How Many Tweets Do We Need?: Efficient Mining of Short-Term Polarized Topics on Twitter: A Case Study From Japan

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ABSTRACT
In recent years, social media has been criticized for yielding polarization. Identifying emerging disagreements and growing polarization is important for journalists to create alerts and provide more balanced coverage. While recent studies have shown the existence of polarization on social media, they primarily focused on limited topics such as politics with a large volume of data collected in the long term, especially over months or years. While these findings are helpful, they are too late to create an alert immediately. To address this gap, we develop a domain-agnostic mining method to identify polarized topics on Twitter in a short-term period, namely 12 hours. As a result, we find that daily Japanese news-related topics in early 2022 were polarized by 31.6% within a 12-hour range. We also analyzed that they tend to construct information diffusion networks with a relatively high average degree, and half of the tweets are created by a relatively small number of people. However, it is very costly and impractical to collect a large volume of tweets daily on many topics and monitor the polarization due to the limitations of the Twitter API. To make it more cost-efficient, we also develop a prediction method using machine learning techniques to estimate the polarization level using randomly collected tweets leveraging the network information. Extensive experiments show a significant saving in collection costs compared to baseline methods. In particular, our approach achieves F-score of 0.85, requiring 4,000 tweets, 4x savings than the baseline. To the best of our knowledge, our work is the first to predict the polarization level of the topics with low-resource tweets. Our findings have profound implications for the news media, allowing journalists to detect and disseminate polarizing information quickly and efficiently.

1 INTRODUCTION
The advent of social media had a profound impact on society, redefining how we obtain information. The traditional one-to-many information spreading has shifted to many-to-many communication, as anyone can easily speak up and share and choose whom to follow and with whom to interact. However, this decentralized nature of social media encourages users to interact with information mostly aligned with their beliefs[18] and has been criticized for fostering filter bubbles[31] and political polarization[29, 34]. A recent study[11] reported that misinformation might quickly propagate when the polarization level is high.

The rise of daily news is shaping distinct communication networks on social media. Identifying the emerging disagreements and growing polarization on social media is crucial for journalists to create alerts and provide more balanced coverage. A recent research[15] suggests that by presenting social media users with a bird’s eye view of an ideologically-fragmented social network and asking them to identify their positions within it, can help cultivate intellectual humility and motivate more diverse content-sharing and information-seeking behaviors.

Though many studies have shown the existence of polarization on social media, prior studies are limited in two main ways. First, previous research mainly observed polarization on social networks collected for more than a month or years [9, 14]. These findings are helpful but too late to create alerts immediately. To our knowledge, no studies have examined polarization in the short term, less than a day. Second, prior research typically focused on a single or a minimal set of related topics, usually political issues. Various topics are debated daily, and polarization may occur on non-political subjects. Furthermore, most studies have been conducted in the United States context. The U.S. has a strong two-party system characterized by ideological and affective polarization along party lines. Such partisans are rarely seen in other countries.

Therefore, our study aims to better understand the nature of the polarized topic in the short term on Twitter on various topics. However, the expensive cost of data collection due to the limitations of the API hinders the analysis of a wide variety of topics every day.

CCS CONCEPTS
• Information systems → Social networks.

KEYWORDS
computational social science, polarization, twitter, network analysis
We compare the polarized and non-polarized topics from the perspective of the news genre, network size, average degree, URL ratio, hashtag ratio, and vocal minority level, which how a small number of people created a large volume of content. (3) How many tweets do we need to collect to obtain reliable results on calculating polarization? Lastly, we assess whether predictions made from randomly chosen subsets of tweets align with the ground truth. Furthermore, we develop machine learning techniques incorporating network statistics, making better predictions with lower resources. To the best of our knowledge, our work is the first to predict the polarization level of the topics with low-resource tweets.

