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Additional Information

CROSA: Context-aware cloud service Ranking approach using Online reviews based on Sentiment Analysis

Emna Ben Abdallah*[1] | Khouloud Boukadi[1] | Jaime Lloret[2] | Mohamed Hammami[1]

[1]University of Sfax, Mir@al Laboratory, BP 1088, Sfax 3018 Tunisia

[2]Integrated Management Coastal Research Institute, Universitat Politecnica de Valencia, Valencia, Spain

Correspondence

*Emna Ben Abdallah. Email: emnabenabdallah@ymail.com

Summary

The explosion of cloud services over the Internet has raised new challenges in cloud service selection and ranking. The existence of a great variety of offered cloud services made the users think deeply about the most appropriate services that meet their needs and at the same time are adaptable to their context. Nowadays, online reviews are used for the purpose of enhancing the effectiveness of finding useful product information, having impact on the consumers' decision making process. In this context, the current paper suggests a Context-aware Cloud service Ranking approach using Online reviews and based on Sentiment Analysis (CROSA). Its main objective is to ease the cloud service selection. The CROSA approach analyzes sentiments associated with SMI (Service Measurement Index) based service properties for each alternative cloud service. Besides, it enhances the cloud service decision-making by supporting fuzzy sentiments through the intuitionistic fuzzy set theory and PROMETHEE II. The experimental results presented in this paper show that this approach is efficient and performing.

KEYWORDS:

Cloud service ranking, Online reviews, Sentiment analysis, Intuitionistic fuzzy set, SMI, Context.

1 | INTRODUCTION

Cloud computing has emerged as a beneficial and a popular computing paradigm thanks to its innovative shifts in the way that it provides services on-demand, with no capital investment, and with modest operating costs [1]. The benefits of cloud computing prompted a "boom" of various cloud services with different service properties including functional properties, such as RAM, CPU and Quality of Service (QoS) properties such as availability and security. Many small and medium-sized enterprises (SMEs) use cloud services to build their cloud-based service applications. When selecting cloud services, these enterprises are facing many challenges, such as "functionally-equivalent" services, the lack of appropriate and sufficient service information and finally tools/benchmarks to assess cloud services with respect to the customers' QoS needs, the context of use and market dynamics [2]. Over the past decade, cloud service ranking/selection through quality (QoS) analysis has gained much attention among service-oriented computing and cloud computing communities [2]. A good service ranking mechanism should allow not only the expression of the requirements that the end-user defines for service properties, but also the deduction of additional preferences from his/her context (service environment, user's location, etc.). Besides, it is interesting to evaluate cloud services based on the experiences and feedbacks of other users who acquired the cloud services in a context similar to that of the end-user.

On the other hand, online reviews have played a crucial role in the selection and purchasing decision of some product/services such as hotels, restaurants, airlines, etc. Until now, few studies have been proposed in the literature to support the consumer in selecting a desirable product/service. However, most of these studies [3,4], ignored the neutral sentiment orientations, which will lead to the loss of valuable decision information. In fact, if a consumer posts a review with neutral sentiment orientation, this means that the opinion of the consumer concerning the service/product

is hesitant and uncertain. This information should not be ignored[5] since it is also valuable for the potential consumers to make a reasonable purchasing decision. Hence, the fuzzy set[6] can be a useful theory to support the consumer's hesitation and uncertainty. However, the fuzzy set involves only the membership degree, but neglects the hesitation and the indeterminacy often involved in the consumer's opinion. For example, to describe his experience with a service/product, the consumer expresses what he likes and what he dislikes. In order to fully reflect the characteristics of affirmation, negation and hesitation of human cognitive performance, Atanassov[7] extended the fuzzy set to introduce the intuitionistic fuzzy set (IFS), which is characterized by a membership function, a non-membership function and a hesitancy (indeterminacy) function. IFS theory is used to deal with vagueness, ambiguity and hesitation[8]. An intuitionistic fuzzy number can simultaneously reflect the degrees of support, hesitation and opposition of the evaluations or judgments about some specific events[8].

In the other side, cloud service reviews play an important role in the selection of cloud services as they offer potential users free assistance to identify the cloud services that fulfill their requirement in the best way. As highlighted in[9], before selecting a particular cloud service, cloud users would like to know the opinion and the degree of satisfaction of other users having already acquired the same service especially if they share the same context as theirs. However, it might be tricky for the user to read online reviews and understand the reviewer opinions due to the huge number of online reviews posted on different web platforms. Moreover, the cloud user is unable to immediately make the purchasing decision since he/she is given contradictory opinions. In fact, the reviewer's experience and opinion depend on his priority of needs and his context. Therefore, to support the cloud user's purchasing decision, it is necessary to develop a suitable approach to rank cloud services using online reviews taking into account his usage context as well as his requirements concerning service properties. Using this approach, the sentiment orientation of each review can be automatically identified, the evaluation of candidate cloud services concerning each service property can be established, and finally, the ranking can be determined.

Therefore, the main objective of this paper is to propose a context-aware cloud service ranking using online reviews based on a sentiment analysis technique. The proposed approach is a two-phased one; offline and online. The offline phase consists in extracting the reviewer's context and analyzing sentiments associated with SMI-based service properties that concern each alternative CS based on SentiwordNet sentiment dictionary[10]. The online phase ranks the different alternative CSs based on the Intuitionistic Fuzzy Set (IFS) theory[7] and PROMOETHEE II method[11].

The rest of the paper is organized as follows. Related works is presented in Section 2. Section 3 present the background, formulates the problem of cloud service ranking using online reviews, and briefly describes the proposed approach. In Section 4, we present the description of the context extraction and SMI-based sentiment analysis. Section 5 illustrates the cloud service ranking using the intuisionistic Fuzzy Set Theory. Then, Section 6 describes and discusses the preliminary evaluation results before concluding remarks and future-work perspectives in Section 7.

2 | RELATED WORK

Ranking cloud services using online review sources implies first a sufficient identification of the sentiment orientations on cloud services using sentiment analysis techniques. Second, based on the identified sentiment orientations, multi-criteria decision making (MCDM) method can be used to rank cloud services. At this point, the related work can be classified into three aspects: (1) the studies on cloud service assessment, (2) the studies on sentiment analysis, and (2) the studies on ranking cloud services using MCDM techniques. In what follows, we will discuss works dealing with each aspect.

2.1 | Studies on cloud service assessment

Many studies have been proposed in the literature in order to evaluate cloud services and providers. These studies are mainly based on cloud service comparison using objective performance analysis or subjective assessment based on user feedback. The objective assessment relies either on monitoring or on benchmarking tools. In[12], Li et al. proposed a systematic comparator, called CloudCmp which could be applied to compare three aspects of the performance and cost of a cloud service (i.e., elastic computing, persistent storage, and intra-cloud and wide area networking). These comparisons are realized using a set of standard benchmark tools, whose results display the objective assessment of a particular cloud. In order to evaluate the security and the privacy, R, Kamatchi et al.[13] proposed a categorization of the security and privacy threats based on the usage of the cloud service. In addition, they presented an algorithm to find the appropriate solution as per the usage category. On the other hand, S. Liu et al.[14] proposed a trustworthy cloud service evaluation method. The proposed method combines the objective and subjective weightings. The objective trust assessment is based on QoS monitoring, while the subjective trust assessment is based on user feedback ratings. On their part, J. Bernal Bernabe et al.[15] presented a Security Ontology For the InterCloud (SOFIC) in order to evaluate security and trust in the federated environment. S. Ding et al.[16] proposed a trustworthiness subjective evaluation based framework (CSTrust) which combined QoS prediction and consumer satisfaction estimation. In fact, the quantitative QoS are calculated using the formerly usage experiences other similar services while the qualitative QoSare determined based on user rating.

