Detecting Causes of Stock Price Rise and Decline by Machine Reading Comprehension with BERT

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Abstract

In this paper, we focused on news reported when stock prices fluctuate significantly. The news reported when stock prices change is a very useful source of information on what factors cause stock prices to change. However, because it is manually produced, not all events that cause stock prices to change are necessarily reported. Thus, in order to provide investors with information on those causes of stock price changes, it is necessary to develop a system to collect information on events that could be closely related to the stock price changes of certain companies from the Internet. As the first step towards developing such a system, this paper takes an approach of employing a BERT-based machine reading comprehension model, which extracts causes of stock price rise and decline from news reports on stock price changes. In the evaluation, the approach of using the title of the article as the question of machine reading comprehension performs well. It is shown that the fine-tuned machine reading comprehension model successfully detects additional causes of stock price rise and decline other than those stated in the title of the article.

Keywords: Machine Reading Comprehension, BERT, Finance News

1. Introduction

Factors that cause stock prices to fluctuate include IR announcements, in which a company communicates its business results and future business plans to shareholders and investors, and news reports on events that are closely related to the companies. When such information is delivered, as shown in Figure 1, the stock price can fluctuate significantly due to an increase in volume, which represents the volume of stock transactions in which the company's shares are sold or bought. When large fluctuations in stock prices occur in this way, news media related to finance on the Web may report on the fluctuations in stock prices as well as their causes as shown in Figure 2. In this paper, we focused on news reported when stock prices fluctuate significantly. The news reported when stock prices change is a very useful source of information on what factors cause stock prices to change, but because it is manually produced, not all events that cause stock prices to change are necessarily reported. Thus, in order to provide investors with information on those causes of stock price changes, it is necessary to develop a system to collect information on events that could be closely related to the stock price changes of certain companies from the Internet.

As the first step towards developing such a system, this paper takes an approach of employing a BERT (Devlin et al., 2019)-based machine reading comprehension model (Pranav et al., 2016), which extracts causes of stock price changes from news reports on stock price changes (Figure 3). Those extracted causes are intended to be further used to train a system to collect information on events that could be closely related to the stock price changes of certain companies from the Internet.

In the evaluation results, overall, the approach of using the title of the article as the question Q of the machine reading comprehension performs well. We also compare the performance of two models, where one is fine-tuned with stock price rise examples, while the other is fine-tuned with stock price decline examples. The former model performs well when evaluated against stock price rise examples and so does the latter model when evaluated against stock price decline examples. It is shown that, however, the former (stock price rise) model performs worse when evaluated against stock price decline examples. It is also the case that the latter (stock price decline) model performs worse when evaluated against stock price rise examples. These results are mainly because words within stock price rise examples and decline examples are somehow different from each other as we describe in section 2. Based on these results, it is also shown that the model fine-tuned with the mixture of stock price rise and decline examples is the most appropriate for the general use where the stock price rise or decline is unknown.

We also examine whether the answer span predicted by the fine-tuned model actually includes additional information other than the question (i.e., the title of the article) or not. The rate of including additional information other than the title of the article is about 70% for the stock price decline and about 50% for the stock price rise[1]. Here, as we describe in section 4, most of them actually do not overlap with the title of the article and hence the fine-tuned model detects causes of stock price rise and decline that are not stated in the title of the article. Thus, this result indicates that the fine-tuned model successfully detects additional causes of stock price rise and decline other than those stated in the title of the article.

The method proposed and the evaluation results of this paper are summarized as below:

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[1]Their rates of exact and partial match with the reference answer are over 60% in the total of rise and decline.
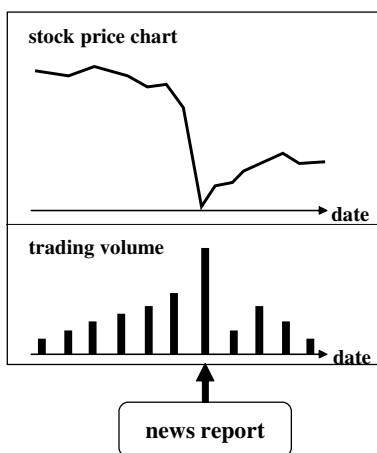
Figure 1: Relation of Stock Price Changes and Trading Volume per Day and News Report

Table 1: Statistics of the Categories of 100 Articles delivered from "MINKABU"

category	# of articles
news on stock price changes and their causes	28
news on companies such as the announcements on new products	13
news on domestic equities	21
news on foreign equities	9
news on exchange market	3
news on bond market	3
news for individual investors	23
total	100

- A BERT-based machine reading comprehension model extracts causes of stock price rise and decline from news reports on stock price changes.

