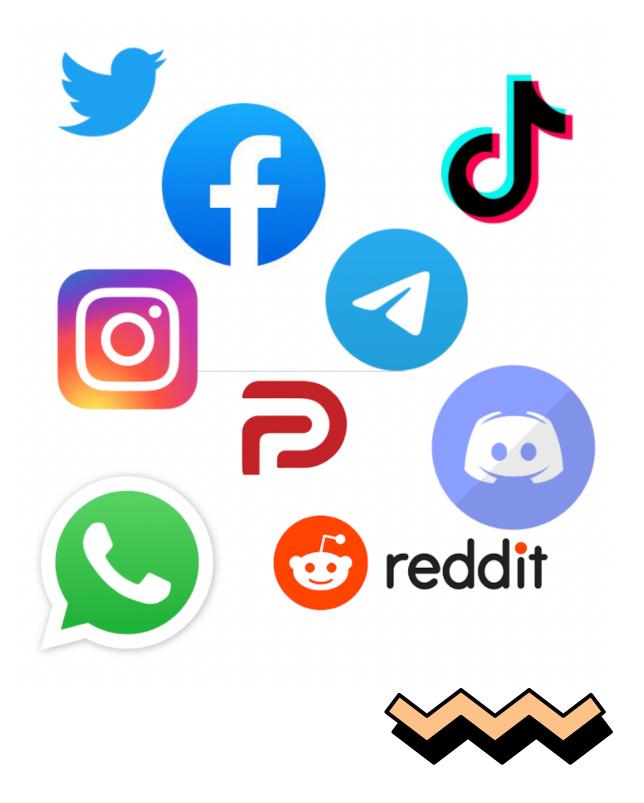


USER ROLES IN ELECTORAL DISINFORMATION ON TWITTER

Group 2: Stephen Prochaska, Chris Fu, Leo Moley, Nayan Kaushal



MOTIVATION

- Movements do not exist on any single platform
- Extremism and disinformation often overlap
- By understanding if roles from extremist groups on Facebook can computationally transfer to disinformation on Twitter, we may be able to better understand the organizational structure that influences the spread of harmful information in digital spaces





DOMINION CONSPIRACY THEORY



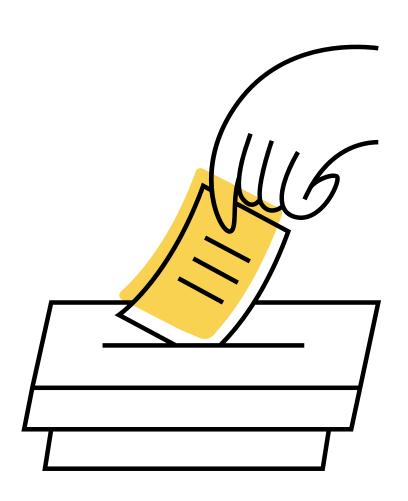
DOMINION VOTING SYSTEMS

Dominion Voting Systems is a company that sells electronic voting software and hardware, and was falsely and/or misleadingly connected to voting irregularities in multiple states



CONSPIRACY

As a major vendor of elections system software, Dominion was discussed prior to Election Day in the general context of election integrity and wrapped into a variety of theories alleging that they were complicit in fraudulently altering votes or otherwise preventing people from voting for their preferred candidate.