Title	Used QoS	Data Source	Rating method	Input elements
Cloud-FuSeR [22]	Rs,Av,Re,La, Th,Ty,Ca,Sc	Simulation	TOPSIS AHP	Weighted properties
TRUSS [14]	Rt;Th;Re	WSDream1	Optimization-CF QoS-Monitoring	Property range (property value range)
CBRSM [23]	Pe;Pri	Simulation	Selection strategies	Prefered properties
CCCloud [24]	Priv;As;Rt;	cloudSleuth CloudHarmony; Simulation	Fuzzy-SAW; SimRank	Prefered properties + context information (location+time)

TABLE 1 Analysis of the ranking approaches. **Used QoS:** Rs-Response speed;Av-Availability;Re-Reliability;La-Latency;Th-Throughput;Ty-Types of support services;Ca-Storage capacity;Sc-Scalability;Rt-Response time;Pe-number of qualified CPU units;Pri-Price per CPU unit per hour;Priv-Privacy;As-After sales services.

All these studies (both objective and subjective) provide valuable foundations in the area of cloud service assessment. Nevertheless, these studies have their own limitations. The objective assessment studies do not precisely evaluate for which property the cloud service is good or bad, while the subjective evaluation studies failed to describe the real attitude and opinion of users about services and what he/she likes and dislikes. Furthermore, there are may be malicious users who give unreasonable feedback to deceive others and/or get benefit for themselves.

Moreover, a multitude of theories in the literature are meant to evaluate and analyze the consumers views on products or services using other users insights through online reviews in several domains. In addition, to analyze and understand the large number of online reviews, many studies have adopted the sentiment analysis techniques.

2.2 | Studies on sentiment analysis

The sentiment analysis, which is also referred to as "opinion mining", identifies the techniques that may be used to foresee the user's opinion, whether it is positive or negative, and expresses an agreement or a disagreement, that is for or against [17]. A great number of research studies are intended to assess and analyze the consumers' opinions about the products or services using other users' perceptions in various fields based on online reviews. The State can obtain public opinions from online texts about the public policies through the use of a sentiment analysis and opinion mining [9]. In addition, companies can conduct market research to detect the anomalies in products and services [18] while the end-users can make better decisions regarding the purchasing of a product or a service [19]. In the context of cloud computing, A. Alkalbani et al. [20] conducted a survey on 6000 reviews of cloud users to determine their opinions (positive or negative) using a document level approach. Moreover, the authors conducted a four-model sentimental analysis by means of the following four supervised machine learning algorithms: K-Nearest Neighbor (K-NN), Naive Bayes, Random Tree and Random Forest. Nevertheless, the document level is unlikely to prove what exactly a user likes or dislikes. In fact, in several cases, the users can express their views on the cloud services or products regarding their properties or characteristics. Authors in [21] have relied on sentiment analysis technique to find the perception on each cloud service performance aspect. For each cloud aspect, they have built a vocabulary which contains words commonly used to refer to that aspect. For example, security, authentication, secure are used to refer to the security aspect. The vocabulary was built by observing manually around 50% of the user reviews. The review structure (pros and cons, likes and dislikes) has been used in this paper to fine tune the sentiment polarity classification of structured reviews.

2.3 | Studies on ranking cloud services using MCDM methods

Many studies have used MCDM methods to rank cloud services using multiple criteria (service properties). L. Sun et al. [22] used fuzzy AHP and fuzzy TOPSIS as MCDM methods to rank cloud services. The fuzzy AHP method calculates the weights of the QoS properties in terms of user preferences. The fuzzy TOPSIS method rates the cloud services based on the weights and the performance of the QoS properties. S. Liu et al. [25] presented a subjective/objective integrated MCDM approach to rank cloud services. With the proposed approach, the statistical variance and the improved techniques for order preference (TOPSIS), simple additive weighting (SAW) and Delphi AHP are combined to identify the integrated weights of the attributes of the decision makers (DMs). Besides, this approach takes into account the objective weights of both the attributes and the DMs along with the subjective choice of the DMs and their differences of identity. As a consequence, the obtained results are likely to be precise

and theoretically acceptable. L. Qu et al.[24] made a comparison between the subjective and objective evaluations using a modified fuzzy simple additional weighting. In his study, they used only the location of the end-user and the time as a context parameter.

2.4 | Discussion

The above cloud service ranking and evaluation approaches are summarized in Table 1 . Compared to the existing works, our approach uses the SMI standard to evaluate cloud services, which covers almost all service qualities. Besides, our approach considers the context information (i.e, information related to the user's situation and needs) to rank cloud services which is ignored by most of the works in the literature. In addition, the subjective evaluation is based mainly either on web service corpus[14] or on conducted simulation[22,23]. Until the present day, rarely if never has a work used the service ranking using online reviews in the field of cloud service ranking and selection. All the proposed works concentrate on the analysis of cloud service online reviews.

Our work relies on online reviews to rank cloud services based on sentiment analysis technique and fuzzy MCDM method. In the field of product/service ranking using online reviews, few studies have highlighted this issue[19,3]. The ranking of products or services using online review approaches is based mainly on two phases. In the first, the sentiment about each product or service feature is extracted from online reviews and then analyzed, while in the second phase, the products or services are ranked based on the obtained sentiment analysis. However, in most of the research studies, the features and the weights (i.e. the importance degree of feature) are not taken into consideration or objectively determined based on the online reviews[19]. However, when a user wants to buy a cloud service from a plenty of cloud service pools, he may prioritize some QoS according to his own needs and preferences. Besides, no study has considered the context similarity between the reviewer and the end-user to rank from online reviews. In addition, the neutral sentiment orientations of the reviews are neglected by most of the existing works[3], which leads to the loss of relevant decision making information. Indeed, if a user posts a neutral opinion, this means that his vision concerning the cloud service is hesitant and uncertain. The presence of hesitation and uncertainty should not be ignored[19] since it is valuable even for the potential cloud users to make a reasonable purchasing decision.

3 | BACKGROUND AND AN OVERVIEW OF THE PROPOSED APPROACH

3.1 | Background

To clarify the suggested approach, this section briefly describes the SMI standard and the intuitionistic fuzzy set theory.

3.1.1 | Service Measurement Index (SMI)

The traditional High Performance Computing (HPC) metrics and benchmarks, which deal with performance and costs[26], cannot be used in the cloud environment because of its distributed and dynamic nature. In fact, this triggered many standard organisms to shape benchmark instruments, such as the Information and Communication Technology Service Quality (ICTSQ), ISO/IEC 9126, Application Performance Index (APDEX), eSourcing Capability Model - Client Organizations (eSCM-CL) and SMI to assess the various services[27]. The SMI is one of the most used standard that helps to compare any kind of service (non cloud textitvs cloud services or cloud services among various cloud service providers)[28]. SMI includes a set of QoS characteristics or Key Performance Indicators (KPIs). The QoS characteristics belong to seven categories each of which involves four or more attributes with each of them is additionally split into subsets of sub-attributes or KPIs. Actually, the most important classes of the SMI metrics are introduced in the following way.

- Accountability: this metric is important for building the trust of a cloud user in a cloud provider. Accountability is evaluated through different properties such as auditability, compliance, data ownership, provider ethics and sustainability.

- Agility: the cloud service agility depends on adaptability, elasticity, portability which are attributes that can be measured by the integration speed of new characteristics into an IT infrastructure.

- Assurance: it can be identified as the probability of the anticipated performance in the SLA (Service Level Agreement) and the initial one. For the purpose of assessing the assurance, the SMI takes into account reliability, flexibility and service stability.

