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Detección de la negación y su ámbito en textos escritos en español
Negation detection and its scope in Spanish written text

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Abstract La detección automática de la negación y de las palabras que son afectadas por esta es un importante problema que podría beneficiar otras tareas del Procesamiento de Lenguaje Natural tales como la Extracción de Información, el Análisis de Sentimientos y las Respuestas a Preguntas. En el presente trabajo se propone una solución al problema de la negación basado en técnicas de aprendizaje supervisado. La esencia de la propuesta es detectar tanto las partículas de la negación como su ámbito, todo ello en textos en español. Se trabaja en dos fases: en la primera las partículas son identificadas y en la segunda el alcance completo de estas es determinado.

Abstract The automatic detection of negation and the words they affect is an important problem that could benefit other Natural Language Processing tasks such as Information Extraction, Sentiment Analysis and Question Answering. In the present work a solution of the negation problem is proposed based in supervised machine learning thechniques. The essence of the proposal is to detect both the negation cues and their scope, all in spanish texts. The work is done in two phases: in the first one the cues are identified and in the second the whole scope of this cues is determined.

Palabras Clave
Detección de la negación — Identificación del ámbito de la negación — Análisis de sentimientos

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Introduction

Natural Language Processing (NLP) include some importants tasks such as Sentiment Analysis, Information Extraction and Question Answering in which the treatment of texts that include information loaded with negation or subjectivity is of great importance. For example, in sentiment analysis the negation is a key element, because there are plentiful negative opinions expressed with positive terms negated and vice-versa. The sentence "No me gusta la carcasa del teléfono" is a clear example of a negated opinion with a positive term (gusta) negated.

Negation is a linguistic phenomenon that is used to change the truth value of a linguistic unit (sentence, clause or word) [16]. Spanish language can express negation by means of different negation markers or cues, being the most common the use of words like "no", "nunca", "nadie", but can also be expressed by means of prefixes: "(in)dispensable", "(im)pensable", "(des)interesado", and idioms like "en la vida". The scope of negation include all the words that are affected by negation and typically the marker will be included in it. In the next example, the cue is represented in bold and the scope in parenthesis:

Una cámara de fotos que (**no** es una maravilla).

At first glance, one might think that interpreting negation could be reduced to finding negative keywords, detect their scope using syntactic analysis and reverse its polarity. Actually, it is more complex. Negation plays a remarkable role in text understanding and it poses considerable challenges.

The identification of negation cues can be complicated: some words that usually express negation don't always do according to context. For example, in the sentence "El coche lo compré para viajar, **no**" *no* has just an emphatic value. In addition, there are cues that can consist in more than one word (multiword cues), some of which are discontinuous, like in the sentence "**No** me gustó **en absoluto**".

In this paper a solution to the problem of negation is proposed, based on supervised machine learning techniques. The essence of the proposal is to detect both the negation markers and its scope, all of it in Spanish texts. The work is done in two phases: in the first one the cues are identified and in the second the full scope of these cues is determined.

Although negation has been largely studied, it hasn't been sufficiently analyzed in several languages like Spanish. Accordingly to our knowledge, it hasn't been done any work with a supervised machine learning approach in this language. Therefore, the purpose of this work will be the implementation of a model capable of handling negation, through a simple solution that seeks to analyze the most important features to identify the negated words of a sentence.

The rest of the article is organized as follows: in the section 1 the related works are introduced and the section 2 describes the algorithm proposed to detect the negation cues and their scope. Subsequently, the section 3 details the evaluation setup performed to check the effectiveness of the proposal, the resources used and the results obtained. Finally, in the section 4 the conclusion and futures works are presented.

1. Related Work

Negation has been a largely studied area of NLP, mainly due to its influence in other tasks of great interest, but the majority of works carried out have been on texts written in English.

The firsts systems developed were typically rule-based. For instance, NegEx [5] algorithm, which determines whether a sickness or symptom in a medical report is present or absence using rules based on regular expressions. Other works presented methods based in the definition of rules through the syntactic trees, such as those develop by Apostolova [2], De Albornoz [10] y Ballesteros [3].

