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A Knowledge-Based Model for Polarity Shifters

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Abstract
Polarity shifting can be considered one of the most challenging problems in the context of Sentiment Analysis. Polarity shifters, also known as *contextual valence shifters* (Polanyi and Zaenen 2004), are treated as linguistic contextual items that can increase, reduce or neutralise the prior polarity of a word called *focus* included in an opinion. The automatic detection of such items enhances the performance and accuracy of computational systems for opinion mining, but this challenge remains open, mainly for languages other than English. From a symbolic approach, we aim to advance in the automatic processing of the polarity shifters that affect the opinions expressed on tweets, both in English and Spanish. To this end, we describe a novel knowledge-based model to deal with three dimensions of contextual shifters: *negation*, *quantification*, and *modality* (or irrealis).

Keywords: opinion mining, sentiment analysis, polarity shifting, negation, quantification, modality

1. Introduction

The term *opinion mining* first appeared in Dave, Lawrence and Pennock (2003) to denote the discipline based on the task of automatically classifying opinions –as positive or negative– that users express about different products on the Web. Since 2004, and especially due to the emergence of the Web 2.0 phenomenon, there has been a rapid growth of publications on the discipline (Mäntylä, Graziotin and Kuutila 2018), which not only arouses interest in academia but also among the general public, since "[...] opinions are central to almost all human activities. Whenever we need to make a decision, we often seek out others' opinions and this is true not only for individuals but also for organisations" (Liu 2015, 3). The Web 2.0 phenomenon means that users share their opinions about products on the Web. On the one hand, this helps them make their purchasing decisions. On the other hand, it also provides organisations with a resource to identify consumer attitudes and opinions about their products and services (Piryani,

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Madhavi and Singh 2017; Khan et al. 2014), with multiple social and business interests and applications. However, although there has been large progress in the last decade, the degree of accuracy and optimisation of computational systems based on opinion mining generally requires notable improvements, including the automatic detection and processing of contextual polarity shifters that change the prior polarity (positive or negative) of user comments.

The aim of this article is to describe the construction of a modular architecture from a symbolic approach that facilitates the computational processing of the various types of contextual shifters in Spanish and English included in three dimensions: *negation, quantification* and *modality*. The study on the automatic detection of these shifters was carried out on the basis of the analysis of theoretical linguistic knowledge, subsequently contrasted with linguistic evidence from messages posted on Twitter. Regarding the methodology employed for this study, it should be noted that the two research approaches traditionally adopted in opinion mining and, by extension, in the treatment of polarity shifters, are the *statistical* (Moreno-Ortiz and Fernández-Cruz 2015; Cruz, Taboada and Mitkov 2016; Jiménez-Zafra et al. 2020; Schulder, Wiegand and Ruppenhofer 2020) and the *symbolic* (Taboada et al. 2011; Periñán-Pascual and Arcas-Túnez 2019). Based on corpora and text mining studies, the first approach is characterised by the construction of systems in which mathematical machine learning techniques are applied. These techniques are mainly based on supervised models, which require prior training through labelled corpora in order to detect patterns and thus infer knowledge automatically. In contrast, the second approach is based directly on linguistic knowledge, i.e. it relies on the storage and reuse of lexical resources and the construction of linguistic rules. In this sense, our purpose is to develop a sufficiently robust linguistic knowledge base to improve the performance of computational systems based on natural language processing without the need to create costly additional resources, such as the extensive corpora used in the training of textual classification systems.

This architecture could be a significant advance for several reasons. First, each shifter receives a specific treatment within its dimension and category, with much more extensive information on the position it can occupy with respect to its focus (fixed or variable), the type of variation on the prior polarity it can generate, and its quantification. In addition to this specific treatment, the configuration of the architecture also allows for a holistic view of its dimensions, as they are not considered isolated modules but interrelated. Second, it contemplates the use of available resources (such as sentiment lexicons) and can be easily integrated into any opinion mining system regardless of the methodology used. Third, we could obtain greater flexibility, transparency and traceability by adopting a symbolic approach, as we can easily obtain an explanation of what the system has performed and, therefore, of possible errors, resulting in a system relatively easy to maintain and improve, either by adding new linguistic rules to increase its recall or by correcting or eliminating existing rules to improve its precision. Finally, from its contrastive analysis for Spanish and English, we conclude that the proposed model could be easily replicated in other languages, such as French, German or Italian.

2. RELATED WORK

Traditionally, the most frequently employed methodology for ranking polarity (positive or negative) in opinion mining was to use dictionaries with lists of individual words endowed with sentiment meaning and annotated with their semantic orientation (positive or negative). Once these words were identified, a tally of their polarity (positive or negative) was made and the one with the highest score was the valuation result of the opinion expressed in the document, regardless of the context in which the attitudinal word was found.

These methods were based on classifying the sentiment in a text as positive or negative based only on the lexical meaning of certain individual terms, without taking into account the context in which they appeared, so the results were not entirely satisfactory. For this reason, Polanyi and Zaenen (2004) considered the reference work carried out to date to be incomplete and erroneous (Turney and Littman 2002; Edmonds and Hirst 2002, among others) and made a proposal to advance the research for English, the language on which the most representative studies to date have been based. First, they showed how individual terms with attitudinal meaning could undergo a change in their valence or polarity from having a *simple* or basic valence to a so-called *contextually determined valence*, generated by the appearance in the text of certain linguistic particles called *contextual valence shifters*. These valence (or polarity) shifters were defined as "[...] several lexical phenomena that can cause the valence of a lexical item to shift from one pole to the other or, less forcefully, to modify the valence towards a more neutral position" (Polanyi and Zaenen (2004, 107). These contextual shifters were classified into two main typologies: *sentence-based contextual valence shifters* and, within a broader scope, *discourse-based contextual valence shifters.*

Based on these contributions, an increasing number of studies attempt to implement, to a greater or lesser extent, the treatment of these contextual shifters in computational systems applied to opinion mining. Thus, a wide variety of models have emerged based on the configuration of different algorithms depending on the type of shifters considered by the researchers, as well as the effect they consider they have on polarity and its functioning.

