Us and Them: Adversarial Politics on Twitter

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***Abstract*—Social-media debates on longitudinal political topics often take the form of *adversarial discussions*: highly polarized user posts, favoring one of two opposing parties, over an extended time period. Recent prominent cases are the US Presidential campaign and the UK Brexit referendum. This paper approaches such discussions as a multi-faceted data space, and applies data mining to identify interesting patterns and factors of influence. Specifically, we study how topics are addressed by different parties, their factual and "post-factual" undertones, and the role of highly active "power users" on either side of the discussion.**

I. Introduction

Motivation. Social media, such as Twitter and large online communities, reflect grassroots opinions on controversial topics. Often, the discussion takes highly polarized forms where people either strongly support one stance or heavily oppose it. Politics is a prominent case: users inclined with either one of two parties engage in *adversarial discussions* over many months. Examples are the 2016 US Presidential Election campaign and the UK Brexit referendum.

A recent trend is that discussions also include original posts by the political stakeholders themselves, for example, Donald Trump and Hillary Clinton. Thus, regular users not only express their opinions, but also interact directly with politicians and other leading figures. These interactions have distinct characteristics that have not been investigated in depth so far. Especially in light of the role of so-called "post-factual" statements (see, e.g., Wikipedia article on "Post Truth"), a fundamental study of these phenomena is needed.

Contribution. This paper aims to analyze adversarial discussions on politics, as observed on Twitter over extended timeframes. We propose a general framework, based on latent topic models and user features, over a multi-faceted data space. The facets of interest are the *topics* of tweets, their *factuality* versus *sentimentality* (aka. post-factuality), the *inclination* of users with regard to the two involved stances ("us" and "them"), and the *roles of users* with regards to how they affect activity within the discussions.

Within this framework we study two recent cases: the US Election and the UK Brexit. These cover more than a million tweets by several thousands of users over 10 and 8 months, respectively. The two cases serve as examples to address the following general research questions about social media:

Question 1: What are the key topics of the adversarial discussion? Which topics are most polarized? Which topics are of factual nature, referring to political issues like jobs or immigration, and which ones are "post-factual", referring to subjective beliefs and sentiments?

Question 2: What are the roles played by different kinds of users? How strong is the influence of the leading figures themselves? Are there other, highly prolific, users who drive the adversarial opinions?

Although there is prior work on analyzing topic profiles and user influence in online communities, the outlined research questions address newly emerging phenomena that have not been studied before. The novel contributions of this paper are 1) the methodology to systematically study adversarial discussions, and 2) insightful findings on the role of "post-factual" topics and the nature of influential "power users".

II. Data Collection

Our datasets consist of discussions rooted on leading figures in the Brexit referendum and the 2016 US presidential election. For the first event, we identify politicians Nigel Farage and Boris Johnson as headliners of the "Leave" stance and Nicola Sturgeon and Jeremy Corbyn as driving the "Remain" campaign. For the second event, we focus on then-candidates Hillary Clinton and Donald Trump.

We collected all tweets posted to the official accounts of these politicians in the past year, as well as all the *replies* their tweets have received. Replies differ from the usual Twitter "mentions" in the sense that they are linked to a specific tweet, instead of linking to a user account. We consider only these reply threads (i.e., trees of tweets), and disregard tweets posted independently of the posts by the leading figures. An overview of our datasets is given in Table I. This data is available at `http://people.mpi-inf.mpg.de/~aguimara/adversarialpolitics/`.

Note that the UK Brexit case had considerably fewer tweets but still enough mass for an in-depth analysis. Also note that the notion of a user is syntactic: one user corresponds to one Twitter account. Some users, especially the leading figures themselves, may employ professional PR teams or pay other people to contribute on their accounts.

Stance / Leader	Clinton	Trump	Remain	Leave
#Posts	2,602	1,861	1,098	539
#Replies	586,335	549,799	101,193	72,190
#Users	153,786	146,255	35,504	27,941
Time Period	01-01-2016 to 15-11-2016		01-02-2016 to 01-10-2016	

TABLE I: Twitter data on US election and UK referendum.

