From Fringe to Familiar: Computationally Tracking Extremist News Media Narratives

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by

Kathryn Hahn-Madole

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Universität Konstanz

Faculty of Sciences

Department of Computer and Information Science

1. Evaluated by Prof. Dr. Andreas Spitz
2. Evaluated by Prof. Dr. Susumu Shikano

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Kathryn Hahn-Madole

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Abstract

As the Far Right gains political power in the United States through figures like Donald Trump, extremist rhetoric has entered public discourse with newfound tenacity. This mainstreaming of marginal narratives has subsequently gained academic attention. However, none of the research characterizing the phenomenon has employed computational methods, despite the analytical power a computational method offers in its capacity to track complex trends across large swaths of text. Therefore, for my Master's thesis I present a four-step pipeline in which I collect over 65,000 articles from a five-year time span and the full partisanship spectrum, deconstruct this text into dense fragments, reaggregate these fragments to form narratives, and finally track these narratives as they evolve across time and partisan dimensions. This pipeline contributes to NLP research on representing a narrative computationally and political science research on the mainstreaming process. In applying this method, I find evidence that some marginal narratives are mainstreamed from the Far Right into centrist publications, particularly anti-immigration narratives. These narratives are highly linked to Donald Trump and his presidency, and several Far Right publications, notably Breitbart, are prolific in their generation of these marginal mainstreamed narratives. I also find evidence of the mainstreaming of Islamophobic and antisemitic narratives, and while a steadily growing number of Transphobic marginal narratives appear in my dataset, none of these reached my operational definition of "mainstreamed." These results and method provide a strong basis for future computational mainstreaming research.

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CHAPTER 1

Introduction

In recent years, especially since the 2016 election of Donald Trump as president of the United States, fringe and conspiratorial far-right narratives have flooded American public discourse. Narratives as extreme as the "Great Replacement," a white nationalist conspiracy theory that Democrats are "replacing" white American voters with immigrants, have floated in establishment and center-right news publications. This mainstreaming of fringe ideas is an important component of the processes of political polarization and distrust in the media. These processes are currently features of heavy interest in American society. In this paper I propose an exploration of the mainstreaming of far-right narratives into centrist news publications through a computational approach that identifies, extracts, and tracks these narratives as they move from the fringes to the establishment.

1.1 Existing Literature and the Computational Gap

Recent works have built a strong theoretical foundation for understanding mainstreaming through research into the extremist movements in the US, explorations of the right wing media ecosystem, and the development of a framework for understanding the mainstreaming process [3, 8, 30]. However, this research is largely qualitative, with some quantitative approaches and even fewer computational approaches. The lack of computational research into mainstreaming represents a significant gap in the literature, as a computational approach that is able to identify how, when, and to what extent marginal narratives reach centrist acceptance would be a powerful tool. The novelty of my approach is therefore to contribute to closing this gap by demonstrating an effective computational method for tracking narratives during the mainstreaming process. Social computational approaches like this one are uniquely powerful in their ability to identify otherwise hidden trends in data and analyze large swaths of text, especially when grounded in the findings of qualitative research.

Tracking the mainstreaming of extremist ideas at scale presents a special challenge, particularly when it comes to representing a narrative computationally. First, the method must be nuanced enough to extract a narrative like "migrants are invading the US" from a span of text, therefore able to isolate the most important elements from a text without losing qualities like tone, emotionality, and negation. Second, the method must be able to match narrative subcomponents that do not necessarily share vocabulary but still form the same narrative. For example, while a far right newspaper may publish something that says "migrants are invading the US," a center right newspaper may write that “a caravan of 100,000 immigrants will arrive at the border tomorrow,” which still contributes to this narrative of migrant invasion. Consequently, the approach must not only be able to extract sophisticated concepts from unstructured text, but also match these concepts in a meaningful way.

1.2 Hypothesis & Research Questions

In this work, I propose to develop a computational method capable of testing one main hypothesis: marginal Far Right narratives migrate from appearing exclusively in the fringes to mainstream acceptance as demonstrated by their publication in politically Centrist newspapers. That is to say, I assert that my pipeline is able to identify and track narrative throughlines across different publications at different times with a high level of sophistication and I demonstrate its efficacy by applying this pipeline to the challenge of tracking extremist narratives in news media as they are mainstreamed.

After confirming this essential hypothesis, I propose two additional research questions to gain further understanding of the mainstreaming process. First, which newspapers are the main agents of the mainstreaming process? In other words, which newspapers on the Far Right most successfully produce marginal narratives that then enter the mainstream and which newspapers from the Centrist or Leftist partisanships most often platform these marginal mainstreamed narratives? Second, how do the marginal narratives change as they become mainstreamed? Specifically, I look at the actors discussed in the narratives and the descriptors attached to them.

1.3 Methodology

To contribute to the work on narrative extraction and the understanding of the mainstreaming process, I have developed a sophisticated four-step pipeline.[1] I first collect over 65,000 newspaper articles from the full partisan spectrum across a five year time span and then deconstruct the text into its essential components. This deconstruction involves combining Binary Relation Extraction, Named Entity Disambiguation, and Coreference Resolution to retain the essential components of the text. Third, I aggregate these essential components into narratives using BERT vectorization and Kmeans clustering, and finally track these narratives as they evolve across time and partisanship. Essentially, I first identify narrative instances, defined operationally as the different clusters that result from the clustering of each cross

[1]See https://github.com/khahnmad/MA-Thesis$_Fringe-to-Familiarforthecompletecode.$

section of partisanship and year. Then, if they pass a threshold of cosine similarity to each other, I unite the narrative instances, deeming them to be different iterations of essentially the same narrative.

With this definition of a narrative as being fragmented across partisanships and years, I can test my hypothesis and answer my research questions, with a thorough and multifaceted analytical phase. I test my main hypothesis by identifying narratives that first appear in the datasets exclusively in the Far Right but have at least half of their instances in later years in the Centrist partisanship categories. I then propose to answer my first research question by identifying the Far Right newspapers that produce the most marginal narratives that are then mainstreamed, both in absolute and relative terms. I also identify the Centrist and Leftist newspapers that platform the mainstreamed marginal narratives most, again in absolute and relative terms. Finally, I answer my second research question by identifying the named entities in the mainstreamed marginal narratives and demonstrating how they change as the narratives move away from the fringes.

1.4 Top Findings

Through analyzing the results of my experimental phase, I was able to confirm that some marginal Far Right narratives migrate from the fringes to the mainstream, particularly anti-immigration narratives. Furthermore, I find that the mainstreaming of anti-immigration narratives peaked in the years 2016 and 2018, coinciding with the US presidential election and the midterm elections, and that the anti-immigrant narratives were inextricably linked to discussion of Donald Trump. Particularly in the immigration and Islamophobia categories, Breitbart emerges as the dominant far right actor contributing to marginal narratives that become mainstreamed, along with a handful of smaller publications. The prominence of a few publications on the Far Right contrasts with the centrist and leftist publications that participate in the mainstreaming process; no publication monopolizes the platforming of marginal narratives into the mainstreamed. Instead, a range of centrist and leftist publications occasionally participate in the mainstreaming process. Finally, I also find a noticeable dearth of mainstreamed Islamophobic narratives, contrasting with some research that suggests that Islamophobia is one of the top concerns of the modern Far Right.

1.5 Outline

In the remainder of this paper, I explain the comprehensive theoretical and computational work that went into the development and execution of this research. I will first discuss the important social and computational science providing the theoretical foundation of the work. Next I will explain my newspaper data collection process, resulting in a dataset of over 65,000 articles spanning seven partisanship categories and five years. Then I will discuss the pipeline that deconstructs the text through Binary Relation Extraction, Coreference Resolution, and Entity Disambiguation, and reconstructs it into narratives through BERT vectorization and clustering. Finally, I will present my approach to tracking the narratives along with a discussion of my results.

CHAPTER 2

Related Work

In this project, I am uniting work from two fields: the study of the mainstreaming of extremist narratives and the study of computationally extracting narratives from text. Both areas have a wealth of recent academic work, providing me with a strong theoretical foundation for my research.

To understand mainstreaming, I examine how to define mainstreaming and the mainstream theoretically and operationally in section 2.1. I also examine the special role of the media in this process and the way that researchers have tracked mainstreamed. Notably, computational methods in this arena are scarce, adding to the necessity of this project's work. I also examine modern narratives in the American Far Right in section 2.2, especially those concerning anti-immigration, antisemitic, Islamophobic, and Transphobic sentiment. An understanding of these types of narratives in particular allows me to make an informed evaluation of my results. Finally, in section 2.3 I discuss the literate on how to define a narrative, conceptually and computationally, and the computational methods that can execute this task. The combination of the methods I outline in this section allows for the dense and meaningful representation of a narrative that serves as the basic unit of my analysis.

2.1 Mainstreaming

Mainstreaming is a controversial and subjective process, which has risen in the public debate in particular since the 2016 election of Donald Trump and the notable shift in right-wing politics that coincided. In this section, I discuss the recent work that aims to create a framework for understanding the mainstreaming process, explore how the mainstreaming process has transpired in recent history, and review the academic approaches that have sought to quantify or track the mainstreaming process.

2.1.1 Defining "Mainstream" and "Mainstreaming"

Closely following Brown's definition, I assert that mainstreaming is the process through which narratives from marginal ideologies shift in the public view towards legitimacy and public acceptance [8]. In other words, mainstreaming indicates a movement of the Overton window of what the public deems acceptable [29]. Importantly, this process is not unidirectional; in order for extreme narratives to move towards the mainstream, centrist and extremist actors must, in a sense, collaborate [29]. To shift the Overton window, the extremist actors push, but certain centrist actors then pull, or at least clear the way. The mainstreaming of a specific extremist narrative, therefore, would indicate a shift in the public view from recognizing and treating the narrative as marginal towards deeming the narrative acceptable.

Implicit in this definition of mainstreaming is an understanding of what the mainstream is. While it may seem obvious to define the mainstream as the ideological center, such a definition can imply a balance between partisanship extremes and lend legitimacy or a sense of "ground truth" to the mainstream that does not necessarily exist. The mainstream is "not essentially good, rational, or moderate" [8]. Therefore, I posit that the mainstream, for the purposes of this project, be defined as the set of ideologies widely accepted by the public and electorally dominant [27].

2.1.2 Recent History of Mainstreaming

While the body of research on mainstreaming has grown significantly since the 2016 election of Donald Trump, mainstreaming as a process has existed much longer, however, with notable examples of radical organizations reaching mainstream acceptance including the KKK and the Nazi Party [29]. In recent years, political figures and organizations like Rush Limbaugh, Pat Buchanan, the Tea Party, and the Unite the Right Rally have introduced extremist narratives to a wider audience [29]. Simultaneously, recently growing subcultures like the alt-right, the Manosphere, and 8chan pol users have consciously attempted to influence mainstream media through trolling, memes and other collective actions [26].

2.1.3 Role of the Media in Mainstreaming

In this project I focus on mainstreaming in the US media ecosystem, as the media can serve as a proxy for the views of the public and because of the unique way in which the US media ecosystem supports the mainstreaming process. Media organizations play an important societal role in agenda setting and framing, therefore serving as an instrumental actors in shifting marginal narratives towards public acceptance. Media organizations are agenda-setters in that they determine which issues the public views as important to talk about. They frame those issues by portraying them from a specific perspective; for example, a topic could be framed as an indicator of positive change or alternatively as a problem. Media organizations can then mainstream far right narratives by asserting that a certain issue should be talked about or should be framed in accordance with the far right's perspective [30].

The profit motive driving media organizations can also lead them to participate in the mainstreaming process, even if they explicitly espouse a distinct ideology from the far right [30]. Featuring stories about extremist ideologies sells. As the 2016 campaign and election of Donald Trump made clear, media organizations often end up promoting the ideology of mediagenic extremist candidates by elevating their public image through continual interviews and coverage [30].

In the United States, the mainstreaming function of the media is particularly strong, as the right wing media ecosystem in the United States is prolific. Compared to five other western democracies in their 2020 study, Heft et al found that the US had the most right-wing online news sites and also the most active ones [17]. The highly partisan nature of the right wing media ecosystems propagates its own "feedback loop" as dissenting opinions receive less attention and therefore profit [4]. In comparison, the left wing media ecosystem is sparse and ineffectual.

2.1.4 Existing Approaches to Tracking Mainstreaming

In recent years, researchers have contributed to the understanding of mainstreaming through a variety of methods. Mondon explores the way opinion polls can function as a tool to mainstream far right ideas [28]. Ekman qualitatively analyzes newspaper text to understand the mainstreaming of the “Great Replacement” conspiracy theory in Sweden [13]. Marwick and Lewis track the mainstreaming of radical ideologies by identifying a number of subcultures purposefully trying to influence the mainstream media environment and enumerating examples of these efforts, along with their motivations [26]. Benkler et al discuss the efforts of extremist propagandists on the Internet pushing their ideologies [3].

However, the bulk of this work uses qualitative methodology, exploring mainstreaming through case studies, text analysis, and similar methods. Ophir et al employ a semi-computational approach to explore narratives from a far-right website, but this exploration does not make an empirical connection between their analysis and the occurrence of mainstreaming [31]. Kaiser et al also inform my understanding of the far right media ecosystem by identifying the links in overlapping coverage between alternative media outlets using LDA and time series analysis [20]. This work is of course crucial to developing a nuanced understanding of mainstreaming, but faces limitations that a computational method could naturally complement. As of the time of writing, no computational approach to tracking the mainstreaming of extremist narratives has yet been developed, clearly establishing a gap for this paper to fill.

2.2 Narratives in the American Far Right

The modern Far Right has gained new power in the public arena since the turn of the century and with this power, its narratives, even those with an ideological core dating back many years, have gained new relevance. Extremist Far Right narratives often center around themes of national decline, conspiracy, inequality, and imperilment, invoking the believer as a wrongful victim [26]. Irrespective of their contents, these narratives share a tendency to invoke intense emotionality [38]. In this project, I focus on extremist narratives of immigration, antisemitism, Transphobia, and Islamophobia. These categories highlight different dimensions of the Far Right ideology and range greatly in how frequently they are discussed and for how long by the Far Right. In this section, I will explain the definition of "Far Right" that recent academics have developed and that I will employ for this paper. I will also examine each of the four chosen topics more closely, providing a foundation for evaluating the narrative extraction pipeline and its results.

2.2.1 Defining the "Far Right"

The contemporary terminology to define the modern American Far Right differs among researchers. Mondon and Winter distinguish between the Far Right and the Extreme Right, holding that the Far Right, while still maintaining an extreme and racist ideology, is less overt than the Extreme Right which openly engages in verbal or physical violence [29]. Mudde alternatively uses Far Right as an umbrella term encompassing both the radical and reformist sides of the movement [30]. The term "alt-right" has also gained popularity, especially in connection to social media and alternative media as it came to being online in forums like 4chan and 8chan. "Alt-right" generally refers to a set of ideologies connected by white supremacist values [26]. In my analysis, I use the term "far right" as an umbrella term, following Mudde, encompassing both extreme, illiberal ideologies and reformist ones.

