Abstract—For efficient policy-making, a thorough recognition of controversial topics is crucial because the cost of unmitigated controversies would be extremely high for society. However, identifying controversial topics is costly. In this paper, we proposed a framework to search for controversial topics comprehensively. We then conducted a retrospective analysis of the controversial topics of COVID-19 with data obtained via Twitter in Japan as a case study of the framework. The results show that the proposed framework can effectively detect controversial topics that reflect current reality. Controversial topics tend to be about the government, medical matters, economy, and education; moreover, the controversy score had a low correlation with the traditional indicators—scale and sentiment of the topics—which suggests that the controversy score is a potentially important indicator to be obtained. We also discussed the difference between highly controversial topics and less controversial ones despite their large scale and sentiment.

Index Terms—Controversial topic detection, Echo chamber, Polarization, Twitter, COVID-19

I. INTRODUCTION

Social controversies have a high priority for being solved by policy makers. The controversies can happen on various topics, such as vaccinations. They can be regarded as the division of society, which creates a bad atmosphere in society, raises the cost of policy-making, and makes the governmental operations less smooth, e.g., the delay of vaccinations [1]. For political decision-makers, given their limited resources, it is natural to prioritize topics that have high levels of controversies for resolution and arbitration as their risk communications [2]. However, detecting society’s controversies is not easy. Indeed, we can find controversies if we use a questionnaire and search for items in which responses are divided extremely. Nonetheless, the distributing questionnaire itself is expensive. Moreover, analysts have difficulty avoiding biases when picking topics for a survey, which leads to overlooking potential controversies that have not yet become apparent. If we can automatically extract society’s controversies, it will be possible to identify the controversies to be solved efficiently.

With this in mind, this study proposes a framework to detect controversial topics on social media comprehensively. Social media data can be analyzed post hoc, repeatedly, and at a low cost, allowing researchers to search for controversial topics, including unexpected ones, more flexibly than questionnaires. If this framework is well established, it will help decision-makers in the future to grasp the “problem to be solved now” early and accurately from social media.

As a case study, we selected COVID-19, an unprecedented pandemic that caused many social controversies in addition to health hazards. Using the longitudinal data of Twitter in Japan, we conducted a retrospective analysis to uncover which topic around COVID-19 was the most controversial and when.

Our contributions are as follows:

- We proposed a framework to detect controversial topics on social media comprehensively. We also compared the degree of controversy with traditional indicators—scale and sentiment—for future researchers using controversy as a new aspect of social media analysis.
- We clarified the patterns of controversial topics of COVID-19 in Japan. They are mainly about the government, medical field, economy, and education. On the other hand, scale and sentiment (mean and std) were also not correlated with controversy scores. Also, there were topics with large scale and sentiment but with low controversy. In particular, when one opinion was overwhelming, and there was no antagonism between opposing opinions, there was a tendency for low controversy (e.g., obvious scandals of politicians).

II. RELATED WORKS

Controversy, sometimes recognized as polarization on social media, is an aspect that requires the attention of the government when it listens to people’s voices. Controversy is a state in which people’s opinions are severely divided [3]–[5], and those adhering to one view rarely communicate with those with differing views. When controversy arises in social matters, it is challenging to address it through communication
because people are divided by their reinforced beliefs, and the cost incurred by society because of these problems is exceptionally high [6]. Moreover, the controversy tends to accelerate if left unmitigated [7]; hence, it is desirable to accurately identify controversial features and mitigate them before the problem becomes severe [8].

There have been researches for quantifying controversy on social media [9]–[11]. Researches already proposed effective methods to quantify controversy, and many of these quantify the controversy of clusters in a network structure [9], [10]. However, these methods aim to quantify a single topic (and not multiple topics) and not investigate social media at large. Similar research was conducted by Coletto et al. [12], where they searched for local discussions in a network created for the main discussion; however, it is a method that searches for intensive interactions rather than controversy. Despite the importance and potential of controversy scores, little research leverages the measure to grasp controversial topics on social media comprehensively.

When it comes to detecting controversy on social media, one might think of traditional indicators such as scale and sentiment [13], [14]. However, it is easy to imagine the topic that many people mention but that there is no controversy (e.g., the death of popular celebrities). Also, it has been reported that stance and sentiment have a low correlation [15]. The stance was calculated from the network information of users, which is similar to the calculation of controversy. The measurement of controversy would provide another aspect of social media research. A new aspect mitigates the common problem of social media research, which is the lack of reliability from practitioners because of the lack of transparency and vagueness [16].

