Computational Controversy

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Abstract. Climate change, vaccination, abortion, Trump: Many topics are surrounded by fierce controversies. The nature of such heated debates and their elements have been studied extensively in the social science literature. More recently, various computational approaches to controversy analysis have appeared, using new data sources such as Wikipedia, which help us now better understand these phenomena. However, compared to what social sciences have discovered about such debates, the existing computational approaches mostly focus on just a few of the many important aspects around the concept of controversies. In order to link the two strands, we provide and evaluate here a controversy model that is both, rooted in the findings of the social science literature and at the same time strongly linked to computational methods. We show how this model can lead to computational controversy analytics that have full coverage over all the crucial aspects that make up a controversy.

1 Introduction

On many topics people from different backgrounds have a shared understanding, or at least have views that are not in contradiction to each other. On some questions, however, like global warming, gun control, the death penalty, abortion, and vaccination, groups of people may strongly disagree despite lengthy interactions and debates [37]. Such situations are commonly called controversies and nowadays unfold to a large extent on the Web via different social media, discussion forums, and news platforms. This digital nature has naturally led to many computational approaches to capture and analyze controversy [3,21,41,7,16,31]. However, while the social sciences have studied the phenomenon of controversies extensively [22,33,12,27,24], there is a lack of a well-founded comprehensive model of controversies for such computational approaches to rely on. For that reason, existing computational approaches have mostly focused on a few hand-picked aspects (such as polarity and emotions), which seems insufficient in the case of the complex and multi-faceted nature of the concept of controversy. To resolve this problem, we present and evaluate here a unified model for controversy, and show how the different relevant aspects can be computationally captured and analyzed.

There are many situations where being able to understand the space of a controversy is essential. For journalists, news agencies and media professionals it is often difficult to present a clear picture of an issue from all perspectives.
Governments need to make laws that deal with issues for which it is essential that they have a complete understanding of such issues from an unbiased source. For the general public, understanding a controversy can help prevent a filter bubble, a potentially biased situation where they are only presented with information that they want to see. These problems can be addressed by the computational discovery and analysis of controversies and their elements and aspects.

2 Controversy, a Disputed Concept?

2.1 Explaining Disagreement

Understanding why societies become divided around specific issues has been a major topic of interest for political scientists, communication specialists and linguists—to name just a few disciplines. To embed our work within this type of literature, this section reviews some of the crucial concepts that have influenced research on public disputes. The following chapter narrows its focus to dissect the “controversy” in its constitutive parts.

Communications scientists have explained disagreement in terms of diverging or opposing frames. According to Gamson and Modigliani [22]: “[a frame is] a central organizing idea or story line that provides meaning to an unfolding strip of events, weaving a connection among them. The frame suggests what the controversy is, [offering information] about the essence of the issue”. Framing bears on how people perceive issues and how they are represented in discourse. Similar to essentially contested concepts, framing involves selection and salience, i.e. a frame tends to highlight one aspect (or a combination of aspects) at the expense of others. Or as Entman argues [17]: framing occurs in communication when aspects of a given problem are made more salient, thus promoting a “particular problem definition, causal interpretation, moral evaluation, and/or treatment recommendations”. Dardis et al. [15] demonstrate how framing affects disagreement by distinguishing between conflict-reinforcing frames, which contain evidence-confirming information, and therefore amplify existing beliefs; and conflict-displacing frames that appeal to both sides of a dispute, and diminish the level of disagreement—changes the adversarial structure of a debate.

Political scientists often invoke the concept of an ideology to explain the adversarial positions actors take on public issues. Converse [13]—in one of the early groundbreaking papers on the topic—describes ideology as a “belief system […] a configuration of ideas and attitudes in which the elements are bound together by some form of constraint or functional interdependence. This line of thinking emphasizes the systemic connections between beliefs. For example, it implies that we can predict attitudes toward gun control, given the opinions on abortion and environment. Freedon [19] develops a semantic approach: he perceives concepts, such as “liberty” and “justice” as the “building blocks” of political thought which acquire meaning by virtue of their position within a broader network of ideas: “ideologies are particular patterned clusters and configurations of political concepts.” The meaning of the concepts, is always relational and contested in nature; “equality” and “social justice” might be related terms—in the sense that
they “naturally” imply each other—for a Labour politician, but not for a con-
servative MP. “An ideology”, Freeden continues, “is hence none other than the
macroscopic structural arrangement that attributes meaning to a range of mu-
tually defining political concepts”. Freeden leans heavily on Gallie’s [20] notion
of “Essentially Contested Concepts” which have the following qualities (1) Ap-
praisive, it signifies a valued achievement (i.e. “Liberty”) (2) internally complex
(3) contains “rivaling” descriptions of its component parts (4) Context depen-
dent, can modified in the light of changing circumstances.

