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Investigating the complete corpus of Referendum and Elections tweets

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***Abstract*—Today, a considerable proportion of the public political discourse that proceeds nationwide elections is happening through Online Social Networks. Through analyzing this content, we can discover the major themes that prevailed during the discussion, investigate the temporal variation of positive and negative sentiment and examine the semantic proximity of these themes. According to existing studies, the results of similar tasks are heavily dependent on the quality and completeness of dictionaries for linguistic preprocessing, entity discovery and sentiment analysis. Additionally, noise reduction is achieved with methods for sarcasm detection and correction. Here we report on the application of these methods on the complete corpus of tweets regarding two local electoral events of worldwide impact: the Greek referendum of 2015 and the subsequent legislative elections. To this end, we compiled novel dictionaries for sentiment and entity detection for the Greek language tailored to these events. We subsequently performed volume analysis, sentiment analysis and sarcasm correction. Results showed that there was a strong anti-austerity sentiment accompanied with a critical view on European and Greek political actions.**

I. Introduction

It is common ground that Online Social Networks (OSNs) have prevailed as the major platform of public expression regarding political matters. Existing studies that investigate this behavior generate patterns that distinguish users' or posts' favoritism towards one political party or certain ideology. The main predicament in these studies was to generate election predictions that are close or even outperform public opinion polls [1], to measure approval ratings [2] or to assess public opinion during political debates [3]. There exist studies that have tried to measure the emotion content in social media [4]. However, the first term of Barack Obama's presidency (2009-2012) coincided with the immense increase of Twitter's user base and its establishment as a channel for personal political expression. As a consequence, one of the first studies that compared sentiment analysis in Twitter with "traditional" opinion polls was from 2010, demonstrating a strong correlation between Sentiment Analysis in Twitter with Obama's approval ratings polls [2]. The application of the same method in 2012 U.S. presidential elections outperformed the public opinion polls [5]. Since then, numerous other studies have performed similar analysis in other countries like Austria [1], UK [1] and Italy [5] with varying election procedures and diverse cultural and language dynamics.

Perhaps the most seminal review in this area is from Gayo-Avello [6]. This work presents the main considerations in data collection including user and tweet selection, geolocation and language use. It also delineates the main research strategies in the area, which are (i) classification according to tweets volume and (ii) classification according to sentiment analysis. Usually, modern studies implement a combination of these two main strategies [7]. Other approaches extract knowledge from the social graph by studying the retweet or mention graph [8] or by averaging on the predefined ideology of the political leaders that the users follow [9]. The tweet volume is a good indicator for a party's success given that the correct time window is defined [10] but studies indicate that this is inefficient without sentiment analysis [7]. Regarding sentiment analysis techniques, researchers use specially tailored dictionaries with positive, negative or neutral colored words, and measure the occurrence of these words in a rich variety of language properties of the posted text [11], [12] or hashtags [13]. Today, sentiment analysis is routinely used even for real-time analysis [14]. Gayo-Avello [6] also lists noise and demographics as the major difficulties that need to be addressed before making Twitter a reliable election prediction mechanism. Regarding noise, it is estimated that approximately half of collected tweets belong to this category [15], [16] and, therefore, need to be detected and filtered. Regarding demographics, studies have indicated that Twitter users belong to a certain age [17], social [18] and ideology demographic group and, therefore, express a partial opinion of the society at best. A study of 2011 concluded that, due to its demographics, Twitter is by far inferior compared to opinion polls for elections prediction in the U.S. [17].

Applying these methods to Greek tweets entails some additional difficulties. First, the online language, primarily used by the youth, is a mix of Greek grammar with Latin letters also called "greeklish". This is a highly complex language with multiple possible writings even for basic and short words that makes automatic detection a very tedious task [19], [20]. Additionally, the demographic subset of Greek Twitter users is narrower than in other western countries thus limiting its representative power [16]. Nevertheless, Charalampakis et al. [16] were able to perform irony detection in Greek political Tweets and inferred similar percentages with studies focusing in U.S. politics.