Our contributions are as follows:

- Our analysis shows that daily Japanese news-related topics in early 2022 were polarized by 31.6% within a 12-hour range.
- We show that polarized topics tend to happen related to the news genre of International, Business, and Social · Culture and often create the large size of the information diffusion networks with a high average degree. Another interesting characteristic is that half of the tweets are created by a relatively small number of people.
- We implement a machine learning approach to estimate the polarization level using randomly collected tweets. Our analysis achieves F-score of 0.85, requiring 4,000 tweets, 4x savings than the baseline.

2 RELATED WORK

2.1 Taxonomy of Polarization Detection Methods

As news consumption shifted to social media, researchers began investigating how news content sharing habits on social media platforms are polarized. From a sociological point of view[12], polarization is understood as the division of individuals into coherent and strongly opposed groups based on their opinions on one or more issues. Therefore previous studies can be classified according to how groups are defined and how dissimilarities of opinions among them are defined.

First, there are mainly two approaches for determining the groups: manual partitioning or network-based partitioning. Manual partitioning means classifying users based on the analyst’s intent, in most cases, political leaning. They are often used by predefined accounts [9, 14], use of predefined hashtags [33], or news URLs[2]. The other approach is network-based methods, utilizing graph partitioning methods[13] on retweet or mention networks to obtain groups. This type of method doesn’t require prior knowledge and extracts groups rather than intentionally obtaining groups such as left or right.

Second, there are also mainly two approaches for determining the similarities of the opinions between the aforementioned groups: network-based and content based. Network-based approaches leverage information diffusion to inform ideological alignment. These models assume that users interact more with people of similar opinions. Interactions can be retweets [28, 38], followings [4], mentions [9] or multi-relational network (combination of retweets, mentions, likes and follows) [39]. A previous study reported those network-based text clustering potentially yields better results rather than topic modeling [37]. Content-based approaches leverage information related to users’ tweets and other textual data [17]. Prior research mainly leveraged for: hashtag [10, 13, 14], lexicon dictionaries [26], sentiment [27], stance [40], word embedding [32].

The most well-known strategy for observing polarization is grouping users manually, namely left or right users, and seeing the disconnectivity between them in the social network. In our study, we group users based on network-based interactions since it is impossible to manually select opposing groups of users without prior domain-specific knowledge of every topic. Then we also use network-based disconnectivity to measure the dissimilarities of opinions. Previous content-based works are short-handed because URLs or hashtags are partially included. Also, using the stance detection method is difficult because we do not know the target people agree with beforehand. Our approach shares the same selection of methods and motivation in [13].

2.2 Data Collection on Polarization Detection

Recent studies mainly investigated polarization in the political domain, with case studies focusing on major, long-term events such as presidential elections. Therefore, in terms of data collection, choosing the data collection period has been event-driven and dependent on analysts’ interests. Conover et al. [9] collected six-week tweets related to the 2010 U.S. congressional midterm elections. Mejova et al. [26] consider discussion of controversial and non-controversial news over seven months. This paper aims to identify and quantify short-term controversies on any topic discussed on social media rather than on a limited set of topics as in prior studies. Therefore, our analysis differs from most studies in limiting the collection period rather than the topic.

Those previous studies can be categorized into two according to their types of data collection. The first type collects tweets or user interaction information based on manually selected seed accounts, such as politicians, influencers, and media accounts [3, 6, 8, 16]. Utilizing their account information, they collect past tweets or follower lists. While these methods can collect a wide range of relevant topics, there are difficulties in determining the accounts to be used for the survey. The second type collects tweets by using keywords or hashtag search. These studies manually select hashtags related to topics interested in [9, 13], or use keywords in their tweets [18]. While these methods make it easier to collect specific topics, they also tend to make it challenging to set keywords when analyzing broad topics such as political divisions. In our study, we employ the second type of method because our research targets polarization in a small discussion of specific news rather than a broader topic such as politics.
3 METHOD FOR IDENTIFYING POLARIZED TOPICS

This section describes the method used to identify polarized topics from collected tweets. The overall framework in this paper is illustrated in Figure 1.

