Text-based crude oil price forecasting

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Abstract

Crude oil price forecasting has attracted substantial attention in the field of forecasting. Recently, the research on text-based crude oil price forecasting has advanced. To improve accuracy, some studies have added as many covariates as possible, such as textual and nontextual factors, to their models, leading to unnecessary human intervention and computational costs. Moreover, some methods are only designed for crude oil forecasting and cannot be well transferred to the forecasting of other similar futures commodities. In contrast, this article proposes a text-based forecasting framework for futures commodities that uses only future news headlines obtained from Investing.com to forecast crude oil prices. Two marketing indexes, the sentiment index and the topic intensity index, are extracted from these news headlines. Considering that the public’s sentiment changes over time, the time factor is innovatively applied to the construction of the sentiment index. Taking the nature of the short news headlines into consideration, a short text topic model called SeaNMF is used to calculate the topic intensity of the futures market more accurately. Two methods, VAR and RFE, are used for lag order judgment and feature selection, respectively, at the model construction stage. The experimental results show that the Ada-text model outperforms the Adaboost.RT baseline model and the other benchmarks.

Keywords: Crude oil price, text features, forecast, Ada-text

1. Introduction

Crude oil is also known as “industrial blood”. Industry currently relies heavily on the supply of crude oil. Crude oil plays an important role in the global economic system. Therefore, the accurate forecasting of the crude oil price is very important to ensure the stable development of the global economic system.
Research has shown that the crude oil price is determined by supply and demand (Hagen, 2010; Stevens, 2007). More importantly, price is influenced by extreme events, such as geopolitical conflicts and natural disasters (Bernabe et al., 2012; Ling et al., 2015). The historical crude oil price reflects the nonlinearity, uncertainty, and dynamics of the price, making crude oil price forecasting difficult, and as a result, the forecasting results have greater uncertainty, which may eventually cause significant uncertainty in the returns of relevant investors and the stable development of the economic system (Zhang et al., 2015).

Many methods have been proposed for forecasting crude oil prices, which can be grouped into 2 categories. Traditional statistical methods, such as autoregressive integrated moving average (ARIMA) (e.g., Mohammadi and Su, 2010; Xiang and Zhuang, 2013) and generalized autoregressive conditional heteroskedasticity (GARCH) (Hou and Suardi, 2012), have been used for crude oil price forecasting. Recently, with the development of big data, an increasing number of machine learning methods, such as support vector machines (SVMs) (e.g., Xie et al., 2006; Jun et al., 2009), decision trees (e.g., Ekinci et al., 2015; Gumus and Kiran, 2017), and neural networks (e.g., Movagharnejad et al., 2011; Moshiri and Foroutan, 2006), have been used to forecast crude oil prices and have produced comparable forecasting performance to that of traditional statistical methods. Recently, the emergence of a large amount of user-generated content (UGC) has brought about new challenges and opportunities to the field of forecasting. Methods for processing text data have emerged in recent research (e.g., Berry and Castellanos, 2004; Aggarwal and Zhai, 2012; Shriharir and Desai, 2015) and appear increasingly mature. Numerous studies have suggested that the information extracted from the internet can contribute to the prediction of financial data (Demirer and Kutan, 2010; Kaiser and Yu, 2010). Online news is an important part of UGC; it conveys the topics (Blei et al., 2003) of the market change and sentiment (Serrano-Guerrero et al., 2015) of the public, which can be used to quantify the changes in the public’s mood and the market. Therefore, to achieve greater forecasting performance, a series of forecasting studies based on the text has been proposed, which adopt the combination of textual and nontextual factors for forecasting. Wang et al. (2004) proposed a novel hybrid AI system framework utilizing the integration of neural networks and rule-based expert systems with text mining. Yu et al. (2005) proposed a knowledge-based forecasting method, the rough-set-refined text mining (RSTM) approach, for crude oil price tendency forecasting. Li et al. (2018) combined some factors (daily WTI futures contract prices traded on the New York Mercantile Exchange (NYMEX), US Dollar Index (USDX) and Dow Jones Industrial Average (DJIA)) related to the crude oil price and information such as topics and sentiment extracted from news headlines to forecast crude oil price, yielding good
forecasting performance. Internet searching has also been identified as a way of quantifying investor attention and helping forecast crude oil prices (Wang et al., 2018). Elshendy et al. (2018) combined the sentiment of four media platforms (Twitter; Google Trends; Wikipedia; and Global Data on Events, Location, and Tone database) to forecast the crude oil price and improve forecasting performance.

