Stance Classification Using Political Parties in Tokyo Metropolitan Assembly Minutes

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***Abstract*—Stance classification is an important component of argument mining. We focus on politicians' utterances in assembly minutes to classify political parties affiliation. This paper describes a novel stance classification task that classifies each politician's utterance for the politician's stance. Our task is to classify politicians into 20 political parties using their utterances in the Metropolitan Assembly minutes. Japanese assembly members are divided into many political parties in the local assembly. Our proposal is to apply several baseline methods to our novel dataset, which includes political parties in the Metropolitan Assembly minutes. In this paper, we define a political stance for a political party in Japan. We assess the difficulty of our dataset to evaluate several baseline methods, such as Support Vector machines (SVM), decision tree, random forest, and Naive Bayes.**

Keywords–Stance classification; Political party; Local assembly minutes.

I. Introduction

Automatic classification is abundant in social science research, such as political science and economics [1], and stance classification is a core component of argument mining [2][3]. We address the problem of classifying politicians' stances in terms of political parties. Previous research has defined a stance classification as a binary classification [4][5], and the datasets are usually generated by tweets or debates.

In this paper, we propose a novel stance classification approach to political parties using both assembly minutes and political parties. We define a political stance for a political party in Japan. The Japanese governmental structure of local governing bodies is called a dualistic representative structure. Assembly members interrogate a governor to confirm whether the governor's master plans should be carried out. These questions and answers are recorded in the assembly minutes, which are transcripts instead of summarized texts in Japan.

Furthermore, our goal is to classify each assembly member's political stance using the Tokyo Metropolitan Assembly minutes. Politicians' stances occasionally change over time, and each politician's stance depends on the individual political issue. Thus, there should be a large spectrum of political stances.

We focus on political parties in the Tokyo Metropolitan Assembly minutes in Japan. The number of political parties in the assembly minutes is usually higher than the number of national parties; there were 20 Tokyo Metropolitan parties between 2011 and 2015.

The main interest of this research is that political stance is primarily a question of classification using domestic political parties. In Japan, assembly members occasionally change political parties through their policies. Previous classification tasks have not used the content of the utterances to classify political stances that reflect political beliefs.

Our contributions can be summarized as follows:

1) Novel dataset for stance classification: We created a corpus for stance classification using political parties exceptional to Japan.
2) New approach to stance classification: Our task was to classify each assembly member into multiple political parties.
3) Evaluation of task difficulty: We applied the previous methods to the dataset.

The rest of this paper is organized as follows. Section II briefly reviews related work on the stance classification. Section III describes the classification of the political party. Section IV describes the experiment. Finally, we conclude this paper in Section V.

II. Related Work

Stance classification is the challenge faced when classifying the attitude taken by an author in a text.

In the International Workshop on Semantic Evaluation, SemEval-2016 Task-6 focused on detecting political stance in tweets [3]. The task is a shared task for detecting stance in tweets; given a tweet and a target entity, such as "Hillary Clinton" and "Legalization of Abortion". A system must determine whether the tweet is in favor of the given target, against the given target, or neither. For articles that mention the claim, the data is divided into the following three stances: "for", "against" and "observing." They classified articles into three stances.

This paper described public debate functions as forums for both expressing and forming opinions, which is an important aspect of public life [4]. It attempted to classify posts in online debates based on the position or stance that a speaker takes on an issue, such as favoring or obstructing the issue.

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Information about a political party was used for stance classification [6]; however, the political party was only used as a feature of classification. They annotated six contexts as features, such as political party, profile, and tweet.

III. Classification of Political Party

A. Task Definition

This task is a classification for determining the political party from an assembly member's utterances. We focused on the Tokyo Metropolitan Assembly minutes as a political dataset. Previous research has created a corpus of the local assembly minutes of 47 prefectures from April 2011 to March 2015 [7]. We provided the political party information to the Tokyo Metropolitan Assembly minutes. The dataset comprised 36,046 lines.

B. Dataset

Figure 1 presents an image of the dataset, which includes a speaker's name, utterance, and political party in the Tokyo Metropolitan Assembly. We used a party identification number (ID) as the political party information. Each utterance included a specific topic, such as the new Tokyo bank, the Tokyo Olympics or a care insurance system. We divided the dataset into portions of the Metropolitan Assembly minutes. In addition, we divided the utterances into a training dataset and a test dataset with the percentage ratio 8:2; the first portion was the training data, which constituted 80% (421 utterances) of the dataset, and the second portion was the test data, which constituted 20% (106 utterances) of the dataset. There were 527 assembly members in total and 174 distinct members.

