Picking Battles: Analyzing User Content Preferences in Online Debates

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Online forums offer users an anonymous platform to discuss and debate controversial topics. This paper explores the topics that users discuss and the participation trends of frequent and non-frequent users within the subreddit ChangeMyView, a moderated, good-faith platform for users seeking to have their views challenged. Prior research has focused on successful discourse strategies in online debate communities. A subset of popular threads spanning a variety of topics (N = 303) were selected. Applying Latent Dirichlet Allocation (LDA) topic modeling to the dataset shows that frequent users on the ChangeMyView subreddit do not constrict themselves to posting on only certain topics. This goes against our initial hypothesis that users who are active in an online debate community will tend to apply their expertise to a narrow set of topics.

Additional Key Words and Phrases: social network analysis, topic modelling, reddit

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1 INTRODUCTION

1.1 Background

The subreddit r/ChangeMyView (CMV) is an online community where users participate in structured debates about personal opinions. Users submit a post describing a personal opinion and challenge the community to "change their view." They are expected to monitor and respond to comments after submitting a post. If a commenter changes the original user's opinion, the original user responds with a "delta" (Δ) symbol and an acknowledgement of their efforts. Delta awards are tracked by an automated DeltaBot and tracked on a leader board.

1.2 Problem

CMV provides a unique environment for observing structured conflict between users. It resembles both problematic aspects of online interaction such as toxic comment sections as well as meaningful, intentional exchanges between users. Compared to simple, supportive signals such as "likes," and "retweets," CMV comment activity in offers a nuanced, inverse view of topics that users find motivating, rather than interesting or pleasing.

1.3 Data

We used the Cornell ChangeMyView dataset, a collection of CMV threads submitted between January 2013 and May 2015. The dataset was collected by Chenhao Tan as part of an article on online debate[14]. It is distributed on his blog[13].

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1.4 Research Questions

Our research attempts to answer the following questions:

- Do CMV commenters select discussion threads based on topic preferences?
- Is the discussion of certain topics driven by a core group of users?

1.5 Results

1.6 Conclusion

We can hypothesize that similar overlapping roles exist within the ChangeMyView community as well. Our dataset includes information on the users commenting on threads, as well as their "delta score", a measure of how many other users that person has been confirmed to have persuaded. In our case, an "answer-person" would be a user who has a high delta score, lending them credibility within the space, and a "discussion-person" would be a user who frequently comments on posts. Due to limitations in our data parsing, we focus on the posting habits of frequently commenting users. We compare the topics high-frequency users post about with users as a whole. We hypothesize that frequent posters on a debate forum where users are expected to be challenged by multiple users, frequent posters will have certain topics of expertise, which they primarily post about.

2 LITERATURE REVIEW

2.1 Online Debate

Prior research on online debate communities has focused on identifying the textual elements which are conducive to successful persuasion[4, 11], as well as creating new methods to parse and summarize raw data from online debate forums[9, 15]. Durmus and Cardie concluded that users' personal characteristics, such as their prior success and similarities to their audience were the primary factor in successful persuasion, but that linguistic features also contribute.

2.2 Online Content Preferences

Our research focuses on the topic preferences of users on the ChangeMyView subreddit. Online content preferences are typically studied through topic modeling. For example, in studying the subreddit Conspiracy, Colin Klein et al. [2] use the non-negative matrix facorization (NMF) method to construct a topic model. They found that while clear subgroups were clearly evident across the subreddit, one subgroup (the "True Believers"), dominated a majority of the topics found on the subreddit.

Similarly, Roja Bandari et al. [7] studied sources of content posted on an Iranian site Balatarin during the "Green Movement" political events of 2009. The researchers grouped users into communities using network characteristics, and examined their edges formed with different content sources over time. They found that transitions in the categories of content posted corresponded to political events. Their methods can potentially provide insights for content moderators on the demographics and expected discussion of their community.

2.3 r/ChangeMyView

In the context of ChangeMyView, there have been multiple recent articles written which focus on determining the effectiveness of commentators using different types of language and interaction dynamics for persuasion[6, 14]. Tan et al. found that the order of which a user enters discussion, as well as the popularity of the thread (number of unique challengers) are correlated with successful persuasion, as well as the characteristics of vocabulary used by the poster and challengers.

