Approval Rating of Peruvian Politicians and Policies using Sentiment Analysis on Twitter

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***Abstract*—Nowadays, using the social network Twitter, a subject can easily access, post, and share information about news, events, and incidents taking place currently in the world. Recently, due to the high number of users and the capability to transfer information instantly, Twitter had attracted the interest of politicians with the goal to interact with their followers and to communicate theirs polices. Fearing the disagreements and disturbances that the application of some policies might cause, usually politicians use surveys to support their actions. However, such studies still use traditional questionnaires to recover information and are costly and time-consuming. Recent advances in automatic natural language processing have allowed the extraction of information from textual data, like tweets. In this work, we present a method to analyze Twitter data related to Peruvian politicians and able to score the latent sentiment polarity of such messages. Our proposal is based on an embedding representation of tweets, which are classified by a convolutional neural network. For evaluation, we collected a new dataset related to the current President of Peru, where the model achieved 91.2% of sensibility and 94.4% of specificity. Furthermore, we evaluated the model in two politic topics, that were totally unknown for the model. In all of them, our approach gives comparable results to renowned Peruvian pollsters.**

Keywords*—*Twitter data analytic; sentiment analysis; Peruvian politicians; approval rating; convolutional neural networks

I. Introduction

Nowadays, it is undeniable that social networks are playing an increasing role of importance in the dissemination of information. Daily, millions of people around the world access to social networks to share information and to communicate. A social network is an internet-based application that allow people to communicate between their families, friends, colleagues, circles of interest, and followers [1]. Actually, there are many social networks and usually they are oriented to specific topics, e.g., news, entertainments, movies, podcasts, professional networks, relations, etc.

Among social networks to disseminate news, Twitter registers the highest daily activity and popularity. In Twitter, a subject can easily share short messages or tweets about current events, that can be accessed by to tens of thousands of people. A subject can also reply and discuss the messages, contributing the message to become “viral”. These short messages of at most 280 characters, also named tweets, can be accompanied by a few photos and a short video. According to the report in [2], more than of 500 million of tweets are published in a day, which highlight the importance of Twitter in people’s day-to-day communication.

Due to high popularity of Twitter and its capability to transfer information between ten of thousand people instantly, social leaders, influencer, politicians, companies, and governments have started using this social media to interact with their followers, clients, political adherents, and citizens. Once a subject gets registered in the social network, he can send and receive tweets and participate into virtual communities of his interest.

Recently, many investigations are being done aiming to analyze the stored data in social networks automatically [3]. However, the large amount of data and its non-structured nature still challenges the proposed methods [4]. The research objective is to discover hidden patterns into data and forecast trends in order to make decisions. Among the diversity of topics, the analysis of posts related to politicians becomes a hot topic of study, where the goal is to predict the approval rating of an important politician (e.g. the president, the prime minister, and others) or to measure the people satisfaction related to government policies carried out. This makes sense, actually, many governments are concerned about their approval rating. A high approval rate indicates a successful and healthy govern, both for their own citizens and foreigner’s eyes. In contrast, a low approval rate reflects a weak govern, without major importance for people, even with detriment for the state itself.

Despite the social media network offers a rich source of information, studies of approval rating of politicians still reside on traditional paper-based questionnaires, which are too slow, time-consuming and expensive studies. On the other hand, an automatic analysis system offers an agile and less expensive manner to predict approval rating. Recent advances in Natural Language Processing (NLP) had produced the technique of sentiment analysis [5]. Sentiment analysis enables to gain insights of opinions in published tweets related to a particular discussion topic [6]. Furthermore, sentiment analysis can help to reveal the psychological and mental state of the subject who wrote a particular tweet, the emotional state, level of education, and others features [7].

In this work, we present a method to predict the approval rating of politicians based on Twitter data, focusing specifically to forecast the popular endorsement the President of Peru. The proposed model consists of an embedding representation, followed by a Convolutional Neural Network (CNN). The embedding is itself a neural network pretrained in one billion of Spanish words [8]. The model is able to learn a rich diversity of tweet messages and classify them according to their sentiment polarity content, as positive/negative or approval/disapproval. Positive and negative outcomes are weighted according to the number of messages that were fed in the model to provide the final approval or disapproval rate. The model was designed to be political agnostics, so it was trained once and tested in multiple politic topics. To evaluate the model, a new dataset of 1150 tweets was collected. Collected messages include tweet posted in Spanish related to the current President of Peru, Pedro Castillo, that were retrieved from August 2021 to February 2022. Data was manually labeled as of positive or negative sentiment, resulting in a balanced dataset.