Linguists, especially the school of “Critical Discourse Analysis” (CDA) pointed
to the dialectical relation between language and societal institutions: language use
reflects as well as shapes relations of power and dominance, and therefore plays
a crucial role in reproducing disagreement. Ideology, according to this tradi-
tion, is defined as common sense, or more precisely as a “pattern of meaning or
frame of interpretation [...] felt to be commonsensical, and often functioning in
a normative way” [47]. It is composed of “taken-for-granted” and therefore un-
questioned premisses that are shared within a specific community. This resembles
the Kuhnian scientific paradigm. as [47] notices: “[paradigms are] specific ways
of looking, based on taken-for-granted premisses that are shared within a com-
munity or generation of scientists.” Ideological disagreement therefore entails a
contestation of these commonsensical norms and prescriptions held by specific
segments of society.

Research of structuralist linguists—a movement which was prevalent during
the seventies or eighties—attempted to unearth language patterns that elicit
or reduce disagreement, by scrutinizing how conflict is initiated (the linguistic
or communicational devices used) and how it develops [26]. This boiled down
to an analysis of the structure of arguments and the sequential organization
of disagreement. Brenneis and Lein, 1977 [9] distinguished three argumentative
sequences in role-played disputes among children: repetition, escalation, and in-
version. In later, cross-cultural, studies they [28] encountered the same patterns
in different countries, but also noted cultural differences related to the tolerance
for overlaps and interruptions. Boggs [6] points to “contradicting routines” as the
main device for performing disputes. Pomerantz [40] defines “dispreferred-action”
turn shapes as triggers for dispute. These turns contain marked “dispreference”
features such as “delays, requests for clarification, partial repeats, and other re-
pair initiators, and turn prefaces”. According to Millar et al. [36], “three consec-
utive one-up maneuvers” serve as a good predictor of verbal conflict: “a conflict
results when speaker B’s one-up response to speaker A’s one-up statement is
responded to with a one-up maneuver by speaker A.”

2.2 Anatomy of Controversies

People of different ideologies, seeing the world through different frames, and pos-
sibly speaking different languages, thereby become divided by the public debates
that are called controversies [33,12,27,24]. The participants in a controversy are
typically varied and can be categorized as (1) core-campaigners, (2) occasional
campaigners (3) participants encouraged by campaigners (4) sympathisers. It is
3 Related Work

In the last few years, many approaches and methods have been proposed to computationally analyze controversies, and many interesting insights have thereby been found. The OpinioNetIT [3] project, for example, attempts to computationally reconstruct public debates as an exchange of pro and con statements using

| Work authors | year | Data |
|--------------|------|------|
| Choi et al. [11] | 2010 | news articles |
| Popescu & P. [41] | 2010 | - Twitter |
| Awadallah et al. [3] | 2012 | - |
| Mejova et al. [35] | 2014 | 15 US news outlets |
| Borra et al. [7] | 2015 | - articles |
| Dori & Allan [16] | 2015 | webpages metadata |
| Lourentzou et al. [31] | 2015 | CNN articles Disqus and Twitter |
| Garimella et al. [21] | 2016 | - Twitter hashtags |

through the interaction between core-campaigners and broader sections of the public (termed occasional campaigners and sympathizers) [33] that such debates spread: Scientific controversies involve non-scientists, as debates are also held outside the scientific laboratories and journals. These discussion usually involve (a combination of) several recurring points on which participants disagree, such as benefits, risks, fairness, economics, human rights, decision-making [33], but ultimately flow deeper rooted and persistent ideological divisions or opposing value systems [34,24].

Controversies have furthermore the characteristic property that they tend to become unsolvable and persist over time, but nonetheless experience clear punctuations, they “flare up and die down”, or even follow a cyclical pattern [25]. Not only does the intensity of a controversy fluctuate over time, it also follows different rhythms depending on the arena of the debate. Issues can be low-key as a public debate, but heavily disputed among scientists, and of course vise versa. A controversial debate can be held in different platforms (among scientists [27,43] or experts [23]), but usually migrates to the public sphere through the media, through which it engages broad segments of the public [14,25].

