Stock Prediction and Prediction Accuracy Improvement using Sentiment Analysis and Machine Learning based on Online News

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Abstract

Investment strategy and predicting technique appeared to analyze pattern of stock market to get economic gain. However, predicting the flow of stock index is quite difficult because stock market contains uncertain factors. To overcome this problem, varieties of methodology is going along. And with ‘big data’, varieties of atypical data come out with social media. Therefore, in this research paper we predicted fluctuation of stock price with using ‘News data’. We used morpheme analysis and sentimental analysis to make digitalize it. Next with this data we applied machine learning and made predicting model. Finally, we got prediction rate and F1 score.

Keywords
Machine Learning, Sentiment Analysis, Online news, Stock Index, text data, Stock-Prediction

1. Introduction

Stock is related to money therefore it is becoming an object of attention to not only professional but also ordinary people. Furthermore, as age of low interest rate is continuing, an importance of stock prediction is gradually standing out.

At present, varieties of research papers are trying with new scientific technology to predict stock index. Fundamental analysis and technical analysis were typical stock-predicting methodologies. Fundamental analysis predicts by analyzing the financial structure, market prospect, inherent value. Contrarily technical analysis predicts by analyzing statistical information such as volume, moving average, trend. Nowadays, as technology develops and big data appears, the range of technical analysis has extended. Technological method became a part of technical analysis. Machine learning, sentimental analysis and text mining are typical exam example of technological methods. Technological method is using for purpose of rapid and accurate calculation of the vast amount of data. A notable feature of technological method is that it can use text data to independent variable. Recently, online news, which comprehensively contains social issue, are using on stock-prediction.

Therefore, this research paper predicted stock index in using online new data. First, select target companies to predict and collect online news data which is related in target company. Second, digitalize new data and apply it on machine learning and make predicting model. Finally, we analyzed relationship between data and predicting model and compared accuracy rate.

2. Related Research

Sentimental analysis is the part of text mining technology which analyzes semi-structured and atypical text and extracts practical information that is defined as the natural language processing technology which analyzes people’s subjective opinions about a certain kind of brand, event and product. Text mining is able to be applied to Social Network Service which contains a lot of subjective information and news which consist of objective information.
Morpheme is defined as ‘the minimum unit of morphologic level of a language’ and the meaning of a language would be lost if further unit is reduced. Morpheme analysis is the process of separating given sentence by morphemic units and then giving them a part of speech or meaning which fits each morpheme such as predicate, noun, adjective, adverb and postposition. In this paper, for the sentimental analysis of atypical text, a process of analyzing morphemes and giving them polarities appropriate for each morpheme and grasping polarities of the whole texts is carried out.

Sentimental analysis is for analyzing a polarity which judges whether given text data means the positive or the negative in certain writing. In this process, if the research is being done by using the sentimental dictionary which contains frequency and positive index of each word, the accuracy of the sentimental analysis will rise. Jong-Sung Song(2011) found out that carrying out an research with an exclusive sentimental dictionary for each field not an universal sentimental dictionary can increase the accuracy of the sentimental analysis and Dong-Sung Kim(2015) confirmed that if sentimental dictionary is expanded as time passes an increase in the accuracy of sentimental analysis will happen, but if sentimental dictionary is neglected without any further expansion that dictionary will lose its efficiency as time goes by. In this research, based on the method of building sentimental dictionary of Dong-Yeong Kim(2015), an exclusive sentimental dictionary for stock prediction for each company is made to conduct sentiment analysis.

So far constant researches for stock prediction have been conducted in various ways. Byeong-Su Jo(2009) found out that despite the differences among each news, the top 10 news presented every year affect the stock index of securities market and Jang-Yeun Um (2015) and II-Ji Choe conducted the research on prediction for stock fluctuation through text mining based on news, and Yu-sin Kim(2012) used the sentimental analysis method to analyze news and produce investment information, and based on this, Yu-sin Kim suggested intelligent investment decision-making model for stock prediction. Additionally, R.Tushar and Saket(2012) analyzed the correlation between social site based on the sentimental analysis about certain company and result of short-term market through extensive social data, and found out that public opinions which show positive and negative perspectives clearly hugely affect stock index of each company. Therefore, this paper is to predict stock by creating prediction model by mechanically educate data set after sentimental-analyzing articles published in economy section in Naver news and refining the data.