For evaluation, the model was assessed in a hold-out validation manner, with a ratio 80:20. Testing the ability of the model to predict the approval rating of the Peruvian president, it outputs 91.2% of sensibility and 94.4% of specificity. Due to the large corpus of the pretrained embedding layer, data augmentation was not required during training. Furthermore, to assess the model agnostic feature, a new data was collected in April 2022 about two widely discussed policies in that month: the approval/disapproval rating of the Peruvian Congress and the agreement/disagreement with a new State Constitution. The model, without further training, predicts 84.0% of disapproval rating for the Peruvian Congress and 75.0% of disagreement with a new State Constitution. Comparing the obtained results against those reported by the specialized Peruvian pollsters, the model predictions correlate to the pollsters' issues. Therefore, the proposed method can be offer as an on-demand tool for text message analysis in social networks.

The remainder of this paper is organized as follows. Section II presents fundamental concepts of sentiment analysis. Section III outlines the literature review related work. Section 4 explains the proposed method. Section V details the experimental results and discussions. Finally, Section VI presents conclusions and future work.

II. Fundamentals

A. Sentiment Analysis

Sentiment analysis or opinion mining is a method into the field of NLP to teach machines to learn, detect and recognize emotional and sentimental information from a given text message [9]. Given an opinion, sentiment analysis can extract its meaning, sense, and emotional charge of the subject who wrote it. Usually, input data for opinion mining consists of text messages stored in structured spreadsheets or in unstructured repositories, such as, text document, web pages, web forums [10].

A common way to detect the sentimental charge of messages is to classify them into categories according their satisfaction or agreement scores. Typical categories can be positive, neutral, or negative sentiment, reflecting a higher satisfaction, none, or dissatisfaction of the subject related to the studied variable [11], [12]. There are many applications using sentiment analyses techniques in the social domain, including the recommendation systems [13], movie reviews [14], identification of cyber-aggression [15], racism [16] and violence against women [17].

B. Twitter

Twitter is a messaging service in which subjects can post and interact by means of short messages or tweet [18]. Tweets consist of written opinions related to current topics of interest and can be used as a source of news and information for decision making [19]. Actually, Twitter is the social network most used by politicians because its capability to allows them to communicate massively with thousands of millions of followers [20].

C. Politician's Approval Rating

In the last decades, it has become a common practice for governments and politicians to know the opinion of people and citizens regarding their activities, decisions, and execution of policies. Such opinions are quantified and presented as a score of popular agreement or disagreement, approval or disapproval, named as approval or favorability rating.

In order to know a reliable approval rating of some politician or a government policy, specialized polling companies carry out statistical surveys in a population sample. Although these studies are reliable, they might present a delayed snapshot of the opinions of people, which are daily changing because of the massive use of communications. As an alternative, opinion mining in Twitter seems to work well like an approval rating method, as presented in Section II-A.

In this work, we study the approval rating of the president of Peru, which is presented monthly by some polling companies. This endorsement rating reflects the citizen's satisfaction related to the work of the government and the implemented policies for the country development. These ratings have many implications: it indicates the aptitude of politicians and the impact of medium and long term polices, reveals the economic strength and politic stability, and the lack or weakens of policies. Therefore, the approval rating becomes an important indicator for decision making for external agents, foreign investors, local entrepreneurs, and Peruvian citizens.

Monthly, historical approval ratings are consolidated in chart plots by several Peruvian polling companies [21], [22], [23], [24]. These results are used for making other studies and forecasting the trend curve. Downward trends indicate bad news: a government weakness and failures in the implementation of policies. For a developing country like Peru, it means capital flight, recession, economic instability, rising unemployment, and disinvestment [25].

III. Literature Review

The study of [26] concluded that there are high limitations when working with text data originated on Twitter, being the presence of colloquial lexicon, informal syntax, short structure, context-dependent and dynamics nature of messages are the major challenges for mining opinion [3]. NLP methods intend to solve that issues and discover meaning in human utterances and translation [27]. Moreover, the recent rising of deep learning methods in NLP has boost the Sentiment Analysis field [28], with the goal to discover the meaning of an opinion, its context and sentimental charge.