Srinivasan et al[12] focus on the effects of content removal in the ChangeMyView community, and their findings support the hypothesis that strong content removal acts as a deterrent for troublesome users' future behavior, as well as improving the user's positive feedback (comment score). Although these debate communities offer potential implications for discourse studies, research into the nature of topics selected is more limited. Instead research is more focused on behavioral trends ([8], [10]).

Buntain et al.[1] found that users on reddit can broadly be categorized into "answer-people" and "discussion-people", with these users appearing in very different ratios across subreddits.

3 METHODS

In this section we describe our dataset and our methodology for network analysis and topic modelling.

3.1 Data Collection

The Cornell ChangeMyView dataset is stored as a text file. Each line contains a JSON object with data about a single submission to CMV- a post and all responding comments. We used a Python script to separate the dataset into two CSV files with a subset of desired fields:

(1) Threads: *thread id*, *title*, *body text*, *author*, *timestamp*, *upvotes*,
(2) Comments: *comment id*, *parent thread id*, *comment author*, *timestamp*,

All of our analysis was performed in R after this point. We removed any threads and comments of threads relating to subreddit moderation or other topics not related to the CMV format. We also removed any comments posted by the author of a thread, a bot, or a deleted account.

This left us with 8,253 threads with 158,256 comments.

3.1.1 Data Exploration. We examined summary statistics from our data to determine the appropriate bounds for sampling. We wanted to capture the most popular threads that would be most likely to appear at the top of the CMV website. Based on these distributions, we reduced the dataset to threads and comments of threads with more than 11 unique commenters and 11 upvotes. This left us with 2,713 threads and their comments.

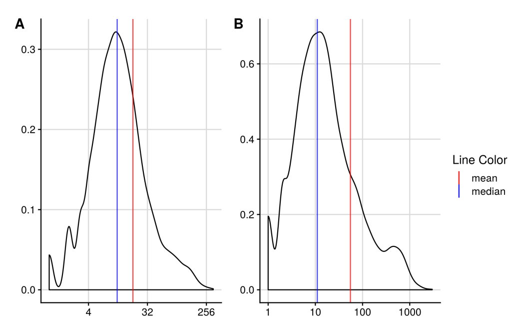

Fig. 1. Distribution of unique commenters per topic (A) and upvotes per topic (B).

3.2 Topic Modelling

We applied topic modelling to the dataset in order to uncover latent themes in each thread. The topics of threads could then be used to categorize user behavior and content preferences.

3.2.1 Document Model. Topic modelling was performed using the LDA algorithm in the topicmodels package from R[5]. LDA requires a corpus of documents and a k value that determines the number of topics. We modelled our documents on the combined body text and title of each thread. This provided a sufficient amount of text content for LDA and ensured that topics would be representative of the original post, rather than the counterpoints in the comments.

3.2.2 Preprocessing. Each document was stripped of URLs, markdown formatting, and moderator notes. After tokenizing the documents by word, we removed standard stopwords and any words that appeared in less than 1% of the corpus. Later, we determined that domain-specific words should also be removed. This included debate words such as *opinion*, *literally*, *unacceptable*, *effective*, as well as online forum words such as *comments*, *responding*, and *reddit*. We found that stemming and stem completion was ineffective in the context of online debates where word choice is very intentional.

3.2.3 Topics. We experimented with a range of k topics. We found that using 10 topics was sufficient to easily understand the subject of the topic as well as clearly delineate between topic themes. Our topic distributions are displayed in figure 2.

