S-APIR: News-based Business Sentiment Index

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Abstract

This paper describes our work on developing a new business sentiment index using daily newspaper articles. We adopt a recurrent neural network (RNN) with Gated Recurrent Units to predict the business sentiment of a given text. An RNN is initially trained on Economy Watchers Survey and then fine-tuned on news texts for domain adaptation. Also, a one-class support vector machine is applied to filter out texts deemed irrelevant to business sentiment. Moreover, we propose a simple approach to temporally analyzing how much and when any given factor influences the predicted business sentiment. The validity and utility of the proposed approaches are empirically demonstrated through a series of experiments on Nikkei Newspaper articles published from 2013 to 2018.

1 Introduction

There exist business sentiment indices computed through surveys, such as Economy Watchers Survey\textsuperscript{1} and Short-term Economic Survey of Principal Enterprise in Japan\textsuperscript{2} in the case of Japan. These diffusion indices (DI) play a crucial role in decision making for governmental/monetary policies, industrial production planning, and institutional/private investment. However, these DIs rely on traditional surveys, which is costly and time-consuming to conduct.

For example, Economy Watchers Survey is carried out in 12 regions of Japan, where 2,050 preselected respondents who can observe the regional business/economic conditions (e.g., store owners and taxi drivers) fill out a questionnaire and then an investigative organization in each region aggregates the surveys and calculates a DI. As the survey and subsequent processing take time, the DI is published only monthly.

On the other hand, so-called alternative data, including merchandise sales, news, microblogs, query logs, GPS location information, and satellite images, are constantly generated and accumulated. The availability of such data has accelerated the development of data-driven machine learning techniques represented by deep learning. In econometrics, there is a growing interest in future/current forecasts of economic and financial indices by using such alternative, large-scale data instead of traditional surveys [Kapetanios and Papailias, 2018]. For example, point of sales (POS) data were used for estimating consumer price index (CPI) [Watanabe and Watanabe, 2014], financial and economic reports for business sentiment [Yamamoto and Matsuo, 2016], newspaper for grain market prices, stock prices, and economic indices [Chakraborty et al., 2016; Shapiro et al., 2017; Yoshihara et al., 2014; Yoshihara et al., 2016] and social media for stock prices [Bollen et al., 2011; Levenberg et al., 2014].

This work focuses on textual data and uses daily newspaper articles to develop a new business sentiment index, named S-APIR index. In addition, using the computed index, we propose an approach to temporally analyzing any given factors that may influence the business sentiment index.

2 Related Work

In the economic and financial domains, there are abundant textual data, such as newspaper articles and financial reports in addition to many numerical data. These texts are intended to be read by people, who consider other sources of information and make decisions on investment, financial policies, and so on. However, it is difficult even for experts to read, grasp, and synthesize all the available information in a limited time. Therefore, there has been much research on computing economical/financial indices from textual data. In the following, we summarize the representative work in business sentiment prediction, which is the main theme of the present work.

2.1 Business Sentiment Prediction

Economy Watchers Survey introduced in Section 1 publishes not only the business sentiment index (hereafter called EWDI for short) but also individual survey responses on which EWDI is based. The survey responses contain a pair of an economic condition on a five-point scale and a statement of the reasons why the respondent chose the particular economic condition in natural language. Some example responses are shown in Table 1.

Based on the responses, EWDI is computed by first computing the composition ratios of the five economic conditions
and then taking their weighted sum. EWDI ranges from 0 to 100 with 50 being the middle (meaning that economic condition is neither positive or negative).

Yamamoto et al. [Yamamoto and Matsuo, 2016] used as training data around 200,000 pairs of an economic condition and its statement of the reasons to learn a regression model so as to predict the business sentiment of a given text. As a regression model, they used a bidirectional Recurrent Neural Network with Long Short Term Memory (LSTM) [Hochreiter and Schmidhuber, 1997]. Then, monthly economic reports were fed to the learned model to compute a business sentiment index. It is reported that the computed index was positively correlated with both EWDI and Short-term Economic Survey of Principal Enterprise in Japan.

