Generating Market Comments on Stock Price Fluctuations Using Technical Analysis Features

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***Abstract*—Recently, there has been significant interest in techniques for generating market comments from stock prices automatically. However, it takes a multitude of time and effort for analysts to generate full-text market comments from stock prices. In this paper, we propose a method for generating "comments on stock price fluctuations" included in market comments to reduce the workload of analysts. The proposed method learns stock price fluctuations and the corresponding expressions, generates comments, and completes market condition comments by assigning them to prepared canned sentences. So far, this is the result of our previous study [1], and this paper improves the results by adding new features to the training data. The new data to be added to the training data in this paper are "Dow Jones Industrial Average" and "Technical Analysis", both of which are expected to improve the results. Because of our experiments, we found that the features used to generate them are effective and the proposed method can accurately generate market comments.**

Keywords-Generate market comments; Stock price fluctuation; Nikkei Stock Average; Dow Jones Industrial Average; Technical Analysis.

I. INTRODUCTION

Recently, there has been an increase in the use of data in various fields, such as weather, sports, medicine, and finance. However, when the data is large or complex, it is difficult for a person without expert knowledge to understand it, and even if they are experts, it takes time to understand the data and extract the important elements. One method to make effective use of such data is data-to-text technology. This is a technology that expresses the outline of data in text to make it easier for humans to interpret, and it has been gaining attention due to its increased demand recently.

The task of generating market comments from stock price data, which is the subject of this research, is also a type of data-to-text technology. Currently, analysts, who are specialists in researching and analyzing social conditions, etc., generate market comments. They analyze stock prices after they are released and generate market comments. However, it takes a multitude of time and effort for analysts to generate full-text market comments from stock prices. Therefore, in this paper, we propose a method for generating a part of the market comment to reduce the effort required for analysts to generate market comments. Specifically, we extract expressions related to the price movements of stock prices and their fluctuation ranges, and then generate comments by learning the price movements of stock prices and expressions through machine learning. By applying the generated comments to the pre-prepared format, the system automatically generates the quantitative analysis results in the market comment, and as a result, analysts can concentrate on their core business, such as factor analysis.

In this paper, we extract various features from the time series data and convert them into text based on the task of generating market comments on the Nikkei Stock Average. First, we form long-term and short-term time series data to capture the changes in the time series stock price data. Next, we extract 12 important phrases from NQN (Nikkei Quick News) so that we can generate an expression in NQN. These phrases are frequent occurrences in the first sentence of the market comment, and the four main expressions are "続落(continued to decline)", "続伸(continued to rise)", "反発(rebound)", and "反落(reactionary fall)", with "大幅(large)" and "小幅(small)" added for 12. Table I shows the details of the phrases. By mapping these expressions to the price movements of stock prices, we create a single data set for learning.

In our experiments, we used the F-measure to compare the phrases generated using the trained data and the phrases extracted from the actual handwritten articles, and we could confirm that the performance of the proposed method was improved compared to the baseline method and those of the previous studies.

So far, this is the result of our previous study [1], and this paper improves the results by adding new features to the training data. The new data to be added to the training data in this paper are the "Dow Jones Industrial Average" and "Technical Analysis." The "Dow Jones Industrial Average" is often mentioned in the text of market comments, and since most of them are involved in the fluctuation of the Nikkei Stock Average, we adopted it as the training data because we consider that it improves the accuracy of the data. Technical analysis is a type of stock price forecasting that has been used recently, and the use of technical analysis in stock price forecasting by machine learning is useful in studies of the impact of technical analysis on machine learning [2]. The difference from using the Dow Jones Industrial Average is that two types of stock prices are used, and one type of stock price is extracted and used, and the accuracy of each type of stock price is checked to see how much the accuracy increases compared to the basic one.

In this paper, as in previous studies, we unified similar expressions among those generated to compare the results with those of a previous study by Murakami et al. [3]. Additionally, sentences that did not require automatic generation by the neural network were omitted. In the future, we will verify whether there are any changes in the experimental results.

TABLE I. Nikkei Stock average.

Phrase	Expression
続伸(continued to rise)	The stock price goes up continuously.
続落(continued to decline)	The stock price falls continuously.
反落(reactionary fall)	The stock price, up, goes down.
反発(rebound)	The stock price, down, goes up.
大幅/小幅続伸	Large or small / continued to rise
大幅/小幅続落	Large or small / continued to decline
大幅/小幅反落	Large or small/reactionary fall
大幅/小幅反発	Large or small / rebound

II. RELATED WORK/METHODS

In this section, we present related work and methods that this paper referred to.

