Stock Price Prediction based on Stock Big Data and Pattern Graph Analysis

Seungwoo Jeon[1], Bonghee Hong[1], Juhyeong Kim[1] and Hyun-jik Lee[2]
[1]*Dept. of Electrical and Computer Engineering, Pusan National University, Busan, South Korea*
[2]*Division of Chronic disease control, Korea centers for disease control & prevention, Cheongju, South Korea*

Keywords: Stock Price Prediction, Hierarchical Clustering, Pattern Matching, Feature Selection, Artificial Neural Network.

Abstract: Stock price prediction is extremely difficult owing to irregularity in stock prices. Because stock price sometimes shows similar patterns and is determined by a variety of factors, we present a novel concept of finding similar patterns in historical stock data for high-accuracy daily stock price prediction with potential rules for simultaneously selecting the main factors that have a significant effect on the stock price. Our objective is to propose a new complex methodology that finds the optimal historical dataset with similar patterns according to various algorithms for each stock item and provides a more accurate prediction of daily stock price. First, we use hierarchical clustering to easily find similar patterns in the layer adjacent to the current pattern according to the hierarchical structure. Second, we select the determinants that are most influenced by the stock price using feature selection. Moreover, we generate an artificial neural network model that provides numerous opportunities for predicting the best stock price. Finally, to verify the validity of our model, we use the root mean square error (RMSE) as a measure of prediction accuracy. The forecasting results show that the proposed model can achieve high prediction accuracy for each stock by using this measure.

1 INTRODUCTION

Stock price provided by Koscom consists of thirty-two items (four groups: domestic buying, domestic selling, foreign buying, and foreign selling) such as domestic selling high price, foreign selling opening price, and domestic buying completion amount. Even if stock prices have the same value, their inside combinations may be different. For example, domestic selling high price may show a downturn and domestic buying completion amount may show an upturn or vice versa. Because the items are highly variable, the objective is to predict the next stock price pattern graph using these items, which would be very useful.

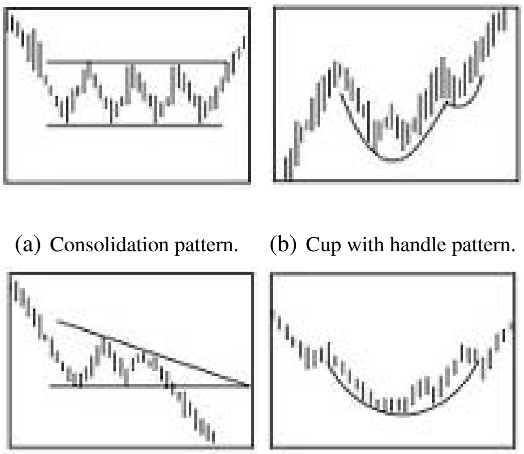
Stock market analysis and prediction are being studied using various methods such as machine learning and text mining. Data mining studies use daily stock data. For example, prediction studies based on support vector machines (SVMs) (Cao and Tay, 2001; Ince and Trafalis, 2007) have been conducted to determine whether the new pattern data belongs to a certain pattern category. In addition, artificial neural networks (ANNs) (Kimoto et al., 1990; Kohara et al., 1997) have been employed to achieve good predictions even in the case of complex relationships of variables, while an autoregressive integrated moving average (ARIMA) model (Pai and Lin, 2005; Wang and Leu, 1996) has been used to identify and predict time series variation. On the other hand, several prediction studies are based on word analysis of news articles (Mittermayer, 2004; Nikfarjam et al., 2010; Kim et al., 2014).

These studies predict daily stock prices using the daily closing price, which is not sufficient to make predictions in a short period of time (e.g., 1 hour and 30 minutes). Moreover, even though these studies have analyzed the significance of variables and increased the prediction accuracy by eliminating unimportant variables, the error rates of the predictions are high owing to the use of outliers.

Stock price consists of several patterns such as consolidation, cup with handle, double bottom, and saucer, as shown in Figure 1. Because these patterns appear repeatedly at time intervals, if we find a parallel pattern to the current pattern, we will be able to predict the following pattern.

By focusing on this point, in this paper, we propose a new method for generating stock price pre-

Jeon, S., Hong, B., Kim, J. and Lee, H-j.
Stock Price Prediction based on Stock Big Data and Pattern Graph Analysis.
DOI: 10.5220/0005876102230231
In *Proceedings of the International Conference on Internet of Things and Big Data (IoTBD 2016)*, pages 223-231
ISBN: 978-989-758-183-0



(a) Consolidation pattern. (b) Cup with handle pattern.

