Stance Classification by Recognizing Related Events about Targets

Akira Sasaki*, Junta Mizuno†, Naoaki Okazaki* and Kentaro Inui*
*Tohoku University
Email: {aki-s,okazaki,inui}@ecei.tohoku.ac.jp
† Data-driven Intelligent System Research Center (DIRECT)
National Institute of Information and Communications Technology (NICT)
Email: junta-m@nict.go.jp

***Abstract*—Recently, many people express their opinions using social networking services such as Twitter and Facebook. Each opinion has a stance related to something such as product, service, and politics. The task of detecting a stance is known as sentiment analysis, reputation mining, and stance detection. A popular approach for stance detection uses sentiment polarity towards a target in a text. This approach is known as targeted sentiment analysis. If a target appears in text, the detecting stance based on targeted sentiment polarity would work well. However, how can we detect stance towards an event? (e.g. "I cannot understand why man can marry only with a woman", "The problem of low birth rate becomes more severe" to the event "Allowing same-sex marriage"). To detect these stances, it is necessary to recognize a situation in which the event *occurs* or *does not occur*. To classify texts including these phenomena, we propose a classification method based on machine learning considering PRIOR-SITUATION and EFFECT.**

I. Introduction

Recently, many people express their opinions using social networking services such as Twitter and Facebook. Each opinion has a stance related to something such as a product, service, and politics. For example, the opinion "I like this camera." indicates that the author has a favorable stance towards the camera. The task of detecting a stance is known as sentiment analysis, reputation mining and stance detection. A large amount of previous work addressed these tasks [1]–[4].

One recent trial of stance detection is Task 6 of SemEval-2016[1]. This is a task to detect a stance (favor or against) in relation towards a target of a tweet. Consider the following example[2]. The task is to detect a stance for a target in the text. In this example, the underlined part suggests that a stance of the text towards the target is FAVOR.

Text Hillary is our best choice if we truly want to continue being a progressive nation.
Target Hillary Clinton
Stance FAVOR

A popular approach for stance detection uses sentiment polarity towards a target in a text. The underlined part of the example expresses positive sentiment polarity to "Hillary" corresponding to the target. This approach is known as targeted sentiment analysis [5], [6]. Because a target appears in text, detecting a stance based on the targeted sentiment polarity is expected to work well.

[1]http://alt.qcri.org/semeval2016/task6/
[2]This example is quoted from trial data of Task 6

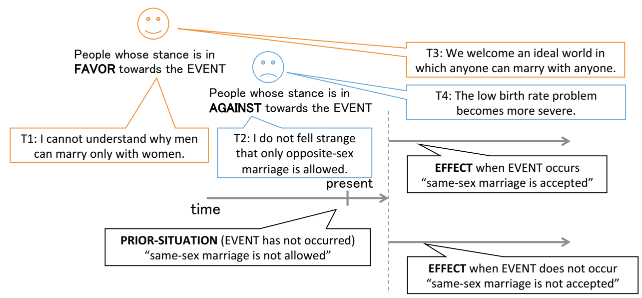

Fig. 1. Overview of PRIOR-SITUATION and EFFECT of the event "Allowing same-sex marriage."

However, we suffer from a variety of examples for which stance detection is extremely difficult. Figure 1 shows four examples for the proposition "allowing same-sex marriage." Note that although our texts are written in Japanese, we provide examples in English for readability. T1 expresses a negative attitude towards the current situation, i.e., "same-sex marriage is not allowed" and T4 expresses negative attitude towards the future situation when "same-sex marriage" is accepted. Both texts express negative attitudes, but the stance of T1 is in favor of the proposition and its of T4 is against it. To make matters worse, T4 does not even contain keywords representing the target (e.g., *marriage* nor *marry*) but only a related situation *low birth rate*. To detect these stances, it is necessary to recognize the situations when the event *occurs* or *does not occur*. We designate the target as an EVENT and call the future situation an EFFECT hereafter. Note that, the future situation in which the event does not occur can be regarded as the current situation. We designate the current situation as the PRIOR-SITUATION.

