Deep Stance and Gender Detection in Tweets on Catalan Independence@Ibereval 2017

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Abstract. This paper discusses deepyCybErNet submission methodology to the task on Stance and Gender Detection in Tweets on Catalan Independence@Ibereval 2017. The goal of the task is to detect the stance and gender of the user in tweets on the subject "independence of Catalonia". Tweets are available in two languages: Spanish and Catalan. In task 1 and 2, the system has to determine whether the tweet is in favor of, against or neutral to the tweets on the subject pertaining to the task in Spanish and Catalan languages respectively. In task 3 and 4, the system has to decide whether the person who tweets is a male or female. We submitted three systems for this task a Bag-of-Words (BOW) representation for tweets with logistic regression classifier, Recurrent Neural Network (RNN) based approach, Long Short Term Memory (LSTM) based approach and gated recurrent based approach. These methods are highly language independent and can be used for the declarations of stance of tweets and identifying the gender of twitter user in any language. These methods have performed better in detecting stance and gender in tweets of Catalan language than in those of Spanish.

Keywords: Sentimental analysis, Bag-of-words embedding, Deep learning: Recurrent neural network (RNN), Long short-term memory (LSTM), Gated recurrent unit

1 Introduction

Stance and gender detection in tweets is the task of automatically determining the polarity of the tweets and the gender of the twitter user who posted this particular message. In stance detection, the system has to detect whether this tweet is in favor of, against or neutral towards a proposition such as "independence of Catalonia".

The internet has given people a plenty of platforms to express their views on different subjects like Twitter, Facebook, WhatsApp etc. So people use these

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media to share their perspective on various topics in the society. So analyzing these twitter information is very much helpful in understanding the opinion of people and it also helps the respective officials to take up necessary action. However, determining the stance and gender of texts which are phrased in figurative languages like tweets are very difficult for machines to unfold. Human can easily understand the underlying meaning of such expressions but, for a machine to unravel the meaning of rhetorical expressions such as sarcasm, irony, metaphor, analogy [14], it requires much additional information.

Many methods have been devised for automatically determining the stance and gender of microblog posts such as tweets. G. Zarella and A. Marsh [14] employed a Recurrent Neural Network (RNN) based method for classifying stance of tweets where word2vec skipgram method was used to represent features. In [3], I. Augenstein et.al used a bag-of-words autoencoder for extracting features and classification was performed using logistic regression. I. Augenstein et.al [2] used Long Short Term Memory (LSTM) with bidirectional embedding for stance detection. W. Wei et. al [13] used a Convolutional Neural Network (CNN) for the effective detection of stance in tweets. Mohammad et.al [11] uses Support Vector Machine (SVM) and n-gram based method to detect the stance in tweets. A. Mislove et. al [10], C. Fink [6] introduced various measures for detecting the gender of the user who tweets.

Our method uses both Bag-of-Words (BoW) and a BoW-based recurrent embedding system for analyzing the stance in tweets. In first case, BOW is used to obtain the feature representation for the tweets and classification is done using logistic regression. We also employed an RNN based method and LSTM based method for mining the stance of tweets. These methods are language independent. So irrespective of the language, we can use these approaches for finding the stance of micro blogging posts.

2 Task description

The main objective of Stance and Gender Detection in Tweets on Catalan Independence@Ibereval 2017 is to detect the stance and gender of people who tweets based on the topic "independence of Catalonia" [12].

The aim of this task can be divided into two.

1. Predict the stance of a given message. i.e., given message, the system has to predict whether the message is in favor of, against or neutral to the subject "independence of Catalonia".
2. Predict the gender of the user who tweets on the subject "independence of Catalonia".

Tweets are given in two languages Spanish and Catalan. The system should be able to analyze tweets in these two languages and to detect the stance and gender of the tweet.

Data for this task are tweets on the topic "independence of Catalonia" during the regional election in September 2015.

Table 1. Statistics of tweets

Shared task	Number of tweets in Training	Number of tweets in Testing
Task 1 and Task 2-Spanish	4319	1081
Task 1 and Task 2- Catalan	4319	1081

3 Methodology

This section discusses the mechanism adopted for Stance and Gender Detection in Tweets on Catalan and Spanish Independence@Ibereval 2017. We have used two methods for stance and gender in Twitter messages; (1) Bag-of-words (BoW) embedding (2) recurrent neural network based word embedding.

3.1 Bag-of-words based system for Analysis of Stance and Gender Detection in Tweets

We set embedding size to 128 and word length to 40. Each word in tweet is mapped in to 128 dimensional vectors. Task 1 and task 2 has 4319 training samples. Thus, we formed a matrix of shape $4319X40$. Each word is replaced in the resultant matrix of shape $4319X40$ with their word embedding. This forms an input tensor of shape $4319X40X128$. Finally, using the max-pooling approach, we converted an input tensor in to matrix of shape $4319X128$ by fixing 40 as maximum value for word length. This matrix is passed to logistic regression classifier and using argmax the prime stance and gender is selected.