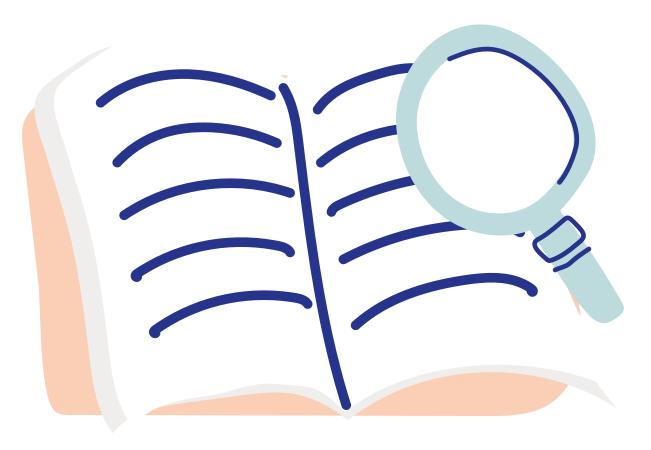


RELATED WORK

EDUCATORS, SOLICITORS, FLAMERS, MOTIVATORS, SYMPATHIZERS

Shruti Phadke and Tanu Mitra identified five primary roles evident in extremist movements on Facebook by generating clusters based on theories surrounding participatory activism, social movements and social psychology (Phadke & Mitra, 2021)

The current study functions to replicate the methods pioneered by Phadke and Mitra in a new setting



TAXONOMY: EDUCATORS, SOLICITORS, FLAMERS, MOTIVATORS, SYMPATHIZERS

Educators	Solicitors	Flamers
"accounts that share intellectual content about extremism and prominently share and like extremist content"	"who solicit participation and funds for the extremist movement"	"accounts that express and incite anger by posting inflammatory content"

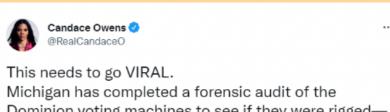


Did you know a foreign company, DOMINION, was counting our vote in Michigan, Arizona and Georgia and other states.

But it was a front for SMARTMATIC, who was really doing the computing.

Look up SMARTMATIC and tweet me what you think?



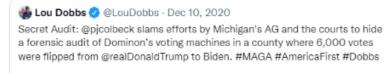


Dominion voting machines to see if they were rigged the Attorney General of the state is now BLOCKING the disclosure of the audit results?

WHY??!!

What is Michigan hiding?!

#STOPTHESTEAL





[redacted] so there was some cheating going on with the Dominion voting systems. Report just came out from Michigan! You are a cheater, a liar, a criminal, and not fit to be President!

TAXONOMY: EDUCATORS, SOLICITORS, FLAMERS, MOTIVATORS, SYMPATHIZERS

Motivators	Sympathizers	
achievement oriented and go-getters of the extremist nity and who post information that portrays a positive image of their extremist agenda"	"accounts that are fringe supporters of the extremist movement who sparingly engage with links from the extremist websites."	

Keep digging Patriots! We need more than 6,000! QT @[redacted]: BREAKING: County clerk in Antrim County in Michigan may have accidentally transposed the numbers for Trump and Biden (and John James) and is investigating. Trump and James will see a gain of about 6,000 votes once corrected.

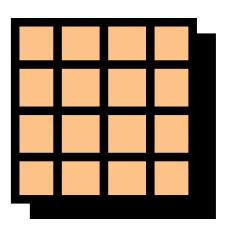
God Bless These Patriots! @[redacted] QT
@[redacted]: BREAKING: Patriots Surround
Michigan Court House To Prevent Dominion
Machine Wipe-Trump Forensic Team Airborne To
Examine-MI Counties Were Forced To Buy
Dominion Machines, Paid For By Zuckerberg
Entity - https://t.co/KIIRkPfQ1t

Hopefully the threats of an investigation will see more clerks seeing the error of their ways. QT @[redacted] BREAKING: County clerk in Antrim County in Michigan may have accidentally transposed the numbers for Trump and Biden (and John James) and is investigating. Trump and James will see a gain of about 6,000 votes once corrected.

RESEARCH QUESTION



DO THE ROLES IN EXTREMIST MOVEMENTS ON FACEBOOK (EDUCATORS, SOLICITORS, FLAMERS, MOTIVATORS, SYMPATHIZERS) TRANSLATE TO DISINFORMATION ON TWITTER?





