Stance Classification of Social Media Users in Independence Movements

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Abstract—Social media and data mining are increasingly being used to analyse political and societal issues. Characterisation of users into socio-demographic groups is crucial to improve these analyses. Here we undertake the classification of social media users as supporting or opposing ongoing independence movements in their territories. Independence movements occur in territories whose citizens have conflicting national identities; users with opposing national identities will then support or oppose the sense of being part of an independent nation that differs from the officially recognised country. We describe a methodology that relies on users’ self-reported location to build datasets for three territories – Catalonia, the Basque Country and Scotland – and we test language-independent classifiers using four types of features. We show the effectiveness of the approach to build large annotated datasets, and the ability to achieve accurate, language-independent classification performances ranging from 85% to 97% for the three territories under study.

Index Terms—social media, national identity, socio-demographics, classification.

1 INTRODUCTION

Social media are becoming an increasingly important source for data mining applications, among others for exploratory research utilised as a means to analyse political and societal issues [1], or for information and news gathering [2]. However, one of the problems with social media is the limited availability of users’ socio-demographic details that would enable developing data mining tools that take into account the many different realities in society [3]. Attempting to mitigate this issue, a growing body of research in natural language processing and data mining deals with the automated inference of socio-demographic characteristics such as age [4], [5], gender [5], [6], country of origin [7], political orientation [8], [9], occupational class [10], income level [11], socio-economic status [12] or a range of social identities [13]. The development of classifiers to determine the users’ socio-demographic characteristics can then be exploited in multiple applications that mine social media data, for instance to produce a breakdown of sentiment analyses by demographic group [14], or for recommending content that is relevant to a specific community.

Following this line of research, we describe and analyse a data collection and classification methodology that enables identifying two groups of social media users in territories with active independence movements: those who support the independence (pro-independence), and those who oppose it (unionists). Independence movements are motivated by conflicting national identities, where different parts of a population identify themselves as citizens of one nation or another, such as the Scots feeling Scottish or British, and hence wanting an independent Scotland or remaining in the United Kingdom. Independence movements occur in many territories worldwide, as is the case in Palestine [15], Kurdistan [16], Sicily [17], Scotland [18], Catalonia [19] or the Basque Country [20]. These situations lead to people with conflicting national identities living together in the same territory, where national identity can be defined as “a body of people who feel that they are a nation” [21]. Quantification and analysis of people with different identities is critical [22], and classification of users by national identity can be very useful to analyse and understand a range of political and societal issues [23].

Our study makes the following novel contributions: (1) we describe the task of classifying the stance of social media users as supporting or opposing the independence movement in their respective territories, (2) we describe a methodology that relies on Twitter users’ self-reported location for collecting users with conflicting national identities in their territory, (3) we describe the task of classifying the stance of social media users as supporting or opposing the independence movement in their respective territories, (2) we describe a methodology that relies on Twitter users’ self-reported location for collecting users with conflicting national identities, applicable to different territories and languages, (3) we look at the national identity rather than the largely studied partisanship or voting intention of users, and (4) we study language-independent classification approaches using four different types of features, not only looking at tweet content but also at interactions, the network, and a user’s favoured tweets. Our semi-automated data collection and annotation methodology enables us to collect datasets for three different territories – Catalonia, the Basque Country and Scotland – with over 36,000 users annotated for supporting or opposing stance towards the independence of their nation. Our experiments show that users’ network of followers and followees can lead to highly accurate classification of users, outperforming the use of tweet content.

2 DATA COLLECTION

Our data collection methodology relies on users’ self-reported location as a proxy for identifying the territory that users claim to be citizens of, which is directly indicative of their stance towards the ongoing independence movement in their territory. For each territory, we identify distinctive location names with which either supporters of independence or unionists associate themselves, which gives us
To generate the final dataset for Scotland, we used again the profile metadata of all sampled users. The location strings for the resulting user profiles were manually verified to make sure that they all satisfied our requirements. The methodology was largely accurate, with 96.0%, 95.9% and 98.9% correct instances for Catalonia, the Basque Country and Scotland, respectively. Those users that did not meet our expected locations – e.g. the location keyword EH for the Basque Country is also occasionally used by Canadians – were manually removed from the datasets. The resulting datasets consist of over 36,000 users (see Table 1).

| Location          | Pro-Independence | Unionists | Total  |
|-------------------|------------------|-----------|--------|
| Catalonia         | 2,361            | 8,599     | 10,960 |
| Basque Country    | 5,377            | 2,033     | 7,410  |
| Scotland          | 13,114           | 5,125     | 18,239 |
| TOTAL             | 20,852           | 15,757    | 36,609 |

TABLE 1: Distribution of users identified as pro-independence or unionists in the three datasets.

