

Generating Financial News Articles from Factors of Stock Price Rise / Decline by LLMs

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Abstract

In this paper, we study the task of generating financial news articles related to stock price fluctuations. Traditionally, reporters manually write these articles by identifying the causes behind significant stock price volatility. However, this process is time-consuming, limiting the number of articles produced. To address this, the study explores the use of generative AI to automatically generate such articles. The AI system, similar to human reporters, would analyze stock price volatility and determine the underlying factors contributing to these fluctuations. To support this approach, we introduce a Japanese dataset called JFinSR, which includes stock price fluctuation rankings from “Kabutan” and related financial information regarding factors of stock price rise / decline from “Nihon Keizai Shimbun (Nikkei).” Using this dataset, we implement the few-shot learning technique on large language models (LLMs) to enable automatic generation of high-quality articles from factors of stock price rise / decline that are available in Nikkei. In the evaluation, we compare zero-shot and few-shot learning approaches, where the few-shot learning achieved the higher F1 scores in terms of ROUGE-1/ROUGE-L metrics.

1 Introduction

The utility of news articles in providing information about stock price fluctuations extends beyond merely indicating the magnitude of such fluctuations. They also offer insight into the underlying factors that drive these price fluctuations. Typically, such articles are written manually for each stock. Because of the time and effort required to perform these procedures manually, the top 50 rankings of daily stock price fluctuation such as “Kabutan”¹ do not tend to include a sufficient number of articles. Actually, as shown in the analysis in Section 4

based on Table 1, only 23.9% (= (187 + 100) / (600 + 600)) of the top 50 ranked stocks are accompanied with manually written financial articles.

However, it would be advantageous if these were generated automatically in large numbers. This objective can be achieved by instructing the generative AI to produce the articles as illustrated in Figure 1. The AI needs to identify information that may have contributed to the observed volatility in stock prices and write articles based on that information in a similar manner to that employed by reporters. The generation of articles may entail the synthesis of textual and non-textual information, such as figures and tables. Among those issues on generating articles from textual and non-textual information, this paper concentrates on generating financial articles regarding stock price rise / decline from textual information on the factors of such stock price rise / decline.

Based on those observation, in this study, we first constructed a Japanese dataset for generating financial articles that are directly related to daily stock price fluctuation rankings (JFinSR). JFinSR consists of rankings and articles on the top 50 stocks in terms of daily stock price fluctuation rate from “Kabutan”, and information on factors of stock price fluctuations from “Nihon Keizai Shimbun (Nikkei)”². Both are web media that primarily distribute financial news articles and information. In Kabutan articles, technical terms in the stock domain are frequently used to precisely describe stock price fluctuations. In the process of generating the article, it is essential to select the most appropriate term to describe the stock price fluctuation. However, it should be noted that the term does not appear in the referenced Nikkei information. The method of Utsuro and Nishida (2024) addresses this issue by training LLM and LMM

¹<https://kabutan.jp/>

²<https://www.nikkei.com/>

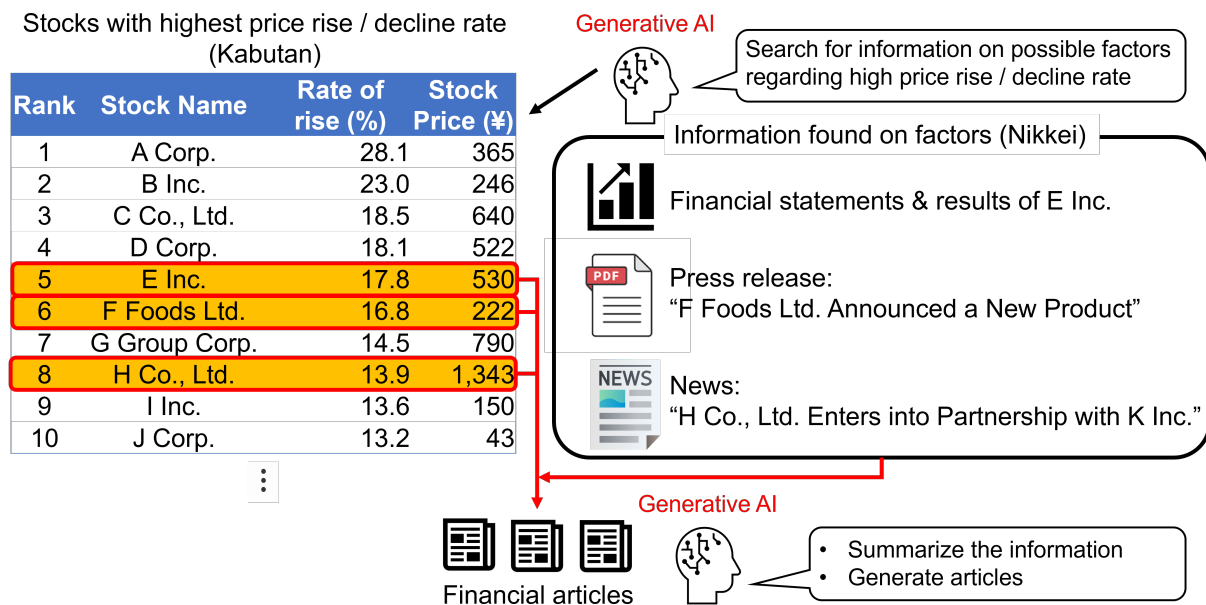


Figure 1: Proposed method for generating financial articles on stock price fluctuations

using time-series numerical data of stock prices³ and stock chart images⁴. In addition, the method of Nishida et al. (2023) can be employed to generate the most appropriate headlines from the text of the generated articles. Using JFinSR, we implement the few-shot learning technique on large language models (LLMs) to enable automatic generation of high-quality articles from factors of stock price rise / decline that are available in Nikkei. In the evaluation, we compare zero-shot and few-shot learning approaches, where the few-shot learning achieved the higher F1 scores in terms of ROUGE-1/ROUGE-L metrics.