3.1 Data collection

To examine the spread of information on a single topic, we use tweets/posts on Twitter to create a network. We collect tweets by using keywords as described in Section 2.2 because we want to make an analysis on a narrow discussion related to specific news rather than a broader topic such as politics. However, discovering the search queries to find polarized topics by trial and error is difficult and time-consuming.

To address this limitation, we employ a two-stage data collection method: First, we collect tweets with a single word (seed keyword) that involves a variety of topics (e.g., "Ukraine"). Then, we extract subsets of tweets based on the smaller topics discussed. Topic models such as LDA[5] are one popular machine-learning approach to identifying topics. However, it requires the number of topics beforehand, and it is known that a too large or too small number of topics will affect the inference process and cause inaccuracies in grouping topics in the training model[36]. Therefore, we improve the basic approach by considering the word’s popularity. Specifically, we compute the frequency of all terms, and we retrieve the top-\(k\) (we use \(k = 10\)) sub-keywords from a given seed (e.g., "Kyiv" given "Ukraine" as seed). Then we extract subsets of tweets containing both seed and sub-keywords. In our experiments, we use MeCab[23] for word segmentation and POS tagging to select nouns for sub-keywords.

3.2 Network Construction

For each dataset queried by seed and sub-keyword, we use retweet information to build the interaction network \(G\). Specifically, we use retweets as a proxy for influence[28] and build directed network \(G = (V, E)\). Whenever a user \(u_i \in V\) retweets a message originally posted by user \(u_j\), we assume that \(u_i\) is influenced by \(u_j\)’s ideas. Hence, a new directed link \((u_j \rightarrow u_i) \in E\) is created.

3.3 Graph Partition

Next, we split the network, aiming to obtain two groups of similar size with the fewest edges between them. We use the graph partitioning setting used in [7]: we use METIS[20] algorithm, setting a maximum imbalance constraint of 3:7 on the partitioning algorithm since forcing the partitions to be perfectly balanced when real groups are not the same size will result in the partition to divide the larger group, which incorrectly inflates inter-group agreement relative to a within-group agreement. The METIS algorithm has a straightforward and intuitive interpretation and has been shown to work well with retweet networks[13].

3.4 Measuring Polarization

Next, we measure how two groups obtained in Section 3.3 are weakly connected. A recent study [35] found well commonly-used structural polarization measures yield high polarization scores even for random networks with similar density and degree distributions networks, and the choice of measurement method is not as critical as normalization. Followed by the suggestions by [35], we use Adaptive E-I Index[7] for measuring polarization which is easy to interpret and employ the normalization technique proposed by [35].
Figure 2: Word cloud visualization of seed keywords translated from Japanese used in our experiments. We select 100 seed keywords using KMeans clustering on 17,620 news articles collected from February 1 to August 4. The size of the words indicates the corresponding cluster size.

Adaptive E-I Index. We calculate our polarization score $\Phi(G)$ as:

$$\Phi(G) = \frac{\sigma_{AA} + \sigma_{BB} - (\sigma_{AB} + \sigma_{BA})}{\sigma_{AA} + \sigma_{BB} + (\sigma_{AB} + \sigma_{BA})}$$  \hspace{1cm} (1)

where $\sigma_{AA}$ is the ratio of links within the community $A$ (similarly for $\sigma_{BB}$) and $\sigma_{AB}$ is the observed number of links between the communities $A$ and $B$ divided by the number of all potential links. This measure is an extension of the E-I Index\cite{22}, as it accounts for different community sizes by using the density of links within each community. When the two groups are the same size, $\Phi(G)$ reduces to the E-I Index\cite{21}.

Normalization. We calculate our normalized polarization score $\hat{\Phi}(G)$ as:

$$\hat{\Phi}(G) = \Phi(G) - \left(\Phi(G_{CM})\right)$$  \hspace{1cm} (2)

where $\Phi(G)$ is the polarization score of the observed network and $\left(\Phi(G_{CM})\right)$ is the expected polarization score of graphs calculated for multiple instances of the randomized network fixing the number of nodes and degree-degree sequences\cite{25}. This score corrects for the expected effect of the size and degree distribution of the network. Each randomized network is repartitioned before computing its polarization score by applying the same graph partitioning algorithm for the original network. We sampled the randomized networks 50 times and calculated the score.

