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CatSent: a Catalan sentiment analysis website

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Abstract
In this paper we investigate, analyze and compare sentimental analysis methodologies in Catalan tweets. The main goal is to develop a high-performance Catalan classifier. There are three main steps: Catalan language preprocessing tool, classification model and corpus training. The preprocessing tool is used for cleaning and extracting features from a document (or tweet). This is a key step due to the great morphological complexity of the Catalan language. The tool will remove empty words from the text and find the roots of other words. The classification algorithm will divide the tweet into "positive" and "negative" classes. To choose the best algorithm, five models are compared: Naïve Bayes, Maximum Entropy, Support Vector Machine, Decision Tree and Neural Networks. Finally, the corpus will be used for training and testing these methods. There is no known public corpus in Catalan, so we created one using a lexicon-based approach. This work aims to enable the tools to carry out sentiment analysis studies in the Catalan language. The last step is to develop a public web service with the best classification model achieved where users will be able to check its effectiveness.

Keywords Sentiment analysis · Natural language processing · Emojis · Catalan · Twitter

1 Introduction

Sentiment analysis [34], also known as opinion mining or emotion Artificial Intelligence (AI), is defined as the research field that studies computational opinions, feelings and emotions expressed in texts. The main goal is to systematically identify, extract, quantify, and study effective states and subjective information. Sentiment analysis aims to determine the attitude of a speaker, writer or other subject with respect to some topic or the overall contextual polarity or emotional reaction to a document, interaction, event, institution, government, etc.

Sentiment Analysis can be divided into two different learning methods: lexicon-based [11, 26] and Machine Learning [6, 18, 19, 25, 41]. In the one hand, in lexicon-based approaches, a

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piece of text message is represented as a bag of words. Following this representation of the message, sentiment values from a tagged dictionary are assigned to all positive and negative words or phrases within the message. A combining function, such as sum or average, is applied to make the final prediction regarding the overall sentiment of the message. In the other hand, in the Machine Learning approach, two learning types can be found [23]: supervised learning (Regression, Decision Tree, Linear, Rule-based and Probabilistic Classifiers) and unsupervised learning (Clustering, Anomaly Detection, Hebbian Learning and Learning Latent variable models, as example).

Due to the remarkable tool that the Twitter social network has become to know users' opinions about a variety of subjects in real time, many studies in this area are focused on this platform. The researchers in [13] present methods, apparatus, and computer-readable media for generating a website network graph to model one or more networks of websites relevant to subject matter of interest in a category that could be helpful. [37] presents a model with the *PoliTwi* tool that detects emerging political topics in Twitter sooner than other standard information channels.

This project is focused on binary classification of Catalan tweets (up to 140 Twitter messages) using different supervised learning models. Specifically, the algorithm models are Naïve Bayes [15], Maximum Entropy [24, 29], Support Vector Machine [7], Decision Trees [40] and Neural Networks [8, 16, 27, 39]. Since it is an initial approach to Catalan sentiment analysis, only classical models have been tested. Before testing different algorithms, data must be prepared and other preprocessing methods and tools must be implemented. Accordingly, the main goal of this project is not to test all the possible sentiment analysis approaches (classical and modern).

Due to the large number of frameworks offered for AI project development, most of the models chosen can seem misleadingly easy to implement. However, Neural Network models are relatively new in this area and adapting a model for this project could prove difficult, although it would be of interest to test and compare these models with the same labeled tweet-corpus.

Moreover, this paper aims to be a first step for sentiment analysis in Catalan. The main contribution is the study of the state of the art of the Catalan morphological analysis and the tools that can be used for sentiment analysis purposes. The project also presents a Catalan labeled corpus from which other studies can start.

