Analyzing Text and Images in Digital Communication: The Case of Securitization in American Radical Right Online Discourse*

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1 Introduction

Security forces—ranging from metropolitan police organizations to paramilitary militias—have long played a key role in the American radical right (Belew 2018). This was recently on display during the riot at the United States' (U.S.) Capitol on January 6, 2021: Armed groups conspicuously participated in the violence and 10 percent of the individuals charged by the U.S. government for joining in the riot have military ties—most of them veterans, but some still active duty.[1] Several of those with military backgrounds also had direct ties to extremist armed right-wing organizations such as the Oath Keepers.[2] Other rioters were active police officers from departments across the country.[3]

The storming of the Capitol additionally highlighted the American radical right's use of online communication for the recruitment and mobilization of supporters (Miller-Idriss 2020; McSwiney 2021). Popular social media platforms such as Facebook, YouTube, and Twitter attracted most of the attention in the immediate aftermath of the attack, yet expressions of mobilization in the days prior to the riot was also common on other platforms, such as Parler.[4] Beyond helping to coordinate the Capitol riot and other instances of collective action, the numerous online discursive spaces popular with the radical right—mainstream and fringe, rudimentary fora and sophisticated social media platforms—have facilitated the right-wing's expression of ostracized beliefs, and helped form shared identities and deeply-valued online "families" (Jasser et al. 2021).

The importance of online communication for the American radical right highlights an underdeveloped dimension of our knowledge about securitization and the movement. Previous scholarship has examined the social conditions and processes that have entwined security forces and the radical right, shedding valuable light on key historical events and organizational dynamics (McVeigh 2009; Belew 2018; Jackson 2020). Relatively less research has focused on the conceptualization and articulation of securitization, or how members of the radical right talk about the need to act as and support (volunteer) security officers, purportedly protecting and policing property and neighborhoods with military-grade weapons.[5]

To advance our understanding of securitization and the contemporary radical right in U.S., we examine whether the notion of securitization plays a major role in shaping radical right online discourse—and if it does, what is its role? To answer these questions, we develop a network-based approach for the analysis of text and images shared through digital and social media platforms. Somewhat surprisingly, we find that the

concept of securitization amounts to a relatively small volume of the radical right online discourse. However, it is imbued with importance by its place within the discursive space of the radical right. Securitization stands out for the degree to which it connects multiple topics, specifically place-based images and references to Donald Trump. Intriguingly, these two concepts of place and personalistic leadership are central to radical right politics in the U.S. and abroad (Cramer 2016; Fitzgerald 2018; McQuarrie 2017; Weyland 2021). Furthermore, securitization is the most important topic for bridging two modes of online communication: text and image. This makes the idea of securitization even more significant, we posit, because text conveys specific information while images can elicit powerful emotions and strongly-felt reactions (Joo and Steinert-Threlkeld 2019; Williams et al. 2020). Thus, by linking modes of communication *and* topics central to right-wing political thought, securitization plays a uniquely important and meaningful role within the radical right online discursive landscape, despite not being the most prominent topic of discussion.

These findings not only broaden our knowledge of contemporary radical right discourse, they also make two methodological contributions to the study of multi-modal online communications. One major challenge facing current research on digital discourse is that online communications increasingly combine multiple modes of media, with meaning arising from the modes' interaction. Social scientists have developed a rich toolkit to analyze social media texts and applied these tools to develop our understanding of, among many other topics, radical right messaging and its social costs (*e.g.*, Hobbs and Lajevardi 2019; Siegel et al. 2021). But, textual expressions—whether on Twitter, Facebook, or Parler—often have images for company (Chen et al. 2021). Consequently, analyzing texts without images may provide a partial or even biased understanding of online discourse. For instance, we would not have been able to observe this unique role of securitization in the radical right's online discourse without developing a methodology that enabled an analytical synthesis of text and image.

To address this concern, we introduce an easy-to-implement automated approach for relationally analyzing both texts and images in large collections of digital and social media data. We apply our approach when investigating our questions about the meaning of securitization in online radical right discourse. Below, we contextualize and explain our approach in detail, since we believe it will be useful to scholars studying various aspects of social media discourse and culture across multiple subfields of sociology and cognate disciplines.

A second methodological challenge is determining how well measurements of online content and communities capture people's understanding of the discourse they experience. This is especially true with automated approaches, which can be complex and difficult to interpret and often generate predictions with associated uncertainty and error (Wang et al. 2020; Fong and Tyler 2021). Yet, quantitative and computational research in a vast and rapidly growing literature on digital culture often treat these approaches' results as accurate measurements of people's perceptions, ideas, and sentiments. While this in itself is not problematic, it is cause for concern that the measurements—and the associated assumptions that they capture individuals' understandings of discourse—are rarely validated. To help overcome this limitation in the scholarship, we use people's judgements to validate the findings we obtained from our methodology for measuring multimodal online discourse. Our positive results lend support to other analyses using network-derived metrics and relational approaches when studying discourse (see Basov et al. 2020).

We intend our substantive, theoretical, and empirical insights to advance research on radical right politics at a moment in which right-wing political unrest in the U.S. is a major issue of concern (Kalmoe and Mason 2019; Mudde 2019; Finkel et al. 2020; Martherus et al. 2021). However, the analytical approach we develop in this manuscript should be useful to sociologists, political scientists, media scholars, and other researchers interested in the multi-model material and processes of meaning-making in any kind of digital discourse. Last but not least, while our analyses center exclusively on the U.S., they are informed by comparative research on the radical right. Our study thus contributes to the recent move toward the comparative study of American radical politics and the threats its poses to democratic norms and institutions (Bonikowski 2016; 2017; Brubaker 2017; Dodd et al. 2017; Lamont et al. 2017; Kuo 2019; Lieberman et al. 2019; Weyland 2020; Rosenbluth and Weir 2021).

2 Securitization and the radical right

Two bodies of literature shape our expectations and interpretation of securitization and the radical right. The first illuminates the historical and contemporary role of armed groups in radical right politics in the U.S., while the second explores how securitization resonates with radical right thought, ideology, and discourse across contexts.

The extreme right is far from a new phenomenon in American politics (Lipset 1955; Lipset and Raab 1973). Throughout its history, veterans of American armed conflicts, from the Civil War to the Gulf Wars, have played a major role in establishing and shaping its trajectory. These veterans' experiences and expertise have been highly valuable resources for the mobilization of paramilitary organizations and militias built on radical right thinking, such as how a small group of Vietnam War veterans in was instrumental in strengthening white power organizations during the 1970s and 1980s (Belew 2018).

During the last decade, these "securitized" groups' ideas and membership have increasingly overlapped with the core of American conservatism (Jackson 2020; Belew and Gutierrez 2021), as well as governmental bodies and mainstream politics. For example, as an observer of the right-wing Oath Keepers militia noted,

> About two-thirds [of Oath Keeper members] had a background in the military or law enforcement. About 10 percent of these members were active-duty. There was a sheriff in Colorado, a SWAT-team member in Indiana, a police patrolman in Miami, the chief of a small police department in Illinois. There were members of the Special Forces, private military contractors, an Army psyops sergeant major, a cavalry scout instructor in Texas, a grunt in Afghanistan. There were Immigration and Customs Enforcement officers, a 20-year special agent in the Secret Service, and two people who said they were in the FBI.[6]

In addition, police unions, including the Fraternal Order of Police—the largest and oldest police union in the United States—endorsed Donald Trump during the 2016 presidential campaign (Thomas and Tufts 2020). The largest U.S. border patrol union, with 16,000 members, endorsed Trump before the 2016 election with its first ever endorsement of a presidential candidate.[7] Such involvement of veterans' organizations and law enforcement in right-wing politics proved crucial for the rise of Donald Trump during the 2016 U.S. presidential election and the radical allies he brought into the mainstream: It "helped mobilize widespread popular support anchored in organizations and networks spread across thousands of places, including in key swing states" (Zoorob and Skocpol 2020: 79), making up for Trump's 2016 campaign's lack of local infrastructure. Police unions and similar organizations disseminated information in favor of Trump, deployed volunteers, encouraged contributions and worked to shape public opinion (Zoorob 2019).

While the violent final days of the Trump administration underscored the importance of securitization for

the American radical right, the U.S. is not an exception. In Germany, for instance, radical right ideas have found a receptive audience among military personnel (Bischof 2021). In Austria, veterans have been linked with the popularization of populist radical right ideas (Art 2011). And in Spain, support for right-wing populism is especially high among military personnel (Villamil et al. 2021). Furthermore, this relationship between security-minded and security-linked individuals and the extreme right in Europe is not new. Veterans of World War I were crucial supporters of early fascist movements in Italy and Germany (Paxton 2005).

These cross-national patterns are largely attributable to one of the core tenants of the contemporary radical right: authoritarianism (Mudde 2007). While it has been measured in various ways, authoritarianism is a general preference for protecting and solidifying traditional social hierarchies (Stenner 2005; Engelhardt et al. 2021). Doing so is vitally important to supporters of radical right parties and movements. These groups emphasize traditional social hierarchies in their campaigns (Mudde and Kaltwasser 2017)—and are rewarded for it. Voters' authoritarian preferences explain, for example, much of the support for Trump in the 2016 presidential election (Hetherington and Weiler 2018). And, importantly for our study, authoritarian preferences also characterize members of security forces, whether the military or governmental and civilian organizations (Simi et al. 2013). It is thus not surprising that the authoritarian impulses of the radical right resonate with security forces personnel across countries, historical periods, and political contexts.

