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Alternative method sentiment analysis using emojis and emoticons

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Abstract

Our research aims to develop an alternative method for analyzing the tonality of the texts. Most of the traditional methods for determining tonality classes are based on text analysis and ignore various emotional indicators that users actively used in social networks. Therefore, it improves the quality of predicting the tonality of the class. The study is focused on three methods of expressing emotions in a text, emojis, emoticons, and punctuation marks that express emotions. We have developed a special lemmatizer for data preprocessing and built several text classifications models to classify the text into two classes, positive and negative, where emotional indicators are used as predictors. We have also used the RuSentiment corpus to create the classifier. The study has demonstrated that the proposed methods improve prediction of tonality classes by 6% compared to the traditional models. We have obtained the best results using a model ensemble based on the emotional indicators model and the Word2vec model. The model has demonstrated convincing results 91% accuracy and 0.937 area under the ROC curve. We have identified several patterns. Emotional indicators have a pronounced connection with tonality classes. Positive emotions are much more than neutral and negative. The model of emotional indicators has 85% accuracy; therefore, emotional indicators are very crucial in the analysis of the text tonality.

Keywords: data preprocessing; sentiment analysis; natural language processing

1. Introduction

Sentiment analysis [10] is the classification of emotions (positive, negative) in the text data using text analysis techniques. The problem of sentiment analysis has been widely studied for the past several decades. The research in

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the area has been predominantly based on the data collated from social networks, microblogs, reviews and other sources. Most of the methods for determining tonality classes are based on the analysis of plain text. It will be demonstrated that emotional indicators are a relevant source of information about tonality classes.

These days, text is one of the main information posted on the social network. The text can be contained in status, posts, reposts, and comments. In order to analyze the user's profile and get information, we can apply the sentiment analysis. Text classification models are widespread and used not only independently, but also as predictors in more complex systems.

Users express emotions in social networks through the emotional indicators. Texts that users post on the Internet consist of both clear text and emotional indicators. Emotional indicators allow us to determine which emotions are conveyed in the text. Some studies involving the replacement of emotional indicators [2] have been conducted for English language. When analyzing the tonality of a text, we usually remove all punctuation marks, leaving all letters. Emotional indicators carry a clear emotional content and, considering emotions indicators, allow increasing the accuracy of the text classification. We can see the importance of the influence of emotional indicators in the text in [6]. Emotional indicators have strong correlation with polarity classes.

The novelty of this method lies in the fact that emotional indicators are used as predictors in the proposed models, as well as in methods of extracting useful information from emotional indicators when drawing conclusions from the data. The models were built to predict the probabilities of a post belonging to two independent classes: negative and positive.

The rest of the paper is organized as follows. In Section 2, we overview the papers related. In Section 3, we describe our data for this study. The proposed method is described in Section 4. Section 5 contains all results of the sentiment analysis research of the suggested model and a comparison of the suggested model with the baseline models. The conclusion is in Section 6.

2. Related work

This section presents other similar research related to the sentiment analysis. Many studies have been conducted related to the sentiment analysis, but most of them remove emotional indicators and examine only the texts. [2, 3, 18] describe the methods that work with emotional indicators.

One of the largest emoji studies is Petra Kralj Novak et al. [6]. Sentiment analysis of emoji and emoticons allowed the authors to conclude that most popular emoticons are positive and the distribution of feelings on a tweet with and without emoji is different. Moreover, there were no significant differences with the use of emoji in 13 languages and the ranking of emotions.

Yuxiao Chen et al. [1] studied the sentiment analysis in the text, but with the use of emoji. The authors of the article used two methods of Word-guide Attention-based LSTM and Multi-level Attention-based LSTM to build the model to conduct the sentiment analysis.

Elena Rudkowsk et al. [30] demonstrated the alternative procedure based on distributed word embeddings instead the dominant bag-of-words. The strength of word embeddings is the ability to capture similarities in the word meaning. They used word embeddings as a part of the supervised machine learning procedure which estimates negativity levels in parliamentary speeches. The accuracy of this procedure is evaluated with crowd coded training sentences. The results demonstrated the potential of the word embeddings approach for the sentiment analysis.