Topic	F/S	Salient Words
T0: pro Clinton	S	hillary, president, potus, imwithher, bernie, vote, berniesanders, love, clinton, trump, good, win, sanders, feelthebern, great, woman, hope
T1: contra Clinton	S	hillary, white, potus, house, liar, people, obama, black, lying, vote, clinton, woman, flotus, crooked, bill, corrupt, pandering, prison, billclinton
T2: contra Clinton	S	benghazi, neverhillary, hillary, liar, americans, crookedhillary, potus, hillaryforprison, maga, people, killed, die, america, lies, lockherup
T3: contra Clinton	S	hillary, trump, timkaine, lies, potus, usaneedstrump, lie, clinton, kaine, pence, truth, liar, video, lying, debate, mike_pence, crooked
T4: Social Issues	F	women, rights, care, health, pay, abortion, children, life, babies, hillary, woman, kids, support, change, gay, marriage, equal, healthcare, lgbt
T5: Gun Control	F	gun, vote, law, guns, potus, bernie, hillary, laws, berniesanders, party, voting, democrats, stop, nra, illegal, violence, control, amendment
T6: FBI	F	hillary, emails, fbi, clinton, potus, email, criminal, jail, wikileaks, server, investigation, classified, benghazi, lies, security, corruption
T7: Foreign Politics	F	money, hillary, clinton, foundation, wall, war, street, countries, millions, saudi, isis, foreign, iraq, russia, state, iran, obama, libya
T8: Economy	F	jobs, pay, money, taxes, tax, trump, people, class, debt, business, work, free, plan, middle, obama, raise, economy, wage, obamacare
T9: Bill Clinton	S	bill, women, hillary, rape, clinton, husband, trump, rapist, billclinton, child, victims, sexual, raped, victim, monica, girl, assault, wife
T10: Racism	F	trump, racist, hillary, people, hate, white, black, kkk, supporters, vote, support, donald, bernie, blacks, racism, anti, party, bigot, violence
T11: Hispanics	S	los, por, con, drudge_report_, hillary, para, una, presidente, usa, jillnothill, imwithher, clinton, pas, ser, pero, usted
T12: Trump Family	S	erictrump, melaniatrump, trump, donaldjtrumpjr, ivankatrump, mike_pence, happy, love, donald, melania, laraleatrump, teamtrump, great, family
T13: Trump Scandal	F	tax, returns, account, trump, delete, release, taxes, show, donald, nevertrump, hiding, trumpdelete, fraud, records, money, liar
T14: Foreigners	F	muslims, muslim, wall, trump, illegal, country, isis, obama, islam, america, americans, build, immigrants, refugees, terrorists, illegals, border
T15: Media Bias	S	trump, cnn, media, hillary, polls, nytimes, poll, news, lies, people, truth, clinton, debate, donald, foxnews, facts, win, lie, rigged
T16: pro Trump	S	trump, cnn, foxnews, makeamericagreatagain, trump2016, megynkelly, trumptrain, fox, news, watch, debate, maga, donald, teamtrump, great
T17: pro Trump	S	trump, america, great, donald, president, vote, god, love, country, people, makeamericagreatagain, win, trump2016, bless, usa, good, maga
T18: Republicans	F	trump, cruz, ted, tedcruz, vote, rubio, gop, win, donald, jeb, people, jebbush, party, establishment, kasich, glennbeck, romney, bush, republican
T19: contra Trump	S	trump, man, donald, nevertrump, loser, good, people, nytimes, racist, cnn, big, sad, ass, president, tweet, stupid, hands, liar, orange

TABLE II: Topics and top representative keywords identified by LDA for US Election data (F = factual, S = sentimental).