3.2 Recurrent neural network (RNN) based system for Analysis of Stance and Gender Detection in Tweets

Recurrent neural network is an appropriate deep learning architecture for sequence data modeling. This has achieved intriguing results in various tasks in the field of natural language processing [8]. It typically looks same as feed forward networks (FFN), additionally contains self-recurrent connection in units [5]. This cyclic loop carries out information from one time-step to another. As a result, RNN are able to learn the temporal patterns, value at current time-step is estimated based on the past and present states. Generally, RNN takes input as $x_t \in R^q$ and $h_{t-1}^i \in R^p$ of arbitrary length to compute succeeding hidden state vector h_i^t by using the following formulae recursively.

$$h_t = f\left(W_{xh}X_t + W_{hh}h_{t-1} + b\right) \tag{1}$$

$$o_t = sf\left(W_{oh}h_t + b_{ot}\right) \tag{2}$$

Where f is the nonlinear activation function, particularly logistic sigmoid function $(\sigma\sigma)$ applied on element wise, h_0^i is usually initialized to 0 at time-step t_0 and $W_xh \in R^{pxq}$, $Wh \in R^{px}$ and $b \in R^m$ are arguments of affine transformation. Here o_t is the output at time step t.

We implemented a system based on RNN for stance and gender detection and run all experiments of them in GPU enabled Tensorflow [1]. Using the previously discussed mechanism such as bag-of-words embedding, we formed an input tensor of shape $4319X40X128$. Each tweet embedding $40X128$ is reduced to 128 dimension embedding vectors. This embedding vector are given to RNN layer to obtain optimal feature representations and followed by logistic regression and argmax function for classification.

3.3 Long short-term memory (LSTM) based system for Analysis of opinion and the figurative language on Twitter tweets

RNN has vanishing and exploding gradient issue. To alleviate and to learn the long-term dependencies [7] introduced long short-term memory (LSTM). LSTM has a memory block instead of a simple RNN unit. A memory block contains one or more memory cell with a pair of adaptive multiplicative gates such as input and output gate. A memory block stores an information and updates them across time-steps based on the input and output gates. Input and output gate controls the input and output flow of information to a memory cell. Additionally, it is has a built-in value as 1 for Constant Error Carousel (CEC). This value will be activated when in the absence of value from the outside the signal. The newly proposed architecture has performed well in learning long-range temporal dependencies in various artificial intelligence (AI) tasks [9]. Generally, at each time step an LSTM network considers the following 3 inputs; x_t, h_{t-1}, c_{t-1} and outputs h_t, c_t through the following below equations.

$$i_t = \sigma\left(W_i X_t + U_i h_{t-1} + V_i m_{t-1} + b_i\right) \tag{3}$$

$$f_t = \sigma\left(W_f X_t + U_f h_{t-1} + V_f m_{t-1} + b_f\right) \tag{4}$$

$$o_t = \sigma\left(W_o X_t + U_o h_{t-1} + V_o m_{t-1} + b_o\right) \tag{5}$$

$$m_t = \tanh\left(W_m X_t + U_m h_{t-1} + b_m\right) \tag{6}$$

$$m_t = f_t^i \odot m_{t-1} + i_t \odot m \tag{7}$$

$$h_t = o_t \odot \tanh\left(m_t\right) \tag{8}$$

where X_t is the input at time step t, σ is sigmoid non-linear activation function, tanh is hyperbolic tangent non-linear activation function, $\odot$ denotes element-wise multiplication. Concretely, at $t = 0$ hidden and memory cell state vectors such as h_0 and c_0 are initialized to 0.

We developed LSTM based system for stance and gender detection by replacing RNN layer with LSTM.

3.4 Gated recurrent unit (GRU) based system for Analysis of opinion and the figurative language on Twitter tweets

As from the above formulae, we can say that LSTM has complex set of processing units. As a result, this needs more training time. Further the research on LSTM,

[4] introduced Gated recurrent unit (GRU). GRU has less number of units in compared to LSTM, computationally efficient. The mathematical formulae of GRU is given below,

$$i\_f_t = \sigma\left(W_{x_{i-f}} + W_{h_{i-f}} h_{t-1} + b_{i-f}\right) \tag{9}$$

$$f_t = \sigma\left(W_{xf} X_t + W_{hf} h_{t-1} + b_f\right) \tag{10}$$

$$m_t = \tanh\left(W_{xm} X_t + W_{hm}\left(fr \odot h_{t-1}\right) + b_m\right) \tag{11}$$

$$h_t = f \odot h_{t-1} + (1 - f) \odot m \tag{12}$$

Where 9 represents Update gate, 10 is for Forget or reset gate, 11 shows the equation for Current memory and 12 gives the equation for Updated memory.