The difficulty in appropriately characterizing and categorizing the American Far Right extends beyond terminology alone; the right wing media ecosystem is highly skewed, with a heavy extremist wing and almost no center right representation [3]. Partisan outlets dominate the media ecosystem, triggering a "propaganda feedback loop" wherein political and media actors are trapped in a state of only producing "identity-confirming" content, or facing obsolescence [4]. In this environment, outlets like Fox News and Breitbart have become central influencers.

For this work, I focus in particular on four topics popular in the far right: anti-immigrant sentiment, antisemitism, Transphobia, and Islamophobia. These topics capture different aspects of central themes to the far right, like security, corruption, and nativism [30]. They also range in how much they are discussed and for how long, as the far right has had agenda setting power on immigration themes much longer than any other topic, while Transphobic rhetoric has only recently entered the discourse significantly [30].

2.2.2 Anti-Immigration

Globally, immigration is a core issue for the far-right [26, 30]. Anti-immigrant narratives typically base themselves in fear and dehumanization, implying that immigrants bring disease, criminality, and violence, particularly violence towards women [26, 3]. As with other far right narratives, extremists present themselves as the victims. At the most extreme, these narratives frame immigration as an existential, immediate threat, serving as a call to action [26, 29].

A notable example of this type of narrative is the "Great Replacement" conspiracy theory, which loosely holds that some group of elites are bringing in immigrants to replace the population and influence the political agenda. The conspiracy theory has been increasingly mainstreamed in the past few years. It was popularized within certain subcultures in the 21st century, but has even older roots, and ties together ethnonationalist ideas and fear of the corruption of the elites [30].

During the 2016 presidential campaign, anti-immigrant narratives surged to the mainstream through actors like Donald Trump and media organizations like Breitbart. With his "build a wall" campaign, Donald Trump propagated a security-based narrative that also reveals the irrationality of this kind of ideology by somehow suggesting that by building a physical border, crime in the United States will stop.

2.2.3 Antisemitism

Antisemitic narratives are typically centered in conspiracy and in the idea of corruption. Antisemitic conspiracies vary in their details, ranging from drinking the blood of children to organizing communist or anarchist political movements, but essentially tend to invoke a fear of a secret conspiracy of Jewish people controlling or aspiring to control society [29, 38]. The theme of corruption extends also to the idea that this secret "cabal" is corrupting the minds of members of society and manipulating historical truth [30]. Since the 2016 election and with the explosion of conspiracy theories like QAnon, antisemitic narratives have entered public discourse in a new way.

2.2.4 Transphobia

Far right organizations typically advocate for strong traditional gender roles in their ideology, limiting women to the domestic space, restricting sexuality to strictly heteronormative, and enforcing an inflexible gender binary. Transphobic narratives from the Far Right mostly base themselves in violation of these three norms. Transphobic narratives also often play into the concept that the elites are corrupting the minds of the population, particularly those of women and children, by implying that trans-identifying people have been tricked or coerced into this identity [30].

Studying Transphobic narratives in this project presents a few challenges. One challenge as it relates to detecting the mainstreaming of Transphobic narratives is that these narratives are already quite present across partisanships in news media [5]. Further, while there is extensive research on women in the Far Right, there is not as much investigating the role of gender for men in the Far Right and even less for trans individuals [30]. These challenges simultaneously make the topic more interesting as it pertains to this project.

2.2.5 Islamophobia

Mudde suggests that the most important "Other" of the 21st century far right is "the Muslim," as Islamophobic discourse has come to dominate far right news [30]. Islamophobic discourse often centers on either security, especially anti-terrorism, and "islamization" [30]. Islamophobic narratives centered on security invoke images of a fundamentalist, terrorist Muslim zealot [38]. Meanwhile, narratives centered on islamization appeal to fears that an extreme, foreign and unjust Islamic ideology will come to dominate western democracies.

Like with extremist immigration narratives, Breitbart in particular helped to popularize Islamophobic narrative during the 2016 US presidential campaign period [3].

2.3 Defining Narratives Conceptually and Computationally

Narratives serve as the central unit of observation for this project, so a clear conceptual and computational definition is necessary. Researchers in communications, psychology, political science, and journalism have enumerated many characterizations of what a narrative is. Braddock and Horgan define a narrative as "any cohesive and coherent story with an identifiable beginning, middle, and end that provides information about scene, characters, and conflict" [7]. Marcks and Pawelz propose that narratives aim to evoke emotion or a certain attitude and recount a situation with a certain implied goal [26]. In journalistic context, researchers have suggested that narratives serve as an embedded element that anchors a given article in culturally familiar archetypes, so that the audience will view the article as part of an ongoing process [22, 24].

Translating these definitions for a computational application represents an obvious challenge, as these definitions focus on a comprehensive, meta-level understanding that comes from being able to derive a classification through higher-order reasoning. An effective computational representation of a narrative would be a powerful analytical tool, lending the capacity to analyze narratives that span large quantities of text, but represents a significant challenge. Narratives can be seen as collective negotiations with many contributors lending consistency to its definition over time, so a computational approach may therefore be able to provide valuable insights on the large quantity of sparse data that creates a narrative [26].

2.3.1 Existing Techniques for Computationally Representing a Narrative

Several principle NLP tasks center around core elements of the narrative definitions aforementioned. Entity identification or Named-entity recognition (NER) can identify the scene and characters in a narrative, which are key components of a narrative according to Braddock and Horgan. Sentiment analysis identifies the emotionality of a text and stance detection the polarity of the text, in accordance with the narrative definition of Marcks and Pawelz. Furthermore, many existing frameworks focus on determining sequential events in a text or identifying the key plot units of a story [11, 10]. On a higher-level, topic modeling techniques like Latent Dirichlet Association inductively reveal themes in a corpus [6].

Through combining these NLP tasks and methods, NLP researchers have proposed several narrative extraction methods, fitting with my conceptual aim of relying on several of the narrative definitions examined. In these proposed methods, the extraction pipeline typically begins by processing the unstructured text into a reduced form. This deconstruction process may employ NER, chunking, part-of-speech (POS) tagging, semantic role labeling (SRL) and related methods. Next, these methods form narratives out of the processed text by reaggregating the reduced elements in a variety of ways.

In one example of this kind of pipeline, Bandeli et al used POS tagging and chunking to extract noun and verb phrases from their input sentences and then devised a formal grammar that sorts these phrases into narratives [2]. This method closely restricts what can be defined as a narrative. Ceran similarly extracted subject-verb-object triplets from unstructured text and then applied an agglomerative hierarchical clustering method that relied on semantic and syntactic matching criterion to create narrative clusters [9]. This method, while still restrictive in its identification of a narrative, provides cleanly interpretable results. As it employs algorithms instead of black box models, the connections between subject-verb-object triplets are obvious and logical and Ceran's demonstration of the "contextual synonyms" that appear in extremist texts is valuable.

Tangherlini et al present the most sophisticated and relevant narrative extraction pipeline in their 2020 publication. They used a parse tree and SRL to extract "actants" and the relationships between these actants from the text as the building blocks of their graphical model for how people construct narratives through social media posts [37]. To rebuild these essential components into narratives, they compute BERT embeddings for these phrases and cluster the embeddings using Kmeans.

2.3.2 NLP Tasks Contributing to Narrative Extraction

To design the pipeline I employ in this project, I examined several NLP tasks to chose which tasks best fit together to make up the pipeline of narrative extraction. Here, I will highlight the existing literature I explored to make this decision for the four tasks that compose the deconstruction phase of my pipeline and the two tasks that compose the reconstruction phase of my pipeline.

2.3.2.1 Information Extraction

Relation Extraction or Information Extraction is an NLP task in which attributes and relations for entities in a sentence are predicted. Typically it is executed through five different strategies: hand-built patterns, bootstrapping methods, supervised methods, distant supervision, and unsupervised methods. Unsupervised methods, the most recent innovation, have proven to be the most powerful, and models like OpenIE 5.0, Stanford OpenIE, ClauseIE, PropS, and OPENIE4 now compete on their abilities to learn shallow and deep dependencies, label equivalence, and provide an end-to-end approach [1, 16].

Stanford OpenIE operates through three main steps. Given an input sentence, it first segments the sentence into autonomous clauses. Second, it splits the clauses into every shortened version possible, removing, for example, different combinations of adjectives. Last, it processes these fragments into a triplet format: subject, relation, object [1]. While this method is no longer state-of-the-art, its performance is still excellent on tasks like the TAC KBP Slot Filling challenge and its accessibility for implementation gives it a significant advantage [25].

2.3.2.2 Coreference Resolution

Coreference resolution is an NLP task that aims to identify all the mentions of entities in a text and pair them with their antecedents. It generally consists of mention identification and mention-antecedent resolution and can target pronouns, nouns, or both. For example, the sentence "Marie rides her bike," would be resolved to "Marie rides Marie's bike."

The CorefAnnotator was introduced by Lee et al in 2011, expanding on the work of Raghuanthan et al in 2010 [23, 32]. This system executes three steps, mention detection, coreference resolution, and post-processing. Its relevant innovation is its use of sorted deterministic models to do coreference resolution. The models are ordered from most to least strict, thereby ensuring that when data is passed through the models, the most important features are captured first. While this method is no longer state of the art, it performs very well and is packaged together with other tools in Stanford's CoreNLP model, allowing for smooth implementation.

2.3.2.3 Named Entity Recognition

An entity in NLP is an object in text like a person, organization, date, or other similar category. Named Entity Recognition (NER) is the task of extracting these entities from unstructured text. In the scope of this project, NER is an important tool for understanding the contents and allowing analysis of the text.

A variety of methods exist to carry out this task, including grammar-based, statistical, and neural network approaches, but one of note is Stanford NER, a model developed by the Stanford NLP Group [15]. This approach combines both grammar-based and statistical methods, specifically a Conditional Random Field model. It is trained on Reuters news through CoNLL-2003, Newswire articles through MUC-6 and MUC-7, as well as internal Stanford text data. When this pipeline was first released, it achieved near state-of-the-art results and has since been improved, although no more recent publication attests to the improvements specifically.

2.3.2.4 Clustering

Clustering is a typical machine learning task in which data points are assigned to different "clusters" based on their distance in an unsupervised manner. Different clustering algorithms can handle different kinds of data by determining clusters by density, through different distance metrics, or by soft or hard clustering.

The Kmeans algorithm is one of the most popular clustering algorithms. It requires the number of clusters k as input. In the typical execution of this algorithm, the process is initialized by randomly assigning k data points as centroids. It then iterates through the remaining data points, assigning each one to the closest clusters. Then, the centroid is recalculated as the mean of the cluster. The process repeats until the centroids no longer change. The weaknesses of this method include the requirement of the number of clusters as input, which can require a intensive optimization, and its tendency to converge to a local instead of a global minimum due to its random initialization.

2.3.2.5 BERT Vectorization

Vectorizing text is an important NLP method that allows users to represent spans of text numerically, thereby making the data computer-readable and mathematically manipulable. From one-hot embeddings to Word2Vec to BERT, large strides have been made in this field in the past 15 years that mean that text embeddings can now capture sophisticated semantic and syntactic concepts and are not restricted by missing words in the training corpus or homonyms.

Specifically for my pipeline, I focus on the task of creating a single embedding for a subject-relation-object triplet. In their pipeline for extracting narratives from unstructured text, Tangherlini et al use BERT to vectorize their subject-relation-object triplets [37]. BERT is a transformer language model trained primarily on next-sentence prediction that has been proven effective at many downstream tasks, introducing a new state-of-the-art on eleven NLP tasks when it was first released [12]. Its wide ranging applicability is largely due to its ability to generate sophisticated contextualized embedding representations of input text.

CHAPTER 3

Methodology

In this project I propose to test one primary hypothesis and answer two subsequent research questions:

H: The online news environment between 2016 and 2021 has participated in a mainstreaming process through which some marginal Far Right narratives appear first exclusively in hyperpartisan contexts but in later years appear primarily in Centrist news publications.

RQ 1: Which newspapers most often launch marginal narratives that are mainstreamed and which newspapers most often platform marginal narratives into the mainstream?

RQ 2: How does the content of the marginal narratives evolve across the mainstreaming process?

To test this hypothesis and answer these questions, I built a large dataset of newspaper text covering the full partisan spectrum and spanning several years. I then built a pipeline that deconstructs the newspaper text into dense, reduced fragments and reaggregate these fragments into narratives. I can then apply my analysis to these extracted narratives. For a visualization of this pipeline, see figure 1.

In this chapter, I describe this system that I built to operationalize and answer these questions. First, in section 3.1 I explain the assumptions and definitions that I rely on to make these hypotheses and research questions testable. Second, I introduce the datasets I built for this task using Media Cloud in section 3.2. Next, I explain the pipeline that deconstructs the text into its essential components in section 3.3 and reconstructs these components into narrative instances in section 3.4. The text deconstruction phase is more straightforward, relying predominantly on well-document and -evaluated end-to-end methods, while the narrative reconstruction phase depends more on my own innovations, although still thoroughly based in the literature. After that, I discuss the methods I employ to join the narrative instances and subsequently track the narratives as they move across partisanships in section 3.5. Finally, I explain the various steps I took to evaluate the components of my pipeline and limit the propagation of error in section 3.6. For the code to this project, see https://github.com/khahnmad/MA-Thesis_Fringe-to-Familiar.

3.1 Operationalizing "Narrative"

The narrative is the core unit of analysis for this project, so the way I define a narrative and its subsets are of high importance. To operationalize my hypothesis and research questions, I make a series of assumptions and assert some definitions.

I define a narrative as being made of narrative instances, which are in turn made of clusters of fragmented text. The fragmented text is produced in the text deconstruction phase in section 3.3 and looks like "Migrants Invade Europe," or "Refugees arrive in Mexico." When clustered via Kmeans, these text fragments make up a narrative instance. For example, the narrative instance for those text fragments contains the following: "Migrants Invade Europe," "Refugees arrive in Mexico," "refugees is in 2007," "refugees is in Europe," "cost cost of providing for refugees in Europe," and "refugees is in Europe."[1]

The combination of all narrative instances across datasets and years form a single narrative. In other words, a narrative n is the union of all narratives instances i. So, a narrative instance from the Far Right 2017 dataset that also discusses themes of migrant invasion would be part of the same narrative as the aforementioned example from the Far Right 2016 dataset.

To identify a narrative, I begin by identifying a starter narrative instance, which, for the majority of my analysis, is a marginal narrative, although it can be any narrative instance. A marginal narrative is a narrative that has its first instance in a Far Right dataset. That is, the earliest instance of the narrative occurs in a Far Right dataset and within this time frame it does not occur in any other partisanship. The example in figure 2 shows a marginal narrative as the starter narrative.

Given this starter narrative, I then iterate through narrative instances from other datasets and years to identify direct matches, which are narrative instances meeting a high threshold of similarity to the starter narrative. Finally, I identify peripheral matches, which are narrative instances with a high degree of similarity to the direct matches. This process is explained in greater detail in section 3.5 and can also bee seen in figure 2. See definition 1 for the formal definition.

