Controversy Detection Using Reactions on Social Media

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***Abstract*—In this work we demonstrate a method to detect controversy on news issues. This is done by performing an analysis of people's reaction on social media to news articles reporting these issues. Detecting controversial news topics on web is a relevant problem today. It helps to identify the issues upon which people have divided opinion and is specially useful on topics such as a presidential election, government reforms, climate change etc. We use sentiment analysis and word matching to accomplish this task. We show the application of our method for detecting controversial topics during the US Presidential elections 2016.**

***Index Terms*—Controversy Detection, Social media mining, NLP, Sentiment Analysis, Politics.**

I. Introduction

Given that the usage of online social media is increasing, many political parties and news sources are using this as a platform for spreading news. This helps us to collect more data about people's opinions on a topic and utilize this data as the key to understand some aspects regarding controversy. In the recent times, social media has been playing a role in how individuals process information and form political opinions. So, there has been a need to offer the user a view that differs from what they are mostly exposed to, for gaining the overall picture on a topic before coming to a conclusion or an opinion. However, behind all such applications, the fundamental yet challenging task that needs to be solved is to automatically classify whether a topic of discussion is controversial or not.

Newspaper networks are also using social media platform as a means of engaging users and strengthening their reach and influence because millions and millions of users around the world are connected through these social platforms. We would like to understand how users perceive a topic in politics through the lens of their social media feed. Our work is regarding the observation of the controversies and possibly understanding which issues are becoming controversial and why.

One aspect that is the focus of these studies is how the social media user interaction can be used to predict a controversy. Collecting this data from social media will be biased, noisy and has many other issues, but the effect of these issues can be reduced by taking data on a single topic from different sources and different groups, posts, comments. We combine the analysis of facebook user interactions along with text written by journalists from different sources biased towards different political parties. In this paper, we investigate the topics related to US 2016 elections. We find that our quantitative analysis can correctly classify the topic as being controversial or not.

Many previous studies have analysed some aspects of these posts and comments or other social media news feed, such as most number of likes and most retweets. Most previous works can be characterized as case studies, where controversy is identified in a single carefully-curated dataset, collected using ample domain knowledge and auxiliary domain-specific sources (e.g., an extensive list of hashtags regarding a major political event). We aim to overcome those limitations.

Our goal is to identify controversy regarding topics without prior domain-specific knowledge about the topic in question. In addition, we aim at complementing these results by comparing these topics from different sources, in order to consider the opinions from the people of all the groups to gain the whole view on a topic in question (like Republicans and Democrats). To the best of our knowledge, none of the prior studies used the opinions of different groups of people from different sources which are biased towards different political parties, along with linguistic and sentiment analysis on the same topic using user opinions as well as the journalist's data. This is the core contribution of this paper. The following sections will then explain the background in section II, data acquisition in section III, the core approach or pipeline in section IV, Results in section V, conclusion and future work in section VI.

II. Background

Controversy is a state of prolonged public dispute where there is a strong disagreement, usually concerning a matter of conflicting opinion or pint of view [1]. It can also be defined as a serious argument about something that involves many people. To our knowledge there has been no major works in this field which automatically detects controversies considering the textual information as well as user opinions on a topic. Some of the existing works used wiki data by phrasing a query based on the topic to get the related wiki pages and then based on some features like edit wars of the pages for the detection of controversy [2]–[5].

A. Word Embeddings

We use word embeddings to find most similar articles from our dataset for a given topic. Recently *dense word embeddings*

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TABLE I
ABOUT THE DATASET

Nature	Page	Share Count	Reaction Count	Comment Count
Left	Addicting Info	1270	3120	392
	Occupy Democrats	29250	34669	2858
	The Other 98%	18007	20971	915
Mainstream	ABC Politics	44	177	71
	CNN Politics	183	678	322
	Politico	182	900	170
Right	Eagle Rising	616	520	79
	Freedom Daily	2474	3685	516
	Right Wing News	1398	2454	360

have become very popular in various NLP and text analysis techniques. We use *word2vec* word embeddings introduced by [6], to find similar articles for a given topic. *Word2vec* vectors are trained on large text corpus to obtain vector representation of words that are semantically meaningful such that similar meaning words have similar vector representations. We take advantage of word embeddings to find similar articles.