As follows, we summarize the most relevant works related the topic investigated in this study:

The study of [29] compared a supervised learning model against a simple voting algorithm to classify tweets into three categories (positive, negative, and neutral). First, the tweet sentence is split into words (or token). Next, words are scored according to a lookup table of 2014 positive and 4783 negative words. Each positive word adds one to the sentence score, in contrast each negative word subtracts one to sentence score. The amount of positive words minus the amount of negative words provide the sentiment score of a tweet message. For classification, the voting algorithm just take in account the final score of the tweet: if the score is greater than zero, then the sentence is classified as positive; if the score is zero, then the sentence is negative; otherwise, the sentence is neutral. Following the same criteria, using a dataset of 1500 tweets, they trained a Naive Bayes (NB) classifier, achieving an average accuracy of 81%, against 74% using the simple voting algorithm. The major limitations of this work is that the scoring is strong dependent on the number of words in the lookup table.

Later, the work of [30] applied sentiment analysis in order to know the political opinions of citizens in the Indian electoral process of 2019. They proposed sentiment-based classification model to predict the electoral results. First, a dataset of 3896 tweets were collected from Twitter taking in account the two most popular political parties. Preprocessed messages were classified using the Long Short-Term Memory (LSTM) neural network, achieving a F1-Score of 0.74. In comparison against traditional machine learning (ML) methods, although relatively slow during inference time, LSTM outperforms such other methods.

The study of [9] collected data from Twitter aiming to predict the Congress election outcome in India by using sentiment analysis. To label tweets, they used the Valence Aware Dictionary and Estiment Reasoner (VADER) [31], and used a manual feature extraction [32] which are combined in a bag of words fashion (BoW). For classification, a set of MLs algorithms were compared: Logistic Regression, Decision Tree, XGBoost, Naive-Bayes and Linear Support Vector Machine [33]. Among them, the decision tree method predicted the winner political party with an accuracy of 86.3%.

Next, the study of [18] used Twitter data to analyze the opinion of people against policies of Donald Trump during the Covid-19 pandemic. First, tweet data was recovered by means of the Twitter service using the keyword DONALD TRUMP from February to May 2020. The study does not provide the number of collected tweets. Next, the collected tweets were labeled manually as either of positive or negative sentiment. And finally, for classification, they used two learning algorithms for comparison. The first one, the LSTM model achieved an average accuracy of 69%, whereas, the second one, the NB algorithm, 63%. Again, it is noticeable that LSTM outperforms the traditional ML methods due to its capability of automatic learning features.

Recently, in the context of the COVID-19 pandemic, the work of [10] used sentiment analysis to identify the Brazilian population's perceptions about their Public Health System (named *Sistema Unificado de Saúde* in Portuguese) by analyzing Twitter content. They collected 27500 tweets using the Twitter service with the keywords SAÚDE and SUS. Data was recovered from December 2019 to October 2020. A message is scored based on the polarity of words contained in it and receives a final score, either positive, negative, or neutral. For the whole message processing and scoring, they used a dictionary of emotion lexicons [34] and its implementation in the R language programming [35]. Note that no learning model is used. As results, the authors show word clouds comparing qualitatively the sentiments of people, before and after the pandemic.

In summary, sentiment analysis is a good choice for opinion mining because it can capture underlying characteristics of messages. Among the studies, the majority of them prefer to NN models as a classifier in opposite to ML ones, which resides on hand-crafted features. However, the complex syntax, the short structure, and the use of colloquial lexicon in most of tweets still challenges current methods [3], [28].

Furthermore, yet there is scarce proposals of sentiment analysis in other languages than English, e.g., in Spanish. To the best of our knowledge, in the context of Peru, the study of [36] is a pioneering work aiming to detect cyberbullying in tweet messages written in Spanish, we assume that other works are ongoing or not published yet.

In contrast, in this work we propose a general method for approval rating of Peruvian politicians, which is evaluated in two politic scenarios to measure its generalization capability. The model trained to predict the favorability rating of the President of the Republic of Peru is used to predict the popular support of two hot topics widely discussed in Twitter: the approval rating of the Peruvian Congress and the agreement with a new State Constitution. Our method is simple, but effective, achieving high sensitivity and specificity scores in all tested cases.