I use this definition of a narrative with the purpose of locating mainstreamed narratives. A mainstreamed narrative, is a narrative whose instances appear mostly in the center three partisanship categories: Center Right, Center, and Center Left. A marginal narrative can also be a mainstreamed narrative, for example, if its instances first appear only in the Far Right in 2017 but in 2019 appear mostly in the center three partisanship categories. See definition 2.

[1] This narrative instance corresponds to cluster seven in the Immigration category of the Far Right 2016 dataset

3.2 Datasets

The central goal of this work is to devise a computational approach to track narratives through the mainstreaming process, with the secondary goals of one, understanding what newspapers manipulate this process, and two, how the mainstreamed narratives evolve during the journey. Therefore, I extracted newspaper text covering the full partisanship range from Far Right to Far Left and spanning the years from 2016 to 2020.

In this section, I explain the carefully curated sources for the newspaper text I use in my analysis in subsection 3.2.1 and the method I employed to scrape and evaluate text for these varied sources in subsection 3.2.2. Finally, I give an overview of the completed datasets in subsection 3.2.3.

3.2.1 Newspaper Sources

To collect the newspaper data necessary for this analysis, I used Media Cloud and its "collections," which sort online news media into various categories. For each partisan category (Far Right, Right, Center Right, Center, Center Left, Left, Far Left), I chose at least one corresponding Media Cloud collection, which are enumerated in table 1. In some cases, I chose more than one collection as a source, because either one, there was an insufficient number of articles retrievable from only one collection, or two, the collection retrieved data primarily corresponding to a certain year and I wanted urls from a range of years. For a plot of the number of unique newspapers in each Media Cloud collection used, see figure 3.

For the Left, Center Left, Center, Center Right, and Right collections, I used collections that were built using analytics from Twitter by researchers at the Berkman Klein Center [14]. They reflect two time periods, 2016 and 2019. For the 2016 collections, an article receives a partisanship category according to how often it is tweeted by followers of Hillary Clinton compared to followers of Donald Trump. For example, the Center Left collection is comprised of articles tweeted slightly more by Clinton followers than Trump followers. The 2019 collections assign a partisanship category to an article based on how often it was tweeted by followers of Liberal politicians versus followers of Conservative politicians. This method of partisanship designation also means that the articles are not limited to English language, United States newspapers, but may also include foreign publications. Also, despite their focus on the 2016 and 2019 years, they also contain articles for the surrounding years. See table 1 for the titles of each of these collections, which indicate their source.

The hyperpartisan categories, Far Left and Far Right, come from Buzzfeed and Mediacloud partisanship designations. For both the Far Left and Far Right, Mediacloud uses a Buzzfeed analysis to populate two collections of hyperpartisan news [36]. Notably, the Far Left collection is the only collection of this partisanship available and it only includes 173 newspaper sources, compared to 468 newspaper sources from the Buzzfeed Far Right collection. To supplement the Far Right collection, I use two more collections, US Far Right and US Conspiracy, which are internally create Media Cloud collections.

For each collection, I made a query to the Media Cloud API from the same time period, the first 10 days in February, for the years 2016 to 2020. I chose this date and range because I wanted a snapshot from the same period each year, and for this period to be one with relatively few seasonal stories. I chose a ten day date range because the typical new cycle is well within this range. I also made no distinction for the type of media source and instead collected any online publication the Media Cloud collection gave as output. This query returned 2,064,388 urls total, an average of 147,456 per collection.

Because the partisanship categories I use in the project are crucial to my results, I cross checked the newspapers in the collections I used with Benkler et al's results for the most popular media on the left, center left, center, center right, and right and newspapers cited by Mudde as important to the far right [3, 30]. Of Benkler's 79 sources, 67% also appeared in our datasets. Heft identified 36 right-wing news sources, and only six of those appeared in our datasets. The classifications made by those academics largely overlapped with Media Cloud's classifications, with one exception. I use the term "overlapping" because most outlets express ideologies that could be slightly more or less partisan, and Media Cloud accommodates this by having the same outlet appear in multiple collections, although with different articles. To see this overlap broken down across partisanship category, see table 2. The exception to this general agreement between the collections I used and the academics' categorizations was the Media Cloud collection for US National News, which I had used as a source for the Center datasets. The collection in reality included sources from the full range of partisanships, like Fox News, Breitbart, and Mother Jones. I therefore removed the articles from this collection from the Center datasets and replaced them with news articles from the Centrist Media Cloud collection.

However, treating partisanship as an ordinal variable on a left to right spectrum still introduces a number of tenuous assumptions. First, political ideologies are far too complex to cleanly order on a linear spectrum. Second, the US American right wing media ecosystem is unique in its heavy right-leaning skew and insularity, therefore making the "Center Right" difficult to define [3]. Finally, the far left news media is far less robust than its right wing counterpart. This partisanship category was the only one for which I could not gather sufficient articles to meet my goal.

3.2.2 Newspaper Url Scraping

After collecting urls across year and partisanship, I scraped the full article text from as many of the urls as possible. I iterated through the list of urls collected from Media Cloud and first filtered out articles that Media Cloud designated as not in English and articles from newspapers that I marked as "never scrapeable." Never scrapeable newspapers either one, feature only video or photo content, two, included non-newspaper websites like Google or Itunes, or three, were on a list I created of thirty websites like "conservative101.com" and "learnprogress.org" that were no longer maintained. This filtering process eliminated a significant number of urls, as 26.7% of all collected urls were not in English.

With the filtered list of urls, I used requests, an open source package, and beautifulsoup to access the url and collect the html [33]. If I accessed multiple urls from the same website, I paused for a random number of seconds in between to prevent spamming the server. I checked the soup contents for 19 different error messages, like a server-side connection error, a cookies requirement, or text informing me that I was blocked from the website. If there was no error message, I tried getting the p tags from the html and if they were not available, I tried an alternative method, primarily getting the text content from a JSON object stored in the html. I then stored the error message or the successfully scraped text. For fixable errors, like a connection timeout, I ran the script a second time.

I had an overall success rate of 44%, with the best scrape rate coming from the Far Right datasets at 61% and the worst from the Left datasets at 30%. See figure 5 for a plot of the scrape success rate per Media Cloud collection. The most common reasons for failure to get the article text were that the text was not in English, a 404 error that the page was not found, and a 403 error that access to the page has not been authorized. For a breakdown of the top ten most common errors, see figure 4. I also manually evaluated 0.7% of the 257,170 scraping attempts and found a 90% precision and 95% recall.

Because my analysis relies on tracking narratives as they move across time, I conducted an analysis of the article publications times. I found that the publications times given by Media Cloud largely seemed authentic, as the times did grow more frequent on the hour, but varied in the appearance over the working day and appeared much less frequently at night. For a plot of the publications times of the articles by frequency, see table 6.

Despite a concerted effort to collect sufficient text for Far Left category, there simply were not enough articles in this partisanship category at the queried time to fill out the dataset. My attempt to resolve this issue included two steps: one, I extensively reviewed my error handling for these datasets to make sure I fixed every error possible, and two, I expanded my search query as much as possible within the limits of my study design. In reviewing the error handling, I found that the vast majority of the errors were 404 errors, 403 errors, or video/ image content errors, none of which are fixable. I widened my search query by querying for data not only on February 2nd, as with other datasets, but also on each of the following ten days. However, these efforts still did not result in 2,000 articles for each year. This insufficiency could affect my results as it prevents me from asserting the relative quality of each of the seven partisanship categories. However, this lack of data also suggests a confirmation of other research that holds that the American Far Left media environment is sparse, especially in comparison to the Far Right.

3.2.3 Outcome

At the end of this stage, I created a set of 30 datasets corresponding to seven different partisanships and five years. Each dataset contains 2,000 articles that were marked as successfully scraped, except for the Far Left datasets, which only contain between 760 and 1,298 articles. For the number of articles per partisanship and year, see table 3

3.3 Text Deconstruction Phase

At the start of the deconstruction phase, I have 65,844 newspaper articles spanning five years and seven partisanships. In following with other research in this field, I begin my pipeline with the assumption that to track patterns in such a large body of text, the text must first be broken down into its most essential elements, without sacrificing important qualities like tone. Therefore, in the deconstruction phase I apply a number of methods to the unstructured text, namely Binary Relation Extraction, Named Entity Disambiguation, and Coreference Resolution. For a visualization of the pipeline, see figure 1. In the end, I have a dense, informative representation of a sentence segment, which I call an enriched triplet.

Applying this deconstruction phase has a number of advantages. One, breaking the text into fragments further allows me to more accurately classify it by topic, when assigning a topic label to an article or even a paragraph would be misleading in many cases. The enriched triplet structure is also conducive to analysis, allowing for easy recall of the composition of a narrative in terms of vocabulary, and entities. While the inclusion of the deconstruction phase adds complexity to the pipeline, increasing computational expense and the likelihood that error will propagate through the pipeline, I focus on using efficient end-to-end methods and evaluate the different components where possible in an effort to minimize these two drawbacks.

3.3.1 Stanford CoreNLP

For the Binary Relation Extraction, Named Entity Identification, and Coreference Resolution, I use the Stanford Core NLP OpenIE model [25]. As input, I give the raw text of an article and as output, I receive a series of sentences fragments in JSON objects. These data points indicate the subject, object, and relation of the sentence fragment, the locations of these items, the entity locations in the sentence fragment, and a tokenized version of the sentence from which the sentence fragment originates. The coreference resolution is already completed during the running of the model, so any prononimals or nominals in the subject, relation, or object of the sentence fragment are replaced with their antecedent. For an example of what this process looks like, see figure 8. I package this information together with an id for the article and the sentence into a JSON object, which can be seen in figure 7.

3.4 Narrative Reconstruction Phase

After deconstructing the text into enriched triplets, I classify these triplets into four topics and identify narrative instances within these topics during the narrative reconstruction phase. Immigration, Islamophobia, antisemitism, and Transphobia are the four ideological topics on which I focus. The reconstruction phase consists of a two part classification process, vectorization of the enriched triplets, and clustering of the triplet embeddings into narrative instances.

In developing this second step of the pipeline, I tested two different approaches before deciding on the method that I implemented and will explain in this section. The approach ultimately chosen, involving vectorization and clustering, follows closely the pipeline presented by Tangherlini et al, with several innovations for the different context of this project [37]. I also considered an approach that mirrored Ceran's 2016 dissertation [9]. Ceran's approach relied on algorithms to reaggregate the deconstructed text, while Tangherlini et al take advantage of large language models and clustering. While the transparency and linguistic foundation of Ceran's approach initially appealed to me, the sophistication of the model created by Tangherlini et al ultimately made it the stronger approach and therefore serves as the basis for the narrative reconstruction phase.

In the following subsections, I first discuss the process for vectorizing the enriched triplets in 3.4.1. Next, I explain the keyword identification process that I used as the basis for my classification task in 3.4.2 and then the two-part classification task in section 3.4.3. Finally I explain how I identified narrative instances through K-means clustering in section 3.4.4.

3.4.1 Vectorization

To create the embeddings, I used bert-large-cased and passed the triplets through as if they were a single sentence [12].[2] To obtain a single embedding for each triplet, I averaged together the token embeddings.

[2]For example, if the triplet was (energy, is in, renewable) I would pass to the model as "[CLS] energy is in renewable [SEP]".

3.4.2 Keyword Identification Process

To be able to identify specific narratives in the sea of triplets, I first classify the triplets according to whether they belong to four categories: Transphobia, immigration, Islamophobia, and antisemitism. I do this by matching the triplets to keywords linked to these topics. These keywords should be linked only to situations in which the given topic is actually being discussed; that is to say, there should be as few false positives as possible.

Before deciding to use keywords as the foundation of my classification procedure, I considered a variety of other methods. I reviewed approaches to the issue of classifying categories within a dataset from research with goals similar to those of my own project, taking careful consideration for how to best limit injecting any personal bias. Common approaches include using a clustering method or LDA, training a classifier on an existing dataset, or relying on other variables from the data, like time [35, 2, 34, 21]. However, these approaches are unsatisfactory for my goals because I am aiming to identify content belonging to fairly specific topics. Ultimately, I decided that a straightforward manual keyword identification process would be the most reliable and transparent method.

I first manually classified 300 articles in my dataset according to whether they included rhetoric that related to Transphobia or trans issues, Islam or Islamophobia, antisemitism or Judaism, or immigration. To determine the classification, I followed a set of conservative classification rules, aiming to minimize false positives. These rules can be found in figure 9. During the manual classification process, each article then received as many classification tags as applied, as well as a label for which of the classification criterion were matched. Additionally, I identified any keywords that seemed to pertain to the category in question. This classified dataset can be reviewed upon request.

This classification process resulted in 165 keywords across all four topics. To ensure the relevance of these keywords, I passed them through an evaluation process. I randomly selected enriched triplets from my dataset and if a keyword appeared in the triplet, I evaluated whether the original sentence producing the triplet did in fact pertain to the classification category or not. In this step, I reviewed 1,435 enriched triplets. If the keyword pertained to the classification category 95% of the time, I added it to my final list of keywords, shown in table 4. Eighty-three keywords met this criterion, with the Immigration category having the most keywords at 31 and Transphobia having the fewest at 12.

This process, despite its effectiveness, has some limitations. For one, I am unable to estimate how many false negatives are present. If an important keyword has been left out of my dataset, I have no way of knowing beyond evaluating more of the dataset. Secondly, this process is a time-consuming manual task. Finally, I am not a subject matter expert on these four topics, so while I designed the process to limit injection of personal bias, it is possible that I am missing the expertise necessary to carry out this task more effectively.

3.4.3 Classification

Having captured embeddings for the triplets in my datasets, I then classified them according to the four topic categories aforementioned: trans issues or Transphobia, Islam or Islamophobia, antisemitism or Judaism, and immigration. I executed this classification in two steps: first, keyword string matching, and second, cosine similarity matching.

In the first step, keyword string matching, I iterated through the enriched triplets, noting when an identified keyword occurred in the triplet and saving it to a list corresponding to the topic category of the keyword. Importantly, this process allowed multiple category annotations for a single triplet. If no keyword appeared, I marked the triplet as unclassified. For a visualization of this process, see figure 16.

At the end of this process, an average of 887 triplets per dataset pertained to at least one category. The Immigration and Islamophobia categories overlapped most often and 1.5% of all triplets received more than one category annotation. The immigration category consistently had the most triplets across partisanship and year, while the Transphobia category had the least, with seven datasets containing less than 10 triplets in this category. For an overview of the number of triplets classified by this process, see figure 14. This distribution mirrored my expectation given my understanding of the popularity of each of these topics in public discourse.