However, having revisited the literature on text-based crude oil price forecasting, we find the following:

(1) To improve forecasting accuracy, some scholars tend to combine text information and some other relevant factors as much as possible, causing more human intervention and more complex computation.

(2) Some methods are designed specifically for crude oil price forecasting and are not transferable to the forecasting of other commodity prices.

(3) When referring to the method of text mining, some research focuses more on the usage of the method itself, ignoring the feature and nature of the text data.

In this article, we propose a framework for forecasting crude oil prices based on text. Specifically, to reduce human intervention and enhance the generality of the model, we only use news headlines associated with the futures price. We extract two marketing indexes (the sentiment index and the topic intensity index) from the news, which are used as dependent variables for forecasting. For short news headlines, we use a short topic model called SeaNMF to characterize the topic intensity of the market. Compared with other research, we consider time continuity for the construction of the sentiment index. The experimental results show that crude oil price forecasting based on text, with fewer factors and a more accurate characterization of the market, yields better performance. Additionally, this text-based forecasting method has been applied in other fields and performs well, which demonstrates the versatility and robustness of our approach.

The rest of the article is organized as follows. Section 2 presents a framework of text-based crude oil price forecasting. In Section 3, we apply this framework to crude oil price data. Section 4 applies the text-based crude oil price forecasting method to other commodity data. Section 5 concludes the article and discusses directions for future research.
2. Methodology

The purpose of this study is to establish a time-series forecasting framework based on text features. Relevant studies have proven that text features contain information that is not available in historical time-series data. Topic and sentiment information can be extracted from a large number of futures-related news items through text mining. Then, the text-related features are added into the model to make predictions. The specific implementation process is shown in Fig. 1.
2.1. Text Mining

2.1.1. Word Embedding

Prior to text mining, we need to preprocess the news headlines. Preprocessing steps include word tokenization, stop-word filtering and word embedding. In the word embedding step, we use the GloVe pretrained word vector developed by (Pennington et al., 2014) of Stanford
University. GloVe is a very popular word vector representation in the field of natural language processing. It is an unsupervised learning algorithm that obtains a vector representation of words. GloVe uses the global and local statistical information of the words to generate a vectorized representation of the language model and words. Considering that news headlines are short texts, we convert each headline into a 50-dimensional word vector, which is ready to be used as input for the extraction of the topic intensity index and the sentiment index.

2.1.2. SeaNMF Topic Model

The latent dirichlet allocation (LDA) (Blei et al., 2003) model is widely used in text mining and makes the generative assumption that a document belongs to a certain number of topics (Mazarura et al., 2015). However, the length of the news headlines used in this article is no more than 50 words. Research shows that the LDA model is sensitive to short text. Inferring topics from short texts has become a critical but challenging task (e.g., Chen et al., 2011; Jin et al., 2011; Mazarura et al., 2015; Qiang et al., 2017).

(Shi et al., 2018) proposed a semantics-assisted nonnegative matrix factorization (SeaNMF) model to discover topics from short texts. They used a skip-gram algorithm to extract the relationship between words and context from the corpus and successfully associated this semantic information with the model. They experimented with Tag. News, Yahoo. Ans and other short text datasets and achieved better results than did the LDA topic model. Following the instructions of (Shi et al., 2018), we finally obtain three matrices: \( W, W_c, H \). The meanings of these three notations are as follows:

\( W \): Latent factor matrix of words. \( W_c \): Latent factor matrix of contexts. \( H \): Latent factor matrix of documents.