DATA



DATASET

- Collection of Tweets related to the Dominion conspiracy theory,
 n = 2.5 million.
- After removing the accounts
 which post less than 5 tweets, n =
 1.88 million

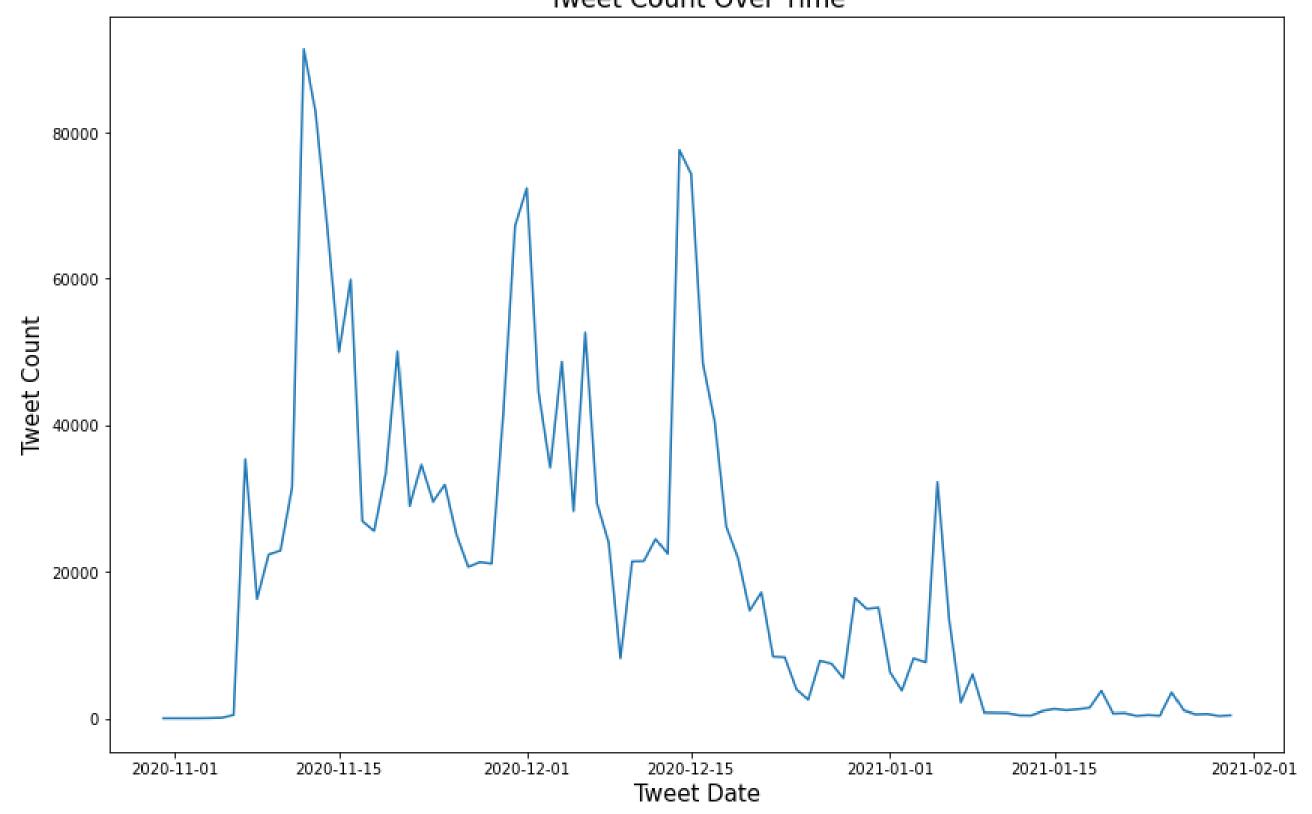


COLLECTION