Because of the strictness of the keyword matching step, it was important to also include a second classification step based on finding highly related triplets that did not include a specific keyword. Therefore, in the next step, I iterated through the remaining unclassified triplets. If the embedding of an unclassified triplet had a cosine similarity of greater than a certain threshold with a triplet that had already been classified in the keyword string matching process, I marked the triplet as also a part of the previously classified triplet's topic category. I ran the pipeline with two different thresholds: 0.97 and 0.985. The differences between these two thresholds are explained further in section 3.6.2.3. For an overview of the number of triplets classified with a 0.97 threshold, see figure 15.

3.4.4 Narrative Identification through K-means Clustering

Entering the final step of the pipeline, the enriched triplets extracted in the text deconstruction phase are categorized by partisanship, year, and topic, as shown in figure 25. With this breakdown, I proceed to the last step- narrative identification. This process consists of feeding the vectors for a topic into a K-means clustering algorithm, following the approach of Tangherlini et al in a similar context [37]. I tested a few other clustering algorithms, but K-means returned the best results for my large datasets with quite a few outliers. The clusters that result from the algorithm serve as narratives instances, the subcomponents of narratives.

Because of the vast quantities of data in use for this project, optimizing the K-means clustering individually for each clustering analysis was infeasible. Instead, I ran the pipeline through with the number of clusters for each analysis set to either 20% of the data points or 30% of the data points. I explain the evaluation for this parameter further in section 3.6.2.4

Therefore, at the end of this process I have four sets of results, having run the pipeline on two different classification thresholds and two different Kmeans clustering thresholds. This breakdown is visualized in figure 10. Within each of these sets, I have a clustering analysis for each topic, resulting in 140 different clustering analyses. As described earlier in section 3.1, the clusters within these clustering analyses represent narrative instances, which, when united, make up the narratives that serve as the center of my analysis.

3.5 Tracking

The ultimate goal of this method is to systematically identify narratives that move from the marginal to the mainstream, focusing specifically on the anti-immigration, Islamophobic, antisemitic, or Transphobic far right narratives. In this section, I explain exactly how this "tracking" element is executed given the narrative instances identified in the previous step.

First, I isolate marginal narratives as the starting point of the tracking procedure. Marginal narratives, as defined in section 3.1, are narratives whose first instance in my dataset is in the Far Right. I use marginal narratives as the starter narratives for the tracking process in order to be able to effectively mimic a starting point for mainstreaming, although in reality, many of the narratives that "start" in my dataset also exist in years previous to the beginning of my datasets in 2016. This procedure can be seen in the left two boxes of figure 26.

In this marginal narrative identification process and the later tracking steps, I use the centers of the clusters calculated during the Kmeans clustering as a representative of each narrative. In Kmeans, centroids are averages of the data points from their cluster and not an actual data point. For this purpose, the centroid works well as a point of comparison therefore, capturing the general semantic meaning of the several vectors in its cluster.

To identify the starter marginal narratives in the Far Right, I take a single cluster from a far right dataset and then iterate through the clusters of the datasets of all partisanships from the same year or earlier. If there is a cosine similarity of greater than 0.97 between the two clusters, then I consider them to be the same narrative, and therefore that narrative did not start in the Far Right, If there are not any matches, then I consider the query narrative to be "starting" in the Far Right. The Immigration category has the most marginal narratives, regardless of the parameter changes to the pipeline and the Transphobia category has the least, as seen in figure

28. The pipelines with a higher number of clusters also generated more marginal narratives than their counterparts.

Next, given these marginal narratives that start in the Far Right, I look for similar clusters that appear in later years across partisanships. If there is a match, I save it, considering it to be essentially the same narrative, just adapted to the year and partisanship it now appears in. This process can be seen in the middle two boxes of figure 26. I call these narrative instances that match directly to the marginal starter narrative "direct matches," and they can be seen in the middle column in figure 27 and in blue in figure 2.

I repeat this process a second time, using the direct matches from the first process as the inputs, looking for matches they have in later years and other partisanships. I call these "peripheral matches." They are indicated in orange in figure 2, in the far right column in figure 27, and in the last two columns of figure 26. This way, I can observe how a narrative changes as it laundered through a different partisan and time context.

At the end of this process, I have three stages of narratives: marginal Far Right narratives, direct matches, and peripheral matches. Their frequencies across different pipeline modifications can be seen in figure 29. Having tracking extremist narratives as they move across partisanship and year, I can turn to testing my hypothesis and answering my research questions.

3.6 Evaluation

Given the complexity and novelty of my pipeline, an extensive evaluation was necessary to be confident in my interpretation of its output. In this section, I review each element of my pipeline through manual evaluation, comparison with the literature, and a system of discerning metrics. I start by reviewing the text deconstruction phase in subsection 3.6.1 and then explore the narrative reconstruction phase in subsection 3.6.2.

3.6.1 Text Deconstruction Phase

The text deconstruction phase of the pipeline relied on two models which have already been evaluated in the respective papers in which they were presented, so my analysis of their participation in my pipeline focused mostly on my implementation. In other words, the evaluation I conducted of this section of the pipeline operated on the assumption that the way to minimize error and achieve the highest quality possible would be to ensure that I used the models as precisely as possible. In the following subsections, I explain exactly what this evaluation entailed.

3.6.1.1 Stanford CoreNLP

The Stanford CoreNLP model has been successfully evaluated and widely used, so I conducted only a brief analysis of its effectiveness, focusing primarily on my implementation of it. This evaluation revealed 1,284 instances in which a badly scraped article had been given as input, mostly coming from the Center Left and Far Right datasets, which were run at the beginning of my data collection process and therefore fewer expected errors were handled. I managed this issue by removing the bad articles from the datasets and replacing them with a new batch of articles. These bad articles were identifiable because they were either not in English, or did not include traditional sentences but instead miscellaneous text from the source website. The model consequently would not run on these articles. I also reviewed 1,072 errors output by the model. These errors came in two forms: one, a CoreNLP request time out and two, a number of characters in the input article that exceeded the maximum length handled by the model. I handled both of these errors by splitting the article and running the model on the fragments of the article separately.

3.6.2 Narrative Reconstruction Phase

To properly evaluate the narrative reconstruction phase, I conducted manual evaluations of elements of the vectorization method, keyword matching method, and developed a set of metrics to evaluate the effectiveness of the cosine classification method and Kmeans clustering. The complexity of evaluating the cosine classification and Kmeans clustering methods ultimately led me to choose two parameters from each of these methods to run the complete pipeline on, in order to continue the evaluation of these approaches with a complete set of results.

3.6.2.1 BERT Vectorization

Given that vectorizing text with BERT is an established method, the relevant element to evaluate was primarily how to feed the triplet text to the model in a way that maximized its ability to match vectors based on their similarity. Initially I theorized that passing the triplet with [SEP] tokens between each element in the triplet would improve my capacity to compare the embeddings. However, in a limited evaluation manually comparing each method's effectiveness at finding similar vectors, passing the triplet through BERT as if it were a sentence performed 1.6 times better than using the [SEP] tokens. I conducted this evaluation by vectorizing a sample of my text in both ways. Then, I matched all of the vectors to their most similar companion in terms of cosine similarity in the sample. Approximately 10% of the time, the two methods matched the same vectors to each other. For the remaining vectors, I blindly manually evaluated which vector pairs matched better.

This procedure ultimately found that passing the triplet as if it were a sentence performed better.

3.6.2.2 Keyword Matching Classification

To limit the propagation of error throughout the pipeline, I conducted a brief manual evaluation of the keyword matching step. I manually reviewed 200 triplets, noting if the labeled category or lack of label was correct or incorrect. This process resulted in a perfect precision and recall; I was unable to find any cases in which a keyword match resulted in a false classification.

3.6.2.3 Cosine Classification

To determine the correct cosine similarity threshold for this process, I tested a range of thresholds and created four different metrics to evaluate the success of these thresholds. First, I determined how many of the triplets that were matched through the cosine matching process contained a keyword in their source sentence. Second, I manually evaluated a sample of the triplets that went through the cosine matching process to determine if they matched or did not match the label or lack of label given. Third, I ascertained the percent of shared vocabulary between the triplets matched in the cosine matching process and the previously classified triplets with which they matched. Fourth, I reviewed the silhouette score of the clustering analysis performed on the results of the cosine matching process.

For the first metric regarding the existence of a keyword in the source sentence of a triplet, I tested a cosine similarity threshold of 0.97 and 0.985. With a threshold of 0.97, the percent of classified triplets with a keyword in the source sentence ranged from 1.7% to 66.7%, averaging significantly lower than with the 0.985 threshold which ranged from 43% to 67%. This percentage also appeared to differ slightly across the four topics of interest, as can be seen in figure 14.

The second metric, the manual evaluation, I conducted by creating a sample of triplets that did not include a keyword in their source sentence, in order to gain a better perspective on the results reviewed by the first metric. I evaluated 230 samples total for the thresholds 0.97, 0.975, 0.98, and 0.985. The 0.97 and 0.975 thresholds performed worse than the 0.98 and 0.985 thresholds, as shown in figure 18.

For the third metric, I used the same data as the manual evaluation - triplets that did not contain a keyword in their source sentence. Among these triplets, I identified what percent of the text in these triplets was shared exactly with the previously classified triplet with which it matched. For example, if the classified triplet was <immigration, increases, 2016> and the matched triplet was <mexican tourism, increases, 2016> two thirds of the text match exactly. This percentage generally tended to rise as the threshold rose, as demonstrated in figure 19.

For the final metric I reviewed the effect the change in threshold had on the next step in the pipeline - clustering the text via Kmeans. The lower threshold corresponded to a higher silhouette score from the clustering analysis across all topics, as shown in figures 21 and 20.

Ultimately these metrics did not reveal a clear partiality between the 0.97 and 0.985 cosine threshold. The manual evaluation lends the greatest support to a higher threshold, but the silhouette scores tend to be higher with a lower threshold. The keyword-in-sentence metric and the shared text metric can be interpreted either way. A higher threshold ensures that only text that is very likely to be related, but homogeneous, is added to the dataset, decreasing the number of false negatives. A lower threshold allows for more flexibility in the vocabulary, but introduces the possibility of more false positives. Because of these arguments, I elected to run the pipeline through completely with two different similarity thresholds: 0.97 and 0.985.

3.6.2.4 Kmeans Clustering Evaluation

As I conduct a clustering analysis for 140 different intersections of year, partisanship, and topic, optimizing the clustering for each dataset was infeasible. Therefore, I conducted an evaluation of different cluster numbers to how to best generalize the number of clusters across datasets. After a brief manual evaluation, I decided to test two scores thoroughly: setting the number of clusters to either 20% or 30% of the dataset in the clustering analysis. Then, for each clustering I calculated the silhouette score and the degree of verb diversity and origin sentence diversity within each cluster. Sentence and verb diversity are crucial metrics in this case as representations of overfitting, providing a balance to the silhouette score. I calculate the degree of sentence diversity by finding the number of unique sentence ids divided by the total number of sentence ids in each cluster, while I calculated the degree of verb diversity as the number of unique verbs divided by the total number of verbs in a cluster.

Across topics, the silhouette score is higher on average with a greater number of clusters, as demonstrated in figure 22. As shown in figures 23 and 24 the clustering analysis with the higher number of clusters also scored higher on sentence diversity and verb diversity than the lower clustering, suggesting that the higher clustering may overall be the stronger option. However, a brief manual evaluation suggested that the clusters that resulted from the lower number of clusters may better suit the conceptual goal of equating the clusters to narrative instances. This ambiguity was strong enough that I ultimately decided to run the pipeline on both the 20% and 30% clustering parameters.

CHAPTER 4

Experimental Design and Results

Having developed a pipeline capable of identifying and tracking extremist narratives, in this chapter I first explain the experimental design I developed to apply the pipeline to my hypothesis and research questions, and second review the results of this application.

4.1 Experimental Design

For my experimental design, I test one main hypothesis and then seek to answer two research questions. In this section, I explain how I test my hypothesis that Far Right narratives have been mainstreamed and answer my questions regarding the important actors in the mainstreaming process and how the mainstreamed narratives evolve as they move from away from the fringes and towards public acceptance.

4.1.1 Hypothesis: Far Right Narratives are Mainstreamed

The primary goal of the development of this narrative extraction method is to test whether narratives can be tracked as they move from the marginal to the mainstream. In this section, I explain how I tested and confirmed this hypothesis.

As previously asserted, my conceptual definition of a mainstreamed extremist narrative is a narrative that shifts in the view of the public from being recognized and treated as marginal towards being deemed acceptable, formally put in definition 2. In the tracking phase, I identified marginal narratives by pinpointing which narrative instances from the Far Right datasets had no matches to narrative instances from other datasets in earlier years. Therefore, by existing only in the far right dataset, I can inductively reason that they are marginal.

Having determined which narratives are marginal, I then suggest that a marginal narrative is mainstreamed if its matches in later years have widespread partisanship promotion. To operationalize this further, I assert that the candidate narrative must clear a threshold of having least 50% of its matching narrative instances, both direct and peripheral, be in the center three partisanships (Center Left, Center, and Center Right). So, to identify mainstreamed marginal narratives, I must identify the intersection of mainstreamed narratives and marginal narratives, as indicated in figure 31.

I identify this intersection by first, testing the direct matches of each marginal narrative against my threshold and second, testing the peripheral matches against the threshold. For a visualization of this process, see figure 27. In this way, I allow for a mainstreaming process that allows for a range of evolution of the narrative. However, for the purpose of my analysis, I rely more heavily on the direct matches, as the peripheral matches leave more room for interpretation when it comes to whether they are actually still representations of marginal narratives.

4.1.2 RQ 1a: Which newspapers push marginal narratives to the mainstream?

After confirming my primary hypothesis that far right marginal narratives are being mainstreamed, I propose to answer the first half of my first question of analysis: which far right newspapers are most successful at launching a marginal narrative to the mainstream? Understanding the actors on the Far Right that are the most prolific and most efficient is an important part of understanding the mainstreaming process and this computational approach allows a unique perspective into the patterns of influence at play. I stop short of trying to establish a causal relationship, instead focusing on identifying patterns in the data.

I answer this question by identifying candidate newspapers, evaluating whether they have successfully launched marginal narratives, and ranking the newspaper according to the degree to which they succeed. Candidate newspapers are any newspaper that contribute to a marginal narrative, meaning that enriched triplets from one of their articles forms a part of the marginal narrative cluster. Newspapers successful at mainstreaming are therefore newspapers that contribute to a marginal narrative that is also a mainstreamed narrative.

Ultimately, two consequential metrics encapsulate the answer to this question: one, the number of mainstreamed narratives to which a newspaper contributes in absolute terms, formally put in definition 3 and two, the number of mainstreamed narratives to which a newspaper contributes relative to the number of articles the newspaper publishes, formally put in definition 4. In this way, I measure how prolific and how efficient a newspaper is at pushing narratives into the mainstream.

4.1.3 RQ 1b: Which newspapers pull marginal narratives to the mainstream?

The mainstreaming process occurs not only when marginal actors "push" their narratives towards the mainstream, but also when mainstream actors and partisan actors from the opposite partisanship collaborate in platforming their narratives. Therefore, another important task in my exploration of the mainstreaming of marginal narratives is the identification of mainstream and partisan actors that contribute to the mainstreaming process.