The \( H \) matrix contains the information about which we are concerned. Different from the LDA model, the \( H \) matrix represents the topic weight distribution of each headline, not the probability distribution. We need to further normalize the \( H \) matrix to obtain the topic intensity. To select the number of topics, the pointwise mutual information (PMI) score is calculated (Quan et al., 2015). Given a set of topic numbers, PMI can help us evaluate the effectiveness of the topic model and choose the optimal number of topics.

Because the media publishes a lot of news every day, we calculate the average weight of news as the topic intensity of the day. The topic intensity index of the \( t \)-th day is defined as follows:

\[
TI_{it} = \frac{1}{n} \sum_{j=1}^{n} DT_{ij}
\]  

(1)
TI_{it} \text{ is the } ith\text{-topic intensity index of the } t\text{-th day; } DT_{ij} \text{ is the weight of } j\text{-th news of } i\text{-th topic in } t\text{-th day.}

2.1.3. Sentiment analysis

TextBlob is widely used to calculate the sentiment value of one piece of news. TextBlob is a python library that can handle a variety of complex NLP problems; certainly, it can also be used to calculate the sentiment values of text. The sentiment values range from -1 to 1, and the smaller the value is, the more negative, and vice versa.

By averaging the sentiment scores of all news headlines in one day, we can obtain the sentiment intensity of this day.

\[ SV_t = \frac{1}{N_t} \sum_{i=1}^{N} PV_{it} \]  \hspace{1cm} (2)

\( PV_{it} \) represents the sentiment value of the \( i\)-th news items on the \( t\)-th day, and \( N_t \) is the number of news items published on the \( t\)-th day. The average \( SV_t \) refers to the sentiment intensity of the \( t\)-th day.

However, the impact of news on people’s sentiment is often continuous in the actual futures market. That is, on a specific day, public sentiment is the result of the combination of the news on this day and that in the previous few days, except that the current news is more influential than is the old news. Given this complex situation, it is assumed that the impact of news on public sentiment is exponentially attenuated. Considering the sentiment continuity, we design a sentiment index (SI) \( e^{-\frac{m}{7}} \) with reference to (Xu and Berkely, 2014). SI is exponentially declining, which is in line with the actual situation of news impact. Assume that a piece of news has the strongest impact on crude oil prices for the next seven days. \( m \) represents the number of days after the news release. On the day of the news release, \( m = 0, SI = e^{-\frac{0}{7}} = 1 \); when \( m = 1, SI = e^{-\frac{1}{7}} = 86.69\% \), the following SIs are 75.15\%, 65.14\%, ....

The sentiment intensity on the \( t\)-th day is the sum of the \( SV \) on the \( t\)-th day and the \( SVs \) in the previous days.

\[ SI_t = \sum_{i=1}^{t-1} e^{-\frac{d_i}{7}} SV_i + SV_t \]  \hspace{1cm} (3)

\( SI_t \) is the sentiment intensity of the \( t\)-th day. \( e^{-\frac{d_i}{7}} SV_i \) is the sentiment impact of the \( i\)-th day on the \( t\)-th day.
2.2. Forecasting and Evaluation

Trend, seasonality and residual factors are obtained as features for forecasting single-variable time series. One common method for forecasting multivariate time series is to convert the forecasting problem into a regression problem. Adaboost.RT, as an ensemble method, can improve single-variable forecasting accuracy. AdaBoost was originally designed as a classification algorithm, and (Solomatine and Shrestha, 2004) proposed Adaboost.RT to forecast time series based on AdaBoost. Its main objective is to map the forecasting problem into a binary classification problem. Adaboost.RT combines a number of weak classifiers to form a strong classifier, which can output the forecasting results through adjustment of thresholds and multiple rounds of iterative calculation. Finally, the root mean square error (RMSE) is used to evaluate the forecast effect of the model.