3. Stock Prediction Model

3.1 Stock Prediction by Online News

In this paper, stock prediction was tried through news data which is atypical data, which have close relationship with stock, and news data of ‘NAVER’, the biggest search engine portal site in South Korea, were used. Data were collected within economy section in NAVER news and ‘articles published in newspaper’, and it was planned to create stock prediction model after sentimental-analyzing collected data and use them for mechanical education. The process of conducting this research is shown in [Figure 1].

![Figure 1. Stock Prediction Model](image-url)
A company is selected and news data which has those keywords are collected. Collected data will go through a morpheme analysis and will be sorted to the words that correspond to nouns and category of assumed noun, and the sorted words of highest frequency of 1% will be registered in sentimental dictionary. Subsequently, frequency, positive figure and positive index about each word will be calculated to complete sentimental dictionary for each company. In the next step, based on sentimental dictionary built for each company, sentimental analysis was applied to refined data and they were used for mechanical education. In mechanical education, multiple prediction models were made through the process of machine learning of each classification method by using refined data and finally, after verification for functions accuracy of models will be compared to each other.

3.2 Data Collection

Web news data are generated in real time, as well as by a variety of routes and it might be hard to collect only data necessary for a study due to extremely wide range of their kinds. In order to use this kind of web news data the work of automated system is required to extract only necessary information. In this paper, through package Beautifulsoup(4.4.1) of computer programming language Python(Ver. 3.4), data-collecting program and database is set, and using these, only necessary data is extracted. In collected text data, irrelevant information like publisher, advertisement and copyright is included so memo program ‘Notepad++’ was used to refine data. Collection process of web news data is shown in [Figure 2], and a part of programming code is shown in [Figure 3].

![Figure2. Data Collection Procedure](image)

```python
import requests
from bs4 import BeautifulSoup

def online_news(max_pages):
    page = 0
    start_input("Start date(Year-month-day) : ")
    finish_input("End date(Year-month-day) : ")
    while page <= max_pages:
        page += 1

        source_code = requests.get(url)
        plain_text = source_code.text
        soup = BeautifulSoup(plain_text)
        for link in soup.findAll('a', {'class' : 'go_naver'}):
            href = link.get('href')
            article_url(href)

def article_url(item_url):
    source_code = requests.get(item_url)
```

![Figure3. Part of Python Code](image)
3.3 Morpheme Analysis

In this paper, as a system for analyzing morpheme for sentimental analysis, Kkokkoma® morpheme analyzer which is developed by research team of IDS in Seoul National University and open-source morpheme analyzer were selected. Kkokkoma morpheme analyzer divides parts of speech of Korean letter into noun, predicate, determiner, adverb, interjection, postposition, ending, affix, root, mark and ‘nor Korean’ and classify each detailed parts of speech. ‘Noun’ which is not sorted in detail will be sorted into normal noun, proper noun, general dependent noun and unit-dependent noun. Moreover, in case of ‘analysis impossible’, it could be sorted into range of assumed noun, assumed predicate and range of analysis impossible, but the range of assumed predicate and analysis impossible are eliminated from the tag chart. In this research, morphemes that correspond to nouns were extracted based on the assumption that it will have biggest effect compared to other morphemes when the noun which means practical concept among various parts of speech performs sentimental analysis, and morphemes that correspond to the range of assumed noun which includes a lot of loanword nouns were also extracted.

3.4 Sentiment Dictionary

Text data is separated into units of morphemes through analysis morphemes, and related part of speech for each morpheme is given. Processed morphemes like above will be given a polarity figure for each word and through this, sentimental dictionary will be built. Sentimental dictionary is a dictionary of collection of polarity figures for each word and depending on how it is being built the accuracy of sentimental analysis fluctuates. As the current status of sentimental dictionary, there is ‘dictionary for English/Chinese sentimental analysis’ which is developed by the English sentimental dictionary SentiWordNet(http://sentiwordnet.isti.cnr.it/) and the knowledge-based database site of China hownet(http://keenage.com/html/c_index.html), and researches related to developing sentimental dictionary are being carried out actively around the world including Korea. However, sentimental dictionary developed by individual researchers is only used in certain fields and not universally used, and even if it is open-source it is inappropriate to generalize it and use it for researches. For preventing this and improving the accuracy of the dictionary researchers need to develop a sentimental dictionary autonomously that can be used in research field. The order of building a sentimental dictionary is stated as follows. First, morphemically analyze the collected data. Second, extract the candidate words that will be registered in the dictionary. Third, calculate frequency of the words. Fourth, extract the words of highest frequency of top 1% and calculate positive index(Dong-Yeong Kim, 2015). Frequency represents the number of register of a word on all of news articles and positive figure is calculated by adding numbers of cases of increase in that day’s stock when news that have corresponding keyword were published(Dong-yeong Kim, 2015). The process of building sentiment dictionary is shown in [Figure 4].