Moreover, the increasing delineation of opposing views results in an ever widening disagreement or polarization [43]: the debate forces participant to develop coherent viewpoints and manage to navigate a debate by consistently picking the “right” side on each of the aspects. Polarization emerges as discussants develop increasingly well-defined but diverging perspectives—a dynamic propelled by core-campaigner who usually develop the templates [33]. Given that disputes flow from the beliefs and values participants hold dear, the exchange of opinions is not limited to the “facts”, but invites strong emotions [29].
person-opinion-topic triples. Other work measures the controversy of a topic by building “conversation graphs” using a set of Twitter retweets on a given hashtag [21]. Another approach uses Twitter to measure the controversy of events [41]. Their model principally relies on are linguistic, structural and sentiment features. Besides Twitter, Wikipedia has proven useful for modeling controversy on historic data. An example of this is Contropedia, where the metadata associated with Wikipedia pages such as the presence of edits and reverts were used [7]. It has furthermore been shown that controversial pages on the Web can be detected through mapping them to their closest Wikipedia pages [16].

Only a few approaches explicitly tackled the problem of detecting controversy in news articles. [31] measured which sentences trigger the largest responses in terms of tweets in order to locate the most controversial points in media coverage. [11] identified controversial topics by looking at which ones tend to invoke conflicting sentiment, and [35] analyzed news using a crowdsourced lexicon that comprises frequent content words for which participants were asked to judge their controversy. Our work aims to put such approaches onto a solid methodological foundation by measuring controversy in a manner that involved all aspects that have been found to be important in the literature on the topic. To summarize, Table 1 shows an overview of the covered related work and the type of data they relied on from news outlets, social media, and Wikipedia.

4 Methodology

Based on the background provided above, we present here our methodology on what we call computational controversy. The main component is our unifying controversy model, which is linked to computational methods to retrieve, capture, and analyze such debates. We also show a generic architecture of how these different aspects can be brought together.

4.1 The CAPOTE Controversy Model

Our unifying model captures the different characteristic aspects of a controversy as identified in the varied literature on the topic. Based on that, a controversy can be generally defined as a \textit{heated and polarized public debate by a multitude of actors persisting over time}. The key words in this definition that point to the different aspects are “heated,” “polarized,” “public,” “actors,” and “time.” With some renaming and reordering, this leads us to claim that a Controversy is made from the key aspects of Actors, Polarization, Openness, Time-persistence, and Emotions, which we can show as an informal equation:

\[
\text{Controversy} \sim \text{Actors} + \text{Polarization} + \text{Openness} + \text{Time-persistence} + \text{Emotions}
\]

As an acronym for this equation, we call our model CAPOTE. The key aspects of controversy are therefore:

- **Actors**: A controversy has many participating actors. We wouldn’t call it a controversy if it had only a handful of participants.
– **Polarization:** Viewpoints are polarized and not uniform or scattered. We call something a controversy only if the participants are grouped in two or more camps that oppose each other, with few people positioning themselves somewhere in between.

– **Openness:** A controversy plays out in an open public space, such as the web. We wouldn’t call it a controversy if it was all hidden and happening out of sight for society.

– **Time-persistence:** A controversy persists over longer stretches of time, typically years or more. A heated debate that is sparked and settled within a single day, for example, would hardly be called a controversy.

– **Emotions:** Strong sentiments or emotions are expressed and are an important driver. It is not a controversy if everybody discusses the matter with a cool head and with no personal emotional involvement.

Therefore, according to our model and definition, a set of opinions and arguments expressed in a debate can be called a controversy only if all five criteria above are satisfied. Importantly, all these five aspects can nowadays be algorithmically assessed and quantified based on a variety of techniques and data sources, as we will see below.

### 4.2 Computational Controversy

With modern techniques on natural language processing, machine learning, and network analytics, all five aspects of controversies according to the CAPOTE model can be computationally accessed. The prevalence and universality of the Web furthermore means that most such data are digital-born and relatively easy to retrieve.

