Politics, Sentiment and Virality: A Large-Scale Multilingual Twitter Analysis in Greece, Spain and United Kingdom

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Abstract

Social media has become extremely influential when it comes to policy making in modern societies especially in the western world (e.g., 48% of Europeans use social media every day or almost every day). Platforms such as Twitter allow users to follow politicians, thus making citizens more involved in political discussion. In the same vein, politicians use Twitter to express their opinions, debate among others on current topics and promote their political agenda aiming to influence voter behaviour. Previous studies have shown that tweets conveying negative sentiment are likely to be retweeted more frequently. In this paper, we attempt to analyse tweets of politicians from different countries and explore whether their tweets follow the same trend. Utilising state-of-the-art pre-trained language models we performed sentiment analysis on hundreds of thousands of tweets collected from members of parliament of Greece, Spain and United Kingdom, including devolved administrations. We achieved this by systematically exploring and analysing the differences between influential and less popular tweets. Our analysis indicates that politicians’ negatively charged tweets spread more widely, especially in more recent times, and highlights interesting trends in the intersection of sentiment and popularity.

Keywords: Politics, Twitter, NLP

1. Introduction

In recent years social media have come to resemble a ‘battleground’ between politicians who constantly aim to reach out to more people and win their votes. This behaviour is not surprising as the influx of people onto social media aiming to get updated on the latest news keeps growing, especially in the west with 48% of Europeans using social media on a regular basis [1]. More specifically, Twitter seems to have become established as the main online platform where politicians attempt to engage with the public in regards to social and political commenting [2], to such an extent that political accounts are often more active than non-political ones [3].

At the same time, thanks to the openness of Twitter’s API, Twitter data have been a major source for academic research in numerous fields. One of those fields deals with the sentiment analysis of tweets. Sentiment analysis, which itself is an important Natural Language Pro-
cessing (NLP) topic, has been utilized in Twitter with various degrees of success. One of the findings in related literature suggests that negatively charged tweets have a bigger network penetration than average \cite{4,5,6}. As to be expected, political tweets, due to their inherent interest, have been also extensively studied. However, even though there have been studies of sentiment in tweets revolving around politics/elections \cite{7,8,9,10}, to our knowledge there has not been a large-scale study of the relation between sentiment and the propagation of politicians’ tweets.

In this paper, we focus on politicians’ tweets to understand the relation between their sentiment and virality. By performing a more fine-grained analysis, a distinction is made between politicians from different political parties and we attempt to identify differences in their tweeting activities. At the same time, an investigation is performed on whether politicians’ behaviour, regarding their tweet sentiment, is independent of the country where they are politically active, and also whether it is consistent or evolves over time.

For this purpose, we bring together and assess the validity of these and other research questions (see Section \ref{sec:2}) with regards to politicians and Twitter by (1) collecting a large-scale dataset of recent tweets by members of parliament (MPs) in three different countries (Greece, Spain and United Kingdom) and multiple languages; (2) establishing a robust evaluation making use of state-of-the-art multilingual sentiment analysis models powered by the recent successes of transformer-based language models; and (3) performing a multi-faceted analysis including control experiments for robustness across different aspects including parties, time and location, among others.

2. Research Questions

The aims of this paper are summarized by the following three research questions.

RQ1. What is the best sentiment analysis classifier when dealing with political content in social media?. This question is mainly answered in Section \ref{sec:5}. To answer this question, we first constructed an ad-hoc sentiment analysis dataset with Twitter messages of members of parliament in Greece, Spain and United Kingdom. Then, we compared a wide range of settings and sentiment analysis models, including language models.

RQ2. Is there a correlation between virality and sentiment in political communication in social media?. This question is mainly answered in Section \ref{sec:6.1}. To answer this question, we relied on state-of-the-art sentiment analysis models (as tested in RQ1) and analysed a large corpus of almost 1 million tweets comprising all Twitter posts by members of parliament from Greece, Spain and United Kingdom. Then, we ran various statistical tests to measure and understand the possible correlation between virality and sentiment.

RQ3. Is there a difference in the sentiment of social media posts between (a) government and opposition, and (b) devolved parliaments?. These questions are mainly answered in Section \ref{sec:6.2} (a) and Section \ref{sec:6.3} (b). To answer these questions, in addition to analyse the data by all MPs in the main governments, we extracted and analysed data split by political party and extended to members of devolved parliaments in Spain (Catalonia and Basque Country) and United Kingdom (Northern Ireland, Scotland and Wales).

In addition to the specific sections where these research questions are addressed, we included relevant
control experiments in Section 7. These control experiments help put in context the prior research questions and provide extra insights about those. Finally, all our findings linked to these research questions are summarized in Section 8.

3. Related Work

The popularity of social media platforms such as Facebook and Twitter is transforming the way citizens and politicians communicate with one another. Political candidates and voters use Twitter to discuss social and political issues, sharing information and encouraging political participation [11]. Politicians in particular, especially in recent years, have eagerly embraced social media tools to self-promote and communicate with their electorate, seeing in these tools the potential for changing public opinion especially during election campaigns [12]. Given the rapid growth of politicians’ engagement through Twitter, there is plenty of research on how the platform is used for political communication.

Many studies across the globe focus on the classification of tweets referring to politicians by sentiment — positive, negative, or neutral — to investigate popularity and voting intention, and whether there is a correlation between post sentiments and political results [13, 14, 15]. Moreover, sentiment is considered to affect message diffusion in social media. Research suggests that the virality of a message — the probability of it being retweeted — is affected by its polarity, as emotionally charged messages tend to be reposted more rapidly and frequently compared to neutral ones [16]. Negative messages in particular are likely to be more retweeted than positive and neutral ones [17]. However, other studies show that the relationship between sentiment and virality in Twitter is more complex and is related to subject area [18]. Literature suggests that sentiment occurring in politically relevant tweets has an effect on their propagation [19, 20].

When considering techniques used to extract sentiment from political text in social media it is common to utilize dictionary based approaches [21, 22, 23] or in cases where the platform offers the functionality to react in one’s post (e.g. Facebook’s like/angry/happy reactions) then an aggregation of such reactions is used to determine the sentiment of the post [24, 25]. These approaches have the benefit of not requiring to train machine learning models for the sentiment analysis task which itself can be a time consuming process while also requiring previously annotated data. Other researchers chose to train their own ML models instead and often utilize neural network architectures such as LSTM and GRU networks [26, 27]. Despite the variety of methods utilized, there seems to be a lack of usage of state-of-the-art NLP methods like language models such as BERT [28] and RoBERTa [29]. In Section 5 we show how this makes an important difference in practice given the important improvement attained by language models in NLP in recent years.

Even though politics and social media is a popular research area, it is often the case that a lot of the research is US [30, 21, 23, 31] or UK [32] centric with work focusing on other countries and particular non-English speaking countries being limited (i.e. Russian: [26], Mexico: [25], cross-European: [22]). This can be explained by the importance that US politics have in a global scale as well as due to the lack of availability of political non-English datasets.