IV. METHODS

The proposed framework for approval rating based on sentiment analysis in Twitter is shown in Fig. 1. This approach is designed to extract tweet posted by Twitter users related to the President of Peru. First, we gather data directly from the web page of Twitter. Next, data is preprocessed in order to prepare input data for the learning model. Then, the proposed model is trained in order to learn how discriminate positive from negative sentiment messages. Once trained the model, it is used as a classifier in order to make prediction of new unknown input data.

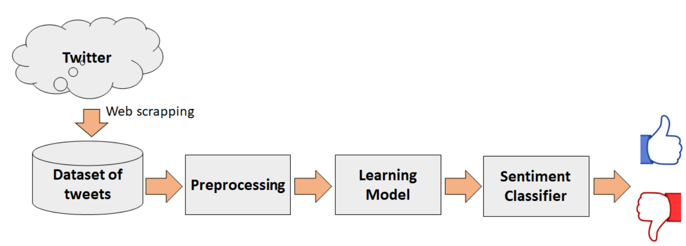

Fig. 1. The Proposed Framework.

As follows, we provide an in deep description of each module of the proposed framework:

A. Dataset

A dataset of 1150 tweets was collected from tweet messages and discussions in Spanish between Peruvian users regarding the President of the Republic of Peru. Due the cost of the Twitter service is prohibitive of us, we used the Beautiful Soup web scrapping library for Python [37].

The data collection about the Peruvian president was conducted from August 2021 to February 2022 using the tags @PEDROCASTILLO and @PRESIDENCIENCIADELPERU, and their related interactions. From August 2021 to January 2022, 900 tweets were collected (150 tweets per month), and during February 2022, 250 messages.

For each discussion topic about the Peruvian Congress (tag @CONGRESOPERU) and the new State Constitution (tag @CONSTITUCIÓN), a short dataset of 200 tweets was recovered in Abril 2022.

The collected tweets of the Peruvian president were labeled manually according to the perceived emotional charge in two categories. Label zero (0) was assigned for approval and label one (1) for disapproval. The Table I shows some tweets and their respective label.

TABLE I. SOME TWEETS OF THE DATASET.

Tweet	Label
This is how to govern for the people! *Así se gobierna para el pueblo!*	0
Thank you for the effort, president *Gracias por el esfuerzo presidente*	0
Get to work seriously, stupid *Ponte a trabajar en serio inepto*	1
I hope you get vacate, idiot *Ojalá te vaquen inútil*	1
Get rid him, I hate him *Sáquenlo lo odio*	1

B. Preprocessing

1) Data Cleaning: Raw tweet messages contain numeric digits, punctuation symbols, and special characters likewise @, #, ?, !, (,), $,&. All of them must be deleted. Next stop-words (i.e., common words in a language) also must be removed [38]. We used the Natural Language Tool Kit (NLTK) library with stop-words in Spanish [39].

2) Lematization: Because tweets can use different ways of a word to express the same meaning, lemmatization intends to reduce the effect of inflectional and derived forms of words to their common base form. For instance, the words blood, bleed and bloody can be represented as the word blood [40].

3) Tokenization: During tokenization, each tweet is split into its smallest possible morpheme called word or token [41].

4) Message Length Standardization: After tokenization, tweets can have a variable length of words, so the idea is to standardize the length of each tweet. In our approach, we used the average length of words on tweets. This gives us 12.40±9.08 of length, so we decided to fix the length of each tweet to the first 12 words. If a tweet contains words lesser than 12, the message is padded with empty words.

C. Learning Model

The proposed learning model is based on an end-to-end trainable deep learning neural network [42]. Fig. 2 outlines the proposed model. It consists of the learnable model itself and the sentiment classifier. Considering an input data, the model processes it aiming to predict the likelihood of belonging to the approval or disapproval class.

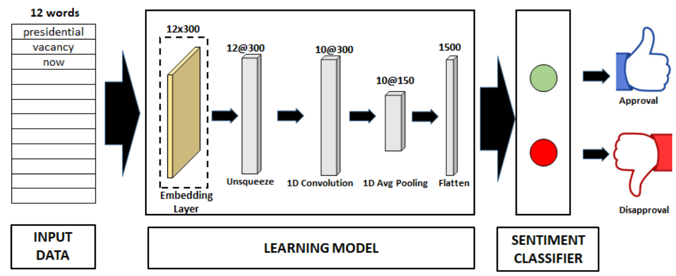

Fig. 2. The Model Architecture.