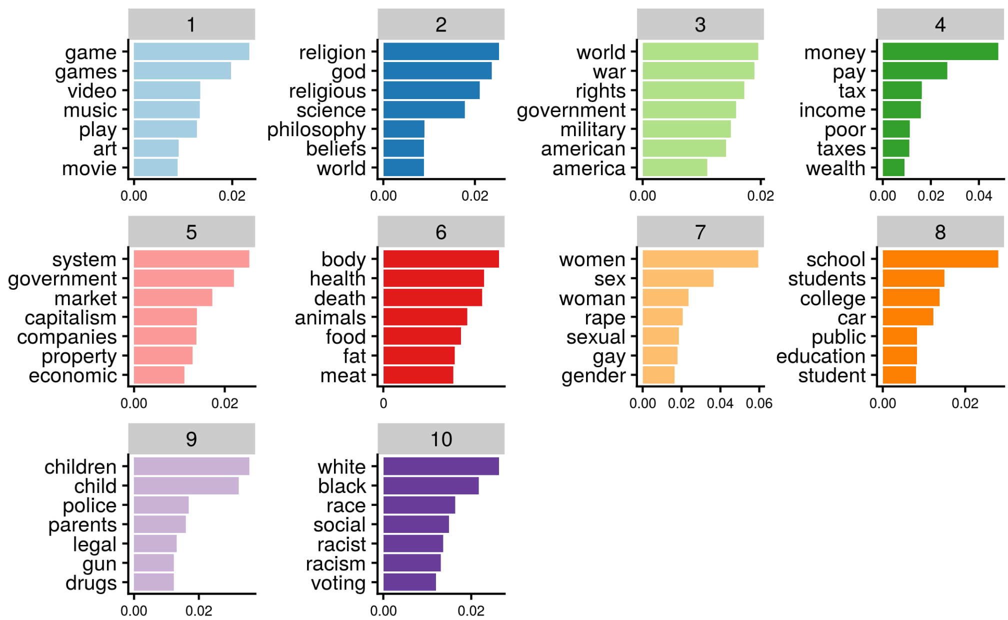

Fig. 2. LDA topic word distributions ranked by β

3.3 Network Analysis

We applied social network analysis to our dataset to better understand the cocommenting behavior of users in CMV. Our analysis was performed using the igraph package in R[3].

3.3.1 Network Model. We began with an unweighted, undirected, bimodal network of user nodes connected to thread nodes that they had commented on. This was transformed into a unimodal network of user nodes connected by cocommenting activity. We weighted each edge using the number of times the users had commented on the same post. Users were assigned a preferred topic based on the topics of the threads that they had commented on. We colored the nodes based on their preferred topic, and altered their size based on their eigenvector centrality metric.

3.3.2 Sampling. Due to the large size of our dataset, we could not model the entire comment network at once. Instead, we selected users who commented frequently and sampled from this group at different time intervals.

4 RESULTS

4.1 RQ1

Our first research question asks if users display a preference for debate threads of a certain topic. We hypothesized that users would select debates based on their knowledge or passion about the topic of debate.

4.1.1 User Topic Distributions. We approached the question by finding the mean topic distribution of all threads that user participated in. We assigned a topic distribution to each thread during topic modelling. This represented the likelihood of a given topic occurring in the thread. We averaged the topic distributions of each thread that each user participated in. This gave us the average topic distribution of the user's total commenting behavior. A higher value in a given topic would mean that the user had participated in debates of that topic more frequently than others. We only included users who commented on a large number of posts as their selective behavior was more apparent.

4.1.2 Mean User Topic Preferences. We visualized the mean user topic preferences across topic categories in figure 3. This shows the amount that users preferred a given topic.