B. Sentiment Analysis

Categorization of sentiment polarity is one of the fundamental problems in sentiment analysis [7]–[11]. Given a text, the problem is to categorize the text into one specific sentiment polarity, positive, negative or neutral. In this paper we have used sentiment analysis to get the opinions of people. Sentiment analysis can be done with words or phrases. It considers each word or phrase orientation and their contribution to overall sentiment. It works at the sentence level, which considers all the words in a sentences as one entity and tries to define its orientation. It can also works at the document level, which can be done by considering all the sentences in a document as one entity and defines the orientation.

III. Data Acquisition

In order to obtain the overall view of any topic of the US 2016 elections we have considered news sources from all the categories like left, mainstream and right in the years 2015 and 2016. We considered the publicly available facebook posts on their facebook official pages which gives us the data of number of likes, number of shares and number of comments on each post. All these links and data are taken from the BuzzFeed News Article repository [12]. The news sources of different categories are ABC News, CNN and Politico from mainstream, Addicting Info, Occupy Democrats from Left wing, Eagle Rising and Freedom Daily from Right wing. The stats regarding these sources are shown in Table I obtained from [12].

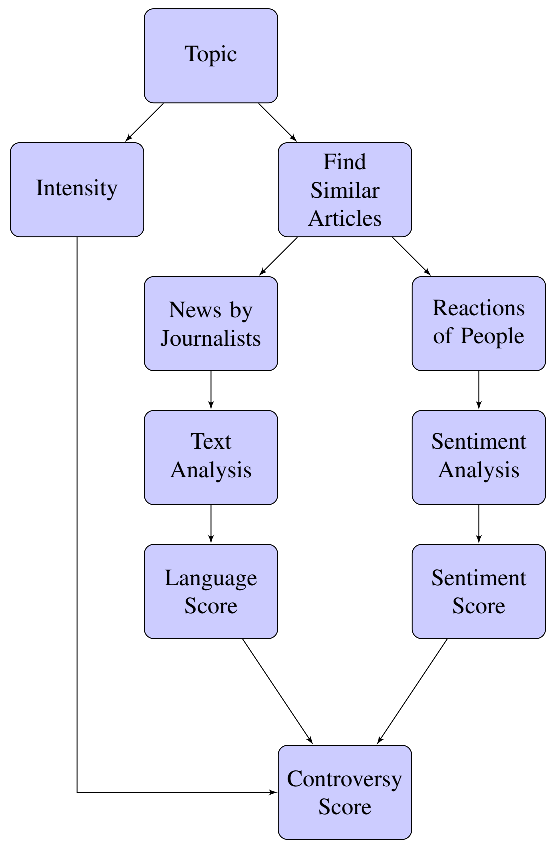

Fig. 1. A Flow Diagram for the Approach

IV. Our Approach

To detect controversy on a given topic, we collect a group of articles from different sources that report the same topic. All these sources shown in Table I are popular news organizations. Journalists of these organizations write articles based on a topic. Along with the user opinions, we take advantage of article content for calculating the Language score. We use user opinions(comments) and interactions(number of shares, comments & likes) for calculating the sentiment score and intensity of the topic respectively. All these scores were used for calculating the final controversy score. The pipeline is shown in Fig.1. Algorithm 1 explains how we classify a topic into controversial or not. Further details and in-depth analysis for calculating controversy score is discussed below:

A. Finding Related Articles

We use cosine similarity to find similar articles for a given news article. The first step is to convert the articles to vectors so that cosine similarity can be computed. A popular method to do this is to use TF-IDF vectors, but we instead use word2vec vectors to get better vector representation. We found out experimentally that representing an article as the mean vector of the vector of all the words contained in the article gives good results. We remove stop words from the article. Our word2vec vectors were trained on Google News Corpus using Skip Gram architecture with Negative Sampling. Our obtained vectors gave us a good vector representation of news articles. Once represented as vectors we find similar articles by using cosine similarity.