Aiba et al. [Aiba and Yamamoto, 2018] used a similar model to compute a business sentiment index from microblogs (tweets), and Kondo et al. [Kondo et al., ] from bank’s internal documents written from interviews with their client corporations. Goshima et al. [Goshima et al., 2019] used a convolutional neural network and Reuters news articles to compute a business sentiment index.

3  S-APIR and its Application

As described in Section 2, Economy Watchers Survey contains pairs of an economic condition and a statement of the reasons. They are filled out manually by respondents and are quality, valuable resources for machine learning. In the present work, we focus on news articles as with Goshima et al. [Goshima et al., 2019] to compute a business sentiment index named S-APIR. However, in contrast to Goshima et al. who fed news texts as they were to the learned model, we attempt to filter out irrelevant news texts and to apply domain adaptation as we will describe shortly in Section 3.1.

Then, Section 3.2 discusses an application of the S-APIR index to temporally analyze any given factors that may/may not influence business sentiment. Business sentiment is formed by many factors including monetary policies, stock prices, exchange rates, unemployment rate, wages, overseas situations, etc. However, those factors do not equally influence business sentiment and it is helpful for business economists if they could understand what factors have a more/less influence to move up/down business sentiment in a particular period. To this end, we propose a simple approach to analyzing when and what factors contributed to S-APIR based on predicted business sentiment.

3.1  S-APIR Index

This section describes three major components of our framework to predict business sentiment from a news sentence. The first component is a regression model that takes a sentence and predicts the sentiment of the input. The second is a classifier to filter out texts irrelevant to the economy/business. Lastly, the third is domain adaptation to update the parameters of an initial regression model to make them more suitable for news texts.

Regression Model

For text classification and regression, it has been a common practice to treat each word as an independent variable, where an input text is represented as a Bag of Words (BoW) disregarding the context [Manning et al., 2008]. However, it is desirable to capture the differences of word meanings in different contexts and word dependencies so as to properly represent the meaning of the text.

In recent years, RNN, combined with LSTM, has been popularly used to represent text to consider the context. This study also uses RNN but with Gated Recurrent Unit (GRU) [Cho et al., 2014], which can be seen as a variant of LSTM. Following the related work, we also use Economy Watchers Survey to train the model, where the five-point-scale economic conditions are converted to \{-2, -1, 0, 1, 2\}.

Filtering

One could use a regression model to be described in the previous section to predict business sentiment for any input text. However, news texts we focus on in this study are in many genres which may be irrelevant to the economy. Using irrelevant sources would be harmful in computing a business sentiment index. Therefore, we attempt to filter out such irrelevant news texts by treating them as outliers.

For this purpose, we adopt a one-class support vector machine (SVM) [Maneitz and Yousef, 2002]. In contrast to an ordinal SVM used for binary classification, a one-class SVM can be learned on documents in only one class and detect documents dissimilar to the training documents as outliers. We use Economy Watchers Survey (statements of the reasons) as the training data for one-class SVM and filter out news text dissimilar to the statements.

For text representation, one could use an output of an RNN or other sentence embeddings [Cer et al., 2018; Pagliardini et al., 2018] so that the context could be better considered. However, our preliminary experiment showed that they resulted in detecting all news texts as outliers. The traditional BoW with term frequency-inverted document frequency (tf-idf) term weighting [Manning et al., 2008] worked better for

| Region | Occupation | Economic condition | Statement of reasons |
|--------|------------|---------------------|----------------------|
| Hokkaido | Taxi driver | × | Although sales are declining, seasonal factors and the downturn in the economy are also affecting. |
| North Kanto | Transportation machinery and equipment manufacturing | ⊗ | Automobile exports to the United States are increasing. |
this task and was used in this work.

**Domain Adaptation**
The Economy Watchers Survey responses to be used for training a GRU-RNN are different from news texts to be used for computing S-APIR in terms of their writing styles, vocabularies, and expressions (collectively called “domains”). Such differences between training and testing would have a negative effect on the resulting performance and adapting the domain of the learned model to the target domain would benefit business sentiment prediction.

