Computational Models for Irony Detection in Three Spanish Variants

Simona Frenda[1,2] and Viviana Patti[1]

[1] Dipartimento di Informatica, Università degli Studi di Torino, Italy
[2] PRHLT Research Center, Universitat Politècnica de València, Spain
{frenda, patti}@di.unito.it

Abstract. The lack of understanding of figurative language online, such as ironic messages, is a common cause of error for systems that analyze automatically the users' opinions online detecting sentiment, emotions or stance. In order to deal with this problem of automatic processing of natural language, IroSvA shared task at IberLef 2019 asks participants to detect, for the first time, irony in short texts written in Spanish language, considering the three linguistic variants from Spain, Mexico and Cuba. Another novelty of this task is the presence of labels specifying the context of the utterance, such as current political or social issues discussed online. In the context of this shared task, we approached irony detection in Spanish short texts trying to exploit the provided topic information. In addition, we investigated the usefulness of stylistic, lexical and affective features during the development of the irony detection models for the three Spanish variants. Experimental results and further analyses allow to shed some light on the analogies and differences in the expression of irony in the three variants, and suggest new research directions, in a perspective of comparison with other languages.

Keywords: Irony Detection · Spanish · Mexican Spanish · Cuban Spanish · Linguistic Analysis · Affective features

1 Introduction

Irony is a special figurative device frequently used in speech and everyday life to communicate something that is different or contrary to what is literally said [29]. Irony has different functions in communications, which have been studied so far in the context of different disciplines such as linguistics, psychology and philosophy. Some of these studies highlight that one of the principal trait of the use of irony consists in emphasizing unexpected occurrences especially amusing the readers [1,44].

Other studies focus on a very common type of verbal irony, sarcastic irony, which is typically featured by a sharper tone of critique and by the speaker's intent to convey scorn or insult [14]. The lack of understanding of irony could deceive the reader into thinking that the transmitted message is true. Especially in texts produced by users online, the lack of context and the shortness of the message often make the correct interpretation more difficult for humans and especially for the machine.

In the Big Data era, the automatic understanding of contents online is one of the current purposes of the majority of companies or political organizations that want to analyze the opinions of the users about products, subjects and individuals. The presence of irony, as well as sarcasm, affects the interpretation of the real opinions of the users, and impedes the correct functioning of systems of sentiment analysis, stance or emotion detection.

For this reason, especially in the campaigns of evaluations of automatic systems of Natural Language Processing (NLP), various shared tasks on irony detection have been proposed. The majority of these competitions provide corpora in English [18,45], but recently the analysis of irony is extended to other languages such as Italian [5,3,12] and French [6]. In the framework of IberLef 2019, for the first time IroSvA shared task organizers [32] ask participants to classify ironic and non-ironic texts in three variants of Spanish: Castilian, Mexican and Cuban. The corpus provided for each linguistic variant is a collection of short texts annotated as ironic and non-ironic. These corpora contain also labels of specific topics referred to current political or social issues discussed online in the chosen geographical areas of Spain, Mexico and Cuba.

Considering the importance of the context in the process of recognition of irony [46], for each variant we analyzed the impact of topic information and semantic context. Moreover, inspired by previous work on computational models for irony detection [21,43,33] we explored the role of features related to the affective information present in the tweets and the psychological response stimulated by the message. On the basis of the analyses in [16], we took into account also the presence of abusive language. Finally, considering the previous studies about irony detection in other languages, such as English in [8], we examined also the role of lexical and stylistic features. Comparing our results with the four challenging baselines provided by the organizers, only the system proposed for the Cuban variant overcomes all the baselines. The other two systems overcome only the baseline calculated on majority voting.

A preliminary analysis of errors show some important analogies among the three variants which are in line with the observations emerged in other languages [26,11]. Although from the first experiments in this work some slight differences emerged among these variants, these analogies suggest a new challenge in a multilingual direction.

The paper is organized as follows. The next section summarizes the related work. Section 3 describes the IroSvA dataset and the used approaches focusing on the feature engineering and performed experiments. Section 4 reports the obtained results in the competition. Finally, Section 5 and 6 discuss the results and draw some conclusions, proposing a plan for future analyses.

2 Related Work

In recent years, the importance to recognize the figurative language to understand better the opinion of users have encouraged various researchers to explore texts such as commentaries [47], reviews [38] and tweets [39]. Most of the studies are focused on English language [23], but recently the need to develop linguistic and computational resources also for other languages incited the NLP community to focus on Italian [5,3,12], French [6], Dutch language [30] and Spanish.