The sentiment analysis with the emotional indicators [2, 13, 14] is mainly conducted on English language resources. Classification of Russian language remains difficult due to the small number of open source codes and also the small number and quality of thematic text corpora.

There are many sentiment classification algorithms tend to reach accuracy about 60-70% on social media data [7, 20, 21, 28]. Researchers use methods to conduct sentiment analysis, for example, various modifications of the bag-of-words [22], neural networks [23], machine learning [24], support vector machines [19], deep learning [27], and naive bayes classifier [25,26].

Kirill Svetlov et al. [18] built the classifier with two text corpora: Rubtsova's corpus and RuSentiment corpus. The algorithm of sentiment analysis was implemented on the basis of bidirectional recurrent neural network. The authors obtained the 91% accuracy using Rubtsova's corpus, and the 84% accuracy using RuSentiment. The best results in the analysis of posts and comments were obtained using an ensemble of models based on both corpora.

As the main conclusion after the related work analysis, that predicting the polarity of the text using emotional indicator, relying on the open source data, is a solvable task. Emotional indicators have a strong impact on a sentence and correlate with polarity classes. The studies mentioned clearly show the presence of persistent determinants for the polarity classes.

3. Data

In our research, emojis, emoticons and punctuation marks that express emotions are called emotional indicators.

Emoticon is a pictorial representation of a facial expression using characters to express a person's feelings or mood. Characters for displaying emoticons are letters, numbers, and punctuation marks.

There are two types of emoticons:

- Classical emoticons (':-), XD')
- Japanese emoticons (‘∧_∧, ヽ(o`皿′ o)ノ’)

Emoji are the graphic language where a combination of pictures is used instead of words (🐵, 🤗,😍). Punctuation marks can express emotions, for example, '...' - understatement, confusion, '???' - surprise.

Rusentiment [7] is a dataset that consists of posts from the social network Vkontakte and these posts marked out in five classes ‘positive’, ‘neutral’, ‘negative’, ‘speech’, and ‘skip’.

For our study we used posts with class marks 'positive' and 'negative'. Number of posts:

- with emotional indicators: 6957
- without emotional indicators: 3598
- total: 10558

To classify the tonality of the text, we preprocess datasets before applying supervised learning.

The preprocessing stage contains the following steps:

- Use a dataset with emotional indicators (see Table 1)
- Replace emotional indicators with their textual meaning in the text
- Delete punctuation marks
- Delete non-Russian words
- Lemmatizing strings using Yandex Mystem [11]

4. Methods

4.1. Data analysis

The dataset consists of 6957 posts; each post contains at least one emotional indicator. Statistics was collected for all posts from the dataset. For the further analysis, we selected emotional indicators contained in at least 0.5% of the posts.

Moreover, we used the dataset that consists of emotional indicators, their code, values, meanings in English, and tonality assessments. We also consider whether the emotional indicator belongs to the class of basic emotions.

The number of emotional indicators is:

- Emoji: 277
- Emoticons: 125
- Punctuation marks that express emotions: 20

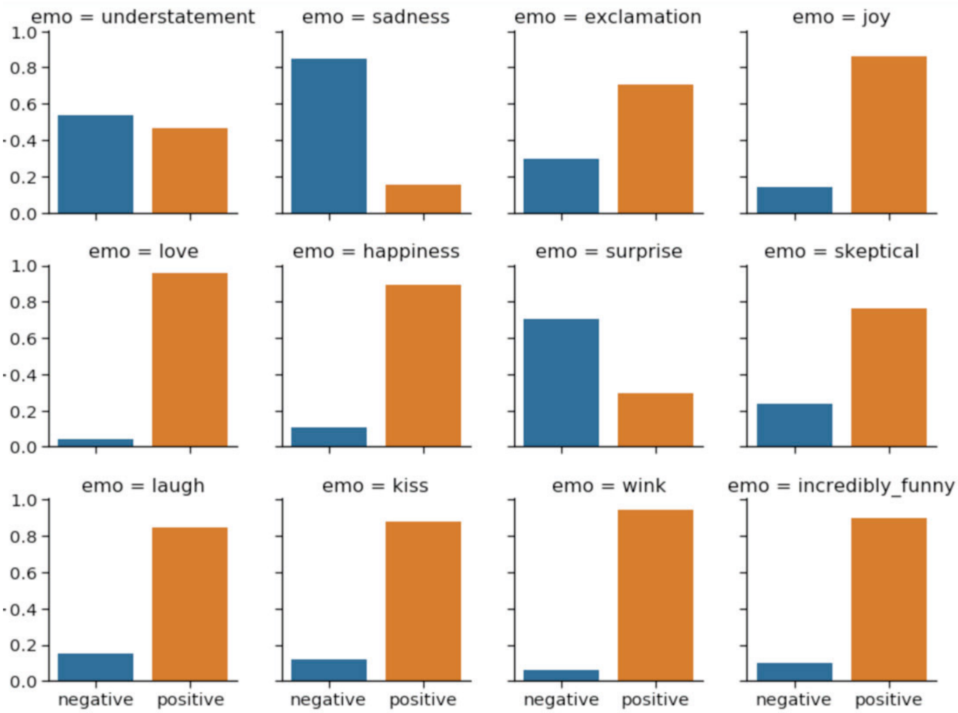

Fig. 1. Proportion of positive and negative posts using emotional indicator.

Table 1. Datasets of emotional indicators

emoji	eng_mean	label	happiness	sadness	disgust	anger	surprise	love
😂	incredibly funny	1	2	0	0	0	0	2
😀	joy	1	2	0	0	0	0	0
🤩	star-struck	1	0	0	0	0	0	2
🤫	silence	1	0	0	1	0	0	1
😕	unsatisfied	0	0	2	0	0	2	0
🙏	thanks	1	2	0	0	0	0	0

There were only selected those emotional indicators that are not neutral and express emotions. It was tested the hypothesis that there was no relation with the tonality label. The test results are revealed in Table 2. It should be noted that the null hypothesis was rejected for all emotional indicators, except for one ‘exclamation’. Emotional indicators are statistically related to the tonality class.

Table 2. Emotional indicator testing statistics in their prevailing classes

Emotion	Class	P-value	Chi2
understatement	negative	0.00	218.21 > 0.0
sadness	negative	0.00	270.15 > 0.0
exclamation	positive	0.43	0.61 > 0.33
joy	positive	0.00	256.79 > 0.0
love	positive	0.00	52.52 > 0.0
happiness	positive	0.00	92.34 > 0.0
surprise	positive	0.00	47.99 > 0.0
skeptical	negative	0.03	4.6 > 0.0

laugh	positive	0.00	12.05 > 0.0
kiss	positive	0.00	50.08 > 0.0
wink	positive	0.00	54.18 > 0.0
incredibly_funny	positive	0.04	4.02 > 0.0

In Fig 2 we can see how emotion indicators are located in the space of tonality classes S, the transition to which is performed:

$$S : s_{pos}(e) = \log(P_{pos}(e) * W_{pos}), s_{neg}(e) = \log(P_{neg}(e) * W_{neg}) \quad (1)$$

$$W_{pos} = \frac{|p_{pos}|}{|p_{pos}| + |p_{neg}|}, W_{neg} = \frac{|p_{neg}|}{|p_{pos}| + |p_{neg}|} \quad (2), \text{ where}$$

- s_{pos} and s_{neg} are two dimensions of the space S
- e - emotion indicator
- $P_{pos}(e)$ and $P_{neg}(e)$ are sets of posts containing emotion indicators data, with a positive and negative tonality class
- W_{pos} and W_{neg} are weights needed to balance the sample
- P_{pos} and P_{neg} are the set positive and negative posts of the dataset