Our novelty is two folds. First, we grasp controversies comprehensively on social media rather than focusing on a single topic. By investigating multiple topics quantitatively, we can answer what the most controversial topic is. Second, we propose to use controversies as a new aspect to diagnose the state of social media in addition to the traditional scale and sentiment measures.

III. DATASET

We collected COVID-19-related tweets using Twitter’s standard API. The search queries mixed Japanese and English words, but we only collected Japanese tweets by setting the language for search as Japanese. The queries are below (for Japanese words, the translated English words are in brackets):

- コロナウイルス/コロナウィルス (coronavirus), “corona”,
- ニュース (news), “news”,
- ワクチン/ワックス (vaccine), “vaccination”,
- COVID-19, “covid”,
- 武漢 (Wuhan), “wuhan”,
- 感染症 (infection), “infection”,
- 生物 (biology), “biological”,
- ニュース : コロナウイルス : インフルエンザ (news : corona : influenza),
- ニュース : コロナウイルス (news : corona),
- インフルエンザ (influenza),
- COVID-19 (covid-19),
- コロナウイルス/ウイルス (coronavirus / virus),
- 新型肺炎 (new type pneumonia),
- 新型肺炎/新型 (new type pneumonia / new type),
- ニュース : 新型 (news : new type),
- 新型肺炎 (new type pneumonia),
- ニュース : 新型肺炎 (news : new type pneumonia).

The collection period was from February 1 to August 31, 2020. The tweets, including retweets (RTs), totaled 245,558,103.

IV. METHODOLOGY

We propose a framework to discover controversial topics (Figure 1). This framework is an analytical pipeline that consists of two main phases: topic detection (phase 1) and controversy quantification (phase 2). In phase 1, we obtain single words to represent the topics. Then we pass a subset of tweets associated with each topic to phase 2. In phase 2, we assign the controversy scores to each topic to discover highly controversial topics.

A. Phase 1: Topic Detection

We required two conditions for topic detection. First, for interpretability and search efficiency, one query word sufficiently represents a topic. For example, if the topic concerns vaccines, it is desirable to express the topic with a single word such as “vaccine” excluding “vaccination” or “vax.” This condition enables us to avoid interpreting the acquired topics manually, as is often required when using topic modeling techniques [17]. Thus, the full automation of the framework is possible, which is helpful in practical application. Second, a certain number of tweets on a topic is necessary for phase 2. As reported in previous research [9], the method for quantifying controversy does not work well in a small network. Our preliminary experiments found that it is desirable to have more than 800 nodes in the network to obtain robust results.

To fulfill these conditions, we decided to take the following three steps (phase 1’s box in Figure 1). First, we retained only nouns by preprocessing. Here, we removed meaningless words (e.g., “you”) using the ordinary stopword list. As for the tokenization of Japanese sentences, we used the Japanese morphological analysis library MeCab [18] and the Japanese dictionary NEologd [19]. Second, we created a custom stopword list for further filtering to leave the COVID-19’s topics.

- the topic itself (in this case, COVID-19) (“virus”, “infection”, etc.),
- news-related words (“news”, “breaking”, etc.),
- announcements (calls to action such as “everyone”, etc.),
- region, personal name, time, or person (e.g., “man”),
- words that have no meaning (e.g., “lol”).

Third, we sorted the words by frequency and extracted the top-N words as a shortlist for quantifying controversy in phase 2. For this study, we set the N as 50.
We did not adopt the probabilistic modeling or clustering approaches such as K-means or LDA for topic detection despite them being commonly used topic detection methods because both can retrieve trivial words, which exacerbates the robustness and interpretability of topics. Also, these methods are said not to perform well with short sentences such as tweets [20]. Actually, in our preliminary experiments, we tried these techniques, but satisfactory results were not obtained. Thus, as representations of topics, we decided to use single words, which are easily interpretable and not associated with noise such as trivial words. We also decided to use the top frequent words because we had to guarantee a certain number of tweets for topics, which is the second condition for phase 1. Then, our task was to retrieve topical words worth picking up from top frequent words. Here, we found that this task was almost analogous with carefully crafting stopwords as described above. From the preliminary experiments, as long as we removed trivial words that did not pass to phase 2 (already listed as the crafted stopword list), all the remaining words were independently somewhat topical and worthy of retrieval.

