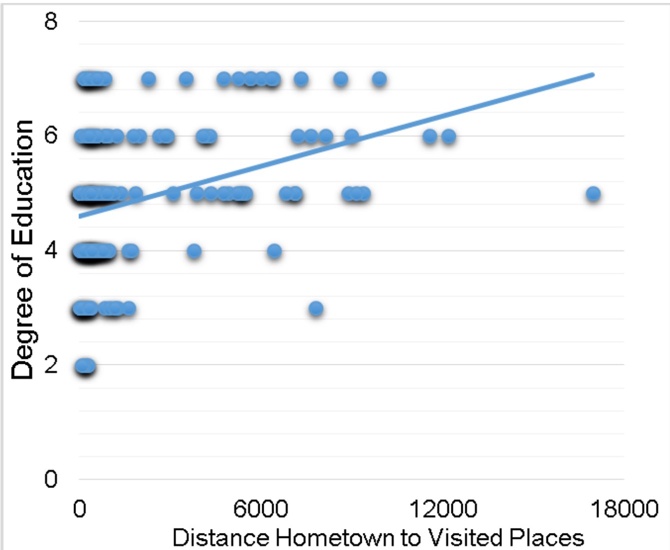
Table 6.3 shows the average of the number of visited places, classified by popularity and by type of user. It can be observed that, in average, extremely curious users visit more places of any popularity, but they are more interested in low popular places, which is consistent with their degree of curiosity, in other words, they are more willing to visit unpopular and unknown places. On the contrary, slightly curious users are much more interested in very popular (high weight) places.

Finally, we have studied the distance from hometown of the visited places by each participant and we have compared this distance with both the degree of curiosity (Fig. 6.6a) and the level of education (Fig. 6.6b). In both cases, it can be observed a positive correlation, that is, as the degree of curiosity and the level of education increases, the distance from hometown to the visited places also increases.

In summary, the results with this new set of participants reinforce the correlation between the level of education, visited places, cities and countries with the user's curiosity, and also a new correlation between visited places, cities, and countries with the level of education can be identified. This way, it is possible to interpret that the relationship between visited places and curiosity just reflects other elements like educational level. However, we can presume that more complex elements that could not be measured can influence this result, such as the relationship between high educational level and high income, which would lead to a greater amount of trips. Nevertheless, it would be necessary to obtain these data to assure such assumptions.



(a) *Degree of curiosity vs distance*



(b) *Level of education vs distance*

Figure 6.6: *Average distance from hometown to visited places vs. degree of curiosity and level of education*

6.4.3 Generating the Model

After having analysed the correlation between the features extracted from the 176 Facebook profiles and the degree of curiosity, our aim is to generate a model to predict the degree of curiosity of a new user, based on her Facebook profile. In this regard, we applied two different approaches with respect to the dependent variable degree of curiosity: a classification approach of three classes (where the user can be classified as slightly, moderately or extremely curious), and a numeric approach, where the curiosity can be a numeric value between 10 and 50. However, in the numeric approach we achieved weak results in relation to the first experiment, thus it will not be detailed here.

The models for the classification into three classes were generated by means of the tools Weka[267] and BigML[268], configured with a 10-fold cross-validation. 9 different prediction algorithms from Weka were tested, besides one from the tool BigML. Their performance was evaluated by the analysis of three measures, namely correctly classified instances, Kappa statistic, and F-measure, shown in Table 6.4. It can be observed that the best algorithm from Weka is the Decision Tree (REPTree), whose confusion matrix is shown in Table 6.5a, followed by Decision Table, with 69.89% and 68.18% of correctly classified instances, respectively. Their Kappa statistic are quite similar, being .45 and .42 (moderately agreement),[269] and so their F-measure, being .69 and .67, respectively.

On the other hand, a Decision Tree (C4.5 algorithm) was generated by using the tool BigML, where we obtained a higher positive result, with 87.90% of correctly classified instances, Kappa of .69 (substantial agreement), and F-measure of .79. In its confusion matrix (Table 6.5b), we can observe only one misclassification for slightly curious, that is, 93.2% of accuracy, while moderately and extremely obtained 82.4% and 88.1% of accuracy, respectively. This 3-class approach obtained the best result when generated by BigML if compared with the other algorithms, thus being the best option to generate the prediction models.

Among the trees automatically generated by BigML in order to **classify**

Table 6.4: *Classification into three classes*

Algorithm	Correctly Classified Instances	Kappa Statistic	Average F-measure
Weka tool			
Artificial Neural Network - Multilayer Perceptron (MLP)	60.22%	.30	.60
Bayesian network (BayesNet)	67.61%	.45	.68
Bootstrap aggregating (Bagging)	64.77%	.37	.64
Decision Tree (J48)	55.11%	.22	.54
Decision Forests (RamdomSubSpace)	67.05%	.36	.63
Decision Tree Learner (REPTree)	**69.89%**	**.45**	**.69**
Logistic Regression (LR)	60.23%	.29	.59
Random Forest Trees	62.50%	.32	.61
Rules - Decision Table	68.18%	.42	.67
BigML tool			
Decision Tree (C4.5)	**87.90%**	**.67**	**.79**

Table 6.5: *Confusion Matrix for (a) Decision Tree (REPTree) with Weka and for (b) Decision Tree (C4.5) with BigML*

(a)

a	b	c	classified as
12	18	1	a=Slightly Curious
6	84	8	b=Moderately Curious
1	19	27	c=Extremely Curious

(b)

a	b	c	classified as
18	1	0	a=Slightly Curious
10	90	10	b=Moderately Curious
1	10	36	c=Extremely Curious

a new user into slightly, moderately and extremely curious user, the best one obtained a result of 87.90% of correctly classified instances in general, as mentioned above. The tree (Fig. 6.7) was pruned in order to keep only positive trustful instances (>50% of confidence), thus, from the 14 features showed in table 6.2, our model used 10 of them.

Some rules achieved higher confidence values, such as one for classifying users as "moderately curious" (Places $> 11 \leq 78$ and Education ≤ 4 and restaurants ≤ 5 and Cities ≤ 22), with 91.24% of confidence. Another example is for users sharing ≥ 78 check-ins in places in their Facebook profile, classified as *extremely curious* with a confidence level of 87%. Fig. 6.8 depicts the

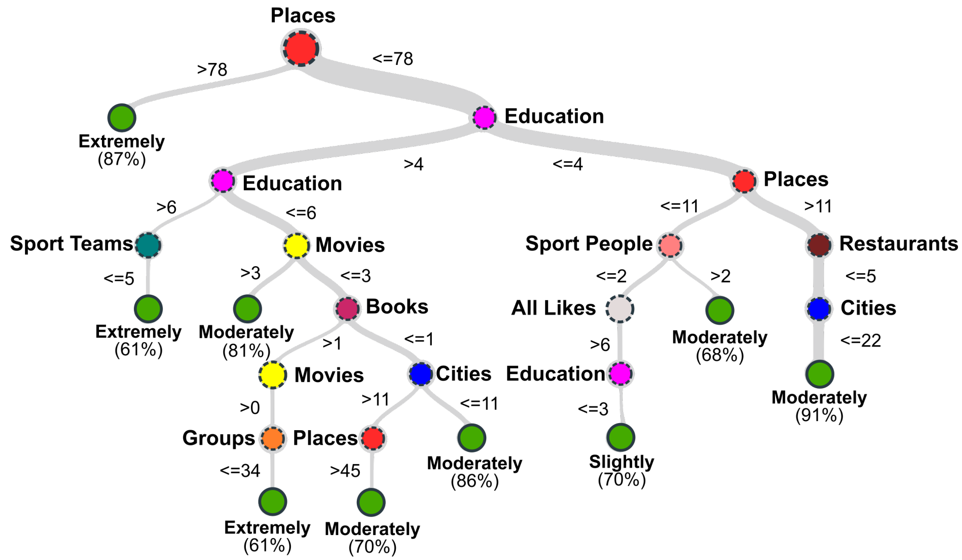


Figure 6.7: *Decision tree for classifying new users.*

10 fields (features) used by the decision tree, ordered by "field importance", a measure of how important a field is relative to the other fields, with en emphasis on places and education, with 41.29% and 30.26% of importance respectively; it means that, the higher the importance of the field, the greater its impact on predictions.

6.5 Conclusions and Future Work

In this paper, we show the details of a method for the extraction, processing and prediction of the human curiosity, using data from Facebook. In our experiments, we have shown that the degree of curiosity of an individual can be predicted by taking information from the user profiles in Facebook and processing them with supervised machine learning models.

In relation to the first experiment that had 105 users,[39] this new experiment with 176 users confirmed a positive correlation between curiosity and number of visited places, cities or countries. We also observed a strong positive

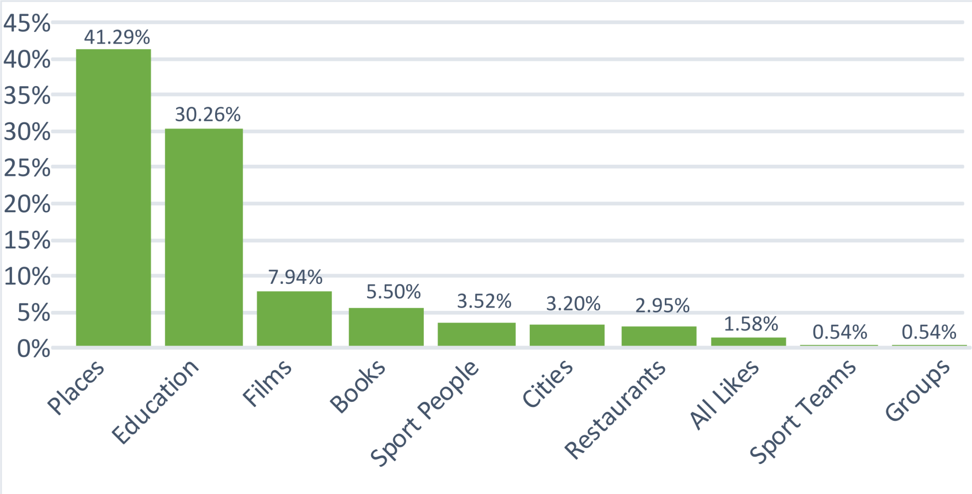


Figure 6.8: *Decision tree field importance.*

correlation between curiosity and level of education, obtaining higher results than those obtained in the first experiment. That is, the higher the level of education, the greater the curiosity and vice-versa.

By using 10 different algorithms, we identified that the Decision Tree (C4.5 algorithm) gave us the best value for correct classified instances (87.90%), followed by Decision Tree Learner (REPTree algorithm) with 69.89%, Decision Table with 68.18%, and finally Bayesian network (BayesNet algoritm) with 67.61% of correctly classified instances generated from Weka.

In spite of the positive advances found in this work, the prediction of the curiosity degree of an individual needs improvements, given that our scenario was limited to Brazilian users. Thus, further studies comprising more users from different countries are necessary to improve our models. Moreover, it would be very interesting to use information from different sources, like other social networks (e.g. Linkedin), which could give us data as salary range, job history, etc., and may allow the generation of more complete forecasting models or even the identification of new correlations.

Finally, we believe that this work can provide a positive contribution to the recommendation systems, demonstrating that, when applying prediction models for the identification of human personality traits, recommendation systems can reach users' needs more efficiently, consequently increasing the satisfaction on the received recommendations.

Chapter 7: Curumim: A Serendipitous Recommender System based on Human Curiosity

Contents

Curumim: A Serendipitous Recommender System based on Human Curiosity

Authors: **Alan Menk, Laura Sebastia, Rebeca Ferreira**

{amenkdossantos, lsebastia, redelferrer}@dsic.upv.es

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Abstract

Tourism is an important source of income of countries, since nowadays 10% of GDP corresponds to a direct, indirect or induced effect of tourism. In European countries like Spain, the activity reached numbers like 11% of GDP in 2016. Therefore, providing an efficient and personalised service for tourists has become an essential issue in the development of new technological resources. This work aims to build a better experience for the tourist through the fusion of three axes: human psychology, namely curiosity, technological innovation and social networks. This article describes CURUMIM system, which, from data available on social networks, predicts the level of curiosity of a user and then, tied to other measures, generates novel and serendipitous recommendations of touristic places around the world. In other words, the recommendations will be accurate and adapted to the level of curiosity of a given user on one hand and, on the other, they will positively surprise the users.

7.1 Introduction

The area of tourism is an important source of income of countries, where 10% of GDP corresponds to a direct, indirect or induced effect of it. In European countries like Spain, this activity represented 11% of GDP in 2016. This way, the tourism industry is demanding an ever-increasing level of value-added services in technologically innovative environments, which are integrated and highly dynamic[270].

On the other hand, we can count on improvements and globalisation of technologies, as it happened with the Internet in the mid 1990s and with the advent of social networks (SNs) in the middle of 2004 [271]. The exponential growth of smartphones and tablets in mid-2009 also have led to a positive scenario. For example, independently of the type of the device used, whether for the online shop, browse the social network or even search for hotels for vacations, the recommendation systems (RS) are usually present in companies from different sectors like Amazon or Netflix.

In relation to the tourism sector, Google Trips[272] for instance, is a personalised tour guide for mobiles, which compiles personal travel info and combines it with top spots to recommend nearby sights. It is also interesting the experiment that sought to analyse the user's emotions to figure out how she is feeling when she is about to book a travel[273] on Expedia[1]. That means, the globalisation have opened up infinite opportunities for exploiting the user's network contribution, by providing personalised recommendations in tourism. Set within this background, this paper represents the fusion of some of the most important trends in RS: serendipity, novelty, social networks, and some traits of human psychology. As it will be discussed later, new value-added tourism services can be provided by combining all these aspects.

In this context, we present CURUMIM, an online system whose aim is to generate serendipitous, personalised and novel recommendations, considering some implicit parameters such as the curiosity and education level of a user, besides other characteristics extracted from the SN Facebook. In other words, this system seeks to create surprisingly positive, novel and adaptive recommendations, considering the implicit psychological values of those who receive it. CURUMIM is a system whose generated recommendations suit the personality of the person and her expectations regarding the degree of serendipity. Thus, the recommendations will be more or less serendipitous depending on the personality of each one, specifically the curiosity, which is defined as the desire for new knowledge or new experiences, and widely recognized as an important antecedent of exploration [243, 244].

The system was designed to be able to recommend items in any context because, as we will explain, the techniques developed are independent of the application domain. However, in order to show the capabilities of CURUMIM, we have applied it to the tourism context and we have elaborated two use cases, demonstrating how this system is able to provide serendipitous

[1] Expedia is a travel website that can be used to book airline tickets, hotel reservations, etc. (https://www.expedia.com).

recommendations in this context.

This paper is structured as follows: Section 2 provides an overview of the state-of-the-art in serendipity, novelty and psychology in RS. Section 3 presents CURUMIM, the solution proposed here, including its architecture, the necessary input data, and the developed techniques to then, in Section 4, detail two complete use cases. Finally, Section 5 discusses the conclusions and future works.

7.2 State of the Art

As the tourism industry grows around the world, technological challenges in the industry follow the same trend. Different approaches, solutions and innovations have been developed in this area. Computational recommender systems have emerged as a means of selecting and recommending items from a wide range of alternatives becoming like a users aid [95]. They can be defined as tools and techniques providing suggestions for items to be of use to the user [47]. They range from approaches that aim for solving the difficulties encountered by tourists from planning to arrival in an unknown city. Some projects of information systems seek to help users through recommendations of places, routes or points of interest, through traditional approaches of recommendations such as Content-Based [96], Collaborative Filtering [98] and hybrid approaches [195]. In the technological current context, the massive use of social networks made the role assigned to recommender systems change from the selection of items through traditional techniques, to a growing need to bring "what really matters to each individual" based on the personality, tastes and wishes of each individual with the items that have not been discovered by him.

In this scenario, the RS turns to an approach of multidisciplinary knowledge, combining the traditional inputs (users ratings, items descriptions, etc.) with psychological aspects of users. For instance, TWIN [34] is a recommender system that creates a bridge between the automatic personality score estimation from plain text and the field of RSs, providing valuable recommendations of hotels of TripAdvisor[2] for "like minded people". Unlike other sectors where products have a more clearly defined utility or used value, in tourism the "product" utility is more often based on the tourists' perception and curiosity. In fact, the understanding of the curiosity is an essential precondition to understand the tourism sector [274]. Bearing this in mind, this section summarizes the state of the art in the two aspects combined in CURUMIM: serendipity in RSs and the relationship between personality and the environment in travel choices.