Topic	F/S	Salient Words
T0: Referendum Day	S	leave, vote, brexit, nigel, ukip, remain, referendum, cameron, voted, country, hope, farage, campaign, voteleave, win, democracy, stay
T1: US Parallels	S	nigel, realdonaldtrump, good, hillaryclinton, brexit, farage, trump, ukip, boris, britain, country, luck, hope, day, love, god, independence
T2: pro Leave	S	boris, nigel, zacgoldsmith, brexit, london, farage, grassroots_out, ukip, daviddavismp, racist, change_britain, cameron, alllibertynews
T3: European Union	F	brexit, trade, leave, control, immigration, europe, free, ukip, world, borders, vote, britain, market, countries, deal, system, movement, economy
T4: Immigration	F	borders, europe, turkey, migrants, control, brexit, immigration, country, open, border, leave, countries, immigrants, free, british
T5: Foreign Politics	F	boris, foreignoffice, johnkerry, ukun_newyork, turkey, isis, syria, war, foreign, russia, stop, erdogan, assad, mfa_ukraine, ukraine, saudi
T6: Media Debates	S	david_cameron, nigel, cameron, brexit, itv, dave, truth, farage, man, head, bbc, people, debate, itvnews, ukip, dodgy, voteleave, lies
T7: Economy	F	tax, steel, david_cameron, money, industry, cameron, chinese, vote_leave, china, nigel, pay, tariffs, fishing, cheap, ukip, avoidance, labour
T8: UK	F	news, rights, human, year, foreign, aid, housing, law, article, nhs, account, build, homes, scotland, scotgov, money, labour, government, british
T9: Altruism	S	sharing, socialism, equal, virtue, failure, ignorance, envy, misery, philosophy, creed, gospel, tin, juice, women, edinburghpaper, snsgroup
T10: before Cameron	F	blair, war, tony, johnmcdonnellmp, hilarybennmp, lindamcavanmep, rcorbettmep, labour, emilythornberry, benn, karenpbuckmp, iraq, israel
T11: David Cameron	S	answer, question, cameron, david_cameron, corbyn, questions, jeremy, ireland, pmqs, northern, answers, scotland, david, north, labour, wales
T12: Healthcare	F	nhs, jeremy, minister, prime, labour, ttip, heidi_mp, doctors, great, corbyn, uklabour, junior, telegraphnews, david_cameron, support, health
T13: Public Services	F	money, public, nhs, labour, pay, steel, private, work, tax, government, train, rail, david_cameron, jeremy, energy, jobs, service, contracts
T14: Middle East	S	anti, labour, corbyn, ira, petermurrell, jeremy, uklabour, hamas, party, petition, israel, parliament, support, semitism, friends, jews, terrorist
T15: Khan election	S	sadiqkhan, happy, sad, jeremy, ruthdavidsonmsp, love, nicola, family, thesnp, hope, labour, thoughts, great, news, london, day, corbyn, peace
T16: Social Welfare	F	tax, labour, pay, money, workers, nhs, people, education, rights, tories, working, class, housing, poor, schools, rich, paid, work, disabled
T17: Scotland	F	scotland, thesnp, snp, nicola, scotgov, vote, scottish, independence, leave, scots, brexit, england, referendum, good, sturgeon, indyref2, scotparl
T18: pro Labour Party	S	labour, party, corbyn, vote, election, win, leader, uklabour, tories, tory, jeremy, resign, government, voters, voted, leadership, general, left
T19: pro Labour Party	S	jeremy, labour, corbyn, party, uklabour, leader, good, owensmith_mp, vote, support, members, resign, people, great, leadership, keepcorbyn

TABLE III: Topics and top representative keywords identified by LDA for Brexit data (F = factual, S = sentimental).

III. Factual and Post-Factual Topics

As a first dimension of the discussions, we start our analyses by looking into the topics brought up over the course of the UK referendum and US election campaigns. Here we are interested in the thematic differences and similarities between issues addressed by proponents of either side.

To this end, we employ Twitter-LDA[1], an adaptation of the Latent Dirichlet Allocation model for topic discovery on tweets [26]. For each dataset, we generate topics from the full corpus of tweets, with removal of stop words and embedded URLs. We set the model hyperparameters as $\alpha = 2.5$, $\beta = 0.01$, $\gamma = 20$ and $N = 20$ topics. To evaluate the topic model for different choices of the dimensionality, we calculate the per-word perplexity for varying numbers of topics N. The lowest perplexity is found at $N = 11$, and only marginally increases for N up to 50. Thus, to tune N, we also consider the aspect of interpretability [5], based on human judgements. Feedback on our data shows that the choice of $N = 20$ topics leads to the clearest interpretation (while having near-minimum perplexity).

The discovered topics are displayed on Table II for the US Elections case and Table III for the UK Brexit case.