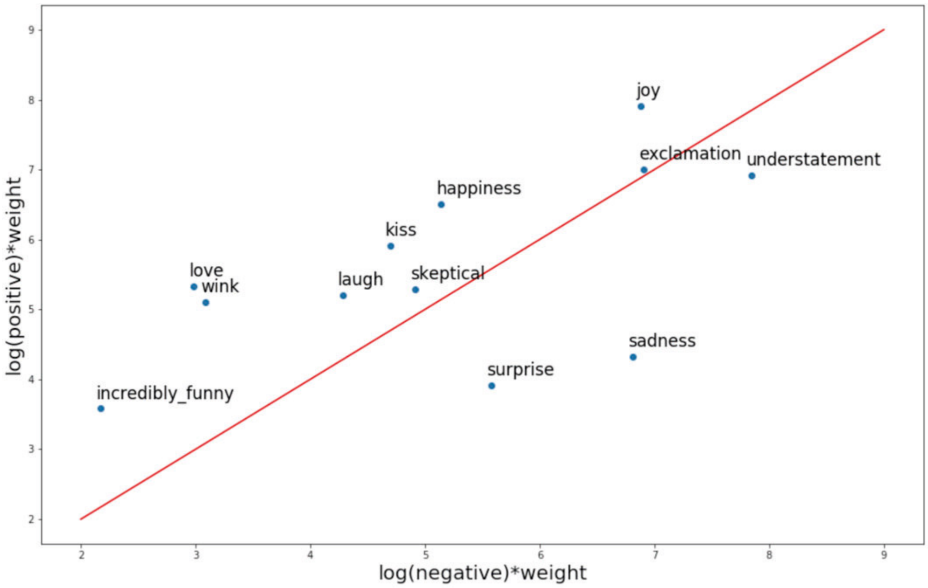

Fig. 2. Location of emoticons in the space of tonality classes.

Emotional indicators are seen to have a pronounced relation with tonality classes (Fig. 2), and there are 'positive' (lying above the diagonal), 'negative' (lying below the diagonal) and 'neutral' (lying in the vicinity of the diagonal) among them. In addition, it can be noted that there are much more positive emotions than neutral and negative ones.

4.2. Model building

The traditional model taken as a baseline, based on TD-IDF vectors [10] as embeddings for a fully connected neural network with several hidden layers. The TF-IDF vectors were compiled from lemmatized posts cleared of stop words and various noise, as well as emotional indicators. The following rules were adopted for the formation of the vectorizer: lemmas occurring in less than 0.5% of documents were excluded, and bigrams with the same frequency quorum were added. As a result, a dictionary of 2545 lemmas were obtained. The model architecture is demonstrated in Fig. 3.

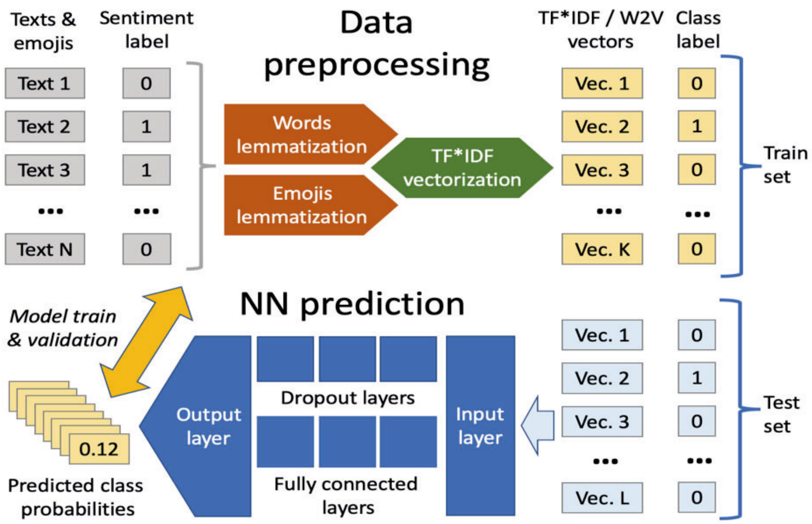

Fig. 3. The model architecture on TD-IDF/Word2Vec vectors.

The second model was based on the bag-of-words vectors [9], displaying the number of emotional indicators of various types in posts (only emotional indicators). The emotional indicators model architecture is demonstrated in Fig. 3. A fully connected neural network with one hidden layer was taken as a predictive tonality class of the model.