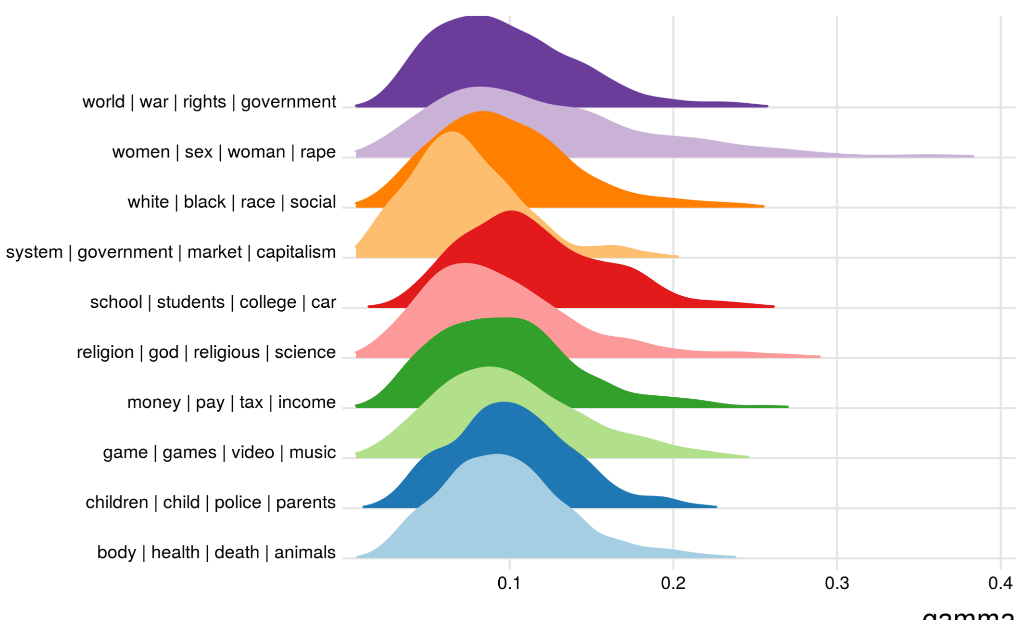

Fig. 3. Topic preferences of frequent users

We found that the user topic preference distributions were not dramatically different. This implies that CMV users are motivated by the activity of debating more so than by debate topic. However, we can see some unique qualities in the distributions that are fitting with our understanding of the topics.

Topic 4 (*system, government, market*) is skewed right with a tail that does not extend as far as the other distributions. This is indicates that the majority of participants in political and economic debates do not favor the topic over others. It is possible that these debates are more polarized or combative than others topics. Perhaps users do not have the energy or patience to exclusively focus on this topic.

In contrast, the long tail on topic 2 (*women, sex*) extends much farther than the other topics. This indicates a group of frequent commenters who focus the majority of their efforts on debates about gender and feminism. This is fitting with the general tone of the CMV discussion, which often features inflammatory and unsavory opinions.

4.1.3 Network visualization. In visualizing the co-commenting behavior of frequent users, we observe that topic preferences are evenly distributed. The larger nodes have a higher centrality and are likely more active on the subreddit. The network has two main clusters. We interpret the smaller cluster as a representation of niche discussions that are active but not widely popular.

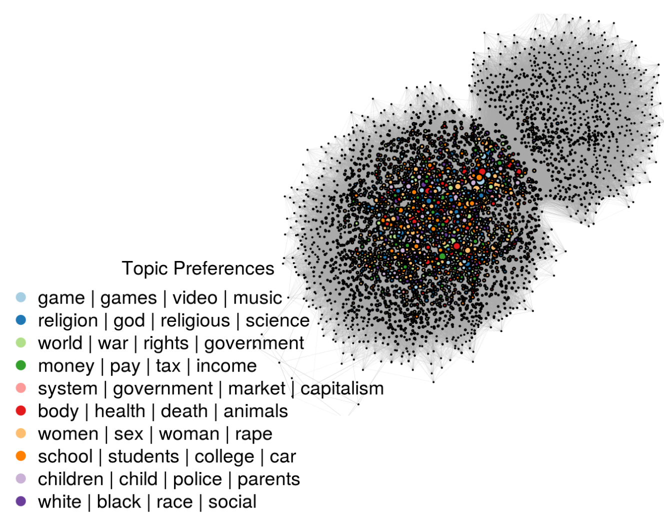

Fig. 4. Co-commenting activity of frequent CMV users

We also plotted the centrality metrics of users based on their topic preferences in 5. The findings were not very informative, but

4.2 RQ2

For our second research question, we investigated how core users could influence the topics of discussion in CMV. We were interested to see if discussions about gender and sexuality, race, or religion were started and supported by the same users. These topics are frequently discussed in CMV, but the original opinions expressed by the authors of their threads are not necessarily made in good faith. Titles such as *Gender identity should not be a 'thing'*, or *Insults such as 'You're gay' are not an affront to gay people*, are submitted to be provocative.

4.2.1 Thread Author Topic Distribution. Our approach mirrored the first research question, but applied to authors of CMV posts. We collected the topic distributions for all threads in the sample set and found the mean topic distribution for each. We used the thread author topic distribution averages to select a preferred topic for each thread author. We gathered all comments made by these authors and found the mean topic distribution of each author's commenting activity. This