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A. Recent Political Background in Greece

On 25th of January 2015, the new "anti-austerity" government of the SYRIZA party was elected in Greece with a percentage of 36.3%, starting a long negotiation with the Eurogroup about debt reconstruction. Until June 2015, there was no visible progress achieved and SYRIZA decided to throw a referendum on the 5th of July 2015 so that the Greek people decide whether to accept or not the current austerity measures proposed by the Eurogroup. Capital controls were enforced in Greece and the result of the referendum was NO (do not accept) with a percentage of 61.3%. Eurogroup did not accept the result of the referendum as a bargaining tool and under extreme pressure, the government decided to accept the proposed measures. Several disagreeing members of SYRIZA party threatened to vote down the measures forcing the prime minister (Alexis Tsipras) to expel them and to announce new legislative elections that took place at 20th of September 2016. SYRIZA won these elections with a reduced percentage of 35.5%.

II. Motivation and Contribution

This work aims to utilize natural language analysis techniques (entity detection, sentiment analysis, advanced lexicons, sarcasm detection) on Twitter data to reveal hidden or hard-to-find content and relations for the political domain, exploring datasets from specific events such as referendum and legislative elections. The choice of the summer 2015 referendum in Greece was a unique, rare event where people expressed opinions that inspired future major societal change, not only for Greece but also for Europe, whereas the elections, right after, combined aspirations, critique and political change.

We select and present the method for deep content analysis focused on two procedurally different but closely related political events of very high societal value, adapted for the Twitter data. The use of natural language methods heavily depends on the pre-processing of the data in order to accurately explore the qualitative aspects of the quantified measurements from the Twitter datasets. By applying the same method to both datasets, we may explore the results in combination, revealing details about the user interaction that both political events share, and differentiate from one another.

III. Twitter Corpus

Our analysis is based on two distinct Twitter datasets. The first includes all tweets that contain the #dimopsifisma (Greek word for "referendum") and #greferendum hashtags from 25th June 2015 which is when the referendum was announced, until 5th July 2015 when the referendum took place. This dataset contains in total 301,000 tweets out of which 84,481 are neither retweets nor replies. In Fig. 1 we show the frequency of these tweets. The second dataset includes all tweets that contain the hashtags #ekloges (Greek for "elections") and #ekloges_round2, which dominated the online discussion regarding the Greek legislative elections of September 2015. In total, this dataset contains 182,000 tweets out of which 45,750 are neither retweets nor replies.

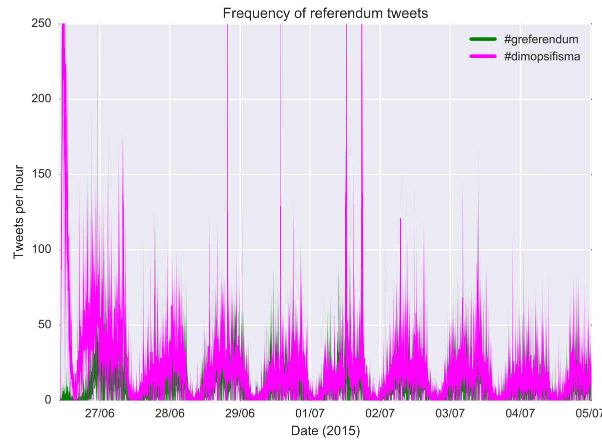


Fig. 1: Frequency of tweets per hour

TABLE I: Entity Variants from Plain Text and Hashtags

	Text Entities	Hashtag Entities
Number of Unique Entities	156	116
Min Number of Variants per Entity	1	1
Max Number of Variants per Entity	74	148
Average Number of Variants per Entity	18.9	21.6

IV. Method

A. Entity Identification

To support our analysis and reveal relationships between persons, institutions, events and abstract notions (such as democracy or liberalism), we performed entity identification on the elections and referendum Twitter corpus. As a first step, we gathered all unique words and Twitter hashtags present in the tweets along with the respective occurrence frequency of each. Then, we manually selected all entities relevant to the political domain of the Greek legislative elections and referendum of 2015, apparently considering the most frequent words and hashtags as of higher importance. Afterwards, we grouped all various forms that a given entity appears in, so that we would be able to identify a certain entity regardless of the variants it assumes in the tweets. For example, all of the following hashtags identify a single entity, i.e. the Greek Prime Minister, Alexis Tsipras: #Tsipras #atsipras #alexistsipras #atsipra #aleksitsipra. We performed grouping of variants for entities found either as plain text in the tweets or mentioned as hashtags. In total, we extracted 156 entities from plain text of tweets and 116 entities from twitter hashtags; the minimum, maximum and average number of variants per entity is listed in Table I. Subsequently, we linked and combined occurrences of a given entity that appeared both as plain text and as hashtag to improve precision of entity identification. Lastly, for each tweet, we located all entities that are referenced either as hashtag or as plain text, distinctively, and annotated our dataset accordingly for further processing.