In our paper, we attempt to validate these claims and others in the recent political landscape. To this end, we
collect a large-scale dataset (see Section 4) and investigate the usage of state-of-the-art multilingual sentiment analysis classifiers based on transformers (see Section 5 for more details and a more detailed background on sentiment analysis), effectively running the first study of this scale.

4. Data Collection

For the purposes of this study, tweets were collected from the MPs (members of parliament) of three sovereign European countries, namely, the United Kingdom (UK), Greece and Spain, including several of their devolved parliaments: Northern Ireland, Scotland and Wales in the UK and the Basque Country and Catalonia in Spain for 2021.

The above countries were chosen because even though they share similar characteristics (e.g. they are all European) they have distinct attributes that makes a comparison between them more interesting. These distinctions are both linguistic, where English, Spanish and Greek are not closely related languages, and also socioeconomic. UK is a large European country both population and economy wise, Spain is a medium sized country and Greece is a less populated one with a smaller economy. Finally, due to the nature of the analysis, it is beneficial that our research team constitutes of researchers that have a good understanding of the languages as well as awareness of the political environments of the countries studied.

Furthermore, in order to establish relevant comparison points with respect to the specific time period examined, January to December 2021, and the general population, we collected additional Twitter corpora. These included (1) tweets from MPs from the UK’s national (London) parliament for 2014 & 2016, (2) tweets from random users from Greece, UK and Spain and (3) tweets from verified users residing in the aforementioned countries see Section 4.2 for more details.

In total 2,933,143 tweets were scraped from 157,333 users of which 2,213 represented members of the parliaments for the aforementioned countries. The total number of tweets acquired from politicians were 1,588,970. The collection of the tweets was achieved using Twitter’s API while utilising Python’s Tweepy [33] and Twarc [34] libraries. Retweets were ignored; only original tweets were considered, as the main metric to measure the popularity of a tweet (the retweet count) is not available on retweeted messages, which is crucial for our sentiment exploration. Finally, tweets that do not contain meaningful text, e.g., text contains only URLs, were also discarded.

4.1. Main 2021 MP Twitter Corpus

To compile our 2021 dataset, we extracted tweets from the members of parliament of the three sovereign countries analysed, i.e., Greece, Spain and UK and their devolved parliaments. Table 1 displays the total number of tweets collected for each of the months under study for all considered parliaments.

4.1.1. Parliaments of Greece, Spain and UK

Our main analysis focuses on tweets from members of the UK’s, Spain’s, and Greece’s parliaments from January to December 2021. For this time period, we scraped a continuous collection of tweets, 2021 Main Dataset, from 1,040 members of parliaments (UK: 577, Spain: 279, Greece: 184). The Twitter accounts of the

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1 We decided to include these devolved parliaments due to their size, idiosyncrasy and nationalist identity.
MPs were manually retrieved and verified using either their respective parliament official website or Google search. There are several cases where MPs do not own a Twitter account or they have a protected account which makes the retrieval of their tweets impossible. Consequently, our dataset is not necessarily proportional to the actual parliaments distributions, e.g., in the UK the governing Conservative party has a 56% of the total seats whereas in our UK dataset the Conservative party represents 54% of the total MPs. Finally, it is worth noting that Greek MPs tend to be the least involved with Twitter with only 61% of them actually having an active account in contrast to the UK's and Spanish MPs with 96% and 85% active accounts respectively.

Table 5 displays text statistics extracted from tweets of the three main parliaments. Specifically, the percentage of tweets that include emojis, hashtags, mentions, and URLs as well as the percentage of upper case characters are shown. The overall majority of the tweets (68%) contain at least one URL which is not surprising as sharing news and commenting on them is one of the main use case of Twitter. It is interesting to note that Greek MPs tend to use less emojis than their UK and Spain counterparts (44% and 40% less), while they include hashtags 44% more often. The above statistics are going to be utilized in our regression analysis in Section 6.1.

| Country | # | @ | emoji | url | up/lower |
|---------|---|---|-------|-----|---------|
| UK      | 0.05 | 0.23 | 0.23 | 0.66 | 0.10 |
| Spain   | 0.05 | 0.33 | 0.25 | 0.70 | 0.11 |
| Greece  | 0.09 | 0.27 | 0.14 | 0.72 | 0.12 |
| Overall | 0.05 | 0.27 | 0.23 | 0.68 | 0.11 |

Table 2: Percentage of tweets that include hashtags (#), mentions (@), emojis, and URLs in the UK, Greece, Spain 2021 main parliaments. The upper to low case ratio (upp/lower) average of tweets texts is also reported.

4.1.2. Devolved Parliaments

Tweets from members of the devolved parliaments of the UK (N.Ireland, Scotland, Wales) and Spain (Basque Country, Catalonia) were also collected for the same time period. These subsets, 2021 Devolved Dataset, are used to identify potential differences in tweets between the main and the devolved parliaments regarding the prevailing sentiments. Again, a manual search and verification was applied for every MP in order to retrieve his/her Twitter handle. Specifically for Catalonia, care was taken when aggregating the MPs handles.
4.2. Control Datasets

4.2.1. UK parliament 2014 & 2016

Aiming to explore the sentiment trends we added a temporal element in our analysis by collecting tweets from UK’s MPs for the years of 2014 and 2016. In this case, the MPs and their respective handles were collected by utilising the SPARQL \[33\] endpoint of Wikidata \[36\]. In total 202,954 and 429,538 tweets were extracted for 2014 and 2016 respectively. It should be mentioned that the number of Twitter handles scrapped for each year was smaller than that of 2021; 156 and 474 handles for 2014 and 2016 respectively in comparison to 577 for the 2021 UK dataset. The increased popularity of Twitter over the years can potentially explain the larger number of handles for 2016 and 2021 over 2014. However, this might also be due to limitations of the Wikidata archive.

4.2.2. Random & Verified Users 2021

To compare politicians’ tweets with those of the general population for 2021, two distinct sets of tweets of random and verified\(^2\) users were also collected (each for any of the country’s parliament studied — Spain, Greece, the UK). Verified users accounts usually belong to recognisable figures such as brands, organisations, and influential persons (e.g. athletes and artists) whose Twitter activity can be deemed to be closer to that of MPs. Each set of random users follows the same distribution of tweets of their respective country shown in Table 1. The geolocalization of tweets was achieved using Twitter’s API country filter (‘place\_country’). An assumption was made that tweets belong to users that reside to the country they are posting from. The verified users set was constructed by extracting tweets only from a list of verified users and combination of keywords\(^3\) alongside with information on the location from user profiles metadata was applied to ensure the accounts resided in the countries studied.

4.3. Sentiment Annotation

Tweets from the 2021 Main Dataset (Section 4.1.1) for each language included in the study were sampled for their respective parliaments. This way three datasets were collected and annotated based on their sentiment for the English, Spanish and Greek languages (Annotated Set).

In sentiment annotation tasks, annotators are asked to either evaluate the overall polarity of the text on scale, e.g., 1 to 5 \[37\] or to distinct positive/neutral/negative classes \[38\]. For simplicity and to follow current state-of-the-art sentiment analysis models \[39, 40\], in our setting annotators were asked to indicate the sentiment of each tweet and classify it in one of the following classes:

- **Positive**: Tweets which express happiness, praise a person, group, country or a product, or applaud something.
- **Negative**: Tweets which attack a person, group, product or country, express disgust or unhappiness towards something, or criticise something.

