

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

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## 1 INTRODUCTION

The "alt-right"<sup>1</sup> has an inordinate influence on American political discourse [8, 60]. This is a cause for concern, not only because the movement has motivated a number of terrorist acts [7, 12, 38], but also as their rhetoric poses a existential threat to democratic social and cultural values [16].

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 [10, 45, 62]. Examples of mainstreaming range from coded expressions of racism to normalization of ideas previously thought unacceptable in polite conversation [10]. Mainstreaming as a strategy to further political influence is rooted in Gramscian thought [53, 62]. Antonio Gramsci, an Italian Marxist philosopher, postulated that non-dominant groups seeking to effect radical change in a civil society cannot do so through confrontation, as encounters would likely evolve into unfavorable wars of attrition [19]. 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* [9]. 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 [8].

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 [34] 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 all of 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%<sup>2</sup> of respondents strongly or somewhat agreed with the 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 [22].

The major blocker between the "alt-right" and more widespread conservative acceptance is shared rejection of flagrant racism. Despite their formidable strides in political influence and the conditions of possibility described, the "alt-right" remains a fringe movement as many sympathizers (and potential converts) disavow white supremacy and assert statuses as non- racists [33, 45]. These sympathizers, similar in many ideological and demographic dimensions to to "alt-right" members but disapproving of white-identity politics, have been dubbed "*alt- lite*" [33, 45]. 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 many scholarly works consider the "alt-right" [32, 45, 53] and related matters such as their mainstreaming efforts [24]

<sup>1</sup>§2.1 discusses the stylistic choice of quotation marks here.

<sup>2</sup>Unlike Hawley [34], these percentages are not after filtering for non-Hispanic whites.

and its effect on public discourse [10, 62], 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)
  - Hawkes processes capturing Twitter as a multi-speaker conversation
- RQ3 by considering "ideas" as different units of speech (words, n-grams, hashtags, topic models, and frames as depicted by word embeddings) and hypothesis testing the parameters of
  - Hawkes processes to determine which communities hold influence in another communities' discourse
  - logistic regressions predicting diffusion of ideas from "alt-right" discourse to general public discourse to pinpoint and compare relative importance of idea diffusion mechanisms.

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 expedite "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' [31, 47] and the Associated Press's (AP) [36] styling 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" [36] to remind readers of the complexity belying the descriptor. I style "alt-lite" in a similar manner for the same reasons.

**2.1.1 Describing Far-Right Groups.** Experts vary in their labels, descriptions, and distinctions for far-right movements and subgroups. This is partially the result of earlier academic and journalist work that interchanged labels without greater deliberation [52]. However, far-right individuals themselves also share responsibility: leaders of the same group disagree on basic points such as whether their platform can be considered racist [52]. Academics agree that the movements we observe and discuss here fall under the very broad umbrella of right-wing politics [52]. However, they lack consensus on many other judgments, importantly how to distinguish different far-right groups from one another and what each group's core features or motivations are [52].

In Table 1, I outline my concepts of the far-right groups mentioned in this proposal. My definitions weigh and reconcile competing frames in an effort to provide fair representations.

Table 1. Key Far-Right Groups

Group	Key Features	Additional Notes
"Alt-Right"	<p>The Internet-age reincarnation or offshoot of white nationalism. Members enthusiastically endorse white identity politics, hyper-masculinity, and bio-essentialism [62].</p> <p>Their social media and optics savvy sets them apart from white nationalist predecessors; for example, more experienced members take care to advise new members to distance themselves from symbols or imagery tied to Nazism or the Ku Klux Klan [32, 62].</p>	Some experts are skeptical that the "alt-right" can or should be understood as a group or movement separate from white nationalism or supremacy [31, 36].
"Alt-Lite"	The "lite" version of the "alt-right". They bear strong demographic and ideological resemblance to the "alt-right", but distinguish themselves from the more well-known group by expressly valuing civic nationalism over white nationalism [33, 42, 45].	It remains an open question whether it is possible to distinguish between "alt-right" and "alt-lite" beyond the civic vs white nationalism criterion. Given the "alt-right"'s mindfulness of standards of social acceptability, an "alt-right" member's publicly expressed points of view may be indistinguishable from an "alt-lite" member's [31].
Far Right	<p>Encompasses both the <i>extreme right</i> and the <i>radical right</i>.</p> <p>The extreme right opposes democracy; many members support fascism.</p> <p>The radical right accepts democracy (e.g. they support the idea of majority rule), but rejects key tenets of liberal democracy, such as multiculturalism, plurality, or minority rights.</p>	Different factions of the "alt-right" fall into extreme vs radical right. However, "alt-right" ideology can squarely be understood as far right [52].
White Supremacist	A white supremacist is "a person who believes that the white race is inherently superior to other races and that white people should have control over people of other races" [49].	I took the liberty of quoting Merriam-Webster's definitions for "white supremacist" and "white nationalist" as these phrases, in contrast to the first three on this list, lend themselves to concise definition.
White Nationalist	A white nationalist is "one of a group of militant whites who espouse white supremacy and advocate enforced racial segregation" [48]	Note that the definition of white nationalist involves white supremacy. Scholarly work [17, 31] caution that self-labelling as a white nationalist (as opposed to a white supremacist) is a rhetorical move—self-styled white nationalists distance themselves from blatant hatred and racism by arguing their motivation is rooted in identity politics that "fellow" marginalized identity groups are able to enjoy without criticism.

