Repackaging for Mass Consumption: An Investigation into "Alt-Lite" Twitter as a Diffusion Channel for "Alt-Right" Ideas

HAYDEN LE, University of Michigan

TODO LIST

1 INTRODUCTION

The "alt-right"[1] has an inordinate influence on American political discourse [7, 50]. This calls for concern, not only because the movement has motivated a number of terrorist acts [6, 11, 32], but also as their rhetoric poses a existential threat to democratic social and cultural values [14].

One of the key drivers behind the "alt-right"'s increasing influence is their successful emphasis on *mainstreaming*, a process where fringe ideas are repackaged for wider consumption in an effort to normalize them [9, 38, 52]. Examples of mainstreaming can range from coded expressions of racism to normalization of ideas previously thought unacceptable in polite conversation [9]. Mainstreaming as a strategy to further political influence is rooted in Gramscian thought [43, 52]. Antonio Gramsci, an Italian Marxist philosopher, postulated that non-dominant groups seeking to effectuate radical change in a civil society cannot do so through confrontation, as encounters would likely evolve into unfavorable wars of attrition [16]. So, he suggests, they must instead influence culture such that it propels institutional change in their favor; he terms this approach engaging in a *war-of-position* [8]. The hallmark of the "alt-right"'s making headway in their war-of-position is the election of Donald Trump, a president not only friendly to but also a superspreader of their previously-considered fringe ideas [7].

Continued growth in the "alt-right"'s political influence is far from a distant possibility—they enjoy a sizeable sympathetic audience in the current American political climate. Hawley [28] estimates that roughly 6% of non-Hispanic whites have beliefs in line with white nationalism. He arrived at 6% by filtering for non-Hispanic white responses to the 2016 American National Election Survey (ANES) then determining the ratio of responses where "a strong sense of white identity", "a belief in the importance of white solidarity", and "a sense of white victimization" were all rated as "very" or "extremely" important. In addition to the 6% who gave those items a high importance rating, many respondents agreed with at least one of the three statements: 28% held a strong sense of white identity, 38% believed in the importance of white solidarity, and 27% held a sense of white victimization. A 2017 Reuters/Ipsos poll found similar patterns: 39% [2] of respondents strongly or somewhat agreed with the

[1] §2.1 discusses the stylistic choice of quotation marks here.
[2] Unlike Hawley [28], these percentages are not after filtering for non-Hispanic whites.

Author's address: Hayden Le, hayde@umich.edu, University of Michigan, Ann Arbor, Michigan.

statement, “White people are currently under attack in this country”; 31% strongly or somewhat agreed with the statement, “American must protect and preserve its White European heritage”; 6% explicitly strongly or somewhat support the “alt-right”; 8% strongly or somewhat support white nationalism; and 4% strongly or somewhat support neo-Nazism [19].

The major blocker between the "alt-right" and more widespread conservative acceptance is shared rejection of fragrant racism. Despite their formidable strides in political influence and the conditions of possibility described, the "alt-right" remains, at best, considered a fringe movement as sympathizers (and potential converts) adamantly assert their statuses as non-racists and defend the idea that "[a]ll men are equal" [27, 38]. These sympathizers, similar in many ideological and demographic dimensions to to "alt-right" members but disapproving of white-identity politics, have been dubbed as *"alt-lite"* [27, 38]. Both “alt-right” leaders and scholars speculate that that the “alt-lite” are a potential conduit through which the “alt-right” can reach a wider audience and, consequently, grow their cultural influence. Though several scholarly works consider the "alt-right" [26, 38, 43] and related matters such as their mainstreaming efforts [21] and its effect on public discourse [9, 52], details about how the "alt-lite" distinguishes itself from the "alt-right" and contributes to the latter’s mainstreaming persist as open questions. To address this research gap, I will analyze "alt-right" and "alt-lite" discussions and networks on Twitter, focusing on the following research questions:

RQ1. What are the distinctive characteristics of "alt-right" or "alt-lite" Twitter? How do they contrast with general Twitter?
RQ2. How are "alt-right", "alt-lite", and general Twitter’s networks connected?
RQ3. Does the "alt-lite" mediate diffusion of "alt-right" ideas? If so, how?

I will address:

- RQ1 by examining the communities’ network structures and language use
- RQ2 by analyzing
  - communities’ networks’ (represented as graphs) exterior pointing edges (i.e. edges that connect community users to non-community users) and overlapping users (individuals who are members of multiple communities)
  - a Hawkes process capturing Twitter as a multi-speaker conversation
- RQ3 by hypothesis testing the parameters of
  - the Hawkes process to determine which communities hold influence in another communities’ discourse
  - a logistic regression predicting diffusion of an idea from “alt-right” discourse to general public discourse to pinpoint and compare relative importance of idea diffusion mechanisms.

At the conclusion of this project, I will contribute to scholarly understanding of “alt-right” mainstreaming efforts by providing language markers with which to differentiate between “alt-right” and “alt-lite” rhetoric, defining the two groups’ relationship to one another and mainstream discourse through a social network analysis lens, and pinpointing social media mechanisms that expediate “alt-right” idea diffusion.

The remainder of this proposal is organized as follows: I explain deliberate style and language choices. Then, I review previous work, detailing current scholarly understanding of the “alt-right” and “alt-lite”. Closing my proposal, I outline my intended methodology and timeline.