\(^2\)According to Twitter, an account is deemed verified if it is authentic, notable and active (https://help.twitter.com/en/managing-your-account/about-twitter-verified-accounts).

\(^3\)https://github.com/cardiffnlp/politics-and-virality-twitter/blob/main/data/keywords.csv
• **Neutral**: Tweets which state facts, give news or are advertisements. In general, those which don’t fall into the above 2 categories.

• **Indeterminate**: Tweets where it is not easy to assess sentiment or sentiments of both polarities of approximately the same strength exist. Tweets annotated with the indeterminate label were discarded from our analysis.

For each set of tweets three native speakers were assigned as annotators. Initially 100 tweets were sampled for each language and were given to each group of annotators. The annotators were advised to consider only information available in the text, e.g., to not follow links present, and in cases where a tweet includes only news titles to assess the sentiment of the news being shared.

Table 3 displays the inter-annotation agreement based on Cohen’s Kappa [41]. It is observable that for all three language sets the agreement between annotators is satisfactory with the lowest score, 0.69, being in the Spanish set when considering entries labelled as ‘Unidentified’ too. It is also worth noting that the divergence between positive and negative labels (which could be the most problematic in our subsequent analysis) was extremely low. Only 9% (Greece), 3% (Spain) and 7% (UK) of all annotated tweets had a contrasting positive/negative or negative/positive labels between any annotator pair. Finally, in order to consolidate the annotations, the final label of each tweet was decided by using the two annotators agreement in each group and in cases of differences the third annotator was used as a tiebreaker.

Having establish an acceptable agreement between the annotators each one was given 300 extra tweets to label. In total, 964, 936 and 963 tweets were collected and labelled for English, Spanish and Greek respectively (the final numbers slightly vary given the different number of discarded tweets with the indeterminate label).

5. **Sentiment Analysis: Evaluation and Model Selection**

Sentiment analysis is an important NLP task often used to create detailed profiles of users behaviours and their world views. It has been extensively used by companies to infer user’s preferences and their attitudes towards products and services [42] in order to implement an optimal marketing strategy. With the explosion of popularity of social media, and the inevitable turn of marketing funds from traditional media to them, sentiment analysis remains an invaluable tool for companies and organisations to acquire an understanding of their customers loyalty and how they’re brand is perceived to the public [43]. However, the value of sentiment analysis is not only appreciated in commercial settings. It has been successfully used on numerous social topics varying from tracking the public’s perspective towards the Coronavirus pandemic [44] and to investigate gender stereotypes [45] to provide insights on how voters view their political representatives [46].

Over the years there have been multiple approaches of dealing with sentiment analysis in text data. Varying from the use of sentiment lexicons [47, 48, 49] to utilising linear machine learning models [50] and, most recently, by applying transformer models like BERT [28].

|                | UK  | Spain | Greece |
|----------------|-----|-------|--------|
| Including Unidentified entries | 0.72 | 0.69  | 0.72   |
| Excluding Unidentified entries  | 0.74 | 0.75  | 0.76   |

Table 3: Inter-annotator agreement based on Cohen’s Kappa
One of the most challenging problems appears when we have to deal with multilingual data. Acquiring a model that is able to perform well on a multilingual setting is a difficult task that often requires large labelled corpora. This stands especially if low sourced languages are taken into consideration [51]. Some cross-lingual approaches, such as language models, deal with this issue by making use of the large amount of training data available in major languages, e.g. English, to essentially transfer sentiment information to low resource languages, e.g. Greek [52]. It is also important to note that despite which architecture is being used an important factor to achieve accurate sentiment classification is the domain of the train and the target corpus [53].

In our use case, we select a number of pre-trained language models, both monolingual and multilingual, which we attempt to further finetune and evaluate them using the manually labelled tweets dataset retrieved (Section 4.3) aiming to find the best suitable classifier for each language (English, Spanish, Greek) studied.

5.1. Experimental Setting

5.1.1. Data

For the training purposes six different datasets are sourced. For each language their respective set of annotated tweets, Annotated Set (in-domain, see Section 4.3), is being utilised along with another language specific datasets for each language (out-domain): the sentiment analysis dataset from ‘SemEval-2017 Task 4’ [54] is acquired for English (out-domain for English); the InterTASS corpus [55] for Spanish (out-domain for Spanish); and a sentiment dataset constituted of tweets related to the 2015 Greek elections for Greek (out-domain for Greek) [56]. These additional sources are used only for training purposes. All the datasets have been constructed for the specific task of Twitter sentiment analysis where each tweet is classified as either Positive, Negative, or Neutral. All Twitter handles are anonymized by replacing them by ‘@username’.

5.1.2. Training/Evaluation

We consider two different approaches to evaluate our models. Firstly, a train/validation/test split method is applied. The testing data are the subset of tweets from Annotated Set that are cross-annotated by all annotators (approximately 100 tweets for each language), the rest of the entries (approximately 900 tweets per language) are used for training and validation with a 85/15 train/validation ratio. The cross-annotated subsets are used for testing as it is assumed to be more precise than the larger subset annotated by a single person.

Secondly, due to the relatively small size of the Annotated Set a 5-fold cross-validation method is also applied where the whole dataset is used. In cases where a multilingual model is trained, the combined Annotated Set is used along with a stratification method that ensures that all languages are equally represented in each fold. This cross-validation experiment is set to complement the evaluation done in the single train/test split, which may be limiting [57].

5.1.3. Comparison systems

Multiple transformer-based language models, including domain-specific models which are state of the art in Twitter-related classification tasks [58] are selected for our experiment.

1. XLM-R [59], is pre-trained on a large multilingual corpus containing 100 languages (CommonCrawl [60]).
2. XLM-T further trained on 198 million multilingual tweets.

3. XLM-T-Sent, similar training to XLM-T but further finetuned for multilingual sentiment analysis.

4. Three different RoBERTa-Base implementations for each language studied: roberta-base and palobert-base-greek-uncased-v1 for English, Spanish and Greek respectively.

5. TweetEval-Sent trained on 58 million English tweets and finetuned for sentiment analysis with the English SemEval-2017 dataset.

6. Bertweet-Sent, based on the Bertweet implementation and further finetuned for sentiment analysis.

All the models are based on the implementations of the uncased versions provided by Hugging Face, and further finetuned and tested for each language individually, as well as in a multilingual setting using the data collected.

In order to assess the difference between these recent transformer models with more traditional approaches, three baseline models were tested: (1) an SVM model using a combination of frequency features, TF-IDF, and semantic, based on the average of word embeddings (2) a neural network with two LSTM layers while also utilizing pretrained word embeddings and (3) a lexicon based approach by utilizing VADER.