To this end, we explore domain adaptation by automatically creating new training data from news texts. To be precise, we feed news articles to an initial regression model (denoted as $M$) and predict the business sentiment of each sentence. Then, we assume that sentences with higher absolute sentiment scores would better represent economic conditions either positively or negatively. We set predefined positive and negative thresholds and treat the sentences with higher/lower sentiment scores than the thresholds as positive and negative examples, respectively.

We use the training data to fine-tune the initial model $M$ to acquire fine-tuned model $M'$. More specific experimental settings (e.g., thresholds) are described in the evaluation in Section 4.

### 3.2 Temporal Analysis

Business sentiment is formed based on many factors including monetary policies, tax reform, trade, and military conflicts. This section describes an approach to analyzing which factor influenced business sentiment *when* and *how much*. Specifically, we define the influence of word $w$ during time $t$, $p_{t,w}$, using the predicted business sentiment.

We first assume that the sentiment $p_s$ of a sentence $s$ is the sum of the sentiments of words ($w$) appearing in $s$ as follows:

$$p_s = \sum_{w \in s} f_{s,w} \cdot p_{s,w} \quad (1)$$

where $f_{s,w}$ is the number of occurrences of word $w$ in $s$, $p_{s,w}$ is the sentiment of $w$ in $s$. We further assume that all the words, $w \in s$, equally influence the sentiment of $s$, that is,

$$p_{s,w} = \frac{p_s}{|s|} \quad (2)$$

where $|s|$ is the number of words composing $s$. Here, let $S_t$ denote the set of news sentences published during $t$. Using $S_t$, we define $p_{t,w}$ as the sum of $p_{s,w}$ over $S_t$, divided by the number of sentences $|S_t|$.

$$p_{t,w} = \frac{1}{|S_t|} \sum_{s \in S_t} f_{s,w} \cdot \frac{p_s}{|s|} \quad (3)$$

Intuitively, S-APIR in time $t$ can be interpreted as the sum of the influences of all the words appearing in texts published during $t$.

### 4 Evaluation

#### 4.1 Experimental Settings

For learning an RNN and a one-class SVM, we downloaded the Economy Watchers Survey data from the web page of the Cabinet Office\(^3\) in October 2018. The number of the pairs of an economic condition and a statement of the reasons was 216,741 in total, of which randomly selected 90% were used for training (and validation) and the rest were used for testing. Note that because Japanese text does not have explicit word boundaries (such as spaces in the case of English), the statements of the reasons were processed by a morphological analyzer, MeCab\(^4\), to be split into words.

The parameters of a GRU-RNN were set as follows based on a preliminary experiment on the Economy Watchers Survey data: the number of GRU units per layer=512, the number of hidden layers=2, and the size of the vocabulary=40,000. Each word was represented as a word embedding vector with 300 dimensions pretrained on Wikipedia [Bojanowski et al., 2017].

To compute the S-APIR index, we used the titles and body texts of news articles from the Nikkei Newspaper from 2013 to 2018. For domain adaptation, we used separate Nikkei Newspaper published in 2010. Each article was split into sentences based on the Japanese period “—” and each sentence was fed to the learned model to predict its sentiment.

#### 4.2 Evaluation on Economy Watchers Survey

First, we evaluated the learned (initial) GRU-RNN on the held-out test data (10% of Economy Watchers Survey). Table 2 compares our model and a ridge regression model in mean squared error (MSE). For ridge regression, we used the classic BoW representation with tf-idf term weighting. The MSE for GRU-RNN significantly decreased as compared to that of ridge regression, which confirms that our model predicted economic conditions more accurately than the ridge regression. This result is similar to the one reported in the related work [Yamamoto and Matsuo, 2016].

| Model         | MSE    |
|---------------|--------|
| Ridge regression | 0.509  |
| GRU-RNN       | 0.351  |

Table 2: Comparison between ridge regression and our GRU-RNN for predicting economic conditions.

