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Twitter-Based Political Ideology Similarity Detection Across Countries

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***Abstract-* The abundance of accessible real-time user information generated from Twitter platform contributes to the utilization in multifarious research domains. In recent years, copious studies manage to classify social media users' latent attributes such as gender, age, and political orientation. In our research, we utilize a multilingual BERT model to create U.S. political dimension based on political activists' user vector embeddings, and project political user vectors from other countries to clarify transnational ideologies. We also build a classifier to categorize tweets into COVID-19 topics and other topics to check if the change of topic alters the political ideologies of the same users.**

I. INTRODUCTION

With regard to political ideologies classification problems, there are basically two types of methodologies, namely content analysis and network analysis, to dissect users' political tendencies revealed by their actions on social media platforms [1]. As the term suggests, Content analysis is to utilize the text, hashtags and so forth, with the assistance of classification algorithms such as support vector machine, to handle binary or multiclass classification tasks. Alternatively, network analysis focuses on retweet, mention and follower network relations, making use of homogeneity properties to categorize users.

Nevertheless, when attempting to detect cross-border political ideologies, difficulties encountered with the fact that users rarely retweet, mention or follow other users who post a language they cannot understand. Therefore, network-based methods are not the best choices to be made when there is a language barrier. In order to explore the possible political ideology similarity and compare the political polarization degrees across countries, this paper includes a multilanguage model, LaBSE, applied to generate language embeddings and to create a political ideology dimension in which the positions of Twitter users can be visualized.

II. MODEL DESCRIPTION

In recent years, transformer-based language models have become the state-of-the-art algorithms for many NLP tasks and BERT (Bidirectional Encoder Representations from Transformers) published by Google can be used for a wide variety of natural language tasks after proper fine-tuning processes. In 2020, a multilingual embedding BERT model, namely LaBSE (Language-agnostic BERT sentence embedding), was presented by google research [2]. This model is pre-trained on 17 billion monolingual sentences and 6 billion translation sentence pairs and is able to encode texts from 109+ languages into a shared embedding space. In this paper, we fine-tune the pre-trained LaBSE model on tweets posted by politicians of American to create a binary political ideology classification model, and to generate tweet embeddings.

III. DESCRIPTION OF DATASET

We adopt the senator-tweets dataset [3], which contains 99693 tweets made by 99 U.S. senators during the first year of Biden Administration, 2021. In this dataset, each tweet has been annotated a party label, either *Republican* or *Democrat*. For cross-border analysis, we also collect all tweets posted in 2021 by Spain, Italy, France and Japan politicians by means of Twitter API. After data preprocessing and fine-tuning, we use the model to compute the vector embeddings of each tweet. Then one user vector is calculated by taking average of all the tweet vectors where the tweets are posted by the same user. After receiving all of the U.S. senator user vectors, we are prepared to build the political ideology dimension.

IV. POLITICAL IDEOLOGY DIMENSION

Studies exploiting vector embeddings to build dimensions of various cultural meanings have proven a feasibility of constructing dimensions of other social meanings. Kozlowski et al [4] use word2vec vector embeddings to create affluence dimension, race dimension and so on, by taking differences of antonyms' vectors. Then the projection of other word vectors (e.g., sports vocabulary) onto these cultural dimensions reflects widely shared associations, and we can read out the degrees of these sports along various cultural aspects.

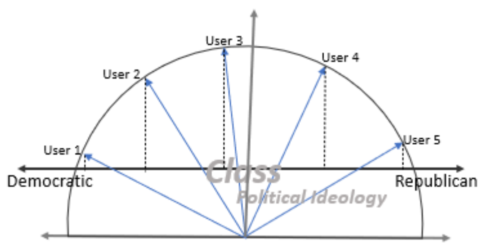

Fig.1 The projection of users onto political ideology dimension

Similarly, as shown in figure 1, we build our U.S. political ideology dimension by taking average of democratic and republican senator user vectors respectively, and project other users' vectors onto this dimension to visualize their polarization levels. We also build the political dimensions of Spain, Italy, France and

Japan by taking differences of left-wing user averages and right-wing user averages of their own countries' politicians respectively.