- Financial: most organizations believe that the cost is a unique measurable metric which plays a crucial role among the different decision attributes when moving to the cloud. Therefore, it is preferable to calculate the cost in relation to the features that are attractive for organizations.

- Performance: the performance of these services can be assessed based on suitability, interoperability, accuracy, service response time and functionality.

- Security and Privacy: it can be evaluated based on confidentiality, data integrity, access control, etc.

- Usability: the cloud service that can be accessible for the users should be easy for use and understandable. The usability of the cloud services can be evaluated according to their accessibility, installability, learnability and operability.

3.1.2 │ Intuitionistic fuzzy set (IFS)

On account of the decision making problem complexities, it is generally difficult to describe decision criteria values of alternatives by real values. In [6], Zadeh presents the theory of fuzzy sets (FSs), which is an advantageous tool to describe the fuzzy information that can be used to process MCDM problems [29]. However, it is tricky to use FSs to present some complex fuzzy information because it cannot describe non-membership degrees of elements in the universe of discourse belonging to a FS. Atanassov presents in [7] the theory of IFSs to describe this kind of complex fuzzy information. Recently, the theory of IFSs has been widely used to handle hesitation, ambiguity and vagueness. Moreover, an intuitionistic fuzzy number can simultaneously expose the degrees of support, hesitation and opposition of the evaluations or judgments about some specific events [29].

Definition 1. Let a set U be fixed. An intuitionistic fuzzy set (IFS) A in U is an object having the form $A = \{x, \mu_A(x), v_A(x) | x \in U\}$ where $\mu_A : U \to [0, 1]$ and $v_A : U \to [0, 1]$ satisfy $0 \leq \mu_A(x) + v_A(x) \leq 1$ for all $x \in U$. $\mu_A(x)$ and $v_A(x)$ are called the degree of membership and the degree of non-membership of the element $x \in U$ to A, respectively. $\alpha = (\mu_\alpha, v_\alpha)$ is called an intuitionistic fuzzy number (IFN) satisfying $\mu_\alpha \in [0, 1], v_\alpha \in [0, 1]$ and $\mu_\alpha + v_\alpha \leq 1$. $S(\alpha) = \mu_\alpha - v_\alpha$ and $H(\alpha) = \mu_\alpha + v_\alpha$ are referred to score function and accuracy function, respectively [30].

3.2 │ An overview of the approach: Context-aware cloud service Ranking using Online Reviews

This section begins with a detailed presentation of the problem of cloud service ranking problem through the use of online reviews. Besides, it gives a general overview of the suggested approach.

3.2.1 │ The problem of ranking cloud services using online reviews

Let us consider an European end-user who wants to use a particular cloud service such as a VM to host his web application. Several acceptable cloud service providers are available on the cloud market, and they are regarded as the alternative cloud service providers. For example, Amazon EC2 offers more than 10 instance types optimized to fit different use cases. Instance types include varying combinations of CPU, memory, storage, and networking capacity. Microsoft azure suggests more than 5 categories; each one includes more than 10 instance types designed for a wide range of computing solutions. However, the end-user hesitates between the different alternatives due to the lack of knowledge and expertise, he cannot choose the cloud service that better matches his needs and his context. The end-user can use dedicated simulation frameworks such as cloudSim to objectively assess the cloud service capabilities. Nevertheless, he would still be interested in knowing other users' opinions from online reviews in order to make decisions. However, the process can be time consuming, and sometimes overwhelming. In fact, it might be difficult for an end-user to read, comprehend, and make purchasing decision after looking at all the available reviews.

3.2.2 │ The proposed approach

To solve the above problem, we propose the CROSA approach (see Figure 1 , which consists of two phases: the first is an offline phase named "Context extraction and SMI-based sentiment analysis" and the second is an online phase called "Intuisionistic fuzzy cloud service ranking". The CROSA has the merit of:

- Considering a great number of online reviews from well known web sites [31,32]

- Relying on the standard SMI to extract cloud service properties from online reviews.

- Modeling the cloud user's context to promote reviews with similar context when ranking cloud services.

- Using the intuitionistic fuzzy technique to handle the problem of uncertain and fuzzy opinions concerning service properties.

- Proposing a relevant cloud service ranking based on PROMETHEE II.

The following notations are employed to indicate the sets and the variables used in the CROSA approach:

- $CS = \{CS_1, CS_2, ..., CS_n\}$: The set of n alternative cloud services, where CS_i denotes the ith alternative cloud service, $i = 1, 2, ..., n$.

- $SP = \{sp_1, sp_2, ..., sp_m\}$: The set of m cloud service properties, where sp_j denotes the jth cloud service property, $j = 1, 2, ..., m$. In our work, we define the service properties based on CSMIC standard.

- $w = (w_1, w_2, ..., w_m)$: The vector of the weights of the service properties, where w_j is the weight of service property sp_j, such that $w_j \geq 0$ and $\sum_{j=1}^{m} w_j = 1, j = 1, 2, ..., m$. In fact, the weight vector can be either directly attributed by the end-user or indirectly obtained through the existing procedures, such as AHP[33].

- $Q = (q_1, q_2, ..., q_n)$: The vector of the online reviews number for each candidate cloud service, where q_i presents the number of online reviews for the cloud service $CS_i, i = 1, 2, ..., n$.

- $D_i = (D_{i1}, D_{i2}, ..., D_iq_i)$: The set of q_i reviews for each cloud service CS_i, where D_{ik} denotes the kth online review concerning the alternative cloud service $CS_i, i = 1, 2, ..., n, k = 1, 2, ..., q_i$.

- $S_{ik} = (S_{ik1}, S_{ik2}, ..., S_{ikl})$: The set of l sentences for each review D_{ik}, where S_{ikf} denotes the sentence containing service property sp_{ikf}^j and the sentiment word sw_{ikf}^j having the positive $polPos_{ikf}^j$ negative $polNeg_{ikf}^j$ and neutral $polNeu_{ikf}^j$ polarities. $sp_{ikf}^j = \phi$, $sw_{ikf}^j = \phi$, $polPos_{ikf}^j = \phi$, $polNeg_{ikf}^j = \phi$ and $polNeu_{ikf}^j = \phi$ if no service property or sentiment word is found in the sentence S_{ikf} from the review.
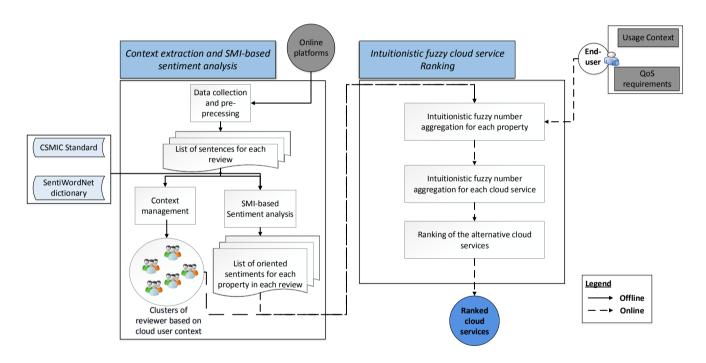

FIGURE 1 CROSA: the whole picture

4 | CONTEXT EXTRACTION AND SMI-BASED SENTIMENT ANALYSIS

The context extraction and SMI-based sentiment analysis phase is carried out offline and is invoked before the cloud service ranking is established. The rationale behind this phase is to collect reviews from review sites and to extract user opinions and contexts from these reviews. This phase is mainly composed of:

- Step 1: Data collection and pre-processing

- Step 2: Context management

- Step 3: SMI-based Sentiment analysis

4.1 | Data collection and pre-processing

Crawler4j[1] is used as a web crawler to collect the set of online reviews $D_i = (D_{i1}, D_{i2}, ..., D_{iq_i})$ for each alternative cloud service $CS_i, i = 1, 2, ..., n$, from the well known review sites. Crawler4j is an open source web crawler for Java which is used to discover web resources (web pages) from world wide web. The scraping is carried out regularly every month in order to check the new reviews and the new cloud service releases. Then, we apply the traditional Natural Language Processing (NLP) data pre-processing procedures to the collected reviews, which include tokenization, Part-Of-Speech (POS) tagging, stop word removal and stemming. The pre-processing eliminates the irrelevant information from the collected user reviews like the user's name and tags. By doing so, we increase the accuracy of the service property detection and opinion extraction. After the traditional NLP pre-processing procedures, the review sentences $S_{ik} = (S_{ik1}, S_{ik2}, ..., S_{ikl})$ are checked to confirm whether they are complete clauses. This pre-processing step segments compound reviews to simple sentences. Sentence splitting is necessary because compound sentences may contain several properties, each of which may represent different opinion information. It divides the input sentence into several candidate clauses based on conjunctive words as 'and', 'or', 'but' and/or punctuation like comma, full stop. Second, it retains only "complete" clauses, i.e., those containing both noun and verb phrases; each incomplete clause is considered as a component of the preceding complete clause, if any [4].

4.2 | SMI-based Sentiment analysis

According to recent studies, the sentiment analysis techniques based on machine learning are more likely suitable when the opinions are analyzed at the document level, while the lexicon-based techniques such as dictionary-based are more suitable when the opinions are analyzed at the sentence level. In an online review, the reviewer usually posts only one or two sentences to express his opinion on the cloud service about a service property. Thus, in the present paper, we rely on a dictionary-based sentiment analysis technique in order to identify the positive, neutral and negative sentiment orientations on the cloud services concerning the service properties. This step can be further divided into two sub-steps: SMI-based feature extraction and property based sentiment analysis.

4.2.1 | SMI-based feature extraction

To identify cloud service property sp_{ikf}^j mentioned in a sentence $S_{ikf}, f = 1, 2, ..., l, k = 1, 2, ..., q_i, i = 1, 2, ..., n$, we use SMI properties. We firstly extract features from the sentence. We suppose that each noun phrase is a feature. For instance, the availability noun in the sentence "availability is exceptional" is extracted as a candidate feature. Then, each extracted feature is compared to the SMI properties. Once the candidate feature from a sentence matches a service property or its synonyms, the property based sentiment analysis step proceeds to the analysis of the sentiments related to this property.

4.2.2 | Property based sentiment analysis

In this step, we first automatically extract the sentiment word sw_{ikf}^j associated with the identified property sp_{ikf}^j in the sentence S_{ikf}. Each sentiment word associated with a service property is automatically linked to the property's category. For example, all sentiment words associated with the service property "Scalability" are linked to the category "Agility". We assume that each adjective, adverb, verb, Adverb-Adjective, Adverb-Verb is a sentiment word. To identify the most pertinent sentiment words associated with each service property, we use the Point-wise Mutual Information (PMI) [34] to compute the strength of the association between the service property and the associated sentiment word. PMI is a statistical method that is frequently used in sentiment feature selection [17]. It aims to measure the co-occurrence between features and sentiment words. The calculation of the PMI of a service property and a sentiment word follows Equation 1.

$$PMI(sp_{ikf}^j, sw_{ikf}^j) = log_2[\frac{Pr(sp_{ikf}^j, sw_{ikf}^j)}{Pr(sp_{ikf}^j)Pr(sw_{ikf}^j)}] \qquad (1)$$

Where $Pr(sp_{ikf}^j, sw_{ikf}^j)$ is the join probability that the service property sp_{ikf}^j and the sentiment word sw_{ikf}^j appear in the same sentence, and $Pr(sp_{ikf}^j)$ (or $Pr(sw_{ikf}^j)$) is the probability that the service property sp_{ikf}^j (or the sentiment word sw_{ikf}^j) appears in a sentence. The probability $Pr(sp_{ikf}^j)$ is estimated based on $\frac{|sent_{sp}|}{|sent|}$ where $|sent_{sp}|$ is the number of sentences containing the service property sp_{ikf}^j and $|sent|$ is the total number of sentences. Similarly, $Pr(sp_{ikf}^j, sw_{ikf}^j)$ is the fraction of the number of sentences containing the service property sp_{ikf}^j and the sentiment word sw_{ikf}^j out of the total number of sentences. Suppose the threshold α and if $PMI(sp_{ikf}^j, sw_{ikf}^j) \geq \alpha$, then we can statistically draw the conclusion that the sentiment word is the real opinion about the service property. Otherwise, the sentiment word will be removed from the candidate sentiment words. After the extraction of the service property sp_{ikf}^j and the sentiment word sw_{ikf}^j related to this property from the sentence S_{ikf}, the evaluation of the polarity of the sentiment word is established based on SentiWordNet dictionary. SentiWordNet is a dictionary of synsets drived from the WordNet

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[1]https://github.com/yasserg/crawler4j

database where each synset is associated with numerical scores that indicate positive and negative sentiment information [10]. According to the polarity found in SentiWordNet of sw_{ikf}^j, the values of $polPos_{ik}^f$, $polNeg_{ik}^f$ and $polNeu_{ik}^f$ are assigned in as below:

$$
\begin{cases}
polPos_{ik}^f = 1, \ polNeg_{ik}^f = 0 \quad and \quad polNeu_{ik}^f = 0 \quad if\, sw_{ik}^f\, is\, positive \\
polPos_{ik}^f = 0, \ polNeg_{ik}^f = 1 \quad and \quad polNeu_{ik}^f = 0 \quad if\, sw_{ik}^f\, is\, negative \\
polPos_{ik}^f = 0, \ polNeg_{ik}^f = 0 \quad and \quad polNeu_{ik}^f = 1 \qquad otherwise
\end{cases}
$$

If there is a negation word in the sentence, then the sentiment orientation of the opinion word will be reversed. Thus, we obtain a list of sentiment orientations for each service in each review concerning each extracted service property. Figure 2 shows an example of service properties and associated sentiments from online reviews.

We suppose the review D_{ik} :

Breck LeSueur

Title: Senior Developer
Job Type: Engineer
Company: ActiveG
Industry: Information Technology and Services
Size: 1-10 employees
Reputation
Points: 30

We are using AWS EC2 to host our customer's campaign website, public videos clips, content management system etc. the bandwidth is virtually unlimited and it is very helpful for video download.
The availability is great.
The ability to scale vertically and horizontally easily.
RAM is expensive!
The documentation is robust

CS_i	AWS EC2		
Review	D_{ik}		
Sentence set S_{ik} in D_{ik} review	S_{ik1}: The availability is great S_{ik2}: The ability to scale vertically and horizontally is easily S_{ik3}: RAM is expensive S_{ik4}: The documentation is robust		
Service property + Sentiment word In the set of sentences	Service property set sp_{ik1}^1		Sentiment set sw_j
	sp_{ik2}^1 : availability $\longrightarrow$ sp_{ik3}^1 : scalability $\longrightarrow$ sp_{ik4}^1 : RAM $\longrightarrow$ sp_{ik5}^1: learnability $\longrightarrow$		sw_{ik2}^1: great sw_{ik3}^1: easily sw_{ik4}^1: expensive sw_{ik5}^1: robust
Context elements extracted from the review D_{ik}	User profile	Expertise	developer
		Industry	Information technology
		Company size	small_businesses
	Environment	-	
	Service profile	Use case	Video processing