- The approach of using the title of the article as the question Q of the machine reading comprehension performs well.

- The rate of including additional information other than the title of the article is about 70% for the stock price decline and about 50% for the stock price rise.

2. Stock Price News of "MINKABU"

In this paper, the news site from which we collect the stock price news is `minkabu.jp`[2], where we used 23,989 articles[3] delivered from "MINKABU".

Table 2: # of Occurrences and their Ratio (%) of Individual Words representing Rise in Stock Prices among 627 Examples of Machine Reading Comprehension of Causes of Stock Price Changes

word	#	ratio
反発 (correction)	176	19.7
続伸 (continued to rise)	172	19.3
高値 (high price)	115	12.9
カイ気配 (bid price)	87	9.7
大幅高 (large rise)	66	7.4
上昇 (rise)	56	6.3
ストップ高 (hit limit high)	54	6.0
急伸 (rise rapidly)	49	5.5
連騰 (winning streak)	40	4.5
堅調 (increase steadily)	38	4.3
急騰 (sharp rise)	35	3.9
other	5	0.5
total	893	100

Table 3: # of Occurrences and their Ratio (%) of Individual Words representing Decline in Stock Prices among 777 Examples of Machine Reading Comprehension of Causes of Stock Price Changes

word	#	ratio
嫌気 (discouraged)	430	22.7
反落 (reactionary fall)	316	16.7
続落 (continued to decline)	221	11.7
赤字 (deficit)	206	10.9
急落 (fall rapidly)	137	7.2
減益 (decrease in profit)	99	5.2
出尽くし感 (material exhaustion)	70	3.7
転落 (fall)	56	3.0
下落 (decline)	44	2.3
下振れ (downside)	40	2.1
大幅安 (large decline)	40	2.1
引き下げ (reduction)	34	1.8
other	202	10.7
total	1,895	100

`minkabu.jp` includes about 290,000 articles (as of November 2021) that are delivered from "MINKABU". Table 1 shows the statistics of the categories (manually classified by the author of the paper) of 100 articles randomly sampled from the collected 23,989 articles. Based on this statistics, out of the overall 290,000 articles delivered from "MINKABU", it is estimated that the number of articles on "news on stock price changes and their causes" amount to 81,200 (28%). Thus, "MINKABU" can be considered as a resource with a sufficient number of articles for devel-

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[2]`https://minkabu.jp/`

[3]Out of 23,989 articles, 15,300 are delivered from June 30th to December 3rd, 2020, while 8,689 are delivered from

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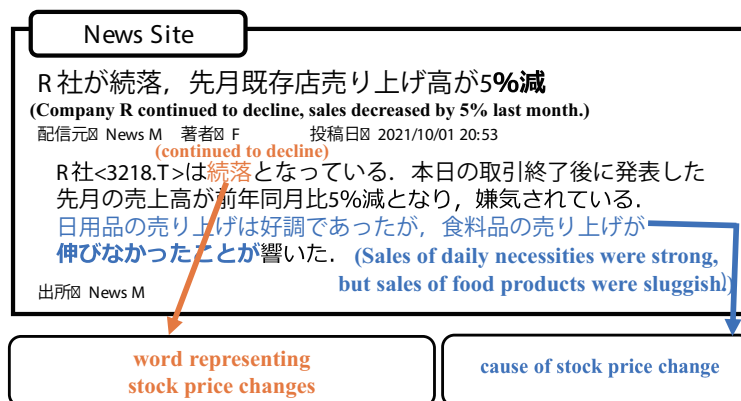
March 5th to June 1st, 2021.