2 STYLE AND LANGUAGE

2.1 “Alt-Right” and “Alt-Lite”

I follow other scholars’ [25, 40] and the Associated Press’s (AP) [30] usage of “alt-right”. Both academic and journalist experts caution that using the phrase “alt-right” lends undue political legitimacy to a group predominantly composed of white nationalists and supremacists by obscuring that connection. As such, many opt to highlight their unenthusiastic use of “alt-right” with “quotation marks, hyphen and lower case” [30] to remind readers of the complexity belying the descriptor. I style “alt-lite” in a similar manner.

2.1.1 *Describing Far-Right Groups.*

Experts disagree on the nonmenclature and description of far-right movements and subgroups. This is partially the result of earlier academic and journalist work that interchanged labels without greater deilberation [CITATION]. However, far-right individuals themselves also share responsibility: members of the same far-right party disagree on basic points like whether their party is racist [cite]. Consequently, while cademics agree that the movements are right-wing, but disagree on what constitutes ’right-wing’.

2.2 Mainstreaming or Radicalizing?

Mainstreaming has many conceptual overlaps with *radicalization*, a more well-known and researched idea, particularly in criminal justice and computer science literature [CITATIONS]. The difference between mainstreaming and radicalization lies in what scale on perception distortion takes place. Mainstreaming refers to efforts to move an idea from the edges (or “fringe”) of *general* social acceptability to the center; to mainstream an idea is to normalize it. Meanwhile, radicalizing refers to warping an *individual’s* sense of acceptable ideas; to radicalize a person involves changing what they perceive as normal.

Also, use of “radicalization” suggests terrorism as the larger concern at-hand [CITATION]. When speaking about the “alt-right”, acts of terror are well within the scope of concern, especially as, since Donald Trump’s election in 2016, a rising number of these extremist-related killings have been attributed to right-wing extremists (in particular, white supremacists) (Greenblatt, n.d.). [3] However, as this project is primarily concerned with measuring cultural change as captured by change in language, I describe the process of normalization I wish to study as “mainstreaming” rather than “radicalization”.

Change the last sentence here to talk about how the existential threat from the alt-right is disinformation warfare -> collapse of democracy.

3 LITERATURE REVIEW

make promised neighborhood friendly table of descriptors and descriptions for the far right + related + sub groups

3.1 “Alt-Right”

The “alt-right” are a loosely connected group of individuals who predominantly support white supremacy and hyper-masculinity, reject multiculturalism and feminism, and interface with one another primarily through the internet [26, 38, 43, 52]. This description is incomplete and a simplification for many reasons, including that “alt-right” is applied as a label inconsistently by supporters and observers alike [26] and “the "alt-right"‘, as a phrase, suggests a monolithic collective [40], which fails to capture the dispersed and disorganized [39] nature of the “alt-right”, a ’movement’ with no formal membership nor accepted leaders [26]. On top of these issues, experts are skeptical that those who label themselves "alt-right" have discernible shared traits aside from those attributed to white supremacists [21, 30]. With these caveats in mind, literature surrounding the “alt-right” can be divided into two categories. One strand describes the “alt-right” as part of a larger global phenomenon where far-right ideology have been amassing legitimacy and power through populist politics [9, 55]. Another positions the “alt-right” as the internet-age reincarnation of white nationalists [26, 38]. In this review, I focus on the latter,

[3]In 2016, 13% of domestic extremist-related killings were committed by right-wing extremists. Compare this to 56%, 78%, and 86% in 2017, 2018, and 2019, respectively [24].

Table 1. Key Terms

Group	Key Features	Additional Notes
“Alt-Right”	The Internet-age reincarnation of white nationalism; notably departs from white nationalism in ’optics’ savvy–has disavowed Nazi and KKK symbols. Influenced by a number of Internet subcultures dominated by white males. Heavy endorsement of white identity politics, hypermasculinity, and bio-essentialism.	[need to add]
“Alt-Lite”	Differentiates themselves from the “alt-right” by outwardly rejecting racism. Consider themselves ’civic nationalists’ as opposed to ’white nationalists’.	[need to add]
Civic Nationalist	A	[need to add]
Far-Right	[need to add]	[need to add]
White Supremacist	[need to add]	[need to add]
White Nationalist	[need to add]	[need to add]

which centers the “alt-right” as an actor exercising agency, as opposed to a symptom or by-product of external phenomena.

Andrew Anglin, a prominent “alt-right” figure, describes the “alt-right” as a movement that came out of various internet subcultures (e.g. troll culture, conspiracy theorism, the manosphere); he states that the “alt-right” can be understood as a reboot of earlier white nationalist movements [2]. For the most part, scholars agree with Anglin. However, experts clash in their portrayals of the *essence* of the “alt-right”[20]. Some assert that the “alt-right” “is fundamentally concerned with race” [26]. Others emphasize that the “alt-right” is a white *male* [4] movement, and so gender, as well as race, is a dominant underlying factor in explaining beliefs and motivation [31]. Gallaher [21] examined 1,000 tweets from six alt-right leaders on Twitter and observed a predominantly cultural and racial lens in their messages’ frames. Surveying a nationally representative random probability sample of Americans and considering several accounts of the “alt-right”, Forscher and Kteily [20] found the most support for those framing the “alt-right” profile as one of acceptance of and eagerness to advance white supremacy, especially at the expense of non-whites. Additionally, they saw that self-identified “alt-right” members were “more similar than different” to those who voted for Trump in 2016. Between the two, "alt-right” members were likely to report greater enthusiasm for Trump, be suspicious of mainstream media outlets, and support white collective action (e.g. agree with statements such as “More needs to be done so that people remember that “White Lives” also matter.”).