3. Application to Crude Oil Price Data

3.1. Data Collection

Investing.com is a world-renowned financial website that provides real-time information and news about hundreds of thousands of financial investment products, including global stocks, foreign exchange, futures, bonds, funds, and digital currency, as well as a variety of investment tools. We collected 28,220 news headlines through the futures news column on Investing.com as the text data of this study. The following two points should be noted:

(1) Why headlines instead of news? News headlines often use short text to state what happened. The news headline itself is a summary of the news content. News headlines can be considered to contain most of the news information.

(2) Why futures news instead of crude oil news? There are two reasons for this choice of news. First, we tried to collect crude oil news but only obtained approximately 2,000. The use of futures news has expanded the text dataset approximately ten times. Second, relevant studies have proven that there are complex correlations among futures prices such as gold, natural gas, and crude oil prices. (Sujit and Kumar, 2011) argues that fluctuations in gold prices will affect the size of the WTI index. For different countries, their dependence on crude oil (import or export) will affect their own currency exchange rate and then affect people’s purchasing power for gold. In the market, if the supply-demand relationship changes, then the price of gold will change accordingly. (Villar and Joutz, 2006) notes that a 1-month temporary shock to the WTI of 20 percent has a 5-percent contemporaneous impact on natural gas prices.
We collected oil price data from March 29, 2011, to March 22, 2019, on this website, and the news collected also covered this period. The selected base oil is West Texas Intermediate (WTI) crude oil, which is a common type of crude oil in North America. WTI crude oil has become the benchmark of global crude oil pricing due to US military and economic capabilities in the world.

3.2. Data Preprocessing

First, we extract news headlines by tokenization, stop-word filtering and word stemming. After these basic operations, the GloVe method is used for word embedding to convert text information into computer-readable word vectors. This step is performed to prepare for the following topic models and sentiment analysis.

When processing oil price data, normalization and HP smoothing are used to obtain the oil price trend. In the step of forecasting the oil price, we forecast the change in the price trend.

3.3. Topic Analysis

SeaNMF is a model that combines word document and word context to extract latent topic categories from the corpus. We input the word embedding matrix into the SeaNMF model and obtain the H matrix, which contains the weight information in which each headline belongs to each topic. When choosing the number of topics \( k \), the PMI score is used. The higher the PMI score is, the better the effect of the model. We set \( k \) from 2 to 10 to calculate the PMI scores in turn.

Fig. 2. The result shows that when the number of topics \( k = 4 \), the PMI value is the largest, at 0.5483.

As Fig. 2 shows, four topics are finally identified. We extract the top 10 keywords from each topic, as shown in Table 12.

From the keywords of the four topics, we can see that the SeaNMF model can indeed extract different topics from the text. The bold font shows that the four topics can be approximately summarized as crude oil, gold, natural gas, and new energy.
Table 1. Top 10 keywords of 4 topics

<table>
<thead>
<tr>
<th>Topic</th>
<th>Keywords</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>oil crude u.s prices data supply opec asia ahead gains</td>
</tr>
<tr>
<td>2</td>
<td>gold prices fed asia dollar u.s data ahead gains higher</td>
</tr>
<tr>
<td>3</td>
<td>futures gas natural u.s weekly outlook data low weather supply</td>
</tr>
<tr>
<td>4</td>
<td>exclusive says energy new sources trump billion coal pipeline saudi</td>
</tr>
</tbody>
</table>

3.4. Forecasting and Evaluation

We also use the method mentioned in 2.1.3 to calculate sentiment intensity. After the above steps, 6 time series including topic intensity, sentiment, and crude oil prices are obtained, as shown in Fig. 3. The time-series data are then divided into a training set and a test set, and fixed-window prediction is performed. That is, the training set is used to train a regression model to forecast the test set data; thus, it is an in-sample forecasting method.

![Fig. 3. Time series of crude oil price and text features. The brown line represents the trend in the oil price, while the other lines are textual features, including the topic intensity index and the sentiment intensity index.](image)

Fig. 3. Time series of crude oil price and text features. The brown line represents the trend in the oil price, while the other lines are textual features, including the topic intensity index and the sentiment intensity index.