B. Sentiment Analysis

For sentiment analysis, we used SentiStrength [21] that is ideally suited for the affective dimension of the social web and Twitter in particular [22]. SentiStrength estimates the strength with which a positive or negative sentiment is expressed in short texts, even for informal language. It reports two sentiment strengths: -1 (not negative) to -5 (extremely negative), and 1 (not positive) to 5 (extremely positive). It uses two scores because humans process positive and negative sentiment in parallel – hence both positive and negative sentiment can coexist within texts. Along with SentiStrength's report on positive and negative sentiment strength per tweet, we also employ SentiStrength's single scale results (-4 to +4), that combine sentiment polarity and strength and assess aggregate sentiment per tweet.

Sentiment analysis is known to be domain-dependent, meaning that applying a classifier to a dataset different from the one on which it was trained often gives poor results [23]. Indeed, the diversity of topics and communication styles in the social web suggests that many different classifiers may be needed. Existing general-purpose social web sentiment analysis algorithms may not be optimal for texts focused around specific topics, such as the political domain in our case. Indeed, a major weakness of SentiStrength is that its general sentiment lexicon performs poorly and achieves very low accuracy in political texts. However, SentiStrength supports topic-specific lexicon extension, which involves adding topic-specific words to the default general sentiment lexicon [24].

Therefore, we enriched SentiStrength for the Greek political domain by creating new general-purpose and political-domain lexicons through manually selecting and annotating words from the Twitter corpora. Human intervention seems likely to be particularly important for narrowly-focused topics for which small misclassifications may result in significant discrepancies if they are for terms that are frequently used with regard to a key aspect of the topic. For the purpose of political domain analysis, we manually created a new SentiStrength-compatible lexicon comprising Greek words with associated positive/negative sentiment strength, aiming to improve the accuracy and effectiveness of political-domain lexical sentiment strength detection.

C. Sarcasm Detection

In order to detect sarcastic content in Twitter, we adapted the method used by the online sarcasm detection service, http://www.thesarcasmdetector.com/, in order to be able to characterize Greek text.

The first step was to construct a sarcasm classification mechanism [25], [26]. For this purpose we built a website that showed random tweets and users got to choose whether each tweet was sarcastic or normal. We promoted the website through social media and after a week we collected 2,642 positive (sarcastic) tweets and 2,002 negative (non-sarcastic/normal) tweets from 134 different user sessions.

Subsequently we proceeded to build a classification model. In particular, for each tweet we extracted 1-grams, 2-grams, average sentiment of words and included topics. The topic analysis was performed with the Latent Dirichlet Allocation (LDA) method implemented in the Gensim Python library. For classification, we used a Support Vector Machine (SVM) classifier with a linear kernel and a Euclidean regularization coefficient of 0.1. Subsequently, we randomly divided the flagged dataset to 70% for training purposes and 30% for testing. We trained our model to the "train" dataset and estimated its performance on the "test" dataset. The classification results are on Table II.

TABLE II: Classification Results

	Precision	Recall	f1-score	Test Samples
Pos(Non-Sarcastic)	0.69	0.62	0.65	621
Pos(Sarcastic)	0.72	0.78	0.75	772
Average/total	0.70	0.71	0.70	1393

For comparison, our TPR estimate of 0.78 for sarcastic tweets is similar to estimates from other studies, such as 0.71 by Gonzlez-Ibez [25] and 0.75 by Liebrecht [26]. Since "sarcasm" is a subtle and ambiguous notion, especially in the political context, it is questionable whether significantly superior results are possible. This conclusion is supported by the fact that even humans have a limited ability to detect sarcasm in Twitter that ranges from 70% [25] to 85% [26].

