Detecting Controversies in Online News Media

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Detecting Controversies in Online News Media

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ABSTRACT
This paper sets out to detect controversial news reports using online discussions as a source of information. We define controversy as a public discussion that divides society and demonstrate that a content and stylometric analysis of these debates yields useful signals for extracting disputed news items. Moreover, we argue that a debate-based approach could produce more generic models, since the discussion architectures we exploit to measure controversy occur on many different platforms.

KEYWORDS
Controversy Detection, Media Analysis, Behavioral Analysis

1 INTRODUCTION
With the advent of Web 2.0, the online world has become an intrinsic part of the public sphere. Growing interactivity and connectivity transformed the Web into a digital forum where discussions develop and societal disagreements arise. Controversies that divide public opinion are increasingly fought in the digital realm and with digital means.

Recognizing controversy is difficult, for algorithms as well as humans. In this paper, we develop a "hybrid" approach, combining insights from both social and computer science: first we determine key concepts coined by social scientists, and subsequently translate these to a generic but nonetheless predictive model of controversy. Instead of relying on platform-specific content or features, we argue that a discussion-based approach could yield a more widely applicable model for monitoring online disputes.

2 RELATED WORK
2.1 Controversy in the Social Sciences
Controversies exist as a type of public debate: they touch on issues that divide large segments of society [2, 9]. They emerge through the interaction between core-campaigners and broader sections of the public (termed occasional campaigners and sympathizers) [9]. Because they bear upon deeper rooted ideological divisions or opposing value systems, controversies tend to be unsolvable and persist over time. The increasing delineation of opposing views results in an ever widening disagreement or polarization [15]. Given that disputes flow from the participants' beliefs and values, the exchange of opinions is not limited to "facts", but invites strong emotions as well [8]. More linguistically inspired scholars such as Clarke [2] emphasized the indexical function of the term, pointing out how producers of discourse construct controversy by strategically naming and classifying events. Moreover, social psychologists [1], have argued that mental states of interlocutors are reflected in their linguistic style, implying that discussions on controversial topics may exhibit divergent stylometric patterns (i.e. a distinct debating style).

2.2 Controversy in Computer Science
Computer scientists, through coincidence or serendipity, concentrated on similar aspects when modeling and detecting online controversies. Debate structure, for example, plays a prominent role in Garimella et al. [5] who elicit public disagreement through "conversation graphs", a network constructed from tweets on a hashtag. Emotions have proven a powerful indicator as well. Popescu and Penneacciotti [11] studied how controversial events develop on Twitter. They captured the level of polarization by computing how mixed the audience’s response was in terms of sentiment. Perceiving controversies as primarily indexical, other studies relied on "Controversy Lexicons" to interrogate their data. Mejova et al. [10] analyze news reports using a crowd-sourced lexicon containing frequent content words for which participants were asked whether they signaled controversy or not. Also, Jang et al. [7] assessed the power of lexicon-derived features, building on the work of Cramer [3]. Roitman et al. [13] apply a manually crafted lexicon to retrieve controversial claims. Besides these feature types, Wikipedia counts as a crucial instrument for controversy detection. Previous research has leveraged the metadata associated with Wikipedia pages—the length of the discussion page, the presence of edits and reverts—to model dispute. Focusing on "editorial wars" Yasseri et al. [17], revealed the "dynamics of conflict" that lay behind the encyclopedia. Also in Dori-Hacohen and Allan [4] Wikipedia was adopted as a yardstick of controversy. Using a nearest neighbor approach they mapped Web pages to their closest Wikipedia articles—assuming that a site is controversial if the Wikipedia neighbors are. Our approach emphasizes the style and content of online conversations; it provides a generic method for detecting controversy not just based on what users discuss, but also how they perform the debate. Similar to Siersdorfer et al. [14] we apply controversy detection to news content. But whereas Siersdorfer et al. [14] focused on detecting controversial comments based on textual features (or polarizing
content based on rate divergence, i.e. the extent to which items receive likes and dislikes at similar rates), we attempt to classify articles by gauging a broader set of features.

