Abstract

Extremist ideologies are finding new homes in online forums. These serve as both places for true believers, and recruiting-grounds for curious newcomers. To understand how newcomers learn ideology online, we study the Reddit archives of a novel sexist ideology known as the “Red Pill”. Matching a longstanding hypothesis in the social sciences, our methods resolve the ideology into two components: a “behavioral” dimension, concerned with correcting behavior towards the self and others, and an “explanatory” dimension, of unifying explanations for the worldview. We then build a model of how newcomers to the group navigate the underlying conceptual structure. This reveals a large population of “tourists”, who leave quickly, and a smaller group of “residents” who join the group and remain for orders of magnitude longer. Newcomers are attracted by the behavioral component, in the form of self-help topics such as diet, exercise, and addiction. Explanations, however, keep them there, turning tourists into residents. They have powerful effects: explanation adoption can more than double the duration of median engagement, and can explain the emergence of a long-tail of high-power engagers. The most sticky explanations, that predict the longest engagement, are about status hierarchies.

Extremist ideologies are not new—“Islamism” (Mandaville, 2010) or “white supremacy” (Zanden, 1959) are decades or centuries old—but a great deal of contemporary attention has centered on the new role of online forums in how they spread, evolve, and attract adherents. The connection between an online forum and an ideology is often made when a forum participant commits an act of political violence (Nagle, 2017), but outliers are only one side of the story. Another side is the hundreds of thousands of individuals who encounter these ideologies, experiment with them or even adopt them for a time, but who do not become terrorists themselves. The goal of this paper is to understand the cognitive processes involved in how people learn ideology.

As we discuss in detail below, all ideologies have a dual nature: they are both explanations of the world, and patterns of behaviors. A sexist ideology, for example, includes not only a network of reinforcing beliefs that explain a person’s experiences in terms of the inferiority of women to men, but also habits of action ranging from degrading comments to physical assault (Manne, 2017). As explanations, ideologies are of great interest because of how they both link together ideas in ways that appeal to basic sense-making drives. As patterns of behavior, meanwhile, they matter because of how they alter and create basic features of social life—and, of course, because of how damaging the behaviors can become.
Psychological studies of ideology have used survey methods to probe the relationship between these two dimensions. In the psychology of gender, for example, “traditional masculinity ideology” (Thompson and Pleck 1995) is studied using the MRNI (Levant et al., 1992), a 57-item Likert scale questionnaire that measures the extent to which the subject endorses beliefs that are consequences of different dimensions of the ideology (e.g., the dimension of “dominance”, which includes agreement to the statement that “men should be the leader in any group”). A subject’s endorsement can then be linked to any number of outcomes on the behavioral side, from aggressive driving (Braly et al., 2018) to systemic aspects of a person’s life such as behavior in intimate relationships, parental engagement, or attitudes towards minority groups (for a recent review, see Gerdes et al., 2018).

By connecting belief and behavior, survey-based research gives us important insights, but it also leaves a number of key questions unanswered. In particular, survey methods have difficulty determining what it was about an ideology that made it initially appealing to someone, and they can not study how an individual came to learn, and adopt, the ideology over time. They also face methodological challenges such as construct validity, because it can take many years to refine a questionnaire, while the ideologies themselves are under constant evolution.

This is particularly challenging when the ideology in question is, as often happens online, a new variant or unexpected combination, rather than a repetition of something already well-understood, and where cultural evolution can act on such a rapid timescale that qualitative construction and iterative refinement can’t keep up. Finally, survey-based methods require recruitment of a sufficiently large number of participants who subscribe to the ideology in question, which makes it difficult, if not impossible, to study ideologies when they are still associated with niche subcultures.

In order to address these gaps, we present a new combination of methods (linkage networks combined with hidden Markov Modeling), and apply it to a detailed study of an ideology, known as “The Red Pill”. The Red Pill appeared in the online forum Reddit between 2010 and 2020, and attracted hundreds of thousands of young men in the U.S. and U.K.. It is a sexist ideology, under the standard definition, anchored in pseudoscience, and is characterized by the dehumanization of women as biological machines, and a call to fight a conspiracy against “masculine” values. It has led to, among other things, more than a dozen suicide attacks against perceived supporters of the conspiracy. It is also a “born-digital” ideology, meaning that its main features developed over the course of online interactions, rather than a traditional, pre-internet ideology whose adherents migrated online.

The large scale of our dataset provides a new window onto how this ideology gains traction and mindshare among internet users. It enables us to study the conceptual structure of the ideology in “high-resolution”, teasing apart different components of the ideology and providing new insight to different variants of “fellow travelers” that coexist within what appears to be a homogenous group. The long time-span of the data also provides longitudinal information. This means that we can study how individuals interact with the ideology over time; we can see where they begin in the conceptual network, which parts of that network are particularly “sticky”, and where, once caught, the individual tends to go next. This enables us to study the mechanisms of joining, learning, and exit, and to connect them to basic questions in cognitive science such as the role of explanatory values (Wojtowicz and DeDeo, 2020) and styles of moral reasoning such as those provided by Moral Foundations Theory (Graham et al., 2013).

1 The Cognitive Science of Ideology

To study the general features of ideology—online or off, extremist or normative—requires clarity about the underlying concept. This is complicated by the fact that the word itself is often used in a pejorative sense: for Marx and Engels, for example, an ideology is an illusion, a falsification of political reality, and those who believe it are fundamentally deceived (Marx and Engels, 1845; Thompson, 1987). By the 1970s, however, sociologists had developed more rhetorically neutral, descriptive meanings; in this second sense, ideologies are simply systems of belief that have to do with political action. While there are a number of different ways this can be fleshed out, a usefully generic definition is that provided by Seliger (1970): ideologies are “sets of ideas by which [people] posit, explain, and justify the ends and means of organized social action with the aim to preserve, amend, uproot, or rebuild a given reality”. Implicit in this definition is the idea that there are two principal dimensions of ideology; Seliger (1970) calls these the “fundamental”, and the “operative”. We take the two in turn.