The "alt-right" set themselves apart from other far-right movements with their emphasis on mainstreaming and their social media savvy. The latter trait enables the success of the first [21, 43, 52].

[4]Important to note that despite the misogyny present in “alt-right” rhetoric and talking points, the movement is not without its women. Forscher and Kteily [20] estimate about 44% of “alt-right” supporters are women.

Fix up this paragraph. Should read about mainstreaming -> political discourse focus warp

Stern [52] provides a vignette to demonstrate how "alt-right" ideas have warped mainstream political discourse: As an “alt-right”-imagined conspiracy theory, "white genocide" had scant mention in public discourse. However, it later found itself the centerpiece issue of a Tucker Carlson news story about how white Southern African farmers were being massacred by their black, African-led government. Later, President Trump announced over Twitter that he had asked his Secretary of State to "closely study the South African land and farm seizures ... and the large scale killing of farmers" [CITATION]. This is all in spite of a lack of data to support that farmers were at heightened risk of being killed in comparison to the average South African [BBC citation]. In summary, as one “alt-right” member boasts, "What Tucker Carlson talks about, we talked about a year ago" [29].

Previous works studying mainstreaming relied on expert judgment to judge whether ‘new’ ideas, frames or concerns in media are actually repackaged versions of “alt-right” ideas. I will computational methods to identify vignettes of “alt-right” influence similar to that provided by Stern [52]. I seek not only to provide more examples of how the “alt-right” have influenced political discourse, but also to clarify the process “alt-right” ideas take to get from point A (“alt-right” circles) to point B (general conversation).

3.2 “Alt-Lite”

The “alt-lite” separate themselves from the “alt-right” with their rejection of overt racism (Anti-Defamation League (n.d.), Main (2018), Hawley (2017)). In other words, while “alt-lite” individuals subscribe to many (if not most) of “alt-right” talking points, they (at least outwardly) reject that individuals of different races have different abilities or are otherwise " not equal“. In the words of Richard Spencer, a leading “alt-right” figure, “The alt-right [sic] fundamentally differs from Trump’s civic nationalism by considering ‘us’ to be all people of European ancestry across the globe” (Anti-Defamation League (n.d.), Main (2018)). In other words, while the “alt-right” concerns itself with white people across the globe, the “alt-lite” prioritizes those within the United States’ borders.

Though some “alt-right” members view the “alt-lite” with derision, others see the latter as useful “entry point[s] for potential converts” (Hart 2016). Ribeiro et al. (2019) investigate this hypothesis on YouTube, seeking to understand whether “alt-lite” video commenters were more likely to become “alt-right” video commenters than those who consumed popular media channels. They find that, in 2018, roughly a quarter of new “alt-right” commenters (users who comment on an “alt-right” video for the first time in their YouTube careers) had previously commented on an “alt-lite” video (Ribeiro et al. 2019). This observation supports the idea that “alt-lite” content can act as a pathway to “alt-right” content, but, as Ribeiro et al. (2019) caution, it does not explain the pathway’s mechanics.

Except for Ribeiro et al. [47], previous scholarly work probing the “alt-right”, “alt-lite”, and/or far-right mainstreaming primarily employ discourse analysis [9, 18, 21, 34]. My proposed project complements previous works by re-examining our shared questions with under-explored quantitative methods and a larger-scale data set. Moreover, while many academics [38, 43, 52] have hypothesized or otherwise observe that “alt-lite” individuals facilitate normalization of “alt-right” ideology, only Ribeiro et al. [47] has quantitatively tested this theory. My project intends to shed light on the mechanics behind how “alt-lite” members or their content facilitate normalization of “alt-right” ideology through examination of network structures and fitted model coefficients.

3.3 Measuring Influence via Social Networks and Language Use

I curated this project’s chosen methods from established social network analysis (SNA) and computational linguistics techniques with previous successful applications in social science research.

Researchers employ SNA to investigate groups and their intra- and inter-group relationships and interactions [10]. Closely related to our work, Morstatter et al. [42] employed SNA methods to distinguish German “alt-right” sub-communities from one another and discern the sub-communities' different themes in conversation, along with the flow of information between the sub-communities.

Contemporary computational linguistics is closely aligned with social science research interests. Computational linguists steadfastly demonstrate interest in social science applications: [33] outline how to use topic models to track emerging trends or interests; [4] cluster and train statistical classifiers on a Twitter corpus to study the relationship between gender, language use, and social networks. Similarly, social scientists have advanced computational linguistics methods by adjusting them to examine questions like "What language would we expect from a Republican vs a Democrat?" or "How tied are stock prices to newspaper headlines?" [22, 41].