2 Related Work

In the context of studies on news article headlines and stock prices, Utsuro and Nishida (2024) proposed the methods for the selection of technical terms in the stock domain that appropriately represent the characteristics of stock price fluctuations, where they conducted evaluation by feeding closing prices to large language models and a chart of stock price fluctuations over several days to large multimodal models. Nishida et al. (2023) studied the task of generating headlines of stock price fluctuation articles from the article’s content, where they solve three distinct tasks of generating article headlines, extracting the stock names, and ascertaining the trajectory of stock prices, whether they

are rising or declining. Tsutsumi and Utsuro (2022) studied the issue of detecting causes of stock price rise and decline from the stock price fluctuation articles by machine reading comprehension models. In the context of stock price prediction using news headlines, Kalshani et al. (2020) studied to combine news headlines with technical indicators to predict stock prices. Chen (2021) studied to predict the short-term movement of stock prices after financial news events using only the headlines of the news. Kalyani et al. (2016) proposed a method for stock trend prediction using news. Two other approaches evaluate different machine learning and deep learning methods, such as Support Vector Machines (SVM) and Long Short-term Memory (LSTM), to predict stock price movement using financial news (Liu et al., 2018; Gong et al., 2021).

3 Data Collection Sources

In order to construct JfinSR, we used “Kabutan” and “Nihon Keizai Shimbun (Nikkei)”, two web media that primarily distribute financial news articles and information.

3.1 Kabutan: “Today’s Ranking”

The “Today’s Ranking” web page published by Kabutan provides information of the top ranked 50 stocks in terms of price rise and decline rates, arranged in a ranking format. They are distributed around 3:30 p.m. after the close of trading hours

³<https://kabutan.jp/stock/kabuka?code=0000>

⁴<https://kabutan.jp/stock/chart?code=0000>

(a) rise

relation of Kabutan and Nikkei	date of Nikkei information's contents (difference from the corresponding Kabutan article date)			total
	same day	one day before	two or more days before	
Kabutan article (= Nikkei) exists	83	41	21	145
Kabutan article (\neq Nikkei) exists	2	7	33	42
total	85	48	54	187

(b) decline

relation of Kabutan and Nikkei	date of Nikkei information's contents (difference from the corresponding Kabutan article date)			total
	same day	one day before	two or more days before	
Kabutan article (= Nikkei) exists	29	34	11	74
Kabutan article (\neq Nikkei) exists	3	4	19	26
total	32	38	30	100

Table 1: Relation of Kabutan articles and Nikkei information's Contents and Dates

on the Japanese stock market's business days. They include the following items for each stock: stock name, exchange name, rate of rise / decline, (%) stock price, and related information. In regard to the "related information" section, it should be noted that the content varies. In some cases, a link to an article on the factors behind stock price fluctuations is provided, while in other cases, only a description of the industry around the specific stock is given, with no link to an article. In yet other cases, the section is left blank.

JfinSR employed the Today's Rankings for 12 days between September 2 and November 6. Thus, in total, 1,200 ($= 50 \times 2$ (rise and decline) $\times 12$ days) examples of the top ranked stocks with financial articles (if any) were collected.

3.2 Nihon Keizai Shimbun: "Kigyō Hatsu Information"

Nihon Keizai Shimbun (Nikkei) has a page called "Kigyō Hatsu Information (report of official statements from companies)" which collects and publishes various information on individual public companies. Kigyō Hatsu Information automatically disseminates information disclosed to the public through the websites of the relevant stock exchanges by approximately 4,000 companies listed on each of Japan's markets. This information is made available to the public in almost real time. The data is presented in a tabular form for each stock.

JfinSR sourced an article in Kigyō Hatsu Information for each of the 1,200 total stocks listed in the rankings collected in the Section 3.1, with the most recent date prior to the date the ranking was published. The information could be referenced

up to one year from the date of viewing, and the articles existed for all 1,200 cases.

4 Data Analysis

In utilizing JFinSR for the automated generation of articles, a series of analyses were conducted.

4.1 Relation of Kabutan Articles and Nikkei Information's Contents and Dates

Among the 1,200 cases included in JFinSR, there are a total of 287 cases with Kabutan articles. For these 287 cases, we examined whether the causes of the stock price fluctuations described in the Kabutan article were included in the information provided by Nikkei. We also classified them according to the number of days that elapsed between the disclosure date of the Nikkei information and the publication of the information in Kabutan rankings. The results are shown in Table 1. Table 1 (a) shows the results for the 187 cases that were listed in the rise rate ranking, while Table 1 (b) shows the results for the 100 cases that were listed in the decline rate ranking.