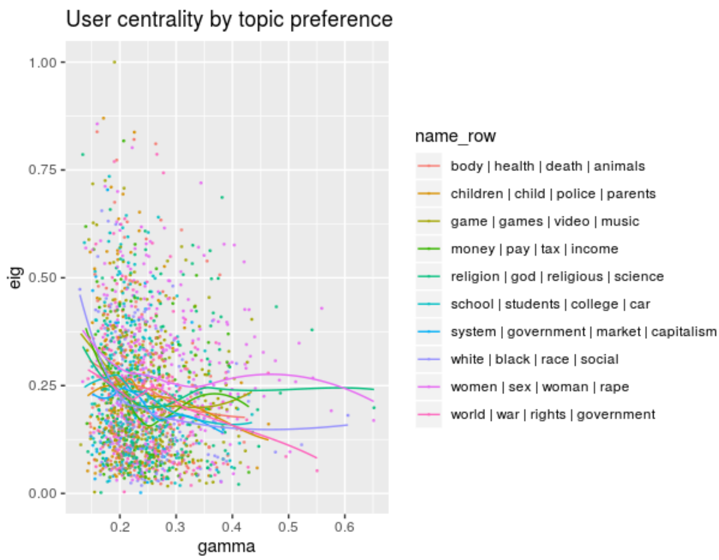

Fig. 5. User centrality by topic preference

allowed us to compare the topics that users comment with the topics of the threads they prefer to submit.

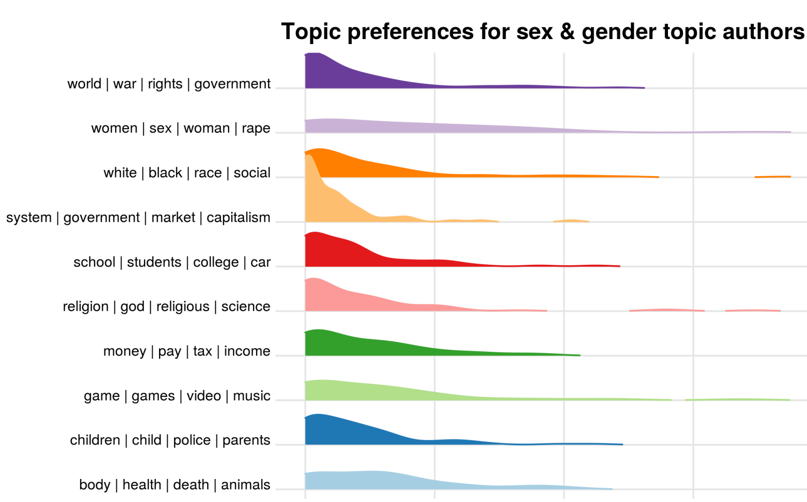

Fig. 6. Topic preferences for authors of sex gender threads

4.2.2 Thread authors about sex gender. We observed that authors of threads about gender and sexuality comment on threads of the same topic as indicated by the long tail. However, when an author is not focused on a single topic, they're likely to comment on threads about government and economics or war. These seems to imply a group of users who are not genuinely interested in the discussion of sexuality and gender, but rather enjoy drawing comments with controversial opinions.

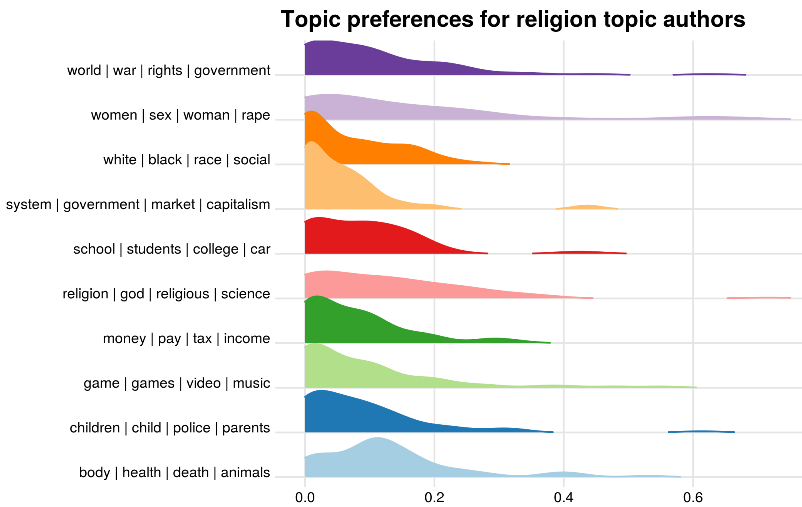

Fig. 7. Topic preferences for authors of religion threads

4.2.3 Thread authors about religion. Authors of religious threads again display a commenting preference for their preferred authoring preference. The topic with the highest mean comment gamma for religion authors is *body, health, death, animals*, which concerns health, ethics and consumer choices. These seems more fitting with a discussion of religion, implying that religion authors may be more interested in a productive discussion of religion. They also show a comment preference for *world, war, rights, government*, which often overlaps with ethical issues as well.