Figure 2: The Word representing Stock Price Changes and a Cause of Stock Price Change: an Example
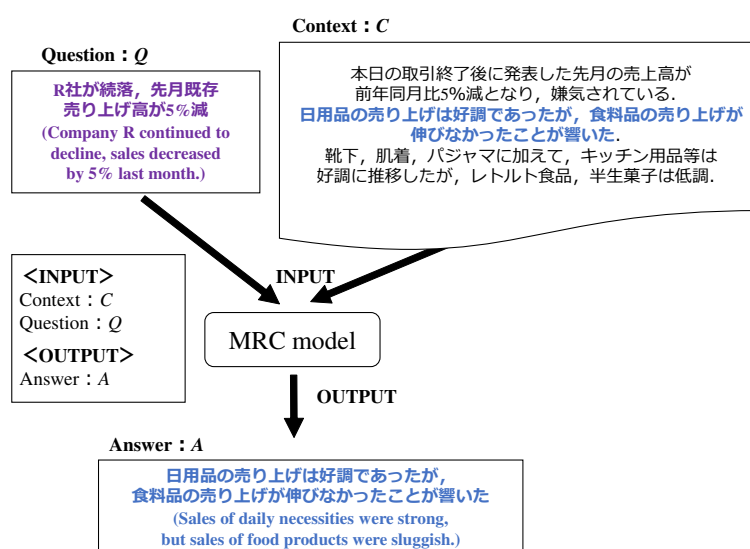

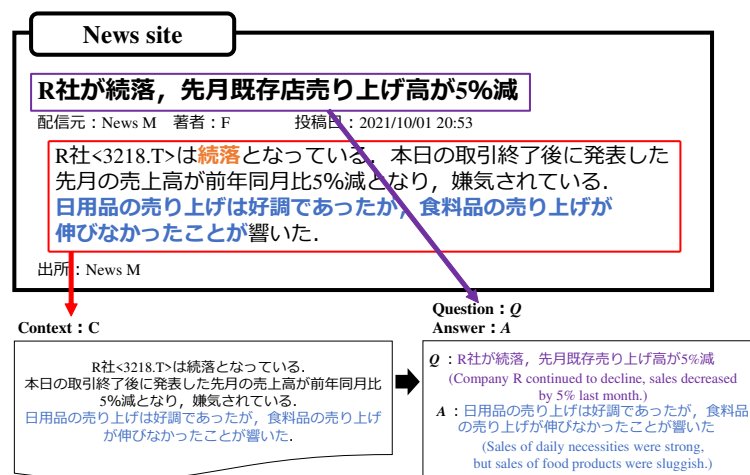Figure 3: The Framework of Machine Reading Comprehension of Causes of Stock Price Changes

Figure 4: The Procedure of Developing an Example of Machine Reading Comprehension of Causes of Stock Price Changes
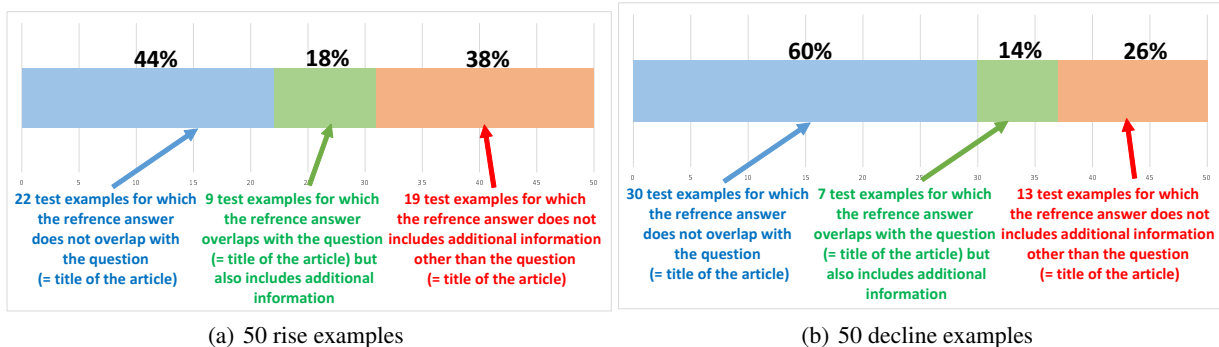
| (a) 50 rise examples | (b) 50 decline examples |

Figure 5: Statistics on whether the refrence answer includes additional information other than the question (= the title of the article) or not

oping a dataset for the examples of machine reading comprehension of causes of stock price changes.