(c) Double bottom. (d) Saucer.

Figure 1: Various stock patterns (Bulkowski, 2011).

diction based on historical stock big data. First, unlike existing studies that mostly use closing price data, the present study uses tick-by-tick data for short-term prediction and aggregates them to transform non-continuous data into continuous data. Then, we make some patterns similar to the current pattern by using a hierarchical clustering algorithm and select important features affecting the stock price by using stepwise regression. Finally, we generate an ANN using the data to be completed, similar patterns, and selected features as input data for high prediction accuracy through learning in order to derive the best results.

Thus, we propose a prediction system based on big data processing (Hadoop, Hive, RHive) and analysis (R) tools for next stock price prediction. The system consists of four connected computers and includes five steps. The first step is a preprocessing step for transforming tick-by-tick data into aggregated data at five-minute intervals in order to facilitate the prediction and make daily patterns with five-minute generation units using Hadoop and RHive query. The second step is to find all similar patterns for one year using hierarchical clustering provided by the R function. Then, the system repeatedly removes insignificant variables through stepwise regression on the R function. Next, the system uses an ANN to generate the final prediction model according to numerous simulations. Finally, we verify the validity of the model using root mean square error (RMSE) as a measure of prediction accuracy.

The main contributions of this paper can be summarized as follows.

- We generate a model for predicting stock prices by applying an ANN through hierarchical clustering for pattern searching and stepwise regression for significant/insignificant variable distinction with real tick-by-tick stock data.
- We evaluate the proposed model using RMSE, which is widely used in stock price forecasts; low RMSE implies high prediction accuracy.
- To generate the predicted stock price automatically, we build a new system based on big data processing open-source tools such as Hadoop and R.

The remainder of this paper is organized as follows. Section 2 reviews various existing studies on stock price forecasting. Section 3 presents the specification of stock data. Sections 4 and 5 describe our new complex methodology and system architecture for handling the overall processes. Section 6 presents our evaluation results. Finally, Section 7 summarizes our findings and concludes the paper with a brief discussion on the scope for future work.

2 RELATED WORK

In this section, we introduce some related studies on various methods such as ANN, feature selection, and text mining for stock price prediction. ANN was the most widely used method a few decades ago. Initially, it was used by itself, and later, attempts were gradually made to combine it with other techniques in order to achieve higher prediction accuracy. In (Kimoto et al., 1990), a buying and selling timing prediction system was proposed using economic indexes (foreign exchange rates) and technical indexes (vector curves) from the Tokyo Stock Exchange Prices Indexes (TOPIX). In another study, an echo state network was used as a novel recurrent neural network to forecast the next closing price (Lin et al., 2009).

The following method involves feature selection for selecting significant input attributes, and it is based on other methods that have been widely used in recent years. In (Huang and Tsai, 2009), a combination of support vector regression (SVR) with a self-organizing feature map (SOFM) and feature selection based on filtering was proposed for predicting the next day's price index using Taiwan index futures (FITX). Important features were selected using the R-squared value as input data for SVR. In (Lee, 2009), a prediction model was developed on the basis of an SVM with a hybrid feature selection method for finding the original input features, using NASDAQ index direction. In contrast to the above-mentioned study, the f-score was used as a selection factor.

However, most of these studies have some limitations for short-term prediction. First, given all histor-

Table 1: Example of stock raw data.

Attribute	Value
Date (yyyymmddhhmmsss)	20140813090024
Type	0
Completion price (won)	77,500
Completion amount	37
Opening price (won)	78,900
High price (won)	78,900
Low price (won)	76,600
Price just before (won)	77,400
Accumulated completion amount	475,021
Accumulated completion price (won)	36,770,000,000

ical stock data as input data, because the next closing price is predicted without removing the outliers, the error rate is high. Second, although the total completion price is determined by a variety of factors such as the foreign purchase closing price and domestic selling completion amount, it is insufficient to consider such factors. In other words, it is necessary to consider a combination of significant factors.

3 DATA SPECIFICATION

In this study, stock data that was gathered over twelve consecutive months (August 2014 to July 2015) from the Korea Composite Stock Price Index (KOSPI) was used as the input .