2.1 User Data Collection

For each of the users in our final dataset, we collect a set of data to perform the classification experiments with. We collected three different types of data for each user: (1) the 500 most recent tweets posted by the user, accessible through their timeline of tweets, (2) the 500 most recent tweets favourited by the user, and (3) the entire list of tweets that the user follows and is followed by. While the tweets favourited by a user have not been used much in previous work, we thought they could capture contents that users do not explicitly tweet about, but are in a more implicit way showing an interest in. With these three types of data we want to capture not only what users post about, but also their interests as expressed in tweets they have in mind. The network of users of which they are part. Experimentation with these three types of data, all of which are independent of the users’ self-reported location that we used for inferring the ground truth labels, enables us to analyse what characterises social media users in territories with independence movements in a way that we can categorise them by national identity. The final collection for the three territories comprises 27.4 million tweets including timelines and favourites, as well as 19.1 million different users occurring in follow networks.

3 Stance Classification in Independence Movements

3.1 Task Definition

We formulate the problem of determining the stance of users towards the independence movement in their territory as...

1. Note that tweets favourited by a user are not available through Twitter’s API, and were instead collected by scraping the web interface.
a binary, supervised classification task. Stance classification of social media users differs from the increasingly popular stance classification of texts [26] in that the stance is explicitly expressed in each text for the latter, while for users one needs to put together behavioural patterns extracted from historical features of their account. The input to the classifier is a set of users from a specific territory. To build the classification model, a training set of users labelled for one of \( Y = \{ P, U \} \) is used, where \( P \) refers to pro-independence users and \( U \) refers to unionists. For a test set including a set of new, unseen set of users, the classifier will have to determine if each of the users belongs to the group of supporters or opposers of independence, namely picking one of \( \hat{Y} = \{ P, U \} \). The classifier will ultimately split the test set into two groups of users with contrasting national identities, i.e. pro-independence and unionists.

We evaluate the output of the classifier using the accuracy, which computes the number of instances that are correctly classified divided by the total number of instances in the test set.

3.2 Classification Settings

We perform the classification experiments in a stratified, 10-fold cross-validation setting separately for each territory. We micro-average the scores to aggregate the performance across different folds and report the final accuracy scores. We use four different classifiers for the experimentation: Naive Bayes, Support Vector Machines, Random Forests and Maximum Entropy. We also use four different types of features for the classification, all of which are independent of the location string that we used for determining the ground truth:

1) **Timeline:** We use Word2Vec embeddings [27] to represent the content of a user’s timeline of most recent tweets. The model we use for the embeddings was trained for each territory using the entire collection of tweets. We represent each tweet as the average of the embeddings for each word, and finally get the average of all tweets.

2) **Interactions:** We consider that a user is interacting with another when they are retweeting or replying to them. We create a weighted list of all the users that are the target of the interactions in each of our datasets. Given the length of this list, we reduce its size by restricting to the 99th percentile of most common interactions. Each of the remaining users belong to a feature in the resulting vectors. For each user, we represent each of the features in the vectors as the count of interactions the user has had with the user represented by that feature.

3) **Favourites:** To represent the content of the tweets favourited by a user, we use the same approach based on word embeddings as for the timeline above, in this case using the content of the tweets favourited by a user instead. With the same embedding model, we average the word vectors for all the tweets favourited by a user.

4) **Network:** Similar to the approach used for interactions, we aggregate the list of users that appear in the networks (followees or followers) in each of our datasets. We restrict this list to the 99th percentile formed by the most frequent users in each dataset. For each user, we then create a vector with binary values representing whether each of the users is in the network of the current user.

4 Results

|                          | NB | SV | RF | ME |
|--------------------------|----|----|----|----|
| **Catalonia**            |    |    |    |    |
| Timeline                 | .940 | .954 | .955 | .944 |
| Interactions             | .841 | .935 | .960 | .946 |
| Favourites               | .919 | .932 | .932 | .923 |
| Network                  | .957 | .970 | .965 | .972 |
| **Basque Country**       |    |    |    |    |
| Timeline                 | .598 | .867 | .846 | .831 |
| Interactions             | .799 | .826 | .857 | .842 |
| Favourites               | .567 | .819 | .810 | .784 |
| Network                  | .889 | .881 | .885 | .903 |
| **Scotland**             |    |    |    |    |
| Timeline                 | .595 | .789 | .742 | .724 |
| Interactions             | .620 | .727 | .803 | .779 |
| Favourites               | .546 | .754 | .724 | .720 |
| Network                  | .588 | .828 | .830 | .849 |

Table 2: Stance classification results for Catalonia, the Basque Country and Scotland. NB: Naive Bayes, SV: Support Vector Machines, RF: Random Forests, ME: Maximum Entropy.

Table 2 shows the classification results for the three territories. They show that among the four feature types under study, a user’s network is the most indicative feature for determining their stance. This suggests that users belonging to different identity groups tend to be connected to different users on Twitter. The rest of the features are significantly behind the performance of network features, suggesting that the content they engage with and the people they interact with are not as indicative.