FIGURE 2 Example of extracted SMI-based sentiments and context from online reviews

4.3 | Context management

In cloud computing, the context of the end-user plays a major role in the customization of the cloud service ranking. The user's context affects the service quality and the user requirements. For example, the availability of cloud service depends on the user location and the user requirements which differ according to their industries and use cases. Thus, the qualities of cloud service observed by one user in different contexts will vary significantly. Hence, we believe that that the user's context in cloud service ranking can improve the accuracy of the results and promote the ranking credibility. The details of each part of the context management are described in the following section.
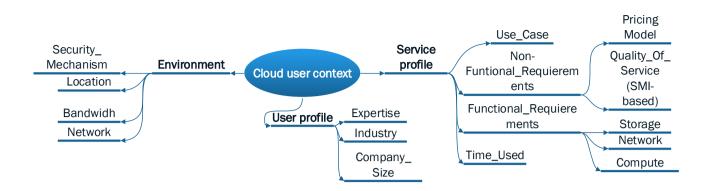
FIGURE 3 Cloud user context modeling

4.3.1 | Context modeling

According to Dey's definition, the context is identified as any information used to identify the situation of an entity which can be a person, a place or an object and which is thought to be important in the interaction between the user and the application, or even the user and the applications themselves [35]. Based on this definition, we can model the cloud user's context using three categories: user profile, service profile and environment. Moreover, based on an extensive literature review exerted on cloud service field [36,24] and cloud standards, such as NIST [37] and OCCI [38], we extract the most elements that impact the cloud user's needs and the service quality. The context pertinent for the cloud service ranking is showed in Figure 3 and defined as follow:

- User profile: it describes the personal characteristics of the cloud user, such as his expertise, the industry and the company size.

- Service profile: it represents how the cloud user used/will use the service (the functional and non-functional requirements adopted/desired, time used and the use case).

- Environment: it is any agent located around the cloud user during his/her utilization of a cloud service and may impact the quality of service, for example, network (bandwidth, security mechanism, etc.) and location.

4.3.2 | Context clustering using k-means

In order to improve cloud service ranking using online reviews, the CROSA approach uses k-means to cluster cloud user context. Thus, sentiments existing in similar reviews as the end-user will be considered in the cloud service ranking. Clustering can be defined as the process of organizing objects into clusters/groups in a way that objects within the same cluster have a high degree of similarity, while objects belonging to different clusters have a high degree of dissimilarity.

On the other hand, the K-means algorithm includes two distinct steps. In the first one, the k centroids are calculated, while in the second, each point is assigned to the cluster that has the nearest centroid to the corresponding data point. Actually, to identify the distance to the nearest centroid, several methods are applied with the most used of which is the Euclidean distance. Once the clusters are joined together, the new centroid of each cluster is recalculated based on the same centroid. Then, the new Euclidean distance is computed between every center and every data point then, the points that have the minimum Euclidean distance in the cluster will be selected. In fact, every cluster in the partition is identified by its members or objects as well as by its centroid. The centroid of each cluster is defined as the point at which the distance that separates the objects in the cluster is reduced. As a result, the K-means in an iterative algorithm where the distance separating each object from its cluster is reduced for all the clusters.

5 | INTUITIONISTIC FUZZY CLOUD SERVICE RANKING

The online phase is activated once the user's query is received. It is intended to rank the alternative cloud services through the end-user's context and preferences. It essentially depends on the IFS theory (see Figure 1) and consists of three stages:(1) Intuitionistic fuzzy number attributed to each cloud service regarding its properties; (2) Intuitionistic fuzzy number attributed to each cloud service, and (3) ranking the alternative cloud services. Detailed description of each stage is given below.

5.1 | Service property intuitionistic fuzzy number

Actually, the Intuitionistic Fuzzy Set theory [7] seems to be an effective means of tackling the issues of vagueness, ambiguity and hesitation [29]. Besides, the Intuitionistic fuzzy number can be calculated to show the efficiency of the cloud service regarding its properties. In fact, thanks to the Intuitionistic Fuzzy Set theory, a considerable number of sentiment orientations of online reviews about the cloud service properties can be represented by an intuitionistic fuzzy number. In this approach, only the sentiments existing in the same cluster as the end-user are taken into consideration. In addition, due to the technical updating and improvement, cloud providers regularly launch new cloud service releases. The sentiments existing in the recent reviews are more consistent than those existing in the earlier ones. For this purpose, it is necessary to take into account the posted time of online reviews, i.e., the more recent the review is, the more important degree it gets. Let wt_{ik} denote the important degree of the posted time of the D_{ik} review . According to the study of Najmi et al. [3], wt_{ik} can be calculated by:

$$wt_{ik} = e^{\frac{(T_{ik}^j - T_i)}{(T_C - T_i)}} \tag{2}$$

Where T_{ik} denotes the posted time of review D_{ik}, T_i denotes the release time of cloud service CS_i and T_C denotes the current time.

Let q_{ij}^{pos} , q_{ij}^{neu} and q_{ij}^{neu} denote the weighted frequencies of the service property sp_j with positive, neutral and negative sentiment orientations for each cloud service CS_i concerning the service property, respectively. The values of q_{ij}^{pos} , q_{ij}^{neu} and q_{ij}^{neu} can be respectively calculated by the Equations 3, 4 and 5.

$$q_{ij}^{pos} = \sum_{k=1}^{q_i} wt_{ik} \times polPos_{ik}^j , \quad i = 1, 2, ..., n, j = 1, 2, ..., m \tag{3}$$

$$q_{ij}^{neu} = \sum_{k=1}^{q_i} wt_{ik} \times polNeu_{ik}^j , \quad i = 1, 2, ..., n, j = 1, 2, ..., m \tag{4}$$

$$q_{ij}^{neg} = \sum_{k=1}^{q_i} wt_{ik} \times polNeg_{ik}^j , \quad i = 1, 2, ..., n, j = 1, 2, ..., m \tag{5}$$

Let p_{ij}^{pos}, p_{ij}^{neu}, p_{ij}^{neg} denote the weighted percentages of service property sp_j with positive, neutral and negative sentiment orientations in similar (selected) reviews concerning the cloud service CS_i, respectively. Then, p_{ij}^{pos}, p_{ij}^{neu}, p_{ij}^{neg} can be respectively calculated by the Equations 6, 7 and 8.

$$p_{ij}^{pos} = \frac{q_{ij}^{pos}}{q_{ij}^{pos} + q_{ij}^{neu} + q_{ij}^{neg}} , \quad i = 1, 2, ..., n, j = 1, 2, ..., m \tag{6}$$

$$p_{ij}^{neu} = \frac{q_{ij}^{neu}}{q_{ij}^{pos} + q_{ij}^{neu} + q_{ij}^{neg}} , \quad i = 1, 2, ..., n, j = 1, 2, ..., m \tag{7}$$

$$p_{ij}^{neg} = \frac{q_{ij}^{neg}}{q_{ij}^{pos} + q_{ij}^{neu} + q_{ij}^{neg}} , \quad i = 1, 2, ..., n, j = 1, 2, ..., m \tag{8}$$

In the CROSA approach, sentiments with positive orientation are regarded as votes in support, and sentiments with negative orientation are regarded as votes in opposition. Thus, the p_{ij}^{pos} and p_{ij}^{neg} can be considered as the support and opposition degrees of cloud service CS_i for the service property sp_j $i = 1, 2, ..., n, j = 1, 2, ..., m$. Consequently, conforming to the physical interpretation of intuitionistic fuzzy number [30], an intuitionistic fuzzy number $x_{ij} = (\mu_{ij}, v_{ij})$ can be computed to represent the evaluation of the cloud service CS_i for the service property sp_j, where $\mu_{ij} = p_{ij}^{pos}$ and $v_{ij} = p_{ij}^{neg}$ respectively depict the support and opposition degrees of the cloud service CS_i for the service property sp_j.