To predict stances considering these phenomena, we propose a classification method based on machine learning with the PRIOR-SITUATION and EFFECT of EVENT. We first annotate the labels PRIOR-SITUATION and EFFECT to our dataset. Then T1 can be generalized to "I cannot understand why PRIOR-SITUATION" and T4 can be generalized to "The problem of EFFECT becomes more severe." After the gener-

978-1-5090-4470-2/16 $31.00 © 2016 IEEE
DOI 10.1109/WI.2016.99

alization, the stance of the text can be detected as favorable when it has a negative attitude to PRIOR-SITUATION or a positive attitude to EFFECT (EVENT occurs), or against when the text expresses a positive attitude to PRIOR-SITUATION or a negative attitude to EFFECT (EVENT occurs).

Our contributions are two-fold:

1. We propose the concepts of PRIOR-SITUATION and EFFECT and annotate these labels to roughly 3,000 texts.
2. We confirm that the accuracy of stance detection can be improved using these labels.

II. Related Work

Most of the sentiment analysis tasks aim at detecting sentiment polarity (i.e. positive/negative/neutral) of a text or a document without focussing on a specific target. Kiritchenko *et al.* [7] expanded the sentiment lexicon for micro-blogs, and attained better results than the previous sentiment analysis works in the micro-blog domain. Using Long Short-Term Memory (LSTM), Wang *et al.* [8] achieved comparable results with data-driven techniques [9]. They also showed that tuned word embeddings improve the performance of sentiment analysis. Apart from that, targeted sentiment analysis task set the goal to predict sentiment towards a specific target [5], [6].

As to stance classification task, Murakami and Raymond [1] and Sridhar, Getoor, and Walker [2] use link-based methods to identify the general positions of users in online debates. Thomas, Pang, and Lee [4] classify the speeches of U.S. Congressional floor debates into support of or opposition to proposed legislation. Somasundaran and Wiebe [3] focus on posts related to debatable topics such as "iPhone vs BlackBerry", and identify which stance the author of a post is taking. In addition, many works have been undertaken to predict political position (i.e. conservative or liberal) of the text, or of the author of the text [10]–[14]. Chambers *et al.* [15] predicted sentiment polarity between each country, which is one kind of targeted sentiment analysis. Furthermore, Tumasjan *et al.* [16] conducted analysis of a micro-blog as political sentiment, and predicted the results of the German federal election.

These studies do not consider temporal changes which are caused by an event. This point is a major difference between previous work and ours.

III. Stance Classification Task

A. Data Preparation

As described in this paper, we use the data of Japanese debate forum *Zeze-hihi* [3]. There are widely diverse questions in *Zeze-hihi*, such as politics (*Are you FAVOR or AGAINST accepting same-sex marriage?*), sports (*Which team do you think will win this match, SPAIN or NEDERLAND?*), game (*Do you like watching a gameplay?*), etc. Each question has two choices for voting (e.g. FAVOR/AGAINST, SPAIN/NEDERLAND, LIKE/DON'T LIKE). *Zeze-hihi* users choose questions freely, and answer them. Users can vote and give comment.

[3]http://zzhh.jp

TABLE I
Top 10 most voted questions.

Question
Are you FAVOR or AGAINST revising article 9 of the Japanese constitution?
Are you FAVOR or AGAINST revising article 96 of the Japanese constitution?
Are you FAVOR or AGAINST changing constitutional interpretation of the right to collective defense?
Are you FAVOR or AGAINST reducing daily life security expenditures?
Are you FAVOR or AGAINST establishing the system of a husband and wife retaining separate family names?
Are you FAVOR or AGAINST establishing the regulation forbidding gambling using daily life security expenditures?
Are you FAVOR or AGAINST inviting the Olympics to be held in Tokyo?
Are you FAVOR or AGAINST introducing the regional system of division?
Are you FAVOR or AGAINST accepting same-sex marriage?
Are you FAVOR or AGAINST establishing the state secrecy laws?