To date, there is no known Catalan sentiment analysis study, the main aim of this work. In this sense, an important contribution is the method presented for text (tweet) preprocessing by applying studies of Catalan vocabulary and grammar. This consists of a morphological analysis, where infected (or sometimes derived) words are reduced to their stem, base or root form to achieve better results. Next, we tackle the construction of a valid and annotated Catalan corpus. We use this corpus to compare the performance of the most popular supervised classifiers applied to such a corpus in other languages as English [6, 18, 19, 25, 41], Spanish [10, 22, 33, 35] or Arabic [1]. Then, we will be able to compare Catalan, Spanish and English sentiment analysis performance based on supervised classifiers.

This project also aims to make an initial sentiment analysis website in Catalan, using the classification model which performs best. Then, the model obtained will be integrated into a public API to be used freely as a *Python* library.

Due to the lack of an annotated corpus in Catalan, it is very important to create one valid and large enough to achieve good results. Moreover, Twitter does not tag Catalan tweets, so the sentiment analysis procedure firstly obtains tweets geolocated somewhere in Catalonia.

Then, only those written in Catalan are selected (an external Catalan detection service will be necessary). Finally, these tweets are classified using a lexicon-based approach classifier and removing all tweets that do not have a clear polarity. The first two steps have already done in the #eMOVIX [12] project, where more than 1500 million Catalan tweets were stored in a 5TByte database. Our work focuses on the lexicon-based classification step using a subset of those tweets.

All the tools, code, dictionaries and corpus used for this project are available in the project *GitHub* Repository[1] and in the *API* Repository[2].

2 Related work

Here we brie y discuss examples of past research in sentiment analysis engines. Many studies have been developed to improve classification tools and propose new ones (basically for English and Spanish). For the lexicon-based approach, A. Moreo et al. [26] proposed a system that consists of an automatic Focus Detection Module and a Sentiment Analysis Module capable of assessing user opinions on topics in news items. In [11], a set of new feature selection schemes was proposed that use a content and syntax model to learn a set of features in a review document automatically. Furthermore, [36] also presents a detailed sentiment analysis methodology for generating a first sentiment score for a first entity based on a content source.

Furthermore, many researchers have studied classification models with different scenarios. In 2012, Marilyn A. Walker et al. [41] worked on classifying stance in on-line political debate. Peter C.R et al. [19] explored the effect of using five different types of features, classifiers and corpora.

Neural Networks are also very present in some projects. In [6], machine learning-based tools for the classification of personal relationships in biographical texts and the induction of social networks from these classifications was developed and tested. They used Support Vector Machine and Neural Networks during the project. In [25], Artificial Neural Networks, Naïve Bayes and Support Vector Machine methods were used for empirical comparisons between them.

With the continuous evolution of social networks, new and improved features have been added to sentiment analysis. Recently, Emojis are a new research focus of interest. For example, in 2017, the authors in [18] used Naïve Bayes and Maximum Entropy in combination with emojis, with the aim of providing companies with a clear idea of what customers really think about their brand.

The latest research projects in sentiment analysis are basically focused on Neural Networks. Researchers in [8, 16, 27, 39] tested Neural Networks in the sentiment analysis area using such different layers and methods as Associative Neural Networks, Convolutional Neural Networks and Recurrent Neural Networks. However, the main objective of these algorithms is more expensive processes like image processing.

Moreover, there are some multilingual sentiment classification studies where different languages are supported by a single model. These approaches present a very interesting point of view since, due to the Internet, all the world is immediately connected and many different

[1] GitHup repository: https://github.com/pbalaguer19/catalan-sentiment-analysis
[2] API repository: https://github.com/pbalaguer19/catsent-api/

languages coexist. On the one hand, [30–32] are good multilingual sentiment classification approaches using different languages. On the other hand, [3] studies the multilingual sentiment analysis for Basque and Catalan hotel reviews and [4] presents a project where Catalan and Spanish tweets debating about Catalan elections are analyzed by using multilingual sentiment analysis approaches, which offers novel views on how to study and understand communication in political debates.