There are two major types of fluctuations in stock prices: rise and decline. First, we focus on the rise in stock prices and created a dataset of examples of machine reading comprehension of causes of stock price rise. Here, we first selected more than 11 kinds of words listed in Table 2 representing "rise" in stock prices. Then, in the procedure of collecting candidates of example articles of machine reading comprehension of causes of stock price rise, we collect articles containing at least one of those words of Table 2. In the case of the evaluation in this paper, we used randomly selected 627 articles containing at least one of those words listed in Table 2, from 3,300 articles[4] of the distributor "MINKABU". This is the result of discarding 14 articles that are not appropriate for developing examples of machine reading comprehension of causes of stock price changes. This is also the result of discarding 35 articles including another 13 words[5] representing "decline" in stock prices.

Next, we focus on the decline in stock prices and created a dataset of examples of machine reading comprehension of causes of stock price decline. The general procedure of collecting candidates of example articles of machine reading comprehension of causes of stock price decline is almost the same as the case of the rise in stock prices. We first selected more than 12 kinds of words listed in Table 3 representing "decline" in stock prices. Then, we simply collect articles containing those individual words of Table 3. In the case of the evaluation in this paper, we obtained 2,117 articles from 23,988 articles from distributor "MINKABU" that contained at least one of more than 12 kinds of words listed in Table 3 representing "decline" in stock prices. From the 2,117 articles retrieved, finally, randomly selected 777 datasets of examples of machine

reading comprehension of causes of stock price decline were created.

3. The Procedure of Developing Machine Reading Comprehension Examples: Comprehending Causes of Stock Price Changes from Stock Price News Articles

We developed 627 examples of machine reading comprehension of causes of stock price changes for rise and 777 for decline, as shown in the procedure of Figure 4. As the context C, the full text of the article that is delivered from "MINKABU" is used. As the question text Q, the title of the stock price change news is used as it is. The title of the stock price change news includes the company name and the word "continued to decline", which indicates the change of the stock price, such as in "Company R continued to decline, sales decreased by 5% last month." So, this information would be useful for extracting the cause of the stock price change from the context C. It is also useful in that the cost of manually developing the question Q is reduced by using the title of the stock price change news as the question Q[6].

Here, it is important to examine whether the reference answer span actually includes additional information other than the question (i.e., the title of the article) or not[7]. Figure 5 shows this statistics, where Figure 5(a) shows the statistics of the stock price rise examples, while Figure 5(b) shows that with stock price decline examples. It is very interesting to see that, for the stock price decline examples, the reference answer does not overlap with the title of the article for 60% cases and

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[4]Delivered from October 30th to December 3rd, 2020.

[5]Those 13 words include "反落 (reactionary fall)", "下落 (decline)", "続落 (continued to decline)", "急落 (fall rapidly)", "売りに押され (drop)", and "安値 (low price)".

[6]The dataset including the span of the stock price changes is represented in the character level, where those input texts are segmented into a morpheme sequence in the evaluation.

[7]This additional information is manually examined, where we ignore the cases of just a fragmental difference of a few functional words. We judge that there exists additional information only when the difference of the information is more than a few functional words.