V. Results

A. Tweets' Volume Analysis

Although the tweets' volume is not a sufficient indicator of political inclinations of users, it can give insights regarding specific events. In Fig. 2 we plot the volume of referendum tweets per hour. We focus only on tweets that contain either *voteYES* or *voteNO* entities. The spikes in this plot are indicative of major events during the pre-referendum period. Analysis of the text from these tweets revealed that they were either prompting people to participate in certain demonstrations or they were retweets of the prime minister, urging for "NO" votes. In Fig. 3 we show the decreasing temporal variation of the ratio of users who included "YES" vs "NO" entities in their tweets. Interestingly, opinion polls that were conducted during the same period showed an opposite trend, which, according to post-referendum analysis, was erratic [27]. The final "YES" vs "NO" ratio right before the referendum was 18%, which, despite the high difference from the final result (38.6%), was very close to the preferences of the demographics of Greek Twitter users. According to [28], users belonging to the age groups of 18-24 and 25-34 voted "YES" with a percentage of 15% and 27.7%, respectively. In Fig. 3 we also observe the effect of Capital Controls on the "YES" vs "NO" ratio. Perhaps unexpectedly, the enforcement of Capital Controls temporarily strengthened the "NO" sentiment. The volume of tweets that were referring to the leading party (SYRIZA) and its leader (Alexis Tsipras) had a decreasing trend during the pre-elections period (Fig. 4). In contrast, there was a slight increase in the volume referring to the SYRIZA's major opposition party, New Democracy (ND).