In [21], the authors studied sentiment polarity detection in Spanish reviews combining supervised and unsupervised approaches. Luciana Dubiau et al. [10] evaluated the performance of Naïve Bayes, Support Vector Machine, Maximum Entropy, Decision Tree and Turney Polarity (non-supervised), the best results being achieved with Bayesian Networks methods. Furthermore, Eugenio Martínez et al. [22] achieved better results with the Support Vector Machine in sentiment analysis in movie reviews (using the review punctuation as the sentiment label).

In 2015, Ferran Pla et al. [33] presented a model based on Twitter in TASS (an evaluation workshop for sentiment analysis focused on Spanish). Finally, we highlight the work done in [35], where Naïve Bayes, Support Vector Machine and Decision Tree were tested on movie reviews. All of them achieved good results.

Moreover, language processing tools can be applied to other fields and sections, such as [14] that presents a machine learning processing for automatic keyword extraction approach for personalized health activities, or [38], with the project: automatic emotion-based music classification for supporting intelligent IoT applications.

3 Methods

This section briefly describes the methodology used. The technology used during the project is explained, as are the main design and programming criteria for the web server and, finally, how the classifier models work. The corpus used, the tweet preprocessing module and the website are also described, as is the API web service.

3.1 Technology

From among the large number of frameworks offered for AI project development, *Python* 2.7 was selected as the programming language. The *Django* framework and its *RESTful API* toolkit, *Django Rest Framework*, were also used for web-service creation.

The tweet preprocessing functions (basically for cleaning and feature extraction) used a list of Catalan stopwords and the synonym corpus described in Data section 3.2. Then, the *Freeling* framework [28] was used for the morphological study.

For the classification models, *NLTK* [20] and *sci-kit learn* [5], an open source machine learning software package for Python development were used. The packages used for scientific computing and data structured design were *NumPy*[3] and Pandas[4] which provide a fast, flexible, and expressive data structure.

TensorFlow[5], an open-source software library for machine learning was also used for Neural Network development.

[3] NumPy: http://www.numpy.org

[4] Pandas: http://pandas.pydata.org

[5] TensorFlow: https://www.tensorflow.org

3.2 Data

The tweets were collected from the *#eMOVIX* [12] project database, where tweets from around the world were sampled. We specifically used the Catalan subset obtained from an external language detection service[6]. This corpus needed to be labeled, so we used a lexicon approach based in an *ML-SentiCon* [9] file, where a large list of Catalan words is classified into positive and negative labels. This file also contains a sentiment classification of the most informative emojis [17] and their polarity. Table 1 shows some examples of Catalan words already classified by *ML-SentiCon* project and Table 2 shows some examples of the ranking of emojis, labeled by [17]. Based on this, the polarity of each tweet (defined by the formula (1)), and its value is the label of the final corpus. So, the final (Catalan) corpus used for training and testing the classifier models, which is 5.29 MB in size, contains 50,000 tweets, labeled in two categories: negative (0) and positive (1). Note that the Catalan tweets were classified into a binary classification (positive or negative) due to the models tested, since there are some approaches that only support binary labels. Also note that the corpus had some limitations since its generation was based on a lexicon approach.

The Corpus quality was obtained by using 500 random tweets (250 from the positive label and 250 from the negative label). Table 3 shows the results obtained.

The AnCoraVerb [2] dictionary was used for synonym detection (see Section 3.3).

Final corpus is available on the project *GitHub* Repository[7].

3.3 Operation

Algorithm 1 (in pseudo-code) explains the operating mode for training and testing each classifier model. There are two main steps: the first one is the preprocessing of each tweet and the second involves training and testing.