#### 4.3 Evaluation of S-APIR

This section compares our business sentiment index, S-APIR, and existing business sentiment index, namely EWDI. It should be emphasized, however, that S-APIR is not intended to replace EWDI, but rather to be a new index using newspaper as the source of information. There is no ground truth for a business sentiment index and EWDI is also an index calculated based on the limited number of 2,050 respondents. The purposes of the comparison in this section are (1) to ensure that S-APIR has a similar trend to the existing index and (2) to investigate the characteristics of S-APIR when the two indices diverge.

\(^3\)http://www5.cao.go.jp/keizai3/watcher/watcher_menu.html

\(^4\)http://taku910.github.io/mecab/
Using the initial GRU-RNN learned as described in Section 4.2, we first computed S-APIR on Nikkei Newspaper from 2013 to 2018. Note that as business sentiment is predicted for each sentence, they were aggregated monthly by taking the average to compute S-APIR for each month. Figure 1 shows the computed S-APIR and EWDI for comparison. We can observe that the two indices show roughly similar movements. In effect, they were found to be positively correlated \( r = 0.546 \).

Next, we applied the one-class SVM to detect and filter out outliers and recomputed S-APIR by using only the texts relevant to the economy. Figure 2 shows the result. Overall, S-APIR exhibited a more similar trend to EWDI and their correlation coefficient significantly increased from 0.546 to 0.686. The result confirms the effectiveness of the filtering process by the one-class SVM.

As shown above, the GRU-RNN learned on Economy Watchers Survey (statements of the reasons) can be used to compute the business sentiment index based on news texts. However, statements of the reasons and news texts have different characteristics and the model learned on the former may not be suitable for the latter. Thus, we applied domain adaptation as described in Section 3.1. To be specific, we took the following procedure:

1. Extracted titles and body texts of news articles from Nikkei Newspaper 2010 and split them into sentences and then into words.
2. Applied the one-class SVM and filtered out outliers.
3. Applied the GRU-RNN to predict the sentiment of each sentence.
4. Identified the sentences with sentiment scores greater (lower) than a predefined threshold \( t_{\text{high}} (t_{\text{low}}) \). To determine the thresholds, we looked at the histogram of the sentiment scores and experimentally set \( t_{\text{high}} = 0.8 \) and \( t_{\text{low}} = -1.0 \). As a result, we obtained 18,947 positive instances and 10,868 negative instances. We gave the former “2” as their labels, and the latter “−2”.
5. Fed the generated training data to the learned (initial) GRU-RNN for fine-tuning.

Then, we used the fine-tuned model to recompute S-APIR after filtering. The result is shown in Figure 3. The correlation coefficient marginally increased to 0.701.

Note that EWDI dropped sharply in April 2014, where there is a large deviation from the S-APIR index. This is when sales tax was increased from 5% to 8% in Japan and it is interesting to learn that the S-APIR index is much less affected by the tax increase. We conjectured that this might be due to the fact that 70% of the respondents of Economy Watchers Survey had occupations related to households. Therefore, factors that have more influence on households (e.g., tax increase) may have more influence on EWDI as well. To verify the intuition, we compared S-APIR and a variant of EWDI computed based on responses only from those who have occupa-
tions related to industries. As a result, the correlation coefficient indeed increased from 0.701 to 0.819. This result suggests that the S-APIR index, computed from Nikkei Newspaper, reflects business sentiment in industries more strongly.

Effect of Domain Adaptation

The previous section empirically showed that domain adaptation increased the correlation between S-APIR and EWDI but only marginally. Here, we look into the models before/after domain adaptation to investigate how the model changed. To this end, we fed single words as inputs to each model and predict the sentiments of the words.

Table 3 compares ten words with higher sentiment for each model on descending order of the sentiment scores, where words with “↑” indicate those went up after domain adaptation and those with “↓” indicate went down. While the rankings of “好調 (good condition)”, “享受 (to enjoy)”, “回復 (recovery)”, and others went up, those of “最高 (best)”, “絶好調 (best condition)”, and “伸 (to grow)” went down.