Algorithm 1 Rule Based Controversy Detection

```
Input : A (Articles), T (Topic)
Output : Controversy Score
while article in A do
    r ← reactions
    s ← share
    c ← comments
    r_a ← average_reactions
    s_a ← average_share
    c_a ← average_comments
    sent ← sentences
    con_sent ← article.sentences_with
    _controversial_vocabulary
    com_sent ← Total_sentences_in_all
    _comments_of_an_article
    com_con_sent ← sentences_in_comments
    _with_controversial_vocabulary_of_an_article
    pos ← positive_comments
    neg ← negative_comments
    i ← (r/r_a + s/s_a + c/c_a)/3
    l ← (con_sent/sent) + (com_con_sent/com_sent)
    if 1.5 * pos < neg then
        senti ← (pos − neg)/(pos + neg)
    else
        senti ← 1 − (pos − neg)/(pos + neg)
    end if
    con_score ← i * l * senti
    if con_score > 0.7 then
        article.label ← con
        final_score ← final_score + 1
    else
        article.label ← non_con
    end if
end while
if final_score/len(A) > 0.5 then
    T.label ← con
else
    T.label ← non_con
end if
return T.label
```

B. Detecting Controversy

By the definition of controversy, the controversial topics have long discussions or debates and conflicting opinions. In the below subsections we discuss different scores and parameters that contribute to the classification of a topic into controversial or not.

User Opinions

As a first step for detecting controversy, we do sentiment analysis of all the comments related to a post and and classify them as positive, negative or neutral. We are interested in finding out disagreement, disapproval, criticism, or opposing opinions, as disparity in views of people should ideally indicate controversy. Therefore by analyzing the count of positive and negative comments on the article we calculate the sentiment score. Considering posts from different sources from different categories helps to gain the overall information about a topic.

Here, there is no need to consider whether an article is being positive or negative regarding a particular topic. Because, the considerable number of user opinions on both positive and negative sides indicates that there are opposing or conflicting opinions which by the definition refers to $controversy$. In the comments in social media, users can tag their friends or write information about their products which will affect the sentiment score. So, to reduce this issue we neglect neutral comments, comments of one word and comments having six or more sentences.

Less difference between positive and negative opinions indicates opposing opinions which refers to controversy. Hence, the $sentiment\ score(SC)$ will be more is such cases.

pos = Total positive comments
neg = Total negative comments
SC = $1 - ((pos - neg)/(pos + neg))$

If indication of strong disagreement in the people's opinions is observed i.e if the number of negative comments are far greater than the number of positive comments then this should contribute more to the controversy score. We observed experimentally that if the number of negative comments are 1.5 times greater than the number of positive comments, the sentiment score can be calculated as follows:
SC = $(pos - neg)/(pos + neg)$

Controversy words

Secondly, we detect words that are similar in meaning to the words "controversy", "disagreement" and "criticism". We build a list of words that are similar in meaning to these words. Then we look for them in the article. This list contains around 600 words. The $language\ score(L)$ is calculated by considering the sentences that have atleast one word from this list. We can see from the news articles and user comments in the social media, journalists use proper language unlike the users in social media. If there is anything related to criticism, disagreement, dispute or controversy, there is high probability that we can find these words in the content of article. The user opinions were also considered for the matching of controversial words. Most of the times the users do not use proper spellings and vocabulary while writing the comments instead use shortcuts and emoticons. So, their contribution will be less to the sentiment score.

$N1$ = Total sentences in an article

$S1$ = Sentences that have atleast one controversy word

$N2$ = Total sentences in all comments of the post.

$S2$ = Sentences that have atleast one controversy word

L = ($S1$/$N1$ + $S2$/$N2$)

Topic Intensity

Finally, along with the language score and sentiment score we consider user interaction. By the definition of controversy, longer the discussions and higher the opposing opinions greater the probability of topic being controversial. We calculate $Intensity(I)$ of the topic by considering the number of reactions, comments and shares of a particular post and all the posts in that news page. This gives us a quantitative measure of how on an average users are reacting to a post in that page. We consider higher the number of users interacting on a post greater the intensity of a topic. Greater intensity with opposing opinions leads to more chance of controversy.