We collected questions along with answers from *Zeze-hihi*. The data consists of the following:

- Questions about debatable topics (e.g. *Are you FAVOR or AGAINST revising article 96 of the Japanese constitution?* [4]).
- Two choices for voting on the question (e.g. FAVOR / AGAINST).
- Votes of users with their comments. (e.g. [FAVOR] *Because article 96 of the Japanese constitution is important, I hope not to revise the article*) Comments are up to 100 characters.

In this research, we set the target to politics. Therefore, we only address questions that have FAVOR / AGAINST choices. Additionally, we filtered out questions which have less than 150 FAVOR or less than 150 AGAINST. We selected the top 10 most voted questions from them (Table I). To balance them, we randomly select 300 votes (150 FAVOR votes, 150 AGAINST votes) for each questions. Votes with no comment are omitted.

B. Annotating PRIOR-SITUATION and EFFECT

As described in section I, we adopt concepts of PRIOR-SITUATION and EFFECT to improve the performance of FAVOR/AGAINST classification. In this section, we describe how to annotate PRIOR-SITUATION and EFFECT to comments posted to *Zeze-hihi*.

1) PRIOR-SITUATION: We define the situation before the target event occurs as a PRIOR-SITUATION (i.e. current status). One example is the following.

Question Are you FAVOR or AGAINST revising article 96 of the Japanese constitution?
Event Revising of the article 96 of the Japanese constitution
Vote FAVOR
Comment *The situation in which* *revising the constitution requires two-thirds agreement of both houses*$_{\text{PRIOR-SITUATION}}$ *is too difficult.*

The underlined part is associated with the current situation related to article 96 of the Japanese constitution.

[4]http://zzhh.jp/questions/0008

2) EFFECT: We define the effect of realization of the target event and the effect of NOT realization of the target event as EFFECT. Note that, although EFFECT (Event does not occur) exists in theory, only a few instance correspond to it. Therefore, we do not use this concept in our classification.

The example of EFFECT is the following.

Question Are you FAVOR or AGAINST revising article 96 of the Japanese constitution?

Event Revising of the article 96 of the Japanese constitution

Vote AGAINST

Comment *If the Japanese constitution can be changed easily*$_{\text{EFFECT}}$*, it is useless.*

Although it depends on author's subjectivity, considering the fact that revising article 96 of the Japanese constitution alleviate the condition of revision of the constitution, this substring seems to refer to EFFECT.

Using these concepts, we perform annotation of data described in section III-A. This annotation was conducted by one annotator (not the authors).

C. FAVOR/AGAINST classification task

We perform the FAVOR/AGAINST classification task using *zeze-hihi* answers that are annotated in section III-B. In this classification task, the input is a comment of an answer with annotated PRIOR-SITUATION/EFFECT labels (e.g. *The situation in which revising constitution requires two-thirds agreement of both houses*$_{\text{PRIOR-SITUATION}}$ *is too difficult.*). The goal of this task is to predict the answer's vote (FAVOR or AGAINST).

IV. Method

We introduce baseline methods and our proposed method in this section. Because *zeze-hihi* answers are written in Japanese, we tokenize them in advance. We employ `MeCab` (0.996) [17] as a tokenizer, and `mecab-ipadic-neologd` [18] as a dictionary. For example, "*kenpou kaishaku henkou wa muda.*" (Changing constitutional interpretation is useless.) is tokenized as Listing 1:

Listing 1. Example of tokenization.

```
kenpou/kaishaku/henkou/wa/muda/.
(constitutional/interpretation/changing/is/
useless/.)
```

FAVOR/AGAINST classification is a binary classification task. In this research, we employ logistic regression to perform a supervised learning, and classify the input text as FAVOR or AGAINST. Note that, although we use the event as a standard for the annotation in section III, we do not use the event as the input. As an implementation of logistic regression, we use `Classias` [5]. When using `Classias`, we set all parameters as default.

[5]http://www.chokkan.org/software/classias/index.html.en

A. Baseline Method

In this section, we explain three baseline methods (n-gram baseline, Sentiment lexicon baseline, Nakagawa's model [19]) of FAVOR/AGAINST classification. In these baseline methods, we do not use PRIOR-SITUATION/EFFECT labels. We merely use a tokenized answer.