7.2.1 Serendipity in recommendation systems

Although the broad social and business success of recommender systems has been achieved across several domains, there is still a long way to go in terms of user satisfaction. One of its key dimensions is the concept of serendipity, which is the ability of providing accurate but also surprising recommendations.

Diversity is defined as the opposite of similarity [47]; in other words, diversity refers to how different the recommended items are with respect to each other. There are two levels to interpret diversity [275]: the inter-user diversity refers to the ability of an algorithm to return different results to different users (i.e., the diversity between recommendation lists), and the intra-user diversity measures the extent to which an algorithm can provide diverse objects to each individual user (i.e., the diversity within a recommendation list).

Novelty is defined as recommendations of unknown items [276], and denotes how different the recommended objects are with respect to what the users have already seen before. The simplest way to compute the ability of an algorithm to generate novel and unexpected results is to measure the average popularity of the recommended objects [275].

Serendipity in recommender systems is something new and difficult to measure and simulate; even the term itself has a difficult translation to other

[2]TripAdvisor is a travel website company providing reviews of travel-related content (http://www.tripadvisor.com/)

languages. Therefore, different interpretations can be identified in the literature. Serendipity is a measure of how surprising the successful recommendations are [212]. In general, we interpret that serendipity is comprised of two main aspects: the unexpectedness in the sense of surprising, unfamiliar, and usefulness as perceived by the user [277].

At first, the difference between diversity, novelty and serendipity may not seem objective and clear. While a diverse RS will attempt to maximise the variety of items on a recommendation list, a novel RS will contain items not previously known by the user, and a serendipitous RS will generate a list that, besides being unknown to the user, must also be pleasant and provide a feeling of positive surprise. Overall, these approaches are possible thanks to the analysis of tastes, shapes, personality, comparisons, and similarities between user data [278].

7.2.2 Aspects of personality and the environment in travel choices

The use of implicit elements when generating recommendation models is increasingly considered in the context of touristic recommendation systems. Among them, we highlight the personality and environment of the user, besides economic and social factors (income, education). Some researchers investigated the tourist behaviour plus psychology and economic questions. For instance, there is a framework in which is argued that the built environment[3] has an impact on travel behaviour through its influence on travel costs [279]. Based on the utility maximisation principle of macroeconomics, they reasoned that travel choices are based on an assessment of (I) the individual's preferences for particular trips or travel modes and (II) the relative costs of making those trips or choosing those travel modes.

Based on explanation of implication of long haul travel on the marketing of international tourism, some points that may influence the choice of

[3]Built environment is defined as the human-made surroundings that provide the setting for human activity, ranging from buildings and green spaces to neighbourhoods and cities

tourist destinations can be identified [148]: sociodemographic characteristics, trip characteristics related to the individual, tourist behaviour variables, and motivations when choosing a destination. We below summarise these ideas.

Personal restrictions may affect travelling choices in terms of distance and characteristics of tourism destination. For instance, the level of income (personal budget) has a different influence on individuals, where people with high incomes can have easier access to long-distance destinations, which generally cost more money. Also, the number of children may limit the destination choice, since it reduces individuals' freedom of movement. That means, vacations with children tend to be associated to closer destinations. Therefore, the family size can restrict vacation spending.

Sociodemographic characteristics refer to the life around individuals and their characteristics such as age, gender, religion, size of the city of residence and level of education. The age, although not unanimous among researchers, is considered one of the most important demographic characteristics that influence vacation demand. The size of the city of residence could affect the sensitivity to distance as identified at an empirical level, where the proportion of the population that get involved in tourist activities reaches the lowest levels in towns with lower populations. This is because inhabitants of cities with high population density have a greater need to escape in search of "relaxation", and consequently brings about greater propensity to travel further distances. Finally, based on a previous project, the level of education have demonstrated a positive correlation with the curiosity, number of countries, places and POIs previously visited [39].

Trip characteristics related to the individual refer to the way in which vacation products are purchased, that is, which "intermediary" was involved in the purchasing process, such as apps or travel agencies. Generally, an individual is more likely to book a flight on internet than an all inclusive vacation. However, the purchase of vacation products from travel agents is associated with more complex products, such as long-distance vacations, due to the reduced uncertainty intermediaries bring and the time saved in the organisation of multicomponent trips. Thus, the purchase of vacation products through intermediaries should be associated with long-distance destinations. Another important characteristic is the transport mode, individuals' willingness to travel farther is also contingent on the transport mode selected for the trip, as the physical, temporal, and financial efforts change according to the mode used.

Tourist behaviour is related to the psychographic (interest of the traveller in discovering new places) and the variety-seeking behaviour aspects. The first is about the psychological aspects, having a special relevance in the planning of vacations, through which people feel a deep need to explore the unknown. The second can influence the effect of distance, as it can increase the utility of more distant destinations. In other words, it shows that an individual has a greater willingness to travel long distances if the destination was not previously visited by her.

Motivations for choosing a destination act as push factors leading to the realisation of tourist travel. Three points are worth mentioning. The first one is the search for a place due to its "climate" and/or "relaxation"; we can expect that people who choose a destination for those reasons have a greater propensity to travel farther if they receive these attributes in return. Also, the degree of curiosity, that is indeed the core pillar of many tourism products and services. A tourism product can be almost anything that provokes human curiosity and as long as that "anything" is named, described, priced, and offered. Even with this fundamental role, there has been relatively little contribution in tourism literature to the area of product development in assisting existing and new tourism businesses to create their competitive position in the volatile tourism market. This project incorporates the variables "level of education" and "degree of curiosity" in the process of generating recommendations. Other mentioned variables have not been used in this project due to the lack of data availability (such as income, number of children, motivation for travel, etc.).

7.3 Curumim

As explained above, CURUMIM offers personalised serendipitous recommendations generated from data available in the user profile of the social network Facebook. To do so, it takes into account one of the traits of the human personality, namely the curiosity, and also other aspects of the user, such as the level of education and other information about the context of the recommendation. All this information, conveniently combined, allows the system to present the user positively surprising recommendations whatever it is her degree of curiosity and level of education.

This way, a slightly curious user, in a tourist context, can receive a recommendation like “Barcelona” and feel positively surprised and, at the same time, an extremely curious user would find this recommendation not surprising. On the contrary, the system should be able to recommend extremely curious users items about which they are unaware or have never imagined that such an item existed. Therefore, the goal of this paper is to present an RS that tries to improve the user satisfaction with the recommendations provided (in any context) by adapting these recommendations not only to the user's tastes and preferences, but also to her personality. The architecture presented in this section was developed considering the theory of the traditional psychology, some interpretations of the positive psychology, and also some aspects of the travel behaviour in social psychology [280, 281].

The architecture of CURUMIM seeks to attend the intrinsic needs of individuals when they receive a recommendation, making this experience something positively surprising, and consequently useful. Thus, the understanding of the individual in the psychological context is extremely important, therefore, the adaptation of the recommendation to each individual's personality context becomes something feasible.

CURUMIM uses three different data sources. First, a database of items to recommend. In this case, apart from an id and a name, it is necessary to assign a weight to each item which indicates its popularity. Furthermore, a set

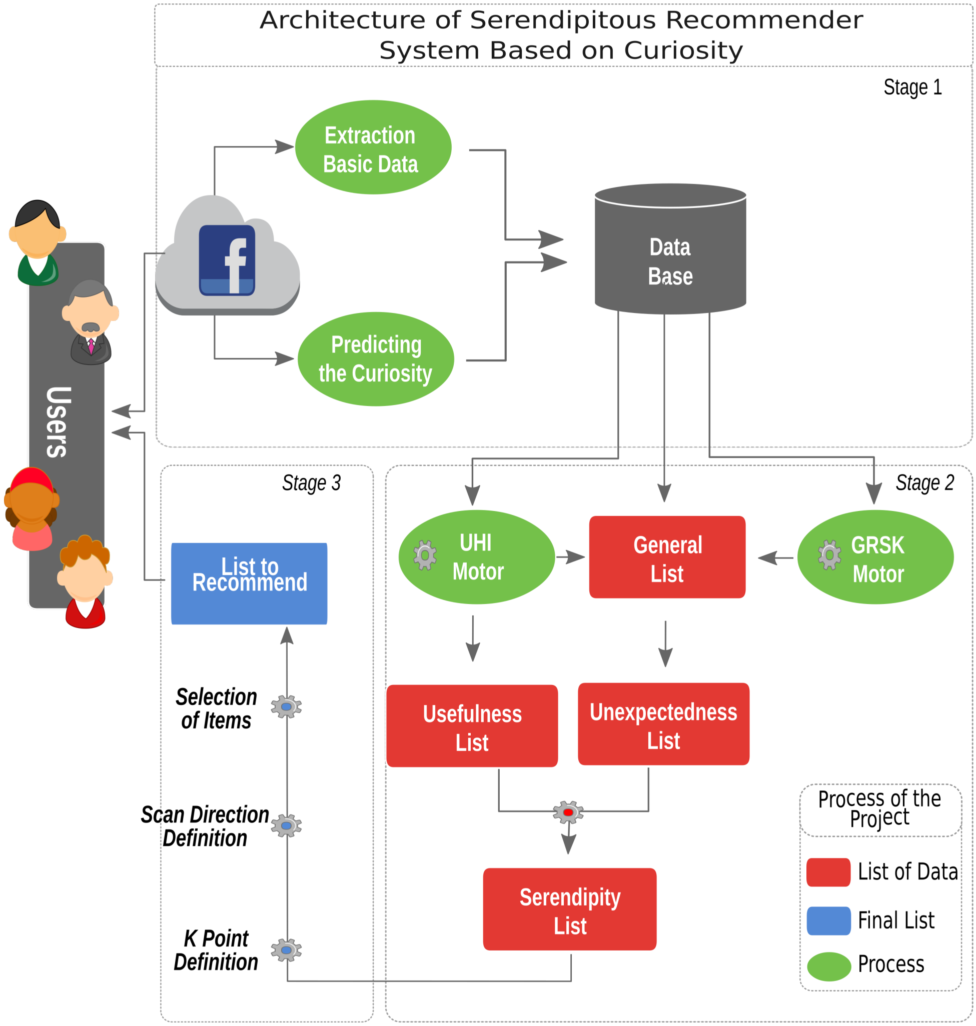

Figure 7.1: *Architecture of Serendipitous Recommender System Based on Human Curiosity*

of labels (e.g. museum, natural, beach, mountains, etc. in the tourist context) is assigned to describe each item. The second one, information about the user extracted from her Facebook profile. It is composed of basic information (e.g. age, gender, relationship status, level of education, etc.) and the total of likes per category (sports, music, films, TV programmes, books, reviews, groups, and check-ins). Finally, information about the history of the user related to the specific application context. For example, purchase history in an e-commerce context, history of places already visited by the user in a tourist context, etc.

Fig. 8.1 depicts the architecture of CURUMIM. The recommendation process is structured in three stages. The first stage is about the extraction of profile data and likes from Facebook users to predict their degree of curiosity; we also need the history of the user regarding the context of the recommendation. The second stage is in charge of generating the serendipity list, which must ensure that the selected items are unknown for the user, by discarding too familiar items and, in addition, this list must also contain useful items, which are the result of taking into account the description of the items already visited by the user [277]. The third stage selects the items that will belong to the final recommendation list. More details of each step can be found below.

7.3.1 Predicting the Curiosity (Stage 1)

The first step is responsible for predicting the curiosity of a given user, denoted by C_U, considering the data obtained from the social network Facebook. The basic data with a prior authorisation from the user are extracted and integrated into our system. The entire process of obtaining data for the generation of the user profile or preferences is implicit, i.e. without the need to fill in forms. In summary, according to work previously developed [39] and some other posterior analysis, the elements that better determine the degree of curiosity of a user are the visited places, cities, countries, and the level of education. The different models generated in these analysis show that, for example: users sharing more than 78 check-ins in places in their Facebook profile are *extremely curious* with a confidence level of 87%; users with a level of education lower or equal to graduate, sharing between 11 and 78 check-ins in places and less or equal to 22 check-ins in cities and less or equal to 5 "likes" on restaurants, can be classified as *moderately curious* users with a confidence level of 91%; users with a level of education lower to graduate, sharing less or equal to 11 check-ins in places, less or equal to 2 "likes" on sports people and more than 6 "likes" in general, can be classified as *slightly curious* users with a confidence level of 70%.

The predicted value C_U is a value in the interval [10, 50], because the prediction model that we use is based on the CEI-II questionnaire [2]. The ranges in which curiosity are split up when predicted are the following: slightly curious are users whose C_U is between 10 and 26; moderately curious have C_U between 27 and 36; and for extremely curious, C_U is between 37 and 50. Once C_U is predicted, this data is recorded in an online database along with basic information, such as id of the Facebook user, the level of education, gender, age, etc.

7.3.2 Serendipity List (Stage 2)

As explained above, serendipity is composed of two essential aspects, **unexpectedness** and **usefulness** [277]. That is, a serendipitous recommendation must be unexpected for the user but, at the same time, it must be accurate in order to be useful for her, which is the ultimate goal of a recommendation. Following this idea, the goal of this stage is to obtain a list of items with a certain degree of serendipity, that depends on the degree of curiosity of the user. That is, the obtained list for a more curious user should reflect a higher degree of unexpectedness than the list for a less curious user, who feels more comfortable with more familiar items. Therefore, our aim is to build a serendipity list S_U for a given user U by taking into account her degree of curiosity C_U to decide the degree of unexpectedness that should be included in the recommendation.

Regarding **unexpectedness**, some authors generate an unexpected list using a primitive prediction model with a traditional recommendation technique [277], assuming that this prediction shows high ratability and produces low unexpectedness. In the same line of thought, we use the result of a Content Based (CB) and a Collaborative Filtering (CF) techniques, in order to discard from the whole set of possible items to recommend, those items that are too familiar or unfamiliar to a given user, according to her degree of curiosity. This list of discarded items is denoted by U_{TT}.

In order to do so, we obtain a recommendation for the user generated by GRSK [282], an RS that uses the traditional CB and CF recommendation techniques. Briefly, the CB technique in GRSK computes the set of preferences that describe the user profile by taking into account the history of the user whereas the CF technique computes the set of preferences of the given user by taking into account the similarity of her profile with other users' profiles; that is, if a user u is similar enough to a user v, then the preferences of user v are included in the set of preferences of user u. Given a list of preferences generated by the CB or the CF technique, the set of items matching these preferences is selected from the whole set of items by simply checking whether the item is described by a label included in the list of preferences. This way, we obtain two lists of items, $CBList$ and $CFList$, respectively, for the given user. Each list is composed of a set of pairs (i, d), where d denotes the estimated interest of the user with the item i.

In a previous work [39], it was stated that more curious individuals prefer CF recommendations, while less curious individuals prefer CB recommendations. This can be explained due to the fact that the CB list contains items which have similar characteristics to previous experiences of the user, thus satisfying the less curious. On the contrary, CF list is more attractive to more curious individuals because it contains unknown items since it is based on other individuals' experiences. Given that our goal is to obtain a list of unexpected items, we can use the CB list to discard those items that are too familiar for the more curious users. However, with respect to the less curious users, we would like to discard too unfamiliar items, that is the items in the CF list. Therefore, we compute the subset of these lists that should be discarded from the whole list of possible recommendations by taking into account the degree of curiosity of the user. The following calculation allows us to select up to M items from these lists (recall that $C_U \in [10, 50]$):

$$N_{TT} = M * \frac{max(50 - C_U, C_U - 10)}{50 - 10}$$

where M is equal to the length of the selected list. Therefore, assuming that $CBList$ is in descending order w.r.t. the estimated interest d, the list of items to discard U_{TT} will contain the first N_{TT} items in $CBList$ if we are dealing with a user whose degree of curiosity is higher than the average[4]. On the contrary, if we are dealing with a user with a degree of curiosity lower than the average, U_{TT} will contain the first N_{TT} items in $CFList$, assuming that $CFList$ is in descending order w.r.t. the estimated interest d.