A. Related works

Various studies have been conducted on data-to-text technology, which automatically generates a summary of time-series data in easy text for humans to interpret. For example, research has been conducted to automatically generate text about weather forecasts from time-series weather information [4], to generate text from clinical data to assist doctors and nurses in decision-making [5], and to generate feedback text for students from time-series data that records their learning status within a certain period [6].

In the past, the mainstream of data-to-text research has been the generation of text using manually created rules or a machine learning model using various linguistic features [7][8]. Traditional approaches for data-to-text generation implement three components: (1) content planning that selects content from input data, (2) sentence planning that decides the structure and lexical content of each sentence, (3) surface realization that generates the final output by converting the sentence plan [9]. However, recently, with the development of information and communication technology, large-scale and complex data have become readily available, and interest in machine-learning type methods that generate text based on large-scale correspondence between data and text has been increasing. For example, research has been conducted on the use of machine learning in various data-to-text techniques, such as image caption generation [10], which generates descriptions from image data, and weather forecast text generation from molded weather data [11].

B. Related methods

Techniques for generating market comments can be approached from various perspectives. For example, there are techniques to generate factors of change, such as events that are said to have affected the price movement of the Nikkei Stock Average and information on other stocks [12], to control the generated text by inputting topics representing the content of the generated market comment in addition to the Nikkei Stock Average data [13], and to generate characteristics, such as the history of the price of the stock and time-dependent expressions [3].

III. TASKS FOR SIMPLE WORD GENERATION

In this paper, we are working on a technique to generate text by appropriately selecting words representing the direction of price movement and the range of fluctuation of stock prices. The task is not a traditional full-text generation task, but a word generation task, which is easy to implement and can be expected to yield good results. In the previous research on the market comment generation task, expressions related to stock price fluctuations have been generated in the process of generating market comments, but there has been no research on generating expressions related to fluctuation ranges such as large or small, which has a novelty. Furthermore, the current market comments in NQN are generated by analysts in about 10 minutes even in a short period, but this research will make it possible to generate simple market comments in real-time.

In market comments, not all expressions written at the same time of stock price fluctuations are the same. For example, Table II shows that a market commentary on one-day notes “続伸(continued to rise)” but on another day with the same fluctuation range, it may not "小幅続伸 (Slight increase)”. (XX is the same number, or there is a small margin of error.)

TABLE II. Example of the same fluctuation range but with different expressions.

Text	Expression
日経平均大引け、続伸終値は XX 円高の ZZ 円 (Nikkei 225 closing continuing to rise. The closing price was XX yen higher at ZZ yen.)	続伸(continued to rise)
日経平均大引け、小幅続伸終値は XX 円高の ZZ 円 (Nikkei 225 closing slightly higher. The closing price was XX yen higher at ZZ yen.)	小幅続伸 (Slightincrease)

One factor that could cause the expression to change for the same fluctuation range is the size of the previous day's fluctuation range. Other factors that could be considered include large fluctuations in stock prices other than the Nikkei Stock Average or a change in the analyst's sentiment based on information obtained from their analysis. This study focuses on the need to consider stock prices other than the Nikkei Stock Average and analysts' sentiments, etc., rather than simply following a rule-based approach where the previous day's fluctuation range determines the market comment generated, and therefore, by using machine learning to analyze big data, we are attempting to generate expressions that are not influenced by analysts' sentiments.

TABLE III. The main text of NQN.

	7 日の東京株式市場で日経平均株価は続落した。終値は前日比 94 円 51 銭（0.59%）安の 1 万 5814 円 37 銭だった。 (The Nikkei Stock Average continued to fall on the Tokyo Stock Exchange on August 7. The closing price was ¥15,814.37, down ¥94.51 (0.59%) from the previous day.) 前日の米株安や外国為替市場で円安・ドル高の流れが一服しているのを受けて売りが優勢だった。 (Selling was dominated by the weak U.S. stock market on the previous day and a lull in the trend of yen depreciation and dollar appreciation in the foreign exchange market.)

IV. VALIDITY OF U.S. STOCK PRICES

In this paper, we use the "Dow Jones Industrial Average," an American stock price index, in addition to the training data from previous studies.