The *openness* of a controversy and the generality of the web allows us to use different types of web content mining [30] to retrieve pertinent data in the first place, in the form of newspaper articles, discussions, social media posts, and contents from collaborative platforms like Wikipedia. The openness criterion thereby establishes the entry point for computational controversy analysis. Based on these data, we can then identify the participating *actors* with techniques including named entity recognition [38] and social network analysis methods [42]. The *emotions* expressed by these actors can furthermore be detected and categorized with a wide array of existing sentiment analysis techniques [39,18]. Additionally, we can of course analyse the content of the posts and articles by extracting their topics and involved concepts. For this, we can apply methods such as topic modeling [5] and ontology learning [32]. These steps may be run independently, or they may depend on each other. For example, the extraction of emotions may depend on the information of extracted actors, or vice versa.

Based on this first round of analysis, we can investigate the remaining aspects of the CAPOTE model. The *polarization* of viewpoints can be assessed and quantified with clustering and network analysis techniques [1], taking as input the network of actors, their expressions, and the contained topics and emotions. The *time-persistence* aspect, finally, can be evaluated with time series analyses
Fig. 1. A generic CAPOTE-based architecture. The black arrows denote the mandatory data flows for a fully CAPOTE-compliant architecture, whereas the gray ones denote optional data flows.

We evaluated our model and our general approach with a small qualitative studies on related work, and a larger quantitative study on the accuracy of our proposed model.

5.1 Qualitative Study on Related Work

First we start with a small qualitative study of the approaches we introduced as related work on computational controversy analyses. We manually assessed which of the CAPOTE aspects were considered for each of these works. Table 2 shows the result.

We see that all existing works on computational controversy cover at least three of our identified CAPOTE aspects, but none covers all five. While the Actors aspect was covered by all, Polarity and Time was covered by most, and Openness and Time was covered only by half of them. In aggregation, these studies had a good coverage, but in isolation each of them missed at least one of the aspects that our literature study identified as a crucial aspect of controversy.
Table 2. Classification of related work with respect to the CAPOTE model.

| Work                    | Actors | Polarity | Openness | Time | Emotion |
|-------------------------|--------|----------|----------|------|---------|
| Choi et al. (2010) [11] | ✔      | ✔        | -        | ✔    | ✔       |
| Popescu & P. (2010) [41]| ✔      | -        | ✔        | ✔    | ✔       |
| Awadallah et al. (2012) [3] | ✔  | ✔        | ✔        | -    | -       |
| Mejova et al. (2014) [35]| ✔      | -        | ✔        | -    | ✔       |
| Borra et al. (2015) [7]  | ✔      | ✔        | -        | ✔    | ✔       |
| Dori & Allan (2015) [16] | ✔      | ✔        | -        | -    | -       |
| Lourentzou et al. (2015) [31] | ✔  | -        | ✔        | ✔    | ✔       |
| Garimella et al. (2016) [21] | ✔  | ✔        | ✔        | -    | -       |

5.2 Design of Crowd Study

To evaluate the accuracy and completeness of our model we ran as our main study a crowdsourcing experiment using the CrowdFlower\(^3\) platform. We wanted to find out whether our CAPOTE model aligns with what people would normally call a controversy and thereby whether it is a faithful model of the concept.

To assess the relevance of each of the five aspects, we showed newspaper articles to crowd workers and asked them whether these aspects apply to the given topic and whether they think it deals with a controversy. For this, we showed them the first two paragraphs from 5,048 Guardian newspaper articles together with five comments. We retrieved that data through the Guardian news API. Figure 2 shows the interface with the questions that was shown to the crowd workers. The questions correspond to the five CAPOTE aspects in addition to the question of whether the participants thought the presented topic was controversial.

The collected annotations from this experiment were evaluated using the CrowdTruth methodology [2] for measuring the quality of the annotations, the annotators, and the annotated articles. This approach allows the measurement of ambiguity using a vector space. The ambiguity is computed by measuring the cosine distance between vectors of the annotators, where the features or dimensions of the vector represent the possible answers of the annotation task. The same measurement is then used to compare the vector of one annotator to the aggregated vector of all annotators for a single annotated article.

We ran two small pilot studies to find the best setting. In a first pilot we used 100 articles to test the use of a five point Likert scale answers versus "yes/no/I don’t know" type answers, and additionally whether showing five comments would help annotators identify whether the topic in an article is controversial. In a second pilot we evaluated with the same dataset whether rephrasing of the aspects and adding the time-persistence would make the identification clearer.

With the resulting data, we are then able to calculate a score between 0 and 1 for each article on these six dimensions, as an average of the workers’ ratings.