## 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 [29, 57, 64]. The difference between mainstreaming and radicalization lies in the scale of perception distortion that takes place. Mainstreaming refers to efforts to move an idea from the edges of *general social acceptability* to the center; to mainstream an idea is to normalize it among many. In contrast, radicalizing refers to warping an *individual's* sense of acceptable ideas; to radicalize a person involves changing what they individually perceive as normal.

In addition to the differences in scale, "radicalization" suggests terrorist acts as the larger concern at-hand [64], which does not convey the "alt-right"'s threat to liberal democracy. Terrorist attacks are well within the scope of concern about the "alt-right", 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) [28]<sup>3</sup>. However, the "alt-right" primarily uses discursive techniques to realize its ends. Given this strategy, mainstreaming, rather than radicalization, is the normalization process to monitor.

## 3 LITERATURE REVIEW

### 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 [32, 45, 53, 62]. 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 [32] and "the "alt-right"", as a phrase, suggests a monolithic collective [47], which fails to capture the dispersed and disorganized [46] nature of the "alt-right", a 'movement' with no formal membership nor accepted leaders [32]. 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 [24, 36]. 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 [10, 67]. Another positions the "alt-right" as the internet-age reincarnation of white nationalists [32, 45]. In this review, I focus on the latter, 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 [3]. For the most part, experts agree with Anglin [33, 42, 45]. However, they clash in their portrayals of the *essence* of the "alt-right" [23]. Some assert that the "alt-right" "is fundamentally concerned with race" [32]. Others emphasize that the "alt-right" is a white *male*<sup>4</sup> movement, and so gender, as well as race, is a dominant underlying factor in explaining beliefs and motivation [37]. Gallaher [24] 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 [23] 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

<sup>3</sup>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 [28].

<sup>4</sup>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 [23] estimate about 44% of "alt-right" supporters are women.

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 has facilitated successes toward the former [24, 53, 62]. Stern [62] provides a vignette that testifies to the "alt-right"'s mainstreaming success: As an "alt-right"-imagined conspiracy theory, "white genocide" had scant mention in public discourse. However, it later became 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" [14]. This is all despite a lack of data to support that farmers were at heightened risk of being killed in comparison to the average South African [1]. This example exemplifies the "alt-right"'s mainstreaming successes, instances in which an "alt-right" idea is propelled from mass disapproval to driving accepted political discourse. As one "alt-right" member boasts, "What Tucker Carlson talks about, we talked about a year ago" [35].

An open question remains: How do "alt-right" ideas make their way from "alt-right" circles to more mainstream ones? (In Stern's vignette, how did the white South African story make its way to Tucker Carlson's desk?) I will address this research gap when examining how unique discussion topics flow through separate communities and what mechanisms promote that migration.

### 3.2 "Alt-Lite"

The "alt-lite" separate themselves from the "alt-right" with their rejection of overt racism [4, 32, 45]. In other words, while "alt-lite" individuals subscribe to many (if not most) "alt-right" talking points, they (at least outwardly) reject the idea 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" [4, 45]. 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" [30]. Ribeiro et al. [57] found evidence to support the "entry point" idea on YouTube: 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. They cautioned that while this statistic indicates association between "alt-lite" and "alt-right" content, it provides no explanation of potential pathways between the two [57]. Scholars have yet to pinpoint the mechanisms behind topic conductance between the "alt-lite" and "alt-right". I will address this knowledge gap by examining the "alt-right" and "alt-lite" as community networks and determining crucial factors driving topic diffusion between the two.