5.2 | Cloud service intuitionistic fuzzy number

After calculating an intuitionistic fuzzy number for each service property $x_{i1} = (\mu_{i1}, v_{i1}), x_{i2} = (\mu_{i2}, v_{i2}), ..., x_{im} = (\mu_{im}, v_{im})$, the overall intuitionistic fuzzy number for each cloud service can be aggregated with respect to the end-user's preference, such as the denoted service property weights $w_1, w_2, ..., w_m$. In order to aggregate the cloud service intuitionistc fuzzy number, we rely on the Intuitionistic Fuzzy Weighted Averaging operator [30] (IFWA). The IFWA is proposed to aggregate the multiple intuitionistic fuzzy numbers when the weights are assigned to the features (in our case service property) and not to the ranking positions of the feature values. We compute the overall intuitionistic fuzzy number for each cloud service using the Equation 9.

$$z_i = w_1 x_{i1} + w_2 x_{i2} + ... + w_m x_{im} = (1 - \prod_{j=1}^{m}(1 - \mu_{ij})^{w_j}, \prod_{j=1}^{m} v_{ij}^{w_j}), \quad i = 1, 2, ..., n, \tag{9}$$

Where $1 - \prod_{j=1}^{m}(1 - \mu_{ij})^{w_j}$ and $\prod_{j=1}^{m} v_{ij}^{w_j}$ denote the overall support degree and the overall opposition degree of the cloud service CS_i, respectively.

5.3 | Ranking of the alternative cloud services

In order to rank the obtained intuitionistic fuzzy numbers of the candidate cloud services, we first compute the dominance degree for each alternative over the other alternative cloud services. To do that, we make use of the method presented in [30]. The dominance degree of the cloud service CS_i over the cloud service $CS_{i'}$ is called $p_{ii'}$. It is calculated by the Equations 10, 11 and 12. Then, according to the obtained dominance degrees, the dominance degree matrix P is established. This matrix (see Equation 13) presents a pairwise comparison of the alternative cloud services where $p_{ii} = "-"$ indicates that the dominance degree of z_i over itself is not considered. Finally, in order to complete the cloud service ranking process, we use PROMETHEE II as MCDM method. PROMETHEE II has been largely applied to solve practical decision-making problems [11]. This method is considered as one of the most well-known MCDM methods. Its main features, compared to the other MCDM methods, are simplicity, clearness and stability [11]. The matrix P is used to implement the PROMETHEE II method in our approach where three degree values are computed for each cloud service, denoted $\Phi^+(CS_i)$, $\Phi^-(CS_i)$ and $\Phi(CS_i)$. $\Phi^+(CS_i)$ presents the dominance degree which is a score indicating that an alternative cloud service CS_i dominates the other alternative cloud services. $\Phi^-(CS_i)$ presents the non-dominance degree which is a score indicating that an alternative cloud service CS_i is dominated by other alternative cloud services. And, $\Phi(CS_i)$ presents the relative dominance degree which measures the difference between dominance and non-dominance degrees of alternative cloud service CS_i. These three measures are calculated by Equations 14 15 and 16 respectively. Evidently, the greater $\Phi(CS_i)$ is, the better alternative cloud service CS_i will be. Therefore, according to the net flows $\Phi(CS_1), \Phi(CS_2), ..., \Phi(CS_n)$, a ranking of the alternative cloud services can be identified.

1. If $1 - \prod_{j=1}^{m}(1 - \mu_{ij})^{w_j} > 1 - \prod_{j=1}^{m}(1 - \mu_{i'j})^{w_j}$, then

$$p_{ii'} = \frac{(\prod_{j=1}^{m}(1 - \mu_{ij})^{w_j} - \prod_{j=1}^{m}(1 - \mu_{i'j})^{w_j})}{(\prod_{j=1}^{m}(1 - \mu_{ij})^{w_j} - \prod_{j=1}^{m}(1 - \mu_{i'j})^{w_j} + max(\prod_{j=1}^{m} v_{ij}^{w_j} - \prod_{j=1}^{m} v_{i'j}^{w_j}, 0)} \tag{10}$$

2. If $1 - \prod_{j=1}^{m}(1 - \mu_{ij})^{w_j} = 1 - \prod_{j=1}^{m}(1 - \mu_{i'j})^{w_j}$, then

$$p_{ii'} = \begin{cases} 1, & \text{if } \prod_{j=1}^{m} v_{ij}^{w_j} < \prod_{j=1}^{m} v_{i'j}^{w_j} \\ 0, & \text{if } \prod_{j=1}^{m} v_{ij}^{w_j} > \prod_{j=1}^{m} v_{i'j}^{w_j} \end{cases} \tag{11}$$

3. if $1 - \prod_{j=1}^{m}(1 - \mu_{ij})^{w_j} < 1 - \prod_{j=1}^{m}(1 - \mu_{i'j})^{w_j}$, then

$$p_{ii'} = 1 - p_{i'i} \tag{12}$$

$$P = [p_{ii'}]_{n \times n} = \begin{matrix} & \begin{matrix} CS_1 & CS_2 & ... & CS_n \end{matrix} \\ \begin{matrix} CS_1 \\ CS_2 \\ \vdots \\ CS_n \end{matrix} & \begin{bmatrix} - & p_{12} & \cdots & p_{1n} \\ p_{21} & - & \cdots & p_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ p_{n1} & p_{n2} & \cdots & - \end{bmatrix} \end{matrix} \tag{13}$$

$$\Phi^+(CS_i) = \frac{1}{n-1} \sum_{\substack{i'=1 \\ i' \neq i}}^{n} p_{ii'} \quad i = 1, 2, ..., n, \tag{14}$$

$$\Phi^-(CS_i) = \frac{1}{n-1} \sum_{\substack{i'=1 \\ i' \neq i}}^{n} p_{i'i} \quad i = 1, 2, ..., n. \tag{15}$$

$$\Phi(CS_i) = \Phi^+(CS_i) - \Phi^-(CS_i), \quad i = 1, 2, ..., n. \tag{16}$$

6 | PROTOTYPE AND EXPERIMENTS

The proposed approach is developed using the Java language under the Eclipse environment [39]. Moreover, a set of components are exploited to better achieve its functionality. The Stanford CoreNLP parser [40] is applied to POS-Tag reviews and the GATE (Generalized Architecture Text Engineering) [41] to stem them.

We conducted experiments on real-life cloud service review datasets from social media platforms [31,32]. These datasets were published between January 2015 and September 2017 and include the IaaS category (especially the VMs). Statistics about the collected reviews as well as users' contexts are depicted in Tables 2 and 3 .

We conducted four series of experiments to evaluate the effectiveness and performance of the CROSA approach: The first experiment applies our approach on a real case study to prove its feasibility; the second evaluates the effectiveness of the approach when changing the end-user's context

as well as the service property weights; the third investigates the optimal setting of the CROSA approach for cluster numbers; and the fourth examines the impact of each context element on the CROSA ranking performance.

To evaluate the ranking performance of the CROSA approach, we generated 500 ratings for the top seven SMI service properties and 50 cloud users' contexts in conjunction with cloud instructors from the IT department of the University of Sfax (considered as experts). The goal is to classify the alternative cloud services according to the reviewers' opinions, on the one hand, and the context and QoS requirement of the end-user, on the other hand. For this reason, we organized ourselves into four groups, where each group examined around 120 queries. Afterwards, we conducted a cross-validation process among the different groups.