In sum, the scholarship on right-wing organization, politics, and thought leads us to expect that the concept and articulation of securitization plays a role in radical right discourse. Yet, securitization's specific role in the discourse—particularly in the relatively newer yet consequential online discourse—is less clear. To shed light on how exactly notions of securitization shape the right-wing's online discourse and drive meaning-making in the movement, we turn to our empirical analysis.

3 Analytical approach

To analyze radical right online discourse, we start from the simple yet important insight from the literary theorist Roland Barthes: when text and images together help constitute a discourse, "there is never a real incorporation since the substances of [text and image] are irreducible, but there are... degrees of amalgamation" (1977: 26). Furthermore, the meaning that emerges from this partial amalgamation depends on

the movement between its elements of text and image. That is, understanding the meaning of a discourse comprising text and image necessitates, in part, understanding their relationship and interplay (Barthes 1977).

Of course, we are not the first researchers of online discourse and digital culture to recognize the importance of analyzing text and images side-by-side. However, we do pursue a relatively unique aim: We focus on measuring and interpreting the *relations* between text and image to make inferences about the discursive meaning emerging from these relations. In this section, we first situate our analytical goal and approach in related scholarship.[8] We then present our data and explain our methodology.

3.1 Related scholarship

While using text as data in studies of online discourse is now commonplace in sociology and related disciplines, social science research has yet to widely pursue large-scale analyses of images, not to mention multi-modal data (*e.g.*, text and image somehow connected). Indeed, in a multi-disciplinary survey of the literature, Chen et al. (2021) found that only 233 out of 2,349 English-language peer-reviewed social science articles published between 2015 and 2019 that empirically examined social media used images as (some) data. This is starting to change, however, with growing data availability, more powerful computers, and new methodological approaches and techniques designed by and for social scientists (Chen et al. 2021).

The image-as-data scholarship—like its text-as-data sibling—centers on two tasks: measurement and inference (Williams et al. 2020). The former tackles content; it detects and labels objects in the images, finds people and their faces, infers humans' attributes (*e.g.*, ethnicity, age) and expressions (*e.g.*, emotion, ideology), and so on. Having identified and measured these dimensions of images, researchers usually then classify the images using a framework relevant to their research questions. Measuring (and understanding) image content can be done through a hermeneutical close reading (*e.g.*, Baishya 2021), a manual coding of concepts within and across observations (*e.g.*, Casas and Williams 2019; van Haperen et al. 2020; Trilló and Shifman 2021), or, increasingly, machine-learning (ML) methods (*e.g.*, Cantú 2019; Zhang and Pan 2019; Xi et al. 2020; Steinert-Threlkeld et al. 2021).[9] Some researchers combine these approaches, such as by first doing manual coding to uncover concepts—and examples of these concepts—that are then

used in a large-scale ML-driven analysis (*e.g.*, van Haperen et al. 2020; Steinert-Threlkeld and Joo 2020; Steinert-Threlkeld et al. 2021).[10]

The latter task, inference, usually happens after images have been measured and classified. Researchers treat images, or, more specifically, their content, as a cause of an outcome or use them to construct predictor or response variables in statistical models. For example, Casas and Williams (2019) examine whether images on Twitter promote online mobilization; Mitts et al. (2020) analyze the effect of sets of images—*i.e.*, videos shared online—on viewers' support for militant groups; and Steinert-Threlkeld et al. (2021) draw on Twitter images to overcome common obstacles in measuring protest, then use their measurement in a study of state repression, protest size, and protester violence (see also Zhang and Pan 2019). Van der Zanden et al. (2021) incorporate images in an experimental design to determine how the kinds of images used in online dating profile affect individuals' impressions of the profiles.

A small portion of the large-n image-as-data scholarship analyzes co-occurring text and image together, such as when a tweet or blog post contain both some text and one or more images. This kind of research often seeks to improve measurement by incorporating textual information into algorithms designed to classify the document (or, frequently, just the image portion) (*e.g.*, Zhang and Pan 2019; Wu and Mebane Jr. 2021; Yang 2021). Some of this work does focus on the interaction of text and image, like we do, but stops short of examining how the interplay helps construct meaning in a discourse.[11] For example, a few studies consider each mode as an input of information about the meaning of a discrete object, such a specific meme, but not a general discourse (*e.g.*, Milner 2016; Baishya 2021). Other research analyzes how the interpretation of one mode affects the interpretation of the other, such as how an online dating profile's picture affects the perception of its written portion (Van der Zanden et al. 2021).

In contrast, our approach enables analyses of how a discourse's meaning emerges from the interplay between its textual and pictorial elements, or, more precisely, from the relations between the concepts and notions captured in the discourse's text and images. In developing this approach, we build on two premises. The first is the general idea that meaning in discourse is relationally constituted by its elements. The second is the more specific insight from formal cultural sociology and semantic network analysis that mapping and analyzing these relations as a network graph can uncover important features of discursive meaning (Carley

and Kaufer 1993; Carley 1997; Bearman and Stovel 2000; Rule et al. 2015; Edelmann and Mohr 2018; Hoffman et al. 2018; Stoltz and Taylor 2019; Puetz et al. 2021; Yung 2021; for reviews, see Basov et al. 2020 and Mohr et al. 2020). Put differently, the relationships between discursive elements (*e.g.*, concepts, ideas, topics) influence not only their own meaning, but the meaning of the discourse they help compose—and using network analysis techniques to systematically study these relations helps us gain unique insight into the discourse. To provide a simplistic example, researchers of militant groups might arrive at new insights if they discover that in the groups' discourse the concept of violence is significantly more bound up with notions of personal morality and punishment rather than with ideas about war-making and a clash of civilizations.

We explain the methodological details of our analytical approach below. In brief, we render a corpus of online discourse captured in both text and images as a two-mode semantic network graph. In the graph, the concepts forming the discourse are the vertices. Vertices (concepts) from one discursive mode, text, are connected both to one another and to the vertices (concepts) in the second discursive mode, images, which are themselves interconnected. Then, because we are interested in how concepts' relations contribute to the larger discursive structure, we calculate the vertices' betweenness centrality, both within a modes' layers and across layers. Between centrality is a network metric well suited for measuring how entities represented by vertices—in this case, discursive concepts—exert influence by linking other vertices (concepts) (Freeman 1977). Measuring inter-layer betweenness centrality further captures a particular influence gained by connecting concepts expressed in text with concepts expressed in images. After calculating the betweenness centralities, we interpret and validate the results.

The validation exercise, which we explain and present after reporting the main analytical results, is an additional contribution of our study. When using a semantic network approach, researchers sometimes make inferences based on analyzing the network using metrics and techniques for *social* network analysis (SNA), as we do (*e.g.*, Nerghes et al. 2015; Shim et al. 2015; Hellsten et al. 2020). Yet, these metrics and techniques were developed for studying people and their relationships, and it is not clear if they are appropriate for *semantic* elements and relations. Few of the studies applying SNA tools to semantic networks validate their results.[12] Basov et al. (2020: 8) explain the problem this way:

> [M]ost of the measures developed within social network analysis focus on the relations between

social actors and are not necessarily suitable as measures of semantic networks of cultural elements, and proper justifications and reconsiderations are yet to be made. For example, while degree centrality signals the importance of a social actor in a network, in semantic networks the words with trivial meaning often have the highest degree centrality.

To summarize, our approach synthesizes and advances three literatures. First, it helps develop the emerging image-as-data scholarship in social science by introducing an accessible approach for measuring the connections between images and text, as well as for analyzing these connections in a way that offers insights about the discursive meaning generated by concepts captured (perhaps uniquely) in the images and text. With regard to the second and third literatures, formal cultural sociology and semantic network analysis, we show how to render a discourse built on images and text as a semantic network. In addition, we offer evidence that using common SNA techniques to analyze such a semantic network can generate valid insights into how people understand the discourse.

3.2 Data

We apply our analytical approach to a corpus capturing online discourse from the U.S. radical right. Since it is not feasible to collect all online material generated by all U.S. right-wing groups, the corpus is a sample of these groups' digital and social media platform content. Constructing the sample involved four steps. First, we created a sampling frame by listing all the groups recorded by the Southern Poverty Law Center (SPLC) as being "white nationalists", "neo-Nazis", "neo-Confederates", or "Ku Klux Klan".[13] Second, we randomly selected 110 groups from this list.[14] Third, we searched for the selected groups' accounts on Twitter, and found that 28 of the 110 groups had had least one unblocked account during data collection in July 2019. Some of these groups were Faith and Heritage (neo-Confederate, according to the SPLC), the National Policy Institute (neo-Confederate and white nationalist), the Pacific Coast Knights of the Ku Klux Klan, and Red Ice (neo-Confederate and white nationalist). We collected all of these active accounts' public text and image content. We also collected tweets' metadata, such as their timestamps and number of views.[15]

Finally, because Twitter, like other mainstream platforms, undertake some effort to censor extreme content, our fourth step entailed gathering additional data from two so-called "free speech" online fora,

BitChute and Steemit. These sites are popular with the right-wing due to their minimal moderation and are similar to social media in that they are spaces of active, participatory online discourse. However, they function differently than social media. Namely, groups typically do not have group-based accounts, and, as a a result, we could not link our selected groups to BitChute or Steemit posts. Therefore, to collect relevant BitChute and Steemit material, we created a dictionary of terms frequently appearing in the selected groups' tweets, then used these terms to identify and scrape corresponding right-wing BitChute or Steemit content. To reiterate, the inclusion of BitChute and Steemit observations in our corpus is our explicit attempt to navigate survivorship bias of extreme right discourse on social media—we can reasonably assume that dimensions of this discourse and groups participating in this discourse are systematically missing from platforms like Twitter because of moderation. To mitigate this bias, we collected the additional data from unmoderated sites.