The dataset contained the minutes of the Tokyo Metropolitan Assembly from April 2011 to March 2015. Japan is divided into 47 prefectures, including Tokyo, Kyoto and Osaka. The corpus contained the local assembly minutes of the 47 prefectures from April 2011 to March 2015 [7], a four-year period that coincides with the term of office for assembly members in most autonomy. In this study, we focused on the Tokyo Metropolitan Assembly minutes in Japan, and used a dataset comprising politicians' utterances and political parties in the assembly minutes. This classification model was used to build a classifier for political party by each politician's utterance. We attempted to classify political parties affiliation in the Tokyo Metropolitan Assembly. Table I contains 20 political parties that are in the Tokyo Metropolitan Assembly.

TABLE I. NAME OF 20 POLITICAL PARTIES IN THE TOKYO METROPOLITAN ASSEMBLY. THESE POLITICAL PARTIES ARE THE POLITICAL STANCES.

ID	Abbreviation	Name of political party
0	DP	Democratic Party
1	TMK	Tokyo Metropolitan Komeito
2	TMLDP	Tokyo Metropolitan Liberal Democratic Party
3	CN	Consumer Network
4	JCPTMA	Japan Communist in Party Tokyo Metropolitan Assembly
5	AC	Autonomous Citizen
6	JCPTMG	Japan Communist Party in Tokyo Metropolitan Government
7	I	Independent
8	I(R)	Independent (Restoration)
9	TRP	Tokyo Restoration Party
10	I(FALDP)	Independent (Fresh Air Liberal Democratic Party)
11	JRP	Japan Restoration Party
12	TMAEP	Tokyo Metropolitan Assembly Everyone's Party
13	EP	Everyone's Party
14	EPT	Everyone's Party Tokyo
15	TMCR	Tokyo Metropolitan Combination and Restoration
16	I(DBT)	Independent (Deep Breathable Tokyo)
17	BT	Bright Tokyo
18	TMRP	Tokyo Metropolitan Restoration Party
19	I(TEI)	Independent (Tokyo Everyone's Innovation)

IV. Experiment

The purpose of this study was to evaluate the difficulty of the dataset. Our task was to classify politicians into 20 political parties using their utterances in the Tokyo Metropolitan Assembly minutes.

A. Method

We assessed the difficulty of our dataset to evaluate several classification methods, such as SVM, Naive Bayes, k-nearest neighbor, random forest and decision trees. We constructed word vectors from segmented words. Experimental data were segmented into words using the Japanese morphological analysis tool MeCab [8] with the Japanese dictionary IPADIC.

B. Results

Table III shows the results of comparative experiment and the parameters. The correct answer rate is calculated as follows:

$$\frac{Number \quad of \quad correct \quad political \quad parties \quad ID}{Number \quad of \quad test \quad data}$$

We confirmed that the highest correct answer rate was 0.5377, given by the Naive Bayes.

C. Discussion

In this comparative experiment, the highest accuracy was 0.5377, determined by Naive Bayes. The difficulty and cause for the low accuracy rate for this corpus are explained. We consider the dataset to be unbalanced, since the number of members depends on political party. The number of members in the test dataset that belonged to party ID2 was 52. Figures 2 and 3 show the confusion matrix for the test dataset and show that their methods nearly predicted three parties: ID0, ID1, and ID2. There were 80 members in the top three political parties. However, SVM and Naive Bayes predicted 105 and 106 members, respectively, in the top three parties, which included ID0, ID1, and ID2. Thus, we should consider the number of assembly members in each party.

V. Conclusion

In this paper, we described a new approach to stance classification and created a new data set. The dataset comprised 168 members, 20 political parties and 527 utterances. We conducted performance evaluation experiments with multiple machine learning methods to evaluate the difficulty of the datasets. The accuracy rate of Naive Bayes had the highest performance, 54%. We evaluated the difficulty of the dataset for stance classification and determined that future work shuld consider the number of members in each party.