### 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 [11]. Closely related to our work, Morstatter et al. [51] 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: [39] outline how to use topic models

to track emerging trends or interests; [5] 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?" [25, 50].

My applications of SNA and computational linguistics methodology will enable me to thoroughly capture and dissect power, influence, and language use in a networked setting.

## 4 DATA PROCEDURES

### 4.1 Source of Data

I will create my dataset by filtering from a Twitter Decahose<sup>5</sup> (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 temporally.

Previous quantitative investigations into the AR on Twitter [2, 6] 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 [13, 65] suggests that user-follower data is an unhelpful, noisy signal 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".

**4.2.1 "Alt-Right" and "Alt-Lite".** I will begin collecting accounts contributing to AR discourse<sup>6</sup> by referring to the Anti-Defamation League's [4] and Southern Poverty Law Center's [61] publicly available determinations of AR groups and leading figures for "seed" AR members. I will 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 will modify the above approach accordingly.

**4.2.2 General.** I will 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' [2, 6] 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 [6]. I will use Davis et al. [18]'s BotOrNot to determine whether users in my dataset are bots and flag them accordingly.
- Reside in the United States  
I will flag 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

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<sup>5</sup>"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."

<sup>6</sup>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<sup>7</sup>.



Both Berger [6] and Alizadeh et al. [2] 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, I will flag "celebrity".

### 4.3 Tweets

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

### 4.4 Community Networks

I will 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<sup>8</sup>. I will 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, identifying significant sub-graphs 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 [66]. 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. [20]'s *Ego-Splitting* framework meets these criteria and is implemented by Rozemberczki et al. [58]'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 and to visualize these 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 will utilize parametric bootstrap sampling [26] to account for finite sample bias and obtain confidence levels for any reported statistics.

### 5.1 Topology

To examine a network's topology is to study how its elements (both nodes and edges) are arranged [27]. I will 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?

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<sup>8</sup>Or have term-vectors with a high Jaccard similarity [54].

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 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?

- 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 will list and describe potential node and graph properties of interest [68] 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 words distinguish one community’s speech from another’s? 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. [50] 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 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 intend to explore what topics the various communities discuss in two ways:

- *Hashtags* Similar to how I will identify a community’s representative words, I will determine its representative hashtags using weighted log-odds ratios.
- *Topic Models* I will employ Zuo et al. [69]’s Word Network Topic Model, a topic model shown to perform better than Latent Dirichlet Allocation (LDA) [44] on short, social media text, to obtain each communities’ latent topics (themes underlying their common discussion points); I will determine the number of topics to uncover for each community by evaluating the model’s performance on topic coherence measures [21] 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 analyze 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 text feature that has no or few appearances in the dataset prior to being used by a non-trivial<sup>9</sup> 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 will identify ideas originating the AR community.
- (2) I will 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 will 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.

### 6.1 Detecting AR Ideas

I will consider several potential ways to capture an "idea": unigrams, bigrams, hashtags, topic models, and contextualized word embeddings. I identify an idea as *AR ideas* if it meets two criteria: (1) it has no or few previous appearances in the dataset prior to being used by a sizeable amount of AR community members; (2) it is not used by non-AR community members at the time of its first appearance in the data.

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<sup>9</sup>Exact number to be determined after more data inspection.

## 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 [15, 55]. 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 [40, 41].

I will slice my dataset into week-long bins and by community (AR, AL, and general public). For each identified AR idea (along with some non-AR ideas to establish baselines for comparison), the data will report, week by week, whether the idea was used and which community used it. I will 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 [56] and use a Bonferroni-corrected significance level to account for the simultaneous multiple comparisons [63].

## 6.3 Modelling Diffusion via a Logistic Regression

I will fit a logistic regression to model whether an AR idea will eventually "diffuse" into the general public. More specifically, this logistic regression will estimate 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 [43]. 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 later 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  $\chi^2$  statistics for each feature in my fitted model to understand their relative importance. Features with a greater  $\chi^2$  statistic will be understood as a more influential mechanism in predicting whether an AR idea is mainstreamed.

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	Model diffusion via a logistic regression model
August 16, 2020	Complete results section draft
August 23, 2020	Complete discussion section draft
August 30, 2020	Complete rough draft of paper

## 7 PROJECT TIMETABLE

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

The broad strokes of my project timeline are: I will spend the rest of June data collecting and pre-processing; I will perform the analyses described in the "Community Snapshots" section in early July; I will dedicate the latter part of July along with the initial weeks of August to exploring diffusion of AR ideas. If all goes well, I should have a first draft of my precandidacy paper by the end of September.

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