Formulae shows, unlike LSTM memory cell with a list of gates (input, output and forget), GRU only consist of gates (update and forget) that are collectively involve in balancing the interior flow of information of the unit. In GRU, input gate (i) and forget gate (f) are combined and formed a new gating units called update gate (i_f) that mainly focus on to balance the state between the previous activation (m) and the candidate activation (f) without peephole connections and output activations. The forget gate resets the previous state (m). GRU networks looks simpler than LSTM with required only less computations.

4 Experiment and Results

We trained all experiments of various deep learning architectures using Tensorflow [1].

Cross-validation performance To select the optimal parameters for tweet length and embedding size, 5-fold cross-validation is done on the given training samples of Catalan and Spanish for stance and gender detection. 10-fold cross-validation accuracy across varied tweet length and embedding size for stance detection in Catalan language is displayed in Figure 1. 10-fold cross-validation accuracy across varied tweet length and embedding size for gender detection in Spanish language is displayed in Figure 2.

4.1 Evaluation results

We have submitted 3 runs for each task; run1 is based on RNN mechanism, run2 is based on LSTM mechanism and run3 is based on GRU mechanism. The detailed evaluation results has been given by the Independence@Ibereval 2017 organizing committee are displayed in Table 2. The scores we obtained for task 1 are 0.285, 0.304 and 0.307 in detecting stance and 0.477, 0.490 and 0.501 in detecting gender for Spanish language. The scores we obtained for task 1 are 0.360, 0.379 and 0.326 in detecting stance and 0.465, 0.483 and 0.486 in detecting gender for Spanish language.

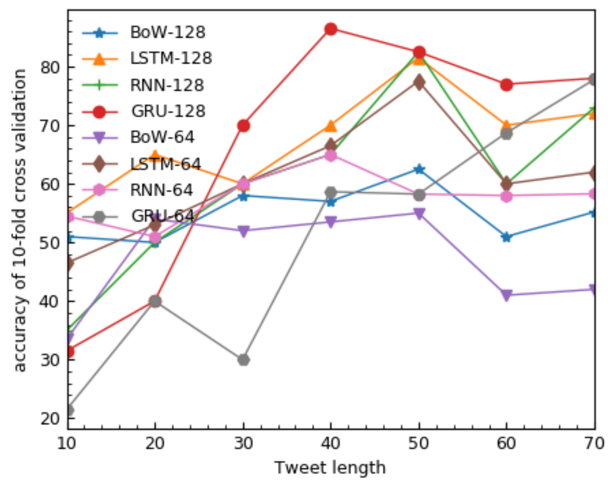

Fig. 1. 10-fold cross validation with Tweet length [10-70] and embedding size [64,128] for stance detection in Spanish language

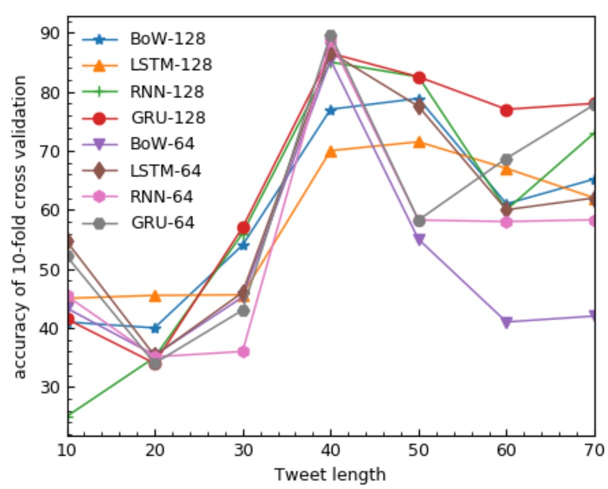

Fig. 2. 10-fold cross validation with Tweet length [10-70] and embedding size [64,128] for gender detection in Catalan language

Table 2. Macro F-score for all tasks

Shared task	Accuracy		
	RNN	LSTM	GRU
Spanish - Stance	0.2849	0.3042	0.3066
Spanish - Gender	0.4764	0.4903	0.5014
Catalan - Stance	0.3603	0.379	0.3257
Catalan - Gender	0.4653	0.4829	0.4857

5 Conclusion

This working note has presented a language independent method for the Independence@Ibereval 2017 shared tasks such as stance and gender in Twitter messages written in Catalan and Spanish using BoWs and embedding of RNN, LSTM and GRU. The presented supervised learning method has not relied on any resources; semantic resources such as dictionaries and ontologies or computational linguistics or feature engineering mechanisms for stance and gender detection in twitter tweets. Due to the less training corpus, the efficacy of RNN in stance and gender detection trails the classical BoWs approach. Though the efficacy of embedding of RNN, LSTM and GRU is acceptable and paves the manner in future to use for the analysis of stance and gender detection on Twitter tweets. Evaluating the performance of RNN, LSTM and GRU embedding with more training corpus for justification will be remained as one direction towards future work.

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