V. RESULT ANALYSIS

A. User projections

We take U.S. political ideology dimension as x-axis and political ideology dimension of other four countries severally as y-axis. After projection of political users of four countries onto these dimensions and assigning left-wing user points blue, right-wing user points red and neutral user points green, we can read from figure 2 that there is a clear rightward distribution of user vectors for Spain and Italy.

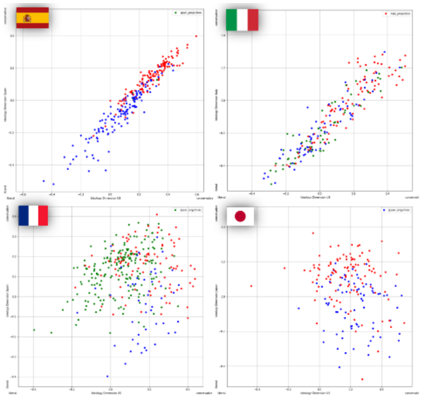

Fig.2 Politician projections on US political dimension

Therefore, it can be inferred that Spain and Italy are more polarized, with the left wing closer to American liberal ideology and the right wing closer to American conservative ideology.

B. A comparison with network analysis

We extract the retweet relationships among politicians in four countries respectively and calculate p-value based on the differences of the probability distributions between users who retweet others with same ideologies and users who retweet others with different ideologies. We also compute the distance differences between the medians of left-wing and right-wing distributions, derived by our projections on political ideology dimensions.

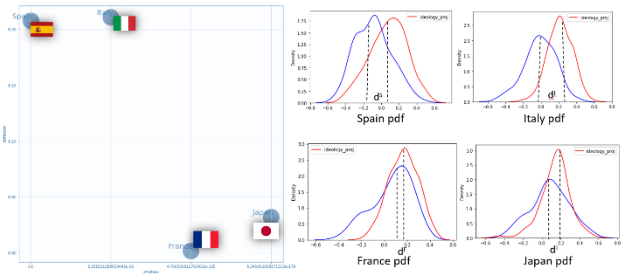

Fig.3 Network distribution differences VS Median distances

Figure 3 suggests that countries with fewer retweets across different political parties also have larger distance differences between left-wing and right-wing, which is coincident with our expectations.

C. COVID-19 topic dimension

We fine-tune another LaBSE model based on COVID-19 related dataset [5] to classify tweet contents as belonging to COVID-19 topic or non-COVID-19 topics, then we build the COVID-19 topic dimension. We project the U.S senators' user vectors on political ideology dimension and topic dimension at the same time to check if the ideologies alter for the same user when topic changes.

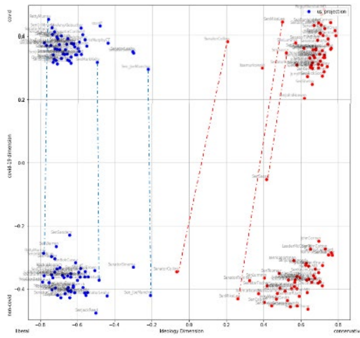

Fig.4 Position change of politicians on COVID-19 topics

The points on the top half of figure 4 shows the ideologies of these senators when they tweet about coronavirus contents, and the bottom half shows the ideologies of these senators when they post tweets of other topics. We draw dotted lines to connect the user points of the same person and infer that although the change in ideologies of democratic senators is trivial when it comes to COVID-19 problems, republican senators' opinions appear to be more conservative when they tweet about COVID-19 problems compared to other general topics.

VI. CONCLUSIONS AND FUTURE WORK

This paper presents an effective architecture to classify user political ideologies across borders by fine-tuning the state-of-the-art multilingual LaBSE model. According to the analysis of politicians from four countries, we show that political ideology similarity of different countries is able to be detected even when there is a language barrier.

We tend to include more topics in our analysis and to compare ideologies of people across countries on the same topics. We also intend to explore if the division and polarization in one country among certain different ideologies is an endemic phenomenon or the same in other countries in the future.

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