![Figure 4. Process of building an sentiment dictionary](image)

At this time, the equation of positive index is stated as follows.

\[
include(i, j) = \begin{cases} 
1 & \text{(if the word } j \text{ contained in news article } j) \\
0 & \text{(In other cases)} 
\end{cases}
\]

\[
NSP(j) = \begin{cases} 
1 & \text{(if the daily stock price increased, after news article } j \text{ published)} \\
0 & \text{(In other cases)} 
\end{cases}
\]
Because it was believed that higher accuracy could be made if the words that have relatively higher frequency among extracted candidate words through morpheme analysis were chosen to be registered in the dictionary and use them for machine learning so the words that have highest frequency of top 1% were selected as the subjects for analysis. Finally, calculate positive index through frequency and positive figure of each word and build the sentimental dictionary. Positive index is the figure of positive figure divided by frequency and the equation is stated as follows.

\[ P(i) = \frac{\sum_{j=1}^{n} \{\text{include}(i, j) \times \text{NSP}(j)\}}{\sum_{j=1}^{n} \text{include}(i, j)} \]

3.5 Sentiment Analysis

By using the building method of sentimental dictionary built in the paragraph 4 sentimental analysis of web news data was conducted. First, after performing the process of morpheme analysis to extract the morphemes of nouns and the range of assumed nouns collected data will be compared with words on sentimental dictionary to calculate positive index of corresponding data. Positive index of text will be presented as arithmetic average figure which is divided by the number added from positive index of morphemes extracted from corresponding data (Dong-yeong Kim, 2015). The equation for positive index of data is stated as follows.

\[ \text{match}(i, j) = \begin{cases} 1 & \text{if the word } j \text{ which is contained in text } i \text{ exist in sentiment dictionary} \\ 0 & \text{In other cases} \end{cases} \]

\[ PT(i) = \frac{\sum_{j=1}^{n} \{\text{match}(i, j) \times P(j)\}}{\sum_{j=1}^{n} \text{match}(i, j)}, n = \text{number of text in } i \]

Going further from just calculating the positive index of data, calculate positive index per each day. Positive index per each day is presented as arithmetic average figure divided by the number added from positive index of texts registered on corresponding day, and equation for positive index per day is stated as follows.

\[ DP(k) = \frac{\sum_{i=1}^{n} PT(i)}{n}, n = \text{number text appeared in date } k \]

Frequencies, positive and positive indexes of each word were calculated to understand the positive index of text of news article and by using this, refine the data to use for mechanical education. Finally, by using frequency and positive index of each word per each day shown in database, positive index per day can be drawn and it is able to complete data set by adding items about fluctuation of the next day’s stock. Because this research predicts only fluctuation of stock it shows only whether stock increases or decreases in the item of the next day’s stock fluctuation. In database, 1 indicates increase and 0 indicates decrease. [Figure 5] is the process of overall sentimental analysis.
3.6 Machine Learning

Human behavior is derived from past experience not unconsciousness. By getting new information and studying over and over, they can bring themselves the best outcome from next actions. What brought this human characteristics to technology is called ‘Machine learning’ which is a serial process of extracting characteristics of collected data and test them to optimize or self-develop, and it is frequently used in prediction areas (Lee, 2016). Data for conducting machine learning consist of class label which confirms whether attribute set and respective data are time series, whole number or real number and through this kind of property, predicting dependent variable with independent variable data is the objective of machine learning (Dong-yeong Kim, 2015). This research predicted stock after creating prediction model using the method of decision-making tree, logistic regression analysis, SVM and artificial neural network which are based on the theory of machine learning as it is stated in [Figure 7].
4. Experiment

4.1 Experiment Protocol

In this paper, the research was conducted by choosing 4 companies that are listed on the KOSPI as the subjects, and news articles published from January 1th, 2015 to December 31th, 2015 were used for the research. The research was carried out based on the contents of chapters 2 and 3 and the order of experiment is data collection, morpheme analysis, building sentimental dictionary, sentimental analysis and machine learning, according to the stock prediction model in chapter 3. Through data refined on each step, prediction models were made and analyses on results of predictions were conducted.