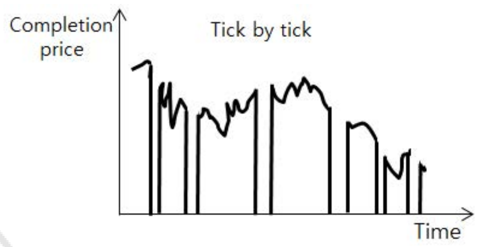
The stock data was provided by Koscom. A data sample is listed in Table 1; it consists of the date, type, completion price, completion amount, opening price, high price, low price, price just before, accumulated completion amount, and accumulated completion price. Because there are four types (domestic purchase price (0), domestic selling price (1), foreign purchase price (2), and foreign selling price (3)), the stock price is the sum of thirty-two items. The size of each data set was 168 GB and the data was collected during the one-year period from August 2014 to July 2015.

4 OUTLINE OF PROPOSED MODEL

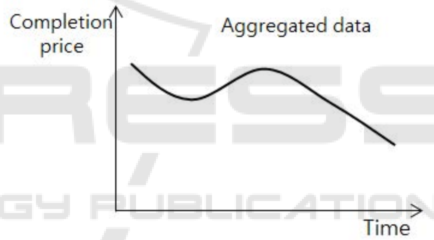
In this section, we describe the overall process, from data preprocessing for making continuous data, the search for similar pattern data, and the selection of input data to the generation of the prediction model from the perspective of data analysis and processing.

4.1 Aggregation of Stock Data

Because the tick-by-tick data we have are the data generated per transaction, the completion price at the time is zero if the transaction is not carried out, as shown in Figure 2 (a). In other words, as the data is non-continuous data, it is difficult to predict the price. Consequently, we generate aggregated data at five-minute intervals to obtain a continuous flow of data, as shown in Figure 2 (b).



(a) Completion price per transaction.



(b) Completion price after aggregation.

Figure 2: The need for aggregation.

4.2 Searching for Similar Patterns

Above all, it is necessary to make patterns from aggregated data for searching similar patterns. Figure 3 shows the processes of patterning the aggregated data. The length of a pattern is one day and patterns are generated at five-minute intervals, e.g., by the sliding window method, for pattern matching analysis using various patterns. The number of patterns for one hour will be twelve.

Figure 4 shows similar patterns in the graph of real stock price. The similar patterns can be found by comparing historical patterns and the current pattern. There are various methods for pattern matching. We use a hierarchical clustering algorithm that can find similar patterns quickly and simultaneously. The patterns are structured by hierarchical clustering and similar patterns are neighbor or sibling nodes of the current pattern. If there are only a limited number

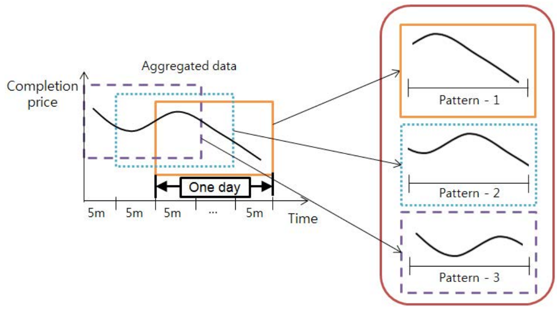


Figure 3: Method of patterning the aggregated data.

of similar patterns, it is possible to extend the range of the similar patterns.

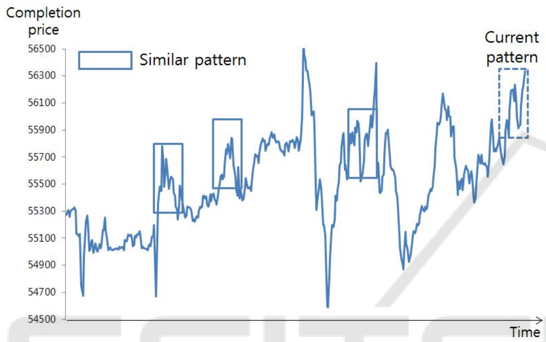


Figure 4: Similar stock patterns.

Figure 5 shows a hierarchical structure based on the clustering algorithm; the numbers denote patterns. Given 1 as the current pattern, 4 and 15 are similar patterns in the initial range because of the neighbor and sibling nodes. If we do not get satisfactory results in the next steps, the range is extended and the number of similar patterns is eventually increased from 2 to 12.