\(^3\)http://crowdflower.com
This in turn allows us to run a linear regression analysis to find out about the kind and extent to which the five aspects contribute to the degree to which a given topic is perceived as controversial or not. The five CAPOTE aspects serve as the independent variables in this regression analysis, with the score for controversy serving as the dependent variable to be predicted.

5.3 Crowd Study Test Runs

The results of the first pilot showed that displaying the article comments to the crowd workers significantly decreases the number of annotators that select “I don’t know” ($p$-value = 0.003). Additionally, we found that the "yes/no/I don’t know" setup always finished faster. Although this difference is not significant ($p$-value = 0.0519), it may indicate that annotators were more willing to perform this task. Based on this we conclude that the variant with comments and yes-no answers gave the best performance in terms of speed and annotation quality. The results of the second pilot showed the rephrasing of the questions improved the identification as the number of people that selected the "I don’t know" option dropped from 15% to 3% with $p=0.0001$.

5.4 Results from Crowd Study

In the main experiment 5048 articles were annotated by 1659 annotators resulting in 31888 annotations. This dataset is available for download at the
Table 3. Results of the crowdsourcing experiment. For each answer the correlation with the other answers is shown, followed by the ratio of positive answers, the majority vote for yes and the average CrowdTruth relation clarity score as described in section 5.2.

| Ratios of yes | Controversy | Actors | Polarity | Openness | Time | Emotion |
|---------------|-------------|--------|----------|----------|------|---------|
| Majority vote yes | 0.43 | 0.62 | 0.57 | 0.71 | 0.44 | 0.49 |
| relation clarity score | 0.50 | 0.81 | 0.73 | 0.88 | 0.52 | 0.62 |
| correlation clarity score | 0.907 | 0.887 | 0.886 | 0.915 | 0.883 | 0.890 |

CrowdTruth data repository. Before we turn to the results of the main linear regression analysis, we can have a look at some descriptive results including Pearson correlation coefficients between the different aspects.

Table 3 show the results of the descriptive analysis. 43% of the individual judgment on the overall controversy aspect were positive, leading to a positive controversy classification in 50% of the articles if a simple majority vote is applied. Out of the five CAPOTE aspects, openness was the most prevalent (71% of the individual judgments), while time persistence was the least prevalent (44%).

The openness scored highest with .915 for the relation clarity score, which indicates that it is the least ambiguous relation. In contrast, the actors, polarity, time and emotion aspect had similar lower clarity scores, indicating there is more disagreement between the annotators for these relations. The correlation values show the emotion aspect is most strongly correlated with controversy followed by polarity and time persistence, and with actors and openness showing the weakest correlation.

To find out whether these correlations together amplify, we can have a look at the regression results, which are shown in Table 4. The top part of the table shows the regression involving all five CAPOTE aspects to predict the controversy aspect. Overall the regression provides a good fit given the inherently noisy nature of human annotations and social science concepts, with an adjusted $R^2$ of 59%. The effect of all variables is positive, and significant for all of them except Actors. Therefore, we do not have evidence so far that the Actors aspect contributes to the definition of a controversy.

If we look at all combinations of four aspects out of the five, however, we get a more nuanced picture, as shown in the bottom part of Table 4. No matter which four aspects we pick, they turn out to be all significant in predicting the controversy of a topic. Therefore, while the Actors aspect does not significantly add to the controversy concept when all other four aspects are present, it does...
Table 4. Linear regression analysis on all five aspects (above) and on four of the five aspects (below)

|                  | All 5 |               |               |               |          |          |
|------------------|-------|---------------|---------------|---------------|----------|----------|
| coefficient      | -0.15386 | 0.00787 | 0.30629 | 0.10345 | 0.21832 | 0.47036 |
| p-value          | < 10^{-15} | 0.64 | < 10^{-15} | 3.1 · 10^{-10} | < 10^{-15} | < 10^{-15} |
| significant      | * | * | * | * | * | * |
| adjusted R^2     | 0.5885 |               |               |               |          |          |

|                  | 4 of 5 |               |               |               |          |          |
| coefficient      | -0.15267 | 0.30687 | 0.10650 | 0.22040 | 0.47095 |
| p-value          | < 10^{-15} | < 10^{-15} | 1.7 · 10^{-12} | < 10^{-15} | < 10^{-15} |
| significant      | * | * | * | * | * |
| adjusted R^2     | 0.5885 |               |               |               |          |          |