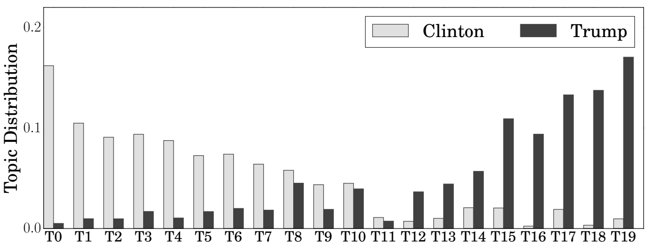
[1]https://github.com/minghui/Twitter-LDA

A. *Factual vs. Sentimental Topics*

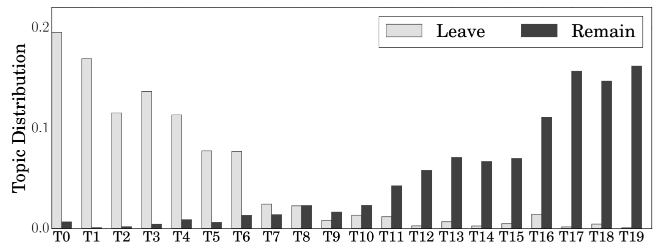
To derive further meaning from the topics, we employed the help of 10 judges for labeling them as *factual* or *sentimental*, where factual topics refer to concrete issues, facts, events and candidate agendas, while sentimental topics refer to personal opinions, emotional claims and speculation (aka. “post-factual”). Although some topics naturally include a mix of facts and opinions, we note a high agreement on their factuality, with 70% of topics receiving the same label from at least 8 out of the 10 judges, and an inter-annotator agreement (Fleiss’ Kappa) of 0.42.

Contrasting the topical content of either side of the discussions, Figure 1 shows the distribution of topics across replies posted to Hillary Clinton and Donald Trump over the US Election campaign, and the Remain and Leave campaigners on the UK Brexit campaign.

In the US case, Clinton discussions display a wider topical spread, particularly across factual topics: while 16% of replies are sentimental messages of support (T0) and 29% are general criticism (T1, T2 and T3), factual topics T4, T5, T6, T7 and T8 each make up at least 5% of the replies. Meanwhile, replies to Donald Trump are largely sentimental: 10% of tweets are reactions to media coverage and preliminary poll results (T15), 22% express support (T16 and T17), and 17% criticism (T19). Topic T18, which incorporates terms relating to other Republican party members and the Republican primaries, is



(a) US Election topics and replies to Clinton and Trump.



(b) Brexit topics and replies to Leave and Remain campaigners.

Fig. 1: Distribution of LDA-generated topics over replies to leaders of either stance.

the main factual topic discussed, making up 18% of replies.

The Brexit case behaves similarly, with the Leave side displaying a narrower topical focus than its adversary. 48% of replies to the Leave side express pro-Leave sentiment (T0, T1, T2), while 25% address factual topics about aspects of the European Union and immigration (T3 and T4). On the Remain side, 30% of replies are devoted to pro-Labour party sentiment (T19 and T18), while 15% and 11% discuss Scotland (T17) and welfare issues (T16), respectively.

Replies on both sides are dominated by sentimental topics, and indeed more of such topics were detected for the US Election case. The overall distribution for each dataset is shown on Table IV.

B. Prominent Hashtags

The most popular hashtags are primarily sentimental in nature and often among the salient words of the LDA-generated topics. Top hashtags `#makeamericagreatagain`, `#trump2016` and `#trumptrain`, with over 30,000 combined uses, are captured in pro-Trump topics T16 and T17 of the US Election, while `#crookedhillary` and `#neverhillary` are picked up by contra-Clinton topic T2, and the `#imwithher` campaign motto features in pro-Clinton topic T0.

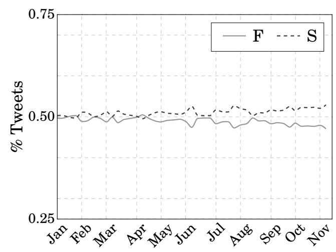
A potential exception to this pattern is `#Brexit`, which is picked up by factual topic T0, and thus may refer to the event itself rather than its endorsement. We find that the hashtag was much nonetheless more frequent on the Leave side, with 2,433 uses versus 685 on the Remain side.

Interestingly, we find a frequent use of Trump-related hashtags in replies to Clinton, with hashtags `#trump`, `#trump2016`, `#makeamericagreat` and `#trumptrain` appearing more than 9,000 times. This phenomenon is not expressed in the reverse direction (i.e., hardly any Clinton hashtags appear in Trump threads).