1) n-gram baseline: We extract n-gram (uni- and bi-grams) from a tokenized answer, and use them as features to perform a supervised learning.

2) Sentiment lexicon baseline: In this baseline, we employ sentiment polarities of words in a tokenized answer, and classify the input text into FAVOR or AGAINST based on these sentiment polarities. The motivation behind the usage of sentiment polarities of words is that sentiment polarities are widely used in sentiment analysis tasks and stance classification tasks [3], [15], [20]. We use Japanese Sentiment Polarity Dictionary [21], [22] [6] as a sentiment lexicon. In this lexicon, terms are assigned as positive, negative, or neutral. For example, "*ii*" (good) is assigned positive, "*muda*" (useless) is assigned negative, and "*aisatsu*" (greeting) is assigned neutral. Here, we only use positive terms and negative terms. By counting positive terms and negative terms in the input text, we can define the polarity score as follows:

$$polarity\_score = p_+ - p_- \tag{1}$$

Here, p_+ represents the number of positive terms; p_- represents the number of negative terms in the input text. We regard the input text as FAVOR if $polarity\_score$ is greater than zero, otherwise AGAINST. For instance, Listing 1 contains the negative term "*muda*". Other terms are not included in the sentiment lexicon. Therefore $polarity\_score = -1$. Then, we classify an answer as FAVOR if its $polarity\_score$ is greater than 0, or classify an answer as AGAINST if its $polarity\_score$ is lower than 0. In terms of answers for which the $polarity\_score$ is 0, we perform classification of two kinds. SEN-P treat these answers as FAVOR, and SEN-N treat these answers as AGAINST.

3) Nakagawa's model: We employ Nakagawa's model [19] which is the state-of-the-art method of a Japanese sentiment analysis task. This method is a dependency tree-based. It uses conditional random fields [23] with hidden variables. As an implementation of it, we use `extractopinion` [7]. This implementation expects a text as input. The output is a sentiment polarity (positive/negative/neutral). Then, we classify an answer as FAVOR if its sentiment polarity is positive, or classify an answer as AGAINST if its sentiment polarity is negative. Note that, in terms of an answer for which the sentiment polarity is neutral, we perform classification of two kinds. NAK-P treat these answers as FAVOR. NAK-N treat these answers as AGAINST.

[6]http://www.cl.ecei.tohoku.ac.jp/index.php?Open%20Resources%2F Japanese%20Sentiment%20Polarity%20Dictionary

[7]https://alaginrc.nict.go.jp/opinion/

B. Proposed Method

In section IV-A, we introduced baseline methods based on previous studies. In this section, we introduce our proposed methods, which use PRIOR-SITUATION/EFFECT labels. Using these labels, we aim to examine whether these labels are effective for FAVOR/AGAINST classification or not.

1) PRIOR-SITUATION/EFFECT replaced n-gram: For a tokenized text, we replace words labeled PRIOR-SITUATION/EFFECT in section III with special tokens `%PRIOR-SITUATION%` and `%EFFECT%`. Texts will be simplified by doing this replacement. It is expected that more robust features can be extracted. Consider the following example:

(1) *watashi wa kenpou kaishaku henkou shi te*$_{\mathrm{EFFECT}}$ *hoshii.* (I prefer changing constitutional interpretation$_{\mathrm{EFFECT}}$.)

This text is an answer to the question "Are you FAVOR or AGAINST changing constitutional interpretation of the right to collective defense?". The event of this question is "changing constitutional interpretation of the right to collective defense". Then the underlined part of "*kenpou kaishaku henkou shi te*" (changing constitutional interpretation) is annotated EFFECT in section III, because it means the event itself. Next, we tokenize (1) and get Listing 2. Then we replace tokens that are in the above underline with special tokens `%EFFECT%` (Listing 3). When doing this replacement, we merged a succession of identical special tokens (e.g. "`%EFFECT%,%EFFECT%,%EFFECT%`" becomes "`%EFFECT%`"). Then we extract n-gram (uni- and bi-grams) from this tokenized text. The aim of this replacement is to learn domain-independent features.