There were a total of 68 cases (42 in Table 1 (a) and 26 in Table 1 (b)) in which articles with different content from the Nikkei information appeared in Kabutan. The majority of them were objective information such as brokerage firm ratings, where most of them can be definitely regarded as appropriate as the cause of the fluctuation.

4.2 Relation of Article's Contents and Formats

Based on the findings of the analysis conducted in the previous section, an analysis was conducted of

(a) rise

format of Nikkei information	classification of Nikkei information’s content			total
	companies’ performance ^a	new products & services ^b	business partnership ^c	
w/ fig/table	57	3	2	62
w/o fig/table	5	42	36	83
total	62	45	38	145

(b) decline

format of Nikkei information	classification of Nikkei information’s content			total
	companies’ performance ^a	new products & services ^b	business partnership ^c	
w/ fig/table	47	4	1	52
w/o fig/table	5	8	9	22
total	52	12	10	74

^areports related to stock managements and companies’ performance

^blaunch of new products, services, etc.

^cbusiness alliances with other companies

Table 2: Relation of Article’s Contents and Formats (date of Kabutan article is same day as or one day before Nikkei information) (Kabutan article with content *same as* Nikkei exists)

the content and format of Nikkei information, focusing on cases where Kabutan article with content same as Nikkei exists. According to the content of the Nikkei information, a total of 166 such cases were classified into the following three categories: reports related to stock managements and companies’ performance (companies’ performance), launch of new products, services, etc. (new products & services), and business alliances with other companies (business partnership). In addition, according to the format of the Nikkei information, the cases were also classified into the following two categories: text and PDF files *without* figures or tables, and text and PDF files *with* figures or tables.

Table 2 shows relation of article’s contents and formats when a Kabutan article with content *the same as* Nikkei exists. It is evident that cases with diverse combinations of form and content are distributed in a relatively uniform manner. Figure 3 ~ Figure 5 in Appendix A show examples of Kabutan articles and Kigyo Hatsu Information of Nikkei when a Kabutan article containing *the same information as* the Nikkei information exists.

5 Generating Financial Articles from Factors of Stock Price Rise / Decline

5.1 The Procedure

In this section, the method employed in the generation of financial articles with JFinSR is described.

From JfinSR, we used 105 cases (83 rise and 22 decline) where Kabutan articles with the same content as Nikkei’s Kigyo Hatsu Information exist, and where Kigyo Hatsu Information does not

include charts. The data set was divided into two subsets: one comprising 100 cases for evaluation purposes and the other comprising 5 cases for few-shot training. For each case, stock name and stock code number, closing price for three days up to the date of “Today’s Ranking” publication, and “Kigyo Hatsu Information” corresponding to the article were input into a large language model (LLM). For the model, the state-of-the-art LLM, GPT-4o (OpenAI, 2024), was employed.

The following two prompts were prepared to generate articles. The first is a baseline prompt, which creates articles with a single instruction. An example of one of the baseline prompts is shown in Appendix B.1. The other is a two-step prompt, which is divided into two steps: an instruction to extract and summarize the possible causes of stock price fluctuations from the Kigyo Hatsu Information, and to generate an article using that output. An example of one of the two-step prompts is shown in Appendix B.2. For both prompts, a comparison was performed between the articles generated by zero-shot and the articles generated by few-shot using 5 cases of aforementioned training data.

5.2 Evaluation

5.2.1 Overall Results

Evaluation was performed on 100 generated articles of test data. We used ROUGE-1 and ROUGE-L (Lin, 2004) as evaluation metrics and calculated precision, recall and F1 for each value. Table 3 shows the results of the ROUGE evaluation for articles generated by each method. Based on the results, generation with few-shot learning outper-

method	ROUGE-1			ROUGE-L			Average number of characters in Japanese output
	precision	recall	F1	precision	recall	F1	
zero-shot (baseline)	0.537	0.373	0.444	0.327	0.226	0.260	160.7
zero-shot (two-step)	0.555	0.519	0.530	0.348	0.323	0.335	242.3
few-shot (baseline)	0.626	0.472	0.554	0.418	0.312	0.355	200.0
few-shot (two-step)	0.577	0.520	0.541	0.374	0.333	0.348	237.0