Among the classifiers under study, we find that the Maximum Entropy classifier performs better than the rest when network features are used. This is consistent for all three territories, achieving 0.972, 0.903 and 0.849 for Catalonia, the Basque Country and Scotland, respectively.

|                          | P  | R  | F1 |
|--------------------------|----|----|----|
| **Catalonia**            |    |    |    |
| Catalan (PI)             | .963 | .904 | .932 |
| Spanish (U)              | .974 | .990 | .982 |
| **Basque Country**       |    |    |    |
| Basque (PI)              | .941 | .924 | .933 |
| Spanish (U)              | .809 | .848 | .828 |
| **Scotland**             |    |    |    |
| Scottish (PI)            | .880 | .915 | .897 |
| British (U)              | .758 | .680 | .717 |

Table 3: Stance classification performance by national identity using the Maximum Entropy classifier and network features. PI: pro-independence, U: unionist.
### Table 4: Top distinctive keywords in timeline and favourited tweets for different territories and national identities.

| Favourites | Timeline |
|------------|----------|
| **Catalonia** | **Basque Country** | **Scotland** |
| Catalan | Spanish | Basque | Spanish | Scottish | British |
| vinos (wines) | via (via/way) | almutw (Twitter account) | alberguescamino (Twitter account) | caitlinday10 | girlnscotland |
| banderacatalana (Catalan flag) | dimensionvegana (Twitter account) | almunomtero (Twitter account) | curso (course) | xstephx3x | kxckit |
| xusram (Twitter account) | barcelona (city) | junkaletsegarai (Twitter account) | profesahorrador (Twitter account) | indyre | darthmattius |
| svqtovarich (Twitter account) | carolinamaiko (Twitter account) | maidenperales88 (Twitter account) | descuento (discount) | phdammarie | sermattius |
| iusevillacidad (Twitter account) | elseaquecatalan (Twitter account) | geroarural (Twitter account) | athletic (football team) | documentingyes | lunchquest |

Table 3 shows the results of the best-performing classifier (Maximum Entropy with network features) broken down by national identity. We observe F1 scores that are remarkably high for both national identities in Catalonia, as well as Basques in the Basque Country and Scots in Scotland. Performance drops slightly for the Spanish in the Basque Country and the British in Scotland, most likely due to the imbalance of classes in the datasets.

To further understand the results, we look into the features and their distribution across national identities. Table 4 shows the top keywords for each of the territories and national identities, extracted from the users’ timelines and favourited tweets. The top keywords are extracted by using the Kullback-Leibler Divergence (KLD) as a metric to compute the most indicative keywords of each national identity in comparison with its opposed national identity. This enables us to extract the most distinctive keywords with respect to the opposing national identity, rather than the most popular. The list of top keywords suggests that only few of them are actually related to either their national identity or to the pro- or anti-independence groups. There is a significant overlap in that both the pro-independence and unionists mention city names as well as vocabulary specific to social media such as user accounts or content liking or sharing. While some Twitter accounts are quite indicative, such as “elsaqueocatalan” in the case of the Spanish in Catalonia which is an anti-independence account, this does not suffice to achieve high performance. Both the overlap and lack of distinctive vocabulary across national identities lead to the difficulty of performing an accurate classification using either timelines and favourited tweets. The use of more sophisticated feature selection methods might help improve performance.

In Figure 1 we look at the interactions and network features by visualising connections within and across national identities. The layout of all graphs is computed with Gephi’s Force Atlas algorithm to make sure they are comparable. This analysis reveals a big difference in how interactions and follow networks are shaped. A look at the interactions shows that users of different national identities regularly interact with each other, with no clear separation between communities. However, when we look at the network visualisations, we see a totally different picture where users are mainly connected to users of the same national identity, with a clear separation between national identities, especially for Catalonia and the Basque Country. Indeed this suggests that pro-independence users are connected with one another, while unionists are connected within their own group too, with significantly fewer connections across communities. This emphasises the findings of our classification experiments, showing that network features are the best to classify users as pro-independence or unionists, however interactions are not as useful as interactions across communities are frequent.

5 Discussion

The methodology described here enabled us to gather large datasets that enable tackling the unexplored task of deter-
mining the stance of Twitter users towards independence movements, as well as a classifier that can determine this stance automatically. Our methodology and classifier have been tested in three territories with ongoing independence movements and conflicting national identities: Scotland, Catalonia and the Basque Country. Our classification experiments on the three territories show encouraging results with high performance scores that range from 85% to 97% in accuracy with the use of a Maximum Entropy classifier that exploits each user’s social network. Further to this experimentation and in a realistic scenario, the classifier trained from users whose self-reported location field reveals their national identity can then be applied to other users in that particular territory. Classification of users by national identity can then be exploited for further analysis of societal and political issues, as well as to target the segment of users in that particular territory.

Our plans for future work include further generalising the data collection and annotation approach introduced here so that it can also be extended to other territories with similar independence movements, such as Palestine or Kurdistan, or countries with varying perceptions of nationalism, such as people who identify themselves as English or as British in England \[31\]. While limited to binary classification in our experiments, we also plan to explore other scenarios that require considering a higher number of national identities (e.g. the UK’s four nations), as well as different levels of identities – e.g. only Basque, more Basque than Spanish, both, more Spanish than Basque, and only Spanish \[20\].

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