3 DETECTING CONTROVERSY

3.1 Research Questions

The aim of this paper is to propose a debate-based method for detecting disputed content. To demonstrate our method, we look at comment threads associated with news articles—but the model applies to other contexts and platforms, as long as the discussion can be transformed to a post-reply tree. Our emphasis on online debates as a source of information, was driven by the scarcity of generic and adaptive approaches. The state-of-the-art relies heavily on platform-specific content (e.g. Wikipedia articles) or features (e.g. retweets on Twitter)—while discursive exchanges between users, the focus of this study, are found everywhere online. The paragraphs below demonstrate how monitoring discussions helps detecting controversial content by answering the following research questions: RQ1 How to detect controversial newspaper articles based on their surrounding discussions? Which features prove most informative? RQ2 How does this approach compare to other relevant baselines? Can different models be combined to improve accuracy?

3.2 Data Selection and Annotation

The data was sourced from the *theguardian.com*, the online version of the British broadsheet. According to the National Readership Survey, *guardian.com* ranks third in terms of popularity in the UK, just after the online editions of the Daily Mail and the Daily Mirror.1 As the website content is freely accessible, the Guardian attracts a wide and ideologically diverse readership. This is reflected in the variety of opinions articulated by readers in the articles’ comments section, which makes this platform an ideal location for monitoring disputed news. Using the Guardian API, we scraped all articles and their associated comments, published between September and November 2017, and selected a sample of 900 for manual annotation. We organized a crowd-sourcing task in which participants were asked to rate each article as either clearly non-controversial, possibly non-controversial, possibly controversial and clearly controversial. The labels were converted to an integer scale, from 1 (clearly non-controversial) to 4 (clearly controversial). For each article we obtained three annotations. Those with an average higher than 2.5 were categorized as “controversial”. Using this cut-off, the annotated corpus split almost evenly into controversial and possibly non-controversial, possibly controversial and clearly non-controversial articles.

3.3 Feature Space

The features extracted from the comments draw on different sources of information. **Linguistic Aspects**: These features capture linguistic variation between debates by counting the Part-of-Speech tags. **Structural Features**: Features that measure the formal aspects of the debate, such as the number of comments, the speed at which they were posted, and the percentage of replies. **Lexicons**: Instead of creating a hand-crafted or crowd-sourced lexicon, we chose to automatically generate an “agreement” and “disagreement” word list [12]. Starting with a list of manually selected seed-words that unambiguously mark agreement or its antonym we extracted related words from embeddings trained on the Google News Corpus (referred to as V below). For each word wi in V we computed a Lexicon score: li = ∑k j=1 cos(vi, vj), with vi and vj being the vector representation of the word wi and the seed word wj respectively. Consequently, we ranked all words by their li scores from high to low and selected the first 1000. 3 **Emotion**: Sentiment detection was performed with SentiStrength, a tool which has proven to obtain human-level accuracy on short texts. For each comment it produces a score between −4 (very negative) or +4 (very positive). Texts with a sentiment score between −1 and +1 were classified as neutral. To estimate how mixed the response was to an article, we followed the formula proposed by Popescu and Pennacchio (11), with #emo referring to the number of comments with sentiment orientation emo:

\[
\frac{\text{Min}(\#C_{pos}, \#C_{neg})}{\text{Max}(\#C_{pos}, \#C_{neg})} \cdot \frac{\#C_{pos} + \#C_{neg}}{\#C_{pos} + \#C_{neg} + \#C_{neut}}
\]

**Other Features** The Wikipedia Score WSj of a given article aj—or concatenation of the comments appended to that article—is defined as the sum of the cosine similarities of the Tf-Idf representation of the article (or comments) and the Tf-Idf vector of the pages listed as controversial on Wikipedia.

4 RESULTS

4.1 Comment-based Models

To answer RQ1 we assess how accurately subsets of the comment-based feature space (see Table 1) predict the controversiality of a news report. We tested different models but opted for Random Forests (RF) and Support Vector Machines (SVM). The tables below show scores produced by Random Forests—which scored slightly better—than the exception of Table 3 which reports the weights of a SVM with linear kernel after training. Table 2 shows accuracy, f1 and precision scores obtained after 5-fold cross-validation by feature group: linguistic, structural, emotional, controversy and combined. The linguistic characteristics don’t perform well, with only the structural features faring worse: opposed to our initial expectations, the size of the debate—expressed by the number of comments, or the rate at which they were posted—serves as a weak predictor. Emotion slightly outclass the linguistic and structural subsets, with an accuracy of 70 per cent. The features we explicitly designed to capture the “controversial” aspects of a discussion work truly better, obtaining an accuracy of 75 per cent and a precision outclassing all previous models. Combining the feature sets improves the performance, irrespective of the chosen metric.