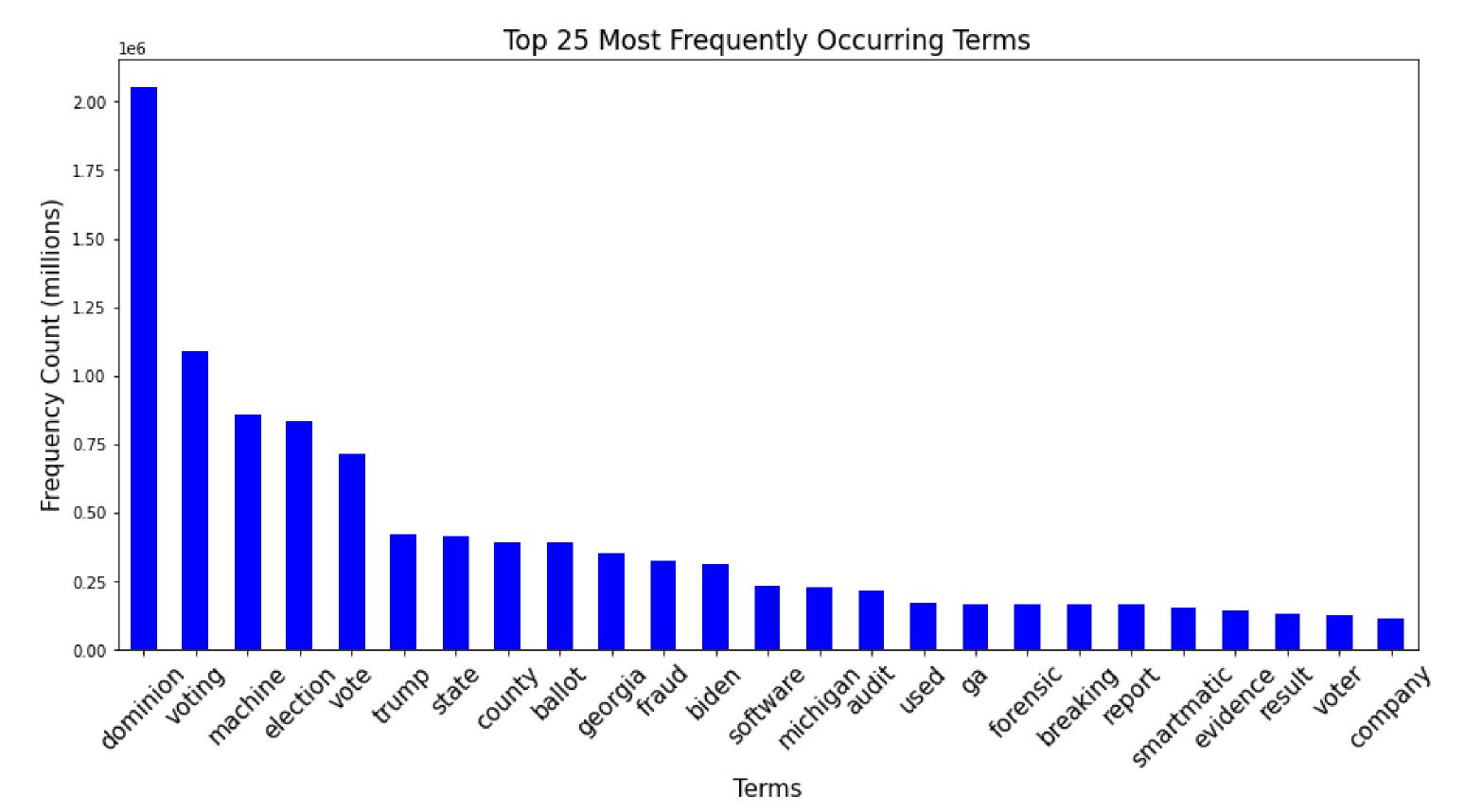
- Tweets were collected from the Center for an Informed Public's database for Tweets related to election fraud
- This data was collected in real time and therefore is not limited by traditional constraints