4.3 Feature Selection According to Stepwise Regression Analysis

Although there are significant variables affecting the stock price among the thirty-two variables, some variables do not have a major effect on the price. To distinguish these variables, we adopt feature selection, which is performed using a bidirectional elimination approach in stepwise regression, as a combination of forward and backward approaches. Each step reviews whether already selected variables are removed owing to a new important variable, while the new variable is selected one by one. The procedure is conducted as follows.

- Repeatedly add and remove a variable among all the variables; then conduct regression analysis

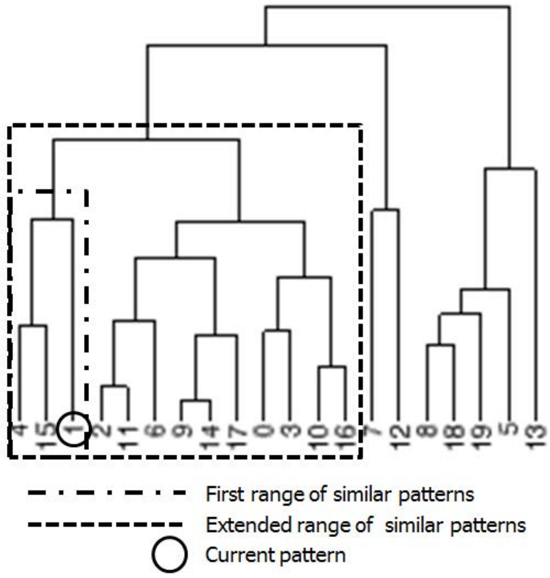


Figure 5: Similar patterns defined through hierarchical structure.

with the remainder.
- Select the final variable association with the highest value of R-square as the explanatory power of the regression model.

In this work, we consider the total completion price as a dependent variable and thirty-two variables as independent variables in the regression analysis, which is provided as two functions in R as shown below. We use the lm function to fit a linear model, where y is a dependent variable and x_1–x_{32} are independent variables.

```
fit <- lm(y~x1+x2+x3+...+x32, data=stock_data)
```

After fitting, we use the step function for determining the final independent variables; the first factor represents the linear model and the second factor determines the direction of the stepwise process, which combines the forward and backward approaches. A total of eight variables are removed after applying stepwise regression, as can be seen in Table 2.

```
bidirectional <- step(fit, direction="both")
```

4.4 Prediction Model Generation using Artificial Neural Network

After feature selection, to generate the predicted stock data, we use an ANN algorithm, which is widely used in stock price forecasts (Kuo et al., 2001; Kim and Han, 2000; Cao et al., 2005). Moreover, it has the advantage of high prediction accuracy through learning by iterative adjustment. The learning is performed in

Table 2: Results of stepwise regression in real stock data of Hyundai Motor Company.

Domestic purchase price		Domestic selling price		Foreign purchase price		Foreign selling price	
Name	Choice	Name	Choice	Name	Choice	Name	Choice
Completion price	O	Completion price	O	Completion price	O	Completion price	O
Completion amount	O	Completion amount	O	Completion amount	O	Completion amount	O
Opening price	X	Opening price	X	Opening price	O	Opening price	O
High price	O	High price	O	High price	O	High price	O
Low price	O	Low price	O	Low price	O	Low price	O
Price just before	O	Price just before	X	Price just before	O	Price just before	O
Accumulated completion amount	X	Accumulated completion amount	O	Accumulated completion amount	O	Accumulated completion amount	O
Accumulated completion price	X	Accumulated completion price	X	Accumulated completion price	X	Accumulated completion price	X

Table 3: Explanatory powers according to hidden layers.

Hidden layer 1	Hidden layer 2	Hidden layer 3	Hidden layer 4	Hidden layer 5
37.6%	95.5%	95.9%	94.2%	95.3%

one or more hidden layers. The learning rate increases with the number of hidden layers. However, the connection point between input and output could be lost if there are too many hidden layers, and the learning could be disturbed (Dominic et al., 1991).

We employed five hidden layers to ensure that the system can bear the processing load and created the final model with a hidden number that shows the highest explanatory power (R-squared value) by performing learning in sequence from hidden layer 1 to hidden layer 5 for each stock item. Table 3 summarizes the explanatory power in each hidden layer, and the layer with the highest value is layer 3.