However, most works in this field are based on supervised machine learning approaches. A notable example of this is the research conducted by Morante and Daelemans [17]. Their system consists of four classifiers. Three classifiers predict whether a token is the first token, the last token, or neither in the scope sequence. A fourth classifier uses these predictions to determine the scope classes. Another work was the one develop by Agarwal [1], which detects negation/speculation cues and its scope using Conditional Random Fields (CRF) as machine learning algorithm. A similar method was used by Chowdhury [6], standing out for his use of contextual features, apart from those specific to the token.

Some systems are characterized by their use of syntactic information, such as the one carried out by Council [8]. This is trained and evaluated in a review corpus concluding that, as expected, introducing scope detection improves significantly the polarity classification performance . Other works were those develop by Lapponi [14] [15] and Enger [11], using both a wide set of lexical and syntactic features and labels that capture the token level behavior of the scope using Support Vector Machines and CRF as machine learning algorithm for the detection of the negation cues and their scope respectively. Cruz Díaz [9] presented a system to handle negation and speculation on review and medical texts, and introduced the first review corpus labeled for negation and speculation. The model introduced by Reitan [19] studies the effect of the treatment of negation for the polarity classification task by developing a sophisticated system to determine the negation scope.

Other approaches used for the detection of the negation scope are those conducted by Basile [4] and Packard [18] that are based in the semantic representation of the text through *deep parsing*. The research carried out by Fancellu stands out, proving that neural networks are a valid alternative to detect the negation scope, offering a detailed analysis of their performance in text of different genres and containing several negation types.

Regarding the treatment of negation in Spanish documents the systems are mostly rule-based. One example of this is the work by Costumero [7]. They adapted the NegEx algorithm to be applied to detect negation regarding diseases in Spanish written medical documents. This is carry out translating the list of terms previously identified for English in NegEx, and they enriched it with synonyms and terms extracted from the manual annotation of medical texts in Spanish.

Jímenez-Zafra [20] proposed a model based in the syntactic structure of text for the resolution of the negation scope in Spanish. They use different rules based in the dependency tree for the treatment of several cues. In addition, the identification of the negation scope is made in a polarity classification system, evaluating their contributions in this task.

We can conclude that most of the research made until now about the treatment of negation is focused on texts written in English. Despite the similarities of the concepts related to negation, the mechanisms to express it vary depending on the language. Therefore, each of these languages requires a specific way to handle negation. The few works done for its analysis in Spanish are carried out by means of rule-based systems. For this reasons, one of the purposes of this project will be the introduction of an approach based in supervised machine learning techniques to handle negation in Spanish.

2. Methods

The task of identify the words affected by negation is divided in two consecutive classification subtasks. They are implemented using supervised machine learning methods.

In the first phase it is determined if a certain sentence is negated or not, identifying the words that express negation. In the second step a classifier decides at sentence level the words affected by the cues identified in the previous phase.

First, the raw text is processed and enriched with lexical (tokens, parts-of-speech, and lemmas) and syntactic information (dependency analyses). Next, the data is converted for input of the negation detector. Finally, after obtaining their prediction, this is used to determine the negation scope. The process is explain in more detail in the following subsections.

Cue Detection

In the first phase the words that express negation are determined. These markers are the lexical elements that indicate the negation in a sentence.

Negation detection is solved using Logistic Regression. All the words are presented to the classifier, being this the one that determines if a word is a negation cue or not.

Features	Description
Token_i	Current token
Lemma_i	Lemma of the current token
POS_i	Part-of-speech of the current token
Lemma_{i-1}	Lemma of the previous token x
POS_{i-1}	Part-of-speech of the previous token
Lemma_{i+1}	Lemma of the next token
POS_{i+1}	Part-of-speech of the next token
Lemma_{i-2}	Lemma of the token_{i-2}
Lemma_{i+2}	Lemma of the token_{i+2}

Table 1. Features in the cue detection phase

Features are introduced based on the context, with the objective of treating complex cues (composed of more than one word), mainly complex continuous cues (the words for which the marker are composed are followed) like “ni siquiera". However, cues depend mostly in the token itself and not the context. Therefore, lexical information is the key in this phase. The features used are detailed in table 1

Scope Resolution

Once the negation markers are identified, the following task is to detect the scope of this cues. To accomplish this a classifier, Logistic Regression, predicts if a token belongs or not to the scope of a marker. Therefore this problem is seen as a binary classification task.