Table 3: Results of the ROUGE evaluation

method	article
Kabutan article (reference)	<p>Future Link Network Co., Ltd.<9241> stock has been on the move (動意づく) and is currently trading at a stop price. Before the start of trading today, the company announced the establishment of a new company, “Regional Revitalization AI Technologies”, with the theme of artificial intelligence (AI) x regional revitalization. This was seen as a material factor in the company’s decision to establish the new company. The new company’s business includes “regional revitalization business using AI technology”, “development and verification business of advanced AI technology”, and “reskilling/learning business centering on AI,” etc. While utilizing FL-Net’s know-how and structure, the company intends to flexibly promote its business by acquiring new technologies, hiring human resources, and forming alliances with other companies. The company will also promote its business flexibly by acquiring new technologies, hiring human resources, and forming alliances with other companies.</p> <p>(# of characters ^a: 250)</p>
zero-shot (baseline)	<p>The stock price of FL Net (stock code: 9241) has fluctuated widely (大きく変動) over the last three days, falling briefly from 1645 yen to 1616 yen before rising sharply to 2016 yen. Behind this volatility was the company’s announcement on September 2, 2024 of the establishment of a new company, “Regional Revitalization AI Technologies”, This new company will start providing community revitalization business using generative AI and reskilling services using AI technology, and is expected to aggressively expand in the growing field. The announcement raised market expectations for earnings growth and sent the share price soaring.</p> <p>(F1 (ROUGE-1) ^b: 0.462, F1 (ROUGE-L) ^c: 0.283, # of characters: 217)</p>
zero-shot (two-step)	<p>FL Net <9241>’s stock price has seen significant fluctuations (大きな変動) over the past three days. After falling once from 1,645 yen to 1,616 yen on the first day, it recorded a sharp rise to 2016 yen on the third day. This can be attributed to a new company that the company announced the establishment of, “Regional Revitalization AI Technologies”, This new company will focus on regional revitalization business and reskilling services using generative AI technology, and will also develop and verify AI technology through alliances with other companies. In particular, the expansion of the AI market and growth expectations in the hot area of regional revitalization have likely stimulated investor sentiment. In addition, the company’s risk-skilling business, which has the potential for earnings growth, is also likely to have been highly valued, causing the stock price to soar.</p> <p>(F1 (ROUGE-1): 0.503, F1 (ROUGE-L): 0.309, # of characters: 280)</p>
few-shot (baseline)	<p>Future Link Network Co., Ltd. (FLN) <9241> soared (急騰). On September 2, the company announced the establishment of a new company, “Regional Revitalization AI Technologies” and the full-scale launch of a community revitalization business utilizing AI technology. Expectations for the AI business, which aims to solve regional issues, have been rising, and investors have been buying the company in droves. In particular, the market’s evaluation of the company’s unique approach centered on generative AI boosted the stock price.</p> <p>(F1 (ROUGE-1): 0.529, F1 (ROUGE-L): 0.336, # of characters: 212)</p>
few-shot (two-step)	<p>The stock price of Future Link Network Co., Ltd. (FLNet) <9241> is soaring (急騰). The company attracted market attention when it announced the establishment of a new company, “Regional Revitalization AI Technologies”. The new company plans to use AI technology to create businesses that promote regional revitalization, develop advanced AI technology, and provide AI skill training for local businesses. The company’s partnerships with other companies in AI technology development and the market demand for reskilling services may further boost the growth potential of the business. The announcement appears to be driving FL-Net’s share price higher on expectations for future developments.</p> <p>(F1 (ROUGE-1): 0.530, F1 (ROUGE-L): 0.335, # of characters: 296)</p>

^a number of Japanese characters in the reference article and generated text

^b F1 scores of ROUGE-1

^c F1 scores of ROUGE-L

Table 4: Examples of Kabutan article and generated articles

formed that with zero-shot in terms of F1 scores of ROUGE-1/ROUGE-L metrics for both baseline and two-step prompts. The results show that articles with content more similar to manually written articles can be generated by performing few-shot learning with JFinSR. Another finding is that the two-step prompt improved F1 scores of ROUGE-1/ROUGE-L metrics when generated in zero-shot, but did not produce a significant improvement in few-shot learning. This may be due to the fact that the average number of characters is much higher for the two-step prompts than the baseline in the zero-shot generation, but almost the same in the few-shot training.

5.2.2 Examples of Generated Articles

Table 4 shows the examples of Kabutan article and articles generated by each approach. It should be noted that the articles are written or generated in Japanese and are presented here in English translation. In the zero-shot approach, the stock name is abbreviated as “FL Net,” whereas in the few-shot approach, it is written in the same format as the original article (formal name followed by a code number surrounded by “<>”). It is also impressive that, in baseline and two-step prompts of few-shot approaches, the financial term “soar” is used in the first sentence of the articles. In the comparison of the two prompts, baseline and two-step, the F1 scores are higher in two-step prompts.

6 Evaluation of Term Selection for Stock Price Fluctuation

In the results of Section 5.2, it was found that in many cases, terms which describe stock price fluctuations were not successfully generated from numerical data of stock prices. Therefore, we considered applying the methods of Utsuro and Nishida (2024) for the selection of such terms. In their method, the LLMs were used for selecting terms from a list of ten terms⁵. Table 5 shows the examples of stock price fluctuation terms used in stock search articles, and Figure 2 shows the examples of stock price fluctuations corresponding to stock terms. Among the overall 100 occurrences for evaluation used in Section 5.1, eight out of those ten terms actually appear. The initial eight examples in

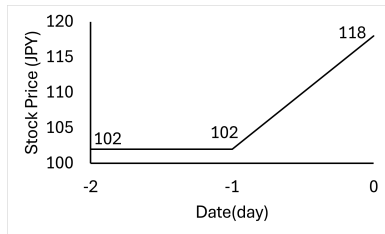
⁵Terms used to describe short-term stock price fluctuations that are “sharp rise”, “sharp decline”, “continuous rise”, “continuous decline”, “continuous sharp rise”, “continuous sharp decline”, “rebound”, “pullback”, “sharp rebound” and “sharp pullback”.