A large majority of these studies focus only on negation, and for English, with the intention of specifically targeting its automatic detection and scope so that it can be processed in computational systems (Morante and Daelemans 2009; Wiegand et al. 2010; Hogenboom et al. 2011; Lapponi, Read and Øvrelid 2012; Asmi and Ishaya 2012; Reitan et al. 2015; Sharif et al. 2016; Diamantini, Mircoli and Potena 2016; Pandey, Sagnika and Mishra 2018; Mukherjee et al. 2021; Morante and Blanco 2021; Bos and Frasincar 2021; Singh and Paul 2021; Barnes, Velldal and Øvrelid 2021). Faced with this fact, several authors have pointed out the convenience of incorporating, in addition to negation, more types of polarity shifters in computational models. Thus, Li et al. (2010) consider it inadequate to contemplate only negation in treating contextual shifters, especially at the document level. Li et al. (2013) also point out this limitation and attribute the low level of improvement in the systems when incorporating negation items to the fact that negation represents a lower percentage than is thought with respect to the rest of the contextual shifters. Schulder, Wiegand and Ruppenhofer (2021) attribute this low performance to the fact that research on negation has so far been based almost exclusively on a very small set of lexical particles, which they call *closed-class* negation words, e.g. *no*, *not*, *without*. Therefore, current negation training corpora are not prepared to detect other words which, being part of negation, are *open word classes* (e.g. adjectives, verbs or nouns) that meet the criteria set out in the new definition of contextual shifters presented by these authors: "Polarity shifters are defined by their ability to negate or diminish facts or events that were either previously true or presupposed to occur" (2021, 155). Finally, Carrillo-de-Albornoz and Plaza (2013) studied different contextual polarity shifters –i.e. negation, intensification and modality– separately and combined and concluded that, by combining all modifiers, better results were obtained than considering the sum of each of them in isolation. They also considered *intensifiers* as special terms that amplify or diminish the strength of the emotions affected by them.

Therefore, in this line of openness towards incorporating more contextual shifters in the models applied to their computational treatment, other studies have emerged that include a greater diversity of them, with different names, classifications and effects contemplated on the prior polarity of the opinionated text. Some examples can be found in Musat and Trausan-Matu (2010), who analyse two types of shifters or modifiers applied to the domain of Economics, i.e. negation and diminishers, and conclude that the latter have the same effect as the former in this context of economic indicators. On the other hand, Taboada (2016) considers polarity modifiers as the most relevant polarity shifters, classified into amplifiers, downtoners, presuppositional particles, irony and those linguistic phenomena that express events that are not part of the real world of the opinion holder, or of existence or truth, known as irrealis (real world, existence) and non-veridicality (truth), respectively. These phenomena include, among others, modal verbs, intentional verbs (e.g. *believe, think, want* and *suggest*), imperative, interrogative, conditional or subjunctive –for those languages that have it– (Trnavac and Taboada, 2012). On the other hand, in an extensive study, Liu (2015) contemplates those shifters included in negation, modality, adversative coordination with *but*, conditional sentences, sarcasm and comparison, among others, and proposes various compositional rules for their treatment. Li et al. (2013) consider *negation* particles, *contrastive transition, modality, implicature*, and *irrelevance*. *Contrastives* are those that express contradiction or contrast when connecting paragraphs, sentences, propositions or words, *implicature* refers to those opinions in which the holder is not the person implied in it, and *irrelevance* is associated with those sentences that are not related to the topic or theme of the opinion and, therefore, do not have a contextual polarity shifter. Furthermore, Kiritchenko and Mohammad (2017) take into account negation particles (e.g. *no* and *cannot)*, modals (e.g. *would have been* and *could*), adverbs of degree (e.g. *quite* and *less*), and their combinations in units larger than the word, such as phrases or sentences, to build what they call *a sentiment composition lexicon*. Sintsova, Bolívar-Jiménez and Pu (2018) broaden the scope and focus on six major typologies of modifiers: negation, intensification, conditionals, modality and, added to previous studies, verb tense (e.g. past tense) and interrogation, as two types of polarity shifters that modify the degree of certainty in the states or events represented in the expressions of emotion included in the tweets they analyse. Yoo and Nam (2018), in their study for Korean, classify contextual shifters into four main typologies: *intensifiers, polarity switchers, nullifiers, and activators*. Thus, *intensifiers* intensify initial polarity values and are divided, according to their effect, into amplifiers and downtoners, *polarity switchers* switch the orientation of prior polarity and include lexical and grammatical negation particles. *Nullifiers* nullify the initial polarity values and include imperative, interrogative, suggestive markers or auxiliary verbs. Finally, *activators* activate the polarity of words starting from a neutral polarity and are divided into positive activators and negative activators. Periñán-Pascual and Arcas-Túnez (2019), within a context of automatic detection of natural disasters through social networks for Spanish, classify contextual shifters into two main typologies: *neutralisers,* which include *negation* and *irrealis markers*, and *modifiers,* which can be intensifiers and diminishers. Neutralisers neutralise the polarity of the text or change it to a value of 0; modifiers intensify or diminish the degree of intensity of the polarity depending on the type of modifier. Xu et al. (2020) focus on the automatic generation of training corpora to detect contextual shifters through what they call "natural annotation", based on eight types of shifters associated with the following linguistic phenomena: explicit negation (e.g. *not*, *no* or *without),* contrast transition (e.g. *but, however* or *unfortunately*), implicit negation (with words like *avoid* or *hardly*), false impression (with verbs like *look* or *seem*), likelihood (with adverbs like *probably* or *perhaps)* counter-factual particles (e.g. *should* and *would),* exception particles (e.g. *the only*), and, finally, the particle *until.* Ayeste and Noferesti (2022) mention different classifications of contextual polarity shifters. First, from a syntactic point of view, according to these authors, the two main groups into which shifters can be classified are: short-distance shifters (e.g. *I do not like this drug*), which syntactically affect the lexical meaning of the sentiment word, and long-distance shifters (e.g. *No one thinks that it is good*), which do not go together with the sentiment word and are those on which current studies should focus. Second, according to their effect on the initial polarity, they classify shifters into two other large groups: those that reverse polarity, which include negation particles such as *not* or *never*, and those that directly affect the intensity of polarity such as *mild* and *severe.* Finally, they make a more detailed classification of those shifters that can change polarity into six main categories: negation particles, modals, adverbs, contrastive particles, structures expressing sentiment inconsistencies and verbs. Finally, it is also worth mentioning the studies by Carrillo-de-Albornoz and Plaza (2013), Strohm and Klinger (2018) and Sintsova, Bolívar-Jiménez and Pu (2018), who create models to classify the effect that contextual shifters produce, not only on the intensity of polarity, but also on the emotions that are affected by their presence. The first ones focus on negation, intensification and modality (irrealis) particles; the other two focus on negation, downtoners and intensification particles.