An alternative model based on the TF-IDF vectors was built on lemmatized posts, with the exception that emotional indicators were also used as lemmas. For this purpose, a corresponding conversion was previously performed. The rules for the formation of the lemma corpus were the same — lemmas occurring in less than 0.5% of documents were excluded, and bigrams were added. Thus, a dictionary of 3037 lemmas distributed in the corpus was obtained, including lemmas of emotional indicators and their bigrams. The model architecture on TF-IDF vectors and emotional indicators is demonstrated in Fig. 3.

The following model was based on Word2Vec embeddings [12], previously calculated for the Russian text corpus. We used a set of word vectors with a 14 GB volume, which includes the vectors of all indexed words of Russian language, calculated by the skip-gram model with the size of the context window of 10 words and the 500-vector space dimension. As a prediction model, a recurrent neural network with a hidden LTSM layer [8] with a dimension of 256 elements was selected. The model architecture on Word2Vec vectors is demonstrated in Fig. 3.

Finally, the last model was an ensemble consisting of the word2vec model and the model based on emotional indicators embeddings. The concept of these models is described above. A simple fully connected neural network with one hidden layer was integrated into the model. The model architecture is demonstrated in Fig. 4.

All the models described above were optimized and trained individually on a balanced oversampling dataset and cross-validation. The final metrics were calculated on the test dataset with a natural balance of tonality classes (524 posts in total, 146 of which were negative and 378 were positive).

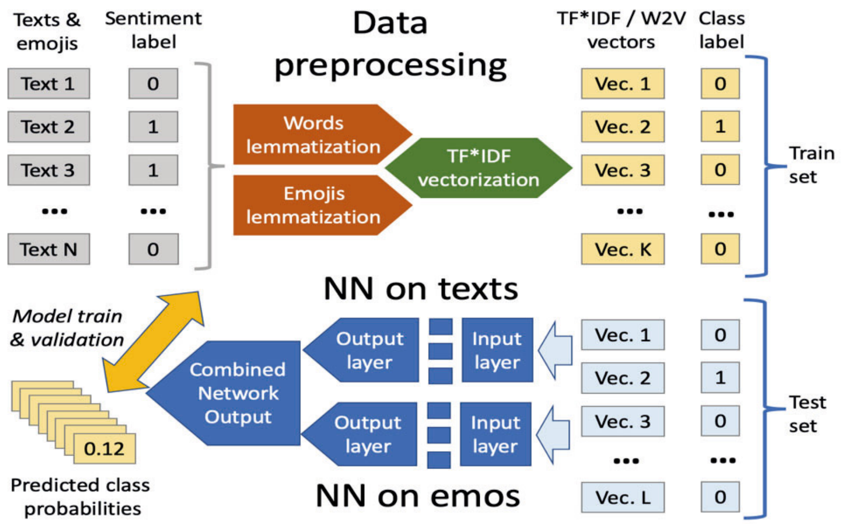

Fig. 4. The ensemble model architecture.

5. Results of experiments

This chapter represents the results of our experiments. To perform the evaluations, we used accuracy, roc curves, and precision-recall curves. The results are demonstrated in Table 3.

We used ROC curves to assess the quality our models. AUC ROC curves are a measurement for binary classification. ROC (receiver operating characteristic) perform probability curves. AUC (area under the curve) represents degree or measure of separability. The model has an AUC close to 1. It means that it has a good degree of separability. The poor model has an AUC close to 0, it has the worst degree of separability. The AUC is 0.5, the model does not have the capacity to separate classes.

Table 3. Text polarity prediction accuracy

Model	Accuracy	Roc curve area
TF-IDF + CNN	0.83	0.863
TF-IDF+emo	0.89	0.928
Word2Vec + RNN	0.85	0.884
emo + CNN	0.85	0.872
Word2Vec + emo	0.91	0.937

For each run, we train five different models and calculate their metrics on the test set: (1) 'TD-IDF + CNN' model is TF-IDF vectors as embeddings for a fully connected neural network with several hidden layers, (2) 'TD-IDF+emo+ CNN' model based on the TF-IDF vectors which are built on lemmatized posts for a fully connected neural network with several hidden layers, (3) 'Word2Vec + RNN' based on Word2Vec embeddings for a recurrent neural network with a hidden LTSM layer, (4) 'emo' model based on the bag-of-words vectors for a fully connected neural network with one hidden layer, (5) 'Word2Vec+emo' model is an ensemble consisting of the word2vec model and the model on emotional indicators embeddings.