The "Dow Jones Industrial Average" is an American stock price index that uses the same calculation method as the Nikkei Stock Average. In this paper, NQN headlines are used as article data; the Dow Jones Industrial Average has been added as additional stock price data because the word "U.S. stocks" referring to the Dow Jones Industrial Average appears frequently in the text of the NQN. Examples are shown in Table III. The word "米株(U.S. stock)" appears with a probability of about 60% in the data of all articles covered in this study and is considered to have a large effect on the sentences or words before and after the article. The expression representing the fluctuation of the Nikkei Stock Average, which is a word generated in this study, is an example of such an expression, so this study confirms the effectiveness of using U.S. stock prices as training data. As shown in the table, the Dow Jones Industrial Average stock price is often expressed as "low" or "high," and few statements mention the Dow Jones Industrial Average stock price. Therefore, instead of adding the numerical value of the U.S. stock price to the training data, two values indicating whether the stock price was high or low were added to examine how this affected the results.

V. STOCK PRICE FORECASTING USING TECHNICAL ANALYSIS

In this paper, technical analysis, which is used to forecast stock prices, is used in addition to the study data from previous studies. Technical analysis is the process of predicting stock prices by identifying trends and patterns based on past stock price movements. The results obtained from the analysis are called technical indicators. For example, if there has been a similar pattern of stock price fluctuation in the past, there will likely be a similar pattern in the future. 15 factors of technical analysis are used in the paper [2] introduced in Section I to construct a model to predict stock prices. The actual model predicts whether the stock price fluctuation will increase or decrease on the next day using the stock price fluctuation and the factors obtained from technical analysis. However, what is predicted in this paper is not the stock price fluctuation, but the expression of the market comments generated by the stock price fluctuation. Technical indicators were employed because once it is known whether the stock price is going up or down, an accompanying expression can be generated.

Two technical indicators were used: the psychological line and the momentum indicator. Although these two types are unrepresentative of the technical indicators used, they were chosen for ease of implementation. The results of using one of each of these two types of indicators as well as the results of using the two types of indicators as factors will be used to confirm whether the factors are valid or not.

A. *Psychological line*

The psychological line is a quantification of the investor's truth. More and more investors will judge that a stock price that has risen consecutively has an increased likelihood of falling. The indicator that quantifies this investor psychology is the psychological line. The calculation method is based on the number of days in a calculation period (generally 12 business days) on which the stock price rises as a percentage, regardless of the rate of fluctuation of rises and falls. Generally, the stock tends to be undervalued when the winning rate (rate of increase) is 25% or less and overvalued when the winning rate (rate of increase) is 75% or more. In this paper, we divide the calculation period, which is usually 12 business days, into 3, 6, 9, and 12 periods to see which period gave better results.

B. *Momentum*

This is a technical indicator that evaluates the momentum of the market. It is calculated by subtracting the closing price of a certain number of days back from the closing price of the day. The most used days are 10, 20, and 25 days. In this paper, we use 10 days. A larger positive value indicates a stronger market, and a larger negative range indicates a weaker condition.

C. *Other technical indicators*

Here are some other typical technical indicators used to predict stock prices that were not used in this study.

RSI is an indicator to determine whether the market is overbought or oversold based on the ratio of the rate of the price increase. Generally, when the ratio is below 30%, it is considered oversold and the stock price often improves, while when the ratio is above 70%, it is considered overbought.

MACD is an indicator that uses moving averages. It is plotted on a technical chart and determines when to buy and sell based on the movement of the short-term moving average and the medium- and long-term moving averages.

VI. PROPOSED METHOD

In this section, we present a method for extracting words and phrases representing the price movement and fluctuation range of stock prices from the Nikkei Stock Average and NQN and the data used in this paper.

A. *Overview*

Figure 1 shows the execution procedure of the proposed method.

First, we molded the data to create a correspondence between stock price and article data. Since the article data contains many noisy expressions, we set the conditions to remove the noise and extract the original phrases of the expressions generated from the article data. Details will be described later.

Next is the stock price data, which also contains a multitude of noise and is inefficient for machine learning, so we molded it into a form that is easy to learn.

We then created a correspondence between three days of stock price data and a single expression and used it to start learning. For machine learning, we used a Multilayer Perceptron (MLP), which is commonly used as an encoder.

Finally, using the trained data, we predict phrases by inputting test data containing the Nikkei Stock Average, Dow Jones Industrial Average data, and technical indicator data. The generated phrase is substituted into the prepared format to complete the market comment. However, the generated phrase is used as the evaluation criterion in this paper, and it is not compared with the full text assigned to the format.