On the other hand, and from a technical and general point of view, Benamara, Taboada and Mathieu (2017) point out the three tasks that computational systems must perform to carry out the processing of contextual shifters automatically: first, the automatic detection of the shifter and determination of its scope; second, the analysis of the effect on polarity; and, finally, the updating of that initial or prior polarity. Two main types of approaches or methods are used to carry out these specific tasks for the treatment of contextual polarity shifters: statistical and symbolic approaches (Carrillo-de-Albornoz and Plaza; 2013; Ayeste and Noferesti, 2022). It is worth mentioning that the former uses mathematical machine learning techniques, mainly supervised, which, especially in the early studies (Kennedy and Inkpen 2006; Wilson, Wiebe and Hoffmann 2009), try to solve the problem by adding specific suffixes to the words affected by the contextual shifters and using these new words as attributes to be automatically classified by the computational system (e.g. *good* is represented by four attributes: *good, not_good*, *intensified_good*, and *diminished_good*). These systems are widely criticised in the scientific community as simplistic, as these attributes generate a lot of noise and are inefficient:

> this method does not efficiently handle the linguistic context of sentiment words, since the classifier cannot learn that these 4 features are in any way related. Moreover, creating 4 features for each sentiment word increases the feature space in an unnecessary way. (Morsy and Rafea 2012, 254)

> this representation is linguistically inaccurate and does not model the actual effect of the modifiers. (Carrillo-de-Albornoz and Plaza 2013, 1619)

From here, several models emerged that use different statistical techniques to solve the problem of detecting contextual shifters (Mathew and Krishnan 2017; Zirpe and Joglekar 2017), such as that of Li and Huang (2009), focusing on the treatment of negation and contrastive expressions (with particles such as *however*, *but* or *notwithstanding*) and using a classification algorithm that divides sentences into two, those with reversed polarity and those without it, according to the presence of contextual shifters. Moreno-Ortiz and Fernández-Cruz (2015) try to solve the problem in the context of specialised domains, creating lexical resources that can be plugged into any system for this purpose. Cruz, Taboada and Mitkov (2016) present a machine learning model for detecting negation and speculation based on two phases: first, shifters are detected, and second, their scope. Xia et al. (2015) use a dual algorithm that considers in parallel both poles of an opinion, the original and the inverted one, to achieve the training of a classifier, taking into account contextual shifters and antonyms of the words. Ayeste and Noferesti (2022) point out the lack of studies that use machine learning techniques to detect contextual shifters and their scope automatically because they require training corpora labelled for these two aspects, and building them manually is costly in time and resources. In this sense, Li et al. (2010), motivated by the lack of representative training resources for machine learning-based systems and the difficulty of extending the detection of shifters such as negation to other languages, build an automatic contextual shifter detector from a classification algorithm based on attribute selection, in order to create a large-scale training corpus automatically. However, Zhang et al. (2011) decided to build a corpus for contextual shifters manually, given the lack of accuracy and presence of noise in the automatic generation models and the need to better understand the problem of contextual polarity shifters. Given the resource requirements and cost associated with the manual creation of training corpora for shifters mentioned above by Ayeste and Noferesti (2022), it is noticeable that more recent studies focus on achieving their automatic construction (Xu et al. 2020; Schulder, Wiegand and Ruppenhofer 2021; Bos and Frasincar 2021) or rely on more complex deep learning techniques (Singh and Paul 2021). These studies are based on English, being very scarce for Spanish (Jiménez-Zafra et al. 2020; Pabón et al. 2022).