4.2.4 Thread authors about race. For authors of threads regarding race and racism, we again see a comment topic preference for the same topic. Many of the CMV submissions in this topic are particularly noxious and racist. The top preference for these authors would appear to be gender and sexuality. This should come as no surprise, assuming a lack of goodwill in their CMV submission in this topic. Fittingly, the other main topics with dense tails at higher gamma levels are education and childhood. This paints the picture of an author group with a large proportion of suburban teenagers.

5 DISCUSSION

We systematically analyzed the content preferences of frequent users in the ChangeMyView community. Our contribution to this area is in exploring topic preferences in ChangeMyView and in speculating about the types of contributors that are drawn to each topic.

5.1 Implications

Our results have implications for several areas of importance. First, given that some topics show more focused users, users who follow these topics may be more interested and receptive towards focused content. Users who post in topic four (*system, government, market* tend to engage in other topics more frequently than a user interested in *body, health, death.* Furthermore, our topic modeling can allow us to speculate distinctions between the types of users who are active in certain topics.

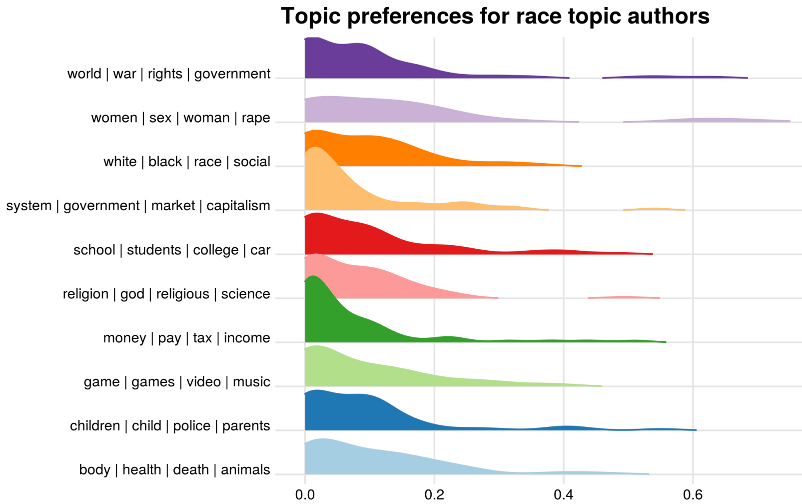

Fig. 8. Topic preferences for authors of threads about race

Further research could be performed to determine if users with narrower ranges of topics they actively contribute to are more disruptive, and content moderation can be allocated accordingly.

5.2 Challenges

We were challenged by the application of network analysis to our dataset. The connections formed through cocommenting behavior were difficult to contextualize in a meaningful way. Our topic model focused on the subject of the initial post. It was difficult to rationalize why two users would be impacted by their shared presence in a thread's comment section. This made it difficult to connect our topic model with our network model.

We also found it difficult to discern between CMV submissions that were intentionally provocative, and submissions made in good faith. This is an intriguing aspect of the dataset that deserves further research.

5.3 Limitations

Our analysis was limited by our use our use of the CMV dataset. We did not make use of the delta award system to determine the success of commenters. We did not apply topic modelling to comment text. Further analysis of the thread structure could have revealed additional findings. Comments are arranged in a tree structure, and this could have been used to create a directed network graph which may have been more informative than our undirected graph.

Using Reddit as a research domain also imposes limitations due to the demographics of it's user base and the specific, intentional nature of the CMV subreddit. Online debate does not typically occur in such a formal setting and this limits the application of CMV findings to other contexts. As we observed in our research, CMV users are generally more attracted to debate than to specific topics or motivations.

5.4 Future Work

In this work, we focused on analyzing topics and network structure sampled from threads and comments across a four-month period. In future works, topic modeling can be performed at different time periods (or continuously) to compare users' interests in relation to real-world events (i.e. [7]) on ChangeMyView or other online debate communities. We also believe that these topic modeling approaches can be used to better understand other online communities. Applications also apply to studying the effects of automated and targeted content moderation to pinpoint controversial and disruptive topics, similar to Srinivasan et al.'s work[12].