Table 5 are terms that are included in the list of candidate selections, whereas the subsequent five are not. In 71 out of 100 occurrences, one of the eight terms is used. For these 71 cases, we followed this method and let GPT-4o select terms. In 25 cases, terms are correctly selected under strict criterion and in 49 cases, they are correctly selected under lenient criterion⁶. These accuracy is considerably lower than that described in Utsuro and Nishida (2024), indicating that a more sophisticated term selection system is needed for data with large term bias.

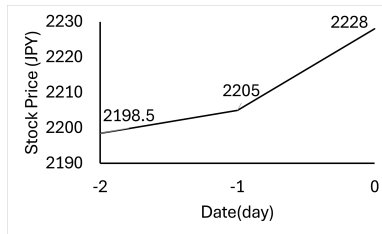
7 Conclusion

In this paper, we studied the task of generating financial news articles related to stock price fluctuations. We first constructed a Japanese dataset for generating financial articles using daily stock price fluctuation rankings (JFinSR). JFinSR consists of rankings and articles on the top 50 stocks in terms of daily stock price fluctuation rate from Kabutan, and information on factors of stock price fluctuations from Nikkei. We examined the correspondences between the Kabutan articles and Nikkei information presented in Section 4.1 by classifying them according to the number of days that elapsed between the disclosure date of the Nikkei information and the publication of the information in Kabutan rankings. The results of those analyses indicate that the JFinSR is a sufficiently useful dataset for the automatic generation of financial articles in the Kabutan rankings based on those factors of stock price rise / decline. We then implement the few-shot learning technique on LLMs to enable automatic generation of high-quality articles from factors of stock price rise / decline that are available in Nikkei. In the evaluation, we compared zero-shot and few-shot learning approaches, where the few-shot learning achieved the higher F1 scores in terms of ROUGE-1/ROUGE-L metrics. Our future work definitely includes generating financial articles not only from textual information but also from non-textual information such as figures and tables. Another future work includes extending the approach of stock price fluctuation term selection employed in Section 6. The approach employed in Section 6 is limited to the 10 types of stock fluctuation terms examined in Utsuro and Nishida (2024). Beyond them, there exist other types of stock price

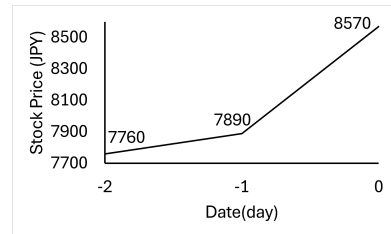
⁶Lenient criterion allows for errors between pairs of terms that are difficult to distinguish even manually.



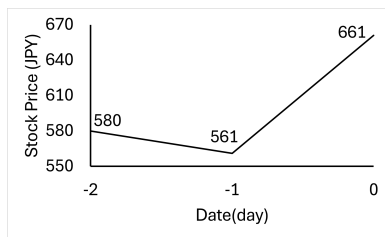
(a) sharp rise



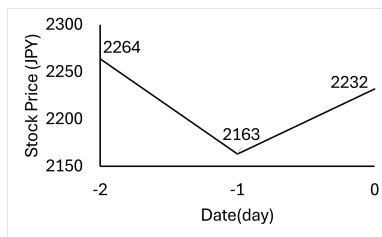
(b) continuous rise



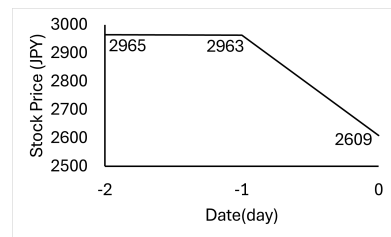
(c) continuous sharp rise



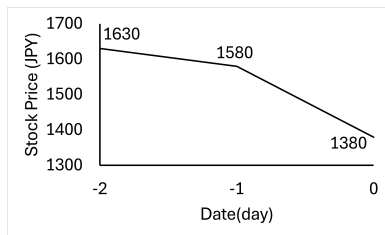
(d) rebound



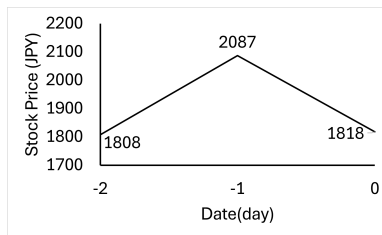
(e) sharp rebound



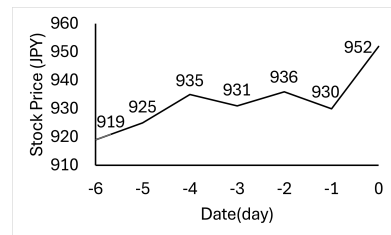
(f) sharp decline



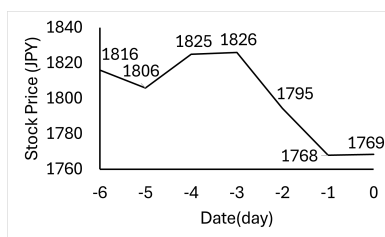
(g) continuous sharp decline



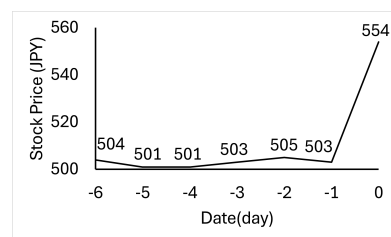
(h) sharp pullback



(i) steady (The upward trajectory of the price has been observable for a relatively long period of time.)