The literature about figurative language detection in the Spanish language is actually limited. The authors of [10] organized the HAHA shared task in the context of IberEval 2018 about identification of humor in Spanish tweets. About satire detection, the authors of [13] proposed a psychological based approach exploiting news satirical sources on Twitter for Mexican and Castilian variants of Spanish, while the authors of [4] employed linguistic and semantic features (such as ambiguity and synonyms), sentiment analysis and slang words in a similar collection of tweets from Spain. The studies about figures of speech of irony and sarcasm are really few for the Spanish language. To the best of our knowledge, the study proposed in [22] is the first to explore the irony in Spanish tweets considering the sarcasm as a subclass of irony. In particular, they explored word and character level of the texts employing n-grams of words and characters and word embedding, using Support Vector Machines (SVM) and Random Forests as classifiers. Recently, the authors of [25] explored deeply the function of sarcasm in Spanish dialogues online creating a corpus annotated taking into account the presence of sarcasm and the tone of nastiness.

Since the literature about the identification of ironic texts in Spanish is poor, the studies that inspired this work examine the characteristics of irony based on corpora developed on other languages. The larger part of works on this field exploits various combinations of features and computational techniques. Especially with classic machine learning techniques, some researchers examined the impact of stylistic features [8], pragmatic symbols (such as hashtags, mentions and emojis in tweets) [28,19], syntactic patterns [20,41], sentiment and emotional lexica [21], semantic context and users information [2,24]. Recently, technique of deep learning have been exploited also for irony detection [50,49].

On the basis of these previous studies, we carried out a deep analysis of the three corpora examining the impact of emotions, psychological reactions of readers, topics, semantic contexts, lexical, abusive speech and stylistic features. In the next sections, we describe our approach and the performed analyses that show some analogies and differences among the ironic characteristic of the texts in the three variants of Spanish.

3 Datasets and Approach Description

The IroSvA shared task is separated on three subtasks:

- Subtask A: Irony detection in Spanish tweets from Spain
- Subtask B: Irony detection in Spanish tweets from Mexico
- Subtask C: Irony detection in Spanish news comments from Cuba

For each subtask the organizers provided a collection of short texts about specific social and politic issues. For the Subtask A and B the datasets contain tweets about the administration of Mexico city, the theory of the flat Earth, the exhumation of the dictator Francisco Franco or the actions of some politicians. For the Subtask C, the organizers provided a collection of news comments especially about Internet services and economical problems in Cuba extracted from the news papers journals Cubadebate (`http://www.cubadebate.cu/`), Granma (`http://www.granma.cu/`) and OnCubaNews (`https://oncubanews.com/`).

Each short text (tweet and news comment) is annotated as ironic and non-ironic and contains the label of the referred topic. Below, Table 1 describes the composition of the released datasets.

Table 1. Composition of the datasets including information about data: the number of topics (N_topics) and genre of texts.

	Training set		Test set		N_topics	Genre of texts
	ironic	*non-ironic*	*ironic*	*non-ironic*		
Subtask A	800	1,600	200	400	10	Tweets
Subtask B	800	1,600	200	400	10	Tweets
Subtask C	800	1,600	200	400	9	News comments
Total	7,200		1,800			

For the classification of ironic and non-ironic texts, we employed for each variant a classical supervised machine learning approach exploiting a combination of stylistic, semantic, affective and lexical features, named SCoMoDI (Spanish Computational Models to Detect Irony). In particular, we used a simple SVM classifier with radial basis function kernel using the following parameters: $C = 5$ and $\gamma = 0.01$. The kernel and the parameters of the SVM classifier have been set on the basis of various experiments. Considering the imbalanced collection of data, we used the function to balance the weights of the classes provided by Scikit-learn library [34] for Python.

3.1 Features Engineering

In this section, we describe the features used to build the models of irony detection in the three variants of Spanish.

Lexical Features As lexical features we used unigrams of words weighted with TF-IDF (Term Frequency-Inverse Document Frequency) measure. To extract the unigrams, we pre-processed the texts deleting all symbols and numerical characters and selecting words using a tokenizer able to take into account the compound nouns. Finally, in order to weight the words without considering their inflectional morphology, we used the SnowballStemmer for the Spanish language provided by NLTK (Natural Language Toolkit) [7].

Stylistic Features Taking into account the corpora-based analyses carried out in [27] for English, French and Italian, we examined the impact of features such as hyperbole expressed by exclamation marks (!, ¡), ellipsis expressed by dots (...), questions denoted by question marks (?, ¿) and quotes expressed by inverted commas ("", ''). Considering the fact that some ironic texts could be characterized by a sarcastic tone against someone, we took into account also the typical symbol of mention in Twitter (@). In the features vector, these features are represented by a simple count of the number of times each item appears in the text.