Listing 2. Tokenization result of "*watashi wa kenpou kaishaku henkou shi te hoshii.*" (I prefer changing constitutional interpretation.) Note that "*watashi wa*" means "I".

```
watashi/wa/kenpou/kaishaku/henkou/shi/te/
hoshii/.
(I/constitutional/interpretation/changing/
prefer/.)
```

Listing 3. Replaced tokenization result. Note that, we merged a succession of identical special tokens.

```
watashi/wa/%EFFECT%/hoshii/.
(I/%EFFECT%/prefer/.)
```

2) Patterns around PRIOR-SITUATION/EFFECT feature: Because there are various representations among questions, we are concerned about coverage of our training data. Although PRIOR-SITUATION/EFFECT replaced n-gram is aim at simplifying texts, its classification performance depends heavily on the training data. In contrast, in this method, we semi-automatically gather patterns which tend to indicate FAVOR/AGAINST from the other data. In doing so, it is expected that we can classify texts more correct, even though there are no clues in the training data. Consider the following example:

(2) *san bun no ni*$_{\mathrm{PRIOR-SITUATION}}$ *wa muimi. watashi wa sou giin no kahansuu ga hitsuyou de atte*$_{\mathrm{EFFECT}}$ *hoshii.* (Two-thirds agreements$_{\mathrm{PRIOR-SITUATION}}$ is meaningless. I prefer that revising the constitution requires agreements of the greater part of both houses$_{\mathrm{EFFECT}}$.)

In this example, the author express a negative attitude about PRIOR-SITUATION and positive attitude about EFFECT. However, if we just use sentiment lexicon, then the $polarity\_score$ of this text will be calculated as zero because "*muimi*" (meaningless) is a negative term and "*hoshii*" (prefer) is a positive term. The other terms are neutral. However, because the author's negative attitude related to PRIOR-SITUATION means that he is complaining about the current situation when EVENT is not happening already, this text is apparently FAVOR. Similarly, the author's positive attitudes in relation to EFFECT might indicate that the whole text is FAVOR.

Using this method, we semi-automatically gather patterns which are effective for the classification. When gathering patterns, we use Zeze-hihi's questions except for Table I. Which consists of 93 questions (10,490 answers). These answers also have labels of FAVOR/AGAINST, but PRIOR-SITUATION/EFFECT are not annotated. To gather patterns from these data, we perform the following procedures:

1. Tokenize all 10,490 answers. (The setting is the same as Listing 1)
2. Gather sequences of tokens from any noun to the next noun/verb/adjective as pattern, and replace the noun with a special token `%X%`.
3. Sort these patterns by frequency.
4. Select patterns by hand that seem to indicate a positive attitude or negative attitude related to `%X%`. For example, patterns such as "`%X%` *wa muimi*" (`%X%` is meaningless) and "`%X%` *hoshii*" (prefer `%X%`) are selected.
5. Classify these patterns whether indicating a positive attitude or negative attitude related to `%X%`. For example, when "`%X%` *wa muimi*" (`%X%` is meaningless) matches the input text, the text seems to indicate a negative attitude related to `%X%`.

By performing the followed procedures, we finally gathered 32 patterns. However, because they are not abstracted, some concern arises that few patterns match. For that reason, we perform the following procedures to gather abstracted patterns.

1. Tokenize all 10,490 answers. (same as above)
2. Gather sequences of tokens from any noun to the next positive/negative term as pattern, replace the noun with a special token `%X%`, and replace the positive/negative term with a special token `%PN%`. The definition of positive/negative terms is the same as the sentiment lexicon baseline.
3. Sort these patterns by frequency.
4. Select patterns by hand that seem to indicate a positive attitude or negative attitude related to `%X%`. For example, patterns such as "`%X%` *wa* `%PN%`" (`%X%` is `%PN%`) are collected. Note that these patterns indicate a positive attitude about `%X%` if `%PN%` is positive term, and indicate

a negative attitude with respect to %X% if %PN% is a negative term.