B. *Pre-processing*

In various fields, such as image processing and natural language processing, it is common to perform preprocessing to generalize machine learning models and to remove noise from data. Also in this paper, preprocessing is applied to the Nikkei Stock Average data, which is numerical data. We used the standardization and difference from the previous day as the preprocessing methods for the numerical data. The equations of the processing methods are given below.

$$x_{std} = (x_i - \mu)/\theta \quad (1)$$

$$x_{move} = x_i - r_i \quad (2)$$

x_i denotes the stock price.

In (1), standardization is performed using the data x, mean value μ, and standard deviation θ used for learning.

Equation (2) calculates the difference between the price x_i at each time step from the previous day's closing price $r_i$to capture the change in price from the previous day's closing price.

As in previous studies [1][3], we prepared short-term time series data to capture both short-term and long-term stock price fluctuations: daily stock price data "XShort" consisting of 62time steps, and long-term stock price data "XLong" using past closing prices as input.

However, it is difficult to extract the expressions of short-term data from the articles. This is because the number of market commentaries including expressions on stock price fluctuations is not sufficient for the 62 pieces of short-term data. Furthermore, the number of market commentaries generated in a day is also different, making it difficult to map the data. Additionally, we generated expressions corresponding to the short-term stock price data based on the long-term stock price data and attempted to generate expressions on the training data, but the generation rate did not exceed that of previous studies, so the results

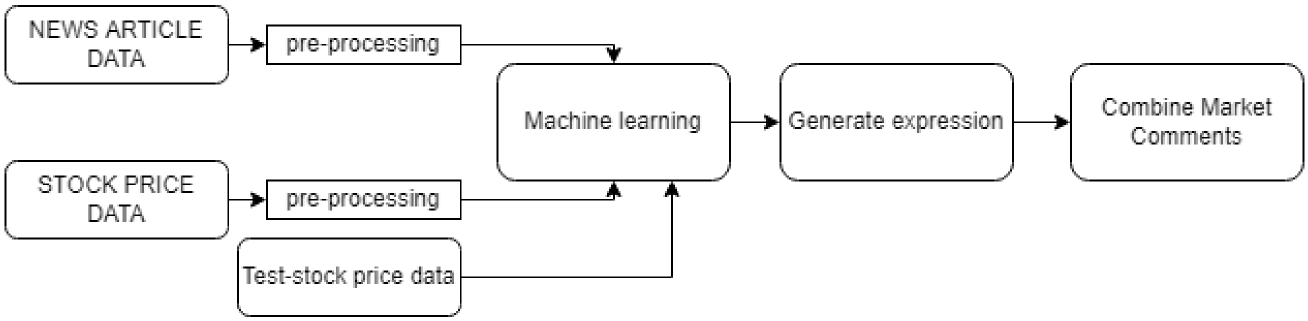

Figure1. Overview. NQN is used for article data, and the Nikkei Stock Average and Dow Jones Industrial Average are used for stock price data. Each model is preprocessed, and three models are created and trained. When combining the Dow Jones Industrial Average and technical indicators as features, the models are added to X_move_std. Note that in this study, the "Combine Market Comments" part is not considered, but the expressions generated by the "Generate expression" are compared.

are omitted from this paper, which shall deal mainly with the long-term stock price data. The long-term stock price data is composed of the closing price of the Nikkei Stock Average, and since the market commentary of NQN, which summarizes the day, is generated around 15:00, just when the closing price is about to be released, it is appropriate to link the stock price with the article to create the training data. Three xstd features and two xmove features are extracted from three days of stock price data, combining a total of five features and one expression.

The preprocessing of article data is performed in the following order:

1. Collect article data for the period related to the stock price data. The period data to be collected is the closing price (15:00). However, since not all articles are posted at exactly 15:00, a one-hour threshold is set.

2. Select the article written at the earliest period among the collected article data and extract the expressions in the article. The expressions extracted are converted into appropriate numbers for machine learning.

C. *Dataset*

In this paper, we use the Nikkei Stock Average, technical indicator, and the Dow Jones Industrial Average as stock price data and NQN as article data. The data used are for the four years from 2014 to 2017. Tables IV and V show examples of the Nikkei Stock Average and the Dow Jones Industrial Average used in this paper. Table VI shows the values for Table IV with the B preprocessing applied, and these three types of data are treated as training data to check their validity. Table VII shows the dataset with the addition of U.S. stocks. The Dow Jones averages are added only to Xlong_move_std, not to all three types. Table VIII shows the dataset with the addition of technical indicators.