On the fundamental dimension, an ideology is a cognitive artifact, a connected set of ideas that people use to make sense of the world. Ideologies serve as frameworks that knit statements of fact together with
metaphysical, aesthetic, and moral claims, to make a more-or-less coherent and rationally-justified whole. Any particular claim that an ideology makes is meaningful only when understood as part of that larger system. An ideology is not a list of disconnected grievances, but a “programmatic congerie of ideas” (Friedrich 1965) that forms a compelling whole, an abstraction “less abstract than the abstractions contained within it” (Seliger 1979).

Along this dimension, the study of ideology is the psychology of explanation. We value explanations not just for how their component ideas account for the facts at hand (how well they describe the world, or “descriptiveness”), but also for the ways in which those ideas link the facts together (“co-explanation”), and the ways in which the ideas themselves are linked together (“unification” and other forms of simplicity; Wojtowicz and DeDeo 2020). In a similar fashion, an appealing ideology is, in part, an appealing explanation, one that simplifies the world and helps satisfy the basic psychological drive for sense-making (Chater and Loewenstein 2016). For this reason, we refer to the first dimension as explanatory.

On the operative, or behavioral, dimension, an ideology is a political artifact, directed towards the goal of either preserving or transforming a social order. In this sense, ideologies are interpersonal objects, something that we hold in common with other members of a group and that gives us the ability to organize and act together. Laws and social practices may be part of the operative side of an ideology: a racist ideology, for example, may include both laws that discriminate against minorities, as well as oppressive patterns of behavior by members of the majority group in everyday life. These aspects of the operative dimension then accompany the fundamental dimension’s explanations for why those behaviors are justified.

Seliger (1970)’s account emphasizes the conscious adoption of behaviors, and in as much as the operative dimension of an ideology is strategic, members may wish to seek common knowledge that others share it (Chwe 2013). However, as the example of racist ideology suggests, much of what is operative may be part of a group’s habitus (Bourdieu 1990)—patterns of action that individuals produce “without thinking”, and judgements that individuals would say “go without saying”. The behaviors may be unreflective, but this does not mean they are incoherent, or any less aligned with the ideology’s fundamental, explanatory dimension. As pointed out by Converse (1964), the ordinary citizen has very little conscious awareness of the explanatory frameworks of the political elites, and often relies on simple habits and heuristics, such as identity and judgements of relative power and benefit, to guide the practical behaviors those explanations imply. Indeed, a habitual logic in the behavioral dimension may stabilize before the explanatory dimension does, as happens in Elias (1939)’s account of how the emergence of the modern ideas of the state’s monopoly on violence was preceded by shifts in habits of interpersonal etiquette.

The explanatory and behavioral dimension of an ideology are intimately related. The behavioral dimension is often highly structured by the explanatory dimension, and even when an agent experiences his actions as instinctive or “natural”, they can still be playing out a complex explanatory logic. As pointed out by Manne (2017), for example, a man who subscribes to a sexist ideology may not generically “hate” women; he may, in fact, display sincere affection to them so long as they fulfill expectations set by the underlying explanations he holds about their proper role in society; laboratory studies can tease apart different kinds of sexist ideology in part by the valence of these responses (Glick et al. 1997; Connor et al. 2016). In a similar fashion, a woman who subscribes to a sexist ideology may gain self-esteem by fulfilling the ideology’s criteria for what it means to be a “good” woman (Oswald et al. 2019). As suggested by these examples, the behavioral dimension of an ideology is often interpersonal. Ideologies may occasionally involve private actions (e.g., secret acts of “mortification of the flesh”), but with rare exceptions they center around behaviors towards others, and usually include public acts and political behaviors such as voting.

Once we see ideologies in this way, two basic questions arise. First, what makes an ideology satisfying or appealing? What aspects of the explanatory and behavioral features of an ideology draw people in, and what aspects are “sticky”, i.e., act to keep them there once they arrive? A simple answer is that people adopt ideologies that make them feel good, but as Chater and Loewenstein (2016) point out, there are constraints on our thoughts that limit the ways in which we can adopt beliefs for purely hedonic reasons (Epley and Gilovich 2010). Ideologies might be more appealing if they make a person feel important, but they also have to make sense—if only to the person and his fellow ideologues.

Another answer is that people adopt ideologies for purely instrumental reasons. This answer suggests, for example, that a neoliberal ideology (Slobodian 2018) will attract wealthy capitalists seeking lower taxes. Ideologies are not “single issue” positions, however, and it is it not clear if a person can forecast whether or not adopting an ideology will lead to the desired outcome. Nor are ideologies necessarily easy to abandon, and the capitalist who becomes a neoliberal because of taxes may later find himself arguing against government
subsidiaries that would be in his own self-interest. Fanon (1967) provides a particularly affecting account of how ideologies can turn upon those who adopt them.

Second, how are ideologies learned? Does one dimension, explanatory or behavioral, tend to precede the other? Althusser (1971) cites Blaise Pascal as saying “kneel down, move your lips in prayer, and you will believe” — i.e., in our framing, that the behavioral precedes the explanatory — but it is also somewhat hard to see how something as sophisticated as worldview could be transmitted solely through imitation. Humans spend a great deal of time providing reasons to each other (Mercier and Sperber 2017), and it seems equally plausible that a person comes to adopt an ideology by first being shown how it explains things that matter to them.

Our work aims to provide new answers to both questions, using the Red Pill’s extremist ideology as a case study. As we will show, automated methods allow us to extract the explanatory and behavioral components of the Red Pill ideology in discussions online; we can then study the ways in which people engage with different components over time. This enables us to study what is attractive to a user at first, where such an initially intrigued user goes next, and what happens to those users if they choose to engage with the ideology over timescales of months and years. One of our innovations is the use of Hidden Markov Modeling to study the ideological formation of a user over time, which allows us to infer an underlying “position” in ideological space on the basis of the user’s engagement with the surface content.