A brief description of the model is described as follows:

- Word embedding: In NLP, words must to be encoded to be processed by the model. A common encoding method is to use an embedding, which generates a representation vector for each word. Words of the same meaning or similarity will have close feature vectors in the embedding space [5].
  In this work we used the Spanish Billion Words Corpus and Embeddings (SBW). It furnishes an embedding that was pretrained on more than 1.5 billion words of the Spanish language [8]. The embedding produces a 300-dim vector for each word in the input data.
- Squeezing: The input data after embedding has a shape of 12×300. To be processed in the next layer, we reshape in order to become likewise a 300-dim sequence with a feature map of 12 filters.
- 1D-Convolution: Reshaped embedding vectors are fed to a 1D-CNN layer. The CNN has a kernel of size 3, stride 1, and padding 1. The CNN has 10 neuron filters and the Rectified Linear Unit (ReLU) is used as activation function. Also batch normalization helps us to prevent overfitting.
- Pooling: An average pooling layer, with a kernel of size 2 and stride 2, is used to down-sample the feature maps coming out from the CNN.
- Flatten: After down-sampling, feature maps are flattened and fed into a fully connected layer. The output of the flatten layer is used as feature vector and is used to perform classification.

D. Sentiment Classifier

The sentiment classifier module implements classification. Given a feature vector, to predict either the approval or disapproval likelihood, we used a fully connected layer of two neurons with a Softmax activation function to furnish prediction (see Fig. 2).

E. Model Training

In order to train the model in an end-to-end manner, we used the cross-entropy as loss function and the Adam optimizer. In our experiments, the embedding layer is not freezing, but to avoid overfitting we used a low learning rate (1e-5) and a short batch size (16), and the model was trained for just a few epochs (25).

F. Model Evaluation

To assess the model performance in the dataset of the President of Peru, we split the dataset into training and test set. Tweet data collected from August to December 2021 is the training set, whereas messages from January–February 2022 is the test set.

The model performance is scored using the metrics of sensibility and specificity, being the approval rating the true positives we want to predict.

V. Results and Discussion of Results

A. Collected Dataset

We performed collection of tweet related to the President of Peru, from August 2021 to February 2020. Table II summarizes the number of tweets recovered by months.

TABLE II. Dataset about the President of Peru.

Months	N° Tweets
Aug–Dec 2021	750
Jan 2022	150
Feb 2022	250

Fig. 3 shows the word cloud or a visual representations of words with more frequency in the collected dataset of the President of Peru.

Fig. 3. The Word Cloud about the President of Peru.

Additionally, we collected a few tweets relate the Congress and the State Constitution of Peru. Table III outlines the number of tweets by the respective topic.

TABLE III. Miscellaneous Data.

Topic	Months	N° Tweets
The Congress	Apr 2022	200
The State Constitution	Apr 2022	200

B. Classification Performance

As exposed in Section IV-F, the trained model was assessed in the data of President collected during January and February 2022. Note that this data is totally unknown for the model. As a results, the model achieved 91.2% of sensitivity and 94.4% of specificity.

In order to provide a historical curve of trend likewise Peruvian pollsters furnish, we used the trained model and 40% of the data for each month to construct the trend curve of the approval/disapproval rating of the President of Peru. Fig. 4 shows the constructed historical curve with our predictions versus the surveys from IPSOS [21].

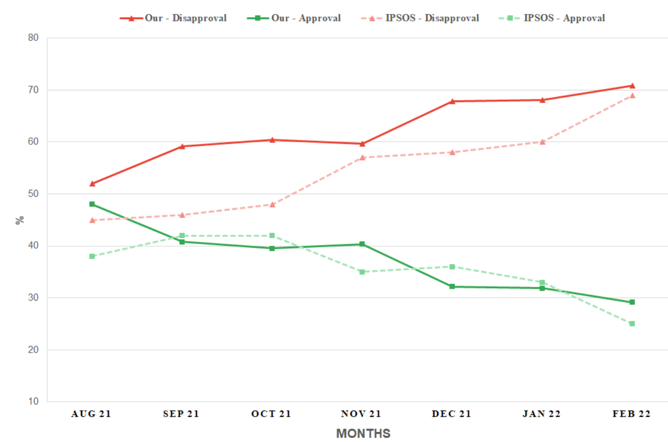

Fig. 4. Trend Curve of the Approval/Disapproval Rating of the President of Peru. Our Predictions vs IPSOS Surveys.