DATA: DESCRIPTIVES

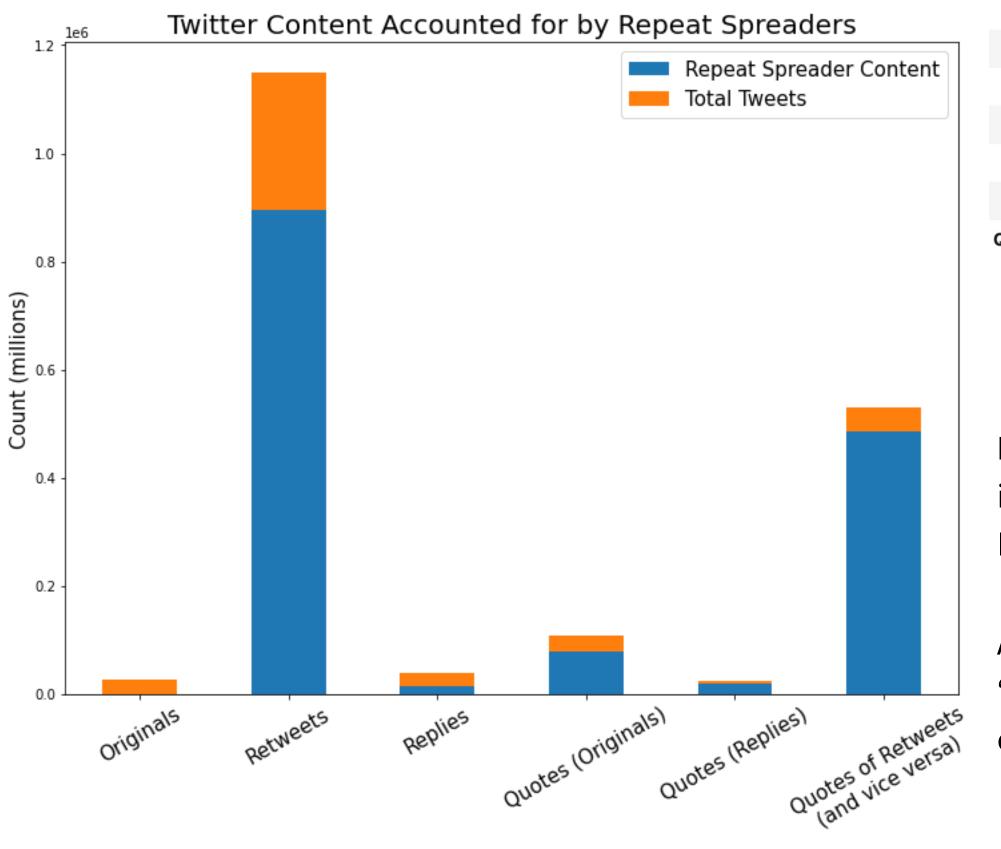




DATA: DESCRIPTIVES



DATA: DESCRIPTIVES



Twitter Content Accounted for by Repeat Spreaders

	Full Dataset Count	Repeat Spreader Count	Repeat Spreader %
Total tweets	1881491	1499288	79.686164
Originals	28010	843	3.009639
Retweets	1148647	895915	77.997418
Replies	40004	15654	39.131087
Quotes (Originals)	108858	80316	73.780521
Quotes (Replies)	25955	20758	79.976883
Quotes of Retweets (and vice versa)	530017	485802	91.657815

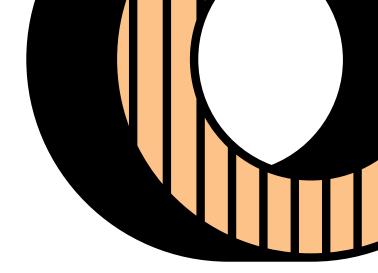
Figure: Summary of the Dominion dataset ("Full Dataset Count") and a comparison showing the prevalence of "repeat spreaders" of mis/disinformation in the dataset. "Repeat Spreader %" is the proportion of the full sample that referenced repeat spreader content.