2 Methods

Forums associated with the Red Pill ideology are a core component of a larger “mansosphere”. Prior work has studied these groups as a source of extremism (Jane 2018; Van Valkenburgh 2018), antifeminism and misogyny (Lin 2017; Mountford 2018; Farrell et al. 2019; Talton 2020), as a companion to in-person “pickup culture” (O’Neill 2018), and as virtual spaces that provide new affordances for articulating an aggrieved manhood (Schmitz and Kazyak 2016; Cing 2017). Researchers interested in the extreme views in these spaces focus on how such views are propagated through anonymity, accompanied by aggressive use of trolling and doxxing, and how rhetorical tactics, such as the strategic use of irony, help normalize extremist material under the guise of ambiguity and exacerbates group polarization (Aikin 2013).

Our primary data source here are the archives of the main “subreddit” group, r/TheRedPill (“r/TRP”). As with all of Reddit’s content, r/TRP follows the familiar pattern of an online bulletin board. An r/TRP user is presented with a scrolling list of “submissions”, which range from extended 10,000 word user-authored essays, to laconic, one-sentence commentaries on a link to a news article hosted elsewhere. Users are able to comment on submissions, and to reply to the comments of others; they are also able to create new submissions (despite the name, these appear automatically). Both comments and submissions can be up-voted and down-voted by other users, and these votes influence placement and prominence. For simplicity, below, we use the word “post” to refer to both submissions and comments.

Users are free to delete anything they contribute, as are privileged users (“moderators”, or “mods”) who intervene to remove posts they consider inappropriate. They are also able to edit the “sidebar”, on the right-hand of the screen, that all users are presented with; the sidebar contains links to the site’s norms and rules, and a curated list of submissions intended to serve as an introduction to the group. We used the pushshift.io website, which continually scrapes and archives content from Reddit, to gather both comments and submissions for further analysis. Our full download collected 3,091,290 comments and 115,527 submissions from 26 October 2012, r/TRP’s founding date, to 25 January 2021. Our sample is nearly complete; due to what appears to be a database error in the scraped archive, we are missing some posts from the first three months of 2019.

2.1 Topic Modelling

In order to determine the semantic content of the site, we build a topic model (Blei and Lafferty 2009) from the user comments and submissions. A topic model is an unsupervised clustering method that takes a collection of documents (in this case, all of the individual comments and submissions), and decomposes them into sparse combinations of “topics”, or co-occurring word patterns. Topic models are a well-tested and long-standing tool that provides a window into the semantics of the content; a vast array of studies in different domains has used them to show how texts combine together different ideas. Each topic that the topic model discovers corresponds to a pattern of word usage, and the output of the model includes both a description of the word patterns, and a decomposition of each comment and submission into a weighted
We can also measure linkage at the level of users; in Eq. 1, we can set

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results are largely insensitive to the detailed parameter choices of the topic model. We find that the results of

because our linkage clustering method ends up grouping large numbers of topics into the same cluster, our

In our analysis we followed work such as Allen et al. (2017) and experimented with a range of different choices

for the number of topics, between 20 and 100. We found that even at the highest-resolution setting of 100,

In order to build the topic model, we pre-process the raw text by filtering stop-words and finding common

2-grams, and then use the MALLET software package (McCallum 2002) for the inference itself. Because

our goal is to study the full spectrum of user generated content, we model both comments and submissions

For our final analysis, we use a 100-topic model. We inspect the output of this model by hand, and drop a total of seventeen “non-semantic” topics associated with automatically-posted material, complaints about the site or users, idiosyncratic slang, and meta discussion (thanking other users, asking for links, and so forth); our analysis focuses on the remaining 83. The Online Appendix lists each of these topics individually, showing the top fifty words in the topic, and providing twenty examples of texts heavily loaded on the topic.

Following Salmon et al. (2021), we then compute the linkage between topics. Linkage measures the extent to

which two topics tend to co-appear; two topics (say, i and j) have high linkage when, if you encounter topic

i, you are more likely to also encounter topic j. In the simplest case, we measure “text-level” linkage, i.e.,

the extent to which the appearance of topic i in a particular text predicts the appears of topic j. We first

compute the joint probability, \( p_{ij} \) of seeing topic i and topic j in texts drawn from a particular era; if \( p_i(k) \) is

the fraction of topic i found in text k, we have

\[
R_{ij} = \log_2 \frac{p_{ij}}{p_i p_j},
\]

(2)

and then linkage is defined as

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p_{ij} = \frac{1}{N} \sum_{k=1}^{N} p_i(k)p_j(k),
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Linkage is connected to the information-theoretic concept of mutual information; indeed, mutual information

is simply the system’s overall average linkage, weighted by the joint probability distribution \( p_{ij} \). Text-level

linkage provides a fine-grained map of how ideas are connected together in any particular post or comment.

We can also measure linkage at the level of users; in Eq. 1 we can set \( p_i(k) \) to the probability that user k

uses topic i over all their posts, and sum is over all users, rather than all texts. User-level linkage tells us the

extent to which, if a user tends to write about topic i, they become more likely to write about topic j; in our

analysis, we find that both networks are broadly similar, meaning that individual users tend to associate

topics in the same fashion as the group as a whole, and so, for simplicity, we present only the text-level

results below.

Linkage enables us to do two things. First, it is a measure of the cognitive structure of the ideas in play; if
two topics have high linkage, this is a signal that there is something that repeatedly draws people to associate

the underlying ideas. Second, it provides a powerful tool for coarse-graining the topics found by a topic

model. When the topics are represented as a nodes in a network, with the edge weights given by the linkage

strength, network clustering algorithms such as Louvain clustering (Blondel et al. 2008) can reveal large

collections of co-associated topics that correspond to distinct conceptual units.