5.1.4. Optimization

All models were trained with the same set of hyper parameters. Specifically, Adam optimizer and a linear scheduler with warmup are applied. We warm up linearly for 50 steps with a learning rate of 5e-5, while a batch size n=16 is used. The models are trained up to 20 epochs, with a checkpoint in every epoch, while an early-stop callback stops the training process after 3 epochs without a performance increase of at least 0.01. We select the best model out of all the checkpoints based on their performance on the validation set.

5.1.5. Evaluation metrics

We report results both in the usual macro-average F1 and the F1 average between positive and negative classes (F1PN henceforth). For sentiment analysis tasks the average of the F1 scores of the Positive and Negative classes is often used as an evaluation measure instead of other metrics such as Accuracy. This is mainly justified as firstly F1 scores are more robust to class imbalance, and secondly due to the fact that classifying correctly Positive and Negative classes is more crucial than the Neutral class, especially in our subsequent analysis.

5.2. Results

Table 4 displays the average F1 score for only the Positive and Negative classes F1PN of the models trained in 5-fold cross-validation experimental setting (More detailed results can be found in Table B.9 in the Appendix). The performance of the classifiers varies depending not only in their architecture but also on the data that they are trained on. In the UK dataset, the default implementation of ‘Bertweet-Sent’ outperforms all the other models achieving a F1PN of 83%. For Span-
ish tweets the multilingual version of ‘XLM-T-Sent’ performs the best with F1$^\text{PN}$ cross-validation score of 81%. Finally, when considering the Greek dataset the results are not as clear as in a cross-validation setting the multilingual implementation of ‘XLM-R’ seems to perform better (F1$^\text{PN}$=78%) while in the train/test split setting the implementation of ‘XLM-R’ trained only on both Greek datasets (out-domain and Annotated Set) performs the best while achieving a similar score.

5.3. Model selection

Considering our use case, classifying tweets from members of parliaments in different countries, we decided against the use of mono-lingual models such as ‘Bertweet-Sent’\textsuperscript{6} for two reasons: (1) there is no certainty that a tweet will follow the same language as the main language of the parliament, e.g., Welsh tweets in the UK parliament, Catalan tweets in the Spanish parliament, Turkish tweets in the Greek parliament; and (2) using a multilingual model will make the comparison across countries easier. As such, for the purposes of our experiment, the multilingual implementation of ‘XLM-T-Sent’ fine-tuned on our in-domain data is selected as a classifier and applied across all of the data collected. Our choice is further justified as the selected option produces consistently strong results in all countries (73%, 87%, 76% F1$^\text{PN}$ score for UK, Spain and Greece, respectively, when considering the train/test split setting), including state-of-the-art results for Spanish and Greek.

6. Analysis

Having acquired a suitable sentiment analysis classifier capable to successfully distinguish sentiment polarity in MP tweets (see Section 5.3) we applied it to our collected Twitter corpora (see Section 4) and perform an in-depth analysis aiming to explore whether politicians’ tweets containing negative sentiment have a bigger network penetration than tweets that are positive or neutral.

Initially, we attempt to establish what is considered a ‘popular’ tweet in the context of our analysis. Table 5 displays the percentiles of how many times a tweet has been retweeted for the UK, Spanish and Greek parliaments (2021). It is noticeable that the vast majority of tweets are retweeted only a few times; 75% of tweets having a retweet count below 40 across all parliaments, indicating a long tail in the distribution of the retweets count. In our analysis, we consider a tweet to be ‘popular’ and to belong in the ‘Head’ of the distribution when it is included in the top 5\textsuperscript{th} percentile of the retweets count. On the other hand, a tweet is labelled as ‘not popular’ and it belongs in the ‘Tail’ of the distribution when it falls under the 50\textsuperscript{th} percentile.

6.1. Sentiment and Virality

To directly answer the research question RQ2, we investigate whether there exists a correlation between retweets count and sentiment based on our collected data (see Section 4) and sentiment analysis classifiers (see Section 5).

6.1.1. Correlation analysis

In our initial attempt to answer RQ2, we ran several correlation experiments based on statistical testing and regression analysis. For the purposes of these experi-

\textsuperscript{6}In Section 7.4 we further present a control analysis in which we compare the trends between our selected multilingual model and the best performing ‘Bertweet-Sent’ in English.
Table 4: Average F1 scores of positive and negative classes (F1\textsubscript{PN}) when trained/evaluated with 5-fold cross-validation. The results displayed are the averages of three runs. Models were trained on both 'in' and 'out' of domain. Both multilingual and monolingual train-setting results are reported.

| Train setting | Model       | UK | Spain | Greece |
|---------------|-------------|----|-------|--------|
| Monolingual   | XLM-T       | 80 | 80    | 73     |
|               | XLM-T-Sent  | 80 | 81    | 75     |
|               | XLM-R       | 74 | 80    | 73     |
|               | RoBERTa-Base| 80 | 80    | 49     |
|               | TweetEval-Sent| 81 | -     | -      |
|               | Bertweet-Sent| 82 | -     | -      |
|               | SVM         | 61 | 58    | 44     |
|               | LSTM        | 67 | 60    | 57     |
|               | VADER       | 64 | 63    | 58     |
| Multilingual  | XLM-T       | 81 | 80    | 75     |
|               | XLM-T-Sent  | 80 | 81    | 77     |
|               | XLM-R       | 78 | 76    | 76     |
| Random - Baseline | 33 | 30 | 27     |

Table 5: Percentiles of retweet counts for UK, Spanish and Greek parliaments from January to December 2021. Highlighted are the percentiles used for determining if a tweet belongs in the ‘Head’ or ‘Tail’.

| Parliament/Pct | 0% | 25% | 50% | 75% | 95% | 100% |
|----------------|----|-----|-----|-----|-----|------|
| UK             | 0  | 0   | 2   | 9   | 52  | 36689|
| Spanish        | 0  | 1   | 5   | 36  | 185 | 25132|
| Greek          | 0  | 0   | 3   | 9   | 28  | 3357 |

Statistical Testing. As the comparison includes numerical (retweets count) and categorical values (sentiment) approaches such as the Spearman’s correlation are not suited. Instead we perform a Chi-Square test which indicates the existence of a dependency between popularity and sentiment. Then the Kruskal-Wallis H-test is performed on the retweets count populations for Positive, Negative and Neutral charged tweets to test whether their median values differ. Our test clearly confirms the existence of a difference in the distributions of the populations among sentiment labels (\textit{p-value} < 10^{-16}, \textit{a}=0.05\textsuperscript{7}) Even though there is no evidence for direct correlation, we manage to establish that there is a relation between sentiment and popularity, and also that retweets count distributions differ between sentiment labels.

Regression Analysis. To complement the statistical tests multiple regression models are fitted and the significance of sentiment is examined\textsuperscript{8}. In our experimental setting, the retweet count is set as the dependent variable while the existence (or not) of positive and negative sentiment constitutes the independent variables. Neutral sentiment is not taken into account in order to avoid potential collinearity problems. Furthermore, we utilize four lexical statistics (Table 2) as control variables. Specifically, the presence of emojis, URLs, hashtags (#), and mentions (@) in a tweet are used as binary variables\textsuperscript{9}. We did not consider features such number of followers, favourite count or time posted as our main focus was to identify the importance of features extracted from text.