4.2 Data Collection

Web news data extracted only articles published in newspaper which were in economy section of NAVER news using ‘parser’ which is the news developed autonomously by using ‘python’, and collected articles of 62,765. It was believed that news related to economy would reflect the flow of stock market the most so the news published in economy section of NAVER news were selected as data subjects. [Figure 8] is the arrangement of texts of collected news articles in MS Excel, there are the dates when the news was published in the first row and dates are written in the order from December to January. There are the contents of articles of news published on corresponding dates in the second row. [Figure 8] is a part of collected news articles and [Table 1] is the number of news articles collected by each company.

4.3 Building an Sentiment Dictionary

Using news article data and stock fluctuation data, calculate frequency, positive figure, positive index and positive index per day in order and build sentimental dictionary for each company. News article is the python the programming language, and stock fluctuation data were extracted from ‘Yeong Ung Mun’ which is HTS(Home Trading System) of Ki Um Securities Inc. the Internet stock firm. Through preprocessing of data candidate words will be extracted and those have highest frequency of top 1% will be registered in sentimental dictionary and positive figure of each word will be calculated. Among sentimental words, those of only one letter such as ‘억’ and ‘판’ are mostly used to refer to units or something else so they were judged to be inappropriate for having sentiments which makes them be eliminated from sentimental dictionary. Furthermore, morphemes of numeral like ‘1200’, ‘200’ and ‘31km’ are thought to indicate only quantity, distance and degree thus they were also eliminated.
from the dictionary. Through the process above candidate words will be narrowed and by calculating positive figure(PF), positive index and frequency of each word, sentimental dictionary for sentimental analysis will be finalized. [Figure 9] is a part of the sentiment dictionary and [Table 2] shows the number of candidate words for each company and the number of words that are registered in real sentimental dictionary.

<table>
<thead>
<tr>
<th>Company</th>
<th>Candidate words</th>
<th>Sentiment words</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>237408</td>
<td>1983</td>
</tr>
<tr>
<td>B</td>
<td>214012</td>
<td>1968</td>
</tr>
<tr>
<td>C</td>
<td>58677</td>
<td>556</td>
</tr>
<tr>
<td>D</td>
<td>142133</td>
<td>1122</td>
</tr>
</tbody>
</table>

4.4 Sentiment Analysis

Based on the method of sentimental analysis of Dong-yeong Kim suggested in chapter 3 sentimental analysis applies to sentimental dictionary of each company. The analysis was conducted in automated fashion by changing suggested equation of sentimental analysis to function of MS Excel and with positive index per day, frequency of sentimental words per day, positive index(PI) of sentimental word, item of stock fluctuation and opening day of stock market, data set for machine learning for each company was set. [Figure 10] is a part of the data set and input PI per day and PI of word are presented as the figures that are rounded off to four decimal places from their original figures. From second row of second column whether stock of that day has increased or decreased is indicated, 0 means down and 1 means up. From first row of fourth column there are words that are registered in the dictionary and from second row of fourth column frequency of sentimental words per date are written.

The data subject of this paper, NAVER news, is published every day regardless of weekends and holidays but data about the next day’s stock fluctuation do not get renewed on weekends and holidays. Even though, if news’ are used on the day when there is no data on stock fluctuation it might cause a waste of data and inappropriate outcome of sentimental analysis so in case of above, from the day when data on stock fluctuation to the day when that data will be generated, news data were added into one datum. In this research, the research was carried out with the belief that the news article about a certain date would affect the stock price on that day so for an example for the situation above, it is written as follows. News published on December 25th, 2015 was expected to affect the stock price on that day but because December 25th is Christmas which is a holiday data for the next day’s stock cannot be generated. As an alternative, sentimental analysis could be practiced by adding data of stock price from 25th to 28th. Thanks to this, the amount of data of the day when the holiday ends and Monday could be twice to 4 times as big as other days.