6 CONCLUSION

Seeking to understand online debaters' discussion tendencies, we use topic modeling and network analysis to examine user topic preferences across ChangeMyView. We were specifically interested in the behavior of frequent users as they could better display preferential behavior. While we did not find much indication of topic preference in commenting behavior, we were able to identify preferential patterns among authors of threads. Authors preferred to comment on threads that align with their own CMV submissions. The preferred topics of an authors own submissions also influenced their choice in comment behavior outside of their favored topic. This shows a divide in the CMV community between provocative users and open-minded users. This line of research could be extended to improve content moderation efforts in large online communities.

REFERENCES

[1] Cody Buntain and Jennifer Golbeck. 2014. Identifying Social Roles in Reddit Using Network Structure. In *Proceedings of the 23rd International Conference on World Wide Web (WWW '14 Companion).* ACM, New York, NY, USA, 615–620. https://doi.org/10.1145/2567948.2579231

[2] Vince Polito Colin Klein, Peter Clutton. 2018. Topic Modeling Reveals Distinct Interests within an Online Conspiracy Forum. *Front. Psychol.* 9, 189 (2018). https://doi.org/10.3389/fpsyg.2018.00189

[3] Gabor Csardi and Tamas Nepusz. 2006. The igraph software package for complex network research. *InterJournal* Complex Systems (2006), 1695. http://igraph.org

[4] Esin Durmus and Claire Cardie. 2019. A Corpus for Modeling User and Language Effects in Argumentation on Online Debating. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics.* Association for Computational Linguistics, Florence, Italy, 602–607. https://doi.org/10.18653/v1/P19-1057

[5] Bettina Grün and Kurt Hornik. 2011. topicmodels: An R Package for Fitting Topic Models. *Journal of Statistical Software* 40, 13 (2011), 1–30. https://doi.org/10.18637/jss.v040.i13

[6] Elena Musi, Debanjan Ghosh, and Smaranda Muresan. 2018. ChangeMyView Through Concessions: Do Concessions Increase Persuasion? arXiv:cs.CL/1806.03223

[7] Vwani P. Roychowdhury Roja Bandari, Hazhir Rahmandad. 2013. "*Blind Men and the Elephant: Detecting Evolving Group in Social News. arXiv:cs.SI/1304.1567v2*

[8] Hardik Meisheri Tushar Kataria Aman Agarwal Ishan Verma Sachin Thukral, Arnab Chatterjee and Lipika Dey. 2019. Characterizing behavioral trends in a community driven discussion platform. arXiv:cs.SI/1911.02771v1

[9] Nattapong Sanchan, Ahmet Aker, and Kalina Bontcheva. 2017. Automatic Summarization of Online Debates. 19–27. https://doi.org/10.26615/978-954-452-038-0_003

[10] Eytan Adar Srayan Datta. 2018. Extracting Inter-community Conflicts in Reddit. arXiv:cs.SI/1808.04405v1

[11] Dhanya Sridhar and Lise Getoor. 2019. Estimating Causal Effects of Tone in Online Debates. CoRR *abs/1906.04177 (2019). arXiv:1906.04177 http://arxiv.org/abs/1906.04177*

[12] Kumar Bhargav Srinivasan, Cristian Danescu-Niculescu-Mizil, Lillian Lee, and Chenhao Tan. 2019. Content Removal As a Moderation Strategy: Compliance and Other Outcomes in the ChangeMyView Community. Proc. ACM Hum.-Comput. Interact. *3, CSCW, Article 163 (Nov. 2019), 21 pages. https://doi.org/10.1145/3359265*

[13] Chenhao Tan. [n.d.]. Chenhao Tan's Homepage - changemyview. https://chenhaot.com/pages/changemyview.html

[14] Chenhao Tan, Vlad Niculae, Cristian Danescu-Niculescu-Mizil, and Lillian Lee. 2016. Winning Arguments: Interaction Dynamics and Persuasion Strategies in Good-faith Online Discussions. In Proceedings of the 25th International Conference on World Wide Web (WWW '16). *International World Wide Web Conferences Steering Committee, Republic and Canton of Geneva, Switzerland, 613–624. https://doi.org/10.1145/2872427.2883081*

[15] Amine Trabelsi and Osmar R. Zaiane. 2019. Contrastive Reasons Detection and Clustering from Online Polarized Debate. arXiv:cs.CL/1908.00648