On the other hand, we define a similarity function $s(i, j)$ that can be used to determine which items are within a distance of other items in the history of the user U_{HI} and, therefore, could be familiar for her. More specifically, $s(i, j)$ can be used to discard an item i within a specific distance to an item $j \in U_{HI}$, meaning that item i is too similar to an already known item j by the user. This similarity function can be defined in terms of items description (i.e. similarity with respect to the set of labels), their weight or ranking, geographical distance in a tourist context, etc. Then, we define the set of items within a distance with respect to a given similarity function as follows (G_L denotes the whole list of items that can be recommended):

$$U_{WD} = \{i \in G_L / \exists j \in U_{HI} : s(i, j) \leq f(C_U)\}$$

where $f(C_U)$ denotes a threshold that depends on the degree of curiosity of the user. For example, in the tourist context, we can define $s(i, j)$ as the geographical distance between two cities; so, as the degree of curiosity increases,

[4] The average of the degree of curiosity in an adult is considered to be 33 [2].

more distant places can be considered as similar. With this calculation, it is obvious that items belonging to U_{HI} are automatically considered similar because they are at a distance equal to 0. This is a desirable property, given that we assume that the RS will not recommend already known items to a user. Thus, the list of unexpected items for user U, denoted by $UNEXP_U$, will be computed as:

$$UNEXP_U = G_L - U_{TT} - U_{WD}$$

This list will have a proper composition since its content will vary according to the items history and the degree of curiosity of the users. In summary, we seek to guarantee that serendipity will be satisfactorily applied for any degree of curiosity.

With respect to **usefulness**, recall that for a recommender system to be serendipitous, it is not enough just to recommend something new and different from the user's knowledge; it is also necessary this item to be relevant and useful for the user, which may cause that sometimes an unexpected recommendation may not be always useful [283]. In order to guarantee the usefulness of the recommendations, we extract the labels of each item in U_{HI}, which are stored in the list $USEFUL_U$ and these labels are used to select those items from $UNEXP_U$ that are described by at least one label in $USEFUL_U$, which will be the final items in the serendipity list

$$S_U = \{i \in UNEXP_U / \exists l \in labels(i) : l \in USEFUL_U\}$$

7.3.3 Selection of the final recommendation list (Stage 3)

Once the serendipity list S_U has been computed, it is sorted in descending order according to the weight of each item. Therefore, the most popular items in S_U will be on top of the list. This implies that, for a user with a high degree of curiosity, these items could still be too popular; that is, a user with $C_U = 47$ should receive more serendipitous recommendations than a user with $C_U = 38$, even when both are considered extremely curious.

For this reason, we try to skip those too familiar items by finding a starting point lower in S_U. We refer to this point as the K point and it is defined as:

$$K = round\left((|S_U| - 1) * \frac{C_U + E_U - A}{B - A}\right)$$

where E_U denotes the level of education of the user, which is a value in the interval $[-3, 3]$; therefore, $(C_U + E_U)$ belongs to the interval [7,53], which are the values of A and B, respectively, and are used to normalise the value of K in the interval $[0, |S_U|]$. For calculating the K point, besides the curiosity, we are using the level of education of the user E_U, since previous works have shown a strong correlation between them [40, 39]. It is a way to rectify anomalies, in case of extremely curious users who have a low level of education and vice-versa. Moreover, it also emphasises this correlation, since it penalises users who have lower values for both level of education and degree of curiosity, whilst it rewards users whose values for education and curiosity are higher.

Finally, once the K point is defined, we still have the option of going through the list S_U in ascending or descending order. If the degree of curiosity of the user C_U is greater than the average, the scanning direction will be bottom-up; otherwise, the scanning direction will be top-down. Here again, we follow the idea that less popular items will increase the satisfaction of the more curious users and vice versa. Once defined the starting point K and the scanning direction, we then select the number of items that will belong to our final recommendation list.

In summary, this architecture sought to combine serendipity and novelty, but at the same time to incorporate sociodemographic characteristics, used for predicting the curiosity and for further processes described above.

7.4 Use Case

This section will show two typical use case scenarios aimed to a tourism context, where we can place CURUMIM functionalities, showing an advancement in serendipity and novelty, adapted to the degree of curiosity.

Both scenarios pictured in Fig. 7.2 and Fig. 7.3 require the users to be connected to the internet with a device (mobile, tablet, laptop, etc.) and have active Facebook accounts. They will access the online system CURUMIM and will receive a recommendation composed of 10 cities around the world. We intend that list to be positively surprising and novel to the users. To do so, we use a database of 34610 cities around the world with name, country, continent, coordinates, Flickr id, and weight (a value in the interval [1, 119334]) which indicates the popularity of a given city.

When accessing the system, CURUMIM will have access to their profiles on Facebook (e.g. age, gender, relationship status, etc.), besides the schools where they have studied (to measure the level of education), and the total of likes per category (sports music, films, TV programmes, books, reviews, groups and check-ins). With these data, the system will be able to predict their degree of curiosity. In our use case, this degree is extremely curious for Bach (Fig. 7.2), and slightly curious for Liszt (Fig. 7.3). This finishes stage 1.

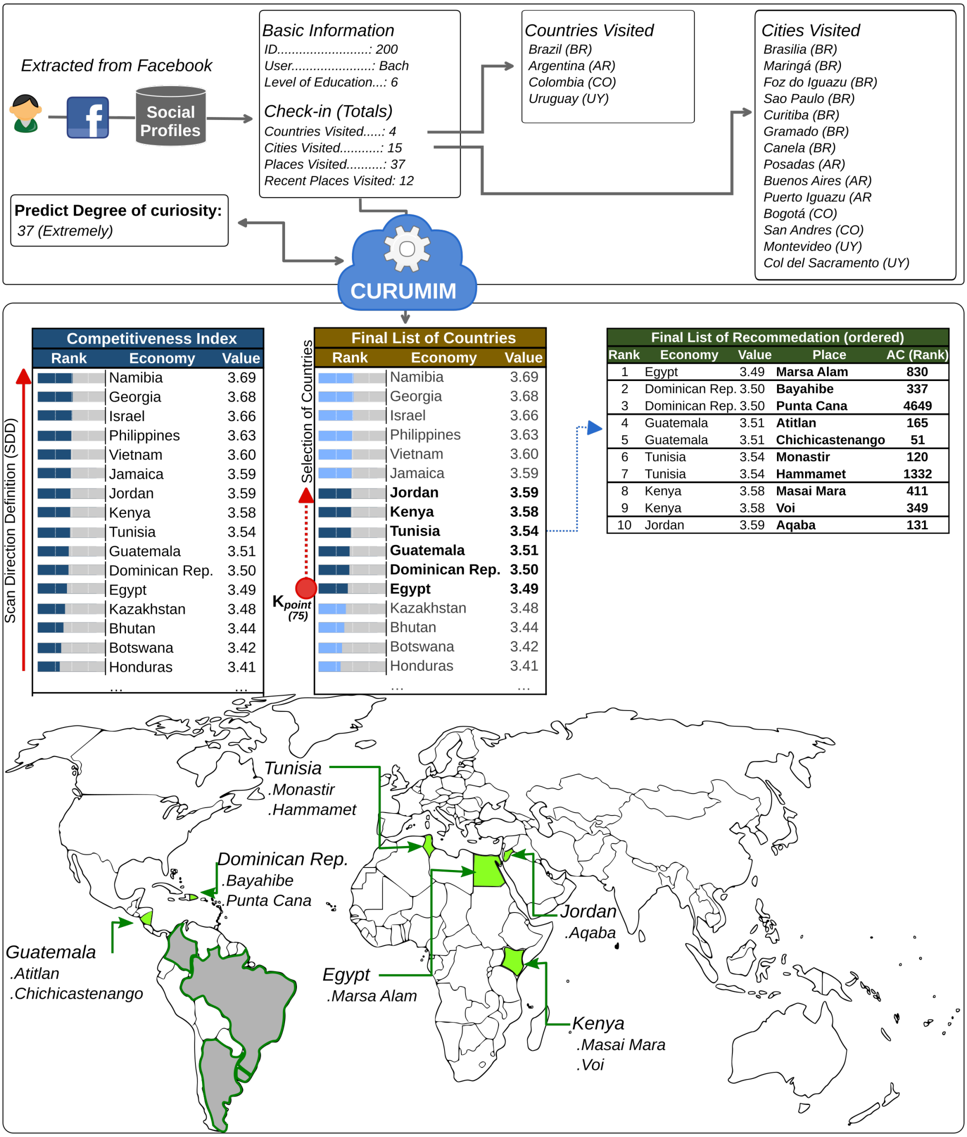

Figure 7.2: *Use case of an extremely curious user with a high level of education.*

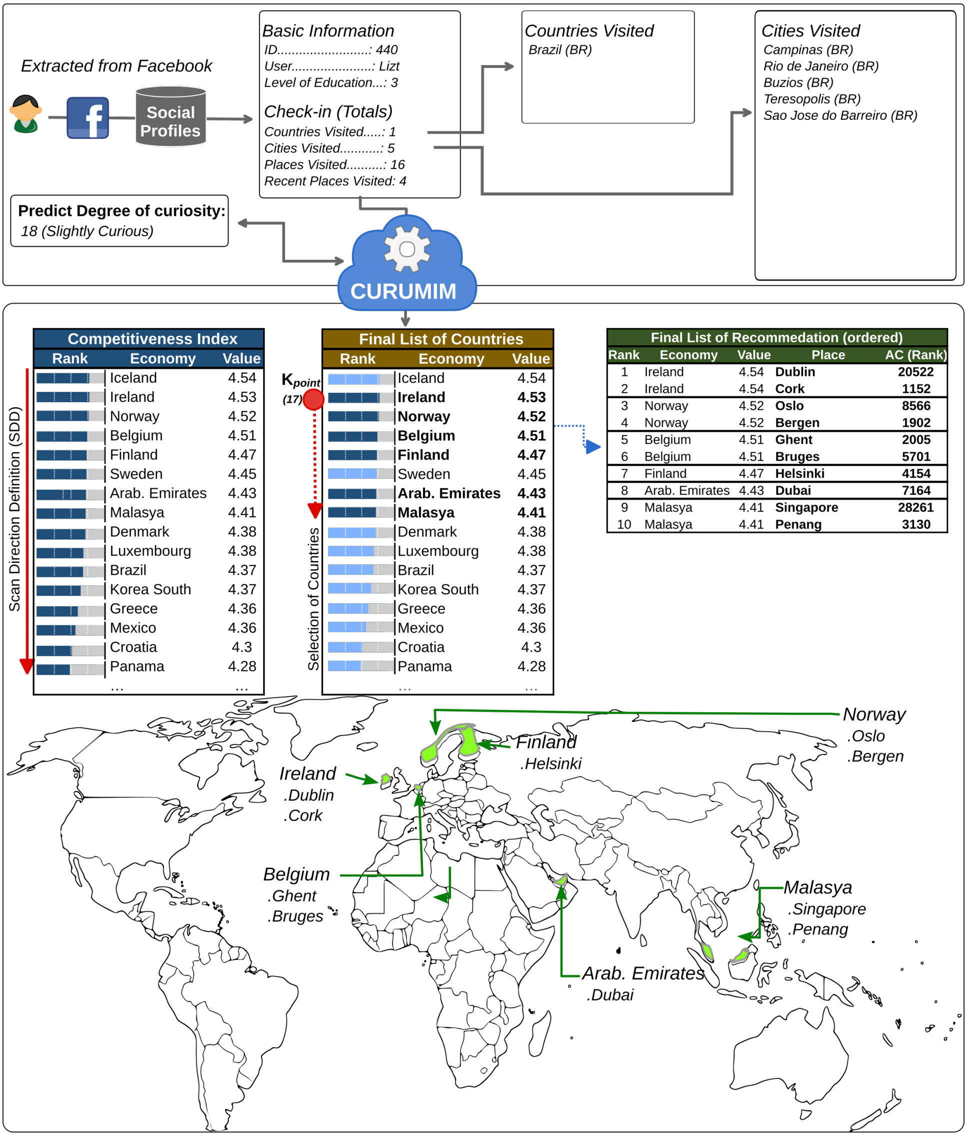

Figure 7.3: *Use case of a slightly curious user with a low level of education.*

In the second stage, the system computes the list U_{WD} by means of a distance function, thus taking into account how "familiarised" is the user with the cities. Specifically for this tourist context, CURUMIM looks at the user history and, for those with a high degree of curiosity (Fig. 7.2), it removes all the cities belonging to countries the user have visited in the past. For instance, the cities from 4 countries are removed in Bach's list, thus remaining 33299 cities. On the other side, for slightly curious users (Fig. 7.3), CURUMIM only removes the cities already visited. So Liszt's list will contain 34605 cities. In summary, the higher the degree of curiosity, the lesser "familiar" to the user (consequently, novel) the cities to recommend will be.

Next task is to filter the cities by relevance according to the curiosity of the user. Hence, CURUMIM uses CBList and CFList provided by GRSK to discard a number of cities, that is, to build the list U_{TT}. For Bach, 18384 cities are removed, remaining 14915 cities. For Liszt, 16472 cities are discarded, remaining 18133 cities. By implementing this task, we seek to guarantee that the list $UNEXP_U$ contains cities less familiar to the more curious users, whereas slightly curious users will be recommended "more familiar" cities.

In order to compute the list $USEFUL_U$, we use the labels that can be found in the database, assigned to each city. They categorise the cities, and are organised in three levels of labels (subtypes). For example, Barcelona (Spain) contains the label "architecture and monument:worship building:church", organised in three levels. We consider that the first level ("architecture and monument") is highly general, while the last level ("church") can be very precise, which leads us to choose the second level into the label as the best option to describe that city. Barcelona is also described by other labels such as "leisure:casino", "architecture and monument:worship building:church", "leisure:aquarium", "architecture and monument:castle", etc. Another relevant factor lies in defining a label that does not make the recommendations become very specific, avoiding the superspecialisation and generalisation, thus having low usefulness. That said, the list $USEFUL_U$ stores a set of labels from the cities contained in the user history, without distinction regarding the degree of curiosity. It contains 136 labels for Bach, while Liszt's contains 43 labels.

Therefore, the serendipity list S_U is created by filtering the cities in the $UNEXP_U$ list which are described by a label contained in the $USEFUL_U$ list. Then, S_U will contain 7205 cities belonging to 110 countries for Bach, and 1859 cities from 81 countries for Liszt. For ordering this list, we take into account the popularity of the countries, as it is considered that, the higher the curiosity, the less popular have to be the recommended cities. To do so, we used the Travel and Tourism Competitiveness Index (TTCI) of countries, developed by UNWTO[5]. This ranking looks at 4 sub-indexes (Natural and Cultural Resources, Infrastructure, T&T Policy and Enabling Conditions, Enabling Environment), which are believed to enable the sustainable development of the Travel & Tourism sector, which in turn, contributes to the development and competitiveness of a country. This way, the better those sub-indexes are, the more suitable is the country for the tourism, hence the best scored it will be in this ranking.

That said, in order to build the recommendation list, we group the cities in the S_U list by country. It is descendingly ordered according to UNWTO index, as explained above. Now, 3 tasks have to be carried out: *KPoint* and scanning direction definitions and, finally, the selection of cities to compose the final list (Table Final list of recommendation shown in Fig. 7.2) and 7.3). We have stated that this final list will consist of 10 cities from at least 5 different countries.

The first task is to calculate and find the *KPoint* in the serendipity list, which is the starting point to then select the cities. The higher the level of education and the degree of curiosity of the user, the closer to the bottom the *KPoint* will be located in the list, and vice-versa. Such approach seeks to recommend countries with lower values (thus less popular countries) to highly curious users. As shown in Fig. 7.2) and 7.3), CURUMIM have calculated the *KPoint* for Bach as Egypt (position 75), whose value is 3.49, while *KPoint* for Liszt is Ireland (position 17), whose value is 4.53.

[5]UNWTO: World Tourism Organization (http://www.unwto.org).

The second task is to define the scanning direction from $KPoint$, where we again look at the curiosity. If the user's curiosity is below the average, the scanning direction will be bottom-up, which means that the serendipity list will be scrolled in a bottom-up direction. If the user's curiosity is above the average, the scanning direction will be top-down. Then, the selection of items process will select the first 2 cities with the higher AC Weight from each country. In case the country selected holds only 1 city, CURUMIM will bounce to the next country in the list, until the final list contains 10 cities.