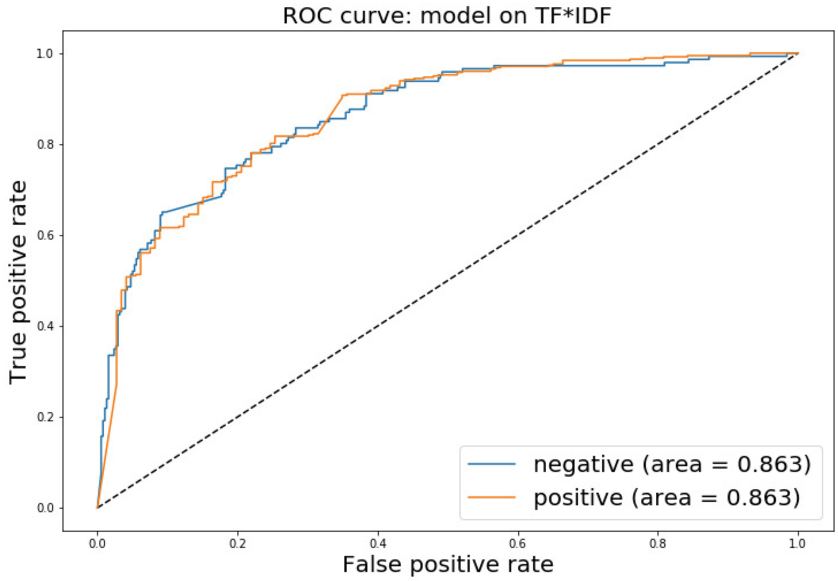

Fig. 5. ROC model on TF-IDF.

The model on embedding TF-IDF is a baseline, with 83% accuracy for both classes and the area under the ROC curve is 0.863 (see Fig. 5). It seems relevant to look at the model based on embeddings exclusively of emotional indicators. The model shows an accuracy of 85% and the area under the ROC curve of 0.872 (see Fig. 6) on the average for two classes. This result means that people who write posts on social networks often prefer to convey the emotional coloring of their message not only through the words, but also through emotional indicators.

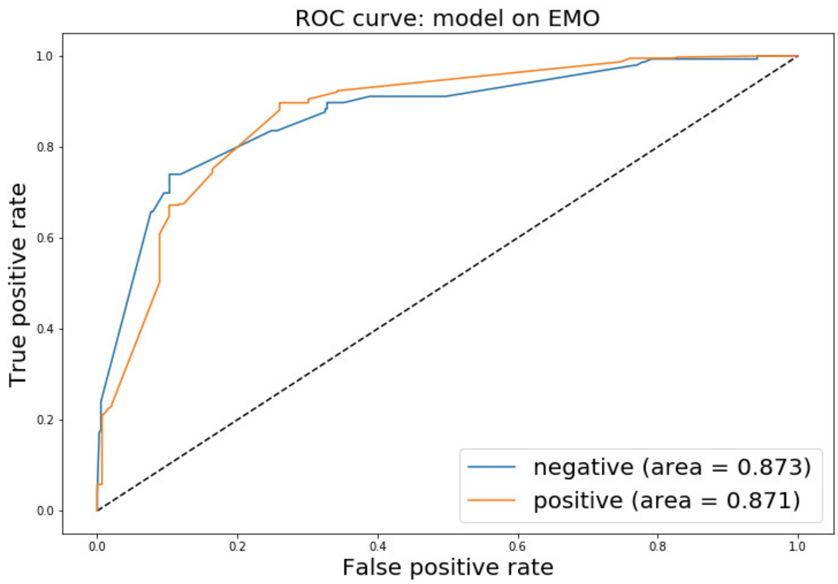

Fig 6. ROC model on EMO.