(j) softness (The downward trajectory of the price has been observable for a relatively long period of time.)



(k) sudden rise / decline (A state in which the price has not changed for a relatively long period of time and suddenly fluctuates.)

Figure 2: Examples of stock price fluctuations corresponding to stock terms

term	example
sharp rise	Ishin Co.,Ltd. <ID of TSE: 143A> stock rose sharply in the afternoon session and was bought at a stop price of 1,007 yen. . . .
continuous rise	Hotto Link Inc. <ID of TSE: 3680> stock has continued to rise substantially.
continuous sharp rise	GFA Co., Ltd. <ID of TSE: 8783> stock has continued to rise sharply .
rebound	Exawizards Inc. <ID of TSE: 4259> stock rebounded .
sharp rebound	<ID of TSE: 186A> Astroscale Holdings Inc. stock rebounded sharply .
sharp decline	Daiichi Sankyo Co., Ltd. <ID of TSE: 4568> stock is declining sharply .
continuous sharp decline	Renova, Inc. <ID of TSE: 9519> stock continued to decline sharply .
sharp pullback	Hamamatsu Photonics K.K. <ID of TSE: 6965> stock pulled back sharply .
bid price ^a	Susmed, Inc. <ID of TSE: 4263> stock is bid price .
asked price ^b	General Oyster, Inc. <ID of TSE: 3224> stock is asked price .
steady	Yapli, Inc. <ID of TSE: 4168> stock is steady .
softness	Healios K.K. <ID of TSE: 4593> stock has softened .
sudden rise / decline	Amita Holdings Co., Ltd. <ID of TSE: 2195> stock suddenly started to rise in the afternoon session.

^a“TSE” refers to the Tokyo Stock Exchange.

^a a situation in which there is no corresponding sell order for a buy order, and the trade is not executed and the price is not quoted

^b a situation in which there is no corresponding buy order for a sell order, and the trade is not executed and the price is not quoted

Table 5: Examples of stock price fluctuation terms used in Kabutan articles

fluctuation terms that represent stock price gradual rise or decline continuing in a much larger number of days compared with those 10 types of terms studied in [Utsuro and Nishida \(2024\)](#). In our future work, we plan to extend our stock price fluctuation term selection approach to those incorporating those terms other than the 10 types.

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A Examples of Kabutan Articles and Kigyo Hatsu Information of Nikkei

Figure 3 ~ Figure 5 show examples of Kabutan articles and Kigyo Hatsu Information of Nikkei when a Kabutan article containing *the same information* as the Nikkei information exists.

Figure 3 is a pair of Kabutan article and Kigyo Hatsu Information from Nikkei when “format of Nikkei information” = “w fig/table” and “classification of Nikkei information’s content” = “companies’ performance”. In addition to the textual information in the explanatory materials for financial results (Figure 3(b)), the Kabutan article (Figure 3(a)) summarizes information such as net sales of 8,059 million yen and an operating loss of 650 million yen, which can be read from the table, as factors that contributed to the rise in the stock price.

Figure 4 is a pair of Kabutan article and Kigyo Hatsu Information from Nikkei when “format of Nikkei information” = “w/o fig/table” and “classification of Nikkei information’s content” = “business partnership”. In this case, the information that the

company has entered into a partnership with another company, which can be read from the text of the PDF file (Figure 4(b)), is summarized as a factor that contributed to the rise in the stock price in the Kabutan article (Figure 4(b)).

Figure 5 is a pair of Kabutan article and Kigyo Hatsu Information from Nikkei when “format of Nikkei information” = “w/o fig/table” and “classification of Nikkei information’s content” = “new products & services”. The Nikkei information (Figure 5(b)), which addresses the satellite situation, is most accurately classified within the content type of “new products & services”. This is a rare example, as the content type is “new products & services”, but the information is considered as a factor in the stock price decline.

B Examples of Prompts

B.1 The Baseline Prompts

These prompts were entered in Japanese, and the following are English translations of them.

B.1.1 zero-shot

###Instructions####

You are a professional reporter. Write an article based on the following conditions and information.

####

###Conditions####

- The article consists of the stock name, a term describing the stock price fluctuation, and a brief summary of the reason for the fluctuation.
- Write in sentences, not bullet points.
- The text should be about 300 characters.
- Write in the standard form.

####

###Text####

stock name: FLNet<9241>

stock price fluctuation over three days: 1645, 1616, 2016

information on the event that is the reason for the variation:

September 2, 2024 (Monday)

Future Link Network Co., Ltd.

FLN establishes a new company, “Regional Vitality AI Technologies, Inc.”

with the theme of AI x regional revitalization. AI-based reskilling service was launched. . . .

####

B.1.2 few-shot

###Instructions####

You are a professional reporter. Write an article based on the following conditions and information.

####

###Conditions####

- The article consists of the stock name, a term describing the stock price fluctuation, and a brief summary of the reason for the fluctuation.
- Write in sentences, not bullet points.
- The text should be about 300 characters.
- Write in the standard form.