The final list generated for Bach (Fig.7.2)) has the following cities: Marsa Alam (Egypt), Bayahibe and Punta Cana (Dominican Republic), Atitlan and Chichicastenango (Guatemala), Monastir and Hammamet (Tunisia), Masai Mara and Voi (Kenya), and Aqaba (Jordan). For Liszt (Fig. 7.3)), the final list contains: Dublin and Cork (Ireland), Oslo and Bergen (Norway), Ghent and Bruges (Belgium), Helsinki (Finland), Dubai (United Arab Emirates), Singapore and Penang (Malasya).

The system will display to the user pictures of the cities to be recommended; those pictures are retrieved via Flickr API in order to evaluate qualitatively the architecture developed in this work.

As a result, CURUMIM generates a serendipitous and novel recommendation of cities around the world (maps shown in Fig. 7.2 and 7.3)) based on a characteristic of human personality and in a sociodemographic factor, which are the degree of curiosity and the level of education, respectively. This way, we expect that both high and low curious users will feel positively surprised with their recommendations.

7.5 Conclusions and Future Works

In this work, we have described the full architecture of CURUMIM, a recommender system capable of predicting one of the traits of human personality, the curiosity; combined with sociodemographic characteristics (level of education, the number of places visited), it allows the system to provide serendipitous and novel recommendations.

We also have developed two use cases in the sector of tourism with data extracted from Facebook. In order to demonstrate the range of capabilities and the characteristics of CURUMIM, we have used it in a real context environment, by generating a recommendation of cities (places) around the world.

In other words, this paper describes a fullyfledged platform and architecture and a proof-of-concept implementation; it presents, in one hand, an approach that applies concepts and methods of human psychology in data extracted from the social network Facebook to predict the degree of curiosity; and, on the other hand, the combination of relevant approaches, such as serendipity and novelty.

As a future work, we will analyse the behaviour of CURUMIM by submitting it to tests with real users, but also including other sociodemographic characteristics (size of the city of residence, the goal of the travel, visiting or not friends and relatives, etc), personal restrictions (level of income, number of children), and characteristics related to the individual (transport mode, the type of tool used to organize a vacation). Another important point will be to compare it with other serendipitous recommendation systems.

To conclude, we consider that serendipity is not only a matter of algorithms or classification, it is a very intrinsic topic within each person, so what it is serendipitous for one may not be so for another one. Its measure can be interpreted as how surprising the successful recommendations are. It is personal, therefore it is personality.

Thus, we hope to demonstrate that the combination of data from social networks and characteristics of human personality enable the recommendation systems to recommend different items, even when the individuals have similar profile and tastes. In other words, the inherent characteristics of human personality do count when choices are made, so they have to be considered when a recommendation process is performed.

Chapter 8: Curumin: A Serendipitous Recommender System for Tourism Based on Human Curiosity

Contents

Curumin: A Serendipitous Recommender System for Tourism Based on Human Curiosity

Authors: **Alan Menk, Laura Sebastia, Rebeca Ferreira**
{amenkdossantos, lsebastia, redelferrer}@dsic.upv.es

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Abstract

In recent years, an evolution of recommendation systems has been observed. New advisory systems have been gaining space, using new tools, algorithms and recommending techniques, not only to increase accuracy, but also to positively surprise the user, that is, to provide serendipitous recommendations. Following this trend, we describe CURUMIM, an online tourism recommender system, able to generate serendipitous recommendations of places around the world. In summary, from data available on social networks, it predicts the degree of curiosity of a user, which is then used, along with the user history and her level of education, to select the most appropriate recommendations. We have performed an experiment with real users who reported positive levels of satisfaction with the recommendations in terms of accuracy, serendipity and novelty.

8.1 Introduction

Nowadays, there is a need of applying new technologies in businesses to get through an increasingly digital world. The expansion of artificial intelligence is considered as a technological revolution, where innovative recommendation systems (RSs) play a fundamental role in this scenario. Multinational companies like Amazon, Google, Facebook or Netflix use RSs far beyond to simply recommend items, making them a business strategy in their market niches [284, 285, 286].

Companies that exploit RSs have been used and accepted by the users, since such recommendations are significantly more accurate than a decade ago [287]. In relation to the tourism sector, Booking.com for instance, developed an app to harness artificial intelligence technology and powerful machine-learning to predict individual traveller intent and create a truly convenient, personalised in-destination experience. To do this, this company has leveraged insights from its millions of travellers about what they liked and disliked about various destinations and the experiences they had there and has combined this data with a customer's previous travel preferences, where that person is at the moment in a specific destination, as well as third-party data like the current waiting time at the most popular museum. Consequently, over time the system provides travellers with increasingly personalised, relevant and timely suggestions to personalise the in-destination experience [288]. Expedia [273], on the other hand, have analysed the users' emotions when navigating through their website; their aim was to examine their emotions and reduce frustration when they are about to book a travel.

The future recommendation systems need to deal with the challenge in making a computer system recommend something as if it was recommended by the "best human friend" of a person. That is, considering the time and location (context), but also achieving the positive surprise effect (serendipity), recommending something new (novelty), heterogeneous (diversity), besides taking into account the personality of the recipient [289, 290]. Thus, a crucial point to improve, not only in terms of accuracy but also of user satisfaction, is the "positive surprise" of the recommendations, that is, serendipity.

From the point of view of the individual, the selection of a tourist destination involves several aspects, for instance: *Personal restrictions* may affect travelling choices in terms of distance and characteristics of tourism destination (e.g. the level of income, the number of children, the family size, etc) [148]; *Sociodemographic characteristics* refer to the life around individuals and their characteristics such as age, gender, size of the city of residence and level of education [148, 291, 39]; *Tourist behaviour* is related to the psychographic (interest of the traveller in discovering new places) and the variety-seeking behaviour aspects [148].

As stated above, RSs are challenged to converge those aspects and convey accuracy and usefulness in serendipitous recommendations. However, we understand that the idea of serendipity is relative, that means, for a person, the city of Barcelona can be surprisingly positive, while for another person not. In order to contribute with the enhancement of the RSs in this context, we describe the CURUMIM system, an online tourism recommender system, able to generate serendipitous recommendations of places around the world. It aims to measure this relativity of the serendipity by combining the variables "level of education" as a sociodemographic factor and the "degree of curiosity" as a tourist behaviour factor, as well as other personal factors of the individual, such as visited places and absolute values for popular places etc. This way, the recommendations will be adapted to the user personality, thus achieving higher levels of user satisfaction.

This paper is organized as follows: in section 8.2 we summarize the state of the art. Section 8.3 explains the architecture of our RS. In section 8.4, the evaluation results are detailed. Conclusions and future works are presented in section 10.1.

8.2 State of the Art

Currently, recommendation systems must combine different areas of knowledge, for instance the psychology by means of the human personality [17], administration [292], marketing [293], or also, new concepts of recommendation (e.g diversity, context-aware, serendipity).

In this context, [283] proposed the concept of unexpected recommendations as recommending to a user those items that depart from what the specific user expects from the RSs. It was used a method for deriving recommendations based on their utility for the user and the quality of the generated unexpected recommendations was compared with some baseline methods using the proposed performance metrics. In their experiments, the results demonstrated that the method improves performance in terms of both unexpectedness and accuracy. That is, the method is indeed effectively capturing the concept of unexpectedness since in principle it should do better than unexpectedness-agnostic classical CF methods.

Some projects discussed methods for retrieving novel cases in both case-based reasoning systems and collaborative filtering. For instance, [294] presented an evaluation methodology from the perspective of their ability to recommend novel and relevant items. Yet [295] focused on serendipity, describing the design and implementation of a hybrid RS that joins a content-based approach and a serendipitous heuristic in order to provide surprising suggestions using a museum scenario.

Another way to work with serendipity is described by [296], who proposed a social network-based serendipity RS that uses interactive information from the social network to find out which items are interesting for users but hard to discover by themselves. Their experiment results showed that this method can provide more useful recommendations than random choosing method whether the filtering threshold changes or the number of group members changes.

It also should be highlighted projects that use psychology to generate recommendations, such as [165], which presented an approach to deriving users' personality implicitly from their behaviour in the film domain, and furthermore used the derived personality to augment online film recommendations. Their results indicate that the algorithms incorporated with both implicit personality and ratings significantly outperform the non-personality approach. Also taking into account personality traits, but in this case for generating recommendations for groups, [167] presented a novel method based on existing techniques of collaborative filtering and taking into account the group personality composition, generating recommendations of films domain. Their experiments demonstrate that RSs for groups could be improved when using the conflict personality values, obtaining up to 7% of improvement.

8.3 The CURUMIM System

CURUMIM offers personalized serendipitous recommendations generated from data available in the user profile of the social network Facebook. To do so, it takes into account the human curiosity, and also other aspects of the user, such as the level of education and other information about the context of the recommendation. All this information, conveniently combined, allows the system to present the user positively surprising recommendations whatever it is her degree of curiosity and level of education.

This way, a slightly curious user, in a tourist context, can receive a recommendation like "Rio de Janeiro" and feel positively surprised and, at the same time, an extremely curious user would find this recommendation not surprising. On the contrary, the system should be able to recommend extremely curious users items about which they are unaware or have never imagined that such an item existed. Therefore, the goal of this paper is to present an RS that tries to improve the user satisfaction with the recommendations provided (in any context) by adapting these recommendations not only to the user's tastes and preferences, but also to her personality. The architecture presented in this section, depicted in fig. 8.1, was developed considering the theory of the traditional psychology, some interpretations of the positive psychology, and also some aspects of the travel behaviour in social psychology [280, 281].

Our system uses two different data sources. First, a database of items to recommend, described by a set of labels (e.g. museum, natural, beach, etc.). In our case, we have a list of over 34k cities (places) around the world, containing, among other features, a weight in the interval *[1, 11934]* corresponding to the popularity of each place, according to Flickr API, where the higher the weight, the more popular the place is. Those places are representative of all the continents from 141 different countries, whose popularity was obtained from the Travel and Tourism Competitiveness Index (TTCI), created by UNWTO[1], which have a value in the interval *[1,6]*. The second data source contains information about the user extracted from her Facebook profile. It is composed of basic information (e.g. age, gender, level of education), the total of likes per category (sports, music, films, TV programmes, books, reviews and groups), and finally, information about the history of the user, in this case, the places already visited (check-ins).

In summary, the recommendation process is structured in three stages. The first is about the extraction of profile data and likes from Facebook users to

[1]UNWTO: World Tourism Organization (http://www.unwto.org)

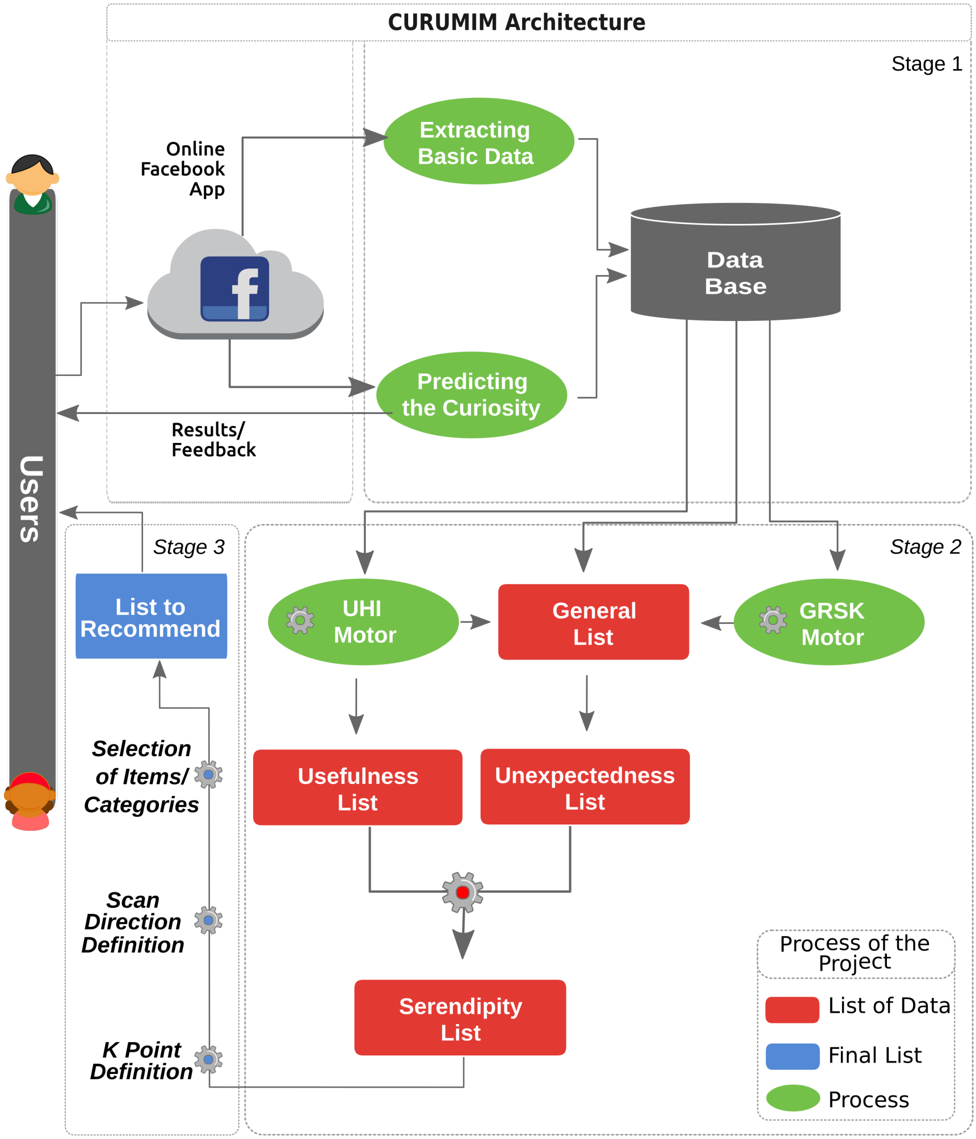

Figure 8.1: *Architecture of Serendipitous Recommender System Based on Human Curiosity*

predict their degree of curiosity; we also need the history of the user. The second is in charge of generating the serendipity list, which must ensure that the selected items are unknown for the user, by discarding too familiar items and, in addition, this list must also contain useful items [277], which are the result of taking into account the description of the items already visited by the user. The last stage selects the items that will belong to the final recommendation list. Each step will be detailed below.

ALGORITHM 8.1: CURUMIM System

Input: G_L, C_U, E_U, U_{HI}
Output: *List to recommend*

$A \leftarrow 7$
$B \leftarrow 53$
$(CB_{List}, CF_{List}) = GRSK(U_{HI},\ G_L)$
Compute N_{TT} ▷ following eq.8.1
if $C_U \geq \bar{x}(C_U)$ **then**
    $U_{TT} = extract\ (N_{TT}, CB_{List})$
else
    $U_{TT} = extract\ (N_{TT}, CF_{List})$
end if
Compute U_{WD} ▷ following eq.8.2
Compute $UNEXP_U$ ▷ following eq.8.3
$USEFUL_U = labels\ (U_{HI})$
Compute S_U ▷ following eq.8.4
Compute K ▷ following eq.8.5
if$C_U \geq \bar{x}(C_U)$ **then**
    scanning direction $\leftarrow$ *bottom-up*
else
    scanning direction $\leftarrow$ *top-down*
end if
List to recommend $\leftarrow$ *items selected from* S_U

8.3.1 Predicting the Curiosity (Stage 1)

The first stage is responsible for predicting the curiosity of a given user, denoted by C_U, considering the data obtained from the social network Facebook.

The basic data with a prior authorization from the user are extracted and integrated into our system. The entire process of obtaining data for the generation of the user profile or preferences is implicit, i.e. without the need to fill in forms. The elements that better determine the degree of curiosity of a user are the visited places, cities, countries, and the level of education. More details can be found in [39].

The predicted value C_U is a value in the interval [10, 50], because the prediction model that we use is based on the CEI-II questionnaire [2]. The ranges in which curiosity are split up when predicted are the following: slightly curious are users whose C_U is between 10 and 26; moderately curious have C_U between 27 and 36; and for extremely curious, C_U is between 37 and 50. Once C_U is predicted, this data is recorded in an online database along with basic information, such as id of the Facebook user, the level of education, gender, age, etc.