**B. Phase 2: Quantifying Controversy**

We employed the method suggested by Garimella et al. [9] because this method is state of the art for quantifying controversy and was proved its superiority compared with other methods in [9]. This method measures controversy by quantifying the connectivity of the two clusters when the network is bisected. If the connectivity of the two clusters is low, the controversy will be high. For the connectivity of two clusters, a random walk with restart is employed, and the random walk starts from each cluster to quantify how easy it is to move from one cluster to another. This random-walk controversy score (RWC) is formulated as follows,

$$RWC = P_{XX} + P_{YY} - P_{XY} - P_{YX},$$

(1)

where $P_{AB+}$ indicates the possibility of moving from the nodes in cluster $A$ to the high-degree nodes in cluster $B^+$. $RWC$ captures the difference in the probability of staying on the same side and crossing the boundary and takes a value from -1 to 1. For dividing the network, we employed the METIS algorithm [21] following the original paper [9], which splits the network into two clusters of almost equal size.

To obtain $RWC$, we created a network with the following conditions. The nodes indicate users. We created an edge between users with more than two RTs (including mutual RTs), which more robustly incorporates the meaning of the endorsement into the edges [9]. After creating the network, we applied $k$-core decomposition ($k$=2) to exclude users with only weak connections to the primary discussions [22]. Then, we extracted the maximum connected components in the network to remove tiny network fractions.

As mentioned, we set the threshold for the number of nodes to 800. Additionally, since tweet volumes differ by topic, in practice, we had to set the appropriate period for obtaining tweets according to the topics. In this study, however, we set a fixed term for comparatively analyzing the extracted topics. We adopted a conservative period of one month.

**V. Validation of Quantifying Controversy**

Before using the topic detection method, we manually selected topics on COVID-19 that were well-known to the public to validate whether the method for quantifying controversy robustly reflected reality.

We selected the following five words as pre-specified topics: “オリンピック (Olympic),” “ワクチン (Vaccine),” “GoTo,” “発熱 (Fever),” “死者 (Fatality).”

We assumed “オリンピック (Olympic),” “ワクチン (Vaccines),” and “GoTo” are controversial topics. “Olympic” is a topic that concerns holding a sporting event. In Japan, after the COVID-19 outbreak, a huge discussion occurred on the postponement or cancellation of the biggest global event. Vaccine concerns the healthcare policy. Recent studies have shown vaccination is one of the most controversial topics online [4] especially in Japan [23]. “GoTo” indicates a unique Japanese policy for supporting the travel industry. Go To Travel, which allows travelers to obtain discounts when they travel. The policy was announced in May 2020 and implemented from July to December. Although the Japanese government managed to execute this policy, there was criticism that the policy spread the COVID-19 infection. We also assumed fever and fatalities as non-controversial topics because they indicated the factual situation with which opinions have a lower probability of association. Added to these five words, we quantified controversy without any query as the reference for COVID-19 itself (shown as “ALL”).

Table I shows the controversy scores for each topic by month. There are cells with dashes where the number of users did not reach the threshold of 800. We set the threshold of the high/low controversy score to 0.3 based on [9], and the ones that exceeded this score are shown in bold. First, the score for “ALL” is below 0.3 for the entire period, although there are some fluctuations over time. This means that no major controversy was detected for the topic of COVID-19 as a whole. Then, for “Olympic”, the controversy score is high in March and decreases in April. This result is interesting because the postponement of the Tokyo Olympics 2020 to 2021 was officially decided on March 24. It is agreed that the public debate was intense in March before the official announcement was made, and the controversy settled after the announcement in April. Following this, the debate on the Olympics gained momentum again in July because the Tokyo Olympics marked one year to the 2021 Games without little sign of COVID-19 abating, which also appears to align with the higher controversy score. We can see a gradual increase in controversy scores on vaccines from May to July. In May and June, the government started securing the vaccines for

https://olympics.com/en/news/tokyo-olympic-games-postponed-ioc
https://www.japantimes.co.jp/news/2020/07/10/national/politics-diploma/cy/high-risk-tokyo-olympics-coronavirus/
COVID-19 and the public debate peaked in July when the pharmaceutical companies such as Pfizer and AstraZeneca began announcing the results of their vaccine development, and this was widely reported in Japan. Interestingly, the controversy score on vaccines only increased when people realized that this issue was serious, although there had been a certain volume of tweets since March.