R = Total reactions or likes

C = Total comments

S = Total shares

$Avg.R$ = Avg. reactions of the news source page

$Avg.C$ = Avg. comments of the news source page

$Avg.S$ = Avg. shares of the news source page

I = $((R/Avg.R) + (C/Avg.C) + (S/Avg.S))/3$

Controversy Score

The $Controversy\ score(CS)$ indicates the topic being controversial or not. Higher the controversial score greater the controversy. We calculate controversy score by considering the Intensity(I) of the topic in question, the Language score(L) and the Sentiment score(SC). From the above explanation, it is clear that each score is directly proportional to final controversy score. Hence, controversy score can be given as follows:

CS = $I * L * SC$

V. Results

Table II shows the results of some topics. Using some threshold (T) on the $controversy\ score$, each article is given a binary score. The final controversy score of the topic can be calculated by dividing the number of articles having score greater than T by the total number of similar articles. A controversy score 1 of the topic indicates that the topic is highly controversial and score of 0 indicates that the topic is not controversial. Experimentally, we observed that results are good for T as 0.7.

Consider the first topic from Table II, "Report:George H.W. Bush to vote for Hillary Clinton". In this topic the former president being Republican told that he will support Hillary Clinton who is a member of Democratic party. This leads to some disagreement from the Republican supporters and some appreciation from the democratic supporters which ultimately creates a strong opposing opinions and supporters from both the parties engaged in serious arguments. The intensity of the topic comes high because of the involvement of the many people and the difference between the number of positive and negative comments is less in 4 out of 5 articles as shown in the Table II. So, based on the definition of controversy, this topic leads to a state of public dispute where there is a strong disagreement and serious arguments about something that involves many people. Hence, this topic can be classified as a controversial one.

Coming to topic 2 in Table II, "President Obama criticising Trump" leads to strong discussions among the users who supports and opposes Republicans. And in Topic 3, "Cops killing an innocent black man" shows the strong disagreement as we can observe that 2 out of 3 articles has 2 times more negative comments than positive ones. In topic 5, Trump complains about the mic in the debate. The intensity of topic is high and as we can observe that 4 out 5 articles shows more negative opinions than the positive ones. The majority of users contradicted the reason given by Trump and language scores are also high indicates that articles also contains words from our controversy vocabulary.

In topic 6 of Table II, "Mark Cuban takes the front-row seat for the Presidential debate". Without prior knowledge about differences between Cuban and Republicans this seems a normal topic. But our approach classifies it as controversial. If we go into details from the news sources, then one can find that Cuban takes that seat intentionally to closely watch as Hillary Clinton tries to "overwhelm" Donald Trump. Mark Cuban plans to make sure Trump sees at least one unfriendly face. So, this made the topic debatable. In classifying these topics each score has its importance. Without considering intensity and language score even Topic 10 and 11 in Table II also seems controversial with the sentiment scores comparable to controversial topics. This show that all these scores has equal importance and all are directly proportional to controversy score.

VI. Conclusion and Future work

In this study we analyzed social network activity on the topics of the US 2016 elections from different popular news sources from different categories with a special focus on polarity of the user interaction. We performed the first combined study of sentiment and textual analysis for quantifying controversy in social media. Our results suggests that user interaction from all these different categories of political parties will give the overall views or opinions of the people on that particular topic which really contributes to the classification of a topic being controversial or not. Besides, our process is domain independent and can be applied to any dataset from other domains.