Repeat spreader: an account that was present in multiple incidents of mis/disinformation tracked by the Center for an Informed Public (CIP)

A significant proportion of tweets are either generated by "repeat spreaders" of mis/disinformation or amplify their content



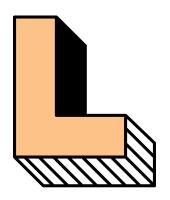
METHODOLOGY



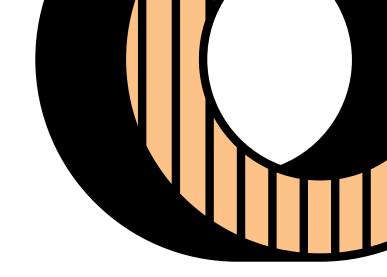
PREPROCESSING

Sift out users tweeted < 5 from our → 1/10 sampling from 1,881,491 records → Clean up: dataset

- Remove emojis
- Remove punctuation
- Remove retweets keywords
- Remove url
- Remove hashtags
- Remove emojis
- Remove mentions
- Remove quote tweets keywords
- Remove stopwords NLTK package
- lemmatization
- Use the similarity as the features for clustering







GENERATING NLP FEATURES

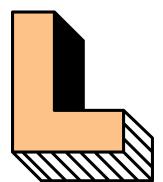
- Dictionary LIWC and MFD: find the word embedding for each word in dictionary using Word_to_vector embedding
- Calculate the tweet similarity to each categories' average embedding score
- **Generate score** for each tweet for each categories

GENERATING OTHER FEATURES

- **Favorites**: average favorites of particular user compared to average favorites of all users
- Retweets: average retweets of particular user compared to average retweets of all users
- Replies: average replies of particular users compared to average replies of all users
- Degree of participation: total proportion of both retweets and quote tweets/ all tweets and quote tweets