To identify these "pull" actors, I determine which newspapers contribute to narrative instances of a mainstreamed marginal narrative. These newspapers cover the partisan spectrum; while I consider a narrative's appearance in the centrist partisanships to be evidence of its mainstreaming, many mainstreamed marginal narratives also continue to appear in left wing and right wing media. Among the direct matches in the marginal mainstreamed narrative, I identify the centrist newspapers and the partisan newspapers that platform a marginal mainstreamed narrative the most, both in absolute terms and relative to the number of articles that newspaper published in the given time frame and topic. I also review the newspapers that contribute to peripheral matches of the mainstreamed marginal narratives. For these newspapers, I calculate the same metric as for the direct matches.

4.1.4 RQ 2

My final research question aims to identify trends in the content of the mainstreamed narratives. This question is based on the assumption that as a marginal narrative moves from the partisan fringes to the center, the vocabulary, emotionality, or other contents may evolve.

To answer this question, I focus on the named entities identified in the deconstruction phase of the pipeline and track their evolution through three metrics. One, I determine the number of named entities generated in the marginal, direct, and peripheral stages of the narrative. Two, I measured the overlap of the named entities between the marginal narrative instances of the narratives and the direct and peripheral narrative instances of the narratives with the Szymkiewicz–Simpson coefficient, or overlap coefficient. Third, and most importantly, I identify the named entities that appear most frequently across narratives in each of these stages and which entities are unique to each stage.

4.2 Results

Through a careful execution of the experimental design outlined in the previous section, I generated four sets of results which I will explain in this section and in figures 32 through 43.

As discussed in subsections 3.4.3 and 3.4.4, evaluating my pipeline led me to chose four different sets of parameters. Optimizing Kmeans for this application represents a significant challenge, so I chose to run my dataset with two different numbers of clusters: 0.2 times the size of the dataset and 0.3 times the size of the dataset. In the following sections, the results that are labelled as having "fewer clusters" indicate the data run with 0.2, while "more clusters" refers to the data run with 0.3.

Additionally, extending the classification task by automatically classifying related vectors led to the inclusion of some false positives with a low cosine threshold. Therefore, I ran my datasets with two different thresholds for this task, 0.97 and 0.985, and in the following sections this data is referred to as "lower classification threshold" and "higher classification threshold" respectively.

Within each set of results, I will explain the outcomes of testing my hypothesis and answering my two research questions.

4.2.1 Fewer Clusters, Lower Classification Threshold

4.2.1.1 Hypothesis: Far Right Narratives are Mainstreamed

For the pipeline with a lower number of clusters and a lower classification threshold, about 2% of the marginal narratives identified were mainstreamed, as shown in figure 32 which summarizes the results of the pipeline. Approximately half of the marginal narratives in this pipeline were from the 2016 year, although no Transphobic marginal narratives were identified in 2016. Only 32 marginal narratives from the Transphobia category were identified, none of which were mainstreamed. In each year, about half of the marginal narratives identified were from the immigration category, and 61% of the total mainstreamed narratives came from the immigration category. Furthermore, only one of the mainstreamed narratives, from the Islamophobia category, reached this status in the peripheral step, despite a high number of peripheral matches to the marginal narratives.

An example of a mainstreamed immigration narrative from this category begins in 2016 in the Far Right with a narrative instance discussing Trump's planned hardline immigration reform. This narrative instance matches to a Center Right 2017 narrative instance discussing specifically Trump issuing an executive order on immigration. Then, in peripheral matches, narrative instances in the Center Right continue this discussion while Far Left narrative instances discuss Trump's racist or restrictive immigration reform.

4.2.1.2 RQ1a

Across each year and for the immigration and Islamophobia topics, Breitbart contributed to the most mainstreamed narratives, as listed in tables 5 and 6. Church Militant, Center for Security Policy, and humansarefree.com were the most efficient in mainstreaming narratives in the categories immigration, Islamophobia, and antisemitism, respectively.

For the immigration category, Breitbart dominated the production of marginal and mainstreamed narratives. Each year from 2016 to 2019, Breitbart was the most frequent contributor to marginal narratives, contributing to almost 3.5 times more narratives than the second most common newspaper in each year. It also contributed largely to the mainstreamed narratives, along with Clash Daily, Washington Times, and VDARE also appeared frequently in these narratives.

In 2016, Breitbart again contributed heavily to Islamophobic marginal narratives, but in later years faded in significance. Clash Daily continued to be a significant contributor to these narratives, as well as other publications like Shoebat, The Real Side, and Washington Times. However, for the narratives mainstreamed in the direct step, the largest contributors were Right Wing News and Breitbart. For the second step, the only contributors were Breitbart and The Real Side.

For the antisemitism category, Breitbart's contribution followed a similar pattern to that of the Islamophobia category; in 2016 it produced more marginal narratives than any other newspaper, but in later years its influence was not as notable. Other significant contributors to antisemitic marginal narratives are The Truth Seeker, Right Side News, nsm88.org, and truthandaction.org. Unsurprisingly, several of the newspapers making content for this category openly express support for Nazism, like nsm88.org, as its title alone is a Nazi dog-whistle. Breitbart contributed more than any other newspaper to the narratives that were mainstreamed in the direct step for this category, followed by Newsmax and The Truth Seeker. Among narratives mainstreamed in the second step, Breitbart, Washington Times, and Newsmax equally contributed more than any other newspaper.

As so few marginal Transphobia narratives were identified, it follows that very few newspaper contributed to these narratives. Need to Know News, Right Wing News, Blaze and Conservative Daily Post each contributed to the marginal narratives, although none of these were mainstreamed.

Some notable Far Right newspapers did not contribute at all to the marginal narratives of these topics. Fox News, the Blaze, and Conservative Fighters all contributed to tens of narratives, particularly in 2017 and 2018, and none of them were deemed marginal.

4.2.1.3 RQ 1b

In the immigration category, 26 different newspapers from the Far Right and Right contributed to narrative instances of a mainstreamed marginal narrative, apart from the original marginal instance.From the Far Left and Left, 22 newspapers contributed to marginal mainstreamed narratives, with the most prolific being Media Matters, Salon, and Truth Dig. The Center three partisanships housed the most newspaper diversity in this category, however, with 93 newspapers contributing to mainstreamed narratives. Of the Centrist newspapers, NBC Breaking News and ruvr-fi, which is a Russian state broadcaster contributed to the most mainstreamed marginal immigration narratives. Relative to the number of articles published, Politico was the Centrist newspaper that platformed the most marginal narratives in this category.

For the Islamophobia category, no right wing or left wing newspapers contributed to mainstreamed narratives. From the Centrist partisanships, the Center Left newspapers contributed more than the other two partisanships, led by the Guardian US in absolute terms and Punch in relative terms. These contributions were heavier in 2016 than in any other year.

Among the mainstreamed antisemitic narratives, from the partisan outlets OpEd News contributed the most in absolute terms, while Common Dreams contributed the most in relative terms. Both of these publications come from the Far Left. From the Centrist publications, thirty different newspapers contributed to mainstreamed narratives, led by Haaretz in absolute terms, and Spiegel in relative terms.

4.2.1.4 RQ 2

In this set of results, narratives from the immigration category produced the highest number of named entities in their narratives, although these named entities were not consistently shared between different narrative instances of the same narrative. The antisemitism category had more narratives sharing named entities between instances, as seen in figure 37, although this percentage was still fairly low.

The immigration category had the largest number of mainstreamed narratives and also a relatively high number of named entities in its narrative instances. Entities like "Trump" and "Donald Trump" had high relevance in 2016, during the election year, but less in later years. The top entities also tended to peak in appearances in the Center partisanship, with little evidence of words appearing predominantly in one partisanship. While the marginal and mainstreamed narrative instances overlapped little overall, words for Trump and "president" were some of the most frequent across both marginal and mainstreamed narrative instances. On the other hand, "American(s)," "America," and "Muslim" appeared across many marginal narrative instances, while these word did not appear at all in direct or mainstreamed narrative instances.

The Islamophobia category held few named entities, with the most frequently appearing ones being "Muslims," "Muslim," and "Sunni," appearing mostly in 2016. This category had a slightly higher overlap coefficient than the immigration category, but still quite low. Still, words for Muslims appeared frequently in marginal, direct, and peripheral narrative instances. The most frequent entities from marginal narratives that did not appear in direct or peripheral iterations were "Islamists," "American," "Christian," and "Americans."

The antisemitism category had the highest average overlap coefficient, at 0.266, and its most frequent entities, "Jewish" and "Jews" appeared very frequently in the mainstreamed marginal narratives across narrative instances. The top entities tended to appear more frequently in the left wing narrative instances than in the right wing instances, with the exception of the entity "Jew." The entity "jew" in fact only appeared in marginal narratives, where it appeared frequently across different narratives. On the other hand, entities like "Israeli" and "Palestinians" occurred only in direct matches to marginal narratives, and never in marginal narratives themselves.

4.2.2 More Clusters, Lower Classification Threshold

4.2.2.1 Hypothesis: Far Right Narratives are Mainstreamed

Across the years examined, clear trends emerged within this set of results, which are summarized in figure 33. This pipeline had more narrative instances overall than the previously discussed pipeline, but still over half of the marginal and mainstreamed narratives identified came from the immigration category. However, the antisemitism category had the most narratives mainstreamed proportional to the number of marginal narratives for each year in this set of results. Of all the pipelines, this one also had the highest number of Islamophobic narratives mainstreamed, although this still only included seven narratives. None of the 60 marginal Transphobic narratives were mainstreamed.

An example of a mainstreamed narrative from the Islamophobia category in this set of results begins in the 2016 Far Right section by an opaque discussion of the "world of Muslims." This narrative instance then matches directly to a discussion of jihadists in the Center Right in 2017 and further discussion of the world of Muslims in the Center Left in 2017.

4.2.2.2 RQ1a

For the top actors responsible for creating the marginal narratives instances of mainstreamed narratives, see tables 9 and 10.

As with the previous set of results, Breitbart dominated the production of marginal immigration narratives, appearing over three times as often as the second most common newspaper for each year. Other newspapers also contributed heavily, including Washington Times, CIS, the National Review, and Newsmax. This pattern largely continued on in the narratives that were mainstreamed in the direct step, as Breitbart contributed to the most mainstreamed narratives, followed by Washington Times and Shoebat. Among narratives mainstreamed in two steps, Breitbart was again the largest contributor, followed by Washington Times, National Review, and The Truth Seeker. Relative to the number of articles produced, the Conservative Daily Post ranked highest.

For the Islamophobia category, Breitbart was the most common newspaper for the 2016 and 2018 years and the second most common in 2019. Other publications like Shoebat, Washington Times, The Real Side, Clash Daily, and pamelageller.com also contributed heavily. Shoebat, Washington Times, and The Real Side contributed to the most narratives mainstreamed in the direct step. Across the years, Shoebat contributed to the most narratives mainstreamed in the firs step in absolute terms, and The Real Side contributed to the most relative to the number of articles produced. For narratives mainstreamed in the second step, Breitbart contributed the most, followed by Shoebat and The Real Side.

The antisemitism category was more evenly split among different publications, with Breitbart producing the most marginal narratives in 2016, the American Thinker producing the most in 2017, nsm88.org producing the most in 2018, and Right Side News producing the most in 2019. The Truth Seeker also contributed heavily. For narratives mainstreamed in both the first and second steps, Breitbart was the largest contributor in 2016, while Newsmax was the largest contributor in 2017. Overall, Breitbart contributed to the most directly mainstreamed narratives in absolute terms, while humansarefree.com contributed to the most in relative terms.

Finally, Transphobic marginal narratives were published by a smaller handful of publications, most notably the Western Journalism Center, the Conservative Daily Post, Right Wing News, and Gateway Pundit. None of these narratives were mainstreamed.

4.2.2.3 RQ1b

In this version of the pipeline, a range of newspapers contributed minimally to platforming the mainstreamed narratives, with no newspapers clearly rising to the top in terms of their role in this process. For a summary of the results in the section, see tables 11 and 12.

From the immigration category, 41 newspapers from the partisan newspapers contributed to mainstreamed narratives. Breitbart and rewire.news contributed to the most mainstreamed marginal immigration narratives in absolute terms from the partisan newspapers and Fair Us contributed the most in relative terms. Ninety-four newspaper from the centrist partisanships contributed to these narratives, almost all of them contributing only minimally. Overall, the Washington Post contributed most in absolute terms while the Montreal Gazette contributed most relatively.

While no newspapers from the left wing contributed to narratives in the Islamophobia category, 13 newspapers from the right wing contributed to the mainstreamed narratives, led by SGT Report and the Real Side. Newspapers from the Center Right dominated the platforming of these mainstreamed narratives, with ruvr-fi contributed the most in absolute terms while Punch contributed the most in relative terms.

The antisemitism category had the a high degree of newspaper diversity, with 94 newspapers contributing to the mainstreamed narratives. Thirty-five of these newspapers came from partisan outlets, with OpEd News from the Far Left, contributing the most in absolute terms, while creation.com from the Far Right contributed the most in absolute terms. From the Centrist papers, Haaretz dominated the contributions to mainstreamed marginal narrative in absolute terms, particularly in 2016 and to a lesser degree in 2017 and 2018. Spiegel led the platforming in relative terms.

4.2.2.4 RQ2

In this section, the antisemitism narratives had the highest degree of overlap between named entities in the marginal and mainstreamed narratives, but all three categories displayed evidence that the entities of the narrative were evolving through the mainstreaming process.

From the mainstreamed immigration narratives, there was little overlap between the mainstreamed and marginal narratives. From the mainstreamed narrative instances, the entities tended to appear most frequently in the Center partisanship and in the years 2016 and 2018. In the marginal, direct, and peripheral narratives, words for Trump and president occurred frequently across narratives instances. Unique to the marginal narratives, but frequently occurring there, were the entities "America," "Muslim," and "Obama," among others.

The Islamophobia category had a slightly large overlap coefficient than the immigration category, with some of the most frequent entities, like "Muslim," "Muslims," and "President" appearing in several years and across marginal, direct, and peripheral narrative instances. Several of the most common entities also appeared more frequently on the right wing than the left, including "Muslim," "Muslims," "Islam," and "Islamists." In fact, few words appeared uniquely in the marginal, direct, or peripheral categories.

The mainstreamed narratives in the antisemitism category contained fewer named entities than the previous categories. Some entities did appear in almost every partisanship category, but peaked in the Center. This category also had the highest overlap coefficient, which is explained by the fact that most of the most frequently appearing words across the marginal and direct narrative instances were shared. Still, words like "jew," "president," and "Christians" appeared only in the marginal narratives.