The second approach, i.e. the symbolic or knowledge-based approach, is characterised by the use of lexicons with words that have an initial polarity associated with them (sentiment lexicons) and the incorporation of predefined linguistic rules to automatically detect the shifters, their scope and the change on the initial polarity they generate (Taboada et al. 2011; Periñán-Pascual and Arcas-Túnez 2019). Usually, scope detection has been specifically based on using a fixed window or fixed number of words between the polarity shifter and the word with polarity affected by it (called *focus)*, and in other studies on the use of syntactic parsers. With regard to the latter, as Periñán-Pascual and Arcas-Túnez (2019) point out, the resources available are very scarce and focused on English; for example, the parser developed by Kong et al. (2014) for natural language processing of tweets is available, but there is none for Spanish applied to micro-texts in social networks and their specific characteristics. At the same time, we must consider the lack of specific corpora for the processing of contextual shifters in this discursive framework, since, as Reitan et al. (2015, 99) point out for negation in English, "several negation annotated corpora are available but none for the twitter domain".

It is also worth noting that, apart from these two traditional approaches, different studies considered as *hybrids* have also emerged, which advocate combining both methods to improve contextual polarity shifter detection models (Andreevskaia and Bergler 2007; Prabowo and Thelwall 2009; Lu and Tsou 2010; Xia et al. 2016; Rahimi, Noferesti and Shamsfard 2018; Yoo and Nam 2018; Mendon et al. 2021).

Finally, we can conclude that, regardless of the methodology used, the reviewed studies do not express doubts about the convenience of incorporating contextual polarity shifters to improve and optimise computational systems in opinion mining. However, they also show the difficulties of carrying it out, making it one of the key challenges in this field. Among these difficulties, it is worth mentioning, as mentioned above and apart from the more technical challenges, the lack of agreement among researchers, mainly with regard to what is considered a change of polarity, which linguistic phenomena can be associated with the generation of this change, as well as the intensity of the change produced.

3. PROPOSED MODEL FOR POLARITY SHIFTERS

Our model is based on the construction of a modular architecture that allows the detection and computational processing of the types of contextual shifters included in the linguistic phenomena of *negation, quantification and modality*. Hereafter, we describe two fundamental aspects of our model (i.e. the polarity degree scale and the typology of contextual shifters), as well as the main components that make up our modular architecture.

3.1. Scale of degrees of polarity in the sentiment lexicon

This architecture requires a prior scale of polarity degrees in a sentiment lexicon included in the computational system where it is implemented. We consider that, first of all, the computational system must identify the word or set of words that are included in this sentiment lexicon, built from existing resources such as SentiWordNet (Esuli and Sebastiani 2006). In this type of resource, these sentiment words are associated with a type of initial polarity (positive or negative) and a degree of intensity of that polarity. This degree of intensity is identified by a number on a predefined linear scale, accompanied by a + or - sign depending on whether the polarity is positive or negative, respectively. Regardless of the resource used, this predefined numerical scale of the lexicon is automatically translated into three degrees of intensity (i.e. very strong, strong and low) for each of the poles or polarity senses (i.e. positive or negative), i.e. a range of [-3, -2,-1, 0, +1, +2, +3]. The three degrees specify the intensity of the absence or presence of the quality, with values assigned in relation to the magnitude that the speaker presupposes. Table 1 shows this polarity scale with the different degrees of intensity. We call this degree of polarity and initial intensity *Input Polarity* (IP).

Scale	DEGREE	TYPE OF POLARITY AND INTENSITY	Examples
Pole NEGATIVE	-3	Negative Polarity with Very Strong Intensity	*Detestar / Horrible* *Detest/ Horrible*
	-2	Negative Polarity with Strong Intensity	*Disgustar / Malo* *Dislike/ Bad*
	-1	Negative Polarity with Low Intensity	*Desagradar/ Regular* *Displease /So-so*
	0	Absence of polarity	
Pole POSITIVE	+1	Positive Polarity with Low Intensity	*Agradar/ Aceptable* *Please/ Acceptable*
	+2	Positive Polarity with Strong Intensity	*Gustar / Bueno* *Like / Good*
	+3	Positive Polarity with Very Strong Intensity	*Fascinar/ Excelente* *Love /Excellent*

TABLE 1. SCALE OF DEGREES OF POLARITY OF THE SENTIMENT LEXICON

3.2. Typology of contextual polarity shifters

Polarity Modifiers are shifters that can modify, in a positive or negative pole, the IP offered by the system at first. We have called the polarity resulting from the effect of these modifiers *Modified Polarity* (MP). These Modifiers can be classified into two types:

a) Intensifiers, which increase the degree of a given polarity (in a positive or negative pole). For a shifter to be considered an intensifier, the final effect it has on the polarity must be taken into account, which may be an increase in intensity or graduation in the same pole the IP, or an increase in the opposite pole.

b) Diminishers, which decrease a given polarity (in a positive or negative pole). In the same way, for a shifter to be considered a Diminisher, the final effect it produces must be taken into account, which in this case consists of a reduction in intensity or graduation on the polarity scale in the same pole as that of the IP.

In order to measure the intensity of this increase or decrease generated by the intensifiers or diminishers, two scales of the intensity of variation have been considered to facilitate the quantification of this effect: *low* intensity and *strong* intensity.

On the other hand, apart from the Modifiers shifters –intensifiers and diminishers–, there are also polarity *Neutralisers*, which change the polarity of the IP –positive or negative– neutralising it, until a degree of polarity intensity equal to 0 (absence of polarity) is obtained. The polarity resulting from the effect of the polarity neutralisers is called *Neutralised Polarity* (NP). In Table 2, we briefly outline how these three types of contextual shifters work.