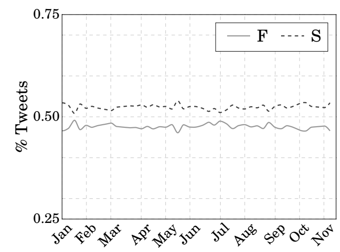
This predominantly one-sided adoption of sentimental hashtags indicates that, though adversarial in nature, the opposing sides of the discussions are not often directly confrontational: topics referring to a particular candidate or stance, both favorably and unfavorably, are usually targeted at its stakeholders. This is particularly notable on pro and contra Clinton and Trump topics, as well as pro Labour Party topics. We also note that while unfavorable topics hint at a tendency to support the opposite stance, they do not necessarily convey this explicitly.

Label	Clinton	Trump	Remain	Leave
Factual	0.44	0.39	0.47	0.41
Sentimental	0.56	0.61	0.53	0.59

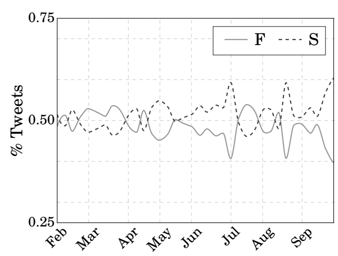
TABLE IV: Proportion of factual and sentimental replies to campaigners in the US Elections and Brexit.



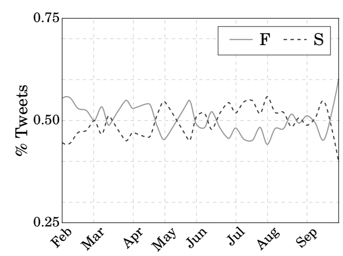
(a) Clinton.



(b) Trump.



(c) Leave.



(d) Remain.

Fig. 2: Timeline for factual (F) and sentimental (S) topic groups for Clinton (a) and Trump (b) on the US Election, and Leave (c) and Remain (d) sides of Brexit.

C. Evolving Topics

To understand the relationship between activity and topical focus, we also investigate the timeline for the LDA-based topics, grouped according to their factuality. Figure 2 shows the evolution of activity, in terms of the number of tweets, of factual topics (F) and sentimental topics (S), for both Clinton and Trump in the US Election case and the Remain and Leave sides of the Brexit case. Here we see a reflection of the overall topical distribution discussed previously, with a consistent predominance of sentimental topics throughout the campaigns. The Remain side of the Brexit discussion is again the exception, with a majority of factual topics on the weeks preceding and following the May 5 elections. The weeks following the announcement of the referendum (made on February 20) also saw an increase in the discussion of factual topics on the Leave side.

Both cases see an increase of activity for sentimental topics immediately after the end of the campaigns (i.e., the election on November 8 and the referendum on June 23. Even shortly before the election, discussions on Clinton's threads displayed a trend of growing sentimental content, following the reaction to new scandals surrounding the candidate. Meanwhile, Trump saw only a slight increase in sentimental tweets around the election itself.

For the Brexit case, Remain and Leave show spikes of sentimental activity which fueled the growing discussions following the decisions. While this burst of activity quickly fades out on the Leave side, the Remain side exhibits a strong signal on sentimental topics for several weeks following the referendum. This reaction has been coined "Bregret", for British regret, in the media.

IV. The Power of Power Users

In this section, we turn our focus to the users involved in the discussions. In particular, we are interested in the role and influence of different kinds of users, as a function of their inclination towards either one of the two stances. We label each user according to:

- *Role*: user is either a leader (i,e., leading politician), power user or regular user;
- *Inclination*: user leaning towards stance A or stance B.

In addition to the leading figures in the discussions (e.g., Clinton and Trump), we distinguish two other kinds of users, motivated by the observation that some accounts have a high activity level that makes them unlikely to be managed by single individuals. We suspect that some of these accounts represent entire teams, either professional PR teams or (paid or volunteering) workers. To identify these, we obtained activity information from users' Twitter profiles, including: i) account life time (in days) since its creation date, ii) number of tweets ever posted (not just within the discussion at hand), iii) number of users that the account follows – called followees. We manually inspected a random sample of the accounts and labeled 50 power users and 50 regular users as the training data with the above features. We then used libsvm[2] [4] to classify all other users. Using 5-fold cross validation, we achieved an accuracy of 93% and 96% for the inclination and power user classification respectively in the US Election case, and 91% and 99% accuracy in the UK Brexit case. This high accuracy is in line with the significant disparity in the posting activity between regular and power users. Table V shows the breakdown of users across these three roles.