4.2.3 Fewer Clusters, Higher Classification Threshold

4.2.3.1 Hypothesis: Far Right Narratives are Mainstreamed

Under this set of results, 2.2% of the 737 marginal narratives identified were mainstreamed. The flow of narratives from marginal to mainstreamed categories can be seen in figure 34. This pipeline stood out compare to other in that it had the lowest number of marginal narratives identified for all years and partisanships. As with the other pipeline, the immigration category dominated the number of marginal, making up 48% of the marginal narratives and 69% of the mainstreamed narratives. More narratives were mainstreamed in the peripheral stage for this set of results than other pipeline, with peripherally mainstreamed narratives making up 27% of the mainstreamed narratives. While 13 marginal narratives in the Transphobia category were identified, none of them were mainstreamed.

An example mainstreamed narrative from this dataset starts with a marginal narrative instance in the Far Right 2018 dataset by discussing how migration from South America is high and a problem. It is then mainstreamed through a direct match to a Center Left 2019 narrative instance that discusses the impact of migration and the building of the southern border wall.

4.2.3.2 RQ 1a

For the immigration category, Breitbart contributed to the most marginal narratives every year. Clash Daily, CIS, and Newsmax contributed the second-most marginal narratives across each year, although this contribution was markedly less than Breitbart's. Breitbart also led in narratives mainstreamed in the direct step and second step for each year and overall in absolute terms. Relative to the number of articles, freedomforce.com ranked highest for most narratives mainstreamed.

Breitbart again contributed to the most marginal narratives for the years 2016 and 2018 in the Islamophobia category, while 2017 and 2019 were led by Clash Daily and Newsmax respectively. Shoebat, however, contributed to the most narratives mainstreamed in the direct step overall. The Real Side contributed to the most mainstreamed marginal narratives relative to the number of articles it produced in this category.

Among the antisemitic marginal narratives, Truth and Action, Nazi website nsm88.org, Right Side News, and Breitbart led each year in the production of marginal narratives. No narratives were mainstreamed from this category in the direct step. In the second step, Breitbart and humansarefree.com were the only contributors to a mainstreamed marginal narrative.

Blaze and Need to Know News led the production of marginal Transphobic narratives, although very few marginal Transphobic narratives were identified. Right Wing News and iotwreport.com were the only publications to contribute to a mainstreamed narrative, and Right Wing News ranked highest in both absolute and relative terms in its production of mainstreamed marginal narratives.

Under this set of parameters for the pipeline, the Washington Times contributed to 531 narratives in 2018 and 144 in 2019, none of which were deemed marginal. Fox News also contributed to 51 narratives in 2016 and 2017 combined, but none of these reached marginal status either.

4.2.3.3 RQ 1b

Under this set of parameters in the pipeline, only narratives from the immigration and Islamophobia categories were mainstreamed and very few newspapers contributed to these narratives. The newspaper that did platform these narratives contributed very evenly, so no newspapers appear to substantially "pull" marginal newspapers to the mainstream. For a summary of these results, see tables 15 and 16.

The immigration category for this set of results had little evidence of influential newspapers pulling marginal newspapers to the mainstream. Fifty-nine newspapers contributed to these narratives, all minimally. From the partisan newspapers, Counter Currents from the Far Left contributed the most in absolute terms, while US Defense Watch from the Far Right contributed the most in relative terms. From the Centrist newspapers, only newspapers from the Center and Center Right contributed, with the Standard contributing the most in absolute terms, while Newsday contributed the most in relative terms.

The Islamophobia category had still less representation in this category, with only 13 newspapers contributing to the mainstreamed narratives. These newspapers only came from the Far Left, Center Left, and Center, and all contributed evenly to the mainstreamed narratives in 2016 and 2017.

4.2.3.4 RQ 2

In the pipeline, the named entities in each category overlapped to a relatively high degree, showing the similarities between the marginal and mainstreamed narrative instances, but giving less of a clue into how the narratives evolve.

In the immigration category, named entities appeared more frequently across almost every partisanship category than in other topics, although the number of unique entities per narrative instance is lower than other categories. Overall, the immigration category had the lowest overlap between named entities in the marginal and mainstreamed narrative instances, although "Trump" still appears frequently in both direct and marginal narrative instances. There are also very few entities that are unique to the marginal, direct, or peripheral categories.

The Islamophobia category had the highest overlap coefficient of the topics in this set of results, with words like "Muslims," "Islam," and "Muslim" appearing across many narrative instances in the marginal and direct steps. Mostly narrative instances from the Center and left wing contributed to the named entities in the Islamophobia category. Only a few words appeared frequently in marginal narrative instances without also appearing in direct narrative instances, specifically "Islamists," "Sunni," and "Obama."

The antisemitism category had an even range of named entities from each partisanship category, with descriptive entities like "Jewish" appearing across marginal, direct, and peripheral stages. However, the entities "Jews" and "Judaism" appeared only in marginal narrative instances.

4.2.4 More Clusters, Higher Classification Threshold

4.2.4.1 Hypothesis: Far Right Narratives are Mainstreamed

Under these parameters, only nine narratives total from the immigration and antisemitism category were mainstreamed. The summarized results can be seen in figure 35. In total 1,089 marginal narratives were identified from every topic, although again mostly from the immigration category, but this pipeline had the lower proportion of mainstreamed narratives of all the pipelines. Also, while the Antisemitism and Islamophobia categories had similar numbers of marginal narratives, only antisemitic narratives were found to have been mainstreamed. This pipeline's internal consistency was high in that all of the narratives that were mainstreamed in the direct stage were also mainstreamed in the peripheral stage.

An example mainstreamed narrative from the immigration category begins the the Far Right in 2016 by discussing migrant men and attacks by migrants. It then matches directly to a Center Right 2019 narrative instance that discusses immigration authorities and migrants committing rape. Finally, in the peripheral stage some Center Left narrative instances discuss immigration authorities and visa permissions.

4.2.4.2 RQ 1a

For a summary of the most important newspapers in pushing marginal narratives in the set of results, see tables 17 and 18.

Breitbart contributed to the most immigration-related marginal narratives for each year in the datasets. The next largest contributors were the National Review, the Washington Times, and the Clash Daily. The only narrative mainstreamed in the direct step in this category came from the 2016 dataset, and those narratives were created mostly by Breitbart, ranking it the highest contributor overall in absolute terms. The next largest contributors were Shoebat and Washington Times, with Shoebat contributing to the most mainstreamed marginal narratives relative to the number of articles. In the second step, Breitbart led the contribution to the mainstreamed narrative, along with a handful of other publications including the Washington Times and rushlimbaugh.com.

For Islamophobic marginal narratives, Breitbart contributed the most in 2016 and 2018, while The Real Side and pamelageller.com contributed the most in 2017 and 2019 respectively. Breitbart, Clash Daily and Shoebat contributed to the mainstreamed narratives that came out of the 2016 in this topic, with Breitbart contributing the most in absolute terms and Clash Daily in relative terms.

For 2016 to 2019, Breitbart, the American Thinker, nsm88.org, and Right Side News respectively contributed to the most marginal narratives in the antisemitic category. Only five newspapers contributed to the narratives that were mainstreamed in the direct step, namely The Truth Seeker, Breitbart, humansarefree.com, ipatriot.com, and radixjournal.com. For the narrative mainstreamed in the second step, Breitbart and humansarefree.com were the only contributors.

Few marginal narratives were identified in the Transphobic category and they were fairly equally contributed to by a small list of newspapers, including Blaze, Breitbart, Newsmax, and Gateway Pundit. Right Wing News and iotwreport contributed to the narrative mainstreamed in the direct step and Right Wing News ultimately contributed to the most mainstreamed narratives in absolute and relative terms.

As in other other sets of results, some notable publications from the Far Right were not deemed to have contributed any marginal narratives. Fox News contributed to 51 narratives in 2016 and 2017, but none of them were marginal. For every year in the dataset, the American Free Press, prisonplanet.com, The Sean Hannity Show, and Fellowship of the Minds contributed narratives that were not marginal.

4.2.4.3 RQ 1b

Very few newspapers contributed to the non-marginal narrative instances of mainstreamed narratives under this set of parameters. The newspapers that did all contributed on an even, low-level, providing no evidence of an influential puller of narratives to the mainstream. These results are summarized in tables 20 and 19.

In the immigration category, only four newspapers contributed to the mainstreamed narratives, ruvr-fi, PR Newswire, the Albuquerque Journal, and the Daily Herald. These newspapers all contributed evenly to the narratives, and only came from the Center and Center Right.

The antisemitism category follows a similar story; seven newspapers contributed, coming from the Left, Center Left, and Center Right. These newspapers all also only contributed once to each narrative, so no newspaper can be considered a "top" platformer of these narratives.

4.2.4.4 RQ 2

In the immigration category, narrative instances from a range of partisanships contained entities, particularly from the left wing. The category had a low overlap coefficient between entities from marginal and mainstream narrative instances, and the only entity appearing frequently across narrative instances from marginal and mainstreamed narrative instances was "Trump." On the other hand, "Muslim," "America," and "Obama" all appeared in many marginal narrative instances, but not in any direct or peripheral narrative instances.

The narratives in the antisemitism category generated the most named entities, particularly those in the left wing. This category also had the highest overlap between marginal and mainstreamed narrative instances across topics and pipelines. Descriptive words like "Jewish" appeared in marginal, direct, and peripheral narrative instances. However, "politician," "Judaism," "Israelis," "Barack Obama," and "Christians," still appeared frequently across marginal narratives while never appearing in mainstreamed narrative instances.

CHAPTER 5

Discussion

In this chapter, I present four key elements to conclude the paper. First, I explain my evaluation of the impact the different parameters in my pipeline made on my final results in section 5.1. Next, I explain an alternate approach that I developed before deciding on the finished pipeline design in section 5.2. These two sections in combination provide some closing insights into the construction of the pipeline and the different innovations that tailored it specifically to this application. Third, I contextualize the results of my hypothesis and research questions, highlighting where my findings confirmed, rejected, or expanded on the existing literature in this field. Finally, I close by discussing the limitations of this project and highlighting some questions for future work.

5.1 Evaluation

Running my pipeline on four sets of parameters allowed me to identify how these parameters affect the results and therefore how to interpret the results. Beyond comparing the outcome of each pipeline, I also conducted a manual evaluation of the narrative cohesion of each pipeline. In short, I reviewed the text of the narrative instances of each mainstreamed narrative and evaluated whether the narrative instance was internally cohesive, meaning that the internal text was meaningfully related, and whether the narrative instance text was meaningfully related to the other narrative instances in the narrative. Thus, I obtain four metrics: first, internal cohesion; second, marginal to direct cohesion, meaning the cohesiveness between a marginal narrative instance and direct narrative instance; third, marginal to peripheral cohesion; and fourth, direct to peripheral cohesion. This system of metrics allowed me to determine how successful each pipeline was at identifying narratives that are humanly interpretable. A summary of the average cohesion level for each metric and pipeline can be seen in figure 44.

In this analysis, the pipeline with a high number of clusters and a high classification threshold corresponded with the highest overall cohesion score, while the pipeline with a lower number of clusters and lower classification threshold scored the lowest overall. Without a ground truth with which to compare the results of my pipeline, this analysis provides important insights into its effectiveness. It also suggests that ultimately a combination of change from the clustering and classification parameters make a meaningful impact on the success of the pipeline. However, I conducted a MANOVA test and failed to find a statistically significant association between the different pipelines and the four metrics, imposing a limit on the interpretability of these metrics.[1]

In the following subsections, I explain how the number of clusters the classification threshold impacted the results, in context with the outcome of the manual evaluation of cohesion.

5.1.1 Clustering Comparison

The number of clusters in the clustering analysis made a difference in some key aspects, primarily in the number of marginal narratives identified. A higher number of clusters correlates with a higher number of marginal narratives identified as demonstrated in figures 39 and 43. This correlation makes intuitive sense as the narrative instances are the clusters resulting from each analysis. Regardless of the number of clusters, there were some consistent similarities in the results as well. The year of origin of the marginal narratives followed a similar trend despite changes in the number of clusters, as well as the number of narratives directly mainstreamed per year. The trends can be seen in figures 38 and 39.

5.1.2 Classification Threshold Comparison

The classification threshold seems to have had a larger impact on the results than the difference in the number of clusters, as the number of mainstreamed narratives, marginal narratives, and direct matches all appear to be heavily influenced by the change in threshold. With a lower classification, more narratives were identified as directly mainstreamed in almost every year in the dataset. This trend stays clearly apparent when examining the Immigration and Antisemitism categories specifically, while it is slightly more ambiguous for the Islamophobia category. Furthermore, for every year in the dataset the lower classification threshold corresponded to more marginal narratives and more direct matches to marginal narratives. This impact makes sense intuitively, as the higher classification threshold makes for a much smaller and more homogeneous dataset than than the lower classification threshold.

Even with these differences, there were still some trends in the data shared by the different classification thresholds. The number of marginal narratives identified over time, for example, stayed consistent despite a change in threshold.

[1] Pillai's Trace = 1.16, $F(12, 15) = 0.79$, $p = 0.66$

5.2 Alternate Approach

Before finalizing my pipeline, I extensively explored an alternative approach, which I will explain in this section, as it informs the work done to create the finalized pipeline In this approach, I first modified an algorithm from Ceran's 2016 dissertation that merges triplets based on syntactic and semantic similarity into "concepts," which can be represented in graph form [9]. Then, I used the identified keywords from the process described in section 3.4.2 and Tangherlini's supernode algorithm to classify the concepts according to the categories to which they pertain [37]. Finally, I identified subgraphs within these concept networks, which represented narratives.

Ultimately, I decided not to use this pipeline and to instead employ the version described in the Methodology chapter in which I vectorized the triplets and clustered them because the results of this alternative approach were not sophisticated enough. While the syntactic and semantic matching criterion merged triplets on logical and transparent grounds, the subgraphs that results were highly simplistic.

5.2.0.1 Ceran Algorithm

In Ceran's 2016 dissertation, she used Semantic Role Labeling to extract subject-verb-object triplets from raw text [9]. First, she created from these triplets a set of initial concepts making up every possible subject-verb-object pairing (See figure 11 for an example). Then, she applied a syntactic matching criterion to these triplets: when comparing two triplets, if two out of three of the objects matched, the two triplets were eligible for a merge (See figure 12 for an example). After, she applied a semantic matching test based on identifying words that often reappeared near each other in the dataset. Finally, she used a bottom-up agglomerative hierarchical clustering method to group the triplets into "stories."

I updated this method in my approach by using a language model to carry out the semantic matching process, instead of her algorithm. I first applied her syntactic matching criterion, generating a query triplet and a candidate triplet for merging, and both triplets share two out of three objects. In my update, I passed the query triplet's non-matching object through a word2vec model and obtained a list of words with a high cosine similarity. If the candidate triplet's non-matching object was listed there, then I merged the two triplets. After evaluating variations of Word2vec and GloVe models, I found that training Word2Vec on the full text dataset I scraped resulted in the best accuracy.

After iterating through the entire dataset and merging when possible, I obtain a series of overlapping triplets. They group together similar ideas but are generally unclassified according to topic. For an example of what a sample of these overlapping triplets look like after the classification is complete, see figure 13.