TYPOLOGY OF SHIFTERS ACCORDING TYPE OF VARIATION	TYPE OF VARIATION	INTENSITY VARIATION	FINAL EFFECT ON INPUT POLARITY	OUTPUT POLARITY
MODIFIERS				
Intensifiers	Final Effect: Increase Input Polarity (positive o negative)	• Low • Strong	• Positive ⇒Δ Positive • Negative ⇒Δ Negative • Positive ⇒Δ Negative • Negative ⇒Δ Positive	Modified Polarity (MP)
Diminishers	Final Effect: Reduce Input Polarity (positive o negative)	• Low • Strong	• Positive ⇒∇ Positive • Negative ⇒∇ Negative	Modified Polarity (MP)
NEUTRALISERS				
Neutralisers	Final Effect: Neutralise Input polarity. **Polarity = 0**	---	• Positive ⇒ 0 • Negative ⇒0	Neutralised Polarity (NP)

TABLE 2. TYPOLOGY OF CONTEXTUAL POLARITY SHIFTERS

3.3. Main components of the modular architecture

The basic components of the modular architecture of contextual shifters are *dimension, categories* of shifters, *linguistic rules*, *matrices* of linguistic rules, and variation *formulae.*

3.3.1. Dimension

The dimension constitutes the module where the contextual shifters associated with a linguistic phenomenon are included. The architecture has three dimensions: IRREALIS, QUANTIFICATION and NEGATION. Furthermore, each dimension incorporates a series of categories of shifters, as well as linguistic rules, matrices and formulae.

On the other hand, it is important to note that, in order for the system to function correctly, we have found that an order of execution or activation of each of these dimensions of contextual shifters must be established. This order is shown in Figure 1.

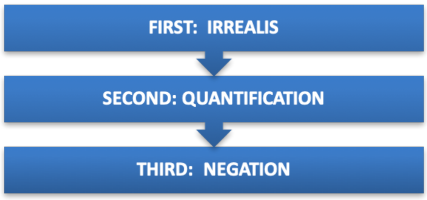

FIGURE 1. ORDER OF EXECUTION OF DIMENSIONS

This processing order is based on Liu and Seneff (2009) and their linear additive or cumulative compositional model, which was devised with the intention that it could deal with multiple adverbs (including negation), of the form *not (very (good))*, and could therefore process that "*not very good"* is less negative than "*not good"*. In short, these authors rely on the definition of compositional rules of the 'adverb-adjective' or 'negation-adverb-adjective' type through a hierarchical representation model, which involved a holistic view of contextual shifters, thus dealing with polarity as a *continuum* and not as a binary classification. A workflow diagram of the architecture is shown in Figure 2.

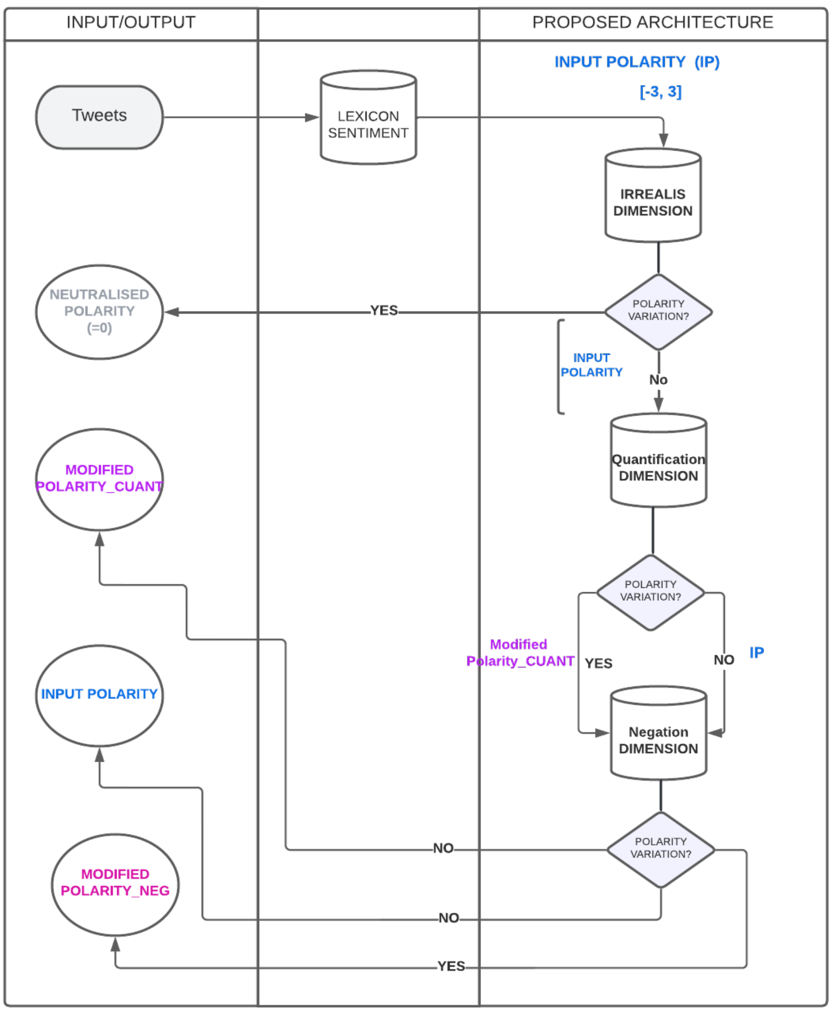

FIGURE 2. WORKFLOW DIAGRAM OF THE ARCHITECTURE

As can be seen in Figure 2, as a result of the processing of the text by the different dimensions of the architecture, any of the following four polarity typologies can be obtained as an output according to the variation generated by the contextual shifters considered:

- *Neutralised Polarity* (NP), or absence of polarity. The IP (from the sentiment lexicon and translated into a three-degree scale) varies after being processed in the IRREALIS dimension, and this results in such NP, which is a polarity equal to 0. This implies that the execution is no longer continued in the following dimensions since a final valuation result has been reached for the text entering the system. Those shifters that produce the NP are called neutralisers (see Table 2).
- *Modified Polarity_QUANT*, or the MP after the processing of the text in the QUANTIFICATION dimension. This Modified Polarity_QUANT is the polarity entering the next NEGATION dimension, and those shifters generating it can be of two types: intensifiers or diminishers (see Table 2).
- *Modified Polarity_NEG,* or the MP resulting after being processed by the NEGATION dimension. As with the Modified Polarity_QUANT above, those shifters giving rise to this polarity can be of two types: intensifiers or diminishers (see Table 2).
- Input Polarity (IP) or polarity that matches the polarity coming from the sentiment lexicon (once translated into a three-degree scale of polarity as shown in Table 1) because no variation has occurred in previous dimensions. In this case, none of the contextual shifters is activated.

On the other hand, for the design of each of these dimensions, we have previously defined the following four basic components: categories of shifters, linguistic rules, linguistic rule matrix, and variation formulae.

3.3.2. Categories of contextual polarity shifters

Within each dimension, contextual shifters are classified into categories according to the similar morphosyntactic patterns they show and the effect they produce on Input Polarity. It should be noted that not all kinds of shifters amplify or reduce polarity with the same intensity.

3.3.3. Linguistic rules

Each of the categories of shifters previously defined is associated with a linguistic rule that explains the variation that occurs in polarity. Since these rules express the cause-effect relationship between those shifters included in the category and the variation in polarity they generate, they take the form IF..., THEN... To construct the linguistic rules, the different attributes of the shifters are taken into account:

1. The *focus* of the shifter, i.e. the item directly affected. It is the word which is included in the sentiment lexicon and which determines, without the effect of the contextual shifter, the initial or prior polarity of the text. Each linguistic rule specifies one or more *foci,* each of which being defined by the following attributes:

   a) The grammatical category of the focus, which, in our case, may be associated with an adjective, verb, adverb or noun.

b) The Input Polarity, whose value is in the range [-3, +3].

c) The effect the shifter has on the Input Polarity, which is expressed in terms of whether it changes the pole of its prior polarity and with what intensity (i.e. low, strong).

2. The *scope* of the shifter, i.e. the maximum number of words from the focus to the contextual shifter.

3. The *direction* of the shifter, i.e. the direction to be followed to measure the scope of the shifter. That is, it indicates whether the shifter is placed before the focus (left direction) or after the focus (right direction).

3.3.4. Matrices of linguistic rules

Each linguistic rule is represented in a matrix to facilitate its incorporation into the system as a computational rule. Table 3, Table 4 and Table 5 show the five sections that make up each matrix.

ITEMS (1/3)	TAG	TAG EXTENSION	DESCRIPTION
I. DIMENSION AND BEGINNING OF STATEMENT	<NEG_Statement>		It indicates the beginning of a statement of dimension NEGATION. A closing tag is associated with it.
	<QUANT_Statement>		It indicates the beginning of a statement of dimension QUANTIFICATION. A closing tag is associated with it.
	<IRR_Statement>		It indicates the beginning of a statement of dimension IRREALIS. A closing tag is associated with it.
II. POLARITY SHIFTER CATEGORY	ESP_NEG_Xn n=1,...n	"SHIFTER (AND/OR)"	Identification of category of shifters within the NEGATION dimension for Spanish. Each category includes a set of shifters that have similar focus effects and functioning. The features of Shifters are as follows: • They can be a word, a group of words. They can refer to one or more possibilities using the Boolean shifters AND (all elements must occur) and OR (at least one of them must occur). • The category tag which identifies it, consists of three parameters: language (ESP/ENG), dimension (NEG/QUANT/IRR) and its identification variable (Xn) with a subscript n for each category within the dimension.
	ENG_NEG_Xn	"	Identification of category of shifters within the NEGATION dimension for English.
	ESP_QUANT_Xn	"	Identification of category of shifters within the QUANTIFICATION dimension for Spanish.
	ENG_QUANT_Xn	"	Identification of category of shifters within the QUANTIFICATION dimension for English.
	ESP_IRR_Xn	"	Identification of category of shifters within the IRREALIS dimension for Spanish.
	ESP_IRR_Xn	"	Identification of category of shifters within the IRREALIS dimension for English.
SHIFTER Attributes	SHIFTER ATTRIBUTES		It defines the set of attributes of the identified category of contextual shifters.
	SCOPE	NUMBER	It Indicates the maximum number of words or positions from the contextual shifter to the focus (word within the sentiment lexicon) that is affected by it. It is a number.
	DIRECTION	RIGHT/LEFT	Scope direction. Direction followed when counting the number of words from focus to contextual shifter. It can be to the right (RIGHT) or to the left (LEFT). If the shifter is placed before the focus, the direction will be LEFT; if it is placed after the focus, the direction will be RIGHT.