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1 The seeds word list comprises words which are related to “disagreement” or “agreement” according to http://www.thesaurs.com/browse/agreement/

2 Because antonyms are often closely located to each other in the vector space—the vector representation of “good” lays near to “bad” “disagreement” words sometimes rank quite highly in the Agreement Lexicon. To filter out this noise, we discarded word wj from lexicon La for it happened to have a higher rank in lexicon Ldis, and vice versa.

3 To measure offensive language we used the lexicon provided by Luis von Ahn http://www.cs.cmu.edu/~blou/seed/summary/seed_words.txt

Table 1: Feature Space of the Model

<table>
<thead>
<tr>
<th>Feature Name</th>
<th>Social Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>LING-POS</td>
<td>Debate Style</td>
<td>Percentage of tokens that belong to the same Part-of-Speech category. With P-o-S either NN (noun), PR (pronoun), RB (adverb), JJ (adjectif), MD (modal), UM (interjection).</td>
</tr>
<tr>
<td>LING-QU</td>
<td>Debate Style</td>
<td>Percentage of tokens that are quotation marks</td>
</tr>
<tr>
<td>LING-LENGTH</td>
<td>Debate Style</td>
<td>Average (or variance) number of tokens per comment</td>
</tr>
<tr>
<td>LING-OVERLAP</td>
<td>Debate Style</td>
<td>Average (or variance) number of overlapping tokens between a post and a reply</td>
</tr>
<tr>
<td>EMO-POS-NEG-NEUT</td>
<td>Emotion</td>
<td>Relative number of positive, negative or neutral comments</td>
</tr>
<tr>
<td>EMO-REP-NEG-POS</td>
<td>Emotion</td>
<td>Relative number of replies with negative or positive sentiment</td>
</tr>
<tr>
<td>EMO-REP-DIFF</td>
<td>Emotion</td>
<td>The mean of the differences between the sentiment score of a post and the sentiment score of a reply to that post.</td>
</tr>
<tr>
<td>STRUC-REP</td>
<td>Debate</td>
<td>Relative number of comments that are replies</td>
</tr>
<tr>
<td>STRUC-NUM</td>
<td>Debate</td>
<td>Absolute number of comments</td>
</tr>
<tr>
<td>STRUC-ONE</td>
<td>Debate</td>
<td>Absolute number of comments posted one hour after the article was published</td>
</tr>
<tr>
<td>STRUC-RATIO</td>
<td>Debate</td>
<td>Number of comments divided by the time (expressed in seconds) between the first and last comment</td>
</tr>
<tr>
<td>CONTRO-EMO-MIX</td>
<td>Polarization</td>
<td>Indicates how mixed the response is in terms of sentiment.</td>
</tr>
<tr>
<td>CONTRO-CONTRA</td>
<td>Polarization</td>
<td>Contradiction score C developed by Tsytsarau et al. [16].</td>
</tr>
<tr>
<td>CONTRO-LEX-DIS</td>
<td>Indexical</td>
<td>The probability that a word belongs to $L_{dis}$.</td>
</tr>
<tr>
<td>CONTRO-LEX-AGR</td>
<td>Indexical</td>
<td>The probability that a word belongs to $L_{agr}$.</td>
</tr>
<tr>
<td>CONTRO-LEX-OFF</td>
<td>Emotion</td>
<td>The probability that a word is an “offensive” term.</td>
</tr>
<tr>
<td>CONTRO-ANTONYM</td>
<td>Polarization</td>
<td>Number of WordNet antonym pairs divided by the number of posts</td>
</tr>
<tr>
<td>CONTRO-CL</td>
<td>Polarization</td>
<td>The Silhouette score obtained after k-means clustering of comments by user (k=2).</td>
</tr>
<tr>
<td>CONTRO-WIKI-SCORE</td>
<td>Context/Time</td>
<td>Summed similarity of the newspaper article to the set of controversial Wikipedia articles.</td>
</tr>
</tbody>
</table>