From the application point of view, our controversy score can be used to generate recommendations for trending or hot topics in news feeds on social media. In future work we intend to investigate these metrics in other domains to generate a

TABLE II
CONTROVERSIAL AND NON CONTROVERSIAL TOPICS

Topic	**Article**	**Intensity score**	**Positive comments**	**Negative comments**	**Neutral comments**	**Language score**	**sentiment score**	**Controversy score**
Report: George HW Bush to Vote for Hillary Clinton	Article 1	1.34	97	93	192	1.4	0.95	1
	Article 2	2.37	147	106	275	1.75	0.72	
	Article 3	47.09	392	286	572	1.47	0.73	
	Article 4	1.13	11	14	27	1.75	0.78	
	Article 5	2.37	22	15	31	1.8	0.68	
President Obama says Trump doesn't have Preparation, Temperament and Values.	Article 1	6.3	148	129	344	1.47	0.87	1
	Article 2	1.01	37	25	53	1.45	0.67	
	Article 3	1.78	24	33	61	1.60	0.72	
Protests Erupt in Charlotte after Cops kill disabled Black Man who was reading a book in his car.	Article 1	0.42	63	137	145	1.7	1.17	1
	Article 2	1.04	51	122	100	1.55	1.39	
	Article 3	4.10	158	189	536	1.76	1.99	
Republicans push Bill to legalize voter intimidation to help Trump in Pennsylvania	Article 1	5.10	250	212	424	1.5	0.85	0.8
	Article 2	0.38	22	33	63	1.92	0.66	
	Article 3	4.24	145	116	289	1.55	0.80	
	Article 4	0.422	52	42	148	1.88	0.80	
	Article 5	2.08	34	60	95	1.79	0.76	
Trump complains about debate mic, He gives pathetic reason for why he sucked at Debate.	Article 1	2.15	73	66	131	1.74	0.90	0.8
	Article 2	0.60	91	140	195	1.80	0.54	
	Article 3	1.27	124	150	236	1.80	0.83	
	Article 4	8.90	322	554	775	1.82	0.72	
	Article 5	2.93	91	155	200	1.86	0.70	
Mark Cuban takes the front-row seat for the Presidential Debate.	Article 1	0.79	718	486	1038	1.3	0.67	0.6
	Article 2	0.47	254	166	428	1.27	0.65	
	Article 3	0.26	13	7	16	1.5	0.53	
	Article 4	1.73	44	41	96	1.78	0.93	
	Article 5	2.75	65	52	104	0.96	0.80	
Crooked Hillary has been fighting ISIS, or whatever she has been doing these years - Trump presses Clinton on growth of ISIS	Article 1	0.28	14	30	49	1.24	1.14	0.6
	Article 2	0.50	27	30	63	1.76	0.90	
	Article 3	0.54	36	73	139	1.84	1.02	
	Article 4	0.71	35	67	121	1.47	0.91	
	Article 5	0.32	27	49	59	1.80	0.81	
Assistance to Syria suspended after attack on Aid Convoy	Article 1	0.75	49	14	48	1.5	0.28	0.33
	Article 2	0.20	31	53	53	0.56	0.70	
	Article 3	0.77	966	1924	2964	1.5	0.99	
First presidential debate is just a week away	Article 1	0.14	81	13	30	1.50	0.70	0.2
	Article 2	0.02	8	6	7	1.80	0.75	
	Article 3	0.5	160	111	155	1.89	0.85	
	Article 4	0.17	324	386	553	1.40	0.85	
	Article 5	0.44	7	8	14	1.63	0.88	
Ivanka Trump to meet with female GOPers at RNC	Article 1	0.37	67	45	125	0.72	0.67	0
	Article 2	0.70	71	50	126	1.2	0.70	
	Article 3	0.53	114	53	156	1.68	0.46	
	Article 4	0.64	78	51	129	0.84	0.65	
Obama looks for peace opening in final meeting with the Prime Minister of Israel, Netanyahu	Article 1	0.13	9	5	12	1.33	0.55	0
	Article 2	0.10	11	7	21	0.14	0.64	
	Article 3	0.30	37	26	57	0.40	0.70	
	Article 4	0.08	13	8	13	1.01	0.62	

generalized platform to give details with respect to controversy and extend this work to find predict the probability of a post being fake or not. This will require more sophisticated analysis methods, but it could allow to capture factual information from all the sides of views to the users which is a valuable solution to the major drawbacks of social media which captures non-authenticated and possibly non-factual information.

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