As for Go To Travel, the number of users was smaller than expected, and even the scores were less than expected. The score became measurable in July rather than May, which shows that many people tweeted about their use of Go To Travel, not their opinion on it. Also, the low scores are realized that this issue was serious, although there had been a certain volume of tweets since March.

report in April, which estimated 400,000 deaths if no action was taken. Overall, these results confirm that the degree of controversy aligned with the discussion in the mainstream media.

Additionally, in Figure 2, we show six examples of the networks used for calculating the controversy scores. The networks with high scores (subfigures 2a 2b 2c) and with low scores (subfigures 2d 2e 2f) were selected from Table I. We used the visualization tool Gephi with the layout algorithm ForceAtlas2 [25]. The colors indicate the clusters divided by the METIS algorithm. We can confirm that the two clusters with relatively small connections gain a high controversy score.

VI. WHICH COVID-19-RELATED TOPICS WERE CONTROVERSIAL?

In this section, we did not pre-specify the topics but automatically extracted the keywords indicating topics. Table II shows the top 10 controversial topics extracted by the proposed framework for each month. We added the English translation of each word (shown in brackets). The topics with controversy scores of more than 0.3 are shown in bold. For ones that exceeded the threshold, we also colored them according to the larger category we recognized: purple for government, pink for medical issues, green for economy, blue for education, and gray for others.

This table shows how controversies transition over time: governmental issues/policies are the main controversies in February (“Cherry blossom” indicates the cherry blossom viewing party, where immense suspicion revolved around the ex-prime minister Abe about inviting antisocial elements to his party); the concerns around economic activities emerged in March (“Live” and “Economy”); medical concerns emerged in April (“Medical” and “Mental”) as well as economic issues (“Subjects” indicate the subjects of the government’s support policy); the controversy on education issues exacerbated in May (“School,” “Teacher” and “Online”), and the medical experts meeting for COVID-19 received attention (“Expert”); the news on vaccines began going viral in June as stated in the previous section (“Vaccine”); the disastrous rain that
hit southern Japan\footnote{https://asia.nikkei.com/Economy/Natural-disasters/Torrential-rain-triggered-massive-flooding-in-southwestern-Japan} in July ("Disaster" and "Rain"); the controversial topics in August were already noticed in the previous months.

In general, governmental issues are always top on the list. Also, we could see some important topics associated with the terms economic issues, medical issues including vaccines, and educational issues. These controversial topics all conform to the public debates in the news media. Interestingly, each topic tops the list in turn. We wondered whether the shift of people’s interests produced general patterns, although this point could not be tested.

VII. What was the Scale and Sentiment of the Controversial Topics?

A. The correlation of controversy score with the scale and sentiment of topics

In this section, we analyze the topics with a high controversy score, using the traditional indicators of scale and sentiment, which are the de facto standard measures for social media analysis\cite{26}. For this purpose, we drew scatter plots shown in Figure\,\ref{fig:scatterplots}, in which each dot indicates a topic in a month. The number of users indicates the number of nodes for calculating the controversy scores for topics, which also indicates how substantial attention is gathered to the topics. We also calculated the mean and standard deviation (std) of the sentiment for each topic. Here, we used the standard deviation, not only the mean, because we assumed the sentiment would be polarized by clusters, i.e., positive on one side and negative on the other. We calculated the sentiment scores using Oseti\footnote{https://github.com/kkegami-yukino/oseti} a Japanese sentiment analyzer using major Japanese dictionaries\footnote{[accessed: 2021/05]}.

We did not discern strong correlations in these scatter plots. We calculated each correlation coefficient with the controversy scores and obtained $0.186$ ($p=0.002$), $0.086$ ($p=0.013$), and $0.039$ ($p=0.020$) respectively for the number of users, sentiment mean, and sentiment std. This result indicates that the controversy score is independent of these traditional indicators for social media analysis; hence this score offers another dimension for understanding the discussions taking place on social media. Primarily, it is interesting that the sentiment std and the controversy score are not strongly correlated. This implies that controversy that takes the form of an echo chamber is hard to detect by using only sentiment scores, which appears to enhance the value of the controversy quantification method.