5 SYSTEM ARCHITECTURE FOR STOCK PRICE PREDICTION

This section describes the series of operations that were implemented when generating the final artificial neural network model. All the processes were conducted on a cluster consisting of four connected computers (one master and three slaves) with Hadoop and RHive installed.

5.1 Series of Operations for Generating Predicted Stock Data

We propose the following steps to generate a prediction model for big data processing and analysis tools, as shown in Figure 6.

Step 1 (Stock Data Aggregation and Pattern Generation as Data Preprocessing): We stored the one-year stock data provided by Koscom in Hadoop distributed file systems (HDFSs) of the Hadoop-based cluster. Because we could not manually modify the source code of MapReduce for extracting the desired data from each HDFS of the Hadoop cluster, we used the RHive tool to provide HiveQL, which facilitates the search for the desired data, e.g., through select query of RDBMS. After the data was extracted, it was aggregated at five-minute intervals by using R based on the tick-by-tick data. Then, patterns were generated from them because of concatenation of similar patterns in R of the master computer. The size of a pattern was one day and the generation unit was five minutes. The total number of patterns was 17,323.

Step 2 (Pattern Matching with Hierarchical Clustering): To retrieve similar patterns with the current pattern, we used the hclust function in R, which offers two advantages: it can quickly autodetect similar patterns and freely determine the range of similar patterns simultaneously. Algorithm 1 describes the procedure for finding similar patterns. After inserting the current pattern into the aggregated patterns as a historical dataset, clustered patterns were generated via the hclust function. Then, similar patterns of the same level as the current pattern could be found.

Step 3 (Feature Selection using Stepwise Re-

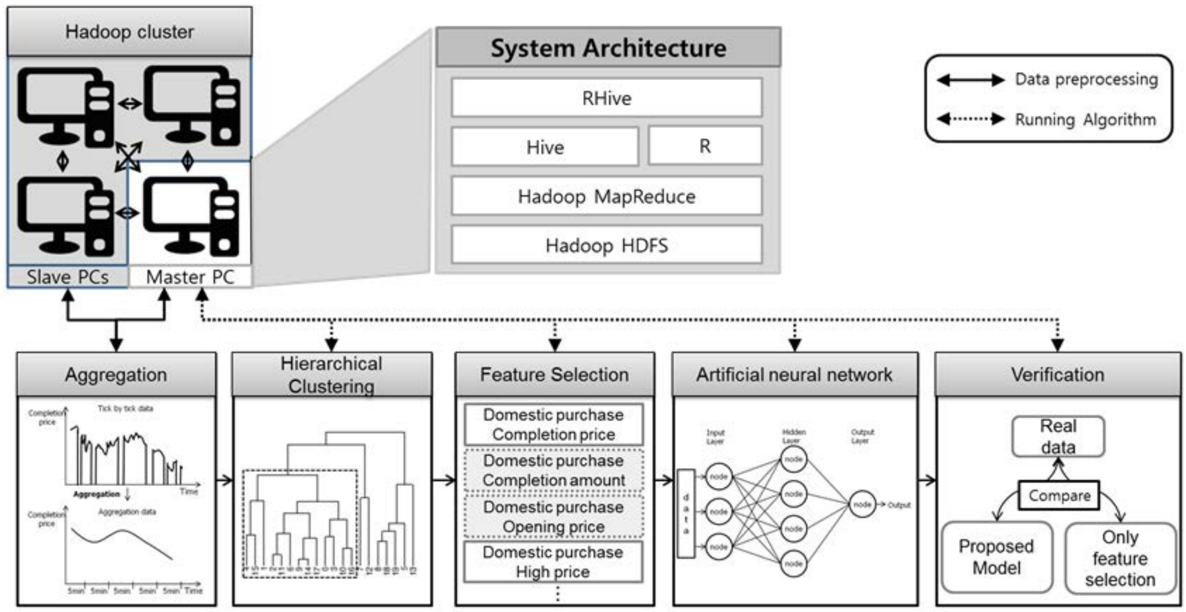


Figure 6: Dependent and independent variables should be defined in stepwise regression analysis.