Our data collection yielded 16,776 observations of digital posts containing text and images from January 2013 through July 2019. To be clear, by "text and image" we mean an online, digital expression composed of both a message in text and a picture. Figure 1 offers an example of an observation from our corpus. Table 1 shows the number of observations by platform and time. We understand our corpus as relatively representative of recent general radical right online discourse in the U.S., largely due to our sampling procedure. The representativeness is attenuated by the fact that not all our sampled groups had active social media accounts, as well as Twitter's moderation policies. This attenuation is somewhat mitigated by the original sampling procedure being random and the inclusion of right-wing BitChute or Steemit content. Of course, our discourse of interest is the extreme right's *online* discourse, which is made up of the digital material that does in fact exist online—and which we observe and collect.

[Figure 1 about here]

[Table 1 about here]

3.3 Methodological details

Implementing our approach entails first arranging observations' written text into one sub-corpus and images into a second sub-corpus, with both kinds of content indexed by the observation and associated with

metadata. Then, the sub-corpora are analyzed in six stages:

1. Measuring topics in text;
2. Transforming images into text ("image-text" or "image-word lists");
3. Measuring topics in the image-text;
4. Constructing a two-mode semantic network graph;
5. Analyzing the graph; and
6. Validating the results.

We discuss the first five stages in this section. We explain and present the results of the final stage, validation, after presenting the main results.

The first stage of our approach involves measuring topics in the text sub-corpus. Since the introduction of Latent Dirichlet Allocation (LDA) to infer topics in text (Blei et al. 2003), scholars across a wide range of disciplines have developed numerous methods for detecting patterns of word-usage in unstructured text data, ranging from, say, conditioning the estimation of topics on document metadata (Roberts et al. 2019) or words of particular interest (Eshima et al. 2020) to identifying topics from vectorized text (Angelov 2020). While each method has distinct features, they often draw on the same logic: The way that words tend to appear near one another within documents can shed some light on latent topics or themes constituting both the documents and the collection of documents. For our approach, any method for measuring topics in text—whether unsupervised, semi-supervised, or supervised—would work, as long as it (1) allows for the identification of multiple topics in documents and (2) estimates the degree to which each of these topics are present in a document.

In our own application of the approach, we used structural topic models (STMs).[16] Structural topics models allow for the inclusion of covariates when estimating topics' proportion in documents (Roberts et al. 2019). This capability is important for our study because we aim to analyze the *general* online right-wing discourse, and therefore do not want the estimated topics to directly reflect any one attribute of the data or context, such as a particular platform or moment in time. Before fitting the STM, we selected a topic

solution using a common data-driven technique; the results suggested that 45 topics was ideal (see Appendix A). We then specified the STM as

$$y_i = \alpha + \beta \text{platform}_i + \gamma \text{time}_i + \epsilon_i \tag{1}$$

where the response variable y is the topic proportion of document i, and the variables `platform` and `time` control for the platform on which documents were published and the month they were published.

The second and third stages calls for transmogrifying images into textual topics. There are two reason for this. The first is that recording concepts captured in text and images in the same manner—for example, as latent topics inferred from text data—enables downstream analyses of relations and meaning. The second is that doing so makes the approach accessible to a wider range of social scientists. As earlier mentioned, some recently developed ML-classification approaches consider co-occurring text and images (Zhang and Pan 2019; Wu and Mebane Jr. 2021; Yang 2021), but these approaches eventually collapse both modes into one classification, thereby losing information about relations between text and images. Moreover, these approaches are currently too complex for most social scientists to use. In contrast, the two stages of our approach that convert images into textual topics allow for clear, familiar, and interpretable analyses of the relations between modes, and can be implemented using common (and well-documented) off-the-shelf functions developed for open-source statistical software. Both of these advantages are made possible by rendering images as text.

To transform our images, we first used a publicly available computer vision algorithm.[17] Researchers adopting our approach could select one of several available computer vision algorithms or build their own (for details, see Joo and Steinert-Threlkeld 2019; Williams et al. 2020; Torres 2021), as long as the algorithm detects objects in the images, uses text to report the detected objects, and records this "image-text" or "image-word lists" at the image-level. For example, the algorithm we used outputs a list of words describing the objects in each image, such as "smile", "chin", and "coat", and automatically indexes the words to each image, or document. The algorithm also measures other characteristics of the images, such as the location of specific objects within the image frame (with the location given as coordinates).[18] Figure 2 provides an example of computer vision output, including the detected objects reported as text. This text

is what we refer to as "image-text".

[Figure 2 about here]

After the second stage, there is a list of words per image. This image-text can be treated just like text from any other document, with the images corresponding to documents and the word labels of detected objects as documents' textual content. Then, the transformation of images into textual topics can be easily completed by using an STM (or another text-analysis method) to estimate topics in the image sub-corpus.[19] When we did this, we again used a data-driven technique to identify an ideal number of topics to model. The results pointed to a 25-topic solution (see Appendix A). We also again specified the STM as Equation 1.

The fourth stage of our approach entails constructing an undirected two-mode semantic graph. In this graph, vertices are topics: one set of vertices, or one mode in a two-mode network, are topics estimated from the textual content; the other set of vertices, or the second mode, are topics estimated from the image-turned-text content. The edges between vertices represent semantic relations.

To identify semantic relations, and define edges, we calculated the correlation between topics across documents, a technique used by previous scholarship that inferred relations between topics (*e.g.*, Farrell 2016; Light and Odden 2017; Karell and Freedman 2020). If two text vertices had a Spearman correlation coefficient greater than 0.2, we recorded an edge between them.[20] This created the intra-text network layer of our graph. We then repeated the edge encoding for image vertices, creating the intra-image layer. Finally, we calculated the correlations between text- and image-topics across documents and constructed the cross-mode network layer.[21]

Once the two-mode semantic graph was constructed, the fifth stage of our approach was possible: examining the graph using network analysis methods, which can capture how vertices—thus, topics—across the text and image modalities relate to one another. Network science disciplines have developed numerous measures and methodological techniques, and any of these could be applied to the graph (as long as they are appropriate for semantic data and two-mode structures). In our case, we focus on inter-layer betweenness centrality, or the degree to which vertices fall on the geodesics, *i.e.*, shortest paths, between other text and

image vertices.[22] For each vertex, inter-layer betweenness centrality, b_v, is defined as

$$b_v = \sum \frac{g_{ivj}}{g_{ij}}, i \neq j, i \neq v, j \neq v \tag{2}$$

which calculates the total number of geodesics, g between text vertices, i, and image vertices, j, that pass through v (*i.e.*, g_{ivj}) as a proportion of g_{ij}, the total number of geodesics between i and j, when $i \neq j$, $i \neq v$, and $j \neq v$.[23]

Knowing vertices' inter-layer betweenness centralities is especially useful for addressing our research question because this measure plausibly identifies topics (vertices) shaping, or mediating, conceptual linkages between text-based and image-based topics (Bavelas 1948; Cohn and Marriott 1958; Freeman 1977). This is important because previous research suggests that forming conceptual bridges between text and images likely plays a uniquely influential role in discourse. Namely, this cross-mode bridging links text, which can convey specific, precise information, with images, which can elicit powerful emotions and strongly-felt reactions (Joo and Steinert-Threlkeld 2019; Williams et al. 2020). Of course, other measures and analytical techniques might be more appropriate for other research questions, and these are possible to implement with our approach.

4 Results

We are interested in whether securitization plays a role in radical right online discourse and, if so, how. To answer this question, we present a series of results. First, we confirm that the concept of securitization appears in online right-wing discourse, but show that it is not a major component, by volume. Then, we present evidence indicating that securitization plays a uniquely strong connecting role in the discourse. We gain further insight into how it shapes the discourse by examining the particular ideas securitization connects. Finally, we validate our findings using a human-based test.

4.1 Topic model results

We investigated and interpreted the topics in the right-wing discourse by reading topics' most frequent words, most frequent and exclusive (FREX) words,[24] and most strongly associated documents. Table 2 lists three text topics that will be important in the remainder of our analysis and Table 3 nine important image topics, including the "securitization" topic. Appendix B presents all the 45 text topics and 25 image topics. Both tables include the labels we assigned after interpretation, the estimation proportion of each topic in its respective corpus, and each topic's top FREX words. We see in the complete results that the data do capture a general right-wing discourse (Appendix B). We find topics associated with radical right politics in American political discourse, such as anti-Semitism, the Klu Klux Klan, and anti-immigration, as well as more mundane themes, such as electronic gadgets, cryptocurrency, and video games.