Table 2: Accuracy for Comment-based Model

<table>
<thead>
<tr>
<th>Type</th>
<th>ACC</th>
<th>F1</th>
<th>PREC</th>
</tr>
</thead>
<tbody>
<tr>
<td>LING</td>
<td>0.69</td>
<td>0.71</td>
<td>0.65</td>
</tr>
<tr>
<td>STRUC</td>
<td>0.60</td>
<td>0.66</td>
<td>0.56</td>
</tr>
<tr>
<td>EMO</td>
<td>0.70</td>
<td>0.73</td>
<td>0.63</td>
</tr>
<tr>
<td>CONTRO</td>
<td>0.75</td>
<td>0.73</td>
<td>0.75</td>
</tr>
<tr>
<td>COMBINED</td>
<td>0.77</td>
<td>0.76</td>
<td>0.75</td>
</tr>
</tbody>
</table>

Table 3: Features Weights of SVM with Linear Kernel

<table>
<thead>
<tr>
<th>Features Non-Contro</th>
<th>Weight</th>
<th>Features Contro</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>LING-PR</td>
<td>-0.57</td>
<td>CONTRO-LEX-DIS</td>
<td>0.52</td>
</tr>
<tr>
<td>LING-OVERL-MEAN</td>
<td>-0.31</td>
<td>CONTRO-WIKI-SC.</td>
<td>0.29</td>
</tr>
<tr>
<td>STRUC-REP</td>
<td>-0.24</td>
<td>LING-VB</td>
<td>0.26</td>
</tr>
<tr>
<td>EMO-POS</td>
<td>-0.21</td>
<td>CONTRO-LEX-OFF</td>
<td>0.22</td>
</tr>
<tr>
<td>LING-LENGTH-MEAN</td>
<td>-0.18</td>
<td>CONTRO-ANTON.</td>
<td>0.22</td>
</tr>
<tr>
<td>LING-JJ</td>
<td>-0.13</td>
<td>CONTRO-CONTRA</td>
<td>0.22</td>
</tr>
<tr>
<td>LING-NN</td>
<td>-0.04</td>
<td>EMO-REP-NEG</td>
<td>0.22</td>
</tr>
<tr>
<td>EMO-VAR</td>
<td>0.04</td>
<td>LING-MD</td>
<td>0.20</td>
</tr>
<tr>
<td>EMO-REP-DIFF</td>
<td>0.07</td>
<td>LING-MD</td>
<td>0.17</td>
</tr>
<tr>
<td>STRUC-NUM</td>
<td>0.07</td>
<td>EMO-NEG</td>
<td>0.15</td>
</tr>
</tbody>
</table>

The presence of positive sentiments, on the other hand, pushes documents to the zero (non-controversial) class. These results confirm the findings of Mejova et al. [10], who reported a prevalence of negative framing in controversial newspaper articles. Their observation that disputed articles lack strongly emotional words, is only partially corroborated by Table 3, which shows that non-controversial issues are represented in a more positive tone. Exchanges about non-controversial articles tend to be longer and remain on topic—suggested by a higher ratio of overlapping tokens between comments and the replies they invite. Even though linguistic features fare poorly when taken in isolation, they do appear as crucial predictors: debates on non-controversial items exhibit a higher reliance on personal pronouns which suggests that participants give more attention to their “footing”, i.e. the positioning of self and others as participants in a discursive event [6].

4.2 Content-based Models

To answer RQ2 we compare the above method to content-based models. Table 4 compares the above results to other relevant baseline methods: a classifier trained on the Tf-Idf representation of the article content (or concatenated comments). WIKI-ARTICLES predicts controversiality based on the similarity of the article content.
with binary codes—and computed accuracy scores for all samples
were trained with a SVM.

The step size 
the meta-learner pushes the accuracy up to just 78 per cent.

However, this short paper is just the thin edge of the wedge, a
preliminary demonstration of a broader attempt to detect contro-
versies on the Web. In future work, we aim to broaden and refine
the notion of debate by including other Social Media platforms and
distinguish between different types of participants who contribute
to the controversy.

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