Despite the strengths of this method in its transparency and theoretical basis, there are also serious limitations that create error that propagates through the rest of the pipeline for this approach. First, the process is highly computationally expensive. The deconstruction phase generates about many triplets per dataset, so matching elements within these triplets is a timely task. Second, syntactic and semantic matching imposes a very strict criterion for deducing a connection between two triplets and extracting nuanced narratives with ranging vocabulary, more flexibility is necessary. Third, relying on just the text of the triplets means a loss of a great deal of understanding of the concept, which is why additional methods like sentiment analysis need to be paired in order to minimize this loss.

5.2.0.2 Supernode Algorithm and Classification

Having obtained a deconstructed representation of the article text and merged these representations to create a network, the next task in this pipeline was to classify these overlapping triplets.

To classify the concepts in my network, I relied on the keyword identification process and an algorithm introduced by Tangherlini (Tangherlini et al. 2020). Through this classification process, I extracted four categorized concept networks from the one concept network output at the end of the merging process. These networks correspond to the categories of the keywords: trans issues/ Transphobia, immigration issues, Judaism or antisemitism, and Islam or Islamophobia.

In following with the Tangherlini algorithm, I identified every span of text in a triplet that includes a keyword from the keyword identification process. Given this identification, I can then classify the text from each dataset according to which categories it discusses. I do this by considering a concept part of a given category if it includes one of the supernodes from that category.

5.2.0.3 Narrative Identification through Subgraphs

Finally, in the last step, I identified narratives in the text by representing the concept networks in graph form. Each topic has its own network, composed of the concepts created by the Ceran algorithm and classified by the keywords and Tangherlini algorithm. These networks, when represented in graph form, contain many subgraphs. These subgraphs represent the various narratives within each topic and in graph form provide an easy subject for interpretation

5.3 Analysis

To put the results of testing my hypothesis and answering my research questions into context, I consider the trends that emerged across the pipelines, emphasizing the pipeline that scored highest in terms of narrative cohesion. With this lens, interesting patterns emerge that in turn confirm and contradict existing literature.

I find evidence concurring with the recent literature that the Far Right is most effective at mainstreaming anti-immigration narratives and that in the time frame of my research, these narratives are highly linked to Donald Trump and his presidency. My results also support evidence that Breitbart plays an important role in generating extremist narratives that are mainstreamed. However, I also find a strong pattern indicating that Islamophobia does not appear to have the intense relevance in the American Far Right as some researchers have suggested.

In the following subsections, I will discuss the primary findings out of each of the four topics I focused on and then some specific findings from the two research questions.

5.3.1 Immigration

The outcomes with respect to the immigration category highlight the importance of anti-immigration narratives to the Far Right and its success in mainstreaming these narratives, particularly in the 2016 and 2018 elections and through Donald Trump's candidacy and presidency. The Immigration category had the highest number of narratives and of marginal narratives across all topics and pipeline modifications, reflecting its importance in the Far Right and the media environment as a whole (see figure 39). As Mudde suggests, the Far Right has had the most success mainstreaming anti-immigration narratives in the past several decades compared to other narratives, and this theory plays out in my results [30]. In my results, anti-immigration narratives starting in the years 2016 and 2018 are most frequently mainstreamed. These two years correspond to the US presidential election and the midterm elections, two periods in which many politicians, notably Donald Trump, campaigned on hardline immigration policy. As Hinojosa Ojeda and Telles found, Trump and other Far Right actors rallied their voters through anti-immigrant narratives for the 2016 and 2018 elections, and this finding is strongly supported by my work [18].

The content of the immigration narratives also supported this finding. The close connection between Trump and anti-immigration narratives was demonstrated as "Trump" and other words for president were the most commonly occurring words across narratives and between marginal, direct, and peripheral narrative instances, regardless of the change in pipeline parameters. No other entities achieved the same level of universal association with the immigration category, especially considering that words for Trump or president were not included in the immigration-related keywords that started the classification process.

The influential Far Right newspapers in the mainstreaming process also confirmed existing research like that of Benkler et al. Breitbart is indisputably prolific, dominating the creation of marginal and mainstreamed anti-immigration narratives, regardless of the modifications to the pipeline. Interestingly, however, Breitbart is clearly more generative than it is efficient in pushing the mainstreaming process, as it never ranks in the top newspapers for contributions relative to number of articles published.

5.3.2 Islamophobia

The mainstreaming of Islamophobic narratives is noticeable for its relative absence. Mainstreamed narratives were identified in each set of results except for the pipeline with the higher classification threshold and higher number of clusters, which scored highest in the manual narrative cohesion evaluation. Across different modifications to the pipeline, the level of marginal narratives stayed similar to that of the Antisemitism category, as demonstrated in figure 39. This minimal exhibition of Islamophobic narratives strikes a contrast to the work of Mudde, for example, who suggested that Islamophobia was one of the primary concerns of the Far Right [30]. In fact, even in the keyword matching phase of the pipeline, in which I identify how many triplets contain keywords relevant to a topic, more triplets are found relating to Antisemitism than to Islamophobia in the Far Right dataset, as shown in figure 14. In every other partisanship category, there are more triplets related to Islamophobia than Antisemitism.

5.3.3 Antisemitism

The mainstreaming of Antisemitic narratives is harder to characterize than that of anti-immigrant narratives. The Antisemitism category had roughly the same number of narratives and marginal narratives as the Islamophobia category, but it included mainstreamed narratives in every set of results, unlike the Islamophobia category. These mainstreamed narratives tended to peak in origin in 2016 and decline afterwards.

The evolution of the mainstreamed Antisemitic narratives reveals a difference in basic descriptive language between marginal and mainstreamed instances of a narrative. The words "Jew" or "Jews" are used only in marginal narrative instances across modifications to the pipeline, while mainstreamed instances are more likely to use "Jewish" to refer to a person.

5.3.4 Transphobia

The Transphobia category was the only one of the four topics to have no identified mainstreamed narratives. This deficit is explained primarily by the fact that few Transphobic narrative instances were identified in the Far Right articles, as demonstrated in figure 42. Furthermore, these narratives were much more abundant in later years of my datasets, particularly 2019 and 2020. This circumstance means that it is less likely that my tracking mechanism would identify a mainstreamed narrative, because I do not have later datasets with which to compare these marginal narratives. However, the striking increase in Transphobic marginal narratives in 2019 and 2020 suggests that these narratives may enter the mainstream in the following years. I theorized that the lack of Transphobic marginal narratives may also be due to these narratives being more mainstream to begin with, but I did not find a statistically significant difference between the identification of Transphobic marginal narratives and the identification of marginal narratives from other categories.

5.3.5 RQ 1

Among the actors involved in the mainstreaming process, several Far Right actors, most notably Breitbart, demonstrate a concerted effort to generate marginal narratives that become mainstreamed. However no clear leaders emerge within the centrist and leftist newspapers in platforming these marginal narratives.

Across the Immigration, Islamophobia, and Antisemitism categories, Breitbart has an outsized representation, as is already well documented by works like that of Benkler et al, but several other newspapers also appear to play a meaningful role in the mainstreaming process [3]. In the Islamophobia category, Shoebat, an explicitly anti-Islam blog featuring content from a father and son, contributed heavily to mainstreamed narratives and in the Antisemitism category, the conspiratorial Humans Are Free publication was highly efficient in its contributions. While the actual impact of publications like these is not measured in this work, my results do demonstrate a trend in a handful of smaller publications that do seem attuned to the narratives of the Far Right that are brought into the mainstream.

5.3.6 RQ 2

An interesting finding across the topics and pipeline modifications for the second research question was the words unique to the marginal narratives. Table 21 shows the most frequently occurring unique entities across marginal narratives. Across the Immigration, Islamophobia, and Antisemitism categories, entities "Obama," "Christians," and "Americans" appeared frequently across marginal narratives in different topics and with different pipeline modifications, but almost never the in the mainstreamed narrative instances. I confirmed the statistical significance of this finding by performing a chi-square test of independence on the appearance of keywords in the marginal versus mainstreamed narrative instances, and rejected the null hypothesis for each pipeline.[2] This trend reflects the ethnonationalist ideological

[2]With the pipeline modifications presented in the same order as in the Results chapter, 1) $X^2 = 172.35, p < 0.001$, 2) $X^2 = 137.04, p < 0.001$, 3) $X^2 = 204.16, p < 0.001$, 4) $X^2 = 172.35, p < 0.001$

base of the Far Right in its fixation on American and Christian identity, when these issues are not a focus of other partisanships. Relatedly, Obama, who is not a figure of much discussion in the majority of the media environment, still occupies the Far Right. Furthermore, in each set of results in the Immigration category, the entity "Muslim" appeared only in the marginal narrative instances, and not in the direct or peripheral narrative instances. This pattern corresponds with the Far Right concern with immigration specifically from Muslim countries as the collision of two primary "Others" in the Far Right imaginary.

5.4 Limitations and Questions for Future Work

Given the large scope and novelty of this project, a number of limitations and unanswered questions remain open for further exploration.

The data collection setup introduces some limitations in the treatment of partisanship as an ordinal variable and with the time frame assumption. As discussed in section 3.2, categorizing the partisanship of a newspaper is already a difficult task as a range of opinions many be represented by different authors, particularly in different sections of the paper. Beyond this challenge, representing partisanship on a linear scale also reduces the complexity of political ideology. Furthermore, in the specific case of the American news environment, treating the environment as divisible into seven evenly spaced categories overlooks the reality of the heavy right-wing skew on the right side of the spectrum and the relative deficiency of content on the left side. Also, I limit my article collection sampling to a ten day period for a range of years. This procedure assumes that narratives stretch across long periods of time and the results of my pipeline appear to confirm this assumption to some extent. However, a more sophisticated approach might seek to follow the narratives more closely as they migrate, instead of take snapshots of the data and looking for jumps from one year to another.

In this work I aimed to unite a variety of literature on defining narratives computationally and conceptually and apply this appropriately to the context of Far Right narratives, but in this process also I faced some limitations. For one, as discussed in section 2.2, the emotionality of Far Right extremist narratives is a crucial aspect. To address this feature I incorporated a sentiment classifier into my pipeline, but the vectorization and clustering process did not incorporate this sentiment. Therefore, while part of my interpretation used the sentiment annotations, I did not fully leverage it in the creation of the narratives. Furthermore, a sentiment classifier may be insufficient at fully capturing the emotionality of these narratives and other methods, like stance detection perhaps, may be necessary to fully satisfy this aspect. Additionally, the definition of narrative instances as clusters from the clustering analysis presents some clear opportunities for improvement. Tangherlini et al, for example, introduce a merging and deletion procedure in their pipeline so as to remove extraneous clusters and increase the cohesion between the remaining clusters [37]. A similar procedure could be undertaken here.

The classification component of the pipeline also leaves room for improvement. The keyword matching process could be improved by expert input and further manual evaluation regarding the keyword choice or substituted by building a classifier from an annotated dataset. While I was unable to find a suitable available dataset over the course of my work, it seems likely that researchers will continue to develop applicable datasets in this field, like that of Holt, Freilich and Chermak in their 2020 publication [19]. In any case, the cosine matching part of the classification could also be improved, possibly by creating a classifier from the keyword matching process, or by adjusting the matching criterion to include other elements besides just cosine similarity.

Finally, an important component missing from this work is an evaluation of the significance of the mainstreamed narratives identified. This design could be greatly improved by additionally developing a probabilistic model to simulate the mainstreaming of narratives and therefore test the significance of the outcomes.

CHAPTER 6

Tables

Partisanship	Title	Collection Number
Far Left	Buzzfeed Hyperpartisan Sources: Left	#31653029
Left	Tweeted Mostly by Clinton Followers 2016 (US Left 2016)	#9360520
Left	Tweeted Mostly by Followers of Liberal Politicians 2019 (US Left 2019)	#200363061
Center Left	Tweeted Somewhat More by Clinton Followers 2016 (US Center Left 2016)	#9360521
Center Left	Tweeted Somewhat More by Followers of Liberal Politicians 2019 (US Center Left 2019)	#200363048
Center	Tweeted Evenly by Followers of Conservative & Liberal Politicians 2019 (US Center 2019)	#200363050
Center	Tweeted Evenly by Trump/Clinton Followers 2016 (US Center 2016)	#9360522
Center Right	Tweeted Somewhat More by Trump Followers 2016 (US Center Right 2016)	#9360523
Center Right	Tweeted Somewhat More by Followers of Conservative Politicians 2019 (US Center Right 2019)	#200363062
Right	Tweeted Mostly by Trump Followers 2016 (US Right 2016)	#9360524
Right	Tweeted Mostly by Followers of Conservative Politicians 2019 (US Right 2019)	#200363049
Far Right	United States (Far-Right)	#214598068
Far Right	United States (Conspiracies)	#214609438
Far Right	Buzzfeed Hyperpartisan Sources: Right	#31653028

Table 1 Media Cloud Collections used for each Partisanship

	CenterLeft	CenterRight	Center	FarLeft	FarRight	Left	Right
CenterLeft	1	0.02	0.18	0.07	0.0	0.17	0.01
CenterRight	0.02	1	0.09	0.01	0.03	0.01	0.08
Center	0.18	0.09	1	0.08	0.05	0.17	0.08
FarLeft	0.07	0.01	0.08	1	0.0	0.44	0.02
FarRight	0.0	0.03	0.05	0.0	1	0.0	0.45
Left	0.17	0.01	0.17	0.44	0.0	1	0.0
Right	0.01	0.08	0.08	0.02	0.45	0.0	1

Table 2 Overlap Coefficient for the Newspapers in each Partisanship Category

	2016	2017	2018	2019	2020
Far Left	1297	951	759	1615	1252
Left	2000	2000	2000	2000	2000
Center Left	2000	2000	2000	2000	2000
Center	2000	2000	2000	2000	2000
Center Right	2000	2000	2000	2000	2000
Right	2000	2000	2000	2000	2000
Far Right	2000	2000	2000	2000	2000

Table 3 Number of Articles Collected for each Partisanship and Year

Immigration	**Islamophobia**	**Anti-semitism**	**Transphobia**
visas	sharia	jewish	transgender
visa	jihad	jews	gender transition
citizenship	hijabs	jew	biological woman
migrant	muslims	anti-semitism	pronoun
immigrants	hijab	synagogue	transphobic
undocumented	jihadi	anti-semitic	anti-trans
migration	muslim	non-jewish	non-binary
immigration	anti-muslim	orthodox jews	biological males
border wall	islamic fundamentalists	jewishness	transphobia
illegal aliens	islam	gas chamber	bathroom bill
foreign workers	islamophobia	antisemitic	transsexuals
refugees	radical islam	judaism	genderqueer
immigrant	islamophobic	judeo	
migrants	islamic extremism	pro-jewish	
undocumented immigrant	anti-islam		
illegal entry	sunni		
refugee	shia		
sanctuary cities	sunnis		
green card	jihadists		
visa holders	koran		
deport	islamists		
anti-immigration	burqa		
open border	jihadism		
illegal immigrants	jihadist		
legal status	qur'an		
xenophobic	islamization		
illegals			
visa waiver			
dream act			
border walls			
border surge			