[Table 2 about here]

We additionally find evidence that securitization is present in the discourse. An image topic, which we label "securitization", comprises words like "police person", "solider", "troop", "protect", and "security" (Table 3). When we viewed highly associated documents (in this case, images), we saw that many were pictures of police with riot-control gear and other instances of armed security individuals. Our models estimate that the securitization topic makes up 2% of the content. This is less than the mean prevalence across topics, 0.4, with a standard deviation of 0.17. (The mean prevalence of text topics is 0.22, with a standard deviation of 0.19.) These results indicate that any discursive importance held by the concept of securitization is not based on volume. Indeed, the next results suggest that the concept's importance comes from the relational role it plays in the discourse, particularly how it connects topics across text and image modes.

[Table 3 about here]

4.2 The discursive role of securitization

Figure 3 shows the undirected two-mode graph of topics' semantic relations. It includes colored fields denoting communities detected by modularity optimization (generalized louvain) to further emphasize that

common network analysis methods are compatible with our approach.[25] The text and image layers have a density of 0.74 and 0.45, respectively; the entire graph has a density of 0.36.

[Figure 3 about here]

With the graph data structure, we can analyze the relations between topics. As explained earlier, we focus on inter-layer, or text-and-image, betweenness centrality, which is especially relevant for answering our research question. Table 4 presents the topics with the top 10 inter-layer betweenness centrality scores, as well as whether the topic appears in text or images. (Appendix B lists the betweenness centrality scores for all 70 topics.) We see that securitization has the highest betweenness centrality across modes. This indicates that the notion of securitization connects the most text and image topics in the discourse—or, put differently, it sits between the most number of concepts represented in text and the most number of concepts reflect in images when their connections are traced along the shortest possible path.

The securitization topic is most correlated with the image topics of crowds ($r = 0.64$), shooting sports ($r = 0.6$), vehicles ($r = 0.48$), and cityscapes ($r = 0.45$). Its strongest correlations with text are with the topics of URL links to Nordic news reports ($r = 0.25$), Trump ($r = 0.22$), and cars ($r = 0.21$). Table 5 presents all of the securitization topics' relationships we detected. Note that three of the connected image topics evoke space and place: "crowd", "cityscape", and "natural landscape". The securitization topic also has second order ties, or connections with yet more topics through its directly connected topics. A straightforward extension of our approach is the analysis of how topics of interest, such as securitization, are connected to broader collections of topics, such as the second-order topics and groups of topics, like the communities shown in Figure 3.

[Table 4 about here]

[Table 5 about here]

4.3 Validation

Our main results rely, in part, on the measurement of network vertices' betweenness centrality. However, although recent research suggests that people's understanding of the world draws on networked associations

(Lynn and Bassett 2020), it is not clear whether betweenness centrality scores accurately capture how people perceive discourse. That is, betweenness centrality, like many other network measures, has largely been applied to and interpreted in the context of humans' social networks (*e.g.*, Bavelas 1948; Cohn and Marriott 1958; Burt 2000; Stovel and Shaw 2012; Lutter and Weidner 2021). And, despite the common application of network measures to semantic networks, little effort has been devoted to validate whether the metrics made for social networks support sound inferences of semantic networks (Basov et al. 2020). Therefore, in the final stage of our analysis, we validated our interpretation of inter-layer betweenness centrality.

Since there is no "true" network graph of radical right-wing discourse to compare our findings to, we built on previous human-based validations of large-n text analyses (Lowe and Benoit 2013; Nelson et al. 2018; Ying et al. 2021) and developed an exercise centered on a simple test: Do our findings correspond with individuals' own understanding of the target semantic relations? In other words, our validation exercise tasked people with implicitly confirming or refuting the securitization topic's betweenness centrality scores that our approach assigned to each document. The validation results show the extent to which people's personal interpretations of relations between texts and images strongly associated with securitization mapped onto our network analysis results.

We presented participants with two sets of three documents. One set reflected the text content connected to the securitization topic; the other set represented the image content connected with securitization. To select the documents in these two sets, we first calculated the document-level prevalence of the topics linked with the securitization topics (*i.e.*, the 11 topics listed in Table 5). That is, we summed the prevalence of securitization's three connected text topics—"Nordic news links", "Trump", and "police cars"—for each document in the text sub-corpus, and then repeated this for the prevalence of the eight connected image topics (*e.g.*, "crowd", "natural landscape") in the documents in the image sub-corpus. Next, we selected the three text observations that had the highest summed prevalence of the text topics. These texts were all generally favorable written expressions of Trump-related policies and politics, and constituted the set of texts shown to individuals. Finally, we selected the three image observations that had the highest total prevalence of image topics. The selected images were all of city- and natural landscapes. They formed the image set shown to individuals. We did not tell individuals the topic labels when presenting them with sets

of documents (or at any other step of the validation task).

After individuals were shown both sets of documents, they were asked to conceptualize what each set represented as a whole. Then, we showed individuals a series of 10 images: the three images most strongly associated with the securitization topic—which can be thought of as a "treatment" doses—and seven images strongly associated with randomly-selected topics among those with very low inter-layer betweenness centrality scores. These latter images served as "placebos". The securitization and placebo images were shown in a randomized order. After displaying each image, we asked individuals whether it linked the two concepts they had earlier formed by considering the Trump texts and landscape images.[26] If our semantic network analysis of radical right-wing discourse accurately captured how people tend to understand topics and their semantic relations, then the participants should have selected the securitization images as bridging the two concepts and not have selected the placebo images.

We implemented our validation exercise via Appen, an online crowd sourcing platform. Individuals in Appen's English-speaking annotator pool who opted into our task first read instructions explaining the task, which included examples of the kinds of text and images they might see. They then had the opportunity to practice the task by completing a short practice task formatted in the same way as the real task. Any participants who finished the practice exercise were able to do the task. Upon completion, participants, or now annotators, were paid a small amount of money. In total, 250 annotators performed the validation exercise. Appendix C shows the exercise's instructions and practice task.

[Figure 4 about here]

Figure 4 presents the results of the validation exercise. The bars indicate the number of annotators who responded that the image they saw linked (or did not link) the two concepts they had formulated from the Trump texts and landscape images. The panel on the left shows the response totals when the displayed images were those identified as having high inter-layer betweenness centrality (*i.e.*, securitization images). The panel on the right shows the response totals when annotators saw the placebo images (*i.e.*, non-securitization images). We see that about 75% of annotators labeled each of the three securitization images as linking the concepts. In contrast, between about 25% and 50% of annotators reported each one of the placebo images as linking the concepts. These results are what we would expect if our semantic network

analysis faithfully captured how people understand the relational meaning of topics in our discourse.

Figure 5 shows the validation exercise results when aggregated and weighted by annotator agreement and quality.[27] The values on the vertical axis—degree of confidence in the best response—indicate the extent to which high-quality annotators agreed on a response. The plotted response—"yes, the image links the concepts" or "no, the image does not link the concept" (each denoted by color)—is the most-agreed upon response. We see that when the displayed images had scored high on inter-layer betweenness centrality, a majority of high-quality annotators agreed that the image linked the concepts (left panel). Similarly, when the displayed image had scored low on betweenness, a majority of high-quality annotators agreed that the image linked the concepts, except in two cases (right panel). One of these two unexpected results also has the lowest confidence, indicating that there was relatively more disagreement among annotators and suggesting that the image's linking role was ambiguous.

[Figure 5 about here]

Overall, the results of our validation exercise indicate that our analysis of topics in multi-modal digital media—including our measurement of betweenness centrality—accurately captures how people understand online discourse. A sizeable majority of participants who performed the the task identified high-betweenness images as connecting the documents our analysis suggested should be connected, and identified low-betweenness images as not connecting the documents they should not have been connected. These results instill confidence in our analytical inferences.

5 Discussion and conclusion

Our findings show that securitization stands out in online radical right discourse not through the amount of text and images dedicated to it, but rather by how it links other concepts across modes of expression. Now, it is worth reflecting and elaborating briefly on what it means for securitization to connect the specific topics that is does. Specifically, what might be the consequences of discursively connecting a topic about geographical spaces and a topic about a right-wing populist leader?

Previous scholarship has argued that the rise of the radical right is a political phenomenon deeply rooted

in a sense of geographical space (Fitzgerald 2018; Hochschild 2018; Wuthnow 2019; Olivas Osuna et al. 2020; Rosenbluth and Weir 2021). Of course, notions of place and geographical boundaries are nothing new to politics in general and electoral politics in particular (Lipset and Rokkan 1967; Rodden 2019; Maxwell 2020). Yet, the spatial specificity of right-wing radicalism has ignited renewed interest in the role of place-based identities, understood as "sense of belonging to a group whose membership is defined by living in a particular place and having a psychological attachment of group-based perception with other group members" (Munis 2020: 3). For instance, Cramer (2016) has emphasized the importance of rural consciousness among the American right-wing.

Our findings extend this insight that place deeply matters for right-wing thinking by showing that notions of place arise even in the discourse of extreme right *online* communities, which are of course physically detached from geographic locations and can involve anyone situated in any place. Based on the results, we suspect that place-based identities will continue to be an important component of right-wing movements even as their members spend increasing amount of time online, and increasing engage in digital discourse.

In addition, scholarship on the radical right has also found that personalistic leadership is important to right-wing populist movements (as well as left-wing populist movements). According to Weyland (2021), populist movements aiming to represent "the real people" quickly face the challenge of how the will of the people could be carried out. The answer often lies in strong leaders. This is why populist movements are inherently leader-centrist.