TABLE IV. Nikkei Stock average.

date	**Price (close)**
2014/1/6	15908.88
2014/1/7	15814.37
2014/1/8	16121.45

TABLE V. Dow Jones Industrial Average.

Date	**Price (close)**
2014/1/6	16425.09
2014/1/7	16530.90
2014/1/8	16462.69

TABLE VI. Pre-processed data.

Training Data	Move -prev	Move-t oday	Std-p prev	Std-pre v	Std-tod ay
Xlong_move	-94.51	307.8			
Xlong_std			0.449 250	0.35459 5	0.66214 4
Xlong_move_s td	-94.51	307.8	0.449 250	0.35459 5	0.66214 4

TABLE VII. Dataset with the addition of U.S. stocks.

Training Data	Training Data (Dow Jones)	expression
Xlong_move	-	rebound
Xlong_std	-	
Xlong_move_std	1	

TABLE VIII. The dataset with the addition of technical indicators.

Training Data	Train Data (Tech indicator)	expression
Xlong_move	-	rebound
Xlong_std	-	
Xlong_move_std	Psy Line or Mom	

D. Encoding

Generally, MLP, CNN, and RNN are considered encoding methods for time series stock price data. However, from the results of previous studies, the model using MLP as an encoder produces better scores than all other models, including the baseline. Therefore, MLP is also used as an encoder in this study.

VII. EXPERIMENT

Table IX compares the dataset used in the previous study with the dataset used in this study. The comparison with the previous paper is made only where the expressions are covered. The reason for the difference in the data used in the training data is that the data of the Nikkei Stock Average for 2013 was in a different format from the data of other years, making it difficult to extract the data. Although there are some differences between the Nikkei 225 data of 2013 and 2017, the differences have been compensated for by increasing the number of train data. Additionally, the test data are all the same, so the results are expected to be fine.

All the technical indicators used in this study refer to stock price values from the previous day or later, which makes a difference in the number of training data. For example, in the case of the Psychological Line, the indicator is calculated by referring to stock prices up to 9 days before the target date. In this case, the target date is the 10th day or later, so the number of training data differs. The same can be said of momentum. Regarding training data, each model is the result extracted from 3 years of stock price data, and differences in the size of the training data are not considered.

TABLE IX. Dataset for the previous paper and this paper.

	Previous paper	**This paper**
Training data	Nikkei Stock Average/ NQN in 2013,2014,2015	Nikkei Stock Average/ NQN in 2014,2015,2017
test data	Nikkei Stock Average / NQN in 2016	Nikkei Stock Average / NQNin 2016
Expressions that describe changes in stock prices	10/Four expressions were used as references for comparison with this study	12

VIII. RESULT

In this section, we present the results when the Nikkei Stock Average is used as the input and when both the Nikkei Stock Average and the Dow Jones Industrial Average are given as the input.

A. Result: Only using Nikkei Stock Average

In this experiment, we use a combination of time series data Xlong and Xshort and preprocessing methods std and move, with one-time series data as a reference and one or both preprocessing methods applied to it. The number of expressions used in the previous study was four, and they are shown in Table X. Table X includes the experimental results. The results in the previous study column refer to the method that produced the highest F value. The red letters represent the best results within Xlong. The blue letters are the ones with good results, but without the expression for the stock price fluctuation range. This is because when generating comments, NQN does not produce expressions at the five-minute version, so we used a rule base to generate expressions without stock price fluctuation ranges. Although it is not directly related to the experimental results, it is described following the execution results of previous studies. If only generating expressions within market comments, the overall results are better when using Xlong's model as training data than in prior studies.

Comparing within xlong, Xlong_move_std is the best model if only the number of occurrences is used (Xlong_move: Xlongstd:Xlong_move_std=7:8:9 (ratio of appearances)).

B. Result: Using the Nikkei Stock Average and the Dow Jones Industrial Average

In this section, results are compared when Dow Jones averages are given as the input values when creating the training data. The comparison will be made with Xlong-move-std, which had the best results in result A. Since the training dataset was modified when the Dow Jones Industrial Average was given as input, and a different F value was calculated than in result A. Table XI includes the experimental results. The results show that although some results are worse than those of the previous studies, the overall F value has increased. Compared to Xlong, the f-values of the four main expressions have not changed much, but the f-values of the expressions representing the fluctuation range have improved.