By performing the followed procedures, we finally gathered 23 patterns. When applying these patterns to the input text, %X% is assumed to be PRIOR-SITUATION or EFFECT. Then, we activate %PositiveToX% when a pattern indicating a positive attitude in relation to %X% matches the input text, or we activate %NegativeToX% when a pattern indicating a negative attitude about %X% matches the input text. Consequently, there are four possible features conditional on %X% (%PositiveToPRIOR-SITUATION%, %PositiveToEFFECT%, %NegativeToPRIOR-SITUATION%, and %NegativeToEFFECT%).

Patterns such as these are also used for target sentiment analysis [15].

3) Sentiment polarity in PRIOR-SITUATION/EFFECT feature: Apart from patterns around the PRIOR-SITUATION/EFFECT, expressions in PRIOR-SITUATION/EFFECT sometimes become an important factor for classifying FAVOR/AGAINST. Consider the following example:

(3) *kokumin touhyou ga naigashiro ni sare sugi*$_{\text{PRIOR-SITUATION}}$.(Referendum is too much neglected$_{\text{PRIOR-SITUATION}}$.)

In this example, although no clue phrases exist for FAVOR/AGAINST classification around the PRIOR-SITUATION/EFFECT, PRIOR-SITUATION itself includes negative term "*naigashiro*" (neglected). Similar to patterns around PRIOR-SITUATION/EFFECT, there is apparently correspondence such that if PRIOR-SITUATION includes a negative attitude, then the whole text is apparently FAVOR, or if EFFECT is containing negative attitude then the whole text is apparently AGAINST. To specify whether PRIOR-SITUATION/EFFECT contains positive or negative attitudes, we do the same way as sentiment lexicon baseline. The only difference between this feature and sentiment lexicon baseline is that this feature takes account of only PRIOR-SITUATION/EFFECT, rather than whole text. For example, if we calculate $polarity\_score$ of PRIOR-SITUATION as greater than zero (i.e. positive), then we set this feature as %PositiveInPRIOR-SITUATION%. Consequently, there are four possible features conditional on $polarity\_score$ (%PositiveInPRIOR-SITUATION%, %PositiveInEFFECT%, %NegativeInPRIOR-SITUATION%, and %NegativeInEFFECT%). Note that, if $polarity\_score$ of PRIOR-SITUATION/EFFECT is calculated as zero, then this feature will be not activated.

V. Evaluation

To evaluate our methods, we measure the accuracy of the FAVOR/AGAINST classification through ten-fold cross validation. For example, we use votes of nine questions except for question "Are you FAVOR or AGAINST accepting same-sex marriage?" as training data. Then we evaluate the classification accuracy on votes of that question.

TABLE II
Classification Results of FAVOR/AGAINST Classification
(Bold Shows the Best Performance)

Method		Mean Accuracy
Baseline Method	NGR	65.59
	SEN-P	56.71
	SEN-N	57.07
	NAK-P	56.70
	NAK-N	54.92
Proposed Method	REP	67.17
	REP+PAT.F	68.02
	REP+SEN.F	68.85
	REP+PAT.F+SEN.F	**69.82**

Then, we calculate the mean of these ten accuracies. Results are presented in Table II. Because of limitations of space, the names of methods are abbreviated as shown below: NGR (n-gram baseline), SEN-P, SEN-N (Sentiment lexicon baseline, treat neutral as FAVOR, and treat neutral as AGAINST), NAK-P, NAK-N (Nakagawa's model, treat neutral as FAVOR, and treat neutral as AGAINST), REP (PRIOR-SITUATION/EFFECT replaced n-gram), PAT.F (Patterns around PRIOR-SITUATION/EFFECT), SEN.F (Sentiment polarity in PRIOR-SITUATION/EFFECT). Note that, although our proposed methods use PRIOR-SITUATION/EFFECT labels, we can improve the classification accuracy when we use answers that have no PRIOR-SITUATION/EFFECT label in training. Therefore, we use 300 answers of each question in training, and use answers that have at least one PRIOR-SITUATION/EFFECT label in evaluation.