TABLE 3. SECTIONS I AND II OF THE MATRIX MODEL OF LINGUISTIC RULES

ITEMS (2/3)	TAG	TAG EXTENSION		TAG EXTENSION	DESCRIPTION
III.BEGINNING OF CONDITIONS OF THE LIGUISTIC RULE	IF	CASE 1	AND/OR	CASE 2	It establishes the beginning of the section of conditions of the linguistic rule, which are related to the attributes of the focus of the contextual shifter. There may be one or several conditions, which are linked by the Boolean AND or OR. Each of the conditions will be identified by the extension CASE and a sequential number.
III. 1. POLARITY SHIFTER FOCUS	ESP_NEG_Fn n=1,...n				Identification of the focus associated with a category of shifters of the NEGATION dimension in Spanish, specified in sections I and II of the matrix: • The focus will always be defined by a grammatical category (PoS), with a defined input polarity and intensity. • The focus is the element subject to polarity variation by the effect of the shifter. • As with the category of operators, its tag is made up of three parameters: the language (ESP/ENG), the dimension (NEG/CUANT/IRR) and its identification variable (FN), which will have a subscript n for each focus. This subscript coincides with the number assigned to the category of shifters that make that focus vary. For example, ESP_NEG_F1 shall be associated with the ESP_NEG_X1 shifter.
	ENG_NEG_Fn				Identification of the focus associated with the category of NEGATION shifters in English.
	ESP_QUANT_Fn				Identification of the focus associated with the category of QUANTIFICATION shifters in Spanish.
	ENG_QUANT_Fn				Identification of the focus associated with the category of QUANTIFICATION shifters in English.
	ESP_IRR_Fn				Identification of the focus associated with the category of IRREALIS shifters in Spanish.
	ENG_IRR_Fn				Identification of the focus associated with the category of IRREALIS shifters in English.
Attributes of Focus	FOCUS ATTRIBUTES				It indicates the attribute section of the identified focus for each category.
	PoS	N/JJ/VB/RB	AND/OR	N/JJ/VB/RB	It Indicates the grammatical category of the focus (included in the sentiment lexicon). For the POS field there can be more than one possibility and each of them is associated with its case (N=NOUN/ JJ=ADJECTIVE/ VB=VERB/ RB=ADVERB).
	POLARITY_I	[POSITIVE/NEGATIVE, DEGREE]		[POSITIVE/NEGATIVE, DEGREE]	Input polarity associated with the focus, without the effect of the contextual shifter. It is identified by its direction (positive or negative), and by its graduation within the range [-3, +3].

TABLE 4. SECTION III OF THE MATRIX MODEL OF LINGUISTIC RULES

ITEMS (3/3)	TAG	TAG EXTENSION	DESCRIPTION
IV. EFFECTS OF THE FULFILMENT OF THE CONDITION (CASE)	THEN	EFFECT ON POLARITY_I (FOCUS)	It indicates the section of the effects of the contextual shifter on the Focus Input Polarity. Each effect will be associated with each condition or case (CASE) detailed in section III above.
IV. 1. NEUTRALISING EFFECT	POLARITY_NEUTRALISER	YES/NO	It Identifies whether the shifter acts as a neutraliser (YES) or not (NO). If the answer is YES, the following two fields of this section must be completed.
	FOMULA	NEUTRALIZADA	It Identifies the formula to be applied.
	POLARITY_N	0	If the shifter acts as a neutraliser, then it automatically changes the polarity to 0. This polarity is identified by the tag POLARITY_N.
IV. 2. MODIFYING EFFECT	POLARITY_MODIFIER	YES/NO	It identifies if the shifter acts as a Modifier (YES) or not (NO).
	T_POLARITY_MODIFIER	INTENSIFIER/DIMINISHER	If acting as a Modifier (YES), it classifies the type: INTENSIFIER or DIMINISHER.
	CHANGE_POLARITY	YES/NO	Indicates whether the pole of the Input Polarity (POLARITY_I) changes (YES) or not (NO).
	INTENSITY_LEVEL	LOW/STRONG	Identifies the degree of intensity of the variation effected by the Modifier. Two possible levels: low or strong.
	FORMULA	POLARIDAD (1)	It Identifies the formula to be applied.
	POLARITY_M	[POSITIVE/NEGATIVE, DEGREE]	It Identifies the Modified or output Polarity due to the effect of the modifier. It is identified by its direction (positive or negative), and by its graduation within the range [-3, +3], as well as the Input Polarity (Polarity_I) of the focus.
V. DIMENSION AND END OF STATEMENT		<NEG_Statement</>	It Indicates the end of a NEGATION dimension statement. It has a starting tag associated with it.
		<QUANT_Statement</>	It Indicates the end of a QUANTIFICATION dimension statement. It has a starting tag associated with it..
		<IRR_Statement</>	It Indicates the end of an IRREALIS dimension statement. It has a starting tag associated with it.

TABLE 5. SECTIONS IV AND V OF THE MATRIX MODEL OF LINGUISTIC RULES

3.3.5. Variation formulae

Each matrix of the linguistic rule has one or more formulae to calculate the Modified Polarity taking into account the following variables:

- The Input Polarity of the word, which is determined by its pole of polarity and its degree of intensity.

- Whether the variation is in the same pole as the Input Polarity (i.e. from positive to positive or from negative to negative), or in the opposite pole (i.e. from positive to negative or from negative to positive).
- Whether there is an increase or decrease in sentiment.
- The intensity of the variation that occurs (i.e. low or strong).