(a) Evaluation with 100 rise examples

(b) Evaluation with 100 decline examples
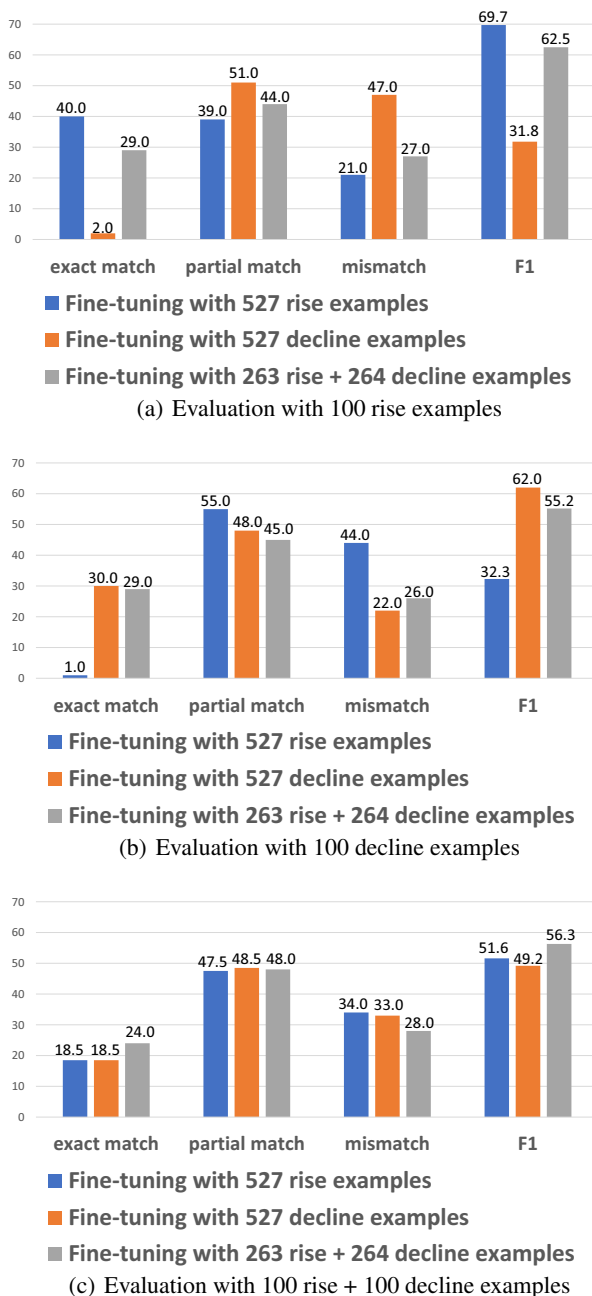

(c) Evaluation with 100 rise + 100 decline examples

Figure 6: Evaluation Results

it does overlap with the title but still has additional information for 14% cases. For the stock price rise examples, on the other hand, the reference answer does not overlap with the title of the article for just 44% cases (less than the decline examples) and it does overlap with the title but still has additional information for 18% cases. Thus, it is important to examine whether the fine-tuned model does actually successfully detect those additional causes information other than those stated in the title of the article.

As for the issue of the difference between stock price decline and rise, the difference of 60% and 44% (the rates of the articles where the reference answer does not overlap with the title of the article) can be interpreted

as below: the title of those stock price news articles do not tend to include the detailed causes of the stock price decline, while they tend to include the detailed causes of the stock price rise.

4. Evaluation

4.1. Evaluation Procedure

As the version of BERT (Devlin et al., 2019) implementation which can handle a text in Japanese, the TensorFlow version[8] was used as the Japanese implementation, and the NICT BERT Japanese pre-trained model[9] was adopted. Before applying BERT modules, MeCab[10] was applied with mecab-ipadic-NEologd dictionary[11] and the Japanese text was segmented into a morpheme sequence. Then, within the BERT fine-tuning module, the WordPiece module with 110k shared WordPiece vocabulary was applied, and the Japanese text was further segmented into a subword unit sequence. Finally, the BERT fine-tuning module for machine reading comprehension[12] was applied. In the fine-tuning procedure, the BERT pre-trained model was fine-tuned with the training examples of machine reading comprehension of causes of stock price changes developed in the previous section.

4.2. Evaluation Results

In the evaluation, the following three types of training examples for fine-tuning are examined.

(a) Randomly selected 527 examples of stock price rise, excluding the 100 examples of stock price rise used in the evaluation.

(b) Randomly selected 527 examples of stock price decline, excluding the 100 examples of stock price decline used in the evaluation.

(c) Randomly selected 263 examples of stock price rise and 264 examples of stock price decline, excluding the 200 examples of stock price rise and decline (100 each) used in the evaluation.