8.3.2 Serendipity List (Stage 2)

Serendipity is composed of two essential aspects, **unexpectedness** and **usefulness** [277]. That is, a serendipitous recommendation must be unexpected for the user but, at the same time, it must be accurate in order to be useful for her, which is the ultimate goal of a recommendation. Following this idea, the obtained list for a more curious user should reflect a higher degree of unexpectedness than the list for a less curious user, who feels more comfortable with more familiar items.

Algorithm 8.1 depicts the process of generation of the recommendations, taking as input the general list G_L, the user degree of curiosity C_U and level of education E_U, as well as the user history U_{HI}. The output is the final list to recommend to this user.

Thus, in stage 2, we aim to build a serendipity list S_U for a given user U by taking into account C_U to decide the degree of unexpectedness that should be included in the recommendation.

Regarding **unexpectedness**, some authors generate an unexpected list using a primitive prediction model with a traditional recommendation technique [277], assuming that this prediction shows high ratability and produces low unexpectedness. In the same line of thought, we use the result of a Content Based (CB) and a Collaborative Filtering (CF) techniques, in order to discard from the whole set of possible places to recommend those places that are too familiar or unfamiliar to a given user, according to her degree of curiosity. This list of discarded places is denoted by U_{TT}.

In order to do so, we obtain a recommendation for the user generated by GRSK [282], an RS that uses the traditional CB and CF recommendation techniques (Algorithm 8.1 line 3). Briefly, the CB technique in GRSK computes the set of preferences that describe the user profile by taking into account the history of the user whereas the CF technique computes the set of preferences of the given user by taking into account the similarity of her profile with other users' profiles. The set of items matching these preferences is selected from the whole set of items by simply checking whether the item is described by a label included in the list of preferences. This way, in our context we obtain two lists of places, $CBList$ and $CFList$, respectively, for the given user.

In a previous work [39], it was stated that more curious individuals prefer CF recommendations, because it contains unknown items since it is based on other individuals' experiences; on the contrary, less curious individuals prefer CB recommendations because it contains items with similar characteristics to previous experiences of the user, thus satisfying them. Therefore, in order to satisfy all users, we compute the subset of CB and CF lists that should be discarded from the whole list of possible recommendations by taking into account their degree of curiosity. First, the following calculation (Algorithm 8.1 line 4) allows us to select up to M items from these lists (recall that $C_U \in [10, 50]$):

$$N_{TT} = M * \frac{max(50 - C_U, C_U - 10)}{50 - 10} \qquad (8.1)$$

where M is equal to the length of the selected list. Given that our goal is to obtain a list of unexpected places, and assuming that $CBList$ and $CFList$

are in descending order w.r.t. the estimated interest d, we can use the CB list to discard those places that are too familiar for the users whose degree of curiosity is higher than the average[2], so the list of places to discard U_{TT} will contain the first N_{TT} places in $CBList$ (Algorithm 8.1 line 6). In the case of users with a degree of curiosity lower than the average, we discard too unfamiliar places, so that the places in U_{TT} will contain the first N_{TT} places in $CFList$ (Algorithm 8.1 line 8).

On the other hand, we define a similarity function $s(i, j)$ that can be used to determine which places are within a distance of other places in the history of the user U_{HI} and, therefore, could be familiar for her. In the tourist context, it can be the geographical distance between two cities; so, as the degree of curiosity increases, more distant places can be considered as similar. The function is defined as follows (Algorithm 8.1 line 10):

$$U_{WD} = \{i \in G_L / \exists j \in U_{HI} : s(i, j) \leq f(C_U)\} \tag{8.2}$$

where $f(C_U)$ denotes a threshold that depends on the degree of curiosity of the user. With this calculation, it is obvious that places belonging to U_{HI} are automatically considered similar because they are at a distance equal to 0. This is a desirable property, given that we assume that the RS will not recommend already known items to a user. Thus, the list of unexpected places for user U, denoted by $UNEXP_U$, will be computed as (Algorithm 8.1 line 11):

$$UNEXP_U = G_L - U_{TT} - U_{WD} \tag{8.3}$$

This list will have a proper composition since its content will vary according to the items history and degree of curiosity of the users. In summary, we seek to guarantee that serendipity will be satisfactorily applied for any degree of curiosity.

In order to guarantee the **usefulness** of the recommendations, we extract

[2]The average of the degree of curiosity in an adult is 33 [2]

the labels of each place in U_{HI}, which are stored in the list $USEFUL_U$ (Algorithm 8.1 line 12), and select the places from $UNEXP_U$ that are described by at least one label in $USEFUL_U$, which will be the final items in the serendipity list (Algorithm 8.1 line 13).

$$S_U = \{i \in UNEXP_U / labels(i) \cap USEFUL_U \neq \emptyset\} \tag{8.4}$$

8.3.3 Selection of the final recommendation list (Stage 3)

Once the serendipity list S_U has been computed, it is sorted in descending order according to the value of each country and, subsequently, the weight of each place. Therefore, the most popular places of the most popular countries in S_U will be on top of the list. This implies that, for a user with a high degree of curiosity, these places could still be too popular; for instance, a user with $C_U = 47$ should receive more serendipitous recommendations than a user with $C_U = 38$, even when both are considered extremely curious. For this reason, we try to skip those too familiar places by finding a lower starting point in S_U. We refer to this point as the K point and it is defined as:

$$K = round\left((|S_U| - 1) * \frac{C_U + E_U - A}{B - A}\right) \tag{8.5}$$

where E_U denotes the level of education of the user, which is a value in the interval $[-3, 3]$; therefore, $(C_U + E_U)$ belongs to the interval [7,53], which are the values of A and B, respectively, and are used to normalize the value of K in the interval $[0, |S_U|]$. To compute the K point (Algorithm 8.1 line 14), besides the curiosity, we are using the level of education of the user E_U, since previous works have shown a strong correlation between them [39, 40]. It is a way to rectify anomalies in case of extremely curious users who have a low level of education and vice-versa. Moreover, it also emphasizes this correlation, since it penalizes users who have lower values for both level of education and degree of curiosity, whilst it rewards users with higher values for education and curiosity.

The K point is defined by taking into account the number of countries in the list, which is in descending order by the value (country) and weight (place). Recall that those in the top of the list are the most popular. Once it is defined, we also have the option of scrolling through the list S_U in ascending or descending order. If the degree of curiosity of the user C_U is greater than the average, the scanning direction will be bottom-up (Algorithm 8.1 line 16); otherwise, it will be top-down (Algorithm 8.1 line 18). Here again, we follow the idea that less popular places will increase the satisfaction of the more curious users and vice versa. We then select up to 2 places per country, totalling up to 18 places in the final recommendation list (Algorithm 8.1 line 20).

8.3.4 User Interface

The application requires the users to be connected to the internet with a device (mobile, tablet, laptop, etc). Once into the system, it asks to connect to Facebook, in order to extract basic profile information and compute the curiosity of the user, predicted from her Facebook data. Finally, the user receives a recommendation composed of 18 cities around the world with 3 photos for each place (Fig. 8.2).

Along with each recommendation, the opinion of the user regarding that place was recorded by means of 3 questions answered with a Likert 5-point scale (from 1-strongly disagree to 5-strongly agree). Thus, we were able to measure the **accuracy** (Did you like this place or would you like to visit it?), **novelty** (Have you already known this tourist place?) and **serendipity** (Were you pleasantly surprised by this place?). In the end of the evaluation, there was a final question asking about the diversity of the recommendation list (In general, do you consider that the tourist places presented were diversified/varied?). The answers to these questions could be used in two ways : 1) to assess the reliability of the approach from different points of view (as explained in Section 8.4); and 2) to enrich the user profile and feed the system back, thus providing better future recommendations.

Figure 8.2: *Interface of CURUMIM recommender system presenting a recommend for a slightly curious user*

8.4 Evaluations

To evaluate our system, we performed an experiment that counted on the participation of 74 users. The goals of this experiment are: 1) to analyse whether the recommendations provided by CURUMIM are adequate from the point of view of the degree of curiosity and level of education of the users; 2) to analyse to which extent the CURUMIM system produces novel, diverse and serendipitous recommendations with a positive level of accuracy; 3) to achieve that the “feeling” or “sensation” of receiving a recommendation of something “positively surprising” be the same, independently of the curiosity degree/education of the user.

8.4.1 Adequacy of the recommendations

In order to more precisely analyse the recommendations generated by CURUMIM, fig. 8.3(A) shows the relation between the degree of curiosity and the average of popularity of the cities (places) recommended to the users. Fig. 8.3(B) compares the popularity of the countries with the degree of curiosity of the users. In both graphs it is clear that, the higher the degree of curiosity, the lower the popularity of the countries and places recommended, and vice versa.

Figures 8.3(C) and (D) have the same purpose of the previous one, but from the point of view of the education of the user. The users are grouped into 3 levels: primary, secondary and graduate/postgraduate studies. Fig. 8.3(C) shows that, the higher the level of education, the lower the popularity (value) of the place recommended. Similar situation is found in 8.3(D), which compares the popularity of countries with the level of education.

Fig. 8.4 shows the distance of the recommendations generated by CURUMIM around the world. The system used the hometown to compute the distances of the recommendations. We can observe that the recommendations of the slightly curious are concentrated below 8.000 kilometres, while for the extremely curious, the places recommended are in general above 8.000 kilometres of distance.

When we inspect the graphs above, we can conclude that the CURUMIM system, on the one hand was able to generate recommendations of distant places for the more curious, and closer for the less curious users, as it is specified in the similarity function. On the other hand, it could guarantee more popular recommendations of places and countries for users with low curiosity and/or

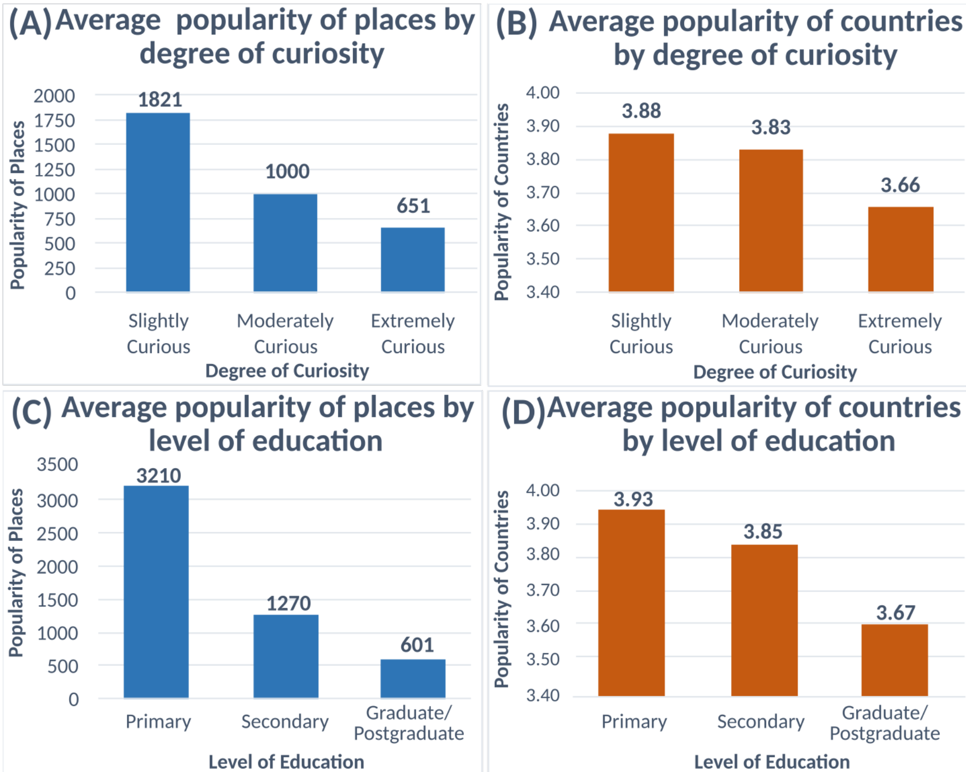

Figure 8.3: *Popularity of cities (places) and countries for each degree of curiosity in (A and (B) and for each level of education in (C) and (D)*

educational level, while more "exotic" or less popular countries were directed towards those users with a higher degree of curiosity and/or level of education. That is, the system was able to generate the recommendations as expected.

8.4.2 Evaluation of the user satisfaction

Here we report the results of novelty, diversity, serendipity and accuracy obtained by our system in a 1 to 5 scale. Fig. 8.5 shows the overall average obtained for accuracy (1), novelty (2), serendipity (3) and diversity (4), grouped by three degrees of curiosity, which are slightly, moderately and extremely curious, besides the total average regardless the degree of curiosity.

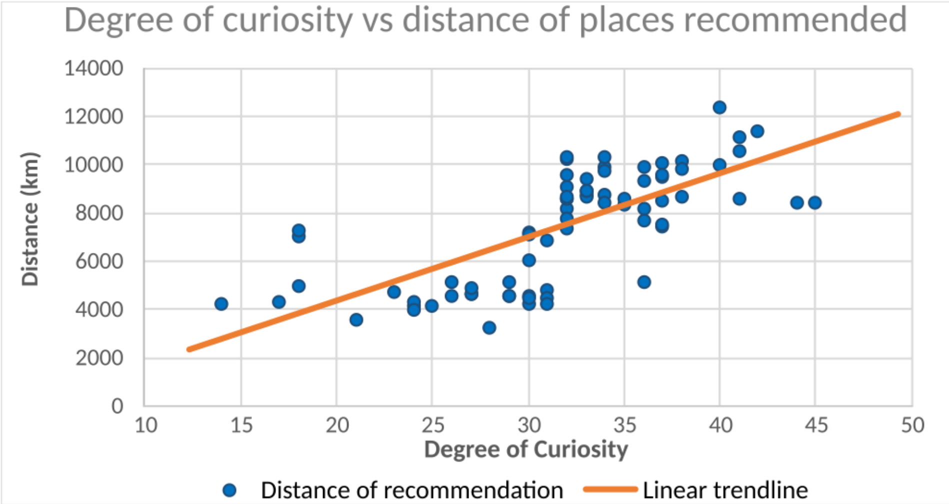

Figure 8.4: *Average distances of the recommendations vs degree of curiosity*

CURUMIM obtained a satisfactory accuracy, whatever the degree of curiosity, with an average of 3.65. Novelty stands out as the best result in all curiosity degrees (slightly curious 4.56, moderately 4.20 and extremely curious 4.71) and, consequently in the overall average (4.73). About serendipity, we see a relation between it and accuracy, which demonstrates that the recommendations generated have positively surprised the users, since serendipity results were equal or greater than the average, with a value of 3.40. Finally, diversity got interim results of 2.77, 3.57 and 3.65 respectively.