A topic model requires that we specify, ahead of time, the number of topics to find. This corresponds to

choosing an effective “resolution”—i.e., with more topics one can resolve, or split, word patterns that would be

merged in a model with fewer topics. Ideally, one would like to choose that number on the basis of a statistical

model-selection criterion. Somewhat surprisingly, however, the standard criteria are difficult to estimate

good (Wallach et al. 2009) and can provide sub-optimal answers (Chang et al. 2009), and best practice in

NLP places a premium on manual analysis and interpretation to validate parameter settings (Roberts et al.

2016).

In our analysis we followed work such as Allen et al. (2017) and experimented with a range of different choices

for the number of topics, between 20 and 100. We found that even at the highest-resolution setting of 100,

the topic groupings were both stable on re-running the fits, and interpretable, meaning that (after filtering)

any particular topic could be associated with a semantic theme, on the basis of both the top words in the

topic, and an examination of strongly-loaded posts. These are shown in the Online Appendix.

Because our linkage clustering method ends up grouping large numbers of topics into the same cluster, our

results are largely insensitive to the detailed parameter choices of the topic model. We find that the results of

our linkage model (discussed below; the grouping into clusters and the overall themes of each cluster) not

only match manual inspection, but do not require fine tuning of parameters. If a lower-resolution model

would merge two topics, these are expected to have high linkage already; similarly, if a higher-resolution

model would split a topic into two, the resulting pair is expected to have high linkage. In either case, the

merge or the split occurs within a cluster, and the overall cluster structure does not change very much.
2.2 Longitudinal Sample Construction

A goal of our analysis is to study users in a longitudinal fashion as they engage with, and potentially learn, the group’s ideas. The simplest approach to this requires a list of “clean” users who have no previous interactions with groups in the manosphere. Using the list of manosphere groups provided by Ribeiro et al. (2020), we construct a list of users who, (1) have not previously interacted with any manosphere groups on that list; but also, (2) have at least one post to a non-manosphere group, at the time they first appear in our data.

Criterion (1) means that we are not including users who have already learned the ideology from interaction with other groups in the manosphere; this provides the cleanest possible set of “newcomers”. Criterion (2) is useful because it enables us to filter out “special purpose” accounts—i.e., accounts created by a Reddit user with the express purpose of interacting with manosphere content, and nothing else. Special purpose accounts (sometimes called “throwaways”) are occasionally used on Reddit by individuals who want to make sure that their regular accounts—whose posting histories may include personally identifying information—are not tied to potentially inflammatory content, and may be a sign that the user is not as unfamiliar with r/TRP as one might otherwise assume.

Producing a “clean” user subset is a critical step in the analysis because it helps eliminate users who may have already accumulated significant experience with the ideology elsewhere. This gives us a clearer insight into what happens immediately after first contact. Such as list is not perfect—in particular, it doesn’t account for the ways in which a user might interact with these ideas in other fora, or the extent to which they only read the material before deciding to join the discussion—but it provides a first step for selecting on the initially less aware and less committed.

Our clean user set contains 39,838 users, all of whom have their first post on r/TRP somewhere between the beginning of 2016 and the end of 2019. By comparison, the set of special purpose accounts is much smaller, 6741; and the total number of users in this time period is 61,404—i.e., roughly a quarter of the participants on r/TRP during that period began posting on the Red Pill only after having had some interaction with other parts of the manosphere, a finding consistent with that of Ribeiro et al. (2020)'s study of cross-posting.

2.3 Modeling Individual-Level Behavior using Hidden Markov Modeling

Each user in our clean sample is associated with a list of posts they have made. A particular user with no prior record of engagement with the manosphere might have entered r/TRP at (say) January 1st, 2016, and made five different posts over the course of six months, with the last recorded post on June 1st. Our topic model will have allocated those five posts to different weighted combinations of the 100 topics in the data. This provides a trace of the user’s interests over the course of their engagement with the site, and, in particular, with the kind of material they are generating for others on the site.

A Hidden Markov Model (HMM) provides a way to model the dynamics of such a user, in terms of a shifting, unobserved “hidden” state. At any particular point in time, the user’s hidden state corresponds to a preference for different topics in the system, and the dominant topic of the user’s next post is drawn from a distribution over those topics. Once the user makes the post, the hidden state then updates; the user might transition to a different hidden state, corresponding to a different set of preferences, or remain in the same one.

A HMM provides a model of an underlying set of user interests, with their own temporal logic, that express themselves in observed posting behaviors. A crucial feature of an HMM is that observed behavior of the user at any isolated point in time does not completely dictate what he will do next; there may be more than one hidden state consistent with the kind of post they made. Intuitively, this captures how different underlying ideological preferences can express themselves, at times, in the same fashion.

The inference of that hidden state is key to correctly modeling a user’s ideology. Consider (to take a general example) two users on a politics forum, both of whom express an opposition to racism. User A’s expression of an opposition to racism comes from an attachment to a free-market and libertarian ideology, while User B’s expression comes from an attachment to a socialist ideology. These users will have, generically, both different pasts, and different futures, and if we want to understand their distinct ideological trajectories, we will need to attempt to infer—on the basis of their other remarks—that their expressed opposition comes from very different conceptual frameworks. This is precisely what the HMM does, in the context of a particularly simple, robust framework that can be expressed as a generative Bayesian model. The inference itself is done using SFHMM (DeDeo, 2016), which implements the standard expectation-maximization algorithm (Baum and Petrie, 1966), along with a model-selection method (Akaike Information Criterion, AIC) that automatically selects the optimal number of states in a Bayesian fashion.
Figure 1: The semantic structure of posts on r/TRP. Each node in the network corresponds to a topic (persistent word pattern) found in posts, with node size proportional to the fraction of attention devoted to the topic overall. An edge between two nodes indicates that the two corresponding topics are often found together in the same post. For example, Topic 17 (pseudo-evolutionary psychology; the orange node roughly in the center of the diagram) is often found in posts with Topic 70 (“decline of civilization”), Topic 83 (“hypergamy” and evolutionary drivers behind male status experiences), and Topic 55 (parental rights). Nodes are arranged so that high-linkage topics are drawn closer together visually; we then use the Louvain clustering algorithm to detect groups of highly interlinked nodes, which are colored by group. Table 1 provides details on each of the clusters.