|                  |          |               |               |               |          |          |
| coefficient      | -0.09763 | 0.04465 | 0.16910 | 0.25043 | 0.53587 |
| p-value          | < 10^{-15} | 0.012 | < 10^{-15} | < 10^{-15} | < 10^{-15} |
| significant      | * | * | * | * | * |
| adjusted R^2     | 0.5378 |               |               |               |          |          |

|                  |          |               |               |               |          |          |
| coefficient      | -0.12328 | 0.05008 | 0.32073 | 0.22726 | 0.48181 |
| p-value          | < 10^{-15} | 0.00126 | < 10^{-15} | < 10^{-15} | < 10^{-15} |
| significant      | * | * | * | * | * |
| adjusted R^2     | 0.5848 |               |               |               |          |          |

|                  |          |               |               |               |          |          |
| coefficient      | -0.16247 | 0.07436 | 0.32261 | 0.12410 | 0.54804 |
| p-value          | < 10^{-15} | 6.7 · 10^{-6} | < 10^{-15} | 3.1 · 10^{-13} | < 10^{-15} |
| significant      | * | * | * | * | * |
| adjusted R^2     | 0.5702 |               |               |               |          |          |

|                  |          |               |               |               |          |          |
| coefficient      | -0.14464 | 0.05969 | 0.39724 | 0.17575 | 0.43056 |
| p-value          | < 10^{-15} | 0.00154 | < 10^{-15} | < 10^{-15} | < 10^{-15} |
| significant      | * | * | * | * | * |
| adjusted R^2     | 0.4803 |               |               |               |          |          |

deliver useful redundancy in the sense that it significantly contributes when one of the other aspects is lacking.

These regression analyses furthermore confirm Emotions being the most important aspect. It increases the adjusted \( R^2 \) by more than 10\%, followed by Polarity, which contributes 5\%, while all other aspects contributing on their own less than 2\%.

6 Discussion

In order to illustrate how the overarching CAPOTE model can lead researchers and developers in their design decisions, we give here a short description of how our own project on computational controversy, called ControCurator\(^5\) [4], implemented the CAPOTE model. The overall result is shown in Figure 3.

\(^5\) [http://controcurator.org/]
As given by the CAPOTE model, the workflow of our system starts by exploiting the openness criterion to get data to work with. ControCurator crawls articles and comments from The Guardian\(^6\) and related social media content through the services of Crowdynews\(^7\). The comments and social media are strictly filtered by removing double posts, retweets, posts with simply article titles and more. This results in a curated dataset of comments and social media entities that contain people talking about or discussing the topic of a Guardian article.

The actors in the content are identified through the Stanford Named Entity Recognizer\(^8\), and detection of emotions using the SentiStrength sentiment detection tool [45]. In order to cluster articles on topic similarity, we apply the topic modeling technique of Hierarchical Dirichlet Processes [44]. This allows the user of the system to more easily learn about the content and topic of the involved controversies. Based on this, we then quantify the polarity of the discussions and emotions by calculating a number of metrics, including sentiment variety, contradiction score [46], WordNet antonym pairs, and silhouette score after \(k\)-means clustering. The last aspect, time persistence, is currently under-developed in our system. We visualize the temporal development, but we currently don’t apply any further analyses on the aspect of time persistence.

These diverse data then flow into the ControCurator front-end interface\(^9\). This interface helps users to identify controversies and to explore the involved contrasting viewpoints. In the main view, users can browse through the listed issues with their controversy score and explore their details. As a further data source, our interface also allows users to provide us with their opinion on the level of controversy for uncertain cases, following an active learning approach.

\(^{6}\) https://www.theguardian.com/
\(^{7}\) https://www.crowdynews.com/
\(^{8}\) https://nlp.stanford.edu/software/CRF-NER.shtml
\(^{9}\) http://controcurator.org/browse/
During the development of ControCurator, which is still ongoing, the CAPOTE model helps us structure our approach and design an appropriate architecture. The model ensures that we are aware of all the important controversy aspects, and it helps us keep track of the ones that are still under-developed. Specifically, we are reminded that the aspect of time persistence is currently still underdeveloped and needs more attention to appropriately cover the concept of a controversy. This underscores the benefit of CAPOTE as a guiding model.