C. Result: Using Nikkei Stock Average and technical analysis

In this section, a comparison of results was made when technical indicators were given as input values during the creation of the training data. Comparisons were made with Xlong-move-std and with technical indicators results.

First, the psychological lines were added to the training data. Table XIII gives the f-score for each calculation period for the psychological line. The results show that the best results were output for 9 days rather than the standard 12-day period. These results are shown, but only the standard 12-day results are significantly worse, and after a certain calculation period, they all calculate the same f-score. Therefore, the 9-day psychological line was used in this study instead of the 12-day psychological line, which is set by default.

Next, momentum was added to the training data. The momentum is calculated by subtracting the closing price 10 days before the target date, but since the value it is not suitable for machine learning, std preprocessing was applied. Table XII contains a comparison between xlong_move_std plus psychological lines, momentum, and xlong-move-std.

TABLE X. Result: Only using Nikkei Stock Average.

Expressions	Xlong_move	Xlong_std	Xlong_move_std	Xshort_move	Previous study
Rebound	0.9	0.85	0.91	0.98	0.803
Reactionary fall	0.94	0.90	0.90	0.98	0.748
Large reactionary fall	0.62	0.38	0.60	-	-
Large rebound	0.55	0.60	0.44	-	-
Large continued to decline	0.00	0.77	0.00	-	-
Large continued to rise	0.60	0.69	0.63	-	-
Small, rebound	0.00	0.00	0.00	-	-
Small,reactionary fall	0.00	0.00	0.00	-	-
Small. continued to rise	0.00	0.00	0,46	-	-
Small, continued to decline	0.00	0.00	0.50	-	-
Continued to rise	0.90	0.89	0.88	1.00	0.814
Continued to decline	0.89	0.87	0.90	1.00	0.753

TABLE XI. Result: Using Nikkei Stock Average and Dow Jones Industrial Average.

Expression	Xlong_move_std	+Dow	Previous
Rebound	0.91	0.78	0.803
Reactionary fall	0.90	0.84	0.748
Large reactionary fall	0.60	0.18	-
Large rebound	0.44	0.67	-
Large continued to decline	0.00	0.73	-
Large continued to rise	0.63	0.38	-
Small, rebound	0.00	0.00	-
Small, reactionary fall	0.00	0.00	-
Small. continued to rise	0,46	0.40	-
Small, continued to decline	0.50	0.29	-
Continued to rise	0.88	0.89	0.814
Continued to decline	0.90	0.71	0.753

TABLE XII. Result: Using the Nikkei Stock Average and technical analysis

Expression	Xlong_move_std	+PSY	+MOM
Rebound	0.91	0.83	0.87
Reactionary fall	0.90	0.95	0.92
Large reactionary fall	0.60	0.00	0.67
Large rebound	0.44	0.36	0.29
Large continued to decline	0.00	0.00	0.00
Large continued to rise	0.63	0.00	0.00
Small, rebound	0.00	0.00	0.00
Small, reactionary fall	0.00	0.44	0.29
Small. continued to rise	0,46	0.00	0.00
Small, continued to decline	0.50	0.00	0.00
Continued to rise	0.88	0.83	0.87
Continued to decline	0.90	0.83	0.85

TABLE XIII. F-score for each calculation period for the psychological line.

calculation period	f-score
12	0.695
9	0.744
6	0.721
3	0.724

IX. DISCUSSIONS

In this section, we will discuss the results.

A. *Expressions about stock price fluctuations and Xshort.*

NQN does not produce expressions every 5 min, but only for important periods (9:00, 12:00, 15:00). Therefore, in the case of short-term data that deals with five-minute data, it is necessary to extract expressions mechanically or by using other data as training data and extracting expressions by predicting them. In this paper, the former method was used. In producing the expressions for short-term data, we used the difference from the previous day in two steps. Specifically, two steps of the previous day's difference are used, with a positive value indicating "続伸(continue to rise)" and a negative value indicating "続落(continue to decline)". However, the thresholds for large or small at this time are not defined, resulting in the results shown in Table V. The NQN shows several instances of large and small falls, but the conditions for their appearance could not be determined because of only two steps of difference from the previous day, so it was impossible to set a threshold. The reason for this is that the analysts who write the market commentary assign "large" and "small" according to their sensitivity.