Generally speaking, the performance of CURUMIM is positive, achieving good levels of serendipity and accuracy, with emphasis on novelty that obtained results higher than the others, reaching 94% of satisfaction (4.71) for extremely curious users (Fig.8.5)

Another examined results were about the relationship between the level of education and the satisfaction of the users. Fig. 8.6 shows the education, divided into levels, from 0 (primary) to 5 (Postgraduate, Master PhD), according to the International Standard Classification of Education (ISCED) [297]. We can see that the level of education and the level of accuracy and serendipity

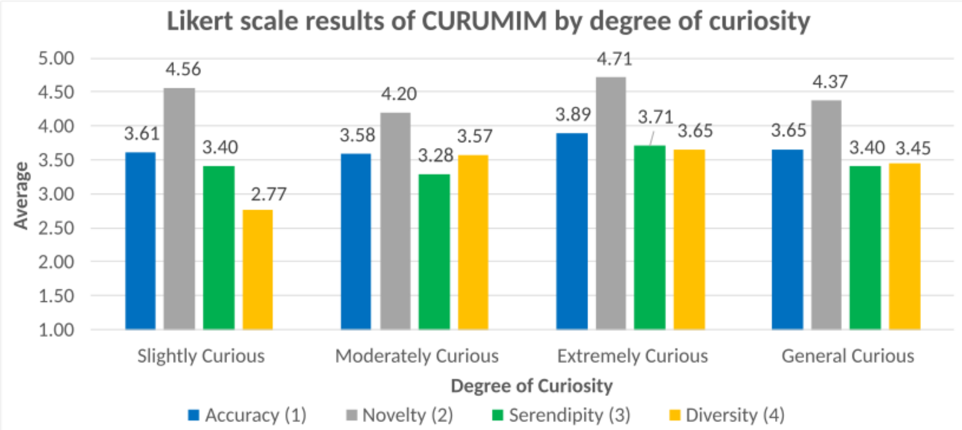

Figure 8.5: *General data of the serendipity test for degree of curiosity*

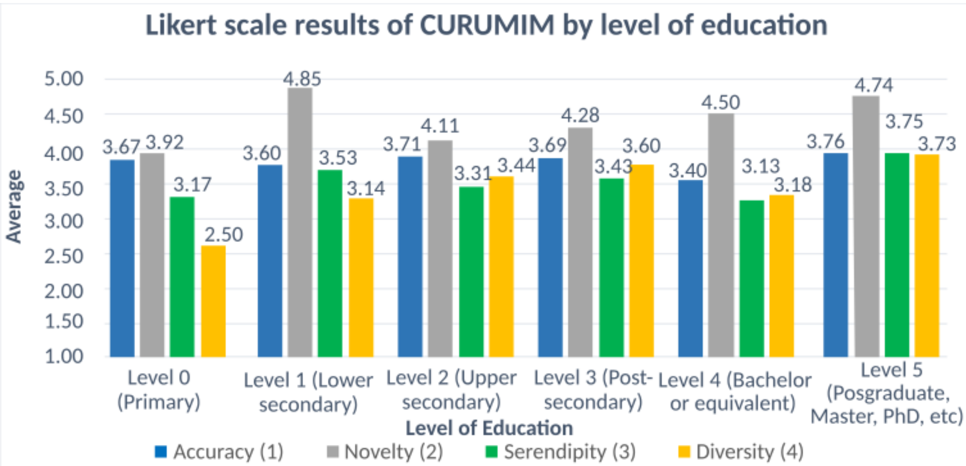

Figure 8.6: *General data of the serendipity test for level of education*

are positively stable, with an exception for users with low educational level (primary), who got a result slightly inferior for novelty and diversity; all other levels of education obtained results positively satisfactory and stable.

In Fig. 8.7 we sought to detail the results we achieved by plotting the degree of curiosity of the users sequentially (from 10 to 50) and separating them by type of evaluation applied, named accuracy (A), novelty (B), serendipity (C)

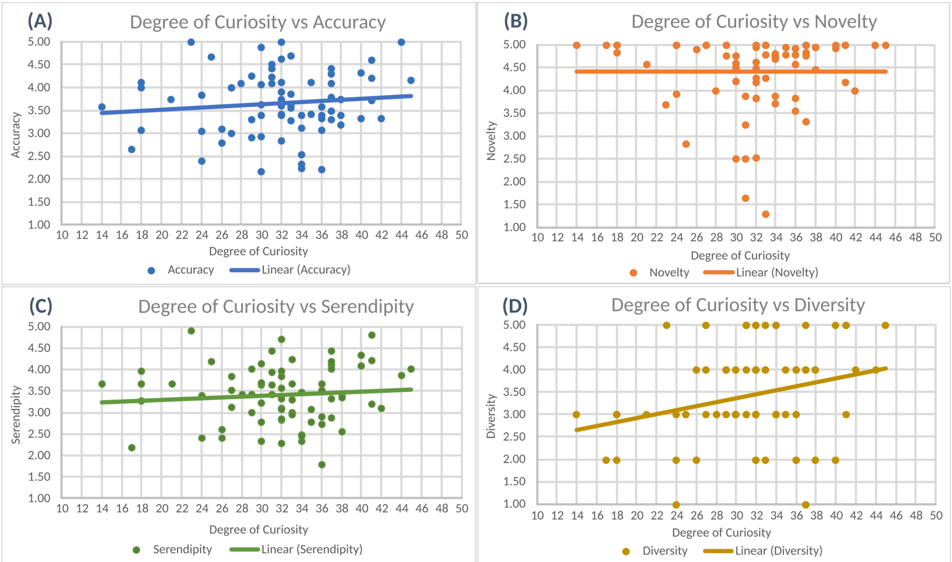

Figure 8.7: *User satisfaction in terms of accuracy (A), novelty (B), serendipity (C) and diversity (D) by degree of curiosity*

and diversity (D). About the three first items, the results show that the level of satisfaction of the users remains stable independently of the curiosity degree of the user, when considering the logarithmic trend line, which is around 3.50 for serendipity and accuracy and 4.50 for novelty. We see that the notion of diversity increases according to the degree of curiosity, while the other values for accuracy, serendipity and novelty remain. Therefore, independently of the degree of curiosity or education of the user, the satisfaction about the recommendation is positively surprising, accurate and novel.

We show here a selection of these opinions:

> *"[slightly curious user] I really liked the places, the pity is that I do not know them yet, but I was tempted".*

> *"[moderately curious user] The photos selected have a strong influence on my choices and my opinion"*

"[moderately curious user]I felt like knowing some places presented, the test was well thought-provoking."

"[extremely curious user] A lot of places I do not know, I had to turn to Google to respond."

"[extremely curious user] I found the places very interesting, especially those in Eastern Europe and Asia, since I do not know them and I would like to know them, especially for the cultures that are very contrasting with ours."

In analysing these and other comments, we see 3 broad consensuses amongst the opinions of participants. First of all, the surprise was positively accepted among all three degrees of curiosity, demonstrating a desire for the new, unknown, when well used, is capable of generating a strong sense of discovery, and challenging to have that, or wanting to go to there. The second point, we detach the distance, once the system combined it, with the popularity of the destinations. On the one hand, the lower the degree of curiosity, the more popular and physically close to the user was the recommendation. On the other hand, the more curious the person, the more distant and unpopular was this recommendation. The third point is the extra factors, such as the importance of the photos presented (style, location taken, whether it was day or night, winter or summer, etc). In a first analysis, this seemed to be of little importance, however, we could see that the photos aided the users 'choices and in some ways have an impact on the users' choice and evaluation. In general, we can say that regardless of the degree of curiosity, degree of education, personal motivations, etc., the system generated positive recommendations to all user groups.

8.5 Conclusions and Future Work

In this work, we have described and evaluated CURUMIM, a complete tourism recommender system capable of generating serendipitous recommendations of cities around the world, using the human curiosity factor into its kernel, combining it with sociodemographic characteristics (level of education, the number of places visited) extracted from Facebook. We counted on the participation of real users to evaluate the system and we obtained a satisfactory level of accuracy, serendipity and novelty.

In other words, we demonstrated that the system is able to, first of all, generate extremely novel recommendations of places around the world; secondly, those recommendations are also positively surprising or serendipitous, and third, they maintain a good level of accuracy independently of the degree of curiosity of its users. In parallel, we also have analysed users' satisfaction through textual feedback, which proves the good level of positive surprise and novelty that CURUMIM was able to generate, achieving results similar to the quantitative experiment performed, but with a higher degree of detail.

As a future work, we will analyse the behaviour of CURUMIM by submitting it to tests with other environments, for instance generating recommendations of products in an e-commerce. Also we will include other sociodemographic characteristics that can be identified in this new context, personal restrictions (level of income, number of children), and characteristics related to the individual. We will also give greater attention to the smaller factors such as the interface of the recommendation. In addition, we will adapt the system according to the users' answers provided in the questionnaires, in order to enrich the user profile and feed the system back, thus enhancing future recommendations.

To conclude, we consider that serendipity is not only a matter of algorithms or classification, it is a very intrinsic topic within each person, so what it is serendipitous for one may not be so for another one. Its measure can be interpreted as how surprising the successful recommendations are. It is personal, therefore it is personality.

Thus, with the development of this system, we showed that the combination of data from social networks, characteristics of personality, and other recommendation concepts enables the creation of recommender systems that generate different items, even when the individuals have similar profile and tastes. That is, the inherent characteristics of human personality do count when choices are made, so they have to be considered when a recommendation process is performed.

III

Discussion

Chapter 9: Discussions

Contents

In this thesis, we have proposed a new approach to computational personality-based recommender systems that use human curiosity according to psychology definitions, in order to improve the user satisfaction and, at the same time, to make more "human" recommendations, which are also closer to the profile of the recipient. In section 9.1, we summarise the main conclusions of this thesis. Then, section 9.2 presents the transformation process of the CURUMIM architecture and its implications, also providing an analysis of the volunteers. Finally, section 9.3 presents a recent publication that supports our findings regarding the correlation between curiosity and some features already analysed in this thesis.

9.1 Summary of the Research

Throughout this project, we identified some works that rely on the user personality to improve the recommendations. However, curiosity is an important aspect in the individual's decision making process, but RSs that use only the curiosity in the recommendation were not identified. Therefore, a theoretical investigation was developed on terms related to human curiosity, what it is, what it represents and what the psychological reliable ways to measure it are. It was observed that the *traditional psychology* offers approaches to measure it through forms or also with different interpretations of the *positive psychology*. In this process, social networks play a fundamental role, and we have performed several experiments to "discover" which data are most suitable for predicting the "level of curiosity" of an individual, only with the use of data available on Facebook. This initial investigation resulted in an online system that could implicitly measure a person's degree of curiosity. It was tested with real users, demonstrating that some data, such as the level of study and places, cities and countries already visited are extremely valuable for the prediction of the curiosity.

Having overcome this stage, a hybrid RS capable of improving the user satisfaction in relation to the generated recommendations, supported by the level of curiosity of this user, was developed. This system was tested with real users who received recommendations of tourist places in South America, obtaining better results when compared to traditional recommendation systems like CB and CF.

The next step was to develop a new theoretical study about which personal factors (psychological, behavioural, and motivational) may influence the choice of tourist destinations, in order to build an enhanced experience for the user. The discovery of these factors was applied in a new recommender system called CURUMIM. In summary, CURUMIM is able to predict the degree of curiosity of a user and, together with other features such as level of education, it is able to generate novel and serendipitous recommendations of cities around the world, by using only data available on SNs.

The first tests with CURUMIM were performed using some use cases, which demonstrated how the system behaves with users of different degrees of curiosity. Also, some experiments were developed with real data and users, which allowed the measure of the effectiveness of the system as a whole, showing positive levels of satisfaction with the recommendations in terms of accuracy, serendipity and novelty.

Our conclusion is that the future RSs will need to deal with the challenge of building a computer system able to recommend something, considering the time and location (context), trying to surprise her positively (serendipity), recommend new (novelty) and heterogeneous (diversity) items, besides taking into account the personality of the recipient [289, 290].

9.2 The evolution of the CURUMIM architecture

From the knowledge obtained thanks to the analysis of the state of the art presented in this thesis, we have constructed the prototype of CURUMIM. Its development has evolved along with our investigations in a few steps that are described in the following sections. Besides, we also present an overview of the characteristics of the volunteers participating in the experiments performed throughout this thesis.

9.2.1 First prototype of the RS

The first version of the architecture of our hybrid RS (based on the Knowledge Discovery in Databases - KDD process, presented by Fayyad et al. [298]) provides a list of items obtained by the combination of recommendations based on CB and CF techniques depending on the degree of curiosity of a given user (Chapter 4). With this project, we validated some hypotheses by performing some preliminary experiments with the participation of 105 Brazilian volunteers, recommending them photos of POIs of South America generated by traditional systems (CB and CF techniques) and our hybrid system. The tested hypotheses are: (1) the degree of curiosity of a user may influence her decisions about what places to visit; (2) the use of data available on SNs as Facebook allows the measure of the degree of curiosity; (3) the degree of curiosity plays a crucial role in the choice of the recommendation technique.

This first developed architecture (Fig. 9.1) is divided into the *model generation* and the *model execution*. The first one is devoted to generate a model of curiosity by using information available on Facebook and the CEI-II psychological test. The second one applies this model to new users in order to measure the curiosity degree and it is also responsible for the recommendation itself.

The *Model Generation* works in three stages. The first stage (circles) is responsible for obtaining basic data from Facebook in an implicit way, for calculating the degree of curiosity of each volunteer through the CEI-II questionnaire and then, for implicitly obtaining Facebook data such as likes, groups, visited places, photo tagging, etc. The second stage (squares) aims "to clean" data obtained in the previous process, and to classify the "likes" of a given user. Finally, the third stage (triangle) generates the curiosity models.

The *Model Execution* is also divided into three stages. First, the system analyses the Facebook data of the user to infer, through the generated model, his degree of curiosity (second stage). The third stage uses CB and CF

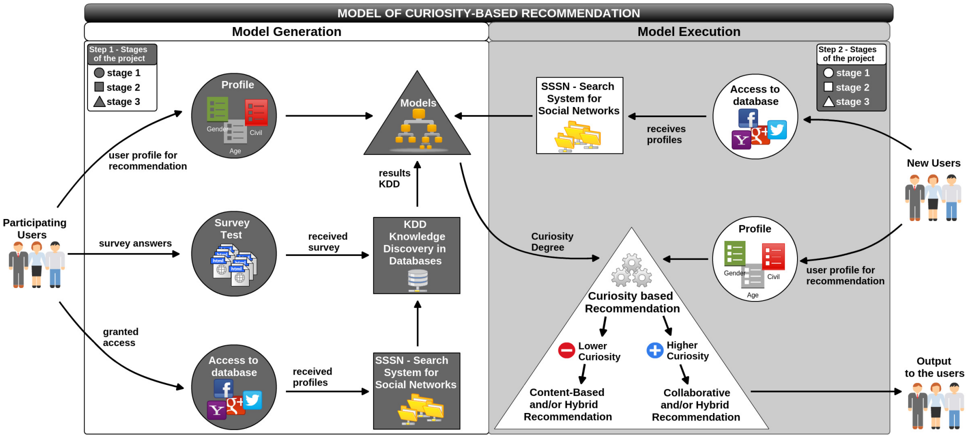

Figure 9.1: *First version of the architecture of our RS based on curiosity*

techniques to generate two lists of recommendations, one based on travelling history and another generated from similar profiles to the user.

The final list of recommendations is obtained by combining both lists in a weighted way, which depends on the level of curiosity of the user. Specifically, for users with a lower curiosity, a higher percentage of items from the CB list is recommended, and for those who have a higher curiosity, a higher percentage of items from CF list is used.

Lately, we have performed a comparison between this hybrid approach and an existing technique able to provide both novel and relevant recommendations [299]. This technique, named *GraphRec*, consists of a graph-based recommender system that uses only positively rated items in users' profiles to construct a highly-connected, undirected graph, with items as nodes and positive correlations as edges. This graph is used to extract a sub-graph representing the items of a user's profile their and neighbouring items which is then analysed using the concept of Shannon's entropy to find novel and relevant recommendations.

We have implemented this technique and we have performed some tests with our set of volunteers, who were asked to rate the recommendations provided by this new technique in the same way as they rated the recommendations of our system. Fig. 9.2 shows a comparison in the average user satisfaction between *GraphRec* and our RS, where the users in the X axis are ordered according to their degree of curiosity. It can be observed that many users are more satisfied with the recommendation provided by our RS and, in some cases, this difference is especially remarkable. Specifically, more than 65% of users prefer the recommendations of our system over the recommendation obtained by *GraphRec*. The satisfaction in average with the recommendations of *GraphRec* is 1.978, whereas with our RS is 2.18. If we analyse these results considering the degree of curiosity of the users, we discover that the difference between our RS and *GraphRec* in the average user satisfaction is 0.14, 0.17 and 0.34 for slightly, moderately and extremely curious users, respectively. Therefore, we can conclude that our approach provides more satisfying recommendations that *GraphRec* (Fig. 9.2).