![Fig. 4. The data in the training set are from March 29, 2011, to July 23, 2016, and the data in the test set are from July 23, 2016, to March 22, 2019.](image)

Fig. 4. The data in the training set are from March 29, 2011, to July 23, 2016, and the data in the test set are from July 23, 2016, to March 22, 2019.

Considering that time series have the characteristics of autocorrelation, we move the time series to align the lag orders with the actual time series. Therefore, we can better identify the pattern of the sequence and determine which periodic frequency the pattern repeats. VAR is used to calculate the lag order of six time series. The results are shown in Table 2:

After obtaining the lag orders of the time series, it is intuitive to regard these lag values as independent variables and oil price series as dependent variables to train the regression model.
Table 2. Lag Order of 6 Time Series

<table>
<thead>
<tr>
<th>Time Series</th>
<th>topic 1</th>
<th>topic 2</th>
<th>topic 3</th>
<th>topic 4</th>
<th>polarity</th>
<th>price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lag Order</td>
<td>18</td>
<td>25</td>
<td>28</td>
<td>28</td>
<td>25</td>
<td>4</td>
</tr>
</tbody>
</table>

To avoid model overfitting and feature redundancy, further filtering of features is needed. RFE is a common feature selection method. In the regression phase, we use random forest regression (RF), support vector regression (SVR), autoregressive integrated moving average (ARIMA), autoregressive integrated moving average with explanatory variable (ARIMAX), the method from Li et al. (2018) (SVR-Li) and AdaBoost.RT(Ada) to fit the crude oil price data and complete forecasting on the test set. At the same time, the RMSE values between the model with and without text features are compared.

The results in Table 5 show that the forecasting accuracy of the Ada model is better than that of the other models. Otherwise, the text-based model performs better than the baseline model, which proves that the attempt of adding text features to the forecasting model is successful.

It is worth mentioning that when selecting features, the RFE method based on logistic regression rules is used. At the same time, the RMSE value varies with the number of features. We represent the relationship of RMSE and the number of features in Fig. 5-7. Noting that the curves in Fig. 5-7 are all “L”-shaped, we focus on the number of features that makes the RMSE value plummet, which is the “knee” in the figure. However, the RMSE value of the “knee” is not necessarily the minimum.

Table 3. Comparison of Models for Crude Oil Price Forecasting

<table>
<thead>
<tr>
<th>Model</th>
<th>No. of Features</th>
<th>RMSE</th>
<th>Model</th>
<th>No. of Features</th>
<th>RMSE</th>
<th>Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>RF-baseline</td>
<td>4</td>
<td>0.0611</td>
<td>RF-text</td>
<td>9</td>
<td>0.0555</td>
<td>9.17%</td>
</tr>
<tr>
<td>SVR-baseline</td>
<td>4</td>
<td>0.0422</td>
<td>SVR-text</td>
<td>9</td>
<td>0.0420</td>
<td>0.47%</td>
</tr>
<tr>
<td>ARIMA</td>
<td>(4, 2, 9)</td>
<td>0.0747</td>
<td>ARIMAX</td>
<td>(7, 1, 8)</td>
<td>0.1235</td>
<td>–</td>
</tr>
<tr>
<td>Ada-base</td>
<td>4</td>
<td>0.0286</td>
<td>Ada-text</td>
<td>9</td>
<td>0.0214</td>
<td>25.17%</td>
</tr>
<tr>
<td>SVR-Li</td>
<td>7</td>
<td>0.0390</td>
<td></td>
<td></td>
<td></td>
<td>45.13%</td>
</tr>
</tbody>
</table>

Taking Ada-text forecasting as an example, we draw a fitted curve between the true value and predicted value, as shown in Fig. 8.
Fig. 5. Feature selection in the *random forest* regression model.

Fig. 6. Feature selection in the *support vector* regression model.