3 Results

We first present the results of our topic modeling, which allows us to characterize semantics the Red Pill ideology. We then present the results on population structure and ideological formation, based on our individual-level modeling of the “clean” user subsample.

3.1 Topic Modelling and Linkage Network Construction

The results of our topic modelling most easily visualized using the linkage network in Fig. 1. This provides a graphical representation of how users create connections between different ideas; a high linkage (strong edge) between two topics means that the presence of one topic in a comment or submission is predictive of the other. For example, when a post includes talk about lifting weights as a form of self-improvement (Topic 87), it often also includes discussion of nutrition and testosterone (Topic 7), or martial arts and physical violence (Topic 50); see Appendix A for a complete account of each topic.
Having represented the topics in this fashion, we can use the Louvain clustering algorithm to reveal the large-scale structure. It finds five principal clusters, listed in Table 1. The two clusters, “self-help” and “pickup-artist culture” are primarily behavioral and concern the ways in which one ought to behave. Two clusters, “hierarchy and status”, and “neoreactionary politics” are explanatory: they are focused in providing users with unifying accounts of the way the world works. A fifth cluster, “men’s rights activism”, is a mixture of the two dimensions.

The self-help cluster includes themes such as emotional self-control and stoicism (Topic 6), breaking addictions, including to pornography (Topic 48), and mental health (Topic 14), along with themes related to exercise and nutrition. The pickup-artist culture (PUA) cluster includes discussion of “game” and how to approach women in bars and social contexts (Topic 28), on communicating in early stages of dating (Topic 38), and advice on body language and non-verbal communication (Topic 80). Broadly speaking, both of these clusters lie along the behavioral dimension of the Red Pill ideology. They are concerned with the details of how participants behave towards others and how they discipline their own bodies and minds to as to achieve right action. Taken together, they are about 28% of all posts on the site.

While the PUA cluster is strongly focused on the social contexts of young men, the third cluster is associated with an earlier, predecessor ideology, Men’s Rights Activism (MRA). It includes discussion of divorce law and alimony (Topic 60), single mothers and paternity (Topic 55), as well as subjects commonly associated with the MGTOW movement such as achieving financial freedom (Topics 74). The MRA cluster is the smallest in our data, consisting of only 7% of all posts.

The fourth cluster, “hierarchy and status”, is the largest in the system by total posts. It contains abstract and (pseudo) scientific discussion of evolutionary psychology (“pseudo-evo-psyclus”: Topic 17), the social hierarchy of “alpha” and “beta” males (Topic 78), and discussion of the sexual “strategies” that women use to attain high-status partners (Topic 83). It also contains more specific discussion of how to rate oneself, other men, and potential female sexual partners on the basis of (for example), height and body shape (Topic 11), visual appearance (Topic 41), or social status and wealth (Topic 40). Roughly 47% of all posts are dominated by patterns from the status cluster.

Finally, the fifth cluster contains ideas associated with neoreactionary politics (NRx), a recently-identified political ideology connected to the contemporary alt-right movement (Jones 2019; Lyons 2019; Sandifer and Graham 2018). Dominant themes in the NRx cluster include the idea that women, as a group, are responsible for the decline of civilization (Topic 70), and that feminism is a collectivist ideology spread by a conspiracy of elites (Topic 16), as well as discussion of contemporary U.S. politics, including racial politics (Topic 3) and comparisons between different countries (Topic 62). NRx accounts for roughly 19% of all posts.

The Status and NRx clusters lie along the explanatory, sense-making dimension of the Red Pill ideology. Posts weighted on these word patterns tend to provide synthetic and systematic explanations for the way things are. They may make scientific arguments, or political arguments, that show how a number of distinct pieces of evidence connect together. NRx topics include explanations in terms of conspiracy theories (i.e., that attempt to explain major world events and features of society in terms of the secret actions of a malevolent group), while Status topics tend to focus on explanations in terms of a pseudo-scientific version of evolutionary psychology. The MRA cluster appears to be a mixture of the two. Some of the content is behavioral, and provides explicit instruction on how to manage finances, divorce, and parenting. Other content is explanatory, and tries to explain (for example) how the different ways that men feel oppression is driven by anti-male prejudice in society and the law.

### 3.2 Population Structure

A visualization of the recovered Hidden Markov Model for user evolution is shown in Fig. 2. The analysis reveals the existence of two distinct types of users, which we refer to as “tourists” and “residents”. Tourists have low overall engagement with the system; they make only a few posts before leaving, in one of two possible posting patterns that matches the overall distribution of semantics on the system. The residents fall into five user types with distinct patterns of engagement; as shown in Table 2, these roughly align with different parts of the linkage network.