Due to the nature of the problem at hand, i.e. modelling a count variable, and to the highly skewed distribution of the target (see Table 5) we test a negative binomial regression model (NBR) and a zero inflated vari-
ation of it (zero-NBR). Previous research suggests that NBR models and the zero inflated variations can be successfully used to estimate tweets popularity (i.e. retweet count) [69, 70, 71]. NBR is a generalised linear model used for modelling count data where the dependent variable is assumed to follow the negative binomial distribution. In contrast to Poisson regression, which is also used to model count variables, NBR does not make the assumption that the mean is equal to variance making it more robust when dealing with overdispersed data. 

For our setting we train six different NBR models using both the combined dataset of the UKs, Spanish and Greek parliaments and data from each individual parliament. The results of both NBR and zero-NBR models (Table 6) indicate that both negative and positive sentiment are statistically significant in predicting the retweet count of a tweet. At the same time, when considering the coefficients of the two variables we can observe that negative sentiment is assigned a greater weight than the positive sentiment with both models assigning coefficient over 5 times larger to negative sentiment when trained on all three parliaments. In fact, for the UK parliament positive sentiment has even an overall negative impact on the retweet count. Finally, it is interesting to note that even though every feature tested appears to be statistically significant, the negative sentiment appears to be the most effective on spreading a tweet.

To verify our regression results we also test a Poisson regression and zero inflated Poisson regression models. Poisson regression is also a generalised linear model that assumes that dependent variable follows the Poisson distribution. Similar to NBR it is used to model count data but makes stricter assumptions (mean = variance). Both implementations confirm our original results indicating that while both negative and positive sentiments are significant, negative sentiment appears to be larger factor on the tweet popularity. Finally, a simple ordinary least square model (OLS) is used while using the softmax outputs of XLM-T-sent as dependent variable. For each tweet we select the highest softmax score (only negative or positive scores are considered) and assign negative and positive signs to each sentiment respectively. By combining the two variables we acquire an overview on the overall impact of sentiment and model confidence (not only the final labels) on the tweets popularity. Similar to the previous experiments the OLS model identifies the sentiment score as significant and assigns a negative weight implying that the more negative a tweet is the more likely is to be shared. Detailed results of all the models tested can be found in the Appendix (Tables B.10 & B.11).

6.1.2. Head and tail distribution analysis

For this extended analysis, we consider the tweets made from politicians of the main parliaments of the UK, Spain, and Greece separately, and compare them based on their popularity following the ‘Head’ and ‘Tail’ partitions presented at the beginning of the section. Figure 1 displays the normalized counts of positive, negative and neutral tweets in the 2021 Main Dataset. Looking at the overall tweets distribution, negative account for a higher percentage for the Spanish and Greek parliaments whilst the reverse is true for the UK. However, when comparing the most ‘popular’
tweets (‘Head’) to those having only a small number of retweets count (‘Tail’), there is clear pattern with negative charged messages being more numerous for all parliaments. For the UK parliament when comparing the ‘Head’ and ‘Tail’ sets, the proportion of negative tweets is higher for the most ‘popular’; ‘Tail’ tweets with negative emotion are 65% less than those of the ‘Head’, whilst positive tweets display a 121% increase between ‘Head’ and ‘Tail’. Similarly, negative tweets are 71% and 88% more numerous in the Spanish and Greek parliaments, respectively, when comparing most to least popular tweets.

### 6.2. Governing Party vs Opposition

Figure 2 presents the difference in sentiment for the top five major parties (based on the number of MPs) in the UK’s, Spain’s and Greece’s parliaments for 2021. Taking into account the governing parties of each country (UK: Conservatives, Spain: Spanish Socialist Workers’ Party (PSOE) & Unidas Podemos (UP), Greece: New Democracy) a distinctive trend appears. In each country, the main governing parties tweets tend to be significantly more positive than those of the opposition.

In the UK, there are 46% more positive tweets than negative posted by the ruling party (Conservatives) whereas only a 10% difference for the main opposition (Labour party). The same pattern appears for Greece with positive charged tweets posted by New Democracy being 28% more than the negative. At the same time, the opposition party, Syriza, being on the ‘attack’ has 59% of its total tweets posted classified as negative. Similarly,
Table 7: Overall, Head & Tail distributions of sentiment for the datasets utilized. Numbers in the table correspond to the percentage of tweets labeled as negative and positive for each subset.

| Source | Year | Country   | Overall | Head | Tail |
|--------|------|-----------|---------|------|------|
|        |      |           | Neg | Pos | Neg | Pos | Neg | Pos |
|        |      | Parliament|      |      |      |      |      |      |
|        | 2014 | UK        | 29  | 41  | 43  | 24  | 27  | 46  |
|        | 2016 | UK        | 29  | 46  | 48  | 31  | 27  | 47  |
|        |      | -N.Ireland| 36  | 44  | 48  | 34  | 39  | 41  |
|        |      | -Scotland  | 31  | 53  | 60  | 27  | 26  | 57  |
|        |      | -Wales     | 22  | 60  | 37  | 49  | 23  | 60  |
|        |      | Spain      | 50  | 39  | 71  | 25  | 41  | 45  |
|        |      | -Catalonia  | 41  | 52  | 68  | 28  | 34  | 58  |
|        |      | -Basque    | 56  | 34  | 75  | 22  | 54  | 36  |
|        |      | Greece     | 41  | 33  | 66  | 24  | 35  | 34  |
|        | 2021 | UK        | 30  | 51  | 27  | 54  | 31  | 51  |
|        |      | Spain      | 46  | 39  | 43  | 43  | 46  | 38  |
|        |      | Greece     | 25  | 26  | 28  | 40  | 26  | 25  |
|        |      | Verified   |      |      |      |      |      |      |
|        |      | UK        | 23  | 43  | 34  | 38  | 21  | 45  |
|        |      | Spain      | 31  | 39  | 45  | 34  | 31  | 38  |
|        |      | Greece     | 38  | 42  | 38  | 45  | 39  | 41  |

For Spain, even though to a smaller degree, PSOE display the biggest contrast between positive and negative tweets with only a 6% difference in favour of positive. On a final note, it is interesting to observe that the VOX and Greek Solution, two right-wing parties, display the largest percentages of negative tweets for their respective parliaments (60% and 79%).

This behaviour becomes even more apparent when we take into consideration only the tweets from the leaders of the governing and opposition parties (Table 8). The UK’s Prime Minister (Boris Johnson) shares a considerably larger percentage of positive tweets compared to the opposition leader Keir Starmer (79% vs. 58%) and only 5% of his tweets being negative, in contrast to the 35% for Keir Starmer. An even bigger contrast is seen between the political leaders in Spain where 84% of all tweets from President Sánchez are negative, compared to only 30% from the opposition leader Pablo Casado. In Greece the trend is similar, with a high contrast of positive/negative tweets between the Prime Minister Mitsotakis and the opposition leader Tsipras (77%/17% vs. 29%/59%).