4 POLARIZATION ON EVERYDAY, SHORT-TERM TOPICS

In this section, we conduct experiments with the aim of answering the following research question using the methodology in Section 3: RQ1. How often do polarized topics exist in everyday news topics?

4.1 Dataset Collection

Since this work aims to create polarization alerts in a short-term period for journalists, we tried to collect a variety of topics related to daily news topics. Specifically, we collect tweets and create networks in the following steps.

First, in order to choose the seed keywords described in Section 3.2, we collect all the news from NHK news web, Japanese public broadcast media, from February 1 to August 4, 2022, to know the newsworthy events that happened in Japan. The overall dataset contains 17,620 news. These news articles have distinct categories, namely International, Politics, Business, Social, Sports, Science · Culture, Life, Weather · Disaster and about 96 news items are published per day.

Second, to reduce the volume of collecting tweets, we extract 100 news articles and their seed keywords, keeping the diversity of the topics. In particular, we convert each news title into 45,590-dimensional Bag-Of-Words vectors. Then we conduct KMeans clustering and select the 100 articles closest to their centers. After obtaining articles, we manually select seed keywords which we may include a relatively broad range of topics related to that news. Figure 2 illustrates the word cloud visualization of seed keywords translated from Japanese, and the size indicates the corresponding cluster size, where the big size of the words suggests that there are large amount of news related to that seed keywords.

Finally, Twitter API v2 for Academic Research was used to collect tweets containing the seed keywords. We collect tweets in a period of 12 hours after the corresponding news was published. As mentioned in Section 3.2, after collecting tweets, we extract top-10 sub-keywords for each dataset based on frequency, which results in 1,000 sub-topics. However, excluding sub-topics that were too small to create a network, a total of 842 networks were created. Network statistics are presented in Figure 3.

4.2 Distributions of Polarization

Here we investigate to what extent the polarization happens related to the Japanese news event in 12 hours. For this analysis, we compute polarization scores for each network. Figure 4 shows the histogram of the polarization scores $\hat{\Phi}(G)$ over the 842 networks we collected. Inspecting this plot, we find that 39.9% of the networks have a polarization score of 0 or less. We show sample networks according to polarization score in Figure 5. The partitions are drawn in blue or red. The graph layouts are generated by ForceAtlas2 algorithm\cite{19} and are based solely on the structure of the graph, not on the partitioning computed by METIS. As shown in Figure 5, topics in which a small number of tweets are largely retweeted show low polarization scores because the structure changes little after shuffling. By manual inspection, we use a threshold of 0.04 to binarize the networks into polarized or not, and we found that 31.6% of all the networks are polarized.

4.3 Characterizing Polarization Topic

This subsection aims to answer the following research question: RQ2. What are the characteristics of polarized topics compared to non-polarized ones?

To get a more detailed view of the characteristics that are related to polarization, we compare how the networks of polarized and
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Figure 3: Scatter plot showing number of nodes and edges of the 1,000 retweet networks obtained in Section 4.1

Figure 4: Histogram of polarization scores $\hat{\Phi}(G)$ calculated from 842 networks related to Japanese news from February to July 2022

non-polarized topics differ. To characterize the difference, we use the following viewpoints: news genre, network size, the ratio of the use of hashtags and URLs, and vocal minority. As in the previous section, we use 0.04 as the threshold to determine polarization.

Genre: First, we connect polarization with the news genre from the original news data. Figure 6 (a) displays a bar plot of the network size and a line plot showing the ratio of polarization across different genres. Our results indicate that in comparison with the rest of the topics, International, Business, and Social are among the more polarized. We found that polarization does not occur at such a high rate on political topics, which have been extensively analyzed in previous studies. Our results suggest that more analysis in broader genres is needed to create polarization alerts.