In this paper, four sample companies’ stock market was open 248 times in January 2nd, 2015 to December 31th, 2015 and New Year holiday excluded from the analysis date. [Table 3] is fluctuating distribution of each company per stock, the [Figure 11] is the average of the daily positive index for each company and entire data. Daily positive index average is 0.473 of the total data, and company A 0.502, B company 0.426, C company 0.493, D company were derived the value of 0.471. Signed value shows the actual values to the nearest point on the fourth digit.
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Figure 10. Part of data set

Table 3. Number of Fluctuation for each company

<table>
<thead>
<tr>
<th>Fluctuation</th>
<th>Rise</th>
<th>Fall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Company A</td>
<td>122</td>
<td>126</td>
</tr>
<tr>
<td>Company B</td>
<td>106</td>
<td>142</td>
</tr>
<tr>
<td>Company C</td>
<td>124</td>
<td>124</td>
</tr>
<tr>
<td>Company D</td>
<td>113</td>
<td>132</td>
</tr>
</tbody>
</table>

Figure 11. Average of the Daily Positive Index

4.5 Machine Learning

Depending on the stock price prediction model presented in Chapter 3, the data set purified in each step and used to utilize the machine learning model generate a prediction model which is corresponding to each machine learning classification techniques. In this paper, we use big data analysis package, RapidMiner®, which measures the performance of a data set through machine learning. RapidMiner providing Logistic Regression, SVM, Decision Tree, Artificial Neural Network of machine learning classifiers and not only basic functions, addition text mining, web mining technology which are specialized in sentimental analysis. In this paper, January to September data, 2015 is for performance evaluation data (test set), October to December data, 2015 is for performance comparison data (validation set) and performance verification method was 10-fold cross-validation.

4.6 Result

Proceeding 10-fold cross-validation after split performance verification data as learning data and evaluation data, it shows more than 70% in a number of model accuracy and F1 score closer to 0.7. In the result sector, D company’s value was comparatively low that average accuracy was 60% and F1 score was near from 0.5. Even, classification technique, decision tree recorded significantly low F1 score 0.3707. The comparison of precision and F1 score based on A company, the accuracy and F1 score of artificial neural network was 77.78% and 0.7766. And the accuracy and F1 score of decision tree was 75.73% and 0.7550. Through this result, artificial neural network shows most good performance and decision tree turn up worst performance. The artificial neural network is appropriate for process of 10-fold cross-validation. The list of the accuracy of each classification techniques with descending order, AHN(77.78%), SVM(77.7%), Logistic regression(76.77%), decision tree(75.73%). [Table 4], [Figure 12], [Figure 13] exhibited each company’s accuracy and F1 score.

After machine learning performance verification data, the accuracy is close to 70% of all four companies showed up and A, B, C company got F1 score of average near from 0.7. B company’s F1 score doesn’t reach to 0.5 in a large
number of classification techniques. The list of arithmetic mean value of the accuracy and F1 score of the prediction model for each companies is as follow as. Order of each classification techniques’ accuracy is Decision tree(71.425%), Logistic regression(69.638%), AHN(69.043%), SVM(66.663%) and Logistic regression(0.645) and SVM(0.645) got equal value in F1 score and Decision tree(0.634), AHN(0.598) stand in a line. Test result, came out highest accuracy from Decision tree 71.425% and came out highest F1 score 0.645 from Logistic regression and SVM. Accuracy and F1 score of verification data were compiled in [Table 5], [Figure 14] and [Figure 15].

Table 4. Accuracy and F1 Score for Each Company (Test Period)