C. Classification of Miscellaneous Political Data

In order to evaluate the agnostic ability dealing with political data, we assessed the model in two discussions that attracted the interest of the Peruvians.

1) The approval rating of the Congress of Peru due to the start of the vacancy process against the president and censorship of some ministers.
   In this case, the predicted outputs are considered as an approval/disapproval rate. Fig. 5 outlines the approval/disapproval rating of our model related the Congress of Peru against the results of two renowned pollsters, CPI [24] and IEP [23].
2) The proposal of the current government to change of the state Constitution. In this case, the predicted outputs are considered as an agreement/disagreement

rate. Fig. 6 shows the outcomes of our model against the results of CPI [24].

It is worthwhile to mention that results of the pollsters were recovered from the same period of study, April 2022, aiming to compare against our proposal.

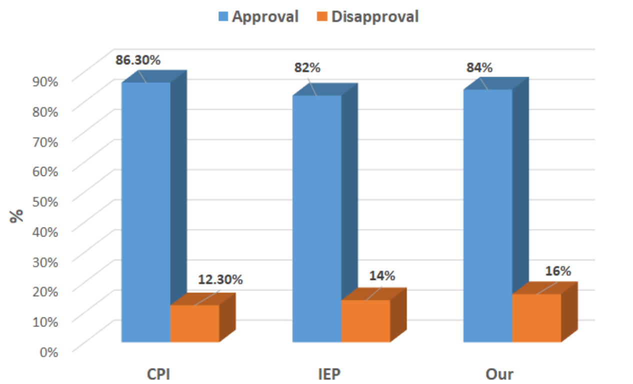

Fig. 5. Approval/Disapproval Rating of the Congress of Peru, Period April 2022.

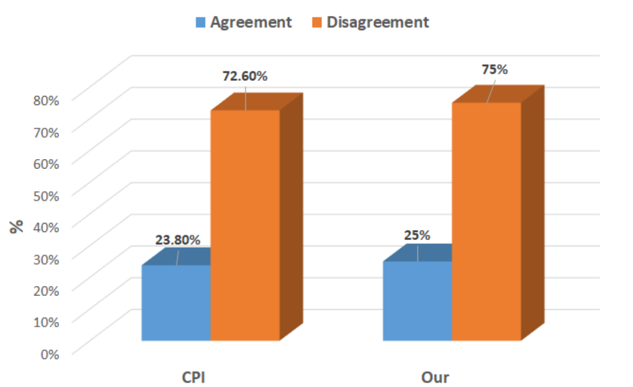

Fig. 6. Popular Agreement/Disagreement to Change the State Constitution of Peru, Period April 2022.

D. Discussion of Results

Taking into account the first experiment to predict the approval rating of the President of Peru, the proposed model achieved high performance to classify positive and negative latent sentiments in tweet messages.

In order to gain insight whether the model is working as expected, we constructed the historical trend curve of approval rating of the president and compared it with the result of one pollster. We can conclude that our model furnishes reliable predictions (see Fig. 4).

Inspecting the model architecture, although the model can seem too simple, the CNN layer improves the input features and the average pooling gives them a degree of invariance. However, it is worthwhile to mention that the simplicity of the model is compensated with the embedding layer, which was trained in a large corpus of Spanish words [8].

Besides, after analyzing the number of words of messages with politic content, we observed that in political discussions people prefer to use short messages, usually with harsh words or words with higher sentimental polarity.

Moreover, in order to evaluate the agnostic feasibility of the model to be applied in other politic cases, we tested it in two cases without any fine tuning. In both cases, the model was able to predict close similar results likewise two Peruvian pollsters (see Fig. 5 and Fig. 6).

VI. Conclusion and Future Work

In this work, we presented an approach to classify Twitter data in order to predict the approval rating of Peruvian politicians and the polices that they intend to implement. Our approach resides on a convolutional neural network model that is able to detect and score the sentiment polarity of tweet messages. To assess the model, we collected a new dataset of tweets about the current President of Peru and a miscellaneous data about discussions of two topics: the popularity of the Peruvian Congress and the possibility to change the current state Constitution. In all cases, the model provides results comparable to those offered by renowned Peruvian pollsters. So, our proposal is a low cost, agile, and reliable alternative against to the expensive and time-consuming traditional opinion surveys.

As future work, we intend to collect more data from other political discussions for more evaluation of the robustness of the model. Moreover, the model will be improved to take attention to syntactic order and semantic meaning.

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