Algorithm 1 Classifier.

```
function Classifier
    /* PREPROCESSING STEP */
    for each tweet, sentiment in Corpus do
        tweet = remove twitter elements(tweet)
        tweet = find synonyms(tweet)
        tweet = remove stopwords(tweet)
        tweet = remove punctuation(tweet)
        tweet = morphological analysis(tweet)
        tweetList.append(tweet, sentiment)
    end for
    /* TESTING STEP */
    Training Corpus, Test Corpus = divide corpus(tweetList)
    for each train tweet, sentiment in Training Corpus do
        classifier.train(train tweet, sentiment)
    end for
    for each test tweet, sentiment in Test Corpus do
        classifier.test(test tweet, sentiment)
    end for
    classifier.getMetrics()
end function
```

[6] Language detection service: https://detectlanguage.com

[7] Project on Github: https://github.com/pbalaguer19/catalan-sentiment-analysis

Table 1 Some examples of Catalan labeled words used for lexicon-based classification

Word	Polarity
Apreci	0.625
Afortunat	0.75
Dolc	0.55
Abatut	−0.344
Angoixar-se	−0.687
Cruel	−0.417

polarity <0 (polarity >0) is considered a negative (positive) word.

The first loop focuses on the preprocessing step. Preprocessing is responsible for modifying the input data in order to improve the performance of the classifier. This step can be divided into different tasks:

1. remove twitter elements deletes user names (@USERNAME), hash tags (#hashtag) and URLs (http://...).
2. find synonyms unifies all words with the same meaning in the same word (one of them, randomly chosen).
3. remove stopwords deletes all the words that are in the stopword corpus.
4. remove punctuation removes all punctuation marks.
5. morphological analysis (also known as stemming) reduces infected (or sometimes derived) words to their word stem, base or root form. Section 3.1 describes the stemming module used for this step.

Different data resources were used in the preprocessing step. The *AnCoraVerb* [2] project offers a corpus that can be used for the Catalan synonym detection. We modified this corpus by adding the most common misspellings. The preprocessing step also performs the stopword extraction function to delete words that do not contribute to the sentence (stopwords). To detect these, we used the *Ranks* NL[8] and LaTeL[9] corpora, putting them together in one file. Therefore, finally a dictionary with 736 Catalan stopwords which can be deleted was finally obtained.

Table 4 shows some tweets before and after pre-processing. Note that user names have been replaced by "username" to preserve their anonymity.

In the training and testing step, we first divided the cleaned corpus into two different lists (with function divide corpus). The Training Corpus represents 75% of the total (37,500 tweets) and will be used for training the classifiers. The remaining 25% was used to test the classifier accuracy and obtain its performance (Test Corpus).

Once the corpus had been divided, each classifier was first trained in order to evaluate it. After finishing the evaluation, the last step was to show the obtained performance (described in section 3.6).

Once the model with better performance was found, 100% of the corpus was used to train it. The model obtained was used in the web application and its API.

[8] Ranks NL: http://www.ranks.nl/stopwords/catalan

[9] LaTeL: http://latel.upf.edu/morgana/altres/pub/ca_stop.htm

Table 2 Some examples of labeled emojis used for lexicon-based classification

Emoji	Polarity
😂	0.221
❤️	0.746
😄	0.421
😩	-0.368
😭	-0.093
😒	-0.374

polarity <0 (polarity >0) is considered a negative (positive) emoji

3.4 Corpus creation

After the lexicon corpus had been obtained (see section 3.2), the development of a simple lexicon-based approach for the corpus classification was easy. Given a tweet, its polarity P is calculated following formula (1).

$$P = \left(\sum_i pe_i\right) + \left(\sum_j ps_j\right), \tag{1}$$

where i is the number of emojis and j is the number of words contained in the text. Therefore, pe_i represents the sentiment of the emoji [17] and ps_j is the polarity of the word based on the ML-Senticon lexicon-approach of [9].

Note that both pe and ps can be any number between −1 and 1. Negative and positive numbers mean negative or positive sentiment respectively. Due to the importance of obtaining correct classifications, all emojis with $|pe_i| < 0.2$ and words with $|ps_j| < 0.3$ were discarded. In addition, tweets with $|P| < 0.2$ were also discarded. These decisions improved the quality of the corpus.