Table 6 and Table 7 show the different variation formulae, according to the three different cases considered:

Case	Degree Input Polarity (IP)						Type of Variation Pole of Polarity	Intensity of Variation	Applied Formula	Formula Description	Degree Modified/Output Polarity (MP)						Type of Shifter
1	-3	-2	-1	+1	+2	+3					-3	-2	-1	+1	+2	+3	
1.1.a)				X	X		Positive ⇒Δ Positive	Low	P. Modificada (1)	IP +1					X	X	Intensifier
1.1.a)				X			Positive ⇒Δ Positive	Strong	P. Modificada (2)	IP +2						X	Intensifier
1.1.b)					X	X	Positive ⇒∇ Positive	Low	P. Modificada (3)	IP -1				X	X		Diminisher
1.1.b)						X	Positive ⇒∇ Positive	Strong	P. Modificada (4)	IP-2				X			Diminisher
1.2.a)		X	X				Negative ⇒Δ Negative	Low	P. Modificada (5)	IP – 1	X	X					Intensifier
1.2.a)			X				Negative ⇒Δ Negative	Strong	P. Modificada (6)	IP -2	X						Intensifier
1.2.b)	X	X					Negative ⇒∇ Negative	Low	P. Modificada (7)	IP +1		X	X				Diminisher
1.2.b)	X						Negative ⇒∇ Negative	Strong	P. Modificada (8)	IP +2			X				Diminisher

TABLE 6. VARIATION FORMULAE. CASE I

Case	Degree Input Polarity (IP)						Type of Variation Pole of Polarity	Intensity of Variation	Applied Formula	Formula Description	Degree Modified/Output Polarity (MP)						Type of Shifter
2	-3	-2	-1	+1	+2	+3					-3	-2	-1	+1	+2	+3	
2.a)				X			Positive ⇒Δ Negative	Low	P. Modificada (9)	(IP x 0) -1			X				Intensifier
2.a)					X	X	Positive ⇒Δ Negative	Strong	P.Modificada (10)	(IP x 0). -2		X X					Intensifier
2.b)	X	X	X				Negative ⇒ Δ Positive	Low	P.Modificada (11)	(IP x 0) +1				X X X			Intensifier
2.b)	X	X	X				Negative ⇒ Δ Positive	Strong	P.Modificada (12)	(IP x 0) +2					X X X		Intensifier
3.							Positive⇒ 0 Negative⇒0		P. Neutralizada	IP x 0							Neutraliser

TABLE 7. VARIATION FORMULAE. CASES 2 AND 3

To date, for the NEGATION dimension, we have proposed a total of 1 category, 7 shifters, 4 rules and 4 associated matrices for Spanish, and 2 categories, 6 shifters, 6 rules and 6 associated matrices for English. For the QUANTIFICATION dimension, we have configured 4 categories, 27 shifters, 4 rules and 4 associated matrices for Spanish, and 4 categories, 17 shifters, 4 rules and 4 matrices for English. Finally, for the IRREALIS (or modality) dimension, we have considered a total of 3 categories, 23 shifters, 13 rules and 13 matrices for Spanish, and 3 categories, 16 shifters, 7 rules and 7 associated matrices for English.

4. CONCLUSIONS

We have proposed a new computational model to deal with three linguistic phenomena (i.e. negation, quantification and modality) within the challenge posed by contextual polarity shifters in opinion mining in Spanish and English. We conclude that, on the one hand, contextual shifters included in the negation and quantification dimensions modify the prior polarity of their focus by increasing or reducing it with a low or strong intensity, and, on the other hand, shifters included in the modality dimension (or *irrealis*) neutralise the prior polarity of the focus. Moreover, we have also considered that not all of these contextual shifters can modify the initial polarity in the same way and must therefore be treated computationally in a specific way. Therefore, we have incorporated the theoretical linguistic knowledge into a modular architecture, where shifters are grouped into categories according to their morphosyntactic patterns, which is a significant advance with respect to what has been investigated so far since each category receives a specific treatment. We have also developed a series of linguistic rules associated with each category that include information about the shifters in terms of, on the one hand, the scope and direction with respect to their focus and, on the other hand, the intensity of the change they generate on the initial or prior polarity through the use of mathematical formulae. Finally, we have designed matrices associated with these linguistic rules, which represent precise instructions so that this linguistic knowledge can be easily programmed in a computational system. It should be noted that this theoretical linguistic knowledge on which the proposed architecture is based has been contrasted with linguistic evidence found in the texts of messages posted on Twitter.

In our model, the automatic detection and treatment of these shifters associated with the three dimensions presented in this paper is carried out from a symbolic approach, i.e. based on knowledge, as opposed to a statistical approach, i.e. based on the use of specific machine learning techniques and corpora. By adopting a symbolic and contrastive approach in Spanish and English, the model offers numerous advantages since (a) it does not require the creation of expensive training corpora, characteristic of statistical systems, (b) it can reuse different existing resources (e.g. sentiment lexicons and linguistic rules), (c) it can be easily replicated for the processing of other languages, and (d) it can be easily extended and improved.

The proposed modular architecture will be incorporated into the knowledge base of the

ALLEGRO project (Adaptive muLti-domain sociaL-media sEnsinG fRamewOrk),[1] a system for the development of multimodal applications that make it possible to reconstruct the state of society through the perspective of the collective intelligence of social network users. Specifically, one of its modules, DIAPASON (a unifieD hybrId ApProach to microtext Analysis in Social-media crOwdseNsing), is designed to process user-generated textual content in English and Spanish in order to automatically detect various types of social problems by integrating natural language processing, machine learning, and knowledge engineering techniques. Therefore, our work will focus on extending and improving the model, replicating it to other languages and incorporating other dimensions of contextual polarity shifters.

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