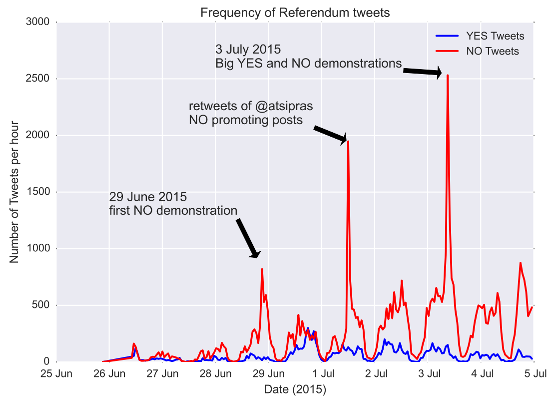


Fig. 2: Frequency of Referendum tweets

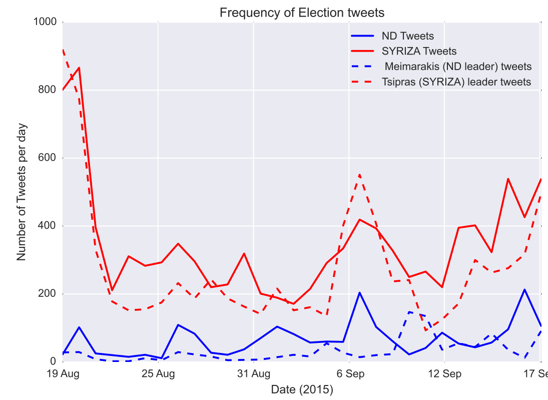


Fig. 4: Frequency of Election tweets

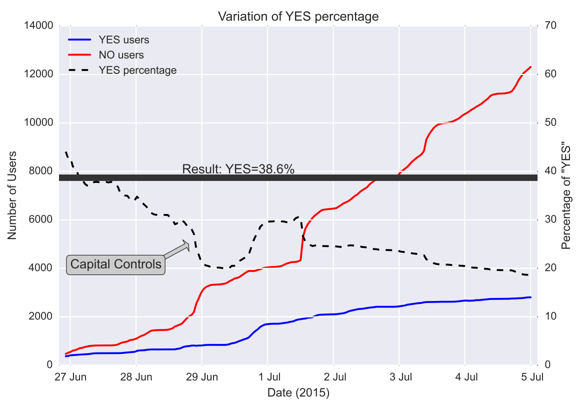


Fig. 3: Variation of YES percentage

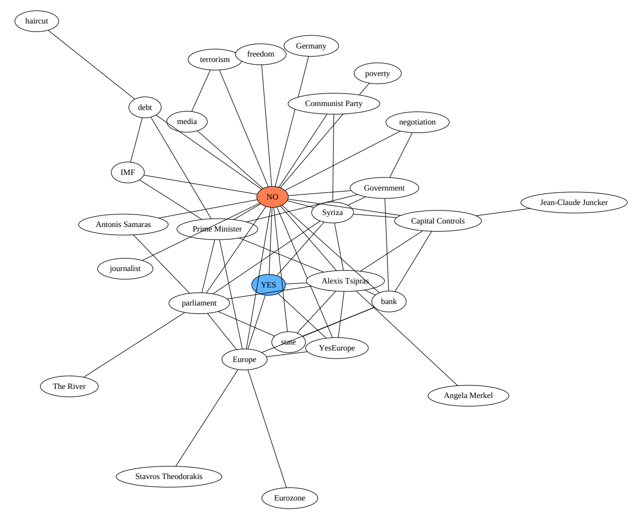


Fig. 5: Entities co-occurence in referendum

B. Entities Co-occurrence

Two entities are co-occurring if there exist at least one tweet that contains both entities. We define distance between entities as: $d = log(10+c_{max}-c)$, where c is the number of tweets that contain a specific pair of entities, and c_{max} is the maximum c (max co-occurrence). We apply the "neato" visualization method of Graphviz software, which emulates spring link attractive forces between nodes. In Fig. 5 we visualize the distances of entity pairs with at least 500 occurences for the referendum dataset. In this figure we notice that *YES* and *NO* entities are central to the discussions with a small in-between distance. Moreover, it is clear that Europe-related entities are closer to the *YES* point whereas entities regarding domestic affairs including *debt* are closer to the *NO* point.

C. Sarcasm, Sentiment and Hashtags

Sarcasm detection revealed some points of interest pertaining to the use of sarcasm in the political domain. Overall, 61.8% of the total referendum tweets and 58.7% of the total election tweets were detected positive for sarcasm. Ironic posts were prevalent for specific hashtags, which, after looking into the text entities, revealed the level of the citizen aversion to the entities involved in the current situation, namely the earlier governments and a company in the center of talk about corruption (Fig. 6). On the other hand, the least use of irony was found to feature the talk about the entities at stake that would be affected the most by the referendum outcome, such as Germany, Greece, Europe, and the EU.

In the referendum data, it is also worth noting that a negative correlation exists between sarcasm and number of hashtags: Fisher Transformation Test, z=43.225, p<0.001 (Fig. 7a). Similarly, with regard to the elections dataset, a negative correlation exists between sarcasm and number of hashtags: Fisher Transformation Test, z=34.839, p<0.001 (Fig. 7b).

Although the sarcasm assignment provided a glimpse into the thoughts of the citizens revealing causes and worries related to the outcome of the referendum, there was a different but equally valuable aspect exposed by the sentiment polarity. Looking at the entities that exhibit the highest polarization of sentiment (albeit mostly negative), one can notice how the citizens thought about the forces that actively tried to influence the outcome of the referendum (Fig. 8). By retrieving the tweets mentioning more than one of the highlighted entities, it was found that extreme polarization could be seen in

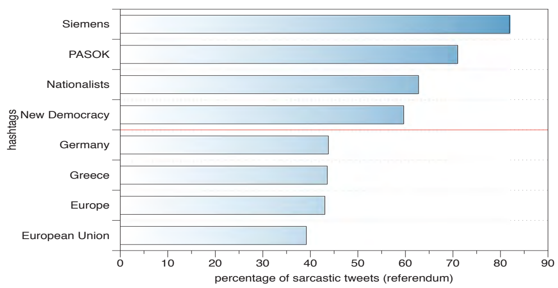
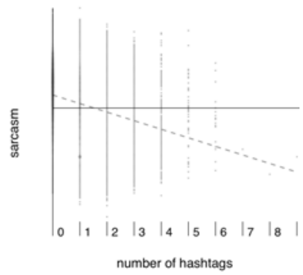
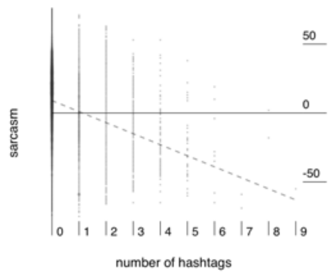


Fig. 6: Hashtags mainly used in sarcastic and non-sarcastic posts



(a) Referendum



(b) Elections

Fig. 7: Number of hashtags and sarcasm

those texts, clearly separating the negative sentiment towards *journalists* and the *mass media* against the positive sentiment towards *Alexis Tsipras* and *freedom*.

Another feature across both datasets is the correlation between sentiment and sarcasm. With regard to the referendum data: a positive correlation exists between positive sentiment and sarcasm, Fisher Transformation Test, z=17.137, p<0.001; and a negative correlation also exists between negative sentiment and sarcasm, Fisher Transformation Test, z=15.954, p<0.001. Similarly, for the elections: a positive correlation exists between positive sentiment and sarcasm, Fisher Transformation Test, z=13.508, p<0.001; and a negative correlation exists between negative sentiment and sarcasm, Fisher Transformation Test, z=19.719, p<0.001.