####

###Text####

stock name: PBSystems <4447>

stock price fluctuation over three days: 534, 534, 594

information on the event that is the reason for the variation:

September 12, 2024

Dear All

PBsystems, Inc.

. . .

Notice Regarding Decision on Acquisition of Treasury Stock . . .

####

###Article####

PBSystems <4447> stock is rising sharply. The company’s announcement that it would buy back its own shares after the close of trading on the 12th was well received. . . .

####

###Text####

. . .

(four more few-shot sets of text and articles)

. . .

```
###Text"""
stock name: FLNet<9241>
stock price fluctuation over three days:
1645, 1616, 2016
information on the event that is the reason
for the variation:
September 2, 2024 (Monday)
Future Link Network Co., Ltd.
FLN establishes a new company, "Regional
Vitality AI Technologies, Inc." with the
theme of AI x regional revitalization.
AI-based reskilling service was launched.
. . .
"""
###Article"""
```

- The article consists of the stock name, a term describing the stock price fluctuation, and a brief summary of the reason for the fluctuation.
 - Write in sentences, not bullet points.
 - The text should be about 300 characters.
 - Write in the standard form.
- ```
"""
###Text"""
stock name: FLNet<9241>
stock price fluctuation over three days:
1645, 1616, 2016
information on the event that is the reason
for the variation: {summary generated in
<First step>}
"""
```

## B.2 The Two-step Prompts

This prompt was entered in Japanese, and the following is an English translation of it.

```
<First step>
###Instructions"""
You are a professional financial analyst.
Extract and summarize the portion of the
following text which describes the possible
causes of stock price fluctuations.
"""
###Text"""
September 2, 2024 (Monday)
Future Link Network Co., Ltd.
FLN establishes a new company, "Regional
Vitality AI Technologies, Inc." with the
theme of AI x regional revitalization.
AI-based reskilling service was launched.
. . .
"""
<Second step>
###Instructions"""
You are a professional reporter. Write an
article based on the following conditions
and information.
"""
###Conditions"""
```

Original text

**ACCESS大幅続伸、2～7月期営業赤字縮小**  
ACCESS<4813>が大幅続伸。前週末8月30日取引終了後に2～7月期連結決算を発表し、売上高は80億5900万円（前年同期比19.6%増）、営業損益は6億5000万円の赤字（前年同期1億2500万円の赤字）となった。大幅な増収と営業赤字縮小を好感した買いが入っている。  
ネットワーク機器向けソフトウェアなどを手掛ける主力のネットワーク事業が大きく伸びたほか、IoTソリューションなどを提供するIoT事業も堅調だった。なお、通期の増収・営業黒字見通しに変更はない。

English translation

**ACCESS Continues to Grow Significantly, Operating Loss for Feb-Jul Narrowed**  
ACCESS<4813>continues to grow significantly. The company announced its consolidated financial results for the February-July period after the close of trading on August 30, the previous weekend, with net sales of 8,059 million yen (up 19.6% year-on-year) and an operating loss of 650 million yen (1,125 million yen loss in the same period last year). Buyers were impressed by the large increase in sales and the narrowing of the operating deficit. The mainstay network business, which handles software for network devices, grew significantly, and the IoT business, which provides IoT solutions, was also solid. There is no change to the full-year forecast of increased sales and operating profit.

(a) Kabutan article

**Consolidated Results: Comparison with Forecasts**

Both net sales and profit at each stage improved from the forecasted figures.

(Millions of yen)	Earnings forecast (Initial forecast)	Earnings forecast (Revised)	Results	primary factor
Net sales	7,000	8,000	<b>8,059</b>	為替影響 +652
Operating income	▲1,630	▲800	<b>▲650</b>	為替影響 ▲60
Ordinary income	▲1,650	▲450	<b>▲321</b>	Impact of exchange rate
Interim income	▲1,700	▲550	<b>▲458</b>	
EBITDA* (Not disclosed)	(Not disclosed)	(Not disclosed)	<b>1,342</b>	

\*: EBITDA=営業利益+減価償却費+のり人権戻費

(b) Kigyō Hatsu Information: “Explanatory materials for financial results.”

Figure 3: A pair of Kabutan article and Kigyō Hatsu Information from Nikkei when “format of Nikkei information” = “w/ fig/table” and “classification of Nikkei information’s content” = “companies’ performance”.

Original text

**ホットリンクが大幅続伸、米子会社がダークネットデータプロバイダー大手とパートナーシップを締結**  
ホットリンク<3680>が大幅続伸している。米子会社のエフィウス（サービスブランド名「Socialgist」）が、ダークネットデータプロバイダー大手のダークアウル（コロラド州）とパートナーシップを締結したと発表しており、好材料視されている。  
ソーシャルビッグデータのアクセス権販売を行うエフィウス社と、ダークネットに精通する主要プロバイダーであるダークアウル社の双方の強みを組み合わせることで、業界最大かつ最も包括的なダークネット、ソーシャル、及び会話型コンテンツのデータベースを構築するのが狙い。これにより、広範囲なライブデータソースへのアクセスが可能となり、利用する顧客はデジタルリスクへの包括的な視点を得ることが可能になるとしている。

English translation

**Hottolink Continues to Grow Significantly; U.S. Subsidiary Enters into Partnership with Major Darknet Data Provider**  
Hottolink<3680>continued to grow significantly. The U. S. subsidiary Effyis, Inc. (service brand name “Socialgist”) announced that it has entered into a partnership with DarkOwl LLC (Colorado), a leading darknet data provider, which is a good sign.  
By combining the strengths of both Effyis, a social big data access rights seller, and DarkOwl, a leading provider of darknet expertise, the goal is to create the industry’s largest and most comprehensive database of darknet, social, and conversational content. This will provide access to a wide range of live data sources and enable clients who use the service to gain a comprehensive perspective on digital risks, according to the company.