Similarly, Table 4 compares ten words with lower sentiment scores. While “悪化 (to worsen)”, “激減 (marked decrease)”, and others went up in the list, “舗装 (pavement)” and “壊滅 (complete destruction)” went down. In both cases, we can observe that words that would be more often used in news text went up and those used more often in survey responses went down after domain adaptation.

Notice that while we predicted business sentiments of individual words to investigate the changes of the model after domain adaptation, resulting business sentiment scores can be seen as business sentiment polarities of the words. That is, the results can be used as a sentiment dictionary in the economic/financial domain. There are several sentiment dictionaries in the general domain but only a few in the economic/financial domain and, as far as we know, none exists in Japanese. Therefore, the result can be useful resources for business sentiment analysis.

4.4 Temporal Analysis of Words

Lastly, we temporally analyzed the influence of a given factor (word) on S-APIR as described in Section 3.2. While our proposed approach can analyze any given words, here we focused on a few representative examples. Specifically, we computed the influence of “中国 (China)” and “貿易 (trade)” for example. The results are shown in Figure 4 and Figure 5, respectively. In both figures, the upper graph is S-APIR from Figure 3 and is shown for reference.

In Figure 4, S-APIR and the influence of China generally have similar movements and thus situations about China appear to be one of the major factors influencing the business sentiment index. Especially, from the middle of 2015 to the beginning of 2016, the influence of China is strongly negative, which is pushing down the business sentiment in Japan. This period is a time when the Chinese economy deteriorated rapidly due to the crash of China’s stock market.

Then, looking into Figure 5, we can observe that “trade” has not had much influence from 2013 to the beginning of 2018, whereas the situation has changed thereafter and started to show a strong negative influence on business sentiment.

This reflects the US-China trade dispute that began in late 2018.

5 Conclusions

This paper reported on our ongoing work to develop a new business sentiment index, called S-APIR, based on news texts and to use the index to temporally analyze the factors that influence business sentiment. We used a one-class SVM to identify news texts related to the economy and fed them to a GRU-RNN regression model to predict the business sentiment of input news text. The GRU-RNN was initially trained on Economy Watchers Survey and then fine-tuned on news texts for domain adaptation. Through our evaluation using Nikkei Newspaper articles, it was demonstrated that S-APIR has a positive correlation with an existing business sentiment index and that the correlation becomes even higher when compared to a variant of the index related to industries. This result indicates that S-APIR is a business sentiment index reflecting that of industries more strongly. Moreover, by dividing sentence sentiment into word sentiments and summing over sentences, it was shown that any given factor that may/may not have an influence on business sentiment can be temporally analyzed.
Table 3: Sentiment of top 10 words before/after domain adaptation.

| Before                      | After                      |
|-----------------------------|----------------------------|
| 増進 (good condition)       | 増進 (good condition)       |
| 向上 (to improve)           | 向上 (to improve)           |
| 最高 (best)                 | 最高 (best)                 |
| 増加 (to grow)              | 増加 (to grow)              |
| 売れ (to sell)              | 売れ (to sell)              |
| 上向き (to look up)         | 上向き (to look up)         |
| 着実 (steady)               | 着実 (steady)               |

Table 4: Sentiment of top 10 words before/after domain adaptation.

| Before                      | After                      |
|-----------------------------|----------------------------|
| 補装 (pavement)             | 悪化 (deterioration)       |
| 不通 (blocked)              | 激減 (marked decrease)     |
| 最悪 (worst)                | 最悪 (worst)               |
| 壊滅 (complete destruction) | 壊滅 (complete destruction) |
| 好転 (to improve)           | 低落 (decline)             |
| 激減 (marked decrease)      | 減益 (profit fall)         |
| エスカレート (to escalate)   | 損失 (loss)                |
| 漁船 (fishing vessel)       | 急落 (significant fall)    |

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