These tables also show how the three user roles are distributed over the two inclinations. To determine these values, we again trained a binary classifier for user inclination with libsvm, using all original posts from leaders on both sides as positive and negative training examples. For each user, we concatenated all her tweets into a virtual document and fed this into the trained classifier. Interestingly, we see that the remain side has twice as many power users than the leave side, whereas in the US election case the number of power users is roughly the same for both sides.

[2]https://www.csie.ntu.edu.tw/ cjlin/libsvm/

Incl.	pro Clinton	pro Trump	Total
L	1	1	2
P	5,362	4,851	10,213
U	167,927	81,861	249,788
Total	173,290	86,713	260,003

(a) US Election

Incl.	pro Remain	pro Leave	Total
L	2	2	4
P	1,042	525	1,567
U	42,310	14,297	56,607
Total	43,354	14,824	58,178

(b) UK Brexit

TABLE V: User roles and inclinations (L = leaders, P = power users, U = regular users).

	pro Clinton		pro Trump	
Incl.	#Tweets	#R2U	#Tweets	#R2U
L	2,602	586,335	1,861	549,799
P	25,147	19,439	134,266	89,983
U	338,925	686,541	606,485	297,771

(a) US Election

	pro Remain		pro Leave	
Incl.	#Tweets	#R2U	#Tweets	#R2U
L	1,098	101,193	539	72,190
P	3,529	2,567	5,991	5,072
U	85,455	56,965	77,582	83,310

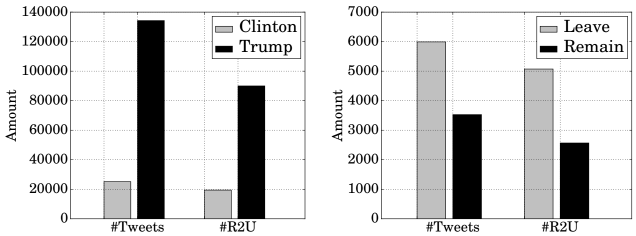
(b) UK Brexit

TABLE VI: Activity of users and their roles (L = leaders, P = power users, U = regular users).

A. Activity and Influence of Users

To assess the influence of users, we use two different metrics: i) their tweet activity in the scope of the adversarial discussion, and ii) the degree to which other users followed up on tweets by replying to them. Table VI shows statistics for these metrics, for each of the US and UK cases. The first metric is given by the number of tweets made by each user category. The follow-up metric is given by #R2U: the number of replies from others in response to users in the different categories.

Table VI shows that power users had a much higher share of activity in the Trump camp than in the Clinton camp. Trump-inclined power users were responsible for 12% of all replies to either candidate, whereas less than 3% of the replies were made by Clinton-inclined power users. The absolute numbers on the pro-Trump side are interesting as well: 134,000 tweets by power users and nearly 606,000 by regular users. This should be interpreted against the fact that Trump-initiated threads include a total of 550,000 tweets. This means there was a large number of pro-Trump tweets among replies to Clinton threads, and a substantial share of these were made by power users. In the reverse direction, this effect cannot be observed.



(a) US Election. (b) UK Brexit.

Fig. 3: Activity of power users.

As figure 3 shows, power users play a more significant role in supporting Trump and Leave respectively.

The #R2U numbers in Table VI confirm this interpretation, and furthermore show that the tweets by power users had additional influence by attracting lots of replies from others.

Compared to the US case, power users in the Brexit case were much less active and showed no indication of one side "hijacking" the other side's posts. As our notion of power users is given by the account's activity over its entire lifetime, rather than activity strictly within the adversarial discussion, this low activity profile is not entirely unexpected. Manual sampling reveals long-lived accounts that were active on earlier or other political topics, but seldom engaged in replying to one of the Remain or Leave leaders.

B. Combined View of Topics and Users

To conclude our analyses, we look into affinities between different user roles and the topics of discussion we identified in Section 3, with the goal of further investigating the impact of users in the themes and activity levels of the adversarial discussions.

In the US case, the most expressive topics for the leaders (Clinton and Trump themselves) are pro-candidate topics T0 and T17, encompassing 25% and 22% of tweets made by each respective candidate. In addition to these, topics T15 (Media Bias), T1 (contra-Clinton) and T19 (contra-Trump) also received considerable attention from regular users and together make up 37% of all their tweets.