CLUSTERING

- Normalization
- **Kmeans** clustering
- PCA to visualize in 2D



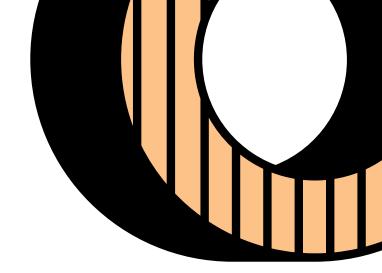
METHODOLOGY

GENERATING FEATURES

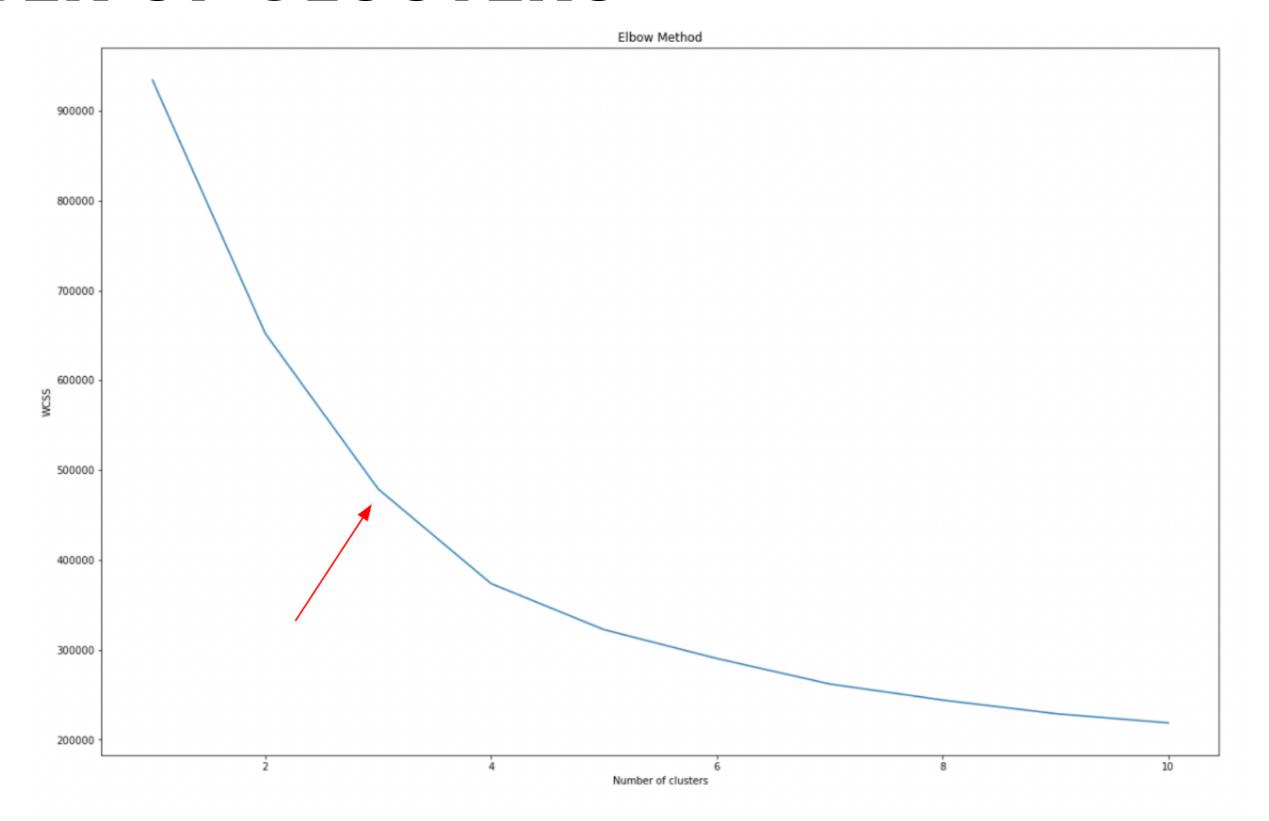
NLP features

Characteristics of Participation	Theoretical Models	References	Behavior	Operationalization
Drives for participation	Expectancy-value models	[36, 44, 54]	Risk	Proportion of LIWC Risk words (e.g., caution, crisis, failure)
		[36, 44, 54]	Reward	Proportion of LIWC Reward words (e.g., benefit, bonus, award)
	Social-psychology models	[83]	Injustice	Proportion of MFD Fairness words (e.g., parity, fair, justice)
		[21, 82]	Achievement	Proportion of LIWC Achievement words (e.g., accomplish, ability, attain)
		[72]	Group Identity	Proportion of LIWC we words (e.g., we, ours, us)
		[84]	Anger	Proportion of LIWC anger words (e.g., resent, argue, angry)
Engagement in the movement	Degrees of participation	[46]	Proportion of links from extremist domains	Ratio of links from extremist domains to total link posts
	Degrees of participation (popularity)	[46]	Likes	Proportion of likes on extremist links to likes on the rest of the link posts
			Shares	Proportion of shares on extremist links to likes on the shares of the link posts
			Comments	Proportion of comments on extremist links to comments on the rest of the link posts
	Trends in participation	[10]	Trend	Trend line fitted on the number of extremist links posts per month
Strategies of mobilization	Opinions	[81]	Expressions of opinions	Proportion of extremist link posts containing opinion patterns (see Table 6)
	Solicitation	[6, 46]	Expressions of solicitation	Proportion of extremist link posts containing solicitation patterns (see Table 7)