Speaker	Utterances in Tokyo Metropolitan assembly minutes	Political party ID	
A	(snip) 次に、株式会社新銀行東京に関する特別委員会の継続調査について、反対する立場から意見を述べます。 Next, I will express my opinion on the continuing investigation by the special committee concerning the new bank corporation Tokyo from the standpoint to oppose. (snip) オリンピック・パラリンピックを、多くの人々に夢と希望を与え、日本を再生させていくシンボルとして位置づけていくことが非常に重要と考えます。 I think that it is very important to give Olympic and Paralympic Games dreams and hopes to many people and to position them as a symbol that makes Japan revitalize.	1	Training data
B	(snip) 次に、介護保険制度について申し上げます。 Next, I will tell you about the long-term care insurance system. (snip) 最後に、オリンピック・パラリンピック招致について申し上げます。スポーツに関する施策の推進を図るべきと考えます。 Finally, I would like to mention about the Olympic and Paralympic Games bid. I think that we should promote measures related to sports.	2	Training data
C	(snip) よって、二〇二〇年にオリンピックを再び招致することには賛成できません。 Therefore, I can not agree to invite the Olympics again in 2020. (snip)	5	Training data
D	(snip) 次に、オリンピック・パラリンピックについてお伺いします。 同時に、東日本大震災から日本が再生するための極めて大きな牽引力となるものです。 Next, I will ask about the Olympic and Paralympic Games. At the same time, it will be an extremely big driving force for Japan to regenerate from the Great East Japan Earthquake.	— Select an ID among 20 political parties.	Test data

Figure 1. Overview of dataset.

TABLE II. EXPERIMENTAL DATASET DIVIDED INTO TWO DATASETS OF 80% AND 20%: TRAINING DATA AND TEST DATA. COLUMNS INCLUDE NUMBER OF MEMBERS, NUMBER OF WORDS, AVERAGE WORDS, MEDIAN, MAXIMUM AND MINIMUM.

ID	Party	Training data (Separation by utterance unit)						Test data (Separation by utterance unit)					
		Member	Word	Ave	Med	Max	Min	Member	Word	Ave	Med	Max	Min
0	DP	132	156,191	1,183	1,036	6,823	14	13	15,939	1,226	1,022	3,164	414
1	TMK	64	100,016	1,563	1,151	4,723	94	15	21,046	1,403	1,089	4,783	371
2	TMLDP	132	179,856	1,363	1,155	6,391	2	52	54,299	1,044	1,106	6,763	14
3	CN	19	14,330	754	754	1,336	203	4	3,476	869	797	1,301	582
4	JCPTMA	30	51,324	1,711	1,170	4,649	28	11	16,650	1,514	1,242	5,046	27
5	AC	2	2,915	1,458	1,476	1,484	1,431	0	0	0	0	0	0
6	JCPTMG	7	8,059	1,151	943	3,406	331	0	0	0	0	0	0
7	I	3	10,264	3,421	2,512	6,247	1,505	0	0	0	0	0	0
8	I(R)	1	1,272	1,272	1,272	1,272	1,272	0	0	0	0	0	0
9	TRP	6	3,272	545	464	1,062	253	0	0	0	0	0	0
10	I(FALDP)	4	3,002	750	851	1,280	19	1	1,329	1,329	1,329	1,329	1,329
11	JRP	2	1,051	526	526	570	481	0	0	0	0	0	0
12	TMAEP	4	3,199	800	904	998	393	0	0	0	0	0	0
13	EP	4	3,471	868	868	1,262	474	0	0	0	0	0	0
14	EPT	3	2,833	944	712	1,576	545	2	2,075	1,038	1,038	1,229	846
15	TMCR	5	4,370	874	741	1,494	418	2	2,608	1,304	1,304	1,849	759
16	I(DBT)	1	1,353	1,353	1,353	1,353	1,353	1	1,289	1,289	1,289	1,289	1,289
17	BT	2	2,172	1,086	1,086	1,272	900	0	0	0	0	0	0
18	TMRP	0	0	0	0	0	0	4	4,016	1,004	1,069	1,528	350
19	I(TEI)	0	0	0	0	0	0	1	754	754	754	754	754
Total	-	421	-	-	-	-	-	106	-	-	-	-	-

TABLE III. RESULTS OF COMPARATIVE EXPERIMENT. TEST SET INCLUDES 106 UTTERANCES.

Method	Parameter	Correct answer rate
SVM	kernel=rbf	0.3962
Decision tree	depth=3	0.3113
k-NN	k=3	0.4334
Random Forest	depth=5 tree=10	0.3490
Naive Bayes		<u>0.5377</u>

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REFERENCES

[1] J. Grimmer and B. M. Stewart, "Text as data: The promise and pitfalls of automatic content analysis methods for political texts," *Political Analysis*, vol. 21, pp. 267–297, 2013, awarded Political Analysis Editor's Choice Award for an article providing an especially significant contribution to political methodology. Replication Data: here.