Considering the previous scholarship on right-wing place-based identities alongside that on right-wing populist leadership, the triptych of place-securitization-leadership that we find is highly disconcerting. A strong sense of securitized localism may generate an actual—rather than metaphorical—call to arms in order to protect place-based identities from perceived outside groups (*e.g.*, immigrants, refugees, members of other ethnic groups) and influences (*e.g.*, norms and ideas associated with other geographic parts of the country) (see also Fitzgerald 2018). Furthermore, the strong network-connection between Trump and securitization indicates that radical right leaders are associated with violence-related concepts in their supporters' discourse. One interpretation of the place-securitization-leadership connection is that, for American right-wing radicals, the populist leader is the one who can mobilize, or at least legitimate, armed protection of place-based

identities.

Methodologically, our study extends the social science toolkit for constructing and analyzing discourses captured in multi-modal data, such as digital communication employing both text and images. It also provides suggestive evidence that other research applying social network analysis measures and techniques to semantic networks may be accurately capturing how people understand discourse. Yet, there are of course limitations to the current iteration of our approach. One of these limitations is the inability to incorporate into the network analyses measures of uncertainty in the prevalence of the various topics (Lowe and Benoit 2013). In addition, there are potential biases in the algorithms translating images into texts.[28] These limitations notwithstanding, we believe our methodological approach can make the analysis and interpretation of text-and-image data accessible to a wide range of social science researchers.

Our approach can be developed in numerous ways. For example, the text-and-image data could be linked with information on social actors, such as the authors of the documents to examine the interaction between cultural and social domains (*i.e.*, Karell and Freedman 2020). In addition, a temporal dimension could be added, perhaps using documents' time of publication, to model semantic change over time. Also, the textual content and relations could be measured using techniques other than STMs, such as word embeddings (see Stoltz and Taylor 2021). Finally, we encourage scholars using semantic network approaches to build on our validation exercise since different research questions, data, and analytical methods might call for different assessments of validity.

Notes

[1]https://edition.cnn.com/2021/05/28/politics/capitol-insurrection-veterans/index.html (last accessed 12/3/21). *The Washington Post* reported that more than 40 veterans have been charged in the riot; see https://www.seattletimes.com/nation-world/nation-politics/national-guard-soldier-is-fourth-service-member-charged-in-capitol-riot/ (last accessed 12/3/21)

[2]https://www.theatlantic.com/magazine/archive/2020/11/right-wing-militias-civil-war/616473/ (last accessed 12/3/21)

[3]https://www.washingtonpost.com/nation/2021/08/06/seattle-police-fired-capitol-riot/

[4] https://www.wbur.org/hereandnow/2021/01/07/social-media-capitol-mob, https://www.vox.com/recode/22221285/trump-online-capitol-riot-far-right-parler-twitter-facebook (last accessed 12/3/21)

[5] https://www.nytimes.com/2021/10/26/magazine/kyle-rittenhouse-kenosha-wisconsin.html, https://www.vox.com/policy-and-politics/22792136/kyle-rittenhouse-verdict-militia-violence-self-defense (last accessed 12/3/21)

[6]https://www.theatlantic.com/magazine/archive/2020/11/right-wing-militias-civil-war/616473/

[7]https://www.texastribune.org/2016/03/30/border-patrol-union-endorses-trump-president/ (last accessed 12/3/21)

[8]We only provide a brief review of the related scholarship here. For more thorough reviews, see Williams et al. 2020 and Chen et al. 2021.

[9]Explaining current ML techniques for analyzing images is outside the scope of this paper. For readers interested in details of the social science state-of-the-art methods, we recommend Torres 2018; Joo and Steinert-Threlkeld 2019; Zhang and Pan 2019; Williams et al. 2020; Torres 2021.

[10]A related body of research on the content and measurement of images focuses on the biases inherent in the ML algorithms and research designs (*e.g.*, Schwemmer et al. 2020).

[11]For a detailed review of recent social science research analyzing co-occurring text and image information, see Chen et al. 2021.

[12]Stoltz and Taylor (2019) offer a simulation-based validation, which surpasses the majority of semantic network studies we are aware of. While this kind of validation is valuable, we see human-based validation as also important since semantic network scholars typically use their results to make inferences about what people think, understand, and perceive.

[13]See https://www.splcenter.org/fighting-hate/extremist-files/ideology

[14]The size of the sample was limited by the time and financial resources available.

[15]We do not use these metadata in this study, but we make them available for further study with the publicly-released dataset.

[16]To implement, we used the `R` package `stm` (version 1.3.6).

[17]Google Vision (https://cloud.google.com/vision)

[18]We do not use this additional information, but we provide it with our publicly available dataset to facilitate future research.

[19]Instead of modeling the text documents and image-text documents separately, as we did, it is possible to combine the text and image information into single strings based on sharing an online document. That is, each observation in the dataset would correspond to one character string, comprising both the text of the observation and the image-text derived from the post's observation. However, since texts are often longer than images' object-word lists, this technique would give much more analytical weight to the written text, relative to the image information. We believe that it is possible to overcome this problem with a weighting scheme, which can be developed in future research.

[20]We replicated the analysis using lower thresholds and the main results remained largely unchanged. Researchers adopting our approach will likely be guided by their own research question when selecting an appropriate threshold.

[21]We built the graph using the `R` package `multinet` (version 4.0).

[22]We measured betweenness centrality using the `R` package `igraph` (version 1.2.6).

[23]The definition of the `igraph` function is provided at `https://igraph.org/r/doc/betweenness.html`; see also Freeman 1977: 37.

[24]FREX scores measure words' probability of appearing in a topic and their exclusivity to that topic (for details, see Roberts et al. 2014).

[25]Communities were detected using `R` package `multinet` (version 4.0).

[26]We additionally asked individuals to offer an open-ended brief explanation of their choice, but most of these responses were too brief or vague to analyze meaningfully.

[27]Appen internally curates the annotator pool, in part by assigning each annotator a quality score based on performance during previous (unrelated) tasks. For more information on calculating the confidence score, see `https://success.appen.com/hc/en-us/articles/201855939-Get-Results-How-to-Calculate-a-Confidence-Score` (last accessed 11/15/21).

[28]While we acknowledge this potential source of bias, we do not see it as a major concern for the analyses we have presented since our focus has been on kinds of images which are not known to be sensitive to algorithmic biases, unlike depictions of, for example, gender and race (Schwemmer et al. 2020). These algorithmic biases are further reason for future work using image data in semantic network approaches to validate any results.

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Online platform	Observations	Date range
Bitchute	10,622	2/2018 through 7/2019
Steemit	253	7/2016
Twitter	5,901	1/2013 through 12/2018
Total	16,776	1/2013 through 7/2019

Table 1: Data across online platforms.

Label	Proportion	Top FREX words
Nordic news links	0.12	https, amp, flaherti, attack, sweden, hour, swedish syrian, london, isi
Trump	0.03	trump, presid, may, russia, protest, limit, open, russian , donald, said
police cars	0.02	polic, forc, behind, start, run, month, oper, system , offic, everi

Table 2: Labels, estimated proportion, and top FREX words of key text topics. Words have been stemmed.

Label	Proportion	Top FREX words
securitization	0.02	uniform, polic person, offic, armi, soldier, troop, militari, protect , secur
cityscape	0.03	architectur, build, citi, area, estat, real , urban,
crowd	0.05	crowd, communiti, protest, fan, rebellion, audienc, social,
music performance	0.02	music, perform, talent, instrument, artist, stage, musician, singer, sing, string
natural landscape	0.04	tree, plant, natur, landscap, atmospher, grass, phenomenon,
shooting sports	0.02	sport, recreat, competit, leisur, gun, shoot, player, firearm , airsoft , stadium
vehicles	0.04	vehicl, car, transport, mode, aircraft , automot, road, part, plate, registr
"Wall Street" imagery	0.02	histori, stock, metal, sculptur, interior, floor , furnitur, money, currenc, wood
white collar worker	0.04	worker, collar, suit, formal, wear, gentleman, businessperson, convers, busi, manag

Table 3: Labels, estimated proportion, and top FREX words of key image topics. Words have been stemmed.

Rank	Label	Type	Inter-layer betweenness
1	securitization	image	490.93
2	fan fiction – stories	text	321.59
3	writing	image	304.83
4	advertisement	image	232.86
5	Twitch advertisements	text	228.67
6	cars	text	178.84
7	Trump	text	148.31
8	Nordic news links	text	141.54
9	white collar worker	image	111.85
10	music performance	image	64.59

Table 4: The topics with the the top 10 inter-layer betweenness centrality scores.

Rank	Alter text topic	Alter image topic
1	Nordic news links (0.25)	crowd (0.64)
2	Trump (0.22)	shooting sports (0.6)
3	police cars (0.21)	vehicles (0.48)
4		cityscape (0.45)
5		white collar worker (0.32)
6		music performance (0.31)
7		natural landscape (0.31)
8		"Wall Street" imagery (0.28)

Table 5: The text and image topics connected with the securitization topic (*i.e.*, securitization's "alter" vertices). Spearman correlation coefficients (r) are in parentheses. Only correlations greater than 0.2 are shown.