The HMM reveals a “tourist–resident” structure, where most visitors (87%) are “tourists” who have only casual interactions with the group; their posting patterns are consistent with sampling the content on the site at random and choosing one particular aspect of the content to imitate. Meanwhile, the remaining 13% are “residents”, who generate the majority of the content (62% of all posts, and 65% of all words). This can
Table 1: Examples of topics drawn from the five major clusters of the linkage network. The Self-help and PUA clusters are primarily behavioral, and focus on the ways in which men ought to live their lives and how they ought to relate to others. Meanwhile, the Status and NRx clusters are more explanatory, focusing on argument-making and providing general and unifying accounts of many different phenomena. The MRA cluster is a mixture of behavioral and explanatory.
Figure 2: Ideological formation online: the HMM for users from our longitudinal “clean” sample. A user starts at the “enter/exit” state, and then proceeds, with different probabilities, to one of seven different content patterns with different dwell times. Two patterns, labelled “tourist”, are associated with very quick exits from the system; for example, 54% of users who enter the system post content in the “tourist 1” pattern, and leave after, on average, just one post. Five styles, however, are associated with much longer-term residence. The “NRx” content pattern, for example, is far stickier; users will remain in the NRx posting style for an average of 13 posts before either exiting, or going on to (for example) post content associated with Men’s Rights Activism, or Status. States are labelled according to the results of Table 2, e.g., the user state associated with (significantly) above average posts from the self-help cluster is labelled “self-help”. For visual clarity in this diagram, very weak transition probabilities are not shown.

| State          | Self-Help | PUA     | Status | MRA     | NRx     |
|----------------|----------|---------|--------|---------|---------|
| Self-Help State | +190%    | -29%    | -33%   | -47%    | -36%    |
| PUA State      | -10%     | +107%   | +11%   | -47%    | -36%    |
| Status State   | -24%     | -4%     | +48%   | -15%    | -7%     |
| MRA State      | -30%     | -25%    | -25%   | +179%   | -17%    |
| NRx State      | -49%     | -49%    | -37%   | -33%    | +62%    |

Table 2: The relationship between resident type and posting content. For each state of the HMM (e.g., “Self-Help State”), we show the probability of a post dominated by the semantics of the five clusters, relative to baseline. Broadly speaking, at any point in time, a resident user is predisposed towards one of the five semantic clusters shown in Fig. 1, e.g., a user in what we call the “self-help state” is 190% more likely to post content related to self-help, and 47% less likely to post content related to Men’s Rights Activism.
be seen in both the numbers of posts the different user types make; Fig. 3. The vast majority of posters who stay longer than a few posts entered the system on the right-hand branch of Fig. 2.

### 3.3 Ideological Formation

The HMM of Fig. 2 allows us to distinguish different modes of engagement with Red Pill ideology. It also allows us to determine which aspects of that ideology are “appealing” (i.e., characteristic of the initial engagement of a long-term resident) and which are “sticky” (i.e., characteristic of later behavior); as shown in Table 3, the most obvious pattern is a shift from the “appealing”, behavioral content associated with self-help talk, and towards the “sticky” explanatory content of the status pattern.

| State   | Fraction (First) | Fraction (Overall) | Dwell Time (Posts) | Residence (Months) | Next State                        |
|---------|------------------|--------------------|--------------------|--------------------|-----------------------------------|
| Self-Help | 30%              | 14%               | 8                  | 7.9                | Exit (38%), NRx (23%), PUA (18%) |
| PUA     | 18%              | 18%               | 19                 | 11                 | Exit (36%), Self-Help (36%), MRA (17%) |
| MRA     | 13%              | 12%               | 10                 | 7.8                | NRx (37%), Exit (21%), Status (16%) |
| Status  | 12%              | 32%               | 29                 | 14                 | NRx (34%), Exit (26%), MRA (19%)  |
| NRx     | 27%              | 24%               | 13                 | 8.1                | Exit (39%), MRA (21%), Status (20%) |

Table 3: Relationships between the different resident patterns. For example, 30% of residents are expected to begin in the self-help state; those in that state spend roughly eight posts there before, say, shifting over to NRx (23% of the time), PUA (18% of the time), or leaving the system entirely (38% of the time). While the plurality of residents join the group as self-help users in the behavioral mode, those who stay either began with, or shift over to, more explanatory content, most notably “Status” and “NRx”. “Residence” here is defined as the (median) observed total amount of time spent in the system by a user primarily associated with that state; for example, a user that posts primarily in the “self-help” pattern has a median residence time on the site of 7.9 months.
The HMM also allows us to understand ideological formation, \textit{i.e.}, how users learn. Consider, for example, a user who begins in the self-help pattern. A user who remains in this pattern will (38\% of the time) leave the system, after roughly eight posts; however, 23\% of the time, the user will “advance” from the self-help pattern to the NRx pattern, where they will remain for roughly ten posts. At this point, they might exit (39\% of the time), or continue on to either the MRA pattern (21\% of the time), or the Status pattern (20\% of the time).

In practice, these shifts have major impacts on user trajectories. For example, the median residence time of a user that begins in the “self-help” state is 7.9 months. However, if a user that begins in the self-help state shifts over to the explanatory NRx state, their median residence time nearly doubles, to 11.4 months. Adopting the Status pattern has the largest effect size of all; those who switch to the Status state increase their median residence time from 7.9 months to 18.5 months. We do not see a strong effect in the other direction; for example, a user that begins in the Status state has a median residence time of 14.0 months; if they switch to the self-help state, the median residence time rises, by a much smaller amount, to 14.8 months. The fact that “self-help, then status” has a longer residence time than “status, then self-help” points to a more complex psychological process where behavioral shifts can make the individual more susceptible to later explanatory indoctrination.

4 Discussion

Seen from the outside, the posts on an extremist forum can look like a confusing mix of in-group language and deliberately offensive, politically motivated trolls (Nagle, 2017). The first outcome of our work is to show how simple tools can bring order to this apparent chaos. Given a topic model where word patterns serve as a proxy for the semantics of the underlying ideas, the information theoretic concept of linkage can then reveal how different pieces of an ideology connect together into larger conceptual units. These results, in turn, provide support for a general “two-dimensional” account of ideology as a combination of distinct explanatory and behavioral modules.