These observations support the hypothesis that politicians use Twitter to promote their agenda and influence the public. Not surprisingly, the governing parties try to depict a positive image of the state of their country. In contrast, the opposition parties challenge the same positions by using negatively charged tweets.
Figure 2: Sentiment per party for tweets from the UK, Spanish, Greek parliaments 2021. Top five parties displayed, ordered from left to right by their seat number.

| Parliament | Party              | Name               | Neg | Neu | Pos |
|------------|--------------------|--------------------|-----|-----|-----|
| UK         | Conservatives      | Boris Johnson      | 5   | 16  | 79  |
|            | Labour             | Keir Starmer       | 35  | 7   | 58  |
| Spain      | PSOE               | Pedro Sánchez      | 13  | 3   | 84  |
|            | PP                 | Pablo Casado Blanco| 63  | 6   | 30  |
| Greece     | ND                 | Kyriakos Mitsotakis| 17  | 6   | 77  |
|            | Syriza             | Alexis Tsipras     | 59  | 12  | 29  |

Table 8: Sentiment distribution for government leaders (Johnson, Sanchez, Mitsotakis) and opposition (Starmer, Blanco, Tsipras) leaders.

6.3. Devolved Parliaments

Aiming to acquire a more detailed representation for each country, we applied our sentiment analysis pipeline to the devolved parliaments of the UK (N.Ireland, Scotland, Wales) and Spain (Catalonia, Basque country). Table 7 displays the sentiment distribution (Overall, ‘Head’ and ‘Tail’) in the main and devolved parliaments for each country. The devolved parliaments of the UK follow a similar pattern as its main parliament, with more positive than negative tweets overall. In contrast, for the Spanish parliaments there is no consistent pattern with the Basque and main parliaments being dominated by negatively charged tweets whereas in the Catalan parliament the tweets tend to be more positive inclined.

Irrespective of these differences, all the devolved parliaments seem to follow the same general trend where tweets conveying negative sentiment travel further. Similar to their respective main counterparts, we observe that in the ‘Head’ of each devolved parliament negative tweets tend to be more numerous than positive ones. The only exception being the Welsh parliament (Senedd) where positive tweets are the majority (49% positive to 37% negative). These findings provide more evidence to the hypothesis of a higher network penetration of negatively charged tweets. It is worth noting that both for the Catalan and Basque parliaments our sentiment model classifies as Neutral only 7% and 9% of the total entries which may indicate a higher number of polarised tweets. Moreover, in these regions we can find a more frequent use of less-resourced languages which the sentiment analysis model may find it harder to deal with: Catalan (62% of all entries) and Basque (27% of all entries).

7. Control Experiments

In this section, we present four additional control experiments to test the robustness of our evaluation.

7.1. Popularity metrics

In addition to the raw retweet counts, we also tested additional metrics of popularity to divide the tweets in ‘Head’ and ‘Tail’. As the retweet count is an absolute measure that does not take into account the existing popularity of the user posting a tweet, it may be
skewed to favour users with a big number of followers. We attempt to incorporate the popularity of each user and explore whether there are differences in the sentiment trend when using normalized metrics. To achieve this, three new metrics are introduced: (1) the ratio between the retweets count and the follower count of the user; and (2) the ratio of the retweets count to the average number of retweets of the user. This way, a heavily shared tweet from a user that tends to get only few retweets will be considered more ‘popular’ than a similar tweet originating from a user that is retweeted often. Finally, we also consider a third popularity metric where a tweet is considered to be viral if its retweet count is at least two standard deviations above the mean for its creator.

These three metrics offer an alternative and more normalized view of popularity.

Figure 3 displays the results of the sentiment distribution for ‘Head’ and ‘Tail’ for the UK’s, Spanish and Greek parliaments using the different popularity metrics. The trends for the four metrics are largely similar, with negative-charged tweets being more popular in all cases. Having established that all four popularity metrics verify the underlying phenomenon, the total retweets count is used as a metric for the rest of our analysis.

7.2. Politicians Vs General Population

We continue our exploration by investigating whether politicians’ tweets spread in the same manner to the general public by comparing the 2021 Main Dataset with a collection of tweets from random and verified users (see Section 4.2.2 for more details). Figure 4 displays the difference in the sentiment of the tweets amongst these groups for the ‘Head’ and ‘Tail’ of popularity distribution. In contrast to politicians’ tweets, the general population seems to post more positive tweets overall. Moreover, positive tweets are significantly more retweeted in comparison to negative by a big margin. When only considering the most popular tweets (‘Head’), in the UK positive tweets for random users are 26% more numerous than negative, and the same stands for Greece with positive tweets being 13% more populous while in Spain we observe a small difference in favour of positive (0.3%). A similar trend occurs when looking at more influential users (random users with more than 1000 followers) where their most shared tweets are mostly positive; 55%, 46%, 40% portion in ‘Head’ for UK, Spain and Greece respectively.

The above results seems to be contradicting the trends observed for MPs. Even though politicians’ negative tweets are being shared more often it is not the same case for an average/random user. This suggests that users tend to retweet more easily a negatively charged tweet posted by a politician than from another random user.

On the other hand, there is not a clear distinction based on sentiment when considering only verified users among all countries. UK and Greek verified users tweet positive messages more than negative. However, the opposite phenomenon is observed for Spain where the proportion of negative charged tweets are significantly higher in the ‘Head’ when the opposite is true when looking at less popular tweets (‘Tail’). This could be evidence that Twitter users are more likely to share negatively charged content when it is originating from widely recognisable and influential accounts (artists, athletes, organisations, etc.) or from figures of authority such as politicians, whose negative messages seem to spread faster overall in all countries analysed.
7.3. Temporal Analysis

Continuing our analysis, we explore whether the tendency where politicians’ negatively charged tweets are more influential is constant through time. To this end, our UK (2021 Main Dataset) (Section 4.1.1) along with 2014 and 2016 UK datasets (Section 4.2.1) are utilized. Figure 5 displays the fluctuation of sentiment (Negative and Positive) in tweets from MPs of the UK’s parliament through time.

Again, the tweets are separated in ‘Head’ and ‘Tail’ based on their ‘popularity’. When considering the ‘Head’ of the distribution, it is clear that tweets with negative sentiment polarity are more numerous than those with positive sentiment throughout the three years studied. As a possibly worrying trend, we can observe how the negativity of tweets in the ‘Head’ grows over time, with a 65% of all 2021 MP tweets being negative. On the other hand, in the distribution of tweets for the ‘Tail’ the opposite stands, where positively charged tweets outnumber negative tweets by a large margin in all three years, further confirming the main trends discussed in Section 6.1.

Discussion. Even if the trend is clearly negative, the idiosyncrasy of each year could potentially explain this trend. For instance, the large discrepancy between Positive and Negative sentiment both in the ‘Head’ and ‘Tail’ of the distribution that is observed on 2021 could be justified due to the Coronavirus pandemic which af-

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11Only the UK parliament is considered due to the lack of resources for the past Greek & Spanish parliaments.
fected the UK during that time. It is also interesting to note the general increase in negatively charged tweets from 2014 to 2016, 5% which could be justified due to the talks that took place that year in relation to Brexit and the eventual referendum that took place on June 2016. Further investigation should be required to explain these sociological aspects, not studied in our quantitative research.