From these results, it can be said that the PRIOR-SITUATION/EFFECT label is effective for FAVOR/AGAINST classification. Specially, REP+PAT.F+SEN.F shows significant improvement over NGR (4.23 point improvement in the classification accuracy). For example, though NGR misclassified following texts, REP+PAT.F+SEN.F correctly classified them.

(1) [gold: FAVOR, system output: FAVOR] Why women have to leave the house$_{\text{PRIOR-SITUATION}}$?
(2) [gold: FAVOR, system output: FAVOR] Because a world-famous event enlivens Japan, and it may also make a special demand$_{\text{EFFECT}}$.

In (1), PRIOR-SITUATION/EFFECT replaced n-gram "Why %PRIOR-SITUATION%" makes it possible to correctly classify. In (2), since there are positive terms "enlivens" and "demand" in EFFECT, our proposed method used it as a clue for classifying.

Note that, though Nakagawa's model is the state-of-the-art method of a Japanese sentiment analysis task, its accuracies were lower than baseline methods and proposed methods. This is likely because Nakagawa's model was already trained by corpus of Web data, which is not restricted to the debate domain.

A. Error Analysis

In this subsection, we investigated texts that were misclassified using the proposed method (REP+PAT.F+SEN.F).

Most errors are caused by not activated PAT.F or SEN.F. The example is the following:

(3) [gold: AGAINST, system output: FAVOR] Because it seems to cause indulge in the Diet$_{\text{EFFECT}}$.

In (3), "indulge" indicates a negative attitude, but this term was not in sentiment lexicon. The enrichment of sentiment lexicon and patterns is left as a subject for our future work.

Next, some errors exists because of multiple opinions included in the text. An example is the following:

(4) [gold: FAVOR, system output: AGAINST] Although changing law easily$_{\text{EFFECT}}$ is bad, simplification of the procedure$_{\text{EFFECT}}$ is needed. Otherwise, old laws will remain.

In (4), the author of the text indicates both a positive attitude and a negative attitude related to `%EFFECT%`. To tackle this problem, one possible solution is to change feature weights according to activated position in the text. For instance, if the author presents a negative attitude in relation to `%EFFECT%` in the first half of the text and presents a positive attitude about `%EFFECT%` in the latter half of the text, then the author is assumed to be in FAVOR of EFFECT all.

VI. Conclusion

As described herein, we proposed the concept of PRIOR-SITUATION/EFFECT, and labeled texts collected from different domains. Then, we demonstrated that many texts cannot be classified into FAVOR/AGAINST without PRIOR-SITUATION/EFFECT. Additionally, we performed FAVOR/AGAINST classification with PRIOR-SITUATION/EFFECT, and showed improved classification accuracy. In future work, we plan to gather knowledge related to PRIOR-SITUATION/EFFECT from Wikipedia, Twitter, and so on, and to use this knowledge to label PRIOR-SITUATION/EFFECT automatically.

Acknowledgment

This work was supported by JSPS KAKENHI Grant Number 15H05318 and CREST, JST.

References

[1] A. Murakami and R. Raymond, "Support or oppose?: classifying positions in online debates from reply activities and opinion expressions," in *Proceedings of the 23rd International Conference on Computational Linguistics*. Association for Computational Linguistics, 2010, pp. 869–875.

[2] D. Sridhar, L. Getoor, and M. Walker, "Collective stance classification of posts in online debate forums," in *Proceedings of the Joint Workshop on Social Dynamics and Personal Attributes in Social Media*, 2014, pp. 109–117.

[3] S. Somasundaran and J. Wiebe, "Recognizing stances in online debates," in *Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference on Natural Language Processing of the AFNLP*. Association for Computational Linguistics, 2009, pp. 226–234.

[4] M. Thomas, B. Pang, and L. Lee, "Get out the vote: Determining support or opposition from congressional floor-debate transcripts," in *Proceedings of the 2006 conference on empirical methods in natural language processing*. Association for Computational Linguistics, 2006, pp. 327–335.