Fig. 7. Feature selection in the *AdaBoost.RT* regression model.
4. Application to Natural Gas and Gold Price Data

Can the *Ada-text* model only work in forecasting crude oil prices? In the above part of the article, we briefly discussed the relationships among the three futures prices of crude oil, natural gas, and gold based on previous research results. The text dataset for this article comes from *Investing.com* and includes news headlines related to crude oil, natural gas, and gold. Since the *Ada-text* model based on these news headlines can forecast crude oil prices pretty well, an intuitive idea is that it can also be migrated to other application scenarios. That is, the *Ada-text* model can be used to forecast the prices of natural gas and gold. The experimental results show that this model can achieve similar good results in forecasting the prices of gold and natural gas.

<table>
<thead>
<tr>
<th>Model</th>
<th>No. of Features</th>
<th>RMSE</th>
<th>Model</th>
<th>No. of Features</th>
<th>RMSE</th>
<th>Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>RF-baseline</td>
<td>2</td>
<td>0.0200</td>
<td>RF-text</td>
<td>12</td>
<td>0.0192</td>
<td>4.00%</td>
</tr>
<tr>
<td>SVR-baseline</td>
<td>2</td>
<td>0.0291</td>
<td>SVR-text</td>
<td>12</td>
<td>0.0272</td>
<td>6.53%</td>
</tr>
<tr>
<td>ARIMA (8, 1, 0)</td>
<td>0.0599</td>
<td></td>
<td>ARIMAX (3, 2, 9)</td>
<td>0.0788</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ada-base</td>
<td>2</td>
<td>0.0071</td>
<td>Ada-text</td>
<td>13</td>
<td>0.0085</td>
<td></td>
</tr>
<tr>
<td>SVR-Li</td>
<td>10</td>
<td>0.0336</td>
<td></td>
<td></td>
<td></td>
<td>84.14%</td>
</tr>
</tbody>
</table>

Table 5. Comparison of Models for Gold Price Forecasting

<table>
<thead>
<tr>
<th>Model</th>
<th>No. of Features</th>
<th>RMSE</th>
<th>Model</th>
<th>No. of Features</th>
<th>RMSE</th>
<th>Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>RF-baseline</td>
<td>5</td>
<td>0.0216</td>
<td>RF-text</td>
<td>6</td>
<td>0.0209</td>
<td>3.24%</td>
</tr>
<tr>
<td>SVR-baseline</td>
<td>5</td>
<td>0.0438</td>
<td>SVR-text</td>
<td>6</td>
<td>0.0288</td>
<td>34.25%</td>
</tr>
<tr>
<td>ARIMA (6, 1, 0)</td>
<td>0.0640</td>
<td></td>
<td>ARIMAX (2, 1, 5)</td>
<td>0.0842</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ada-base</td>
<td>5</td>
<td>0.0129</td>
<td>Ada-text</td>
<td>6</td>
<td>0.0101</td>
<td>21.71%</td>
</tr>
<tr>
<td>SVR-Li</td>
<td>2</td>
<td>0.0382</td>
<td></td>
<td></td>
<td></td>
<td>73.56%</td>
</tr>
</tbody>
</table>
Similar to forecasting the crude oil price, the \textit{AdaBoost.RT} model performs fairly well. We also focus on “knee” points when selecting features. Note that the \textit{RMSE} of \textit{Ada-text} is larger than that of \textit{Ada-baseline} for natural gas price forecasting, as shown in Table 4. In fact, when the number of features equals 77, the corresponding \textit{RMSE} is 0.0063, which is an 11.27\% improvement over that of \textit{Ada-baseline}. Then, we also draw the fitting curves of natural gas and gold price forecasting based on the \textit{Ada-text} model. The blue line represents the true price trend, and the green line represents the forecast result.

Fig. 9. Fitting curve of natural gas price forecasting

Fig. 10. Fitting curve of gold price forecasting

5. Conclusions and future work

The focus of this article comes from Li et al. (2018), who proposed a deep learning approach for forecasting and added various features of text to the forecasting model. This is a very novel view, which provides us with great inspiration. We have reproduced their experimental process, studied their ideas in depth, and proposed some modifications and innovations from the following perspectives:

(1) Obtain better predictions with fewer features. Li et al. (2018) used the CNN model to predict whether crude oil prices would rise or fall the next day, but only with 61\% accuracy. This fact
indicates that not all features can improve forecasting accuracy. Therefore, we only design two indicators, the sentiment index and the topic intensity index, in the process of constructing the model.