7.4. Sentiment Analysis Models Consistency

In order to ensure the validity of our results, a comparison is made between our selected model (multilingual ‘XLM-T-Sent’) and the best performing model for English, ‘Bertweet-Sent’ (see Table 3.9 for our main sentiment analysis results). Using the 2021 UK dataset as a test ground, the two models agree on the classification of 80% of all tweets while reaching a 0.68 agreement score (Cohen’s kappa). Besides their overall similar performance, it is important to note that the general trend where ‘popular’ tweets tend to have a bigger network penetration still stands when using ‘Bertweet-Sent’. More specifically, when considering the ‘Head’ of the dataset tested, both models indicate that the majority of the tweets convey negative sentiment, with 65% and 62% of tweets, for ‘multilingual XLM-T-Sent’ and ‘Bertweet-Sent’ respectively, being classified as negative. Similarly, when inspecting the ‘Tail’ of the data, again the models seem to be in agreement with the ‘multilingual XLM-T-Sent’ classifying 22% of tweets as Negative and 56% as positive, while ‘Bertweet-Sent’ classifies 18% as Negative and 52% as Positive. The above results, provide further evidence to the robustness of the sentiment analysis classifier.

8. Summary of Findings

Having tested several machine learning models and conducted multiple sentiment analysis experiments, we
attempt to answer the research questions we set earlier (Section 2).

**Sentiment analysis classifier:**. When considering which is the best sentiment analysis classifier for our particular use case it is clear that language models like ‘Bertweet-Sent’ and ‘XLM-T-Sent’ are the correct choice. As seen in Section 5, language models outperform lexicon-based approaches and traditional machine learning models. However, there is no necessary clear winner when selecting between language models. In our use-case we used ‘XLM-T-Sent’ for most of our experiments as its performance is consistent for all languages studied while also achieving the best scores for Greek and Spanish. Finally, as our dataset contains tweets in other languages too, i.e. Turkish, Catalan, Welsh, using a multilingual model like ‘XLM-T-Sent’ is ideal. On the other hand, if our dataset was made only be English tweets then our results indicate that ‘Bertweet-Sent’ would have been a better choice.

**Virality and sentiment correlation:**. Similarly to what previous research has indicated, our experiments confirm that the sentiment of tweets from MPs is an important factor for predicting their popularity. By utilizing the sentiment output of ‘XLM-T-Sent’ we performed statistical tests (Chi-square and Kruskal-Wallis H-test) which suggest that there is differences in the distribution of retweets between positive and negative sentiment (being negative tweets more directly correlated with popularity). These results are supported by the Negative Binomial and Poisson regression models that were tested while using as a dependent variable the retweet count and the sentiment as a predictor. The regression results also reveal that negative sentiment has a larger impact on the tweet’s network penetration ability. More details about the regression analysis can be found in Section 6.1.

**Sentiment differences in parliaments:**. We continued our analysis with the aim to explore differences in sentiment of tweets made by different parties. Our results reveal that tweets made by the governing parties tend to be more positive in contrast to tweets made by the opposition parties which are in general more negatively charged (Section 6.2). This behavior stands across all of the three main parliaments studied (UK, Spain and Greece).

Moreover, after investigating potential differences in sentiment between the main and devolved parliaments (Section 6.3) we conclude that even though the overall distribution may differ (i.e. Basque parliament tweets being mostly negative) there is a consistent trend across all parliaments where negatively charged tweets are more popular than tweets conveying positive sentiment.

**Control experiments:**. Finally, we performed several control experiments to test the robustness of our results. Firstly, we considered different popularity metrics (Section 7.1) including the retweets to followers ratio and the retweets to average user’s retweets. Our results indicate that the same general trends, where negatively charged tweets spread further, are consistent independently of which popularity metric is taken into account.

Potential temporal changes where also explored (Section 7.2) by comparing tweets popularity and sentiment from the 2014 and 2016 UK’s parliaments. Our experiment confirms that tweets displaying negative sentiment have a bigger network penetration in every year studied while also revealing a worrying trend where the percentage of negatively charged tweets increases through time.
A comparison between politicians and public twitter accounts was also performed (Section 7.2). Our analysis indicates that tweets from public accounts tend to be more positive. However, when considering only tweets from verified accounts differences in the retweet behavior between countries were identified where in Spain negatively charged tweets were more popular in contrast to UK and Greece where tweets conveying positive sentiment were more retweeted.

Finally, we compare the performance of our model (‘XLM-T-Sent’) with the best performing English model on the 2021 UK dataset (‘Bertweet-Sent’) (Section 7.4). Our results show that the models reach a high percentage of agreement (80% agreement on all tweets) and more importantly ‘Bertweet-Sent’ results confirm that negatively charged tweets are in general more popular than tweets conveying positive sentiment.

9. Conclusion

We have presented an analysis of the relation between sentiment and virality when considering politicians’ tweets. By performing an exhaustive search for a successful sentiment classifier we obtained a robust multilingual model capable of accurately identifying sentiment in politicians’ tweets. This is achieved by utilizing state-of-the-art transformer-based language models, which we also finetune to the domain-specific task at hand. Both the model used in our analysis and the collected dataset of manually annotated tweets used for training and evaluation are made publicly available.\footnote{https://github.com/cardiffnlp/politics-and-virality-twitter}

Our analysis indicates that there is a strong relationship between the sentiment and the popularity of politicians’ tweets, with negatively charged tweets displaying a larger network penetration than tweets conveying positive sentiment. This phenomenon seems to be consistent across all three sovereign countries analysed, independently from the location. Our findings are further verified by the control experiments performed. Among these control experiments, a temporal analysis suggests that the trend of negative tweets being more influential is consistent and getting more pronounced over time. Finally, while tangential to the main research questions, we observe a clear distinction between government and opposition parties irrespective of their ideology, with government parties and leaders being more positive overall.

Future work could follow our methodology to extend our analysis with additional parliaments and a wider set of time periods taken into consideration. Furthermore, a more fine-grained classification process, where sentiment is classified on a scale, e.g., 1–5 or considering various aspects, might be useful to discover subtler relations between sentiment and virality that are unseen when using a three class classification (negative, positive, neutral). Finally, we hope that both our methodology and released multilingual models can be leveraged in future work for subsequent large-scale sociological studies, including other topics.

Ethics Statement. In this paper we explore the relation between sentiment and virality in politicians’ tweets with the aim to acquire a better understanding of how politicians utilize twitter and their relations with the public. As the aim of this work was to identify general trends, only aggregate statistics are displayed and no attempt is made to identify or focus upon individual MPs. In this way our experiments respect the privacy of individuals and also comply with Twitter’s poli-
cies (https://developer.twitter.com/en/developer-terms).

At the same time, as the main focus of our analysis deals with public figures (MPs) the content of our analysis is by definition addressed to the general population. All of the data used in the experiments are public and accessible through Twitter and are also made available in our repository where we share the tweet IDs that are used.