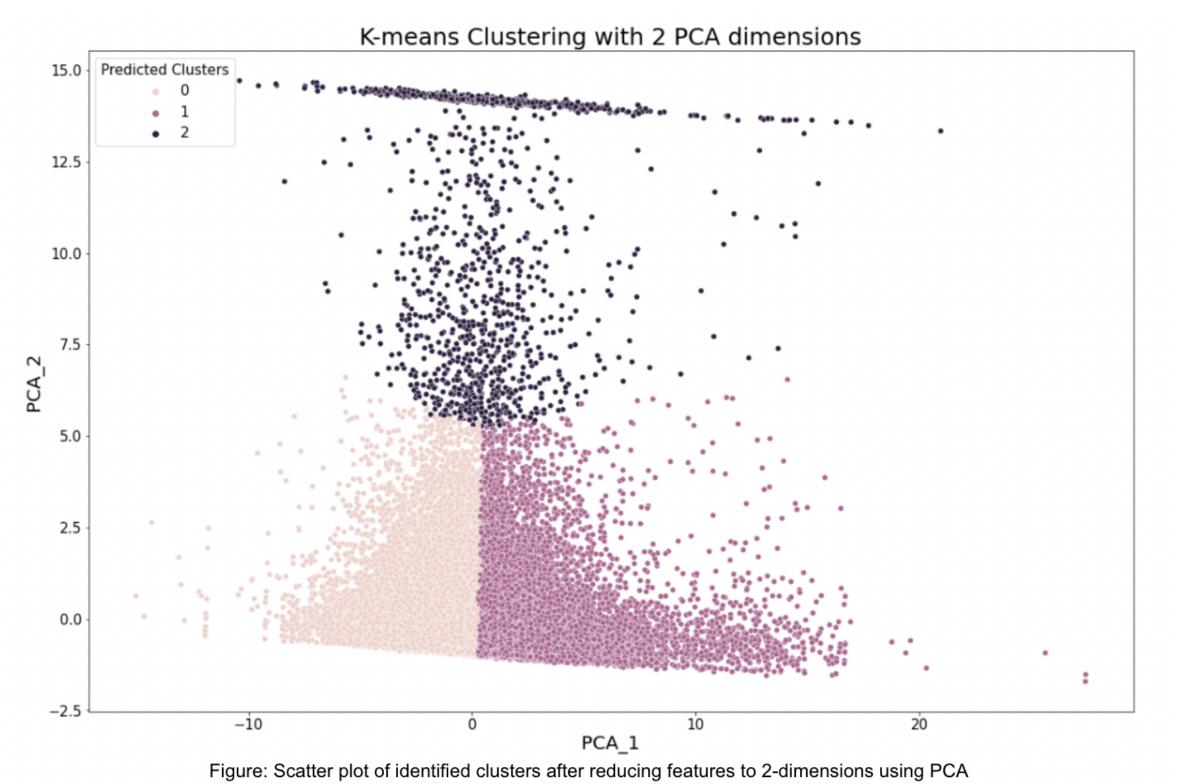
Table 2. Table summarizing features used to identify roles in online extremist movements on Facebook. We build the feature set based on underlying characteristics of participation and the theoretical models describing them.



KEY RESULTS: NUMBER OF CLUSTERS



KEY RESULTS: VISUALIZATION OF RESULTS AFTER PCA



KEY RESULTS: CLUSTER VALIDATION



Accounts which share intellectual content and/or portray a positive image of the agenda



AMPLIFIER/SYMPATHIZER

Accounts that **support** the movement but do not directly add anything to it



ANALYST

Accounts that **critically analyze** the

mis/disinformation

content, either through

supporting conspiracy or

debunking it



DISCUSSION

- Computationally translating an extremist user-role taxonomy from Facebook to Twitter is not straightforward due to platform affordances and different social norms
- There is some overlap between roles for accounts on Twitter (e.g. co-occurence of "educator" behavior and "motivator" behavior)





DISCUSSION

- There appears to be a role unique to
 Dominion related to "analyzing" content on
 Twitter
- Proof of concept for adapting taxonomy to other platforms and content types
- While the method would benefit from further tuning, the identified clusters show some promise for identifying roles on different platforms

LIMITATIONS

- Was the taxonomy identified by Phadke and Mitra an expression of extremist movements, an expression of Facebook, or an expression of extremist movements on Facebook?
- Repeat spreaders are **not the same** as extremist domains
- A narrative of disinformation does not exist in isolation, to properly apply the role taxonomy we need a better picture of the "movement" instead of a specific strategic element

LIMITATIONS

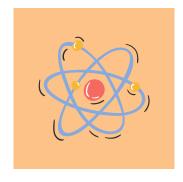
• It is difficult to transfer the taxonomy to both a new (albeit related) domain and a different platform.

 Potential risk that twitter users are identified through behavior data

 Abuse of taxonomy/methodology to categorize users based on other behaviors

FUTURE WORK





Experimentation, validation, and refinement of selected features and user roles



Expand our analysis to include additional mis/disinformation datasets



Identify which user roles are present across different mis/disinformation narratives and how those roles may change over time

Questions?

REFERENCES

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- Benkler, Y., Faris, R., & Roberts, H. (2018). Network Propaganda:
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