3.5 Sentiment model

3.5.1 Naïve Bayes

The Naïve Bayesian classifier works as follows. Suppose that there is a set of training data D, in which each tuple (in our case tweet) is represented by an n-dimensional feature vector, $X = x_1, x_2, \ldots, x_n$, corresponding to n measurements of attributes or features. Assume that there are m classes, $C_1, C_2, \ldots, C_m$ (in our case, there are two classes: positive and negative, so $m = 2$). Given

Table 3 Quality of training and testing corpus

Corpus	WCC	BC	SP	OL
Tweets	96.6%	3.4%	5.4%	2.8%

Percentage of Catalan tweets well-classified (WCC), badly-classified (BC), and those in Spanish (SP) and other languages (OL).

Table 4 Examples of tweet preprocessing

Tweet	Preprocessed tweet
Poca broma, fa 10 minuts era fins es llit i ara a sa peluqueria.	broma minut llit peluqueria
@USER Vaig publicar-ho al moment en que jo hi era;) te bona pinta, eh?	publicar el moment tenir bo pinta eh
Enhorabona @USER. Molt content per tu i tambe x @USER i els seus gols.	enhorabona molt content tambe x gol
Heu d ser claus per la proxima temporada	d clau proxima temporada
Casal d'Estiu 2016 i Curs d'Informatica a #Corbins! https://t.co/fQ9Y69hJ0S	casal estiu curs informatic corbins
Ahir va ser el dia mundial de l'ELA i des d'@esquerratortosa	dia mundial donar suport
vam donar tot el nostre suport #fesungestperlela https://t.co/1uOlQUF1z8	fesungestperlela

The first column contains the input text while the second displays the preprocessing-step output.

a tuple X, the classifier will predict that X belongs to C_i if and only if: $P(C_i|X) > P(C_j|X)$, where i,j ∈ [26, 34] and $i \neq j$. $P(C_i|X)$ is defined in formula (2).

$$P(C_i|X) = \prod_{k=1}^{n} P(x_k|C_i) \tag{2}$$

3.5.2 Maximum entropy

Maximum Entropy is a discriminatory classification model where the documents are described as a list of attributes, each being a constraint model. This model is based on selecting the probability distribution that satisfies all constraints and maximizes entropy. The classification probability is obtained as follows:

- For each word w and class $C_i \in C$ there is a joint feature $f_i(C_i,w)$, defined as the number of times that w occurs as class C_i.

- Via iterative optimization, a weight (λ_i) to each joint feature so as to maxi-

mize the log-likelihood of the training data is assigned.

- Given a document X and weights, the probability of class C_i is defined in formula (3).

$$P(C_i|X) = \frac{e^{\left(\sum_i \lambda_i f_i(C_i,X)\right)}}{\sum_{c' \in C} e^{\left(\sum_i f_i\left(c',X\right)\right)}} \tag{3}$$

3.5.3 Support vector machine (SVM)

The Support Vector Machine (SVM) is a supervised binary classification method. The training of this method is to find a hyperplane[10] that separates the vectors of attributes

[10] In geometry, a hyperplane is a division of a space into two parts

that represent different datasets into groups, these being the highest possible separation. The vectors that define the limits of the maximum separation between the classes are called support vectors. The classifier is based on formula (4) to predict the most likely class given to a document.

$$f(x) = sign\left(\sum_i \alpha_i x_i \cdot x + b\right), \tag{4}$$

x being the attribute vector (or features) of the document to be classified, α_i the weights of the vector attributes, x_i each support feature and b the independent term. The value −1 indicates that the document belongs to a class and the value +1 to the other, representing the hyperplane side of x.

3.5.4 Decision trees

Supervised classification method where the training goal is to build a decision tree with multiple paths. Each node searches for the attribute information that provides higher profits for its representing class. The tree grows to its maximum size and then is pruned to improve its performance. From this model, we can add decision rules about which classifiers it will be based on.