Dataset	AWS EC2	Azure	Google App Engine	Rackspace	All
#Reviews	1532	1638	973	654	4797
#Sentences	4986	4253	1853	1571	12663

TABLE 2 Cloud service dataset description

Dataset	TrustRadius	G2CROWD	Clutch	Gartner peer insights	All
#Reviews	1156	948	1182	1511	4797
%Reviews with contextual information	65%	62%	83%	91%	75.25%

TABLE 3 Social media platform Dataset description

6.1 | Experiment 1: Case study

In this part of our research, a case study of cloud service ranking using online reviews is given to demonstrate the use of the CROSA approach. We consider an offshore petroleum logistic enterprise motivated to outsource to a cloud environment a purchase application recognized to be compute intensive. Thus, the enterprise IT expert wants a VM from the most popular cloud providers such as:

- CS1: Amazon Elastic Compute Cloud (Amazon EC2)

- CS2: Microsoft Azure VM

- CS3: Google Compute Engine VM Servers

- CS4: Rackspace Virtual Cloud

In order to select a desirable VM, the expert considers via a dedicated interface (see Figure 4) the top categories of SMI properties as service properties, i.e., accountability (sp_1), agility (sp_2), assurance (sp_3), financial (sp_4), performance (sp_5), security and privacy (sp_6) and usability (sp_7). Meanwhile, the IT expert provides the vector of weights of the seven service properties, i.e., $w = (0.2, 0.2, 0.1, 0.2, 0.1, 0.1, 0.1)$ and the context description as depicted in Table 4 . Table 5 contains the number of reviews sharing the same cluster as the end-user for each alternative. Based

User profile	Expertise	Developer
	Industry	Logistics and supply chain
	Company size	Mid-size Company
Environment	Location	Africa
Service profile	Use case	Web sites and web applications
	Pricing model	pay as you go

TABLE 4 End-user context description

FIGURE 4 CROSA Prototype

on this table q_{ij}^{pos}, q_{ij}^{neu} and q_{ij}^{neg} are calculated using Equations 3-5, $i = 1, 2, 3, 4$ and $j = 1, 2, ..., 7$. The values of q_{ij}^{pos}, q_{ij}^{neu} and q_{ij}^{neg} for each service property (sp) according to each CS provider are shown in Table 6 . Furthermore, using Equations 6-8, the intuitionistic fuzzy number $x_{ij} = (\mu_{ij}, v_{ij})$ of alternative VMs as CS_i concerning service property sp_j is determined. The obtained fuzzy numbers for each sp according to each CS provider are shown in Table 7 . The overall intuitionistic fuzzy number z_i of alternative CS_i is calculated using Equation 9, i.e., $z_1 = (0.8277, 0.1578)$, $z_2 = (0.8224, 0.1556)$, $z_3 = (0.8236, 0.1586)$ and $z_4 = (0.6722, 0.3010)$. Dominance degree $p_{ii'}$ is calculated using Equations 10- 12, $i, i' = 1, 2, 3, 4$, and the dominance degree matrix $P = [p_{ii'}]_{4 \times 4}$ can be constructed:

$$P = [p_{ii'}]_{n \times n} = \begin{array}{c} \\ CS_1 \\ CS_2 \\ CS_3 \\ CS_4 \end{array} \begin{array}{cccc} CS_1 & CS_2 & CS_3 & CS_4 \\ \left[\begin{array}{cccc} - & 0.7074 & 1 & 1 \\ 0.2925 & - & 0.7146 & 1 \\ 0 & 0.2853 & - & 1 \\ 0 & 0 & 0 & - \end{array} \right] \end{array} \tag{17}$$

Based on matrix P, dominance degree ($\Phi^+(CS_i)$), non-dominance degree ($\Phi^-(CS_i)$) and relative dominance degree ($\Phi(CS_i)$) of each CS can be calculated using Equations 14-16. Table 8 presents the values of $\Phi^+(CS_i)$, $\Phi^-(CS_i)$ and $\Phi(CS_i)$, $i = 1, 2, 3, 4$. According to the obtained $\Phi(CS_i)$, a ranking of the four alternatives can be deduced as such $CS_1 \succ CS_2 \succ CS_3 \succ CS_4$. The ranking result is presented to the IT expert to guide his outsourcing decision.

	CS1	CS2	CS3	CS4
#Reviews	547	511	334	226

TABLE 5 The number of reviews sharing the same cluster as the end-user for each alternative

6.2 | Experiment 2: Effectiveness evaluation

We demonstrate the effectiveness of the CROSA approach when changing service property weights. It can be seen from Table 9 that when using the proposed approach, different ranking results could be obtained if different service property weights are used. We have also conducted an

Service properties	Alternative cs providers											
	CS1			CS2			CS3			CS4		
	q_{ij}^{pos}	q_{ij}^{neg}	q_{ij}^{neu}	q_{ij}^{pos}	q_{ij}^{neg}	q_{ij}^{neu}	q_{ij}^{pos}	q_{ij}^{neg}	q_{ij}^{neu}	q_{ij}^{pos}	q_{ij}^{neg}	q_{ij}^{neu}
sp_1	813.4	274.3	12.3	1241.4	182.5	39.3	1332.7	260.1	16.9	774.3	63.5	4.7
sp_2	672.1	135.1	7.5	631.9	86.1	4.4	315.6	18.2	4.7	12.1	21.1	1.1
sp_3	103.4	12.7	1.1	70.1	33.5	1.2	52.8	33.5	2.3	18.1	25.1	1.1
sp_4	381.4	210.7	13.7	309.7	50.7	11.2	110.4	30.9	1.2	30.3	10.5	1.2
sp_5	536.1	60.4	7.4	90.6	100.3	12.5	80.9	96.2	22.3	80.1	100.5	3.1
sp_6	705.2	37.7	8.9	700.1	111.4	12.4	387.5	55.0	3.6	70.6	79.1	11.1
sp_7	826.2	78.3	11.7	628.2	67.4	12.4	400.4	58.4	3.5	65.6	30.5	6.3

TABLE 6 The values of q_{ij}^{pos}, q_{ij}^{neu} and q_{ij}^{neg}, $i = 1, 2, 3, 4$, $j = 1, 2, ..., 7$.

Service properties	Alternative cs provider			
	CS1	CS2	CS3	CS4
sp_1	(0.7395, 0.2494)	(0.8484, 0.1247)	(0.8279, 0.1616)	(0.9191, 0.0754)
sp_2	(0.825, 0.1658)	(0.8747, 0.1192)	(0.9323, 0.0538)	(0.3528, 0.6152)
sp_3	(0.8823, 0.1084)	(0.6689, 0.3197)	(0.5959, 0.3781)	(0.4086, 0.5666)
sp_4	(0.6296, 0.3478)	(0.8334, 0.1364)	(0.7747, 0.2168)	(0.7214, 0.25)
sp_5	(0.8877, 0.1)	(0.4454, 0.4931)	(0.4057, 0.4824)	(0.436, 0.5471)
sp_6	(0.938, 0.0501)	(0.8497, 0.1352)	(0.8686, 0.1233)	(0.4391, 0.4919)
sp_7	(0.9018, 0.0855)	(0.8873, 0.0952)	(0.8661, 0.1263)	(0.6406, 0.2979)

TABLE 7 Intuitionistic fuzzy numbers of CS_i concerning service property sp_j, $i = 1, 2, 3, 4$, $j = 1, 2, ..., 7$.