Although my chosen methods may appear disjoint at cursory glance, they all work toward capturing and dissecting power/influence and language use in a networked setting.

4 DATA PROCEDURES

4.1 Source of Data

I create my dataset by filtering from a Twitter Decahose[5] (a 10% random sample of Twitter Firehose) collection that began late February 2018 and has yet to cease. This strategy (in contrast to starting from scratch and collecting my own using Twitter API) is the most cost-effective route, both monetarily and with regards to time.

Previous quantitative investigations into the AR on Twitter ([5], [1]) created their datasets by, over time, crawling identified AR users and collecting relevant data via Twitter API. The comparative advantage of this approach is that one would have access to users' follows and followers over time. (The Twitter Decahose tweets do not include user friendship information at time of posting and historical friendship data is not accessible.) However, previous work [12, 54] suggests that user-follower data is an unhelpful signal at best, noisy one at worst in Twitter information diffusion inquiries. Additionally, as the main goal of this project is to investigate a time-series process (how the AL assists in mainstreaming AR ideas) observing a longer period of time is preferable.

4.2 Data Collection

My research questions call for samples of three Twitter communities: "alt-right" (AR), "alt-lite" (AL), and "general". I filter from historical Twitter Decahose tweets to assemble my dataset.

4.2.1 "Alt-Right" and "Alt-Lite". I begin collecting accounts contributing to AR discourse[6] by referring to the Anti-Defamation League's [3] and Southern Poverty Law Center's [51] publicly available determinations of AR groups and leading figures for "seed" AR members. I collect "seed" tweets from these users and extract retweeted or mentioned Twitter usernames to complete this community sample.

To collect accounts contributing to AL discourse, I modify the above approach accordingly.

4.2.2 General. I collect a random sample of users to serve as a control group. This sample's size will be comparable to the other community samples'.

4.2.3 Additional Features. Previous works' [1, 5] data pre-processing and/or descriptive statistics of AR Twitter suggest features with which to flag users.

- Bots
  A non-trivial segment of the AR Twitter is bot-run [5]. I will use Davis et al. [15]'s BotOrNot to determine whether users in my dataset are bots and flag them accordingly.

[5] "Twitter decahose is made available through a Master License Agreement between Twitter, Inc. and the University of Michigan, and its research use is supported by the Michigan Institute for Data Science, Advanced Research Computing - Technology Services, and Consulting for Statistics, Computing & Analytics Research."

[6] I expressly avoid labelling non-public figure users as AR, AL, or otherwise. In other words, when I include a user as part of a community sample, I am not labelling them as a community member. Rather, I label them and their tweets as contributing to a community's discourse[7].

- Reside in the United States
  I will flag out users whose time zones or locations suggest that they are not residing in the United States to leave the potential open of later capturing non-US influence on US public discourse.
- Verified status and/or a large number of followers
  Both Berger [5] and Alizadeh et al. [1] remove atypically popular users from their datasets. Having a verified status on Twitter and/or a "large" (relatively defined) following suggests that one is a public or known figure, so these metrics are good heuristics with which to approximate celebrity. As individual users' level of celebrity likely predictive of network influence [CITATION], I will flag "celebrity".

4.3 Tweets

All collected Twitter users' tweets are extracted from the Decahose data. I preprocess tweets' text by lowercasing all characters and removing URLs.

4.4 Community Networks

I construct three distinct undirected graphs that will represent my data as a social network. Users are represented as nodes; if they are 'linked' to one another, they will have an edge connecting them. One graph will be constructed using *mentions* and *replies* as links (i.e. if a user mentions another, their representative nodes will have an edge connecting them). The second graph is based off of *retweets*. The third graph is potentially many graphs and connects two users if they share usage of a specialized term[8] . I construct these three graphs as they hold potentially different insight for my research questions.

4.4.1 Community Detection. This project's overarching goal is to better understand the extent to which one Twitter community influences the rest of the social media platforms' discourse and what mechanisms support that influence. Consequently, discerning significant sub-graphs within is useful to discern significantly dense sub-graphs in our earlier generated graph. These dense sub-graphs are reflective of communities and identifying them has been shown to be helpful in predicting message diffusion from one community to another [ADD CITATION]. This community detection is done despite users already having been sorted into communities (by way of my data collecting process) because contrasting those labels and communities with those mined using graph features will highlight relevant particulars (e.g. Is there a set of users that act as "in-between" for the "alt-right" and the "alt-lite" communities?).

To distinguish communities as present in the user network graphs' structures, I need a community detection framework that performs well on social media community detection benchmarks, can handle nodes potentially being members of multiple communities, and is scalable. Epasto et al. [17]'s *Ego-Splitting* framework meets these criteria and is implemented by Rozemberczki et al. [48]'s Karate Club, an open-source unsupervised machine learning library extension to NetworkX. I plan to use it to organize the user network graphs into communities; this organization will be visualized using NetworkX.

5 COMMUNITY SNAPSHOTS

In this section, I detail how I investigate the various communities' characteristics (RQ1) and their relationships with one another (RQ2). I do this both by examining the communities' graph structures (topologically) and their language use.

For all analysis, I utilize parametric bootstrap sampling [23] to account for finite sample bias and obtain confidence levels for any reported statistics.

[8]Or have term-vectors with a high Jaccard similarity [44].