Algorithm 1: Algorithm for pattern matching.

input : *Aggregated_patterns* is a list of aggregated data, *current_pattern* represents the current pattern
output: *similar_patterns* is a list of similar patterns after clustering

```
int last = Aggregated_patterns.length()-1;
List<Integer> level = new ArrayList<Integer>();
int level = 0; foreach count in Aggregated_patterns.length() do
    Aggregated_patterns[last][count] = current_pattern[count];
run('sink()');
run('hc< −hclust(dist(Aggregated_patterns), method='ave')');
run('sink('out.txt')');
List result_patterns = Read_File('out.txt');
foreach index in result_patterns.length() do
    if result_patterns[index] == current_pattern then
        foreach level in result_patterns do
            similar_patterns = find_SP(index);
return similar_patterns;
```

gression): Given several similar patterns of stock price, insignificant variables among all the variables constituting the price were removed. Algorithm 2 describes the steps for feature selection using stepwise regression. Before selecting the variables, the time of similar patterns was determined, and then, variables at the time were brought. Variables with p value below a specified threshold were judged as significant variables.

Algorithm 2: Algorithm for feature selection in stepwise regression.

input : *similar_patterns* represents a list of similar_patterns, *variables* represents a list of all variables constituting the price
output: *remainder* is a list of variables excluding the insignificant variables

```
boolean flag = false;
variables = getVariables(similar_patterns.atTime());
while flag == false do
    remainder = run('step(variables, direction='both')');
    foreach i in remainder.length() do
        if remainder[i].p_value > 0.05 then
            break;
        else
            flag = true;
return remainder;
```

Step 4 (Predicted Data Generation on Artificial Neural Network): To create the predicted data, we used an ANN after feature selection. Algorithm 3 describes the steps for generating the predicted data using an ANN. Among the input data, we prepared dependent and independent variables as training data with another time zone because we would predict the next day of the current pattern. Specifically, given historical time of similar pattern ht, the time of the dependent variable is $ht+1$ and the time of the independent variable is ht. After the independent and dependent variables were bound, we generated an ANN-based model using the neuralnet function provided by R. Then, the independent variables at the current time t in the model were input and the predicted data were generated.

Algorithm 3: Algorithm for generation of predicted data.

input : *tr_dependent* represents the total completion price at historical time $ht+1$, *tr_independent* represents the remaining variables excluding the total completion price at historical time ht, *te_dependent* represents the remaining variables excluding the total completion price at current time t

output: *predicted* is a dataset generated by ANN

run('*training* $<-$ cbind(*tr_dependent*,*tr_independent*)');
run('colnames(*training*) $<-$ c('output','input')');
run('ANN_result $<-$ neuralnet(output input, training, hidden=1∼5,act.fct='tanh')');
run(*predicted* $<-$ 'prediction(ANN_result, *te_dependent*)');
return *predicted*;

Step 5 (Verification using RMSE): To verify the validity of the proposed model, we selected RMSE as a measure of prediction accuracy; the function was also provided in R. The measure was computed from comparisons between real and predicted data.

6 EVALUATION

In this section, we describe the one-year test data provided by Koscom and evaluate the accuracy of each stock item by computing the RMSE.

6.1 Dataset and Test Scenario

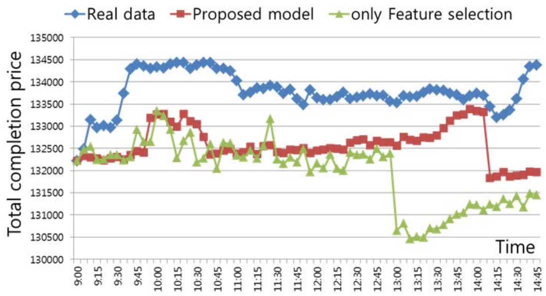
To prove the effectiveness of the proposed model, we used a real historical stock dataset consisting of various items for the one-year period from August 2014 to July 2015. To measure the prediction accuracy, we prepared three items (Hyundai Motor Company, KIA Motors, and Samsung Electronics) as companies representing the Republic of Korea, with their stock data for August 1, 2014, to July 28, 2015, as the training data, and their stock data for July 29–31, 2015, as the test data. As a test scenario, first, two predicted stock data for one day were generated according to the proposed model and feature selection. Then, we checked the prediction accuracy by using the RMSE values to compare the predicted and real stock data.