We note that some of our experiments identify specific groups and aim to differentiate between them. Mainly, a comparison is made between political parties (Figure 2) and their usage of sentiment in tweets; however, our analysis remains neutral, considering only the objective differences between governing and opposition parties, irrespective of their political stances. Nonetheless, we are aware that our analysis, and potential use of our dataset by others, can be potentially used in a politically-biased way.

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Appendix A. Extended classification results

Table B.9 displays the macro average F1 scores along with the average F1 scores of positive and negative classes (F1^{PN}) for all the experiments performed. The experiments were performed by using both a cross-validation setting (CV) and a train/test split approach. For the train/test approach the set of tweets that was annotated by all coders was used (approximately 100 tweets for each language) while the rest of the data was used for training (approximately 900 tweet for each language) (Section 4.3). The results indicate the XLM-T-Sent-multi performs consistently in both the CV and train/test settings and achieves satisfactory performance particularly for Spanish.
Appendix B. Extended regression results

Table B.10 displays the results (coefficients) of the Poisson and zero inflated Poisson regression models while using the retweet count as a dependent variable. Similarly to the NBR models used (Section 6.1: Regression Analysis) both Poisson models indicate that the existence of negative sentiment influences the retweet count greatly than that of positive sentiment.

Table B.11 shows the coefficients for each predictor when using the softmax scores of the positive and negative sentiments of the XLM-T model instead of the final label. For each entry the highest absolute softmax score is considered and is assigned positive or negative sign based on the sentiment. The results indicate, i.e. negative coefficient, that the ”more” negative a tweet the more is retweeted.
| Type       | Model   | Train Lang | Train domain | United Kingdom | Spain | Greece |
|------------|---------|------------|--------------|----------------|-------|--------|
|            |         |            | Out          | In             | CV split | CV split | CV split | CV split | CV split | CV split |
| Multilingual | XLM-T   | Mono       | ✓            | ✓              | ✓ 74 65 80 76 | ✓ 70 76 80 81 | 75 66 73 61 |
|            |         | Multi      | ✓            | ✓              | ✓ 74 68 80 75 | ✓ 70 79 81 87 | 76 70 77 70 |
|            | XLM-T-Sent | Mono      | ✓            | ✓              | ✓ 72 72 78 79 | ✓ 68 71 77 82 | 65 69 64 68 |
|            |         | Multi      | ✓            | ✓              | ✓ 74 66 80 73 | ✓ 69 70 80 80 | 78 72 78 70 |
|            | XLM-R   | Mono       | ✓            | ✓              | ✓ 69 72 77 75 | ✓ 60 65 75 80 | 74 75 73 73 |
|            |         | Mono       | ✓            | ✓              | ✓ 70 67 74 74 | ✓ 66 65 80 78 | 74 74 73 70 |
|            |         | Multi      | ✓            | ✓              | ✓ 74 66 80 73 | ✓ 69 70 80 80 | 78 72 78 70 |
| Monolingual | RoBERTa-Base | Mono     | ✓            | ✓              | ✓ 68 73 78 77 | ✓ 64 70 78 86 | 56 57 50 52 |
|            | TweetEval-Sent | Mono   | ✓            | ✓              | ✓ 73 72 80 79 |         |         |
|            | Bertweet-Sent | Mono   | ✓            | ✓              | ✓ 76 67 81 74 |         |         |
|            |         | Mono       | ✓            | ✓              | ✓ 70 57 78 67 | ✓ 67 70 76 80 | 76 72 76 72 |
| - SVM      |         | Mono       | ✓            | ✓              | ✓ 33 36 50 47 | ✓ 40 40 60 61 | 60 63 56 60 |
| - LSTM     |         | Mono       | ✓            | ✓              | ✓ 47 47 61 57 | ✓ 42 38 58 57 | 52 55 44 51 |
| - VADER    |         | Mono       | ✓            | ✓              | ✓ 52 48 66 55 | ✓ 51 48 60 61 | 59 62 56 61 |
| - Baseline |         | Mono       | ✓            | ✓              | ✓ 58 55 67 63 | ✓ 49 42 60 56 | 59 60 57 59 |

Table B.9: Average F1 scores along with the average of F1 scores of positive and negative classes (F1\text{PN}) when trained/evaluated with cross-validation (CV) and on the ~900/100 train/test split. The results displayed are the averages of three runs. Training domain indicates the data used for training the models. ‘In’ domain indicates models trained on the labelled data collected (Section 4.3). ‘Out’ indicates the model has been finetuned on other sentiment analysis datasets (see Section 5.1).
| variable | Overall | UK | Spain | Greece |
|----------|---------|----|-------|--------|
|          | Poisson | zero Poisson | Poisson | zero Poisson | Poisson | zero Poisson | Poisson | zero Poisson |
| const    | 3.4035* | 4.0809* | 3.7006* | 4.4486* | 3.61* | 4.1586* | 2.3372* | 2.8278* |
| emojis   | -0.193* | -0.1769* | -0.3277* | -0.2978* | -0.2114* | -0.1946* | -0.3298* | -0.3639* |
| has_url  | 0.013*  | -0.3695* | -0.3798* | -0.8422* | 0.41* | 0.0827* | -0.1871* | -0.305* |
| hashtags | -0.5219* | -0.6281* | -0.4001* | -0.5168* | -0.5878* | -0.6266* | -0.3372* | -0.41* |
| mentions | -1.0543* | -0.7944* | -1.4615* | -0.8382* | -0.929* | -0.8291* | -0.9082* | -0.7696* |
| neg      | 1.4129* | 1.1709* | 1.3014* | 1.0566* | 1.1818* | 1.0028* | 0.9232* | 0.6859* |
| pos      | 0.2295* | 0.1629* | -0.1486* | -0.1855* | 0.5513* | 0.4503* | 0.3229* | 0.2315* |

Table B.10: Coefficients for the Poisson Regression and zero inflated Poisson Regression when using tweets from the combined 2021 UK, Spain, Greece parliaments and for each individual parliament. Dependent variable is the retweet count while the independent variables neg and pos indicate the sentiment according to XLM-T results. * indicates p-value < 0.05

| variable | Overall | UK | Spain | Greece |
|----------|---------|----|-------|--------|
|          | Poisson | zero Poisson | Poisson | zero Poisson | Poisson | zero Poisson | Poisson | zero Poisson |
| const    | 72.8914* | 75.9854* | 96.6305* | 96.6305* |
| emojis   | -5.1085* | -7.9482* | -9.7004* | -9.7004* |
| has_url  | -1.3613 | -17.524* | 26.56* | 26.56* |
| hashtags | -20.0335* | -7.811* | -41.0476* | -41.0476* |
| mentions | -41.0511* | -40.4977* | -63.0461* | -63.0461* |
| max_score | -43.16* | -42.5478* | -39.615* | -39.615* |

Table B.11: Coefficients for the OLS model when using tweets from the combined 2021 UK, Spain, Greece parliaments and for each individual parliament. Dependent variable is the retweet count while XLM-T’s softmax scores (negative and positive sentiment) are utilized (sent score) as independent variables. * indicates p-value < 0.05