3.5.5 Neural networks

We used a deep convolutional neural network. Our approach is based on the approaches proposed by Kim [16] following the "Implementing a CNN for Text Classification in Tensorflow" *blog* post[11] and its simplified implementation *GitHub* repository[12].

This slightly simplified implementation works as follows: the first layer embeds words into low-dimensional vectors. The next layer performs convolutions over the embedded word vectors using multiple filter sizes. For example, sliding over 3, 4 or 5 words at a time. Next, we max-pool the result of the convolutional layer into a long feature vector, add dropout regularization, and classify the result using a softmax layer.

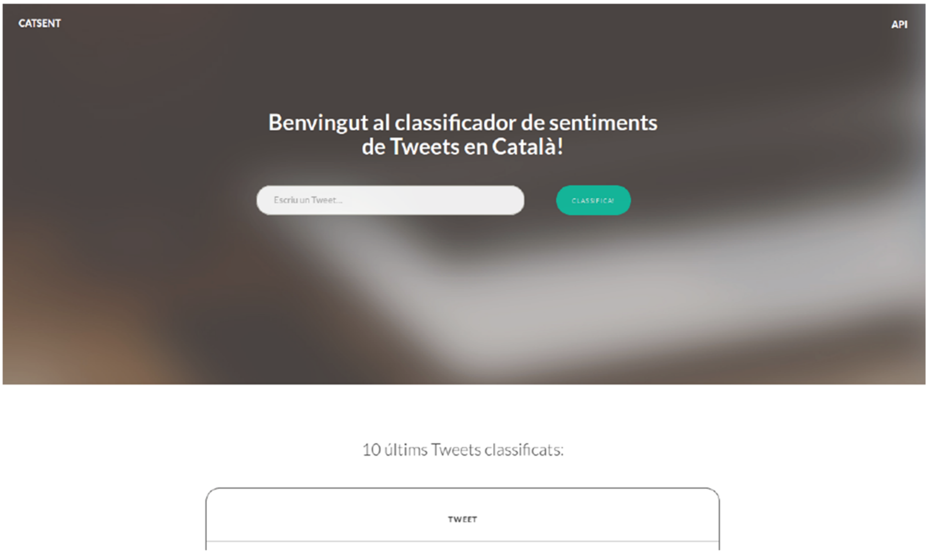
3.6 Performance metrics

The behavior of the classifiers was evaluated by calculating the Precision, Recall, and F-score of each model.

Precision measures the fraction of true positives among all positive predictions made by the method. *Recall* (or specificity) measures the fraction calculated by dividing the number of correct choices by the total number of choices available to the model. *Precision* and *Recall* are

[11] http://www.wildml.com/2015/12/implementing-a-cnn-for-text-classification-in-tensorflow

[12] https://github.com/dennybritz/cnn-text-classification-tf


Benvingut al classificador de sentiments de Tweets en Català!

10 últims Tweets classificats:

Fig. 1 CATSENT website interface

defined in formulas (5) and (6) respectively. *tp* (true positives) is the number of correctly predicted positive tweets, *fp* (false positives) is the number of negative tweets incorrectly predicted as positive and *fn* (false negatives) is the number of positive tweets that are incorrectly classified as negative. The *F-score* is an aggregate measure of the accuracy of a classifier that calculates a weighted average of *Precision* and *Recall* as defined in formula (7).

$$Precision = \frac{tp}{tp + fp} \tag{5}$$

$$Recall = \frac{tp}{tp + fn} \tag{6}$$

$$F\text{-}score = 2\frac{Precision \cdot Recall}{Precision + Recall} \tag{7}$$

Table 5 Naïve Bayes results

Naïve Bayes	Precision	Recall	F-score
Negative	81%	81%	81%
Positive	81%	82%	82%
Total	81%	82%	81%

Table 6 Maximum entropy results

Maximum Entropy	Precision	Recall	F-score
Negative	81%	80%	81%
Positive	80%	82%	81%
Total	81%	81%	81%

3.7 Web service and API

Web service will be created after testing all classifiers. This website will enable users to test the chosen model. There will be an input box where users can write a tweet and the website will return its polarity. There will also be a list with the last 10 classified tweets. Figure 1 shows the interface design of the described website.