<table>
<thead>
<tr>
<th>Classification techniques</th>
<th>Measure</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logistic Regression</td>
<td>Accuracy(%)</td>
<td>76.77</td>
<td>75.73</td>
<td>73.34</td>
<td>59.22</td>
</tr>
<tr>
<td></td>
<td>F1 score</td>
<td>0.7656</td>
<td>0.7379</td>
<td>0.7283</td>
<td>0.5355</td>
</tr>
<tr>
<td>ANN</td>
<td>Accuracy(%)</td>
<td>77.78</td>
<td>72.82</td>
<td>71.84</td>
<td>61.17</td>
</tr>
<tr>
<td></td>
<td>F1 score</td>
<td>0.7766</td>
<td>0.7348</td>
<td>0.7503</td>
<td>0.6079</td>
</tr>
<tr>
<td>Decision Tree</td>
<td>Accuracy(%)</td>
<td>75.73</td>
<td>70.87</td>
<td>69.42</td>
<td>54.37</td>
</tr>
<tr>
<td></td>
<td>F1 score</td>
<td>0.7550</td>
<td>0.6539</td>
<td>0.6725</td>
<td>0.3707</td>
</tr>
<tr>
<td>SVM</td>
<td>Accuracy(%)</td>
<td>77.7</td>
<td>75.73</td>
<td>75.24</td>
<td>61.17</td>
</tr>
<tr>
<td></td>
<td>F1 score</td>
<td>0.7766</td>
<td>0.7174</td>
<td>0.7174</td>
<td>0.6086</td>
</tr>
</tbody>
</table>

Table 5. Accuracy and F1 Score for Each Company (Validation Period)

<table>
<thead>
<tr>
<th>Classification</th>
<th>Measure</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logistic Regression</td>
<td>Accuracy(%)</td>
<td>71.42</td>
<td>57.14</td>
<td>76.19</td>
<td>73.8</td>
</tr>
<tr>
<td></td>
<td>F1 score</td>
<td>0.7035</td>
<td>0.4094</td>
<td>0.7407</td>
<td>0.7255</td>
</tr>
<tr>
<td>ANN</td>
<td>Accuracy(%)</td>
<td>78.57</td>
<td>61.9</td>
<td>64.28</td>
<td>71.42</td>
</tr>
<tr>
<td></td>
<td>F1 score</td>
<td>0.7597</td>
<td>0.4603</td>
<td>0.4457</td>
<td>0.7255</td>
</tr>
<tr>
<td>Decision Tree</td>
<td>Accuracy(%)</td>
<td>78.57</td>
<td>61.9</td>
<td>80.95</td>
<td>64.28</td>
</tr>
<tr>
<td></td>
<td>F1 score</td>
<td>0.7846</td>
<td>0.3550</td>
<td>0.8055</td>
<td>0.5906</td>
</tr>
<tr>
<td>SVM</td>
<td>Accuracy(%)</td>
<td>76.19</td>
<td>59.52</td>
<td>57.14</td>
<td>73.8</td>
</tr>
<tr>
<td></td>
<td>F1 score</td>
<td>0.7846</td>
<td>0.5073</td>
<td>0.5728</td>
<td>0.7136</td>
</tr>
</tbody>
</table>
5. Conclusion

In this paper, to predict rise and downfall in the next day’s stock fluctuation news data were sentimental-analyzed and the method of machine-learning data set was used. Data-collecting program was developed autonomously using computer programming language, and collected data are used to build a sentimental dictionary by getting refined in MS Excel of database. To use news articles which are atypical data for machine learning, the work of digitizing data by applying the method of sentimental analysis to the data refined based on the sentimental dictionary. Next, digitized data set was machine-learned to create prediction model. As the result of the experiment, looking at the average accuracy and average F1 score of each method of classification, high accuracies were checked in the order of Logistic regression (average accuracy -70.451%, average F1 score-0.668), Artificial neural network (average accuracy -69.973%, average F1 score-0.658), SVM (average accuracy -69.561%, average F1 score-0.675), Decision tree (average accuracy -69.511%, average F1 score-0.623). Following the result of the experiment, the method of classification which showed the highest predictability among prediction models built in this paper was Logistic regression analysis, therefore it is considered to be suitable to use that analysis in the process of machine learning. However, in the process of decuple cross verification, when doing the decuple cross verification with arithmetic average figure of each average accuracy and average F1 score of SVM recording 72.46%, 0.705, it looks clear that use of SVM is more suitable.

Through this research, one method for stock price prediction is suggested which is suggested through news data that are the most closely related to stock among atypical data which are considered as the subject for big data analysis recently. By using the morpheme analyzer it was possible to improve the accuracy of sentimental analysis with the building of optimized sentimental dictionary for each company and was possible to apply the method of sentimental analysis in the process of refining data to use for machine learning. Lastly, after making a prediction model by machine-learning the data set, the operation of comparing the performances of models was put into action.

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