Table 2. Community Network Node and Graph Properties

Property	Description	Addressed Question
Average Degree	Average number of edges per community node	How many connections can we expect a user to have?
Internal Density	Fraction of edges that appear between two community nodes	How connected are users to this community as opposed to outside groups?
Expansion	Fraction of edges connecting nodes to non-community nodes	How connected are users to non-community users as opposed to same-community ones?
Average Geodesic Length	Average distance between two community nodes	Would information travel travel quickly from one community user to another, randomly selected one?
Clustering Coefficient	Fraction of "closed" community node triplets	How likely is it that three users within a community are all connected to one another?
Conductance	Probability that of a one-step random walk starting on a community node going outside the community	How likely is it that information is traveling outside the community?
Cut Ratio	Fraction of edges pointing outside the community over possible edges pointing outside	Do users make an active effort to engage with those in different communities?

5.1 Topology

To examine a network's topology is to study how its elements (both nodes and edges) are arranged [ADD CITATION]. I explore each community using node and graph properties in order to address questions such as (but not limited to):

- How connected are users within a community?
- How connected are users to those outside their community (or communities)?
- How quickly would one expect information to diffuse from the community to another?

I list and describe potential node and graph properties of interest [56] in Table 2. Some properties are concerned about *internal* connectivity (e.g. average degree, internal density, average geodesic length, clustering coefficient); some are concerned about *external* connectivity (e.g. expansion, cut ratio); conductance considers both internal and external connectivity. For the node properties in Table 2 (average degree and geodesic length), I will examine them not only as a point value but also as a distribution.

In addition to the node and graph properties listed in Table 2, the following may prove relevant:

- Each communities' size

- Influential users within each community
- How the communities detected through graph-based methods match up with my original user labels
- Details about users who are in multiple communities

5.2 Language

5.2.1 Representative Words. What are the words that "define" a community? Here, I am interested in uncovering the words that are more likely to have been said by one community in contrast to others. Previously, Monroe et al. [41] demonstrated that weighted log-odds ratios were effective in differentiating words typical of speech from a Republican vs. a Democrat. I plan to employ their described technique to determine each communities' identifying unigrams and bigrams. My deliverable from this work will be a table of some finite number of words with the greatest weighted log-odds ratio for each community and discussion about the arrived-upon representative words.

5.2.2 Topics. I explore what topics the various communities discuss in two ways:

- *Hashtags* Similar to how I will identify a community's representative words, I determine its representative hashtags using weighted log-odds ratios.
- *Topic Models* I employ Zuo et al. [57]'s Word Network Topic Model, a topic model shown to perform better than Latent Dirichlet Allocation (LDA) [CITATION] on short, social media text, to obtain each communities' latent topics (themes underlying their common discussion points); I determine the number of topics to uncover for each community by evaluating the model's performance on topic coherence measures [CITATION] in tandem with manual review. I will summarize captured topics by reviewing each topic's most prominent features along with its tagged tweets.

After collecting hashtags and latent topics, I will lay them out in a table and consider the communities' similarities and divergences.

6 IDEA DIFFUSION

In this section, I detail how I probe *whether* the AL helps diffuse AR ideas and *how* they might do so (RQ3).

I define an *AR idea* as a unigram, bigram, or hashtag that has no or few appearances in the dataset prior to being used by a non-trivial[9] amount of AR community members. An AR idea is *diffused* into a community when a non-trivial amount of community members employ it in their speech.

My inquiry into AR idea diffusion is best understood in three steps. I outline them here and go into greater detail in later subsections.

(1) I determine ideas with origins in the AR community.
(2) I model how ideas travel from one community to another using a multivariate Hawkes process. This model will delineate how much influence the various communities have over each other (e.g. How does what the general public talk about affect what the AR talk about?), helping determine whether the AL serve as a "conduit" for AR ideas.
(3) I predict whether an idea with origins in the AR will make a later appearance in the general public's discourse using an estimated logistic regression model. Inspecting this model will both complement findings from the Hawkes process model and identify non-community-related factors that play into AR idea diffusion.

[9]Exact number to be determined after more data inspection.

6.1 Detecting AR Ideas

maybe some clarification here about "idea" vs item of speech + that some other unit of speech might demonstrate itself more salient than n-grams or hashtags (e.g. framing)

I identify unigrams, bigrams, and hashtags as *AR ideas* if they meet two criteria: (1) they have no or few previous appearances in the dataset prior to being used by a sizeable amount of AR community members; (2) they are not used by non-AR community members at the time of their first appearance in the data.

6.2 Modelling Diffusion as a Hawkes Process

A point process is composed of events that occur at random intervals on space-time axes; a temporal point process is composed of time-series data concerning binary events occurring in continuous time [13, 45]. Temporal point processes can be used to describe data with discretized time points wherein an event may have occurred. A Hawkes process is a special point process wherein the probability of an event occurring is increased by its previous occurrences. Hawkes processes have been successfully used to model information cascades, such as the spread of memes or rumors on social media networks [35, 36].