Figure 1: Example of an observation in the corpus. Observations are online and digital expressions comprising both a message in text and a picture. The observation has been anonymized.

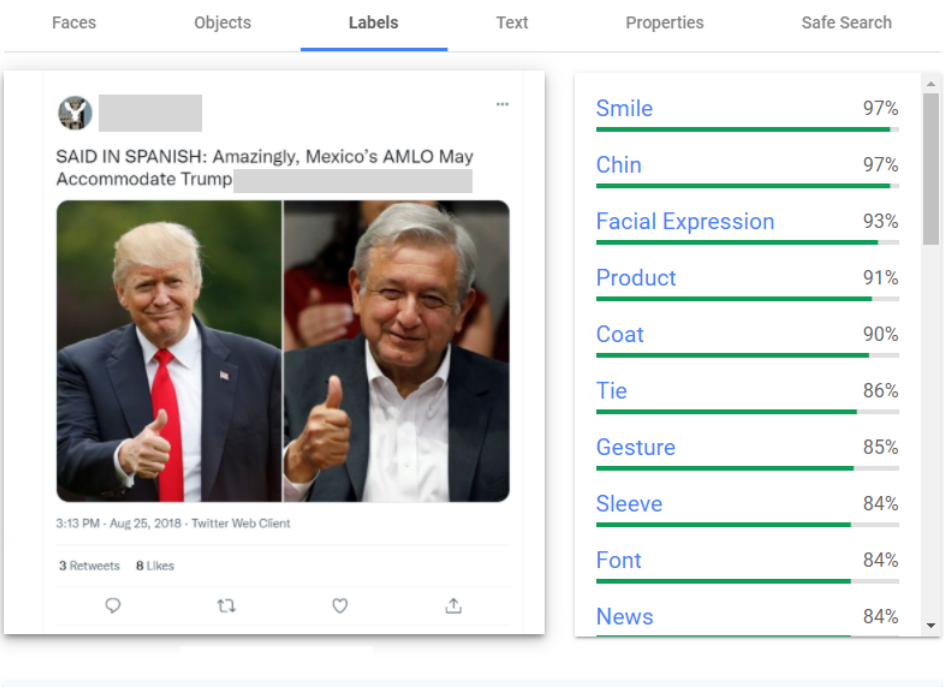

Figure 2: Example of a computer vision algorithm generating "image-text" based on the results of object detection. The observation has been anonymized.

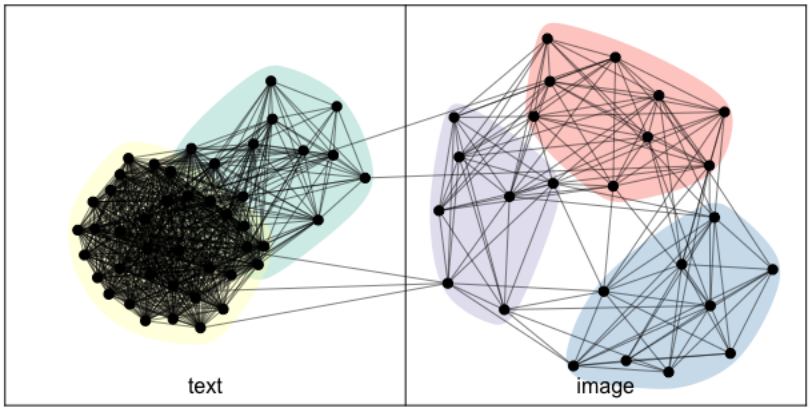

Figure 3: Two-mode semantic graph. The graph is an undirected multi-layer graph comprising three networks: one made of text topic vertices and their connections (left panel); one made of image topic vertices and the connections among them (right panel); and a final one formed by the relations between text topic vertices and image topic vertices. The colored areas demarcate detected communities.

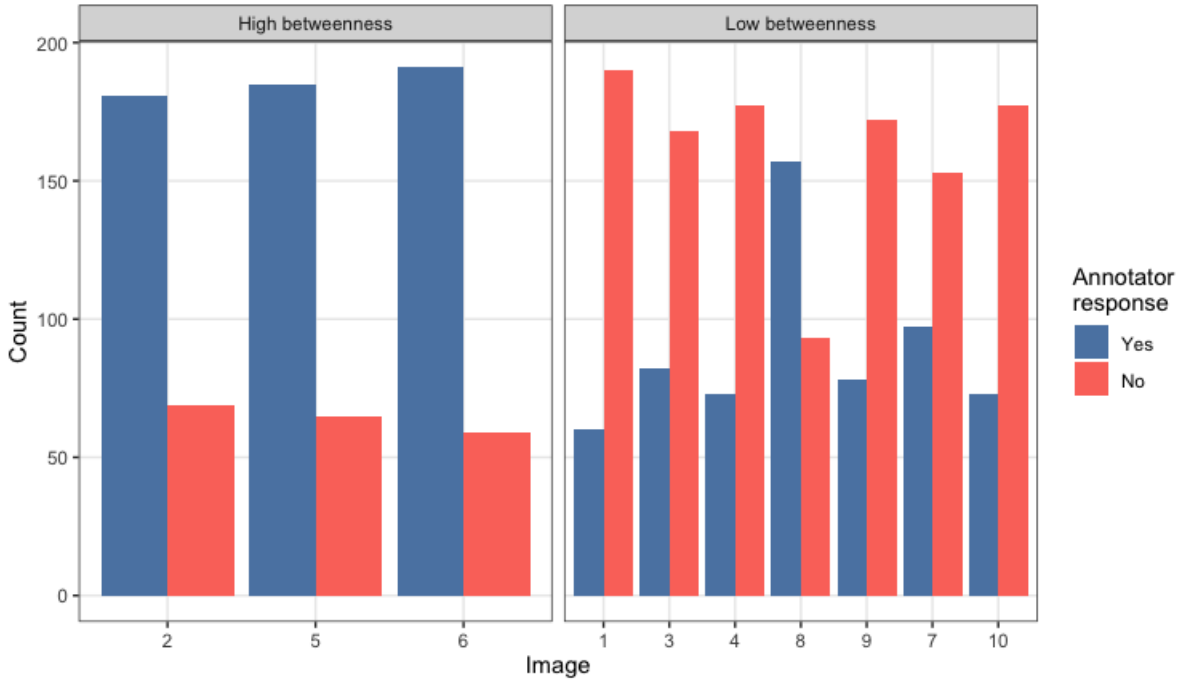

Figure 4: Responses of the validation exercise. The left panel shows the responses when images were scored as having high inter-layer betweenness centrality by our analysis (*i.e.*, securitization images); the right panel presented the responses when images were scored as having low betweenness (*i.e.*, non-securitization images). The results are based on responses given by 250 annotators. The images are numbered in a randomized order in which they were shown to annotators.

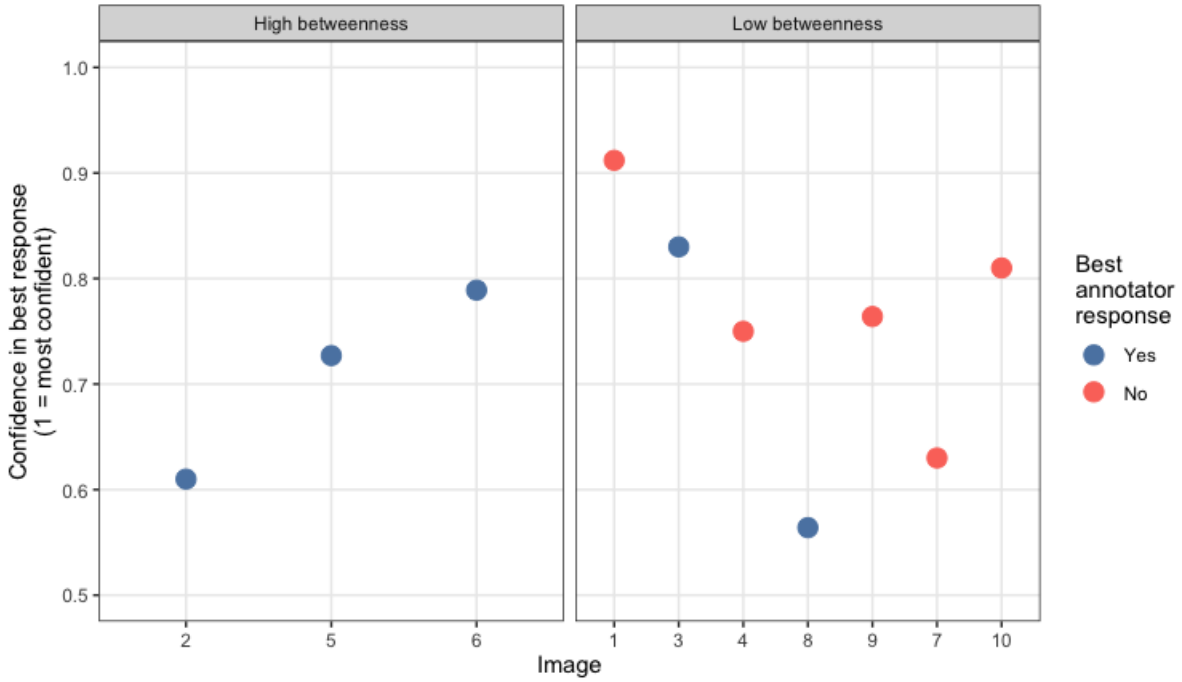

Figure 5: Results of the validation exercise when responses are aggregated and weighted by annotator agreement and quality. Higher confidence in the best response (*i.e.*, the value of the vertical axis) indicates more agreement by higher quality annotators. The online crowdsourcing platform determines annotator quality through its internal curation of annotators.