Network size: We also analyze the relationship between the network size and polarization. This comparison is shown in Figure 6 (b). The pattern is very apparent: as network size increases, the polarization ratio goes up. This is because the smaller size of the network results in a smaller difference from the randomly shuffled network in the calculation of polarization.

Average Degree: The average degree is simply the average number of edges per node in the graph. The higher the value indicates, the more dense the network. This comparison is shown in Figure 6 (c). We can see the dense information diffusion network are more easily polarized. This shows that networks that have many mutual retweet relationships are more likely to be polarized than in a situation where a few tweets are spread out in large numbers.

URLs & Hashtags: Next, we comment on the use of URLs and hashtags contained in tweets. This comparison is shown in Figure 6 (d) (e). These results show that polarization rarely occurs in topics with URL ratio as low as around 0.1 or as high as 0.8 or higher, and polarization tends to happen in the rest of the in-between areas. In terms of Hashtag ratio, we can see that the polarized topics relatively include more use of Hashtag.

Vocal Minority: Another interesting metric for analysis is the vocal minority, the small group of individuals that frequently and strongly voice their opinions. Previous study[1] explored the Facebook dataset from 2009 with almost 40,000 active users and found 7% of them produced 50% of the posts. Inspired by this analysis, we introduce the vocal minority index, what percentage of the active user created the 50% of the tweets. We show these statistics in Figure 6 (f). Our results is very apparent: as vocal minority level increases, ratio of polarization goes up.

5 EFFICIENT ESTIMATION OF POLARIZATION

As seen in the previous section, we confirmed that polarization happens daily. However, the expensive cost of data collection due to the limit of the API hinders the analysis of polarization on wide variety of topics every day. This limitation suggests the potential need for an efficient approach, which would require small subsets of tweets to predict the polarization level. To the best of our knowledge, our work is the first to predict the polarization level of the topics with low-resource tweets. Therefore this section aims to answer the following question: RQ3. How many tweets do we need to collect to obtain reliable results on the calculation of polarization?

5.1 Experimental Setting

We now assess whether predictions made from randomly chosen subsets of tweets align with the ground truth. Figure 7 shows the data sampling procedure. First, we randomly select $k$ points as a start of tweet collection from the considering period. Then we collect $m$ tweets back from each point. In this work, we use $m = 100,$
Figure 5: Sample retweet network visualized using the ForceAtlas2 algorithm with calculated polarization scores $\hat{\Phi}(G)$.

Figure 6: Comparison of the characteristics of the network between polarized and non-polarized topics: (a) news genre, (b) network size, (c) average degree, (d) (e) ratio of the use of Hashtags and URLs, and (f) vocal minority.
the maximum capacity for collecting tweets with one request. Note that reducing the $m$ leads to an increase in API executions.

We implement two variations of estimation methods described in Section 5.2 and Section 5.3 using the randomly chosen subsets of tweets. Then we evaluate the estimation results with the scores obtained from the whole dataset, which constitutes the ground truth. We evaluate performance in terms of $R^2$ score, precision, and recall. We use $k=10, 20, 40, 80, 160$, and $320$ and report the average scores of 10 trials. The overall framework is also illustrated in Figure 1.

**5.2 Results of Naive Estimation**

Naive estimation calculates the polarization score from the network constructed from obtained subsets of tweets using the method described in Section 3. Results obtained for each dataset are shown in Figure 8 (a) ~ (f) showing the scatter density plot of the prediction (x-axis) and the ground truth (y-axis). Figure 8 (g) (h) shows the precision and recall with the x-axis showing accumulated hour-levels of the collection and the y-axis showing the depending on the number of collected points. The last column in Figure 8 (g) (h) shows the overall results of precision and recall. This evaluation aims to understand the performance according to how many tweets are collected and how many hours they occupy, which can estimate the original size of the networks. A single pixel corresponds to multiple networks, showing the average performance. Thus the number of networks in pixels horizontally from 0 hour-level to 11 hour-level is summed up to 842 for all rows. Blanks are provided where no network exists.