Therefore, the results show a high F value because there were only four expressions for three years of data. One of the future tasks will be to determine the threshold for mechanically generating expressions related to the range of fluctuation. Another possible method of generation is to create training data with long-term stock price data, predict the expression of short-term stock price data from it, and then create new training data from it. However, when this method was used simply before, the results were much lower than when the long-term stock price data was used as training data, so the method needs to be considered.

B. *Extraction methods were considered based on differences with previous studies.*

Table XIV shows the comparable areas in this paper and previous studies. This study produced high F values for all comparable expressions. This is thought to be because similar expressions in the previous studies, such as "反発(rebound)" and "上げに転じる(start to move up)", were treated as the same in this study. To improve the accuracy of expression generation, we unified the expressions in this study. It was found that unifying the expressions increased the accuracy by about 10-20%. Instead, the fluency of the sentences has been reduced. However, since there are no clear rules on how to use words such as "反発(rebound)" and "上げに転じる(start to move up)" that occur in market conditions, it is best to unify them.

TABLE XIV. Comparison of previous studies and this study.

Expression	This Paper	Previous paper
Continued to decline	0.91	0.803
Continued to rise	0.90	0.748
Rebound	0.88	0.814
Reactionary fall	0.90	0.753

C. *Number of expressions and number of data*

References

The results show that there are some expressions whose occurrence rate is 0, and the problem is that the number of data is too large for the number of expressions prepared.

The following is a table of the number of expressions that exist in the data (Table XV) and the occurrence rate of the expression that represents the fluctuation range of stock prices in the data used (Table XVI). The red letters in Table VIII and Table IX are the three selected from the lowest values. Looking at Table IX, we can see that several expressions are never generated. As in the case of Short, if the training data is biased, the result will be like this, so it is desirable to have training data where all expressions are generated to some extent. Or it is necessary to review the expressions to be extracted.

TABLE XV. The number of expressions that exist in the data.

Expression	Xlong_move_std F-value
Continue to rise	184
Rebound	150
Reactionary fall	147
Continue to decline	111
Lage rebound	24
Large, continue to decline	24
Small continue to decline	20
Large Reactionary fall	17
Small continue to rise	17
Small reactionary fall	14
Large continue to rise	13
Small rebound	8

TABLE XVI. Occurrence rate of the expression that represents the fluctuation range.

Expression	Xlong_move_std F-value
Large rebound	0.6
Large reactionary fall	0.44
Large continue to rise	0
Large continue to decline	0.63
Small rebound	0
Small reactionary fall	0
Small continue to rise	0.46
Small continue to decline	0.5

D. *Effects of the Dow Jones Industrial Average*

The market comments published in NQN often mention the fluctuation of the Nikkei Stock Average in the first line, and the Dow Jones Industrial Average in the second line or after the second line. In these comments, a sentence like "The Nikkei Stock Average rebounded following the trend of major stock indexes all rising in the U.S. stock market the previous day." appears. As this sentence indicates, Nikkei Stock Average is strongly influenced by the U.S. stock market (Dow Jones Industrial Average), so in this paper, we tested the effectiveness of the phrases. As a result, the F values of the four main phrases (continuous decline, continuous growth, rebound, and decline) stayed almost the same, but the generation rates of the expressions with small and large amounts of percentages increased as a whole. The reason is thought to be that the input of not only the Nikkei Stock Average but also the Dow Jones Industrial Average values resulted in a detailed separation of the expressions related to stock price fluctuations. As in the case of the Dow Jones Industrial Average, we consider whether the results will be further improved or worsened by providing new numerical data affecting the Nikkei Stock Average as an input.

E. *Effects of the Technical indicators*

Technical indicators are effective in predicting stock prices, and we speculated that if it is possible to predict stock prices, it would also be possible to predict the fluctuation rate associated with them, so we added them as training data. The difference between the Dow Jones Industrial Average and technical indicators as additional data is whether they are composed of only the Nikkei Stock Average or whether they are composed of additional stock prices other than the Nikkei Stock Average. This paper confirms how those differences affect the generation rate of the expression. The results showed that the psychological line was not as effective in improving the results, and the momentum was not as effective as when the Dow Jones Industrial Average was added. In other words, it was found that training data consisting only of the Nikkei Stock Average did not produce good results. However, the technical indicators applied in this paper were prioritized for ease of implementation, and major technical indicators such as MACD and RSI were not implemented. It is recommended that these technical indicators be implemented and compared again. Additionally, although the technical indicators were added one by one to xlong_move_std this time, it is considered that the results may be improved by multiplying technical indicators with each other, just as move and std are multiplied with each other.