6.2 Evaluation of Prediction Accuracy

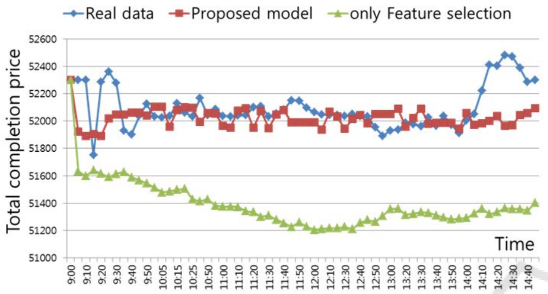
We performed experiments to compute the accuracy of the proposed method. Figure 7 compares the actual data and two data values predicted by the proposed model with only feature selection for July 31, 2015. The x-axis represents the time at five-minute intervals and the y-axis represents the total completion price, i.e., stock price according to the time. First, Figure 7 (a) compares the results of Hyundai Motor Company stock; we can see that the stock movement change of the proposed model is closer to the real stock data than that of only feature selection. In particular, this can be an especially clear view of the rising curve of the morning and the declining curve of the afternoon.

Figure 7 (b) shows the stock data derived from the real and predicted data for KIA Motors. In contrast to Figure 7 (a), there are slight differences between the stock movement change of the proposed model and the real data, whereas there is no clear view of the rising and declining curve in the graph. Lastly, Figure 7 (c) depicts the stock data derived from the real and predicted data for Samsung Electronics. As compared with only the feature selection graph, the stock movement change of the proposed model is similarly drawn to the real data despite a slight difference in price.

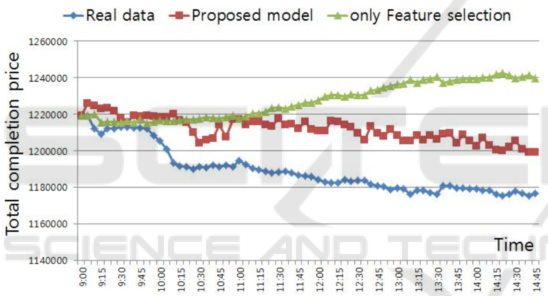
In this study, we selected RMSE as a measure of prediction in order to verify the validity of our model because this measure is frequently used in the stock domain. Figure 8 shows the experimental results of the proposed model and only feature selection using RMSE. In Figure 8 (a) and (b), we can see that there are good predictions except on July 30, when the interesting aspect is the same item. For this reason, we can estimate that there are variables affecting the same theme, not variables that affect individ-



(a) Comparison results for Hyundai Motor Company stock.

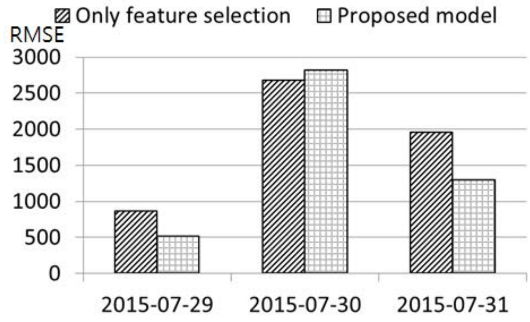


(b) Comparison results for KIA Motors stock.

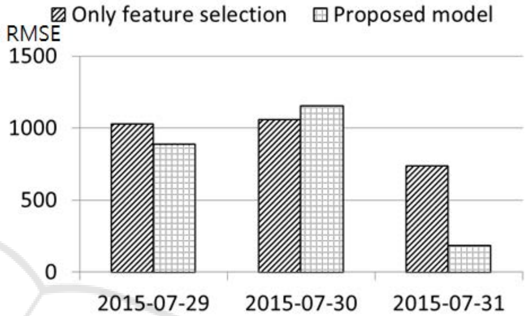


(c) Comparison results for Samsung Electronics stock.

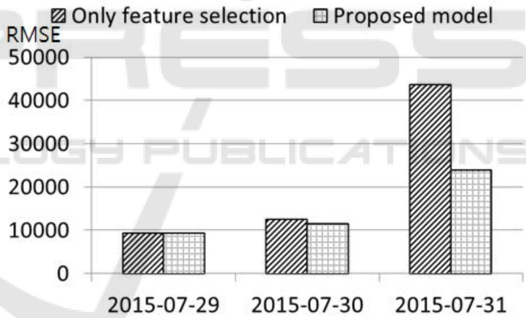
Figure 7: Comparison results according to the proposed model.



(a) Comparison results for Hyundai Motor Company stock.



(b) Comparison results for KIA Motors stock.



(c) Comparison results for Samsung Electronics stock.