The instances that are presented to the model represent a pair: negation cue and a token from the sentence. This means that all the words are analyzed so many times as negation markers are in the sentence. Features of all the words with respect to the cues are analyzed, taken the decision if they belong to its scope or not. The negation markers used were those detected in the previous step. Only the sentences that express negation are used in these phase.

Features introduced in table 2 can be divided into lexical, syntactic and those related with the cues. The features used are based in previous works related to the scope negation resolution.

Based in observations made by Fancellu [12] and with the purpose to avoid features that can take many different values we discretized all distance features that take real values (the cue distance and the directed dependency distance). For the directed dependency path, this was done by choosing two limits, 3 and 7. It was stated that any token that had a distance less than 3 is an immediate neighbor, and any token that had a distance less than 7 is nearby, and any token that had a distance bigger than this is far away. The distance with respect to the cue is the amount of tokens between the word and the current cue. It was made discrete with a limit of 7 to the left and 12 to the right.

The features extracted via dependency graphs model the syntactic relationship between each token and the cue that is being analyzed. This is beneficial in the task of determining the negation scope. Each sentence was parsed to represent its dependency graph.

The token indexes are used as unambiguous identifiers of the vertices of the graph and the dependency relations as the edges. The dependency graph are represented as a set V of vertices and two different sets of edges, A and E, the former containing only the directed edges (arcs) and the latter containing also the reversed.

From the graph G = (V, A) the shortest path from the negation cue predecessor to all other vertices in the graph is extracted. We start from the predecessor of a cue because, being directed acyclic graphs essentially trees, negation cues are very often found in the leaves, hence would yield no path from the cue to anywhere in the tree. From G’ = (V, E) the shortest path is extracted from the vertices to the analyzed negation cue.

These shortest paths are used to record the distances and the paths as a feature. The latter represents the path traversed from each token to the cue, encoding the dependency relation of the arc that is traversed. For instance, the syntactic relation between *fotos* and *no* in Figure 1 is described as *“nmod/acl/advmod/"*.

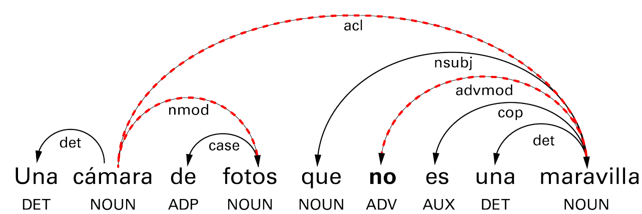

Figure 1. Example of a dependecy graph representing the path between *fotos* and *no*

3. Results and Discussion

To perform the tasks of tokenization, lexical and dependency analysis spaCy is used. This is a library that provides a wide range of tools for NLP in several languages, among them Spanish. NetworkX is used to handle and represent the graphs.

To prove the functionality of the developed proposal a Spanish corpus was used, SFU Review_{SP}-NEG[1] [13]. The corpus consists of 400 reviews of cars, hotels, washing machines, books, cell phones, music, computers and movies obtained from the Ciao.es website. The reviews that compose the corpus are written by users of the web. This increases the difficulty of the task, since the texts can contain grammatical errors and even informal expressions. The corpus contains 9,455 sentences, from which 3,22 are annotated with negation;

[1] http://sinai.ujaen.es/sfu-review-sp-neg-2/

Features	**Description**
Lexical	
$Token_i$	Current token
$Lemma_i$	Lemma of the current token
POS_i	Part-of-speech of the current token
$Lemma_{i-1}$	Lemma of the previous token
POS_{i-1}	Part-of-speech of the previous token
$Lemma_{i+1}$	Lemma of the next token
POS_{i+1}	Part-of-speech of the next token
About the cue	
Right distance	Distance to the right of the negation cue
Left distance	Distance to the left of the negation cue
Cue POS	Part-of-speech of the cue
Syntactic	
Dependency relation	Dependency relation type of the current token
Directed dependency graph path	Path of the cue predecesor to the token
Directed graph distance	Amount of traversed edges in the path
Dependency graph path to the cue	Path of the current token to the cue
Path distance of the cue path	Amount of traversed edges in the previous path

Table 2. Features in the scope resolution task

2,143 of these contain a single negation cue and 879 contains more than one. Only 6.31% of cues are complex continuous markers (composed by more than two consecutive words), therefore the majority are simple and complex discontinuous markers (composed by several discontinuous words) 70.78% and 22.91% respectively. It is worth mentioning that there are more than 400 different types of negation markers, but the 10 most frequent ones make up more that 70% of the cases of negation, with the marker 'no' being the most frequent one (52.14% of the cases).