In the case of the Red Pill ideology, for example, some clusters we uncover are concerned with how members of the group are supposed act in the world, including (in the self-help cluster) their relationship to pornography use, eating, emotional regulation, and physical exercise, and (in the PUA cluster) how they ought to judge women as potential partners, and how to treat them when seeking romantic relationships. Other parts of the ideology are concerned with providing explanations for the way things are. These include the ideas about genetic differences between the races, theories about the role of women in the history of civilizations, and the existence of elite conspiracies that censor and conceal unpleasant truths (in the NRx cluster), the existences of biological imperatives, hardcoded into evolution, that force women to act in certain ways, and that make some men more worthy than others (in the Status cluster).

The second outcome of our work concerns how newcomers interact with these groups. A simple model of individual-level behavior provides a rough division of newcomers into two populations, tourists and residents, with the first group sampling randomly and leaving quickly, and the second group showing more sustained and systematic engagement, with distinct preferences for different features of the ideology. This two-population model has important implications for the experience of the group itself: nine times out of ten, content is produced by a user who has had little interaction with the group, and will almost certainly leave soon after. Many of the same features that make online communities sources of concern for those tracking radicalization—low barriers to entry, the use of pseudonyms rather than real names, proximity to more “ordinary” content—also appear to flood these systems with the disengaged.

The third outcome concerns how the newcomers who do persist navigate these ideas. Table 3 provides the clearest insight into what attracts individuals in the short term, versus what leads them to persist and integrate further into the community. Our major result here is a contrast between, on the one hand, the wider appeal of the ideology’s behavioral dimension, and, on the other, the power of explanatory content to draw users more deeply in. We suggest that a key feature of an ideology, and, at least in this first case study, the aspect that induces long-term and in-depth engagement, is what appeals to the “sense-making” drive (Chater and Loewenstein, 2016; Wojtowicz et al., 2021).

In addition to helping us understand the relationship between behavioral and explanatory aspects of ideology, these results also help us understand the particular nature of extremist ideologies surrounding sex and gender. The central role played by the “Status” cluster, both in the overall semantics of the system and in how it serves to attract and retain users, confirms a key insight of work such as Ging (2017): that Red Pill ideology is concerned not just with the superiority of men over women, but also with explaining, and defining, the gradations in status and power between men. Similar points have also been made by Manne (2018) in her
analysis of a prominent self-help book associated with the movement, and O’Neill (2018)’s fieldwork in (offline) “seduction” groups has noted the particular role that pseudo-evo-psych plays in justification and explanation.

Status may not just be what keeps individuals within the ideology. It may also be what draws them towards violence. Status concerns are often, as both Manne (2018) and Kalish and Kimmel (2010) note, significant motivating factors for young men who go on to shooting rampages; they also appear to be a basic preoccupation of men who engage in domestic violence (Jukes 1999). As Kruglanski et al. (2019) argue, the violence associated with extremist ideology is motivated by a “quest for personal significance”; it may well be that social status serves this role in violence associated with sexist ideology. In this case, the status cluster seen in Fig. 1 connects the ideology to a theory of personal significance that could then serve as a motivation for violence (Kruglanski et al., 2014).

The linkage network of Fig. 1 also points to an intimate connection between sexist ideology and political theories associated with white supremacy and anti-Semitism, which confirms recent work by non-profit organizations on the intersection between these emergent sexist ideologies and older, more familiar traditions (League 2018; DiBranco 2020). Indeed, misogyny itself—as an outcome of a “particular” sexist ideology such as that found on the Red Pill, or as a consequence of more ordinary forms of sexism—may be one of the links that connects extremist ideologies to political violence (Bosma et al., 2019).

A key question, for both scientists and policy makers, is the ways in which people are drawn in to extremist groups, and this work provides at least a partial answer. It also suggests that the same individuals may leave these groups when they become disenchanted by the explanations. This may be driven in part by engagement with individuals explicitly adopt a critical stance against the ideology; large-scale studies of these kinds of “counter-speech” may help us understand the underlying psychology of explanatory disenchantment and the different forms of argument-making that lead to it (Garland et al., 2020). There are many reasons why individuals will become disillusioned with an extremist ideology, and the process is a complex one particularly when it includes relationships in the offline world (see, e.g., Latif et al., 2020). In a world of online interactions, at least, explanatory disenchantment may play a central role in disillusionment and exit.

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A Appendix: Topic Model Samples

A key step in our analysis is the interpretation of the output of our topic model in terms of meaningful semantics. There are two different ways to do this. The first method is to look at the characteristic words associated with each topic; often this provides a clear idea of the general themes. The second method is to look at documents heavily weighted on that topic. This can provide important additional context, in part because it can reveal what different words in the topic are doing when they combine together.

For example, consider Topic 2, the first semantic topic on our list below (recall that we drop 17 of the topics because they are associated with non-semantic word patterns such as automated bots). Topic 2's word list contains a number of argument-related words (“argument”, “point”, “wrong”, “logic”, etc). By visiting a few of the sample posts, it becomes clear that it tracks a certain set of reasoning norms. For example, the full text of the third example is

“You are just choosing to believe whatever you want. Saying they don’t know is the same as not having evidence to support it. Science is pretty straightforward, either you can prove it or you can’t. Everything in your last comment is just speculation, you can speculate and it’s OK, what is not ok is that you present your hypothesis as a fact, it isn’t a fact. You are using a misinterpretation of a scientific article about flies to support your philosophical ideas. You are entitled to an opinion and beliefs, just don’t mislead other people into it.”

Our sample below contains posts from the beginning of 2018 and 2019, that have at least 20 words (after filtering for stop words) and that are weighted at least 50% on the topic of interest. For each post, we present the fractions of the next two highly weighted (semantic) topics, which can help in interpretation. In a few cases, the comment may no longer be accessible via the hyperlink; this is because users and moderators are allowed to delete comments, but they can be caught in the pushshift.io database before this happens, and thus enter our analysis.