[2] F. Boltuzic and J. Šnajder, "Toward stance classification based on claim microstructures," in *Proceedings of the 8th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis*. Association for Computational Linguistics, 2017, pp. 74–80. [Online]. Available: http://aclweb.org/anthology/W17-5210

		Prediction											
	ID	0	1	2	3	4	10	14	15	16	18	19	
Correct party ID	0	7	0	6	0	0	0	0	0	0	0	0	13
	1	1	5	9	0	0	0	0	0	0	0	0	15
	2	23	0	29	0	0	0	0	0	0	0	0	52
	3	3	0	1	0	0	0	0	0	0	0	0	4
	4	10	0	0	0	1	0	0	0	0	0	0	11
	11	0	0	1	0	0	0	0	0	0	0	0	1
	14	2	0	0	0	0	0	0	0	0	0	0	2
	15	1	0	1	0	0	0	0	0	0	0	0	2
	16	0	0	1	0	0	0	0	0	0	0	0	1
	18	3	0	1	0	0	0	0	0	0	0	0	4
	19	1	0	0	0	0	0	0	0	0	0	0	1
Total		51	5	49	0	1	0	0	0	0	0	0	106

Figure 2. Results of prediction by SVM. This prediction unit is a speech unit.

		Prediction											
	ID	0	1	2	3	4	10	14	15	16	18	19	
Correct party ID	0	9	1	3	0	0	0	0	0	0	0	0	13
	1	3	6	6	0	0	0	0	0	0	0	0	15
	2	8	2	42	0	0	0	0	0	0	0	0	52
	3	4	0	0	0	0	0	0	0	0	0	0	4
	4	7	0	4	0	0	0	0	0	0	0	0	11
	11	0	0	1	0	0	0	0	0	0	0	0	1
	14	2	0	0	0	0	0	0	0	0	0	0	2
	15	2	0	0	0	0	0	0	0	0	0	0	2
	16	0	0	1	0	0	0	0	0	0	0	0	1
	18	0	0	4	0	0	0	0	0	0	0	0	4
	19	0	1	0	0	0	0	0	0	0	0	0	1
Total		35	10	61	0	0	0	0	0	0	0	0	106

Figure 3. This figure shows the result of the prediction by the Naive Bayes. This prediction unit is a speech unit.

[3] S. Mohammad, S. Kiritchenko, P. Sobhani, X. Zhu, and C. Cherry, "Semeval-2016 task 6: Detecting stance in tweets," in *Proceedings of the 10th International Workshop on Semantic Evaluation (SemEval-2016)*. San Diego, California: Association for Computational Linguistics, June 2016, pp. 31–41. [Online]. Available: http://www.aclweb.org/anthology/S16-1003

[4] M. A. Walker, P. Anand, R. Abbott, and R. Grant, "Stance classification using dialogic properties of persuasion," in *Proceedings of the 2012 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, ser. NAACL HLT '12. Stroudsburg, PA, USA: Association for Computational Linguistics, 2012, pp. 592–596. [Online]. Available: http://dl.acm.org/citation.cfm?id=2382029.2382124

[5] 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*. Baltimore, Maryland: Association for Computational Linguistics, June 2014, pp. 109–117. [Online]. Available: http://www.aclweb.org/anthology/W14-2715

[6] K. Joseph, L. Friedland, W. Hobbs, D. Lazer, and O. Tsur, "Constance: Modeling annotation contexts to improve stance classification," in *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*. Copenhagen, Denmark: Association for Computational Linguistics, September 2017, pp. 1115–1124. [Online]. Available: https://www.aclweb.org/anthology/D17-1116

[7] Y. Kimura, K. Takamaru, T. Tanaka, A. Kobayashi, H. Sakaji, Y. Uchida, H. Ototake, and S. Masuyama, "Creating japanese political corpus from local assembly minutes of 47 prefectures," in *Proceedings of the 12th Workshop on Asian Language Resources (ALR12)*. The COLING 2016 Organizing Committee, 2016, pp. 78–85. [Online]. Available: http://www.aclweb.org/anthology/W16-5410

[8] T. Kudo, K. Yamamoto, and Y. Matsumoto, "Applying conditional random fields to japanese morphological analysis," in *In Proc. of EMNLP*, 2004, pp. 230–237.