D. Temporal Variation of Sentiment

The computation of sarcasm and sentiment levels allows us to plot the temporal sentiment variation for any entity. To eliminate the influence of sarcasm, we applied "sarcasm correction" to the sentiment for tweets with positive sarcasm. Specifically, each tweet sentiment was corrected towards the neutral side proportionally to the percentage of sarcasm that it contained. Figure 9 shows the local linear regression lines (LOESS) for the top 5 most frequent entities of referendum and elections. In particular, during the pre-referendum period, the positive sentiment towards Europe decreases (Fig. 9a) and the negative sentiment towards the Greek Prime Minister Alexis Tsipras increases and becomes almost stable after the enforcement of the Capital Controls on June 29th (Fig. 9b). Regarding the elections, this trend is reversed since the leading

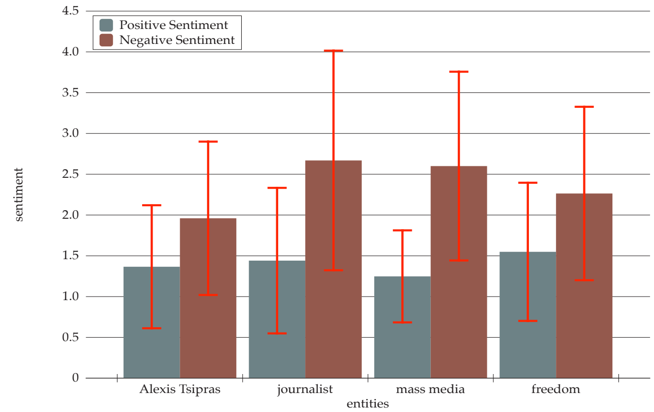
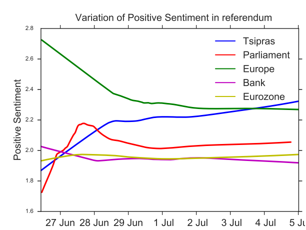
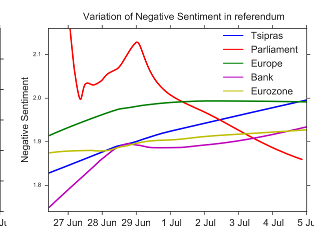


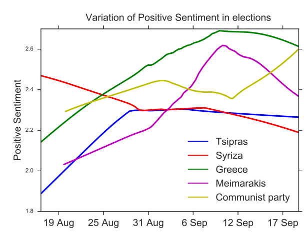
Fig. 8: Extreme sentiment polarity (referendum)



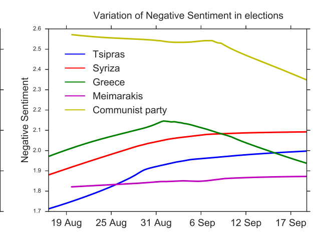
(a) Positive sentiment in referendum



(b) Negative sentiment in referendum



(c) Positive sentiment in elections



(d) Negative sentiment in elections

Fig. 9: Variation of sentiment in referendum and elections

party, SYRIZA, undergoes a decrease in positive sentiment (Fig. 9c) and an increase in negative sentiment (Fig. 9d). This demonstrates a general dissatisfaction of the party actions regarding the post-referendum political developments.

VI. Conclusion

We presented a detailed analysis of two Twitter datasets from political events. Sentiment analysis and sarcasm detection were performed on the data in order to achieve high accuracy. Entity detection combined manual, semi-automatic and scripted processing as well as lexical resources to correctly assign sentiment. This combination was necessary for tackling the traditionally hard-to-analyze political domain by blending entity-level sentiment and data statistics.

Our results shed light on the often unnoticed societal and political trends that guide citizen choices and actions, which traditional polls fail to detect. For the two selected cases, political aspects and justifications that are usually part of argumentation from political analysts during their post analyses, were revealed through the data exploration. The method was applied successfully to both datasets, enabling the creation of lexical resources that were used for both. These resources, as an extension of the previously existing resources, were utilized for entity and sentiment detection, and are available both as general-purpose resources and, most importantly, optimized for the political domain.

The results also hinted further work. Since sentiment is a descriptive work for all emotions, and not all emotions are the same [29], an interesting next step for better understanding citizens and society, could be to detect emotion (sadness, happiness, fear, anger, etc.) and see how emotion drives societal and, consequently, political change.

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