The web service also offers an API where GET and POST HTTP methods can be called up. The GET Method returns a list of last classified tweets in JSON format. The POST method requires a tweet in the body section. The API will return the sentiment label of this tweet.

The services described are available at http://catsent.udl.cat/.

4 Results

Five models were tested and evaluated to find the best results. These were Naïve Bayes, Maximum Entropy, Support Vector Machine, Decision Tree and Neural Network.

All the frameworks used offer the chance to train and evaluate a given corpus. Therefore, the hardest job was to fit the corpus to each model since each framework required a different data format.

The tests were performed on a virtual machine with 4 Gigabytes of RAM with which the average execution time was high (about 2 h). All tests that exceeded a 10-h execution time were overlooked because they were considered too heavy. The following sections show the results and the analysis of each model.

4.1 Naïve Bayes

Due to the flexible and easy model that *NLTK* toolkit offers for Naïve Bayes (NB) classifier, it was established as the framework used for this algorithm. Table 5 shows the results obtained for this classifier.

Table 7 SVM results

SVM	Precision	Recall	F-score
Negative	74%	75%	75%
Positive	74%	73%	74%
Total	74%	74%	74%

Table 8 Decision tree results

Decision Tree	Precision	Recall	F-score
Negative	57%	97%	72%
Positive	89%	26%	41%
Total	73%	62%	46%

4.2 Maximum entropy

The *NLTK* toolkit was also used for this model, given the similarity between the Naive Bayes and Maximum Entropy (ME) algorithms. The difference between these two models is that the features are independent in Naïves Bayes but not in the Maximum Entropy. In other words, Maximum Entropy establishes a relation between the features. Table 6 shows the evaluation results.

4.3 Support vector machines

The *sci-kit learn* toolkit was established as the framework for Support Vector Machine (SVM) algorithm, and more specifically, the linear implementation was *LinearSVC*. The results of the tests are shown in Table 7. Better results were expected for this model and it is thought that the default parameters may influence these.

4.4 Decision tree

The Decision Tree (DT) model was also implemented with the *sci-kit learn* toolkit. In this case, tests were carried out for different tree depths, between 2 and 100. The highest performance scores were obtained with depth 16. The performance increased until depth 16 but then went down when the depth increased beyond 16. Table 8 shows the metrics performance percentages for this model.

4.5 Neural network

The implementation of the Neural Network was hardest due to its complexity and combinations. Finally, a *Github* repository[13] was found with a simple and editable code. Due to its simplified algorithm, the results were not as good as expected but they can be improved with more tests. The execution time in this case was around 8 h and the results are shown in Table 9.

4.6 Discussion

Table 10 shows a comparison between the classifiers studied where the Naïve Bayes and Maximum Entropy models performed best.

The performance of the Neural Network model was unexpectedly poor, since it required a long training time and the Precision was greater in the original paper in

[13] https://github.com/dennybritz/cnn-text-classification-tf

Table 9 Neural network results

Neural Network	Precision	Recall	F-score
Negative	80%	73%	77%
Positive	75%	81%	78%
Total	78%	77%	77%

Table 10 Summary of the classifier results

Classifier	Precision	Recall	F-score
Naïve Bayes	81%	82%	81%
Maximum Entropy	81%	81%	81%
SVM	74%	74%	74%
Decision Tree	73%	62%	46%
Neural Network	78%	77%	77%

English. Nevertheless, note that training and testing algorithms with tweets give less information to the model than reviews or documents as tweets only have 140 characters. Notably, some of the most informative features were emojis. The addition of emojis into social networks can greatly help the tasks of sentiment analysis, expanding the possibilities and improving the old ones.