(2) GloVe instead of the bag of words during word embedding. Glove’s pretrained model makes full use of massive corpus information, retains more semantic relationships, and saves considerable time in word embedding. Bag of words focuses more on syntax than on semantics.

(3) The SeaNMF model is more suitable for short text topic mining than is the LDA. Considering that news headlines are short texts and lack context, the method of (Shi et al., 2018) is cited in this article. During the experiment, we also contacted the original authors and discussed our study with them. They provided us with some valuable suggestions.

(4) Redesign the sentiment index, combined with the time decay of sentiment. The impact of most news events is continuous. We no longer calculate the sentiment value of the news text of each day separately but rather design an index based on the continuity of news, including the cumulative effect of sentiment. This approach is closer to the actual situation.

(5) AdaBoost.RT is selected after comparing multiple regression models. As an ensemble model, AdaBoost.RT performs pretty well in many data mining competitions, which is why we choose it. Based on AdaBoost.RT, we proposed Ada-text to forecast the price of crude oil. The experimental results prove that Ada-text performs pretty well.

(6) Our model Ada-text can also be used to predict the price movements of natural gas and gold. Due to the use of futures-related news headlines as an experimental training corpus, Ada-text also obtained the expected good results in forecasting the prices of natural gas and gold. The research framework of this article can also be transferred to other fields. For example, the news text features of listed companies can be added to the model to enhance the accuracy of its stock price prediction.

This article also has some limitations. The results of the model focus more on forecasting price fluctuations (using RMSE to measure) and lack consideration of the probability of whether the price rises or falls the next day, which may be a concern of future investors. Currently, there has been a great development in the field of natural language processing. In future research, we may consider using a more powerful pretraining model, Bert, to further optimize the forecasting effect. Some methods based on deep learning models, such as LSTM, may also be helpful for forecasting.
In short, this article further optimized the forecasting method of Li et al. (2018) from different perspectives. The idea of introducing external data features into the forecasting model has certain reference significance. In addition to text feature information, picture and audio features may also be considered when optimizing the time-series forecasting effect in different fields.

**Appendix**

**Experimental setup**

- When applying SeaNMF, we set the number of topics from 2 to 10 and choose 4 according to the PMI score.
- Parameter for random forest regression: `max_leaf_nodes = 8`;
- Parameter for support vector regression: `kernel = 'linear', C = 1`; and
- Parameter for AdaBoost.RT: `n_estimators = 100, loss = 'linear'`.

**Product screenshots**

We have implemented the method we proposed into crude oil price forecasting system, which is an important part of the procurement data management system of CHINA COSCO SHIPPING CORPORATION LIMITED. Crude oil price forecasting system has been put into use and helps purchasers better analyze changes in the oil market and make purchasing decisions effectively. This system helped the company achieve excellent results in the special procurement evaluation of the SASAC (State-owned Assets Supervision and Administration Commission of the State Council) in 2019. Some screenshots are shown below.
Fig. 11. This figure shows the price of WTI crude oil in the past decade.

Fig. 12. The proportion and the number of the four categories of topics in the past year are shown in this figure, from January 12, 2019, to January 12, 2020.

Fig. 13. This figure shows the WTI crude oil price forecast for the past month, from December 15, 2019, to January 15, 2020. The red line represents the actual crude oil price, and the blue line represents the predicted value. The red line is discontinuous because WTI crude oil prices are not announced on weekends. The results have proven that using the Ada-text method to predict crude oil prices can achieve good performance.
References


Quan, X., Kit, C., Ge, Y. and Pan, S. J. (2015), Short and sparse text topic modeling via self-aggregation, in ‘Twenty-Fourth International Joint Conference on Artificial Intelligence’.