Figure 6 shows the evaluation results[13], where Figure 6(a) shows that with 100 examples of causes of stock price rise, Figure 6(b) that with 100 examples of

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[8]https://github.com/google-research/bert
[9]https://alaginrc.nict.go.jp/nict-bert/index.html
[10]http://taku910.github.io/mecab/ (in Japanese)
[11]https://github.com/neologd/mecab-ipadic-neologd
[12]run_squad.py, with the number of epochs as 2, batch size as 8, and learning rate as 0.00003.
[13]"Exact match" is defined as the reference answer span and that predicted by the model being identical. "Partial match" is defined as those two being not identical but overlapping. "Mismatch" is defined as those two being not overlapping, which corresponds to false positive. F1 is computed on the level of input sets of tokens (i.e., morphemes).
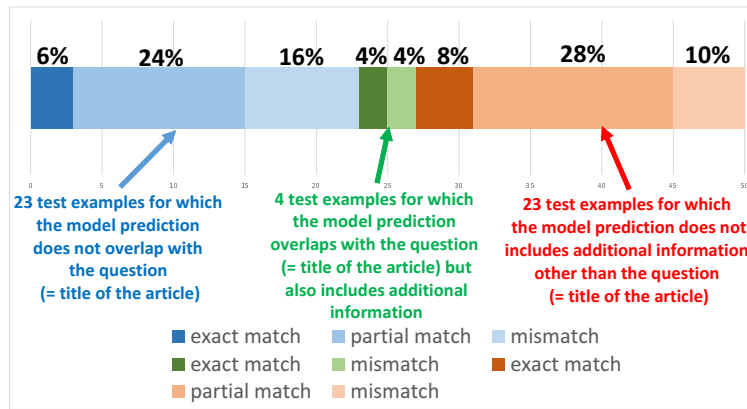
(a) 50 rise examples
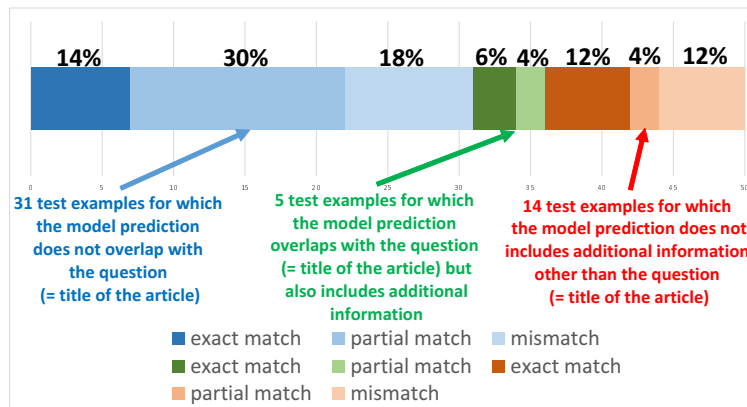
(b) 50 decline examples

Figure 7: Results on whether the model prediction includes additional information other than the question (= the title of the article) or not

causes of stock price decline, and Figure 6(c) that with 200 examples of causes of stock price rise and decline (100 each). Overall, the best performance of evaluation with stock price rise examples is achieved by the model fine-tuned with stock price rise examples (Figure 6(a)). Similarly, the best performance of evaluation with stock price decline examples is achieved by the model fine-tuned with stock price decline examples (Figure 6(b)). These are simply because words representing stock price rise and decline are mostly different from each other. The model fine-tuned with the mixture of stock price rise and decline examples (total number of training examples are fixed as 527 for all the models) performs the best in the evaluation with the mixture of stock price rise and decline examples (Figure 6(c)). This model fine-tuned with the mixture training examples performs relatively high in Figure 6(a) compared with the best performing model, even though the number of stock price rise training examples is just half of the best performing model. This is also the case in Figure 6(b). Thus, it can be claimed that the model with the mixture training examples is the most appropriate for the general use where the stock price rise or decline is unknown.

As described in section 3, in the procedure of developing the question of machine reading comprehension, we use the title of the stock price change news as the question Q as it is. Thus, it is important to examine whether the answer span predicted by the model actually includes additional information other than the question (i.e., the title of the article) or not. Figure 7 shows this evaluation result, where Figure 7(a) shows the result of the evaluation with stock price rise examples, while Figure 7(b) shows that with stock price decline examples. It is very interesting to see that, for the stock price decline examples, the model prediction includes additional information other than the title of the article for about 72% of the cases[14], where for 62% of them, model prediction does not overlap with the title of the article, and for the remaining 10%, model prediction overlaps with the title but still has additional information. For the stock price rise examples, on the other hand, this rate is for about 54% of the cases[15], where

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[14]The exact match and the partial match rate for those about 72% cases is (14+30+6+4)/72%=54%/72%=75.0%. The remaining 25.0% are mismatch and irrelevant to the question.