7 Conclusions

Controversies are a frequent and important phenomenon of public discourse. Many approaches have recently been proposed to measure and analyze such controversies with computational means, but a principled framework has been missing. Based on an extensive literature study and supported by a crowdsourced study, we identified five key aspects that define a controversy: a multitude of involved actors, polarized opinions, open visibility of the debate, time persistence, and strong emotions. The results from our crowdsourced study indicate that each of these aspects is a positive indicator of controversy, but also that there is a clear difference in the extend of their influence. Most notably, the emotion aspect was found to be the strongest indicator, while the actors aspect had the weakest influence.

We can often feel that controversies around important issues, such as climate change, are holding us back to make progress on urgent problems. We think that our CAPOTE model can contribute to better understand these controversies and exploit the potential of computational approaches to their analysis. This, in turn, could be the first step towards breaking up the deadlock of long lasting controversial topics.

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References

1. C. Andris, D. Lee, M. J. Hamilton, M. Martino, C. E. Gunning, and J. A. Selden. The rise of partisanship and super-cooperators in the us house of representatives. PloS one, 10(4):e0123507, 2015.
2. L. Aroyo and C. Welty. The three sides of crowdtruth. Journal of Human Computation, 1:31–34, 2014.
3. R. Awadallah, M. Ramanath, and G. Weikum. Opinions network for politically controversial topics. In Proceedings of the first edition workshop on Politics, elections and data, pages 15–22. ACM, 2012.
4. K. Beelen, E. Kanoulas, and R. N. van de Velde. Detecting controversies in online news media. In Proceedings of thee 40th International ACM SIGIR Conference on Research and Development in Information Retrieval, to appear, 2017.
5. D. M. Blei, A. Y. Ng, and M. I. Jordan. Latent dirichlet allocation. *Journal of machine Learning research*, 3(Jan):993–1022, 2003.

6. S. T. Boggs. The development of verbal disputing in part-hawaiian children. *Language in Society*, 7(03):325–344, 1978.

7. E. Borra, E. Weltevrede, P. Ciucarelli, A. Kaltenbrunner, D. Laniado, G. Magni, M. Mauri, R. Rogers, and T. Venturini. Societal controversies in wikipedia articles. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, CHI ’15, pages 193–196, New York, NY, USA, 2015. ACM.

8. G. E. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung. *Time series analysis: forecasting and control*. John Wiley & Sons, 2015.

9. D. Brenneis and L. Lein. You fruithead*: A sociolinguistic approach to children’s dispute settlement. *Child discourse*, 49:65, 1977.

10. A. Casteigts, P. Flochini, W. Quattrociocchi, and N. Santoro. Time-varying graphs and dynamic networks. *International Journal of Parallel, Emergent and Distributed Systems*, 27(5):387–408, 2012.

11. Y. Choi, Y. Jung, and S.-H. Myaeng. Identifying controversial issues and their sub-topics in news articles. In *Pacific-Asia Workshop on Intelligence and Security Informatics*, pages 140–153. Springer, 2010.

12. A. E. Clarke. Controversy and the development of reproductive sciences. *Social Problems*, 37(1):18–37, 1990.

13. P. E. Converse. *The nature of belief systems in mass publics*. Survey Research Center, University of Michigan Ann Arbor, 1962.

14. S. Dalgalarrondo and P. Urfalino. Tragic choice, controversy, and public decision-making: the case in france of random selection of aids patients for treatment ("lot-drawing"). *Revue française de sociologie*, pages 3–40, 2002.

15. F. E. Dardis, F. R. Baumgartner, A. E. Boydstun, S. De Boef, and F. Shen. Media framing of capital punishment and its impact on individuals’ cognitive responses. *Mass Communication & Society*, 11(2):115–140, 2008.

16. S. Dori-Hacohen and J. Allan. Automated controversy detection on the web. In *European Conference on Information Retrieval*, pages 423–434. Springer, 2015.

17. R. M. Entman. Framing: Toward clarification of a fractured paradigm. *Journal of communication*, 43(4):51–58, 1993.

18. R. Feldman. Techniques and applications for sentiment analysis. *Communications of the ACM*, 56(4):82–89, 2013.

19. M. Freeden. Political concepts and ideological morphology. *Journal of Political Philosophy*, 2(2):140–164, 1994.

20. W. B. Gallie. Essentially contested concepts. In *Proceedings of the Aristotelian society*, volume 56, pages 167–198. JSTOR, 1955.

21. K. Garimella, G. De Francisci Morales, A. Gionis, and M. Mathioudakis. Quantifying controversy in social media. In *Proceedings of the Ninth ACM International Conference on Web Search and Data Mining*, pages 33–42. ACM, 2016.