The Naïve Bayes and Maximum Entropy methodologies are very similar and that is why their results are also close. The same framework was used for these models and this may be another reason for the similarity in performance. The SVM and Decision Tree presented the worst results. SVM gave poor results due to its configuration settings. However, the results obtained are considered good because there is no known previous study of this area in Catalan and therefore the time spent on other steps increased.

Table 11 shows a comparison between Spanish, English and the results obtained. For Spanish performances, precision from [10] was used. English column uses the best performances from [19, 27, 29, 40]. There is higher performance from Spanish and English than the ones obtained. However, these languages have been studied and tested for a long time. In our case, this is the first known study in the area of Sentimental Analysis in Catalan.

The corpus used has a low error rate due to the great restrictions (only clearly positive or negative tweets are part of it). The preprocessing step works well but takes a lot of time. The task that requires the most time is the substitution of synonyms, so it should be studied whether this is worth leaving or removing.

Table 11 Comparison between Catalan, Spanish and English precision performances

Classifier	Catalan	Spanish	English
Naïve Bayes	81%	95%	88%
Maximum Entropy	81%	95%	78%
SVM	74%	95%	95%
Decision Tree	73%	88%	80%
Neural Network	78%	–	86%

In summary, creating the corpus and input-data preprocessing tool was a good job but there is always room for improvement. In the classification models, it is convenient to test new algorithms, do more tests and compare them.

The classifier used for the web server will be the Bayesian network model since it had the best results. In addition, the model on the website will have 100% of the instances to train. So, its performance should be higher. The server will offer a graphic interface and also a RESTful[14] API with GET and POST methods.

5 Conclusions and future work

Catalan Sentiment Analysis is presented in this project. The three main steps are corpus creation, preprocessing tool development and classifier model testing. The model with the best performance metrics is used for the web application service, which offers a user-friendly interface and also a RESTful API. The main contribution of this work lies in the first public classifier in Catalan and the fact that this classifier is able to create new and better corpora for future projects. We also collected many Catalan resources for Sentiment Analysis that can be of great help for new studies.

There are three main issues that need to be solved in future work. First of all, the runtime for the tests is very long due to the preprocessing step. The second challenge is to improve the performance percentages, trying to achieve at least 90% Precision. Also, the last pending issue (and probably the hardest one) is to have a spellchecker for preprocessing since it is very common to find many misspellings. To improve the first issue, a cleaning module would only run once. Another approach might be to prioritize the preprocessing tasks and remove the lowest priority ones. The challenge of achieving a precision greater than 90% can easily be achieved with more tests, models and different corpora.

Including a spellchecker before training model classifiers could greatly help to improve performance since it is very common to find mistakes or abbreviations in some words. However, Catalan is very complex and it is difficult to obtain a good spellchecker and know the correct word. Accents, apostrophes, dialects and irregular verbs are some aspects of the high complexity of Catalan.

Since this is an initial approach to sentiment analysis in Catalan, the performance of this model should be discussed and tested in other environments. Moreover, due to the binary classification of the output sentiment, it is very difficult to find a practical application for the model. However, it is a very important initial step in order to encourage more projects in this direction.

In summary, we will continue with a deeper analysis of the corpus and the preprocessing step to try to improve its quality. Next, we will create new corpora with other methods to have more tests available. Finally, we will apply these two previous steps to different classification algorithms with better hardware and longer testing time.

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[14] RESTful Web services are one way of providing interoperability between computer systems on the Internet.

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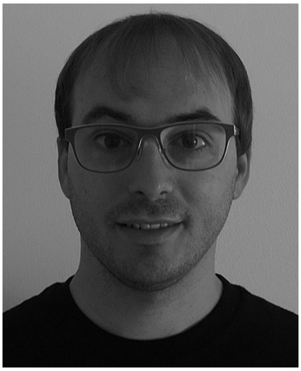

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