B. The relationship between the scale and controversy scores for topics

In the previous subsection, we found little correlation between the size and the controversy of topics. This indicates that controversy does not necessarily occur in topics that attract the considerable attention of the public. In this subsection, we further compare and analyze large topics with high controversy scores and ones with low controversy scores. As before, the controversy threshold is set to 0.3, and we put the topic threshold size as 10,000 by referring to Figure\,\ref{fig:scatterplots}. Table\,\ref{tab:scatterplots} shows, for each month, the topics with users of 10,000, divided into groups with controversy scores greater than 0.3 and those with controversy scores less than 0.3. For visibility, we only included translated English words in the table.

The previous section shows that the high controversy group contains governmental, economic, and medical topics. Figure\,\ref{fig:scatterplots} shows that the low controversy group can also see the considerable attention of the public. In this subsection, we further compare and analyze large topics with high controversy scores and ones with low controversy scores. As before, the controversy threshold is set to 0.3, and we put the topic threshold size as 10,000 by referring to Figure\,\ref{fig:scatterplots}. Table\,\ref{tab:scatterplots} shows, for each month, the topics with users of 10,000, divided into groups with controversy scores greater than 0.3 and those with controversy scores less than 0.3. For visibility, we only included translated English words in the table.

The previous section shows that the high controversy group contains governmental, economic, and medical topics.
that the controversy scores depend on time. Some topics are uniquely found in the low controversy group. For example, the cruise ship topic in February dealt with the luxury cruise ship Diamond Princess\textsuperscript{13} which was anchored on Japanese shores during a round-the-world trip, and COVID-19 infections were found onboard. This became a major topic of discussion on whether to disembark the infected people because infection control measures were lacking in Japan during the time. Nevertheless, it did not become a controversial topic (controversy score=\textasciitilde0.208) because few opinions on social media strongly promoted disembarking the passengers. Next, “Mask” in April means “Abenomask”, a policy announced by ex-prime minister Abe, which was to distribute two masks to all households, but it was criticized because of the vast amount of money spent for it\textsuperscript{14}. Abenomask did not become highly controversial because there was no strong support for it on social media (controversy score=0.189). “Public Prosecutors Office law” was intensively discussed in May, but its controversy score was low (0.022). Ex-prime minister Abe sought to extend the tenure term of the superintending prosecutor of the Tokyo High Public Prosecutors Office, which was regarded as a forced measure to advance Abe’s political agenda. In addition, it was discovered that the prosecutor was gambling at mahjong with news writers, without social distancing, during the COVID-19 pandemic, which led to his resignation and further controversy.\textsuperscript{15} While “Cherry blossom” described in the previous section was also a scandal of sorts and the associated controversy extensive, the prosecutor’s case was less controversial. The difference is that “Cherry blossom” was only a suspicion, while the prosecutor’s case overwhelmingly aroused public opposition, and the controversy was low. The “Campaign” in July indicates “Go To Travel”, and as already mentioned, the controversy score was not significantly high for this topic (controversy score=0.219).

This result shows that public criticism does not necessarily increase the controversy score. For example, while Mask and Prosecutors received extensive criticism, their controversy scores were not high. This appears so because the criticism was overwhelming, and there were few positive opinions on these topics; thus, the controversy did not occur. In a sense, the controversy score is not suitable for the government for extracting only critical opinions from social media, not controversy.

C. The relationship between the sentiment and controversy scores for topics

Next, we look at the relationship between sentiment and controversy for the topics by investigating the controversy scores for those with a low sentiment. However, Figure\textsuperscript{3b} shows that when the level of low sentiment is less than -0.5 (the threshold we set by referring to Figure\textsuperscript{3b}), there are no topics with a high controversy score. Therefore, we examine all the topics with sentiment below -0.5 for each month in Table IV.