Semantic Similarity Features In this group we gather semantic contexts and topic information. The semantic contexts of each text are computed calculating the cosine of similarity between the vocabulary of the text and the vocabularies extracted from each group of ironic texts labeled with the same topic. The cosine of similarity is calculated on the basis of pre-trained word embedding of the Spanish Billion Words Corpus (available at `http://crscardellino.github.io/SBWCE/`) provided by the authors of [9]. To lead the classifier to capture similarities between texts belonging to the same topic, we extracted the topic distribution of the text considering the number of topics of each subtask (see Table 1). To this purpose, we created the Latent Dirichlet Allocation (LDA) models on the provided training sets using Gensim library [37] for Python, taking into account also bigrams and trigrams of words. The idea is to gather the texts that talk about the same topic in a similar manner in the same class.

Affective Features We considered affective features exploiting different types of lexical resources for capturing different facets of affect.

Emotional Categories To identify the emotions involved in each text, we counted the number of words that belong to emotional lexica, such as the multilingual EmoLex provided by the authors of [31] and the Spanish Emotion Lexicon (SEL) provided by the authors of [42] and [36]. We considered for each variant only the emotions that are relevant for the classification. It is surprising that, for all the variants, the most significant emotions are negative, such as anger, fear, disgust and sadness.

Dimensional Models of Emotions In order to understand the mental responses to stimuli of ironic texts, we investigated the impact of psychological dimensions such as imagery, activation and pleasantness. Inspired by [40,21], we use an automatic translated Spanish version of the Dictionary of Affect in Language (DAL) [48]. From our analysis the dimensions that turned out useful for the classification in all the three variants are pleasantness and imagery.

Abusive Language Features Inspired by the work of [25] and considered the relevance of negative emotions, we analyzed also the impact of abusive language counting the words included in the Spanish lexica of derogatory expressions and profanities created by the authors of [17]. These lists of words prove to be significant for the classification especially in Mexican and Castilian tweets.

During the experimental phase, we used 5-fold cross validation on the training sets tuning the system on the metric used for the competition: the average of F1-scores of the classes. To study the impact of the described features, we carried out also the ablation feature test and, on the basis of these analyses, we created the models for each variant. The highest F1-scores values obtained with the relevant features are reported in Table 2.

Table 2. Experimental results on training data.

	Subtask A	Subtask B	Subtask C	Subtask A	Subtask B	Subtask C
Lexical Features	v	v	v			v
Stylistic Features						
hyperbole	v	v	v			v
ellipsis	v	v	v			v
question	v	v	v		v	
quotation	v	v	v			v
mention	v	v			v	
Semantic Similarity Features						
semantic context	v	v	v	v	v	v
topic information	v	v	v		v	v
Affective Features						
Emotional Categories						
anger	v	v	v		v	
fear	v	v	v	v		
disgust	v	v	v	v		
sadness	v	v	v			v
Dimensional Models of Emotions						
imagery	v	v	v	v	v	
activation	v	v	v			
pleasantness	v	v	v		v	v
Abusive Language Features						
derogatory expressions	v	v	v	v		
profanities	v	v	v		v	
F1-scores	45.57	47.69	50.12	**54.86**	**55.34**	**52.26**

4 Evaluation and Results

The organizers of IroSvA shared task provided four baselines calculated considering different representation of the texts. They used: n-grams of words (Word nGrams), word embeddings (W2V) and low dimensionality statistical embedding (LDSE) [35]. They used also the majority voting (Majority) technique as additional baseline.

As evaluation measure for the ranking the average of F1-score (avg) of all three variants is used. In Table 3 we report the results obtained in the competition compared with the provided baselines.

Table 3. Results obtained in the competition

	Subtask A	Subtask B	Subtask C	avg
Baselines				
LDSE	67.95	**66.08**	63.35	65.79
W2V	**68.23**	62.71	60.33	63.76
Word nGrams	66.96	61.96	56.84	61.92
Majority	40.00	40.00	40.00	40.00
Our approach				
SCoMoDI	66.52	55.74	**63.38**	61.88

As we can see, only the model built for the Cuban variant (Subtask C) overcomes slightly all the provided baselines, while the other models overcome only the Majority baseline. This difference could be due to the textual genre of news comments which do not contain Twitter mentions (@USER), hashtags or emojis. Another influential factor could be the use of a set of features able to capture characteristics such as unigrams that in general help the text classification.

5 Error Analysis and Discussion

Although the different genres of texts, analyzing the misclassified texts, we noticed that in all the three variants of Spanish the irony is expressed similarly. Actually, we individuated various figures of speech involved in the expression of irony. With the proposed models we aimed at capturing some of them by exploiting textual marks, but the error analysis highlights that it was not sufficient.

In particular, we found that hyperbole (examples 1) and ellipsis (examples 2) are expressed more at a semantic level. See, for instance, the following examples from the IroSvA test set where irony was not recognized:

(1) Felicidades director muy buena tarifa así se hace.
Congratulations director it is a very good rate, this is how it should be done.

(2) Cuando yo sea grande quiero ser como los inventores del paquete.
When I grow up, I want to be like the inventors of this offer.