[5] M. Mitchell, J. Aguilar, T. Wilson, and B. Van Durme, "Open domain targeted sentiment," in *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, 2013, pp. 1643–1654.

[6] M. Zhang, Y. Zhang, and D. T. Vo, "Neural networks for open domain targeted sentiment," in *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, 2015, pp. 612–621.

[7] S. Kiritchenko, X. Zhu, and S. M. Mohammad, "Sentiment analysis of short informal texts," *Journal of Artificial Intelligence Research*, vol. 50, pp. 723–762, 2014.

[8] X. Wang, Y. Liu, C. SUN, B. Wang, and X. Wang, "Predicting polarities of tweets by composing word embeddings with long short-term memory," in *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing*. Association for Computational Linguistics, 2015, pp. 1343–1353.

[9] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[10] M. Iyyer, P. Enns, J. Boyd-Graber, and P. Resnik, "Political ideology detection using recursive neural networks," in *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics*. Association for Computational Linguistics, 2014, pp. 1113–1122.

[11] D. X. Zhou, P. Resnick, and Q. Mei, "Classifying the political leaning of news articles and users from user votes." in *Fifth International AAAI Conference on Weblogs and Social Media*, 2011, pp. 417–424.

[12] F. M. F. Wong, C. W. Tan, S. Sen, and M. Chiang, "Quantifying political leaning from tweets and retweets." in *Seventh International AAAI Conference on Weblogs and Social Media*, 2013, pp. 640–649.

[13] L. Akoglu, "Quantifying political polarity based on bipartite opinion networks," in *Eighth International AAAI Conference on Weblogs and Social Media*, 2014, pp. 2–11.

[14] D. Bamman and N. A. Smith, "Open extraction of fine-grained political statements," in *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, 2015, pp. 76–85.

[15] N. Chambers, V. Bowen, E. Genco, X. Tian, E. Young, G. Harihara, and E. Yang, "Identifying political sentiment between nation states with social media," in *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, 2015, pp. 65–75.

[16] A. Tumasjan, T. O. Sprenger, P. G. Sandner, and I. M. Welpe, "Predicting elections with twitter: What 140 characters reveal about political sentiment." in *Fourth International AAAI Conference on Weblogs and Social Media*, 2010, pp. 178–185.

[17] T. Kudo, K. Yamamoto, and Y. Matsumoto, "Applying conditional random fields to japanese morphological analysis," in *Proceedings of the 2004 Conference on Empirical Methods in Natural Language Processing*, D. Lin and D. Wu, Eds. Association for Computational Linguistics, 2004, pp. 230–237.

[18] S. Toshinori, "Neologism dictionary based on the language resources on the web for mecab," 2015. [Online]. Available: https://github.com/neologd/mecab-ipadic-neologd

[19] T. Nakagawa, K. Inui, and S. Kurohashi, "Dependency tree-based sentiment classification using crfs with hidden variables," in *Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics*. Association for Computational Linguistics, 2010, pp. 786–794.

[20] S. Mohammad, S. Kiritchenko, and X. Zhu, "NRC-Canada: Building the state-of-the-art in sentiment analysis of tweets," in *Second Joint Conference on Lexical and Computational Semantics, Volume 2: Proceedings of the Seventh International Workshop on Semantic Evaluation*. Association for Computational Linguistics, 2013, pp. 321–327.

[21] N. Kobayashi, K. Inui, and Y. Matsumoto, "Opinion mining from web documents: Extraction and structurization," *Information and Media Technologies*, vol. 2, no. 1, pp. 326–337, 2007.

[22] M. Higashiyama, K. Inui, and Y. Matsumoto, "Acquiring noun polarity knowledge using selectional preferences (in Japanese)," in *Proceedings of the 14th Annual Meeting of the Association for Natural Language Processing*, 2008, pp. 584–587.

[23] J. D. Lafferty, A. McCallum, and F. C. N. Pereira, "Conditional random fields: Probabilistic models for segmenting and labeling sequence data," in *Proceedings of the Eighteenth International Conference on Machine Learning*. Morgan Kaufmann Publishers Inc., 2001, pp. 282–289.