Interestingly, the biggest difference between power users and regular users are also seen in pro- and contra-Trump topics T16 and T19, with the latter receiving more attention among power users: 8% of their tweets fall into topic T16, compared to 4% of tweets by regular users. In the opposite direction, while T19 is still well represented in tweets by power users, it receives the most attention from regular users and ranks as the most expressive topic for this user group. A similar pattern can be seen in contra-Clinton topics, which receive a slightly smaller share of activity from power users. Thus, activity on pro- and contra-candidate topics suggests that regular users tended to engage in more critical discussions about each party, while power users and leaders were mostly concerned with endorsing or promoting either side.

In the UK case, T0 (Referendum day) is among the strongest topics for all three user categories, accumulating 27% of all tweets made by the Leave campaign leaders, 9% of tweets made by power users and 8% of tweets by regular users. In contrast, less than 1% of the Remain campaign leaders' posts feature in this topic, with most of their activity going into topics T17 (Scotland), T15 (Sadiq Khan's mayoral election) and T19 (pro-Labour party). These are more closely related to the political leaders themselves, as well as the other political events they were involved in, than to topics pertaining to the referendum and its implications. We recall from Section III that while such factual topics were discussed by both sides of the campaign and by both user groups, no explicit Pro-Remain topic could be identified from the dataset.

Pro-Leave topic T2 saw the largest difference of activity, encompassing 9% of tweets by power users and less than 5% by regular users. As in the US case, such topics expressing support for one side of the campaign tend to be most polarizing, not only in sentiment but in the attention they receive from different user groups.

V. Related Work

Twitter Analyses: Social media like Twitter have been studied as a source for a wide variety of analyses. These aim to understand (and sometimes predict) the dissemination and virality of topics (e.g., [12], [14]), identify influential users (e.g, [2], [23]) and characterize their behavior, study spatial and temporal patterns of hot topics and user activities (e.g., [6], [25]). Several of these prior works are based on latent topic models (e.g., [20], [26]), typically using variants of LDA [3] or word2vec [16].

Polarized Topics: Identifying controversial topics and their polarized stances has received considerable attention in the literature. Prior work has largely focused on analyzing, modeling and predicting the political leaning of users (e.g., [7], [24]). A fundamental approach to measuring the amount of controversy in social media discussions is presented in [10] and further expanded in [11] to cover the evolution of polarizing discussions. The recent work of [21] studied the role of echo chambers in biased discussions, and proposes countermeasures to polarization.

Political Campaigns: Closest in spirit to this paper is the prior work on analyzing the 2012 US presidential election, based on Twitter data. [22] presents a tool for user sentiments in this context. Other studies on political campaigns or major incidents and their aftermaths have covered the 2008 German parliament election [19], the 2012 US primaries [15], the 2015 Scottish Independence referendum [9], and elections in developing countries [1]. [13] presents an approach for gauging the slant of political news consumption on Twitter, according to the activity of Republican and Democrat-leaning users. Though general analytics such as [17] have emerged, we are not aware of any in-depth analyses of social media discussions surrounding the 2016 US election campaign or the UK Brexit referendum.

VI. Conclusion

We analyzed the Twitter discussions on the 2016 US Election and the UK Brexit as instances of a general model of adversarial discussions in social media. Key insights include our observations on the strength of factual and sentimental (i.e., "post-factual") topics and the notable role and influence of power users. In particular, the US case showed that power users of one side can jump on posts in the opposing side's threads and attract significant follow-up by other users. Such effects were not visible in the UK case.

Future work involves extending our initial findings on the evolution of other adversarial discussions around political events, such as the continued effect of Brexit and upcoming elections in European countries. These would allow the investigation of other common and contrasting facets of the discussions, such as the impact of different demographics and public response to the aftermath of political decisions.

References

[1] Ahmed, S.; Jaidka, K.; Skoric, M.: Tweets and votes: A four-country comparison of volumetric and sentiment analysis approaches. ICWSM 2016.

[2] Bakshy, E.; Hofman, J. M.; Mason, W. A.; Watts, D. J.: Everyone's an influencer: quantifying influence on twitter. WSDM 2011.

[3] Blei, D. M.; Ng, A. Y.; Jordan, M. I.: Latent dirichlet allocation. *Journal of Machine Learning Research* 3:993–1022, 2003.