As defined in [29], hyperbole is expressed by “exaggerated or extravagant terms used for emphasis and not intended to be understood literally”. In fact, the example 1 (from Subtask C) is a clear example of hyperbole that aims to exaggerate positively the actions of someone who is doing bad his work. The importance of hyperbole have been already underlined by [15] in irony and sarcasm detection.

We found this same phenomenon in the misclassified tweets of Subtask A (example 3) and Subtask B (example 4):

(3) @Maras70 @okdiario Te falta Pisarello, Echenique y nuestro gran concejal de tráfico el señor Grezzi.
@Maras70 @okdiario You miss Pisarello, Echenique and our fantastic city councillor of the traffic Mister Grezzi.

(4) El pueblo sabio y bueno salio a expresar su voz @lopezobrador_
The wise and good people came out to express their voice.

In the example 2 (from Subtask C), the irony is expressed by ellipsis. In [29] ellipsis is defined as “omission of a word easily supplied”. In this news comment, the author wanted to subtract, on purpose, some words containing information that could complete the meaning of the sentences. This subtraction is possible because of the presence of context that give us some intuition about the real meaning of the message. This same phenomenon is found especially in Subtask B (example 5):

(5) Será que le da clases particulares el @brozoxmiswebs
It is possible that he teaches him private lessons.

Unfortunately, the simple syntactic features that we used especially for Subtask C are not sufficient to capture these more complex puns based on semantic incongruity.

Another common linguistic phenomenon found during the error analysis in Mexican and Cuban variants is the use of apostrophe to stimulate the ironic interpretation of the message. In [29] the apostrophe is defined as action of “breaking off a discourse to address some person or personified thing either present or absent”, as we can see in the following examples extracted from the misclassified texts in Subtask B (example 6) and C (example 7):

(6) Con todo respeto señor presidente, le solicito atentamente que haga una auditoría al @ColegioNal_mx cuyos miembros se rayan y donde la mafia de Octavio Paz se ha instalado.
With all due respect, Mr. President, I kindly ask you to do an audit in the @ColegioNal_mx whose members benefit and where the mafia of Octavio Paz has settled.

(7) Y ahora es que usted se entera que la honestidad pasó de moda?
And only now you realize that honesty went out of fashion?

Moreover, the rhetorical questions seem to be one of the most used device to express irony in all the variants of Spanish. In [29] the rhetorical question is defined as question "which implies an answer but does not give or lead us to expect one". We noticed that although for Subtask B we took into account the presence of question marks, this expedient is not enough to classify correctly irony. Observe the following texts:

> (8) Cuando pedirán perdón Alemania e Italia a los Valencianos , por mandarnos a la Oltra y Grezzi ? https://t.co/MdFup1pbvu
> *When Germany and Italy will apologize to Valencians, for sending us Oltra and Grezzi? https://t.co/MdFup1pbvu*

> (9) Disculpa, sabes si para trabajar en el @Conacyt_MX ¿Debo llevar mi curriculum impreso o depilado?
> *Excuse me, do you know if to work at the @Conacyt_MX Should I bring my curriculum printed or shaved?*

> (10) Otra interrogante, por qué nadie fuera de Cuba ha denunciado que los cubanos violamos abiertamente los derechos de los productores de esas programaciones?? O será que el paquete ha venido a ser el primer "embajador" en el restablecimiento de las relaciones??
> *Another question, why anyone outside of Cuba have not declared that Cubans openly violated the rights of the producers of these programs? Or has the package become the first "ambassador" in the restoration of relations ??*

In the examples 8 (from Subtask A), 9 (from Subtask B) and 10 (from Subtask C) we can see that rhetorical questions involve also other figures of speech such as apostrophe (example 8 and 9) and metaphor (example 9 and 10) which fill the messages with various allusions, making its interpretation more difficult.

These observations suggest that there are some analogies on how Spanish speakers prefer to express irony. Moreover, some of these features have been already explored also in English, French and Italian ironic tweets [27]. Therefore, it seems that such kind of puns are in general characterizing the expressions of irony independently from the language and genre of the text.

6 Conclusions

In this paper we describe our participation at IroSvA shared task presenting an initial study on irony detection in the Spanish language. In fact, on the basis of the previous works in other languages, we analyzed the impact of various features on the classification of Spanish ironic and non-ironic texts. Moreover, the carried out analyses highlight some analogies and slight differences on the way users express irony in the three proposed variants. We observed that Spanish irony seems to be characterized by specific puns and especially by negative emotions. However, only Mexican and Castilian ironic tweets seem contain abusive language.

As future work, we planned to examine deeply the role that the topic and the context play in Spanish irony detection, proposing a comparison with a topic-independent approach. Moreover, considering our intuition about the use of similar figures of speech to express irony in different languages, we would like to compare multilingual data exploring their real impact in irony detection.

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