X. CONCLUSION

In this paper, we extracted expressions related to the price movements of stock prices and their fluctuation ranges using the Nikkei Stock Average and NQN, learned the expressions and price movements by machine learning, and generated expressions for given stock prices. We compared the generated expressions with those extracted from the original article and verified which training data were superior in terms of correct answer rate and F value.

In conclusion, the results of the training data with two types of preprocessing implemented exceeded those of the previous study. This is thought to be due to the unification of similar expressions in the previous study.

In addition, when generating expressions related to the range of variation of values, such as "大幅(Large)" and "小幅(Small)," it turned out to be difficult to generate them unless the training data contained these expressions with a certain degree of probability.

To examine the influence of the U.S. stock price on the Nikkei Stock Average, we also examined whether there was any change in the generation rate by giving the U.S. stock price (Dow Jones Industrial Average) as a new input. As a result, when the U.S. stock price was given as an input, the generation rate of the main phrases was not significantly affected, but the generation rate of phrases describing the fluctuation range of the stock price was generally improved.

As an additional experiment, a comparison was made between the training data consisting only of the Nikkei Stock Average, including the additional data, and the Nikkei Stock Average with the Dow Jones Industrial Average added.

The additional data were technical indicators, used to predict stock prices. As a result, the accuracy was improved, although not as much as that of the Dow Jones Industrial Average. Further improvement can be expected by using the major technical indicators and by multiplying technical indicators with each other.

Future challenges include setting thresholds to mechanically generate expressions related to the range of variation, creating better training data, revising expressions, and new input values.

REFERENCES

[1] I. Sekino and M. Sasaki, "Generating Market Comments on Stock Price Fluctuations Using Neural Networks," in Proc. eKNOW, 2021, pp. 37-41.

[2] R. Katayose and M. Yoshioka, "Analysis of effect by technical analysis using machine learning," SIG-FIN-024, 2020, pp. 144-148.

[3] S. Murakami, A. Watanabe, A. Miyazawa, K. Goshima, T. Yanase, H. Takamura, and Y. Miyao, "Learning to Generate Market Comments from Stock Prices," Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, 2017, pp. 1374-1384.

[4] B. Anja, "Probabilistic Generation of Weather Forecast Texts," Association for Computational Linguistics, 2007, pp. 164-171.

[5] F. Portet, E. Reiter, J. Hunter, and S. Sripada, "Automatic Generation of Textual Summaries from Neonatal Intensive Care Data," Artificial Intelligence, Volume 173, 2009, pp. 789-816.

[6] D. Gkatzia, H. Hastie, and O. Lemon, "Comparing Multi-label Classification with Reinforcement Learning for Summarization of Time-series Data," Association for Computational Linguistics, 2014, pp. 1231-1240.

[7] W. Lu and H. T. Ng, "A probabilistic forest-to-string model for language generation from typed lambda calculus expressions," the 2011 Conference on Empirical Methods in Natural Language Processing (EMNLP2011), 2011, pp. 1611–1622.

[8] G. Angeli, P. Liang, and D. Klein, "A simple domain-independent probabilistic approach to generation," the 2010 Conference on Empirical Methods in Natural Language Processing (EMNLP2010), 2010, pp. 502–512.

[9] K. McKeown, "Text generation," Cambridge University Press, 1985.

[10] O. Vinyals, A. Toshev, S. Bengio, and D. Erhan, "Show and Tell: A Neural Image Caption Generator," IEEE, Accession Number: 15524253, 2015.

[11] H. Mei, M. Bansal, and M.R. Walter, "What to talk about and how? Selective Generation using LSTMs with Coarse-to-Fine Alignment," Association for Computational Linguistics, 2016, pp. 720-730.

[12] T. Aoki, A. Miyazawa, T. Ishigaki, K. Goshima, K. Aoki, I. Kobayashi, H. Takamura, and Y. Miyao, "Generating Market Comments Referring to External Resources," Association for Computational Linguistics, 2018, pp. 135-139.

[13] K. Aoki, A. Miyazawa, T. Ishigaki, T. Aoki, H. Noji, K. Goshima, I. Kobayashi, H. Takamura, and Y. Miyao, "Controlling Contents in Data-to-Document Generation with Human-Designed Topic Labels," Association for Computational Linguistics, 2019, pp. 323-332.