Appendices

Contents

Appendix A Selecting the topic model solutions

Topic models, including structural topic models (STMs) normally require the selection of a topic solution, or the number of topics to model. Since there is no correct number of topics that a topic model should estimate for any given corpus, researchers usually select solutions that lead to useful representations of the text and, subsequently, analytical insights. That is, the ideal solutions are those that reduce the complexity of text into measurement schemes that are helpful for understanding the text (Quinn et al. 2010; Grimmer and Stewart 2013; Wilkerson and Casas 2017; Karell and Freedman 2019).

One increasing common way to identify topic solutions that will likely generate useful results is a data-driven technique (*e.g.*, Light and Odden 2017; Hofstra et al. 2020). The technique first fits a series of topic models using systematically increasing solution values. Next, researchers evaluate the models' output across solutions. To do so, researchers often compare topics' exclusivity, or the extent to which words appear in single topics, and semantic cohesion, or the tendency for topics' most-probable words to co-occur together (Roberts et al. 2019). Solutions that maximize exclusivity and cohesion should produce topics that are more consistent while also different from one another, thereby increasingly the likelihood of obtaining unique and reliable insights (Roberts et al. 2014).

We implemented the data-driven technique using our text corpus by fitting a series of models using solution values between 10 and 55, at increments of five. We then calculated and plotted the exclusivity and semantic cohesion of topics estimated by each model. The results indicated a 45-topic solution would likely generate among the most useful topics (Figure A1). The results also indicated that other topic solutions, such as 30 and 35, could potentially also generate useful topics, but give the number of topics we did not expect the overall set of topics to be very different and we used 45 for our analysis. Future research could use our dataset, which we make publicly available, to fit models with other topic solutions.

To find a good topic solution of our "image-text" corpus, we again conducted the data-drive technique: we fit a series of models with solution values between 10 and 55, in increments of five, and then measured the exclusivity and semantic cohesion of each model's topics. The results suggested that a topic solution of 25 would be most likely to produce useful topics (Figure A2). This is the number of topics we modeled in the main analysis.

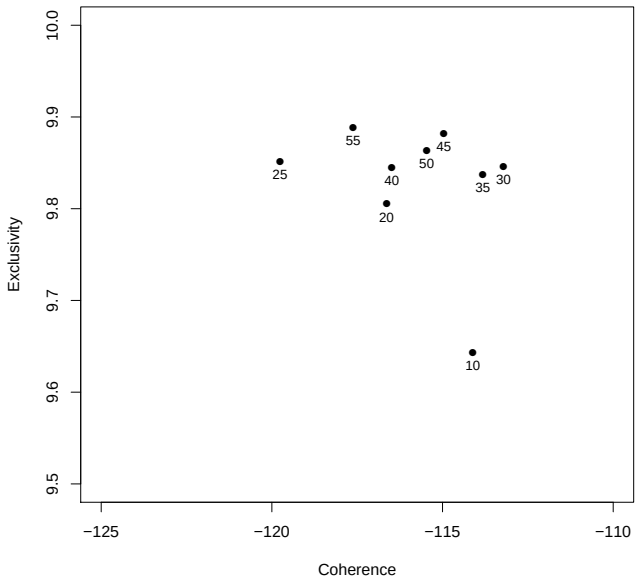

Figure A1: Exclusivity and semantic coherence scores across topic solutions for models of the text data.

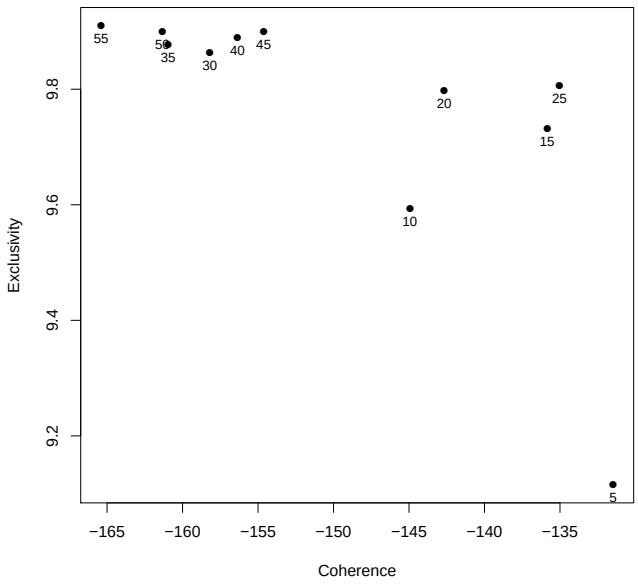

Figure A2: Exclusivity and semantic coherence scores across topic solutions for models of the image data.

Appendix B All topics and betweenness scores

This appendix presents the 45 topics for text in Table B1 and the 25 topics for images in Table B2, as well as all topics' betweenness centrality scores in Table B3. Table B1 and Table B2 include the labels we assigned after interpretation, the estimation proportion of each topic in its respective sub-corpus, and each topic's top FREX words.

Label	Proportion	Top FREX words
book advertisements	0.02	great, need, realli, happen, children, think, name, futur, found, reveal
link description	0.02	http, donat, articl, imgur, sourc, websit, archiv, album, html, info
cryptocurrency	0.01	nbsp, alon, planet, can, cryptocurr, human, get, just, thought, univers
email subscription advertisements	0.02	get, just, cultur, next, bit, non, email, still, win, list
YouTube channel advertisements	0.01	famili, steemit, episod, content, art, seri, jesus, home, babi, king
American Intelligence advertisements	0.02	media, read, fascist, give, elect citi, review, globalist, georg, march
news headlines	0.02	american, talk, help, today, movement, word, michael, destroy, creat, press
podcast advertisements	0.02	lay, anoth, jame, host, antifa, podcast, fbi, base, front, hear
anti-Semitic missives	0.02	call, race, thing, white, must, understand, evil, jew, hook, nose
Twitch advertisements	0.03	com, www, https, bitchut, game, stream, org, daili, youtu, twitch
make custom KKK merchandise	0.02	make, want , shirt, item, flag, comment, white, check, pro, custom
anti-Semitic video advertisements	0.02	peopl, plan, german, immigr, mass, googl, three, detail, canadian, written
outrage link description	0.02	one, can, human, mark, good, even, don, andrew, well, begin
evidence for anti-Semitic theory	0.02	war, germani, david, hoax, gas, holocaust, chamber, jewish, research, third
fan fiction – stories	0.01	one, now, just, back way, someth, time, place, there, black
Trump	0.03	trump, presid, may, russia, protest, limit, open, russian , donald, said
Black violence	0.03	white, black, man, south, kill, genocid, africa, voat, nigge, african
YouTube news about gangs	0.02	youtub, channel, watch, facebook, origin, subscrib, link, page, australia, gang
AfD and Merkel news (in German)	0.08	die, der, und, deutschland, ein, von, ist, den, das, mit
Discord links	0.02	https, support, com, patreon, www, twitter, paypal, discord, friend, project

Table B1: Labels, estimated proportion, and top FREX words of text topics. Words have been stemmed. Table continues on the following page.

Table B1 continued.

Label	Proportion	Top FREX words
Muslim, Jewish, and Mormon slander	0.02	satan, islam, muslim, god, follow, rule, ident, talmud, societi, british
white genocide video links	0.02	video, download, pleas, upload, share, can, bitchut, ask, chang, around
headlines about Jews	0.03	jewish, discuss, murder, control, leader, death, question, communist, secret, million
migrant caravan	0.02	hate, ban, law, tri, migrant, week, bill, illeg, california, arrest
Steemit poll	0.02	year, day, say, work, know, back, old, way, beauti, tell
Red Ice advertisements	0.02	radio, red, ice, europ, men, juli, north, realiti, meet, novemb
Infowars headlines and advertisements	0.02	news, show, live, repory, alex, jone, interview, real, full, present
anti-Semitic conspiracy theory links	0.02	truth, anti, expos, com, www , http, mourning, anci, isra, jewish
Greater Israel Project	0.01	israel, syria, refuge, crisi, rise, greater, born, goyim, west, without
military photograph captions	0.02	nation, global, unit, john, taken, public, freedom, canada, love, date
end times prophecy advertisements	0.02	time, end, come, soon, life, fight , sign, stop, final, current
merchandise links	0.03	new, world, order, book, liber, find, two, offici, sinc, music
fan fiction – description	0.01	just, like, littl, thought, one, fee, didnt, never, someth, make
ancient aliens	0.02	like, look, metal, possibl , seem, noth, close, side, build, cant
debunking the Holocaust	0.02	holocaust, lie, stori, big, believ, fact, made, continu, propaganda, speak
confrontation and violence	0.01	just, robot, dont, one, didnt, get, want, now, back, way
police cars	0.02	polic, forc, behind, start, run, month, oper, system , offic, everi
Nazi documentary	0.02	jew, part, hitler, histori, none, documentari, nazi, zionist, adolf, film
event and competitions	0.02	first, take, see, last, school, play, go, use, let, welcom
attacking the Left	0.03	right, now, free, speech, left, social, alt, break , civil, altern
personal testimonial	0.01	hard, except, matter, like, vote, dark, effort, group, fund, new
Nordic news links	0.12	https, amp, flaherti, attack, sweden, hour, swedish syrian, london, isi
corruption of Western states	0.02	state, america, polit, govern, power, parti, nationalist, european, countri, democrat
Christian YouTube advertisements	0.02	christian, attack, join, post, best, fals, copi, save, everyth, evid
financial planning	0.01	money, box, financi, account, need, can, make, buy, mail, develop