[4] Chang, C.-C., Lin, C.-J.: Libsvm: a library for support vector machines. *ACM TIST* 2(3):27, 2011.

[5] Chang, J.; Gerrish, S.; Wang, C.; Boyd-Graber, J. L.; Blei, D. M.: Reading tea leaves: How humans interpret topic models. NIPS 2009.

[6] Choudhury, M. D.; Jhaver, S.; Sugar, B.; Weber, I.: Social media participation in an activist movement for racial equality. ICWSM 2016.

[7] Conover, M.; Ratkiewicz, J.; Francisco, M. R.; Gonçalves, B.; Menczer, F.; Flammini, A.: Political polarization on twitter. ICWSM 2011.

[8] Conway, B. A.; Kenski, K.; Wang, D.: The rise of twitter in the political campaign: Searching for intermedia agenda-setting effects in the presidential primary. *Journal of Computer-Mediated Communication* 20(4):363–380, 2015.

[9] Fang, A.; Ounis, I.; Habel, P.; Macdonald, C.; Limsopatham, N.: Topic-centric classification of twitter user's political orientation. SIGIR 2015.

[10] Garimella, K.; Morales, G. D. F.; Gionis, A.; Mathioudakis, M.: Quantifying controversy in social media. WSDM 2016.

[11] Garimella, K.; Morales, G. D. F.; Gionis, A.; Mathioudakis, M.: The ebb and flow of controversial debates on social media. ICWSM 2017.

[12] Grabowicz, P. A.; Ganguly, N.; Gummadi, K. P.: Distinguishing between topical and non-topical information diffusion mechanisms in social media. ICWSM 2016.

[13] , Le, H.; Shafiq, Z.; Srinivasan, P.: Scalable news slant measurement using twitter. ICWSM 2017.

[14] Ma, Z.; Sun, A.; Cong, G.: On predicting the popularity of newly emerging hashtags in twitter. *JASIST* 64(7):1399–1410, 2013.

[15] Mejova, Y.; Srinivasan, P.; Boynton, B.: GOP primary season on twitter: "popular" political sentiment in social media. WSDM 2013.

[16] Mikolov, T.; Sutskever, I.; Chen, K.; Corrado, G. S.; Dean, J.: Distributed representations of words and phrases and their compositionality. NIPS 2013.

[17] MonkeyLearn: Donald trump vs hillary clinton: sentiment analysis on twitter mentions. *Blog Post,* `blog.monkeylearn.com/donald-trump-vs-hillary-clinton-sentiment-analysis-twitter-mentions/`, *20 Oct 2016*.

[18] Parmelee, J. H.: The agenda-building function of political tweets. *New Media & Society* 16(3):434–450, 2013.

[19] Tumasjan, A.; Sprenger, T. O.; Sandner, P. G.; Welpe, I. M.: Predicting elections with twitter: What 140 characters reveal about political sentiment. ICWSM 2010.

[20] Vosecky, J.; Jiang, D.; Leung, K. W.-T.; Xing, K.; Ng, W.: Integrating social and auxiliary semantics for multifaceted topic modeling in twitter. *ACM TOIT* 14(4):27:1–27:24, 2014.

[21] Vydiswaran, V. G. V.; Zhai, C.; Roth, D.; Pirolli, P.: Overcoming bias to learn about controversial topics. *JASIST* 66(8):1655–1672, 2015.

[22] Wang, H.; Can, D.; Kazemzadeh, A.; Bar, F.; Narayanan, S.: A system for real-time twitter sentiment analysis of 2012 u.s. presidential election cycle. ACL 2012.

[23] Weng, J.; Lim, E.; Jiang, J.; He, Q.: Twitterrank: finding topic-sensitive influential twitterers. WSDM 2010.

[24] Wong, F. M. F.; Tan, C.; Sen, S.; Chiang, M.: Quantifying political leaning from tweets, retweets, and retweeters. *IEEE TKDE* 28(8):2158–2172, 2016.

[25] Yuan, Q.; Cong, G.; Ma, Z.; Sun, A.; Magnenat-Thalmann, N.: Who, where, when and what: discover spatio-temporal topics for twitter users. KDD 2013.

[26] Zhao, W. X.; Jiang, J.; Weng, J.; He, J.; Lim, E.-P.; Yan, H.; Li, X.: *Comparing Twitter and Traditional Media Using Topic Models*. ECIR 2011.