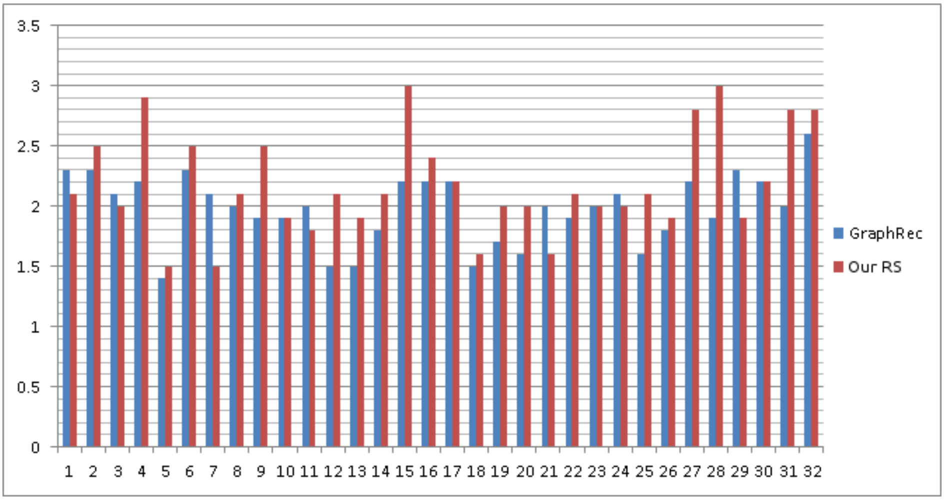

Figure 9.2: *Comparison in the user satisfaction between GraphRec and our RS*

9.2.2 Improvement of the degree of curiosity prediction

When we analysed the results obtained with the architecture presented previously, we realised that curiosity plays a fundamental role to improve the user satisfaction in relation to the received recommendations. Given its importance, and in order to find new features to improve the accuracy of our model, thus enhancing its reliability, we developed two new experiments to improve a specific part of the architecture, the *model generation*.

The first one (Chapter 5) counted with the participation of 105 volunteers, and showed that the degree of curiosity of an individual can be predicted by taking data from the social network Facebook. We identified a satisfactory correlation between the degree of curiosity and a group of labels related to "places", which includes places, recent places, cities, countries and states of South America visited by the user.

The second one (Chapter 6) corroborated that the degree of curiosity of an individual can be predicted by processing the information from the user profiles in Facebook with supervised machine learning models. The experiments were expanded from 105 to 176 volunteers and we tested 10 different algorithms; besides to confirm a strong positive correlation between degree of curiosity and level of education, we also achieved better results regarding the Pearson correlation values. That is, the higher the level of education, the greater the curiosity and vice-versa.

9.2.3 Second prototype and the use cases

Based on the experiences obtained in the previous experiments, the feedback received from the users (subsection 9.2.1), and the positive results obtained in the curiosity prediction experiments (subsection 9.2.2), some changes were made in the project architecture, as we can see in Fig. 9.3. When we compare the architecture presented in Fig. 9.1 with the architecture of the project presented in Fig. 9.3, we can observe a greater maturity of the processes and the consideration of properties such as serendipity, diversity and novelty for the generation of the recommendations based on the curiosity.

It is important to emphasize that, regardless of whether it is the first (simpler) or the second (more robust and with more properties) architecture, the recommendations generated were positive for the users, demonstrating high levels of satisfaction compared to traditional RSs.

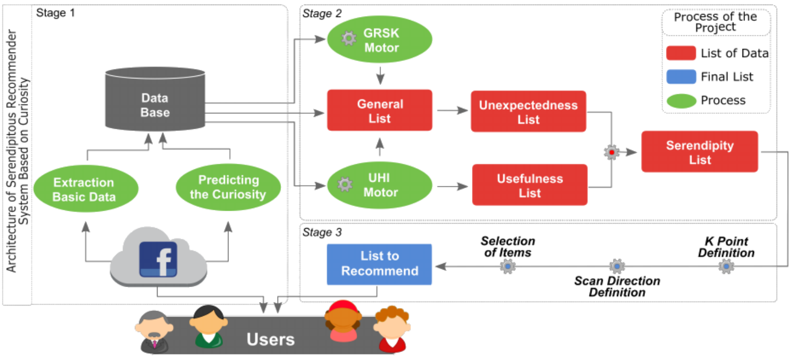

Figure 9.3: *Final version of the developed architecture*

The result of this updated architecture is shown in the use cases presented in Chapter 7, where two possible scenarios (defined for slightly or extremely curious users) detail the process of recommending tourist places around the world. CURUMIM was tested in these scenarios and it was able to predict the degree of curiosity of the user, and to combine it with sociodemographic characteristics (level of education, visited places), providing serendipitous recommendations.

Observing the architecture in Fig. 9.3, the unexpectedness list (based on CB and CF lists generated by GRSK engine) and usefulness list (based on users' history) are used for the generation of a serendipity list containing tourist places. This list considers the user personality previously predicted, for the selection of the items to be finally recommended (Fig. 9.4). The items in the serendipity list are sorted in descending order, that is, the items at the top of the list are considered the most "popular" places. Thus, the system performs a calculation (Fig. 9.4) that defines the starting point for the selection. That is, the selection point is closer to the end of the list and its direction is bottom-up (less popular to most popular places) for the extremely curious users; on the other hand, it starts near the top of the list and it goes up-down for the slightly curious users, until it reaches the number of items desired for the recommendation for both scenarios.

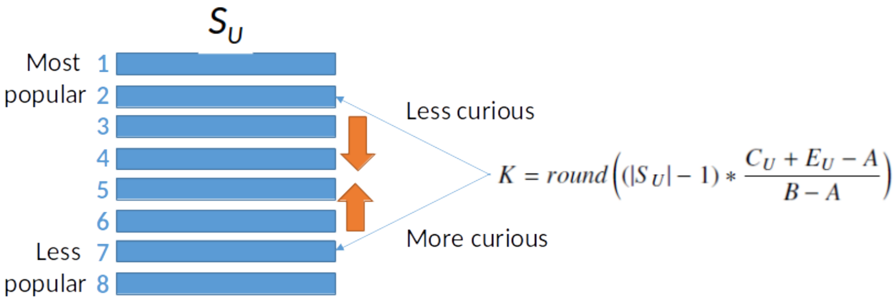

Figure 9.4: *Final recommendation list*

9.2.4 The final architecture

Chapter 8 presents the results of the experiments with the final version CURUMIM. Three approaches were used to generate the recommendations: the sociodemographic characteristics (level of education), tourist behaviour (interest of the traveller in discovering new places and variety-seeking aspects), and motivations for choosing a destination (curiosity). As we can see, the curiosity is an important aspect of the perception of the quality of the recommendation [148].

In summary, CURUMIM is an RS capable of predicting the degree of curiosity of the user from the information in the profile of the user in SNs and of combining it with sociodemographic characteristics (level of education, visited places) to provide serendipitous recommendations. We have performed some experiments with real users and the results reach good levels of diversity, serendipity, accuracy, and novelty; for instance, this last property obtained results higher than the others, reaching 94% of satisfaction for extremely curious users.

9.2.5 Volunteers

The volunteers played a fundamental role in the evaluation of the different versions of our recommendation system, given that they were evaluated by means of an *online* method. The choice of an *online* evaluation provided us clear guidance for the construction and analysis of the RS experiments. When testing with real users, one cannot study algorithms isolated; several system aspects (likewise personal and situational characteristics) have to be combined in a single experiment to gain a full understanding of the user experience [50].

Going beyond, the context of our project considers that, for industry researchers, the user-centric focus of the framework provides a step closer to the customers, who may not consider the accuracy of the algorithm the most important aspect of their experience. Questionnaire-taking and A/B testing (the industry term for testing several versions of a certain system aspect) are an accepted form of research in web technology. For academic researchers, the framework provides an opportunity to check the real-world impact of the latest algorithmic improvements. Besides, *offline* evaluations ignore the "human" factor, which may influence the satisfaction of the users regardless the recommendation received. It is yet really hard to determine the satisfaction of the recommendation in a non-real world environment, thus it makes sense to not use *offline* evaluations to assess an RS [213]. For instance, how is it possible to measure the serendipity of an RS, that is, the user's degree of positive surprise, without having her feedback?

McNee et al. [300] characterize the serendipity evaluation as a level of emotional response associated with serendipity, which is difficult to capture. Therefore, an effective serendipity measurement should move beyond the conventional accuracy metrics and their associated experimental methodologies. New user-centric directions for evaluating new emerging aspects in recommender systems, such as serendipity of recommendations, are required. That is, the adoption of *online* evaluation by the recommendation systems, although it is necessary to spend resources (financial, time, etc.), will bring important benefits to researchers or industries.

In our first experiment presented in Chapter 4, 105 Brazilian volunteers were recruited. They filled in the CEI-II test, but only 75 granted access to their Facebook profile[1]. Finally, in the second experiment (Chapter 5), only 26 answered our test about the recommendations provided by our system. That is, the analysis of the first version of our RS was based on the responses of these 26 volunteers. The responses of this study were compared to the average value of the responses in Kashdan et al. [2], whose results were obtained with a sample of 578 people, which gives a good sample to compare with.

The group of volunteers was formed by 20 men and 12 women, from 8 different cities of the state of Parana, in Brazil, between ages from 18 to 47. Their level of studies is 10% Postgraduate, 70% Graduate, 17% High School and 3% unknown.

Table 9.1 shows a summary of the responses of these volunteers to the CEI-II test. It gives the percent responses by scale value for each question and the average value of the responses. Additionally, we compare the responses of our study with the average value of the responses in Kashdan et al. [2], whose results were obtained with a sample of 578 people, which gives a good sample to compare with.

CEI-II items	1	2	3	4	5	6	7	8	9	10
1 (%)	3.13	37.50	9.38	0.00	0.00	15.63	3.13	15.63	0.00	34.38
2 (%)	9.38	25	18.35	3.13	3.13	15.63	15.63	34.38	3.13	40.63
3 (%)	28.13	21.88	31.25	18.75	18.75	28.13	28.13	28.13	25	9.38
4 (%)	28.13	9.38	21.88	43.75	34.38	37.5	25	9.38	21.88	3.13
5 (%)	31.25	6.25	18.75	34.38	43.75	3.13	28.13	12.5	50	12.5
Average	3.75	2.22	3.22	4.09	4.19	2.97	3.59	2.69	4.19	2.19
Average [2]	3.69	3.15	3.51	3.31	3.59	2.87	3.36	3.03	3.16	3.32

Table 9.1: *Results of the CEI-II*

In our study, the responses 3, 4 and 5 were selected approximately the same number of times, whereas the least selected was 1. The questions with more disperse responses are 3 and 8, whereas questions 4, 5 and 9 concentrate most responses in the values 3-5. Comparing the results of our study with the results obtained in Kashdan et al. [2], we observe that for questions 1 and 6 the result is nearly identical, whereas the biggest differences can be found in questions 2, 9 and 10.

[1] If we were not able to obtain a list of rated places, the corresponding user was discarded

In order to uncover the effect of these differences, we have also performed an analysis by each facet of curiosity, namely stretching and embracing, summarized in Table 9.2. This table shows the average responses for the questions referring to each facet in the curiosity and the total score is shown in brackets. According to Kashdan et al. [141], the average adult completing this questionnaire scores about 17.5 on the stretching facet, and 15.5 on the embracing facet of curiosity, which gives a total score of 33 (these values are also shown in Table 9.2). The total values of the curiosity in our study does hardly differ from the results in Kashdan et al. [2, 141]. However, there is a great difference if we observe the values for each facet. This indicates that our volunteers are clearly more stretching and less embracing than the standard individuals, which means that are more motivated to seek out knowledge and new experiences but less willing to embrace the novel, uncertain and unpredictable nature of everyday life.

	Stretching	Embracing	Total
Our study	3.78 (18.9)	2.83 (14.15)	3.31 (33.1)
[2]	3.46 (17.3)	3.13 (15.65)	3.30 (33)
[141]	- (17.5)	- (15.5)	- (33)

Table 9.2: *Average responses of stretching and embracing questions and total scores for each facet in brackets*

Fig. 9.5 shows the value of the total curiosity and the value for each facet per user (ordered by total curiosity). The value of the total curiosity in our study varies from 21 to 46, and the distribution is quite uniform. As we already mentioned, the stretching facet is more remarkable in the volunteers of our study, all of them (except one) obtained a greater value in this facet than in the embracing facet, which in some cases is less than a half. With respect to the average adult, half of our users have obtained a total score below 33, which is coherent with the study in Kashdan et al. [141]. However, we can observe some differences between the facets, because in our study about 13 users out of 32 have obtained a value for the embracing facet lower than 15.5.

With respect to the intervals of degree of curiosity, our volunteers are classified as follows: 5 as slightly curious, 20 as moderately curious and 7 as extremely curious.

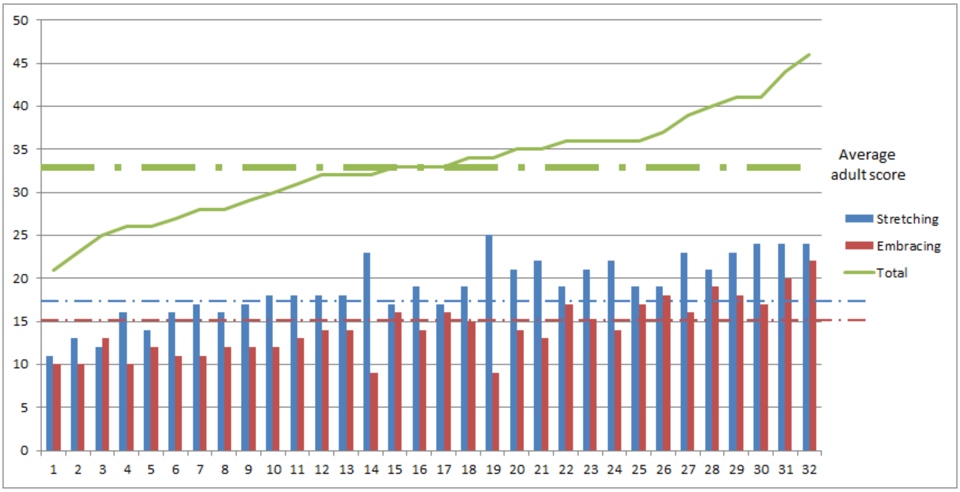

Figure 9.5: *Value of the degree of curiosity for each user*

Fig. 9.6 shows this analysis with respect to the stretching facet (Fig. 9.6-A) and to the embracing facet (Fig. 9.6-B). For each facet, we have divided the users in two groups: those with an score below the standard user and those with an score over the standard user. Then, we have calculated the average of the user satisfaction with the recommendation list computed as indicated in Chapter 4. X axis in Fig. 9.6 indicates the degree of novelty of the recommendation list and Y axis represents the user satisfaction.

From Fig. 9.6 we can conclude that the stretching facet has an important impact on the user satisfaction, whereas the embracing facet hardly affects the user satisfaction when the novelty varies. That is, users with an score in the stretching facet below the standard user prefer less novel recommendations, whereas users with a score in the stretching facet over the standard user prefer more novel recommendations. This lead us to think that it is only necessary to measure the stretching facet in order to provide good recommendations in terms of novelty.

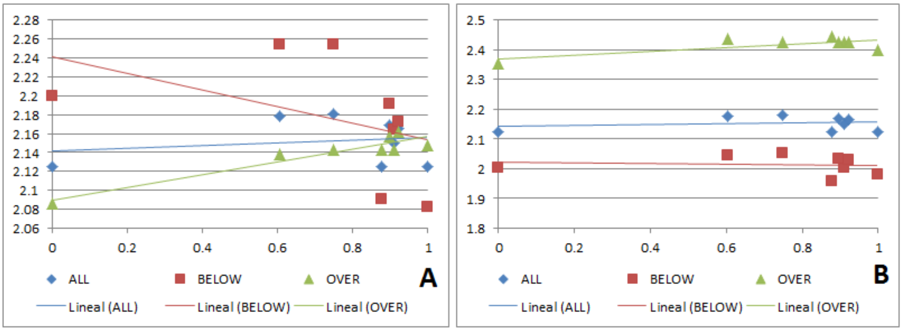

Figure 9.6: *Relationship between novelty and user satisfaction with respect to the stretching facet (A) and to the embracing facet (B)*

It is worth highlight some obstacles we faced when performing the first experiment. Unfortunately, it is not easy to find a wide group of users willing to participate in this kind of evaluations. Nevertheless, even when finding volunteers, their profiles were lacking some needed data for our research (incompleteness issue) or had badly filled in information (incorrectness issue). Another inconvenient was that some volunteers did not complete all the steps of the experiment, sent sequentially (once at a time), which obligated us to discard such volunteers' data. Our workaround to that was to perform new experiments with more volunteers, obtaining the work that follows as a result.