(a) Kabutan article

English translation

**Hottolink Group’s U.S.-based Effyis Partners with DarkOwl**  
~Enhance Conversational Content Datasets to Provide Comprehensive Data Solutions~  
Hottolink, Inc. (Head office: Chiyoda-ku, Tokyo; Securities code: 3680; Representative Director and Group CEO: Yuki Uchiyama), a provider of SNS marketing support services, is pleased to announce that its group company Effyis, Inc. (Headquarters: Michigan, USA; CEO: Yuki Uchiyama; Service brand name: Socialgist; hereafter Socialgist) has entered into a strategic partnership with DarkOwl.

(b) Kigyō Hatsu Information: “Hottolink group’s U.S.-based Effyis partners with DarkOwl.”

(c) English translation of Kigyō Hatsu Information.

Figure 4: A pair of Kabutan article and Kigyō Hatsu Information from Nikkei when “format of Nikkei information” = “w/o fig/table” and “classification of Nikkei information’s content” = “business partnership”.

Original text

**Q P S 研究所はウリ気配スタート、小型衛星 5 号機に不具合確認**


Q P S 研究所<5 5 9 5>はウリ気配スタート。1 1 日取引終了後、打ち上げ済みの小型 S A R 衛星「Q P S - S A R」5 号機について通信系に不具合が確認され、今後の継続的なサービス運用に支障が生じる見込みになったと発表した。地上からの指令や衛星状態のモニターに関する通信系統のうち、衛星側の送信部に不具合が出ている。宇宙空間における放射線の影響を偶発的に受けた電気系統の故障が原因と考えられるという。これを嫌気した売りが優勢となっている。

English translation

**QPS Labs Starts with a Cull Quote, Confirming Defects in the 5th Small Satellite**

QPS Research Institute<5595> started the day with a cull quote. After the close of trading on the 11th, the company announced that a communication system failure had been confirmed for the QPS-SAR-5, a small SAR satellite that had already been launched, and that this was expected to hinder its continued service operations in the future. Among the communication systems related to commands from the ground and monitoring of satellite status, the satellite-side transmitter is faulty. It is considered that this is due to an electrical system failure caused by accidental exposure to radiation in space. Selling has been dominated by sellers who are not happy with this situation.

(a) Kabutan article



各 位

2024年9月11日

会社名 株式会社Q P S 研究所  
代表者名 代表取締役社長 CEO 大西 俊輔  
(コード: 5595, 東証1st市場)  
問い合わせ先 執行役員 管理部長 橋本 亮巳  
E-mail: i1@i-qps.com

**小型SAR衛星QPS-SAR5号機の状況に関するお知らせ**

2023年12月15日に打上げられた当社小型SAR衛星QPS-SAR5号機について、通信系に不具合が確認され、今後の継続的なサービス運用に支障が生じる見込みとなりましたので、お知らせいたします。

本不具合は、地上からの指令や衛星状態のモニタに係る通信系統の内、衛星側の送信部に不具合が生じているものです。2024年9月4日に付いた社内報において確認され、本日(2024年9月11日)に開催された取締役会に報告されたことを受けて公表に至っております。宇宙空間における放射線の影響を偶発的に受けた、電気系統の故障が発生原因と考えられることから、当社では打上げ前の衛星に対する冗長性を付加する等の改良や、軌道上における打上げ済の衛星に対する運用の改善を実施いたします。

なお、本件による当社業績への影響等につきましては、現在調査中であり、開示すべき事項が生じた場合には速やかにお知らせいたします。現時点において当社が投資家の皆様、他の衛星による画像データの取得によって充足できる見込みであります。

以上

English translation

**Notice on the Status of the Small SAR Satellite QPS-SAR5**

We would like to announce that we have confirmed a problem with the communication system of our small SAR satellite QPS-SAR5, which was launched on December 15, 2023, and we expect a problem with its continuous service operation in the future.

This defect is due to a failure in the satellite-side transmission part of the communication system related to ground-based commands and satellite status monitoring.

The problem was confirmed in an internal report made on September 4, 2024, and was reported to the Board of Directors meeting held today, September 11, 2024, leading to this public announcement. The cause of the failure is believed to be an electrical system failure caused by accidental exposure to radiation in space. We will make improvements such as adding redundancy to pre-launch satellites and improve operations for satellites that have already been launched in orbit. . . .

(b) Kigyo Hatsu Information: “Notice on the status of the small SAR satellite QPS-SAR5.”

(c) English translation of Kigyo Hatsu Information.

Figure 5: A pair of Kabutan article and Kigyo Hatsu Information from Nikkei when “format of Nikkei information” = “w/o fig/table” and “classification of Nikkei information’s content” = “new products & services”.