“Fatality” is observed to be present every month. This implies that strong negative sentiments always accompany

\begin{table}[h!]
\centering
\begin{tabular}{|c|c|c|c|}
\hline
Month & High controversy & Low controversy & Topics  \\
\hline
Feb. & Government & Cruise ship & Abe  \\
\hline
Mar. & Government & Economy & Opposition party  \\
\hline
& Prime minister & Medical & Abe  \\
\hline
Apr. & Government & Medical & State of emergency  \\
& & & Life  \\
& Abe & & Economy  \\
& Mental & & Crisis  \\
& & & Governor  \\
\hline
May. & Government & Medical & Abe  \\
& & Admin & Abe admin  \\
& & Public Prosecutors Office & law  \\
\hline
Jun. & Governor & - &  \\
\hline
Jul. & Government & Medical & Governor  \\
& & Campaign & Record high  \\
\hline
Aug. & - & Government & Diet  \\
& & & Abe  \\
\hline
\end{tabular}
\caption{Topics with a large number of users divided into a high controversy group and low controversy group.}
\end{table}

\textsuperscript{13}https://edition.cnn.com/2020/02/04/asia/coronavirus-japan-cruise-intl-hnk/index.html
\textsuperscript{14}https://asia.nikkei.com/Spotlight/Coronavirus/Will-Abenomasks-help-prevent-coronavirus-spread-in-Japan
\textsuperscript{15}https://mainichi.jp/english/articles/20200522/p2a/00m00na/012000c
people. The sentiment score identifies topics with a negative impact on disapproval for the same. This result confirms that the low speculation of a second emergency declaration and strong number of COVID-19 cases on the rise, there was widespread emergency was included in July. This indicates that with the sentiment. Also, a topic regarding the declaration of a state of emergency are particularly appealing to the public. In particular, we found topics on vaccines, mental health, restaurant closures, and children’s school attendance to be major controversies. It is easy for people to express their opinions on such topics. Against this, topics such as cruise ships were less controversial. This may be because people felt such topics were local occurrences and unfamiliar issues.

c) Topics that have not yet been concluded: The inconclusive issues are likely to get high controversy scores such as Cherry blossoms or the Olympic game before the announcement of its postponement. Conversely, the prosecutor scandal was not controversial because the opinion of one side was overwhelming. Also, the controversy of the Olympics was settled after the announcement.

B. Implications for decision makers

We compared controversy with sentiment and topic scale and found that controversy can be an indicator of an aspect that does not correlate with either. We hope that the use of this controversy score will be discussed more deeply in the context of evidence-based policy-making (EBPM) [29] or marketing [30] in the future. In addition, although we did not conduct a deeper analysis of what is discussed in the controversial topic, future researchers or practitioners can analyze the contents of topics using methods proposed in previous research [31] such as network extractive summarization which aims to find tweets that are representative of clusters.

C. Versatility of this framework

We used Twitter in this study. Twitter is indeed an appropriate platform for quantifying echo chambers because it is easy to create endorsement networks there. However, network-based echo chambers can be created on other platforms (e.g., Facebook [32]), which enables the proposed framework to be used there. Also, as the previous research mentioned [9], this method is independent of languages.

D. Limitations of the proposed framework

One of the major limitations of this framework is that it requires a certain number of users to measure the controversy score. Therefore, it is difficult to apply this method to topics that are too small. However, with sufficient data, analysis can be conducted on a smaller time scale instead of the one-month window that we set to compare topics. Also, since we measure the distance between clusters in the network, two clusters may not necessarily disagree. For example, when two clusters occur, both can be negative towards the mainstream but negative for different reasons, such as being critical of a policy instead of a political personality.

IX. Conclusion

In this study, we proposed a framework for discovering controversial topics in social media. In the experiment, we specified well-known topics related to COVID-19 in Japan and examined these controversy scores and their transitions over time. The results confirmed that the framework captured the controversial topics that well reflect current reality. In subsequent analysis, we used the framework without pre-specified

| Month | Topics |
|-------|--------|
| Feb.  | Cruise ship Passenger |
| Mar.  | Fatality |
| Apr.  | Fatality |
| May.  | Fatality |
| Jun.  | Fatality |
| Jul.  | State of emergency Record high Employee |
| Aug.  | Fatality |
topics to examine topics with high controversy scores. The results showed that topics on government, medical matters, economy, and education had high controversy scores. We also compared the scores with the scale and sentiment of the topics and found that the controversy score is minimally correlated with these traditional indicators. If we assume that public controversy is an important political topic, the controversy score can be one crucial indicator for gauging its influence. This study broadens the horizon of existing social media analysis and provides deeper insights for future research into social media.

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