A.1 Topic 2 (Nrx)

[n.b., Topic 2 is provided as a sample; remaining topic data available at http://santafe.edu/~simon/pd_online_appendix.pdf]

Top words:

argument point wrong said logic saying say evidence trying arguments fact argue debate logical anything opinion arguing nothing post discussion statement points agree facts someone making claim prove comment made based something actually without talking true reason disagree right believe instead simply stupid using understand bullshit try completely proof use claims response valid explain clearly reasoning person rational correct anyone mean makes rather attack statements false topic position fallacy case actual conclusion opinions conversation science either see idea support never calling personal theory theres example matter irrelevant ideas hominem sound scientific criticism exactly internet seem read issue entire assumptions could thought original attempt back thinking whether convince yet obvious come otherwise cannot obviously also lack stated counter defend yes truth call idiot nonsense subject thread words emotional clear ignorant assumption provide ridiculous really says win intelligent proven therefore view done logically stating attacks debating please assume insults pointing enough waste need shaming sense intellectual pointless premise discuss literally address seriously absolutely insult engage look conclusions examples strawman context ignore justify respond attacking anecdotal comments sure reply ops question reasonable incorrect discussing real whole troll dumb dismiss claiming simple retarded show seems information ignorance lets take must fine things basis straw

Sample posts:

http://reddit.com/r/TheRedPill/comments/74a5ia/red_piller_here_whos_been_working_in_strip_clubs/dsc5ihh/ 49 filtered words. Topic 2 (50%); Topic 70 (17%); Topic 73 (6%)

http://reddit.com/r/TheRedPill/comments/74a5ia/red_piller_here_whos_been_working_in_strip_clubs/dsc5j7u/ 49 filtered words. Topic 2 (50%); Topic 70 (19%); Topic 19 (6%)
http://reddit.com/r/TheRedPill/comments/7owq63/its_not_your_girl_its_just_your_turn_married/dsftc98/; 31 filtered words. Topic 2 (67%); Topic 10 (8%); Topic 61 (3%)

http://reddit.com/r/TheRedPill/comments/7pzss2/the_culmination_of_the_prowomen_movements_and/dsncwgm/; 48 filtered words. Topic 2 (82%); Topic 8 (14%); Topic 56 (4%)

http://reddit.com/r/TheRedPill/comments/7r0t92/made_this_comment_on_an_aziz_ansari_thread_in_2x/dsu1lq7/; 21 filtered words. Topic 2 (54%); Topic 94 (16%); Topic 49 (4%)

http://reddit.com/r/TheRedPill/comments/7sf3pq/jordan_petersen_cathy_newman_interview_good/dt4umj7/; 24 filtered words. Topic 2 (50%); Topic 92 (11%); Topic 66 (7%)

http://reddit.com/r/TheRedPill/comments/7ts74u/pet_theories_and_newunfinished_ideas_megathread/dth2xjb/; 27 filtered words. Topic 2 (60%); Topic 77 (13%); Topic 35 (6%)

http://reddit.com/r/TheRedPill/comments/7v4aafp/jordan_peterson_is_not_your_friend/dtrfmfw/; 22 filtered words. Topic 2 (52%); Topic 9 (11%); Topic 53 (11%)

http://reddit.com/r/TheRedPill/comments/7y88js/toxic_argumentative_females_should_beavoided_at/duf1r3n/; 31 filtered words. Topic 2 (58%); Topic 45 (20%); Topic 38 (3%)

http://reddit.com/r/TheRedPill/comments/7yug4s/focussing_on_pussy_isnt_beta_behavior/dujp2dt/; 24 filtered words. Topic 2 (64%); Topic 5 (4%); Topic 50 (4%)

http://reddit.com/r/TheRedPill/comments/bcjtns/women_in_ground_combat/ekzwgx6/; 33 filtered words. Topic 2 (58%); Topic 80 (8%); Topic 56 (3%)

http://reddit.com/r/TheRedPill/comments/bi9uic/alpha_fucks_beta_bucks_according_to_a/em2q8y/; 36 filtered words. Topic 2 (51%); Topic 64 (10%); Topic 7 (5%)

http://reddit.com/r/TheRedPill/comments/bsa48u/why_you_should_never_get_married/eonceul/; 24 filtered words. Topic 2 (52%); Topic 76 (11%); Topic 83 (4%)

http://reddit.com/r/TheRedPill/comments/bsa48u/why_you_should_never_get_married/eont340/80 filtered words. Topic 2 (60%); Topic 60 (7%); Topic 36 (5%)

http://reddit.com/r/TheRedPill/comments/c06ve7/what_is_the_red_pill/er52mw4/; 22 filtered words. Topic 2 (56%); Topic 51 (11%); Topic 57 (8%)

http://reddit.com/r/TheRedPill/comments/c28gpx/the_evolutionary_perspective_on_fake orgasms_is/erj42cw/; 79 filtered words. Topic 2 (62%); Topic 42 (10%); Topic 64 (8%)

http://reddit.com/r/TheRedPill/comments/c28gpx/the_evolutionary_perspective_on_fake orgasms_is/erj9jml/; 23 filtered words. Topic 2 (72%); Topic 17 (11%); Topic 4 (0%)

http://reddit.com/r/TheRedPill/comments/eonaqw/dont_get_cucked_by_cuckcervatives/fee7pnp/24 filtered words. Topic 2 (52%); Topic 94 (14%); Topic 73 (14%)

http://reddit.com/r/TheRedPill/comments/eonaqw/dont_get_cucked_by_cuckcervatives/feel2y8/42 filtered words. Topic 2 (51%); Topic 16 (11%); Topic 31 (9%)

http://reddit.com/r/TheRedPill/comments/gqr8yz/go_macros_kill_micros_take_some_real_pills/frw9m91/; 24 filtered words. Topic 2 (59%); Topic 82 (7%); Topic 93 (7%)
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