CS_i	$\Phi^+(CSi)$	$\Phi^-(CSi)$	$\Phi(CS_i)$
CS_1	0.9024	0.0975	0.8049
CS_2	0.6690	0.3309	0.3380
CS_3	0.4284	0.5715	-0.1430
CS_4	0	1	-1

TABLE 8 The values of $\Phi^+(CSi)$, $\Phi^-(CSi)$, and $\Phi(CSi)$, $i = 1, 2, 3, 4$.

experiment with different end-user's contexts. The results of this experiment are presented in Table 10 based on the different used contexts described in Table 11 . This experiment demonstrates the ability of the CROSA approach to propose cloud services meeting different end-user's contexts.

Ranking results of alternative CS providers	Service property weights						
	w_1	w_2	w_3	w_4	w_5	w_6	w_7
$CS_1 \succ CS_2 \succ CS_3 \succ CS_4$	0.1428	0.1428	0.1428	0.1428	0.1428	0.1428	0.1428
$CS_3 \succ CS_2 \succ CS_1 \succ CS_4$	0.2	0.5	0.0	0.0	0.1	0.1	0.1
$CS_3 \succ CS_1 \succ CS_2 \succ CS_4$	0.1	0.3	0.1	0.1	0.0	0.2	0.2
$CS_1 \succ CS_3 \succ CS_2 \succ CS_4$	0.0	0.0	0.0	0.0	0.5	0.5	0.0
$CS_2 \succ CS_1 \succ CS_3 \succ CS_4$	0.2	0.1	0.1	0.2	0.0	0.2	0.2

TABLE 9 Ranking results of alternative CS providers with different service property weights.

	Context-free	End-user context		
		context1	context2	context3
Ranking results of alternative CS providers	CS4 ≻ CS3 ≻ CS2 ≻ CS1	CS4 ≻ CS3 ≻ CS1 ≻ CS2	CS3 ≻ CS4 ≻ CS2 ≻ CS1	CS1 ≻ CS2 ≻ CS3 ≻ CS4

TABLE 10 Ranking results of alternative CS providers with different end-user's contexts.

End-user context		context1	context2	context3
User profile	Expertise	Not_developer	Developer	Not_developer
	Industry	Manufacturing	Internet	Consumer products
Environment	Location	Asia	Africa	Europe
Service profile	Use case	Databases	Big data applications	Business applications
	Pricing model	Pay_As_You_Go	Pay_As_You_Go	Pay_As_You_Go

TABLE 11 End-user contexts description

6.3 | Experiment 3: The number of clusters calibration

The number of clusters, or the number of the reviewers' groups, are the important hyper-parameters to be confirmed for k-means clustering. To obtain the optimal values, we gradually increased the number of clusters (groups) from 1 to 10, k=1 means that all the reviews are considered in the ranking of the alternatives. We also applied the above settings to run two CROSA recommenders; CROSA with fuzzy sentiments (neutral sentiments) and CROSA without fuzzy sentiments, in 30 iterations and obtained the results. In order to assess these results, we mainly relied on Kendall Tau Distance (KTD)[42] and precision.
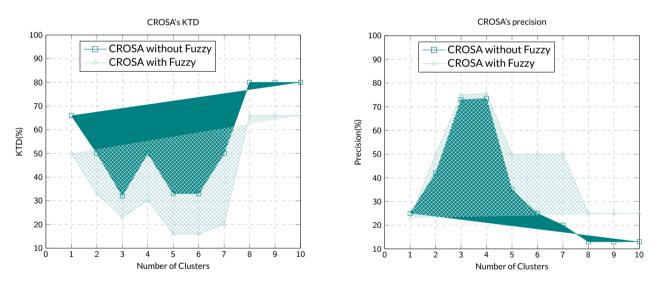

FIGURE 5 The CROSA's performance with different numbers of clusters

As shown in Figure 5 , CROSA with context $(k \succ 1)$ outperforms CROSA without context (k=1). The optimal cluster number refers to a specific cluster number, with which the CROSA approach can achieve a better performance in most metrics. The CROSA with and without fuzzy sentiments took 5 and 6, as its optimal cluster numbers, if we consider the KTD as the evaluation metric. Meanwhile, the approach took 3 and 4, as its optimal cluster numbers, if we consider the precision as an evaluation metric. Therefore, if both metrics, KTD and precision, are considered the CROSA with 3 clusters achieves better results.
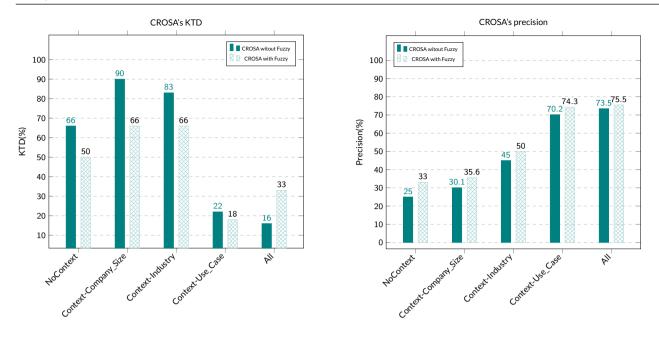
FIGURE 6 The CROSA's performance with different elements of context

6.4 | Experiment 4: the influence of the context elements

This experiment deals with the performance of the CROSA ranking according to each context element. Its objective is to assess the impact of each one. We use "ALL" to represent the whole context with three clusters (k=3). Then, we compare the performance of the CROSA approach where the whole dataset of reviews is considered (indicated by NoContext). We also evaluate the performance of the CROSA approach when only one context element is considered (indicated by Context-X, where X represents the context element). Then, we present the CROSA performance with all the context elements with 3 clusters as well. It can be concluded from Figure 6 that the *use case* has a greater influence on the performance of the cloud service ranking (for simplification purpose, we show in the figure only three context elements). In other words, the use case of such a cloud service has generally impacted the choice and the opinion of the cloud user. Therefore, when selecting a cloud service, the user would like that this service would be suitable and efficient with his use case. Moreover, we can not deny the light impact of other contextual elements, especially on the ranking precision. In fact, Context-Company_Size based ranking reached 2.6% of precision better than *Nocontext* based ranking. Moreover, Context-Industry based ranking outperformed the *Nocontext* based ranking by a precision rate of about 15%.

7 | CONCLUSION

With the increasing number of available cloud services, the selection of accurate ones has become more challenging. We cannot deny, however, the fact that any user would want to know the opinion and the experience of other cloud users concerning the decision making. In the present paper, we have suggested a new Context-aware cloud service Ranking approach using Online reviews based on Sentiment Analysis (CROSA). The CROSA approach includes an offline and an online phases. The former consists in extracting and clustering the reviewers' contexts, and analyzing the sentiments associated with SMI-based service properties using SentiwordNet sentiment dictionary for each alternative cloud service, while the latter ranks the cloud services based on the intuitionistic fuzzy set theory and PROMETHEE II. A set of experiments have been carried out to examine the effectiveness and performance of the approach. The first experiment applied our approach on a real case study. As per this experiment, we proved that the CROSA approach can facilitate the opinion based service evaluation through a large number of online reviews and assisting the end-users in selecting services that meet their requirements and fit their own context. The second experiment proved the effectiveness of the approach when changing the end-user's context as well as the service property weights. The third investigated the optimal setting of the CROSA approach for cluster numbers. Based on this experiment, we noticed that the CROSA with 3 clusters achieves better results. The last experiment examined the impact of each context element on the CROSA ranking performance. The results of this experiment show the higher impact of the user use case in the online review based cloud service ranking.

As a future work, we intend to consider and evaluate the trustworthiness of each reviewer. This will enable us to ensure the cloud service ranking credibility. Moreover, we also aim at enhancing the CROSA approach to consider other cloud services, such as cloud containers.

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