I slice my dataset into week-long bins and by community (AR, AL, and general public). For each identified AR idea (along with 'control' ideas), the data will report, week by week, whether the idea was used and which community used it. I fit a multivariate Hawkes process on this dataset to estimate the communities' influence on one another's discourse. Comparing the magnitudes of estimated parameter values will reveal relative discursive influence. To perform hypothesis testing on the parameter values, I will re-estimate my model from parametric bootstrap samples [46] and use a Bonferroni-corrected significance level to account for the simultaneous multiple comparisons [53].

6.3 Predicting Diffusion via a Logistic Regression

I fit a logistic regression model to predict whether an AR idea will eventually be used by a non-trivial number of general public users. More specifically, this logistic regression will attempt to predict whether, within the next week, a non-trivial number of general public users will use an AR idea.

Out of potential models, I favor a logistic regression model for this task because of its greater ease for interpretation and inference *and* it has previously demonstrated superior ability to predict future popularity of newly emergent hashtags [37]. Both contextual and content features will be included as model features. Examples of contextual features include features of the AR community graph and distance between the AR and general public communities; examples of content features include the AR idea represented as topic and sentiment vectors.

As I will infer from the fitted model, I will ascertain that the logistic regression assumptions (such as independent error terms and absence of multi-collinearity) are met. Steps to meet logistic regression assumptions will include performing careful feature selection and estimating from parametric bootstraps.

I will calculate χ^2 statistics for each feature in my fitted model to understand their relative importance. Features with a greater χ^2 statistic will be understood as a more influential mechanism in predicting whether an AR idea is mainstreamed.

7 PROJECT TIMETABLE

Table 3 describes my planned timeline for this projects' data collection and analysis procedures.

In brief, I plan to complete data collection and pre-processing by the end of June; I will spend most of July performing the analyses described in the "Community Snapshots" section; I dedicate the latter part of July along with the initial weeks of August to exploring diffusion of AR ideas.

Table 3. Planned Checkpoint Completion Dates

Date	Milestone
June 30, 2020	Collect and pre-process users and tweets
July 5, 2020	Construct graphs and perform community detection on graphs
July 10, 2020	Describe, compare, contrast, and visualize community topologically
July 20, 2020	Describe, compare, contrast, and visualize community language use
July 25, 2020	Identify AR-manufactured ideas
August 2, 2020	Model AR idea diffusion as a Hawkes process
August 10, 2020	Predict diffusion via a logistic regression model
August 20, 2020	Write results section of paper
August 30, 2020	Write discussion section of paper
September 15, 2020	Write first draft of paper

REFERENCES

[1] Meysam Alizadeh, Ingmar Weber, Claudio Cioffi-Revilla, Santo Fortunato, and Michael Macy. Psychology and morality of political extremists: Evidence from Twitter language analysis of alt-right and Antifa. *EPJ Data Sci.*, 8:17, December 2019. ISSN 2193-1127. doi: 10.1140/epjds/s13688-019-0193-9.

[2] Andrew Anglin. A Normie's Guide to the Alt-Right.

[3] Anti-Defamation League. From Alt Right to Alt Lite: Naming the Hate. https://www.adl.org/resources/backgrounders/from-alt-right-to-alt-lite-naming-the-hate.

[4] David Bamman, Jacob Eisenstein, and Tyler Schnoebelen. Gender identity and lexical variation in social media. *Journal of Sociolinguistics*, 18:135–160, 2014. ISSN 1467-9841. doi: 10.1111/josl.12080.

[5] JM Berger. The alt-right Twitter census: Defining and describing the audience for alt-right content on Twitter. *VOX-Pol Network of Excellence*, 2018.

[6] Tore Bjø rgo and Jacob Aasland Ravndal. Extreme-Right Violence and Terrorism: Concepts, Patterns, and Responses. page 22.

[7] John Bryden and Eric Silverman. Underlying socio-political processes behind the 2016 US election. *PLoS ONE*, 14:e0214854, April 2019. ISSN 1932-6203. doi: 10.1371/journal.pone.0214854.

[8] Joseph A. Buttigieg. Gramsci on Civil Society. *boundary 2*, 22:1–32, 1995. ISSN 01903659, 15272141. doi: 10.2307/303721.

[9] Bart Cammaerts. The Mainstreaming of Extreme Right-Wing Populism in the Low Countries: What is to be Done? *Communication, Culture and Critique*, 11:7–20, March 2018. ISSN 1753-9129, 1753-9137. doi: 10.1093/ccc/tcx002.

[10] Peter J Carrington, John Scott, and Stanley Wasserman. *Models and Methods in Social Network Analysis*, volume 28. Cambridge university press, 2005. ISBN 1-139-44343-7.

[11] Tammy Castle, Lars Kristiansen, and Lantz Shifflett. White Racial Activism and Paper Terrorism: A Case Study in Far-Right Propaganda. *Deviant Behavior*, 41:252–267, February 2020. ISSN 0163-9625. doi: 10.1080/01639625.2018.1557380.

[12] Meeyoung Cha, Hamed Haddadi, Fabrı cio Benevenuto, and Krishna P Gummadi. Measuring User Influence in Twitter: The Million Follower Fallacy. In *Fourth International AAAI Conference on Weblogs and Social Media*, page 8, May 2010.

[13] Daryl J. Daley and D. Vere-Jones. *An Introduction to the Theory of Point Processes.* Springer, New York, 2nd ed edition, 2003. ISBN 978-0-387-95541-4 978-0-387-21337-8 978-0-387-49835-5.