Label	Proportion	Top FREX words
writing	0.04	line, document, parallel, number, diagram, paper, handwrit, product, write, rectangl
fantasy art	0.04	paint, visual, photomontag, draw, collag, clip, modern, astronom, object, map
colorful print	0.04	newspap, pink, font, newsprint, ident, magenta, violet, purpl, pray, squar
figure reading	0.02	televis, present, newscast, program, news, read, journalist, bishop, learn, school, academ
video game	0.07	fiction, charact, cartoon, comic, adventur, action, video, anim, strategi, game
photograph and caption	0.07	photo, caption, physicist, chun, photographi, style, pray, photobomb, romanc, walk
natural landscape	0.04	tree, plant, natur, landscap, atmospher, grass, phenomenon, water, geolog, cloud
electronic gadget	0.03	technolog, devic, electron, display, websit, multimedia, page, web, screenshot, gadget
"Wall Street" imagery	0.02	histori, stock, metal, sculptur, interior, floor , furnitur, money, currenc, wood
(shooting) sports	0.02	sport, recreat, competit, leisur, gun, shoot, player, firearm , airsoft , stadium
music performance	0.02	music, perform, talent, instrument, artist, stage, musician, singer, sing, string
human face	0.08	forehead, chin, nose , head, cheek, express, eyebrow, skin, face, hairstyl
hand, food, and eating	0.03	finger, muscl, hand, thumb, food, child, arm, leg, drink, cuisin
cityscape	0.03	architectur, build, citi, area, estat, real , urban, landmark , hous, settlement
animal	0.03	adapt, dog , cat, snout, wildlif, carnivor, canida, felida, breed, mammal
smiling meme	0.02	smile, internet, meme, laugh, comedi, human, happi, fun, zombi, friendship
advertisement	0.05	poster, cover, album, movi, advertis, shoe, banner, flyer, footwear, magazin
crowd	0.05	crowd, communiti, protest, fan, rebellion, audienc, social, demonstr, youth, event
white collar worker	0.04	worker, collar, suit, formal, wear, gentleman, businessperson, convers, busi, manag
speaker and flag	0.05	speech , speak , news, day, spokesperson, orat, veteran, speaker, unit, usa
securitization	0.02	uniform, polic person, offic, armi, soldier, troop, militari, protect , secur
logo	0.07	graphic, logo, brand, signag, electr, symbol, trademark, label, emblem, blue
vehicles	0.04	vehicl, car, transport, mode, aircraft , automot, road, part, plate, registr
hat, sunglasses, and facial hair	0.04	beard, glass, moustach, fashion, eyewear, cool , long, cap, hat, care
black and white photograph	0.03	black, monochrom, dark, christma, snapshot, light, midnight, photographi, white , photograph

Table B2: Labels, estimated proportion, and top FREX words of image topics. Words have been stemmed.

Label	Type	Inter-layer betweenness	Intra-layer betweenness
securitization	image	490.93	4.84
fan fiction – stories	text	321.59	0.29
writing	image	304.83	2.46
advertisement	image	232.86	11.23
Twitch advertisements	text	228.67	1.02
cars	text	178.84	1.47
Trump	text	148.31	0.40
Nordic news links	text	141.54	0.18
white collar worker	image	111.85	7.73
music performance	image	64.59	12.52
YouTube channel advertisements	text	43.13	25.96
merchandise links	text	43.13	25.96
Infowars headlines and advertisements	text	37.53	22.91
animal	image	35.12	16.05
headlines about Jews	text	29.35	17.60
crowd	image	26.37	13.88
(shooting) sports	image	25.26	10.69
figure reading	image	25.17	12.95
Christian YouTube advertisement	text	23.91	18.28
Wall Street	image	23.81	10.06
photograph and caption	image	22.52	10.82
hand, food, and eating	image	21.08	20.64
financial planning	text	18.17	14.00
evidence for anti-Semitic theory	text	16.94	14.22
debunking the Holocaust	text	16.64	12.38
anti-Semitic conspiracy theory links	text	16.33	12.06
colorful print	image	13.92	7.82
military photograph captions	text	12.70	9.55
Nazi documentary	text	12.62	9.10
anti-Semitic missives	text	12.21	9.75
video game	image	11.97	5.62
electronic gadget	image	10.64	7.09
white genocide video links	text	10.63	7.74
speaker and flag	image	10.49	3.23
Muslim, Jewish, and Mormon slander	text	9.82	7.39
natural landscape	image	9.50	5.41
news headlines	text	9.12	6.83
fantasy art	image	7.32	4.12
YouTube news about gangs	text	7.06	4.86

Table B3: Inter-layer and intra-layer betweenness centrality scores across topics. Table continues on the following page.

Table B3 continued.

Label	Type	Inter-layer betweenness	Intra-layer betweenness
logo	image	6.70	3.60
fan fiction – description	text	6.54	4.79
black and white photograph	image	6.53	4.17
podcast advertisements	text	6.24	4.67
anti-Semitic video advertisements	text	6.24	4.67
Greater Israel Project	text	5.86	4.29
vehicles	image	5.29	2.74
cityscape	image	5.15	2.88
link description	text	4.11	3.04
American Intelligence advertisements	text	3.85	2.91
Red Ice advertisement	text	3.85	2.91
corruption of Western states	text	3.85	2.91
make custom KKK merchandise	text	3.56	2.73
smiling meme	image	2.74	2.63
Discord links	text	2.57	2.06
Black violence	text	1.87	1.47
event and competitions	text	1.87	1.47
migrant caravan	text	1.70	1.30
AfD and Merkel news (in German)	text	0.85	0.29
outrage link description	text	0.68	0.57
Steemit poll	text	0.68	0.57
end times prophecy advertisement	text	0.68	0.57
attacking the Left	text	0.68	0.57
personal testimonial	text	0.68	0.57
ancient aliens	text	0.62	0.51
email subscription advertisement	text	0.41	0.35
human face	image	0.38	0.38
hat, sunglasses, and facial hair	image	0.33	0.33
confrontation and violence	text	0.29	0.29
book advert advertisement	text	0.23	0.18
cryptocurrency	text	0.14	0.09

Appendix C Validation task instructions and practice exercise

This appendix shows six consecutive images of the validation task's online instructions and practice exercise.

Participants in the task would have seen the images as pages forming a continuous scroll on a webpage.

How Images Help Represent Concepts

Instructions ▲

Overview

In this job, you will be asked to:

- First, look at two collections of text and images and think of any concepts that are represented by each collection.
- Second, look at a series of images and decide whether they help you **link** the concepts from the first two collections or not.
- Third, briefly explain why you decided whether an image is a **linking** image or not.

WARNING!

*Please be aware that while these images are **not** explicit, some of them may cause offense.*

Detailed instructions and necessary information

Please do the following steps:

STEP 1. Look at the following collection of three texts. We will refer to this as the "First Collection". Think of a concept or concepts that the First Collection represents as a group. Make sure to remember these concepts as belonging to the First Collection.

1) SAID IN SPANISH: Amazingly, Mexico's AMLO May Accommodate Trump

2) Chants of "Trump, Trump, Trump" have been heard. #TrumpInauguration

3) Trump Executive Order Kill TPP Trade Deal

***STEP 2**. Now, look at this following collection of three images. We will refer to this as the Second Collection. Think of a concept or concepts that the Second Collection represents as a group. Make sure to remember these concepts as belonging to the Second Collection.*

STEP 3. *You will next be shown a series of 10 images. For each of these images, decide whether or not the image helps you* ***link****, or* ***make a conceptual connection****, between the concepts represented in the First Collection and the concepts represented in the Second Collection. Keep in mind that while some images may establish a connection, other images maynot form a link. For each of the images, you will also be asked to provide a brief explanation for why you made your decision. Here are two examples of images similar to the ones you will be shown, as well as a depiction of the task:*

Examples of potential linking images	**Question**: ***Does this image help link the concepts in the First and Second Collections?***	**Question:** ***Please provide a brief explanation for your choice***
	*Yes or no?*	*Write a brief explanation.*

Yes or no? *Write a brief explanation.*

Does this image help link the concepts represented in the First and Second Collections? (required)

- ○ Yes
- ○ No

Please provide a brief explanation for your choice: (required)

Does this image help link the concepts represented in the First and Second Collections? (required)

- ○ Yes
- ○ No

Please provide a brief explanation for your choice: (required)

Does this image help link the concepts represented in the First and Second Collections? (required)

- ○ Yes
- ○ No

Does this image help link the concepts represented in the First and Second Collections? (required)

- ○ Yes
- ○ No

Please provide a brief explanation for your choice: (required)

Does this image help link the concepts represented in the First and Second Collections? (required)

- ○ Yes
- ○ No

Please provide a brief explanation for your choice: (required)

Test Validators

/