[15]The exact match and the partial match rate for those 54%

Table 4: Stock Price Rise Examples (trained with 263 rise + 264 decline examples, evaluation with 100 rise + 100 decline examples)

(a) the model prediction (= reference answer) overlaps with the title of the article but also includes underline additional information

title of the article	context = full text of the article (the text below is simplified for ease of reference)	model prediction = reference answer (additional information is underlined)
N 社が大幅続伸、T 建物の商業施設で駐車場満空把握ソリューションの活用を開始 (= Company N began using the solution to monitor parking lot occupancy at T Construction company's commercial facilities, and its stock price has continued to rise.)	N 社 <4056.T>が大幅高で 3 日続伸している。午前 9 時ごろ、商業施設「スマーク伊勢崎」(群馬県伊勢崎市)で、T 建物 <8804.T>の運営する商業施設では初の試みとなる、人工知能 (AI) 技術を活用した大型平面駐車場の満空把握・管制ソリューションの活用を開始したと発表しており、これが好感されている。今回の「スマーク伊勢崎」における導入は、人手不足による誘導員の確保の難しさを解消するのが狙い。(= N Corp's stock price<4056.T>has continued to rise. The company announced that it has begun using an AI-based solution to monitor parking lot occupancy for the first time at T Construction company's<8804.T>commercial facility S, which has been favorable impression. The introduction of the system to Commercial Facility S is aimed at alleviating labor shortages.)	人工知能 (AI) 技術を活用した大型平面駐車場の満空把握・管制ソリューションの活用を開始した (= it has begun using an AI-based solution to monitor parking lot occupancy)

(b) the model prediction (= reference answer) does not overlap with the title of the article

title of the article	context = full text of the article (the text below is simplified for ease of reference)	model prediction = reference answer
<注目銘柄 >=I 社、DX 時代の変身株に (= <Stocks to Watch> = Company I has become a hot stock in the DX era.)	I 社 <4056.T>は IT 系を中心としたニュースサイトを運営するほか、非 IT 系メディアの育成も進めている。ネット上「見込み顧客」を発掘して営業機会の創出を支援する事業が好調である。(= Company I operates a news website related to IT and is also in the process of developing non-IT media. Its business of finding "customers" on the Internet and supporting their sales activities is performing well.)	ネット上「見込み顧客」を発掘して営業機会の創出を支援する事業が好調 (= Its business of finding "customers" on the Internet and supporting their sales activities is performing well)

Table 5: Stock Price Decline Examples (trained with 263 rise + 264 decline examples, evaluation with 100 rise + 100 decline examples)

(a) the model prediction (= reference answer) overlaps with the title of the article but also includes underline additional information

title of the article	context = full text of the article (the text below is simplified for ease of reference)	model prediction = reference answer (additional information is underlined)
S 社が急落、第 2 工場の償却費発生で 21 年 7 月期は大幅減益へ (= Company S falls rapidly, posting sharply decrease profit in July '20 due to depreciation costs incurred at its second plant.)	S 社 <9262.T>が急落している。主力の高齢者向け弁当販売で、フランチャイズ店が約 60 店舗の増加を見込むが、第 2 工場の稼働に伴い人件費が増加するほか、減価償却費が発生することが利益を圧迫する。(= S Corp's stock price<9262.T>falls rapidly. The company expects an increase of about 60 franchise stores in its mainstay boxed lunch sales to the elderly, but labor costs will increase with the start of operations at the second plant, and depreciation costs expense will pressure profits.)	第 2 工場の稼働に伴い人件費が増加するほか、減価償却費が発生することが利益を圧迫する(= labor costs will increase with the start of operations at the second plant, and depreciation costs expense will pressure profits)

