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 volume factor in the available literature are classified as equations of state (EOS), empirical correlations and machine learning methods. Unfortunately, EOS requires data on the composition of crude oil, which can only be determined by laboratory analysis; so they don't eliminate the need for laboratory analysis. It has paved the way for making empirical correlations. Studies conducted in this context has led to the development of various correlations such as Katz (1942), Standing (1947), Vasquez et al. (1980), Beggs and Robinson (1975), Glaso (1980) and Al-Marhoun (1988, 1992). The accuracy of these correlations largely depends on the primary data used in the calculations and the composition of liquids in different geographic locations. In recent during, engineers have noted the importance of developing machine learning techniques for predicting PVT properties. In addition, some machine learning (ML) methods were used to improve the prediction of the volume factor of oil formation.

The realization of SVM model. In this model B_{ob} was presented as function of four input parameters: solution gas–oil ratio (R_s) reservoir temperature (T), oil gravity (γ_o), and gas gravity (γ_g). The functional dependence of these parameters can be expressed as follows: $B_{ob} = f(T, \gamma_o, \gamma_g, R_s)$.

The experiments have been conducted with applying selected RBF nuclear function of SVR on Middle East and Malaysia dataset in literature. Experiments were conducted using python programming language (jupyter notebook) on Linux OS (Ubuntu Desktop 16.04) with 1.7GB RAM, Intel(R) Core(TM) i5-2400, 64bit prosessor, 3.10GHz CPU properties. In this work, 160 oil samples of Middle East and 93 PVT data of Malaysian oil-fields were used for research. 70% of this dataset was used for training and 30% for testing. In order to get high accuracy, dataset was scaled in [0,1] range, and applied k-cross validation. The pseudo-code of implementation and graph plots of performance of SVR-RBF model are shown in Fig.1 and Fig. 2, respectively.

```
Bob
import dataset as D[i,j] #253 #import of dataset
import modules #import of modules
   for i=1 to 253
     for j=1 to 5
   begin
   scale Di,j; #scale dataset
   end.
   for i=1 to 112
     for j=1 to 5
   begin
   D1 =Di,j; #split from dataset for training
   end.
   for i=113 to 160
     for j=1 to 4
   D2 =Di,j; #split from dataset for testing
   end.
   Train D1;  #train SVR on D1
   Test D2; #testing on D2.
   Evaluate (MAE, RMSE, R^2, SD); #calculate evaluation metrics
   Print(MAE, RMSE, R^2, SD); #print evaluation metrics
   Plot D2. #visualization of results
```

Fig. 1. Steps for the RBF nuclear function of SVR

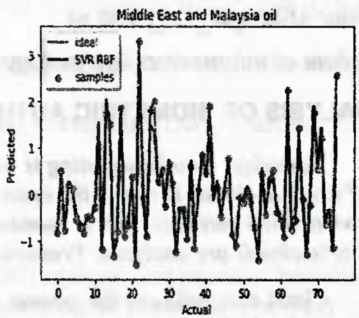

Fig. 2. The Performance of SVR RBF in B_{ob} prediction

Three statistical quality indicators (*correlation coefficient-* R^2, *root mean square error-* RMSE *and mean absolute error-* MAE, *standard deviation* -SD) were used to predict B_{ob}. The comparative analysis of the gained results has been conducted with existing empiric correlations in Table.

The results of statistical analysis

	SVR	Vazuquez	Hanafy	Standing	Al-Shammasi	Glaso
MAE	0.12472	0.14680	0.20948	0.38154	0.30868	0.42734
RMSE	0.17031	0.19114	0.28010	0.51065	0.45487	0.52973
R^2	0.96612	0.95733	0.90837	0.70582	0.77375	0.69316
SD	0.50066	1.03607	1.23058	2.26179	2.36664	1.97890

SVR RBF kernel function showed high accuracy (highest correlation coefficient-96,61%, lowest mean absolute error-12,47%) to predict B_{ob} than other correlation models.

REFERENCES

1. M.A. Al-Marhoun, PVT correlation for Middle East crude oils. Journal of Petroleum Technology, 1988, vol. 40, no.5, pp. 650–666.

2. Omar M.I., Todd A.C. Development of new modified black oil correlations for Malaysian crudes, SPE025338, 1993, pp.211-219.

3. Ramirez A. M. et al., Prediction of PVT properties in crude oil using machine learning techniques. SPE 185536-MS Latin America and Caribbean Petroleum Engineering Conference, 2017.

UDC 004.93

Sh. J. Mahmudova
e-mail: shafagat_57@mail.ru
Institute of Information Technology of ANAS, Baku, Azerbaijan

ANALYSIS OF BIOMETRIC AUTHENTICATION IN CLOUDS

Nowadays cloud computing is widely used in various fields. Ensuring security of users in clouds is one of the main problems. In this study, one of the biometric authentication methods, that is human face recognition methods for providing security in clouds are analyzed. Problems in this field are studied.

Cloud computing is the newest technology. The user can access the files or data on clouds from anywhere over the Internet. The use of cloud computing has its own advantages, such as high availability, low costs, and so on. On the other