Experiments

For experiments the corpus was divided in the following way: the 80% was used as the training set, the 10% as the development set and the other 10% as test set.

Different settings were tried with respect to the features of both the cue and scope classifiers in the development set, however only the results obtained from the final set are shown.

To determine the best values for the parameters of the classifiers 10-fold cross validation grid search was used in the training set. The penalty coefficients L1 and L2 of Logistic Regression was tuned, the parameter C with a space of [0.001, 0.01, 0.1, 1, 5, 10] and max_iter in [50, 100, 150, 200]. The best configurations were: for the cue detection classifier penalty = L1, C = 1, max_iter = 150 and for the scope resolution classifier: penalty = L1, C = 1 and max_iter = 100.

Results

The results reported in this section were measured by employing 10-fold cross validation. For each fold, a partition of the document was used.

As evaluation measures it was used Precision, Recall, F1 and Accuracy, being the first three the most used to evaluate the performance in terms of both cue and scope detection. In addition, F1-score is a well established metric suited for unbalanced data sets.

Precision accounts for the reliability of the system's predictions, recall is indicative of the system's robustness, while F1-score quantifies its overall performance.

In the cue detection task, a token is correctly identified if it has been accurately determined to be a negation marker. In the task of detecting the scope, a token is correctly classified if it is properly identified as part of the token of some cue. In other words, it is evaluated for each marker if a token belongs to its scope or not. This result is processed in such way that if a token is classified as part of some scope then is identified as a negated word. Thus, there are tokens that can be classified more than once and scopes that are mixed. These are interpreted as a single scope that has more than one negation cue, one of this markers acting as reinforcement or modifier of the negation.

Although the F1-score is very popular and suitable for dealing with the class-imbalance problem, it is focused on the positive class only. Therefore, Accuracy has been used as an additional measure since is a good indicator of the overall performance of the method.

In the table 3 the results are presented.

	Prec.	**Rec.**	**F1**	**Acc.**
Cue	97.05	90.06	93.70	99.71
Scope	84.46	78.54	81.34	96.06

Table 3. Final Results

In the cue detection phase recall reaches a lower value than precision. This is mainly due to the difficulty of identifying multiword cues, solved in the majority of the previous systems with post processing.

The results presented here cannot be directly contrasted with previous research since, to the best of our knowledge, there is no work related to recognizing negation in the SFU Review$_{SP}$-NEG corpus. In addition, the few works carried out in Spanish use different approaches and the results of the treatment of the negation are not presented in them. In spite of this, the comparison with some works in other languages such as English would give a good indicator of the results detailed in this paper in relation to others in the same task. Therefore, the table 4 presents the performance of some systems described in section 1.

	Cue			**Scope**		
	P	**R**	**F1**	**P**	**R**	**F1**
Enger	90.15	**93.56**	91.82	**85.49**	80.28	**82.80**
Chowdhury	93.42	91.29	92.34	81.53	**82.44**	81.98
Lapponi	89.17	**93.56**	91.31	82.25	82.16	82.20
Proposal	***97.05***	*90.06*	***93.70***	*84.46*	*78.54*	*81.34*

Table 4. Results of negation cue and scope detection of the approaches developed by related work.

4. Conclusion

In this work, a new approach of the treatment of negation has been presented. The proposal made is based on supervised machine learning techniques, detecting both negation cues and its scope in Spanish written text.

The results show that, despite the differences between the domains and languages used, competitive results are obtained with respect to other works previously developed.

This proposal can be improved in several ways. Only the words that express negation where taking into account, ignoring some prefixes that also express it (in-, im-, dis-, etc), since in the corpus used that kind of negation wasn't annotated. A special treatment of multiword cues is believed to improve performance, since these are the cause of the majority of errors in this phase. In addition, in other works the scope resolution task has been resolved as a sequence labeling problem, using CRF as a learning algorithm and it is believed that the application of a similar approach will improve the results obtained.

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