Figure 8: RMSE results.

ual stocks; it is necessary to make up for this point. Unlike Figure 8 (a) and (b), Figure 8 (c) shows good prediction for all days. In particular, it shows good predictions on the last day in all the graphs.

7 CONCLUSIONS

In this paper, we determined that stock prices sparsely show similar patterns and that not all the variables have a significant impact on the price. For short-term prediction, we proposed a novel method based on a combination of hierarchical clustering, stepwise regression, and ANN model in order to find similar historical patterns for each stock item and predict the daily stock price using optimal significant variables through feature selection. Moreover, we dealt with the overall process using a big data processing framework based on Hadoop and R. Finally, we demonstrated the prediction accuracy for three stock items using RMSE.

In the future, we plan to enhance the reliability of our model by further investigating big and small pattern matching and analysis. In addition, we will develop a distributed parallel algorithm and predict all the stock items instead of only some of them.

ACKNOWLEDGEMENTS

This work was supported by the Research Program funded by the Korea Centers for Disease Control and Prevention(fund code#2015-E33016-00).

REFERENCES

Bulkowski, T. N. (2011). *Encyclopedia of chart patterns*, volume 225. John Wiley & Sons.

Cao, L. and Tay, F. E. (2001). Financial forecasting using support vector machines. *Neural Computing & Applications*, 10(2):184–192.

Cao, Q., Leggio, K. B., and Schniederjans, M. J. (2005). A comparison between fama and french's model and artificial neural networks in predicting the chinese stock market. *Computers & Operations Research*, 32(10):2499–2512.

Dominic, S., Das, R., Whitley, D., and Anderson, C. (1991). Genetic reinforcement learning for neural networks. In *Neural Networks, 1991., IJCNN-91-Seattle International Joint Conference on*, volume 2, pages 71–76. IEEE.

Huang, C.-L. and Tsai, C.-Y. (2009). A hybrid sofm-svr with a filter-based feature selection for stock market forecasting. *Expert Systems with Applications*, 36(2):1529–1539.

Ince, H. and Trafalis, T. B. (2007). Kernel principal component analysis and support vector machines for stock price prediction. *IIE Transactions*, 39(6):629–637.

Kim, K.-j. and Han, I. (2000). Genetic algorithms approach to feature discretization in artificial neural networks for the prediction of stock price index. *Expert systems with Applications*, 19(2):125–132.

Kim, Y., Jeong, S. R., and Ghani, I. (2014). Text opinion mining to analyze news for stock market prediction. *Int. J. Advance. Soft Comput. Appl*, 6(1).

Kimoto, T., Asakawa, K., Yoda, M., and Takeoka, M. (1990). Stock market prediction system with modular neural networks. In *Neural Networks, 1990., 1990 IJCNN International Joint Conference on*, pages 1–6. IEEE.

Kohara, K., Ishikawa, T., Fukuhara, Y., and Nakamura, Y. (1997). Stock price prediction using prior knowledge and neural networks. *Intelligent systems in accounting, finance and management*, 6(1):11–22.

Kuo, R. J., Chen, C., and Hwang, Y. (2001). An intelligent stock trading decision support system through integration of genetic algorithm based fuzzy neural network and artificial neural network. *Fuzzy sets and systems*, 118(1):21–45.

Lee, M.-C. (2009). Using support vector machine with a hybrid feature selection method to the stock trend prediction. *Expert Systems with Applications*, 36(8):10896–10904.

Lin, X., Yang, Z., and Song, Y. (2009). Short-term stock price prediction based on echo state networks. *Expert systems with applications*, 36(3):7313–7317.

Mittermayer, M.-A. (2004). Forecasting intraday stock price trends with text mining techniques. In *System Sciences, 2004. Proceedings of the 37th Annual Hawaii International Conference on*, pages 10–pp. IEEE.

Nikfarjam, A., Emadzadeh, E., and Muthaiyah, S. (2010). Text mining approaches for stock market prediction. In *Computer and Automation Engineering (ICCAE), 2010 The 2nd International Conference on*, volume 4, pages 256–260. IEEE.

Pai, P.-F. and Lin, C.-S. (2005). A hybrid arima and support vector machines model in stock price forecasting. *Omega*, 33(6):497–505.

Wang, J.-H. and Leu, J.-Y. (1996). Stock market trend prediction using arima-based neural networks. In *Neural Networks, 1996., IEEE International Conference on*, volume 4, pages 2160–2165. IEEE.