Let us see how the metrics of the model change on TF-IDF embeddings if emoticons are included in the dictionary. In Table 5 this model is called 'TD-IDF + emo' and it demonstrates a better accuracy of 89% with an area under the ROC curve of 0.928 (see Fig. 7). We compare the result with the traditional model on TF- IDF vectors.

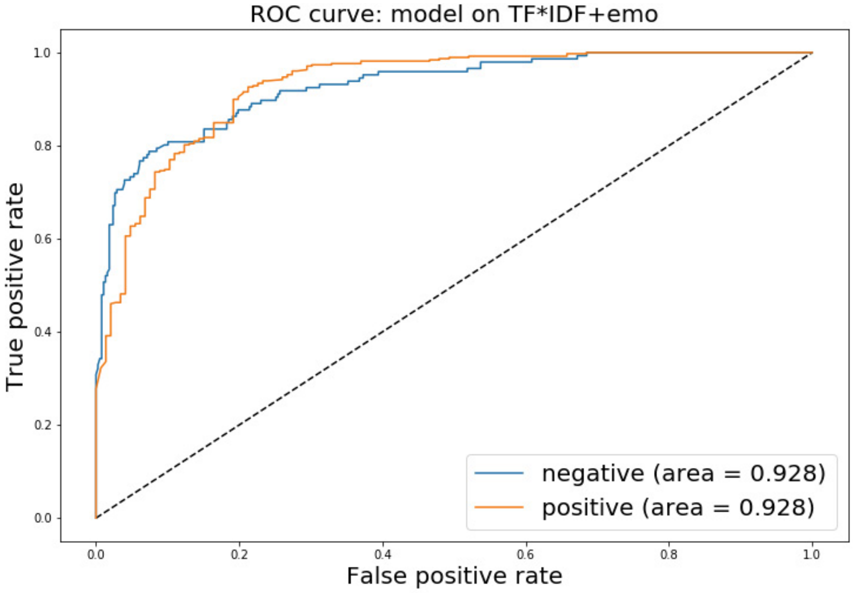

Fig 7. ROC model on TF-IDF and emotional indicators.

Consequently, it may be concluded that emotional indicators as predictors improve the metrics of the model.

It seems more relevant to look at the effect of using emotional indicators as predictors for more complex models; for example, on a model based on previously calculated Word2Vec vectors. The model architecture represents a kind of difficulty with this model because we cannot include emotional indicators in the Word2Vec embedding dictionary, as we did for TF-IDF. We conducted several experiments, replacing emoticons with similar words in meaning, previously calculated values in Word2Vec space, but this showed insignificant results. Moreover, in some cases, the metrics model even worsened.

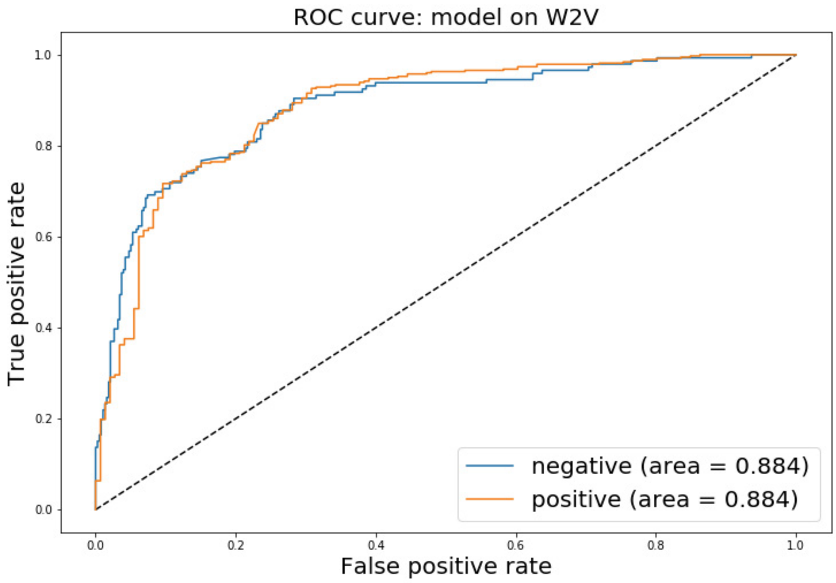

Fig. 8. ROC model on Word2Vec

Therefore, we built a traditional model on Word2Vec embeddings (see Fig. 8), which showed an accuracy of 85% and the area under the ROC curve of 0.884. It is noteworthy that the metrics of this more complex and resource-intensive model are comparable with those of a model that considers exclusively emotional indicators.