As shown in Figure 8 (a) ~ (f), we can see a clear trend that the smaller the number of tweets collected, the lower the predicted polarization score. This insight can help understand the results in Figure 8 (g) (h), showing that precision is relatively high while recall tends to be low. Another interesting finding is that Figure 8 (g) produces low polarization in the right-bottom corner, which suggests that the small polarized networks are hard to predict even if they are collected most of the time. At the same time, it produces 0.73 of precision to the networks by collecting just an hour of tweets.

**5.3 Results of Machine Learning Approach**

Up to this point, we are very interested in whether a prediction can be better by leveraging network or user information seen in Section 4.3. In this subsection, we will evaluate the effectiveness of the combination of the features for predicting polarization scores. We use Random Forest[24] to predict the polarization score $\hat{\Phi}(G)$ using features, news genre, network size, URL ratio, Hashtag Ratio, and Vocal Minority Index. The training uses a 10-fold cross-validation procedure. The training dataset is split into ten smaller sets, and the model is trained using nine folds and validated on the remaining part of the data. To evaluate the performance of the trained model, we report the same metric in Section 5.2. Note that we binarize the network into polarized or not polarized after making predictions using the same threshold in Section 4.3 to calculate precision and recall.

Figure 9 shows the results of the machine learning approach. Comparing the results in Figure 9 (a) ~ (f) and Figure 8 (a) ~ (f), our approach achieves F-score of 0.85 (precision of 0.83 and recall of 0.88), requiring 4,000 tweets, 4x savings than the baseline (precision of 0.96 and recall of 0.76). We can also see significant improvement in recall where collecting just 1,000 tweets can produce rivaling results with the naive estimation results with 16,000 ~ 32,000 tweets. In Figure 9 (g) (h) and Figure 8 (g) (h), we can see large improvement of recall especially in left part of the matrix (large networks) from naive estimation. Our model consistently shows a similar trend: it produces low precision and recall in the lower right, which suggests that small polarized networks are hard to detect with small data. Our results conclude that it is more beneficial to leverage knowledge from another relevant domain when there is less data.

**6 CONCLUSION**

Identifying emerging disagreements and growing polarization is crucial for journalists to create alerts and provide more balanced coverage. In this work, we studied the efficient detection of polarized topics related to newsworthy Japanese events. Our study revealed that polarization occurs in everyday topics, regardless of whether they are political or not. Moreover, polarization is often accompanied by voice minority and contains a relatively high ratio of bot activities. Last but not least, incorporating those features can predict polarization even with a randomly selected small amount of tweets. We have shown that the machine learning approach achieves F-score of 0.85, requiring 4,000 tweets, 4x savings than the baseline.

One possible thing to do in the future is to optimize the strategy of collecting tweets. Although we attempted to extract tweets randomly this time, better predictions may be possible by controlling the next selection of collection time depending on how many minutes were collected. This notion is based on the idea that there may be a segment of time that is important for collecting tweets since the burst in tweets is not constant and may be concentrated at a certain time of the day. Another possible future approach is investigating more features to predict prediction and consideration of different machine learning methods. In this study, we focused on the basic feature of the network and the frequency of statements. However, there may be unexplored features such as followers’ information and the semantic alignment of the tweets.

Our work is the first to show that short-term polarization occurs in a short period on any topic and that they are predictable with a small number of tweets. These results have profound implications.
for the use of news media. This allows journalists to detect and disseminate polarizing information quickly. Prior studies have proposed many techniques to eliminate polarization, suggesting new recommendation algorithms on social media. However, changing the recommendation system involves great cost and risk. Our study is a step toward eliminating polarization for everyone in that we are doing what we can as a media outlet. While some research has shown the backfire effects[30], strengthening of polarization through the presentation of diverse opinions. However, not enough is known about what happens when these effects occur on the other topics, similar to the purpose of this study. In the future, verifying the effectiveness of presenting the various opinions obtained from these studies to users will be necessary.

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