In the third experiment, found in Chapter 6, the number of participants was rather bigger in relation to the first version, obtaining the participation of 176 users, consisting of 47% male and 53% female, from different regions, age groups, gender, marital status. Their level of study are also heterogeneous, were 4% have a primary level, 10% intermediate, 23% secondary, 30% graduate, 16% postgraduate (MBA or Master) and 16% have a PhD or Postdoctorate level.

The last experiment (Chapter 8) counted on the participation of 74 users. It had as objectives to analyse the adequacy of the recommendations, to measure the extent of novel, diverse and serendipitous recommendations with high accuracy, and to evaluate the user satisfaction independently of her degree of curiosity.

9.3 Relevant recent findings by Kashdan et al.

As said before, in our experiments for predicting the curiosity [39, 44], robust correlations were identified between curiosity and some labels extracted from Facebook as the number of visited places, cities, countries and level of education. For all of these correlations, the higher the total number of POIs visited, the higher the curiosity of the person. Besides, the higher the level of education, the greater the curiosity and vice-versa.

In a recent paper published in December 2017, Kashdan et al. [117] presented an unprecedented approach about curiosity. The most interesting part of this study concludes that four types of curious persons can be distinguished: (1) *Fascinated* is an archetype of a person possessing a psychological strength that enables her to explore, discover, develop passionate interests, and uncover their full potential; (2) *Problem Solvers* are people obsessively interested in solving a crossword puzzle on their own; preferring to solve problems and seek information rather than casually talk to friends, independence is high in their ranking of values, and apathy is often low; (3) *Empathizers* are described by themselves as neurotic, and want to give the impression to have their lives under control; social status is a core value, which fits with their interest in what other people think and do; (4) *Avoiders* describe themselves as low on extraversion, agreeableness, openness, and conscientiousness, along with being neurotic and stressed out most of the time [117].

The participants completed a form to measure the curiosity and several personality and consumer behaviour measures were also included, such as: whether they read or looked at a given magazine in the past 6 months (e.g. celebrity and entertainment, home decorating, sports, etc); what are their passionate interests and expertise in life domains (e.g. health and fitness, films and TV, politics, music, travel, technology, etc.); whether they "regularly accessed" some type of SNs (e.g. Facebook, YouTube, Twitter, Instagram, Snapchat, etc.). So, Kashdan et al. were able to identify some very interesting patterns like:

- The users identified as *Fascinated* are the most curious, while at the other end the users identified as *Avoiders* are little or no curious;
- When analysing the Big Five traits, users classified as *Fascinated* have higher values of extraversion, while *Avoiders* users have less than half that value (as already mentioned in subsection 2.2).
- 46% of *Fascinated* (very curious) like to travel, while only 25.1% of *Avoiders* like to travel (little or no curious);
- The educational level and the income of the users *Fascinated* (very curious) are higher than the *Avoiders* (little curious or no curious).

In summary, the results identified by Kashdan et al. [117] are consistent and match the results we have already identified in our research, as well as the interpretations we have made. In other words, our point of view is that the correlation between curiosity and education, and curiosity and travel choices are consolidated. At the same time, it opens up many possibilities for developing new projects or experiments working with this new discovery called by Kashdan et al. [117] as "Five-Dimensional Curiosity Scale", since many topics that were not clear before are now well defined, mapped and tested.

Chapter 10: Conclusions, Limitations and Future Works

Contents

This chapter summarises the main conclusions of this thesis (Subsection 10.1), the limitations and problems (Subsection 10.2) faced during the development of this work, focusing mainly on the difficulty of obtaining data from social networks, and also presents the discussion of the future directions on the personality-based recommendation systems (Subsection 10.3).

10.1 Conclusions

The present thesis introduces a novel approach to a personality-based RSs. In this document, we have presented a compendium of research articles that keeap the record of the progressive advances and developments that led to our final version of the CURUMIM system, which constitutes the main contribution of this research work. The main goal of this thesis was to present a new approach to recommender systems through the use of the human personality and its characteristics, specifically the curiosity, using implicit information from SNs. This goal required us to overcome some challenges that were enumerated in Chapter 1 and that we think that we have satisfactorily succeeded in this goal by the development of the following tasks:

1. Thorougly reviewing the literature related to human personality, from the point of view of traditional and positive psychology and related to RSs, regarding the use of data from SNs and the use of human personality in these RSs.

2. Developing an online application capable of implicitly extracting information from the SN profile of a given user, thus generating predictions of one personality trait. In this case it is important to remark privacy and limitation issues, besides opportunities of the SNs on the future of RSs that have been identified.

3. Developing a tool called CURUMIM, thus spawning online recommendations with different properties, considering the human curiosity trait.

4. Developing use cases for predefined scenarios, such as the recommendation of tourist places, allowing a whole observation of using the characteristics of personality in different interpretations and different recommendation properties.

5. Performing experiments with real users, evaluating their feedback with respect to accuracy, novelty, diversity and serendipity when using CURUMIM.

In summary, all of these tasks have given rise to CURUMIM, a RS able to recommend items based on the degree of curiosity, offering positive results in terms of perceived accuracy, novelty and serendipity. Nevertheless, CURUMIM still has some limitations and weaknesses, mentioned in Subsection 10.2, which can be overcome in future developments of the model.

10.2 Limitations

During the development of our study, we faced different limitations, which can be divided into three groups: users, variables and scenarios.

First of all, our results were limited in terms of the number of participants we recruited. The project with the greatest participation, counting on 225 users, is presented in Chapter 6. In addition, the geographic sample of these volunteers is limited to a single country (Brazil). In this experiment, we classified users into three categories regarding their degree of curiosity: slightly [from 10 to 26], moderately [from 27 to 36] and extremely curious [from 37 to 50] (values related to the CEI-II test). For each of these groups, we had the following number of participants: 40 slightly curious users (17.8%), 124 moderately curious users (55.1%), and 61 extremely curious users (27.1%). Thus, there was a limitation regarding the total number of users representing the slightly and extremely curious groups, besides representatives of different age ranges, for instance people more than 70 years old.

Secondly, we can highlight the limitations in relation to the variables used, that is, the types of data used to predict users' curiosity or even to generate the recommendations. We believe that using other type of variables such as the profession, income, additional sociodemographic characteristics (e.g. people within different religions), behavioural characteristics (e.g. varied interests) could have helped us finding new correlation patterns, besides to have given to our study a wider spectrum, thus a more realistic picture of the society. This also implies that other data sources must be used, combining data from other SNs such as Linkedin to obtain professional data, Twitter to perform sentiment analysis, Instagram to analyse the context of the photos that this individual "likes", etc.

On the other hand, we are aware of the limitations that have been imposed by important SNs like Facebook, and we know that not all SNs offer an API for data extraction, as it is the current case of Instagram. When we look at the legal point, the situation is still unclear. Some countries, like the European Union, have developed a law known as the General Data Protection Regulation (GDPR), that preserves the equilibrium between the necessity of effectively protecting data subjects' rights in a digitalised and globalised world while allowing the processing of personal data, including sensitive data, for scientific research. It reinforces cooperation duties and transparency between the agents of the processing, internally and with regard to the supervisory authorities, which should create a more integrated EU data protection system and diminish some useless administrative costs by decentralising elements of the data protection governance towards data controllers and processors. While the GDPR adopts new specific provisions to ensure adapted data protection in research, the field remains widely regulated at national level [301]. However, many countries still do not have such a specific law, like Brazil [302].

In this scenario, to circumvent this situation, scientific experiments with users who undertake to share their data unilaterally through contracts, submitting to local norms such as universities, rewarding volunteers, etc., may be a feasible option to be followed.

Third, despite CURUMIM be a generic system as presented in Chapters 4 and 7, it was validated in a practical way only in a tourism scenario. That is, the *variables* and *environments* were generated considering only the characteristics of this specific sector. An example is the use of curiosity to define the distance of the recommendations in relation to their hometown. Thus, others experiments with different scenarios should be developed to attest the efficiency of this *generic characteristic*, besides observing the behaviour of CURUMIM in different scenarios.

10.3 Future Works

According to the aforementioned strengths and limitations of our approach, we have identified several potential future lines of research and development. Thus, we consider there are many aspects that can be analysed and/or improved in the use of human personality in CURUMIM. According to the acquired expertise in this process, we propose some future works.

1. To recruit people from different profiles, in order to have a more varied group of users (e.g. from different countries, with different level of study, etc.)

2. To develop new experiments based on the results obtained in the most recent paper published by Kashdan et al. [117], using the five-dimensional curiosity scale instead of the CEI-II scale to measure the curiosity of the users.

3. To include more personality traits in future experiments. In the medium/long term, our interest in this type of analysis is to identify other relevant data to the prediction, not only for curiosity, but also for other personality traits. Our preference is to identify simple data, that is, data available in the most popular SNs and not in very specialised platforms such as Researchgate.

4. To include new variables according to the context in which CURUMIM will be applied. For instance, CURUMIM was validated in a tourism

context, considering several variables such as the degree of curiosity, sociodemographic characteristics, motivations for choosing a destination, tourist behaviour, trip characteristics. However, other variables were identified for the improvement of the recommendation processes, for instance, the "personal restrictions", that may affect travelling choices in terms of distance and characteristics of the tourism destination; the "level of income", which has a different influence on individuals, where people with high incomes can have easier access to long-distance destinations, which generally cost more money; the "number of children", that may limit the destination choice, since it reduces individuals' freedom of movement (vacations with children tend to be associated to closer destinations), and the family size can restrict vacation spending. For this, the integration with new social networks mentioned above must be carried out.

Lessons that can be learnt from this work:

- The CURUMIM system worked with a rule that we consider indispensable in an RS, which is to work implicitly, that is, without the use of forms, selection menus, etc. We believe this encourages users to initiate the use of such applications since there will be no inconveniences of filling out long forms. One point that might be raised is with respect to the cold start problem, because, as we use data already existing in SNs, this problem can be really mitigated.

- The results obtained in this research work can be a relevant indication to the e-commerce RSs developers that they have the possibility of predicting the curiosity of their customers through a greater integration between their e-commerce site and SNs, enabling the system to recommend products and/or services more adjusted to the needs of their consumers.

- This could be a little step forward to show the companies of SNs (responsible for APIs and data storage), governments (responsible for the laws) and the society in general (data owners and beneficiaries of the recommendations) that, when authorising the use of data from SNs, great advances can be made towards improving the RSs based on personality.

Appendices

A.1 Poster presented in ACM Conference on Recommender Systems

Poster that presents an overview of the initial idea of developing a hybrid recommendation system based on the human curiosity.

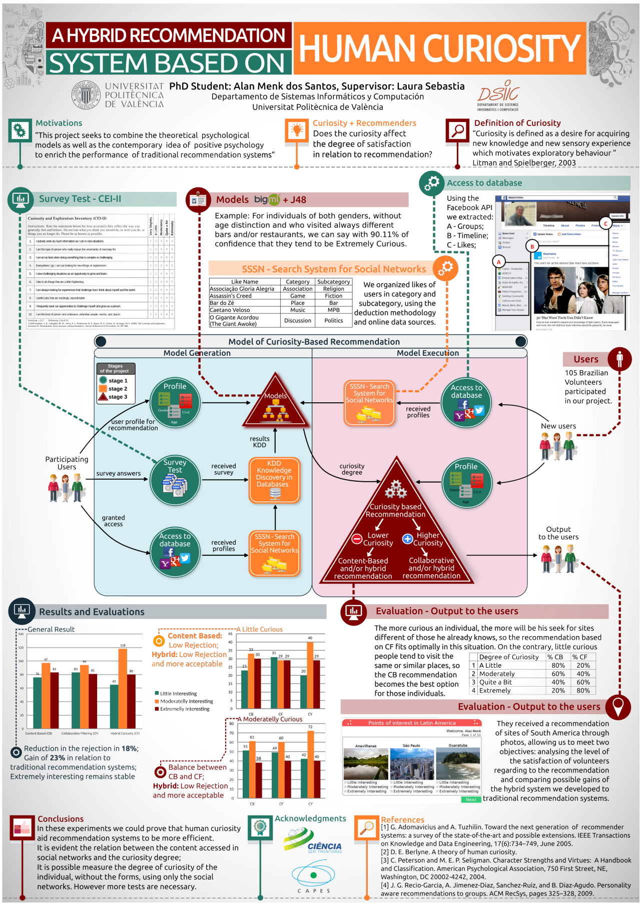

Figure A.1: *Poster exhibited in the 9th ACM Conference on Recommender Systems in 2015 in Vienna, Austria*

A.2 Poster presented in ACM Conference on Recommender Systems

Poster containing a timeline of our recommender system based on the human curiosity over the last four years.

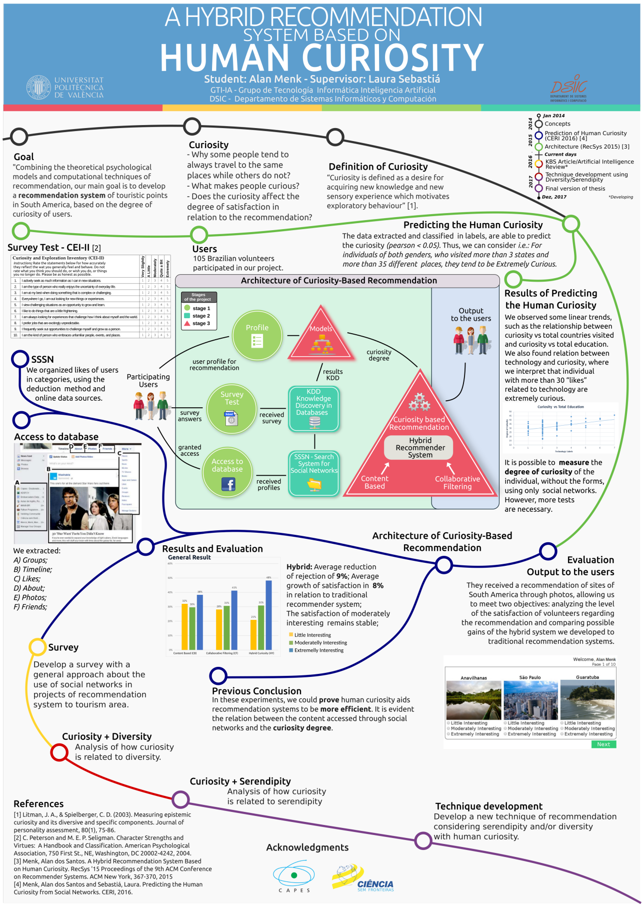

Figure A.2: *Poster exhibited in the III Meeting of PhD Students at UPV in 2016 in Valencia, Spain*

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Abbreviations

Act	Activity
SN	Social Network
IoT	Internet of things
IDC	International Data Corporation
N-Anx	Neuroticism Anxiety
ImpSS	Impulsive Sensation Seeking
Sy	Sociability
BFF	Big Five Factor
KDD	Knowledge Discovery in Database
SSSN	Search System for Social Networks
RSs	Recommender Systems
GDP	Gross Domestic Product
ISSN	International Standard Serial Number
JCR	Journal Citation Reports
IEEE	Institute of Electrical and Electronics Engineers
ICTAI	International Conference on Tools for Artificial Intelligence
IDC	International Data Corporation
CB	Content-Based
CF	Collaborative Filtering
KB	Knowledge-Based
DF	Demographic Filtering
ACM	Association for Computing Machinery
DOAJ	Directory of Open Access Journals
DBLP	Digital Bibliography and Library Project
API	Application Programming Interface
POIs	Point of Interests
DB	Data Base
IT	Information Technology
CARS	Context-Aware Recommender Systems

GPS	Global Positioning System
TAIS	Tourist Assistant
OECD	Organisation for Economic Co-operation and Development
OSSN	Open Source Social Network
UCI	University of California, Irvine
EPCQ	Experimental Perceptual Curiosity Questionnaire
MBA	Master in Business Administration
WEKA	Waikato Environment for Knowledge Analysis
UPV	Universitat Politecnica de Valencia
TTCI	Travel and Tourism Competitiveness Index
UNWTO	World Tourism Organization
ISCED	International Standard Classification of Education
CEI-II	Curiosity and Exploration Inventory
LBSN	Location-Based Social network
NEO-I	Neuroticism-Extraversion-Openness Inventory
NEO-PI	NEO Personality Inventory
GRSK	Generalist Recommender System Kernel
PC	Perceptual Curiosity
EC	Epistemic Curiosity