22. W. A. Garrison and A. Modigliani. The changing culture of affirmative action. *Equal employment opportunity: labor market discrimination and public policy*, 373, 1994.

23. M. Hallberg and E.-M. Rigné. Child sexual abuse-a study of controversy and construction. *Acta Sociologica*, 37(2):141–163, 1994.

24. M. Horst. Collective closure? public debate as the solution to controversies about science and technology. *Acta Sociologica*, 53(3):195–211, 2010.

25. J. M. Jasper. The political life cycle of technological controversies. *Social forces*, 67(2):357–377, 1988.
26. C. Kakavá. Discourse and conflict. *The handbook of discourse analysis*, pages 650–670, 2001.
27. J. Kempner, J. F. Merz, and C. L. Bosk. Forbidden knowledge: Public controversy and the production of nonknowledge. In *Sociological forum*, volume 26, pages 475–500. Wiley Online Library, 2011.
28. L. Lein and D. Brenneis. Children's disputes in three speech communities. *Language in Society*, 7(03):299–323, 1978.
29. D. J. Levi and E. E. Holder. Psychological factors in the nuclear power controversy. *Political psychology*, pages 445–457, 1988.
30. B. Liu and K. Chen-Chuan-Chang. Editorial: special issue on web content mining. *Acm Sigkdd explorations newsletter*, 6(2):1–4, 2004.
31. I. Lourentzou, G. Dyer, A. Sharma, and C. Zhai. Hotspots of news articles: Joint mining of news text & social media to discover controversial points in news. In *Big Data (Big Data), 2015 IEEE International Conference on*, pages 2948–2950. IEEE, 2015.
32. A. Maedche and S. Staab. Ontology learning for the semantic web. *IEEE Intelligent systems*, 16(2):72–79, 2001.
33. B. Martin. *The Controversy Manual. A practical guide for understanding and participating in scientific and technological controversies*. Sparsnäs, Sweden, Reading, Massachusetts, 2014.
34. S. Maynard-Moody. Managing controversies over science: the case of fetal research. *Journal of Public Administration Research and Theory: J-PART*, pages 5–18, 1995.
35. Y. Mejova, A. X. Zhang, N. Diakopoulos, and C. Castillo. Controversy and sentiment in online news. *arXiv preprint arXiv:1409.8152*, 2014.
36. F. E. Millar, L. E. Rogers, and J. B. Bavelas. Identifying patterns of verbal conflict in interpersonal dynamics. *Western Journal of Communication (includes Communication Reports)*, 48(3):231–246, 1984.
37. A. Misra and M. A. Walker. Topic independent identification of agreement and disagreement in social media dialogue. In *Conference of the Special Interest Group on Discourse and Dialogue*, page 920, 2013.
38. D. Nadeau and S. Sekine. A survey of named entity recognition and classification. *Linguisticae Investigationes*, 30(1):3–26, 2007.
39. B. Pang, L. Lee, et al. Opinion mining and sentiment analysis. *Foundations and Trends® in Information Retrieval*, 2(1–2):1–135, 2008.
40. A. Pomerantz. Agreeing and disagreeing with assessments: Some features of preferred/dispreferred turn shaped. 1984.
41. A.-M. Popescu and M. Pennachioiti. Detecting controversial events from twitter. In *Proceedings of the 19th ACM international conference on Information and knowledge management*, pages 1873–1876. ACM, 2010.
42. J. Scott. *Social network analysis*. Sage, 2012.
43. S. Tarrow. Polarization and convergence in academic controversies. *Theory and Society*, 37(6):513–536, 2008.
44. Y. W. Teh, M. I. Jordan, M. J. Beal, and D. M. Blei. Sharing clusters among related groups: Hierarchical dirichlet processes. In *NIPS*, pages 1385–1392, 2004.
45. M. Thelwall. Heart and soul: Sentiment strength detection in the social web with SentiStrength. *Proceedings of the CyberEmotions*, pages 1–14, 2013.
46. M. Tsytserau, T. Palpanas, and K. Denecke. Scalable discovery of contradictions on the web. In *Proceedings of the 19th international conference on World wide web*, pages 1195–1196. ACM, 2010.
47. J. Verschueren. *Ideology in language use: Pragmatic guidelines for empirical research*. Cambridge University Press, 2012.