As a result we can say that, anomaly detector need to be accurate and minimize false positives or false negatives due to the cost of analyzing each anomaly. As well as there is need to develop analysis and visualization methods for detecting new patterns and relationships in analysis and visualization of data.

REFERENCES

1. Aliguliyev R.M., Hajirahimova M.Sh. Anomaly detection model in information security objects based on big data analytics. Actual problems of information security. III Republican scientific-practical seminar 2017, pp.96-99.
2. Alguliyev R.M., Aliguliyev R.M. et al., Multi-criterion optimization method for anomaly detection on big data / Actual problems of information security. Republican scientific-practical seminar. 2017, pp.7-11.
3. Hodge V., Austin J. A survey of outlier detection methodologies. Artificial Intelligence Review, 2004, vol. 22, no. 2, pp. 85–126.

UDC 004.89

Y.N. Imamverdiyev, M.Sh. Hajirahimova, A.Y. Imamverdiyeva
e-mail: yadigar@iit.science.az, makrufa@science.az

Institute of Information Technology, Azerbaijan National Academy of Sciences, Baku, Azerbaijan

A DEEP LEARNING METHOD FOR SENTIMENT CLASSIFICATION

The paper proposes a sentiment classification method for short texts based on deep learning methods and self-attention mechanisms.

Social networks offer people transparent platforms to express and share their thoughts and feelings about various issues of daily life and global challenges. Over the past 15 years, academic circles, the public sector and the service industry have been seriously working on the sentiment analysis of social network data to discover and explore public opinion [1].

Sentimental analysis can be considered as determining whether emotional polarity of a sentence, paragraph, document, or any piece of natural language texts is positive, negative or neutral. There are three basic approaches in sentiment analysis: 1) lexicon-based, 2) machine learning based, 3) combined. Lexicon-based approach is a very challenging task because of requirements for building polarity vocabularies, templates and rules for sentiment determination. Recently, Deep Learning methods in machine learning have been widely used for sentiment analysis and they have significant improvement in comparison with previous methods [2].

Usually social network posts are short texts. There are two reasons for sentiment classification errors in such texts. First, the contextual information in short texts is limited, and therefore, machine-learning methods have difficulty producing useful features. Secondly, social media posts often do not follow written language guidelines, and traditional NLP (Natural language processing) methods do not produce good results in short texts. For the solution of these two problems, this paper proposes an approach to consider long-distance contextual relationship and weights of words depending on the position of words in texts.

The model proposed in this paper consists of five modules. The first module (input module) creates a vector representation of short texts. The second module (feature extraction) uses BiLSTM (Bidirectional Long Short-Term Memory) architecture and extracts features from given short text. In the third module, the weight of the features is determined by using a self-attention mechanism. The fourth module (feature combination) non-linearly combines all representations by using CNN (Convolutional Neural Network) architecture and automatically generates a more relevant combination of features for sentiment classification. Finally, the fifth module (sentiment classification) defines the sentiment classes of short texts based on these features. This module uses *softmax* classifier for sentiment classification.

1. Word embedding. Given a short text $S = [w_1\, w_2 \dots w_T]$ which contains T words. Recently, word embedding methods like GloVe and word2vec has been used extensively. They allow to capture semantic and syntactic information in a vector representation of words. In this paper, word2vec method is used. Assume that by using word2vec, the original text $S = [w_1\, w_2 \dots w_T]$ is represented as sequence of m-dimensional word vectors $(x_1, x_2, \dots, x_T)$.

2. Feature extraction. Bidirectional LSTM is used to create an annotation of words by reflecting information in both directions:

$$\vec{h}_t = \overrightarrow{LSTM}(x_t), t \in [1, T], \overleftarrow{h}_t = \overleftarrow{LSTM}(x_t), t \in [T, 1].$$

For the given word w_t, we get annotation $h_t = \left[\vec{h}_t, \overleftarrow{h}_t\right]$ by concatenating the forward hidden state $\vec{h}_t$ and backward hidden state $\overleftarrow{h}_t$. Thus, BiLSTM allows us to include contextual information in annotation.

3. Attention weighting. In essence, attention methods compute an alignment score between elements of two sequences. Multi-dimensional "token2token" self-attention method is used to extract important words for the meaning of the given short text [3]. Initially the dependency between h_i and h_j (or attention of h_j to h_i) is measured:

$$f(h_i, h_j) = W^T \sigma\left(W^{(1)} h_i + W^{(2)} h_j + b^{(1)}\right) + b.$$

Then these scores are transformed to a probability function:

$$P_{ki}^{j} \triangleq p\left(z_k = i | h, h_j\right) = \frac{\exp(f(h, h_j))}{\sum_i \exp(f(h, h_j))}.$$

Finally, output s_j for h_j is computed as an element-wise product:

$$s_j = \sum_{i=1}^{n} P_{\cdot i}^{j} \odot h_i.$$

4. Feature combination. The obtained information in the previous module is compiled with CNN and vector representation of the short text v is created.

5. Sentiment classification. The vector v is used in *softmax* function to classify sentiment of the short text S.

Experiments were conducted with three short text collections (MR, SST-1, SST-2) to evaluate the effectiveness of the proposed model, and the proposed model was compared to other similar models. Experimental results show that the proposed model is superior to previous models.

REFERENCES

1. Liu B. Sentiment analysis: mining opinions, sentiments, and emotions. The Cambridge University Press, 2015.

2. Zhang L., Wang S., and Liu B. Deep learning for sentiment analysis: A survey. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 2018, vol. 8, no. 4. DOI: 10.1002/widm.1253.

3. Shen T., Zhou T., Long G., Jiang J., Pan S., & Zhang C. Disan: Directional self-attention network for RNN/CNN-free language understanding. In Thirty-Second AAAI Conference on Artificial Intelligence, 2018, pp. 5446-5455.

UDC 004.93

Y. N. Imamverdiyev, M. Sh. Hajirahimova, E. O. Bagirov
e-mail: yadigar@lan.ab.az, makrufa@science.az, elsenbagirov1995@gmail.com

Institute of Information Technology of ANAS, Baku, Azerbaijan

PREDICTION OF PVT PROPERTIES IN CRUDE OIL SYSTEMS USING MACHINE LEARNING METHOD

In the paper, machine learning method has been implemented for the prediction of oil formation volume factor which is one of the important parameter of PVT properties in oil fields. Middle East and Malaysia oils were selected as the object of the study.

The accurate determination of the PVT (pressure-volume-temperature) properties of the reservoir fluids is necessary for the formation evaluation of hydrocarbon reserves, reservoir performance, material balance calculations, well test analysis, numerical reservoir simulations calculations. Oil formation volume factor (FVF) is considered as relative change in oil volume between reservoir condition and standard surface condition. Ideally, the FVF is defined by laboratory experiments. Experimental determination of FVF is associated with high costs and time-consumption. Alternative approaches used in the prediction of oil formation