[14] Jessie Daniels. *Cyber Racism: White Supremacy Online and the New Attack on Civil Rights.* Rowman & Littlefield Publishers, March 2009. ISBN 978-0-7425-6525-8.

[15] Clayton A. Davis, Onur Varol, Emilio Ferrara, Alessandro Flammini, and Filippo Menczer. BotOrNot: A System to Evaluate Social Bots. *Proceedings of the 25th International Conference Companion on World Wide Web - WWW '16 Companion*, pages 273–274, 2016. doi: 10.1145/2872518.2889302.

[16] Charles F. Delzell. Antonio Gramsci and the Origins of Italian Communism. By John M. Cammett. (Stanford, Calif.: Stanford University Press. 1967. Pp. xiv, 306. $8.50.). *Am Hist Rev*, 72:1441–1442, July 1967. ISSN 0002-8762. doi: 10.1086/ahr/72.4.1441.

[17] Alessandro Epasto, Silvio Lattanzi, and Renato Paes Leme. Ego-Splitting Framework: From Non-Overlapping to Overlapping Clusters. In *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 145–154, Halifax NS Canada, August 2017. ACM. ISBN 978-1-4503-4887-4. doi: 10.1145/3097983.3098054.

[18] Andrew Fergus. #whitegenocide, the Alt-right and Conspiracy Theory: How Secrecy and Suspicion Contributed to the Mainstreaming of Hate. *Secrecy and Society*, page 50, 2019.

[19] UVA Center for Politics. New Poll: Some Americans Express Troubling Racial Attitudes Even as Majority Oppose White Supremacists – Sabato's Crystal Ball.

[20] Patrick S. Forscher and Nour S. Kteily. A Psychological Profile of the Alt-Right. *Perspect Psychol Sci*, 15:90–116, January 2020. ISSN 1745-6916. doi: 10.1177/1745691619868208.

[21] Carolyn Gallaher. Mainstreaming white supremacy: A twitter analysis of the American 'Alt-Right'. *Gender, Place & Culture*, 0:1–29, January 2020. ISSN 0966-369X. doi: 10.1080/0966369X.2019.1710472.

[22] Matthew Gentzkow, Bryan Kelly, and Matt Taddy. Text as Data. *Journal of Economic Literature*, 57:535–574, September 2019. ISSN 0022-0515. doi: 10.1257/jel.20181020.

[23] Matthew Gentzkow, Jesse M. Shapiro, and Matt Taddy. Measuring Group Differences in High-Dimensional Choices: Method and Application to Congressional Speech. *ECTA*, 87:1307–1340, 2019. ISSN 0012-9682. doi: 10.3982/ECTA16566.

[24] Jonathan Greenblatt. Right-Wing Extremist Violence is Our Biggest Threat. The Numbers Don't Lie. https://www.adl.org/news/op-ed/right-wing-extremist-violence-is-our-biggest-threat-the-numbers-dont-lie.

[25] Stephanie L Hartzell. Alt-White: Conceptualizing the "Alt-Right" as a Rhetorical Bridge between White Nationalism and Mainstream Public Discourse. page 20.

[26] George Hawley. *Making Sense of the Alt-Right.* Columbia University Press, New York, 2017. ISBN 978-0-231-18512-7.

[27] George Hawley. *The Alt-Right: What Everyone Needs to Know®.* Oxford University Press, November 2018. ISBN 978-0-19-090521-7.

[28] George Hawley. The Demography of the Alt-Right. https://ifstudies.org/blog/the-demography-of-the-alt-right, August 2018.