(b) the model prediction (= reference answer) does not overlap with the title of the article

title of the article	context = full text of the article (the text below is simplified for ease of reference)	model prediction = reference answer
O 社が続落、20 年 10 月期業績は計画下振れで着地 (= Company O has continued to decline, and its performance in October '20 was lower than previously planned.)	O 社 <7827.T>が続落している。17 日の取引終了後、集計中の 20 年 10 月期業績について、売り上げが下振れて着地したようだと発表しており、これが嫌気されている。新型コロナウイルス感染症の影響で、一定の営業制限を余儀なくされたことや、梱包用材などの受注が低迷したことが響いた。(= O Corp's stock price<7827.T>has continued to decline. After the close of trading on October 17, the company announced that sales for October '20, which are still being compiled, were down, and the market discouraged about it. The company's sales activities were limited due to COVID-19, and orders for packaging materials and other products were sluggish.)	新型コロナウイルス感染症の影響で、一定の営業制限を余儀なくされたことや、梱包用材などの受注が低迷したことが響いた (= The company's sales activities were limited due to COVID-19, and orders for packaging materials and other products were sluggish)

for 46% of them, model prediction does not overlap with the title of the article, and for the remaining 8%, model prediction overlaps with the title but still has additional information. Compared with the statistics on whether the reference answer span actually includes additional information other than the question (i.e., the title of the article) or not in Figure 5, these rates are sufficiently high and it can be claimed that the model prediction does include additional information other than the title of the article. This result indicates that the fine-tuned model successfully detects additional causes of stock price rise and decline other than those stated in the title of the article.

Table 4 and Table 5 show the examples of the articles of those stock price rise and decline cases, respectively. In those examples, the model prediction is exact match with the reference answer. Table 4(a) and Table 5(a) show the cases where the model prediction (= reference answer) overlaps with the title of the article but also includes additional information (underlined), while Table 4(b) and Table 5(b) show the cases where the model prediction (= reference answer) does not overlap with the title of the article. As we described in the discussion on the statistics of Figure 7, those cases of detecting fully additional information other than the title of the article are majority cases. Thus, it can be claimed that the model prediction (= the reference answer) successfully includes additional information other than the title of the article in those cases.

5. Related Work

As a related work, Liu et al. (2020) studied the issue of pre-trained financial language model for financial text mining. The task studied is FiQA[16] Task 2 "Opinion-based QA over financial data". This task is closer to general question answering in the financial domain, compared to our task of answering the causes of the stock price rise and decline. As another related work, Mariko et al. (2020) organized the Financial Document Causality Detection Shared Task (Fin-Causal 2020), where the tasks such as detection of causes and effects in the general financial domain are studied (Becquin, 2020; Imoto and Ito, 2020; Ionescu et al., 2020; Pielka et al., 2020; Kao et al., 2020; Szántó and Berend, 2020; Ózenir and Karadeniz, 2020; Chakravarthy et al., 2020). This paper, on the other hand, concentrates on the issue of answering the causes of rise and decline of stock price. Zhu et al. built a large-scale QA dataset containing both tabular and textual data (Zhu et al., 2021). They also proposed a QA model which is capable of reasoning over both tables and text. Liu et al. (2018) also proposed an interface that highlights risk-related sentences in the financial reports based on sentence embedding

techniques, where it provides the function of visualization of financial time-series data for a corresponding company.

6. Conclusion

This paper took an approach of employing a BERT (Devlin et al., 2019)-based machine reading comprehension model (Pranav et al., 2016), which extracts causes of stock price rise and decline from news reports on stock price changes. In the evaluation results, overall, the approach of using the title of the article as the question Q of the machine reading comprehension performed well. It is also shown that the model fine-tuned with the mixture of stock price rise and decline examples is the most appropriate for the general use where the stock price rise or decline is unknown. Future work includes scaling up into beyond the machine reading comprehension setting where only the question Q is available and the candidates of context C have to be automatically collected from a large pool of documents (Chen et al., 2017; Lee et al., 2019).

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cases is (6+24+4+4)/54%=34%/54%=63.0%. The remaining 37.0% are mismatch and irrelevant to the question.

[16]https://sites.google.com/view/fiqa/home

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