Both of these models were used in the ensemble, where their output was combined as predictors for the model integrating them, which was a simple fully connected neural network with one hidden layer. The results of this ensemble model are shown in graphs called ‘WORD2VEC + emo’ (see Fig. 9). The model reveals an accuracy of 91% and the area under the ROC curve of 0.937, this model demonstrates the best metrics compared to the other models.

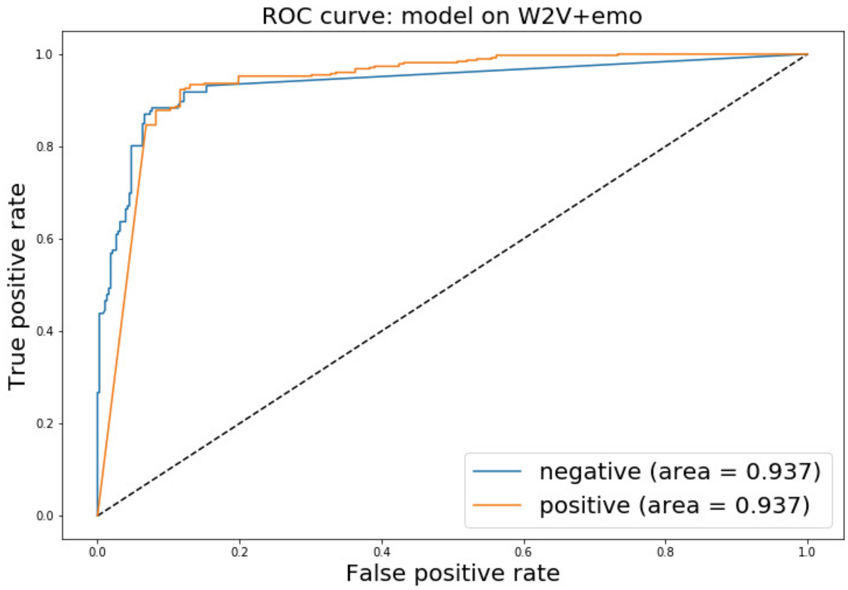

Fig. 9. ROC model on Word2Vec and emotional indicators.

6. Conclusion and future work

In conclusion, the objective of this study was to predict the tonality of the text using existing methods and try to use emotional indicators as predictors. The emotional indicators in the texts are an important source of any information. To achieve the goal, the lemmatizer was developed to highlight emotional indicators and preprocess the text; models were built to predict the tonality of the text.

Our results have demonstrated that model trained only on emotional indicators has good metrics with an 85% accuracy, which has the same result as a model based on Word2vectors.The novelty of this method lies in the fact that emotional indicators are used as predictors in the models proposed.

Therefore, it has been decided to try to combine these two models. Due to this fact, the ensemble method has been chosen. The model consisted of the word2vec model and the model on emotional indicators embeddings. The model showed a 6% more accuracy compared to traditional models.

The topic of ensemble methods for predicting the tonality of texts is of a great interest. The task of including emotional indicators in a single space of predictors is nontrivial and the ensemble method seems to be a universal solution to this problem.

In the future, specialized lemmatizers are planned to be made that implement semantic transformation of emoji into vectors of trained vocabulary spaces (word2vec). We suppose, this should further improve the quality of models based on the use of dictionary vectors as embeddings. Another promising area for the further research is to create models for an expanded analysis of the tonality that make predictions for range of classes that determine the emotional dominance of statements.

The authors prepare for publication some research. The research is devoted to build the model for predicting the 8 basic emotional classes of Robert Plutchik [31]. The models allow to get the emotional presentation of statements posted in social networks or in any other sources. Moreover, the models help to draw conclusions about the static and dynamic people psycho-emotional characteristics.

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