[29] Janet Reitman. U.S. Law Enforcement Failed to See the Threat of White Nationalism. Now They Don't Know How to Stop It. *The New York Times*, November 2018.
[30] John Daniszewski. Writing about the 'alt-right'. https://blog.ap.org/behind-the-news/writing-about-the-alt-right, May 2016.
[31] Kyle Kusz. 'Winning Bigly': Sporting Fantasties of White Male Omnipotence in the Rise of Trump and Alt Right White Supremacy. *Journal of Hate Studies*, 14:113, February 2019. doi: 10.33972/jhs.127.
[32] Walter Laqueur and Christopher Wall. *The Future of Terrorism: ISIS, Al-Qaeda, and the Alt-Right.* St. Martin's Publishing Group, July 2018. ISBN 978-1-250-14251-1.
[33] Jey Han Lau, Nigel Collier, and Timothy Baldwin. On-line Trend Analysis with Topic Models: #twitter Trends Detection Topic Model Online. page 16.
[34] Nuria Lorenzo-Dus and Lella Nouri. The discourse of the US alt-right online – a case study of the *Traditionalist Worker Party* blog. *Critical Discourse Studies*, pages 1–19, January 2020. ISSN 1740-5904, 1740-5912. doi: 10.1080/17405904.2019.1708763.
[35] Michal Lukasik, P. K. Srijith, Duy Vu, Kalina Bontcheva, Arkaitz Zubiaga, and Trevor Cohn. Hawkes Processes for Continuous Time Sequence Classification: An Application to Rumour Stance Classification in Twitter. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 393–398, Berlin, Germany, 2016. Association for Computational Linguistics. doi: 10.18653/v1/P16-2064.
[36] Dixin Luo, Hongteng Xu, Yi Zhen, Xia Ning, Hongyuan Zha, Xiaokang Yang, and Wenjun Zhang. Multi-Task Multi-Dimensional Hawkes Processes for Modeling Event Sequences. In *Twenty-Fourth International Joint Conference on Artificial Intelligence*, page 7, 2015.
[37] Zongyang Ma, Aixin Sun, and Gao Cong. On predicting the popularity of newly emerging hashtags in Twitter. *Journal of the American Society for Information Science and Technology*, 64:1399–1410, 2013. ISSN 1532-2890. doi: 10.1002/asi.22844.
[38] Thomas J. Main. *The Rise of the Alt-Right.* Brookings Institution Press, 2018. ISBN 978-0-8157-3288-4.
[39] Trevor Martin. Dissecting Trump's Most Rabid Online Following, March 2017.
[40] Adrienne L. Massanari. Rethinking Research Ethics, Power, and the Risk of Visibility in the Era of the "Alt-Right" Gaze. *Social Media + Society*, 4:2056305118768302, April 2018. ISSN 2056-3051. doi: 10.1177/2056305118768302.
[41] Burt L. Monroe, Michael P. Colaresi, and Kevin M. Quinn. Fightin' Words: Lexical Feature Selection and Evaluation for Identifying the Content of Political Conflict. *Political Analysis*, 16:372–403, 2008. ISSN 1047-1987, 1476-4989. doi: 10.1093/pan/mpn018.
[42] Fred Morstatter, Yunqiu Shao, Aram Galstyan, and Shanika Karunasekera. From Alt-Right to Alt-Rechts: Twitter Analysis of the 2017 German Federal Election. In *Companion Proceedings of the The Web Conference 2018*, WWW '18, pages 621–628, Lyon, France, April 2018. International World Wide Web Conferences Steering Committee. ISBN 978-1-4503-5640-4. doi: 10.1145/3184558.3188733.
[43] Angela Nagle. *Kill All Normies: Online Culture Wars From 4Chan And Tumblr To Trump And The Alt-Right.* John Hunt Publishing, June 2017. ISBN 978-1-78535-544-8.
[44] Suphakit Niwattanakul, Jatsada Singthongchai, Ekkachai Naenudorn, and Supachanun Wanapu. Using of Jaccard coefficient for keywords similarity. In *Proceedings of the International Multiconference of Engineers and Computer Scientists*, volume 1, pages 380–384, 2013.
[45] Yosihiko Ogata. Space-Time Point-Process Models for Earthquake Occurrences. *Annals of the Institute of Statistical Mathematics*, 50: 379–402, June 1998. ISSN 1572-9052. doi: 10.1023/A:1003403601725.
[46] Alex Reinhart. A Review of Self-Exciting Spatio-Temporal Point Processes and Their Applications. *Statist. Sci.*, 33:299–318, August 2018. ISSN 0883-4237. doi: 10.1214/17-STS629.
[47] Manoel Horta Ribeiro, Raphael Ottoni, Robert West, Virgílio A. F. Almeida, and Wagner Meira. Auditing Radicalization Pathways on YouTube. *arXiv:1908.08313 [cs]*, December 2019.
[48] Benedek Rozemberczki, Oliver Kiss, and Rik Sarkar. An API Oriented Open-source Python Framework for Unsupervised Learning on Graphs. *arXiv:2003.04819 [cs, stat]*, April 2020.
[49] Philippe-Joseph Salazar. The Alt-Right as a Community of Discourse. *Javnost - The Public*, 25:135–143, April 2018. ISSN 1318-3222. doi: 10.1080/13183222.2018.1423947.
[50] Ben Schreckinger. The Alt-Right Comes to Washington. https://politi.co/2OaVQ5u.
[51] Southern Poverty Law Center. Alt-Right. https://www.splcenter.org/fighting-hate/extremist-files/ideology/alt-right.
[52] Alexandra Minna Stern. *Proud Boys and the White Ethnostate: How the Alt-Right Is Warping the American Imagination.* Beacon Press, 2019.
[53] Chenhao Tan, Lillian Lee, and Bo Pang. The effect of wording on message propagation: Topic-and author-controlled natural experiments on Twitter. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 175–185, 2014.
[54] Greg Ver Steeg and Aram Galstyan. Information-theoretic measures of influence based on content dynamics. In *Proceedings of the Sixth ACM International Conference on Web Search and Data Mining*, pages 3–12, 2013.
[55] Owen Worth. *Morbid Symptoms: The Global Rise of the Far-Right.* Zed Books Ltd., October 2019. ISBN 978-1-78699-337-3.
[56] Jaewon Yang and Jure Leskovec. Defining and evaluating network communities based on ground-truth. *Knowl Inf Syst*, 42:181–213, January 2015. ISSN 0219-1377, 0219-3116. doi: 10.1007/s10115-013-0693-z.

[57] Yuan Zuo, Jichang Zhao, and Ke Xu. Word network topic model: A simple but general solution for short and imbalanced texts. *Knowl Inf Syst*, 48:379–398, August 2016. ISSN 0219-1377, 0219-3116. doi: 10.1007/s10115-015-0882-z.