Table 4 Keywords Identified for each Category

Topic	**Absolute**	**Relative**
Immigration	Breitbart	churchmilitant.com
Islamophobia	Right Wing News	Center for Security Policy
Anti-semitism	Breitbart	humansarefree.com

Table 5 Top Pushers by Topic: Fewer Clusters, Lower Classification Threshold

Year	**Absolute**	**Relative**
2016	Breitbart	churchmilitant.com
2017	Breitbart	redoubtnews.com
2018	Breitbart	freedomforce.com

Table 6 Top Pushers by Year: Fewer Clusters, Lower Classification Threshold

Partisanship	Topic	Absolute	Relative
Centrist	Immigration	NBC Breaking News	politico.eu
	Islamophobia	Guardian US	Punch
	Anti-semitism	Haaretz	Spiegel
Partisan	Immigration	Breitbart	hudson.org
	Anti-semitism	opednews.com	Common Dreams

Table 7 Top Pullers by Topic Newspapers: Fewer Clusters, Lower Classification Threshold

Partisanship	Year	Absolute	Relative
Centrist	2016	Haaretz	politico.eu
	2017	Sydney Morning Herald	denver.cbslocal.com
	2018	Washington Post	dailytimes.com.pk
	2019	VOA	Business Insider Australia
Partisan	2016	Breitbart	hudson.org
	2017	WND	theblacksphere.net
	2018	numbersusa.com	nsm88.org

Table 8 Top Pullers by Year Newspapers: Fewer Clusters, Lower Classification Threshold

Topic	**Absolute**	**Relative**
Immigration	Breitbart	conservativedailypost.com
Islamophobia	shoebat.com	therealside.com
Anti-semitism	Breitbart	humansarefree.com

Table 9 Top Pushers by Topic: More Clusters, Lower Classification Threshold

Year	**Absolute**	**Relative**
2016	Breitbart	humansarefree.com
2017	therealside.com	therealside.com
2018	Breitbart	conservativedailypost.com

Table 10 Top Pushers by Year: More Clusters, Lower Classification Threshold

Partisanship	Topic	Absolute	Relative
Centrist	Immigration	Washington Post	Montreal Gazette
	Islamophobia	ruvr-fi	Punch
	Anti-semitism	Haaretz	Spiegel
Partisan	Immigration	Breitbart	fairus.org
	Islamophobia	sgtreport.com	therealside.com
	Anti-semitism	opednews.com	creation.com

Table 11 Top Pullers by Topic Newspapers: More Clusters, Lower Classification Threshold

Partisanship	Year	Absolute	Relative
Centrist	2016	Haaretz	Spiegel
	2017	ruvr-fi	International Centre for Investigative Reporting
	2018	ruvr-fi	sheboyganpress.com
	2019	Sydney Morning Herald	Spiegel
Partisan	2016	Breitbart	fairus.org
	2017	Breitbart	mansfieldnewsjournal.com
	2018	Natural News	fairus.org
	2019	Haaretz	Irish Times

Table 12 Top Pullers by Year Newspapers: More Clusters, Lower Classification Threshold

Topic	Absolute	Relative
Immigration	Breitbart	freedomforce.com
Islamophobia	shoebat.com	The Real Side
Transphobia	Right Wing News	Right Wing News

Table 13 Top Pushers by Topic: Fewer Clusters, Higher Classification Threshold

Year	Absolute	Relative
2016	Breitbart	VDARE
2017	Breitbart	Right Wing News
2018	Breitbart	freedomforce.com

Table 14 Top Pushers by Year: Fewer Clusters, Higher Classification Threshold

Parisanship	Year	Absolute	Relative
Partisan	2016	Daily Kos	usdefensewatch.com
	2017	countercurrents.org	rewire.news
	2018	WND	numbersusa.com
Center	2016	standard.co.uk	Newsday
	2017	Sydney Morning Herald	Forbes
	2018	floridapolitics.com	floridapolitics.com
	2019	VOA	Inquisitr

Table 15 Top Pullers by Year: Fewer Clusters, Higher Classification Threshold

Parisanship	Topic	Absolute	Relative
Partisan	Immigration	countercurrents.org	usdefensewatch.com
	Islamophobia	rewire.news	rewire.news
Center	Immigration	standard.co.uk	Newsday
	Islamophobia	CBC	Forbes

Table 16 Top Pullers by Topic: Fewer Clusters, Higher Classification Threshold

Topic	Absolute	Relative
Immigration	Breitbart	Shoebat
Islamophobia	Breitbart	Clash Daily
Anti-semitism	The Truth Seeker	radixjournal.com
Transphobia	Right Wing News	Right Wing News

Table 17 Top Pushers by Topic: More Clusters, Higher Classification Threshold

Year	Absolute	Relative
2016	Breitbart	humansarefree.com
2017	ipatriot.com	Right Wing News
2018	radixjournal.com	radixjournal.com

Table 18 Top Pushers by Year: More Clusters, Higher Classification Threshold

Parisanship	Year	Absolute	Relative
Partisan	2016	VOA	CBC
Center	2016	ruvr-fi	sbs

Table 19 Top Pullers by Year: Fewer Clusters, Higher Classification Threshold

Partisanship	Topic	Absolute	Relative
Partisan	Anti-semitism	VOA	CBC
Center	Immigration	ruvr-fi	Albuquerque Journal
	Anti-semitism	sbs	sbs

Table 20 Top Pullers by Topic: Fewer Clusters, Higher Classification Threshold

Pipeline	**Entity**	**# Narrative Appearances**	**# Topic Appearances**
Low Clustering,	Americans	19	2
Low Classification	Muslim	18	1
	American	17	2
	America	12	1
	German	12	1
	Islamists	10	1
	politician	10	1
	jew	9	1
	student	8	2
	Judaism	7	1
	Christian	5	1
High Clustering,	America	18	1
Low Classification	Muslim	16	1
	United States	13	1
	German	11	1
	Obama	10	1
	Sunni	10	1
	American	9	1
	jew	8	1
	student	8	2
	Americans	6	1
	muslim	6	1
	president	6	1
	Christians	5	1
Low Clustering,	Jews	65	1
High Classification	Islamists	6	1
	Americans	5	1
	Judaism	5	1
	Sunni	5	1
	Christians	4	1
High Clustering,	Muslims	63	1
High Classification	Muslim	61	2
	Islam	57	1
	America	9	1
	Islamists	8	1
	Sunni	8	1
	Americans	7	1
	German	7	1
	Obama	7	1
	politician	7	1
	Judaism	6	1
	Barack Obama	4	1
	Christians	4	1

Table 21 Most frequently occurring entities uniquely in marginal narrative instances

CHAPTER 7

Appendix

7.1 Definitions

Definition 1 (*Narrative Definition*)

Let N be the set of all narratives n. Let s be the starter narrative instance in a narrative n. Let D be the set of all narrative instances that are direct matches to s. D can be empty. Let P be the set of all peripheral matches to the narrative instances in D. P can be empty.

Every narrative $n = s \cup D \cup P$

Definition 2 (*Mainstreamed Marginal Narrative*)

Let m be the set of all marginal narrative instances.

A narrative n is a marginal narrative if its element s is also an element of m.

Narrative n is also mainstreamed if 50% or more of the elements in D or in P come from the center three partisanships.

Definition 3 (*Absolute Largest Pusher*)

Let m_1 be the marginal instance of a mainstreamed narrative e_1 and m_2 the marginal instance of mainstreamed narrative e_2. Let P be the set of all newspapers p.

Let m_1 be composed of four enriched triplets, which come from the three newspapers, so that $m_1 = \{p_1, p_1, p_2, p_3\}$. In the same way, $m_2 = \{p_1, p_2, p_4\}$.

The newspaper that contributed the most to a mainstreamed marginal narrative in absolute terms would then be:

$p_{abs} = max(\sum_{s \in m_1 \cup m_2} \mathbf{1}_{\{p_i\}}(s))$,

so that in this case, $p_{abs} = p_1$.

Definition 4 (*Relative Largest Pusher*)

Let m_1 be the marginal instance of a mainstreamed narrative e_1 and m_2 the marginal instance of mainstreamed narrative e_2. Let P be the set of all newspapers p, and A be the multiset of the number of articles published by each newspaper p in P.

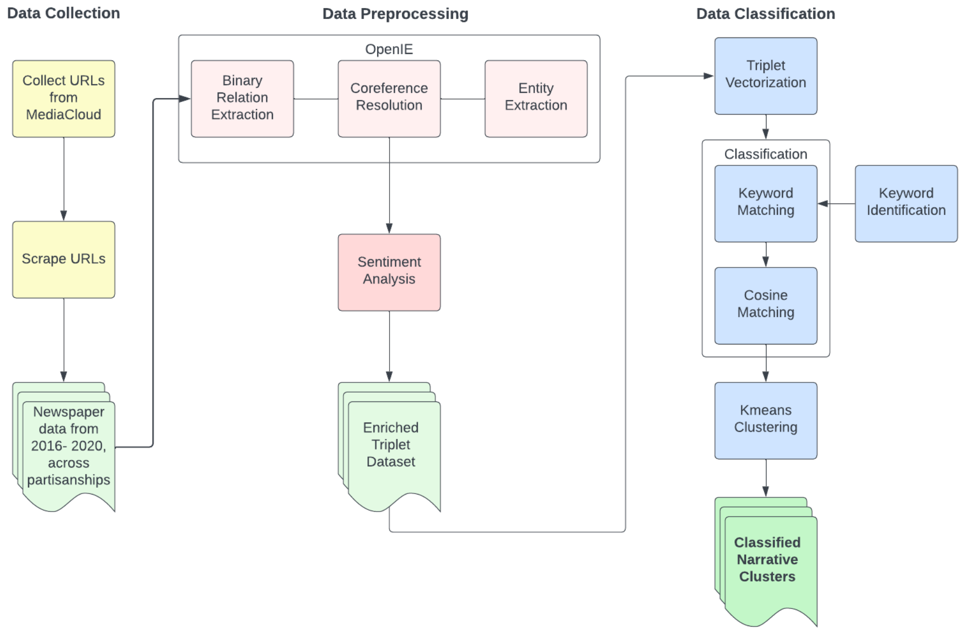

Figure 1 Narrative Extraction Pipeline

Let m_1 be composed of four enriched triplets, which come from the three newspapers, so that $m_1 = \{p_1, p_1, p_2, p_3\}$. In the same way, $m_2 = \{p_1, p_2, p_4\}$. Let A, in the same order as P, be $10, 2, 3, 4$

The newspaper that contributed the most to a mainstreamed marginal narrative relative to the number of articles published would then be:

$p_{rel} = \frac{max(\sum_{s \in m_1 \cup m_2} \mathbf{1}_{\{p_i\}}(s))}{a_i}$,

so that in this case, $p_{rel} = p_2$.

7.2 Figures

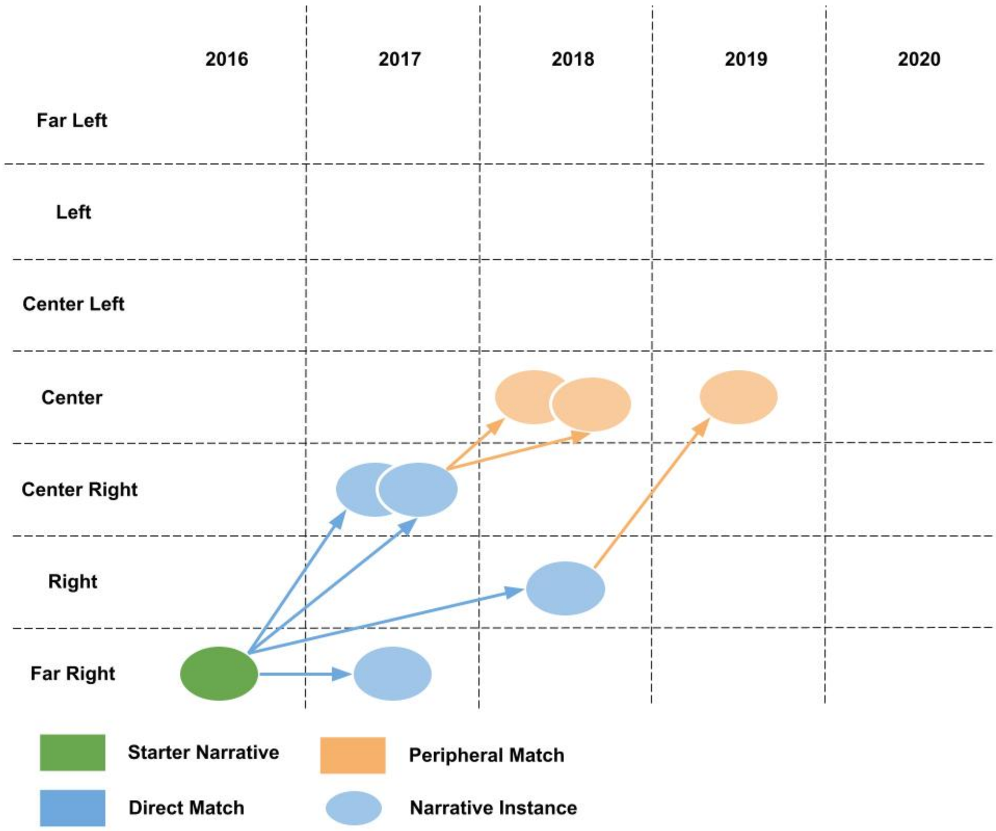

Figure 2 Example of a Narrative, including the Starting Instance, Direct Matches, and Peripheral Matches

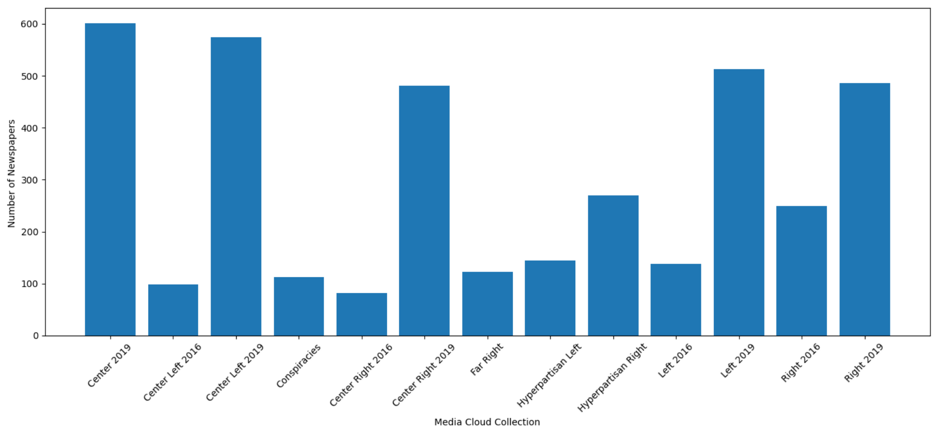

Figure 3 Number of Unique Newspapers per Media Cloud Collection

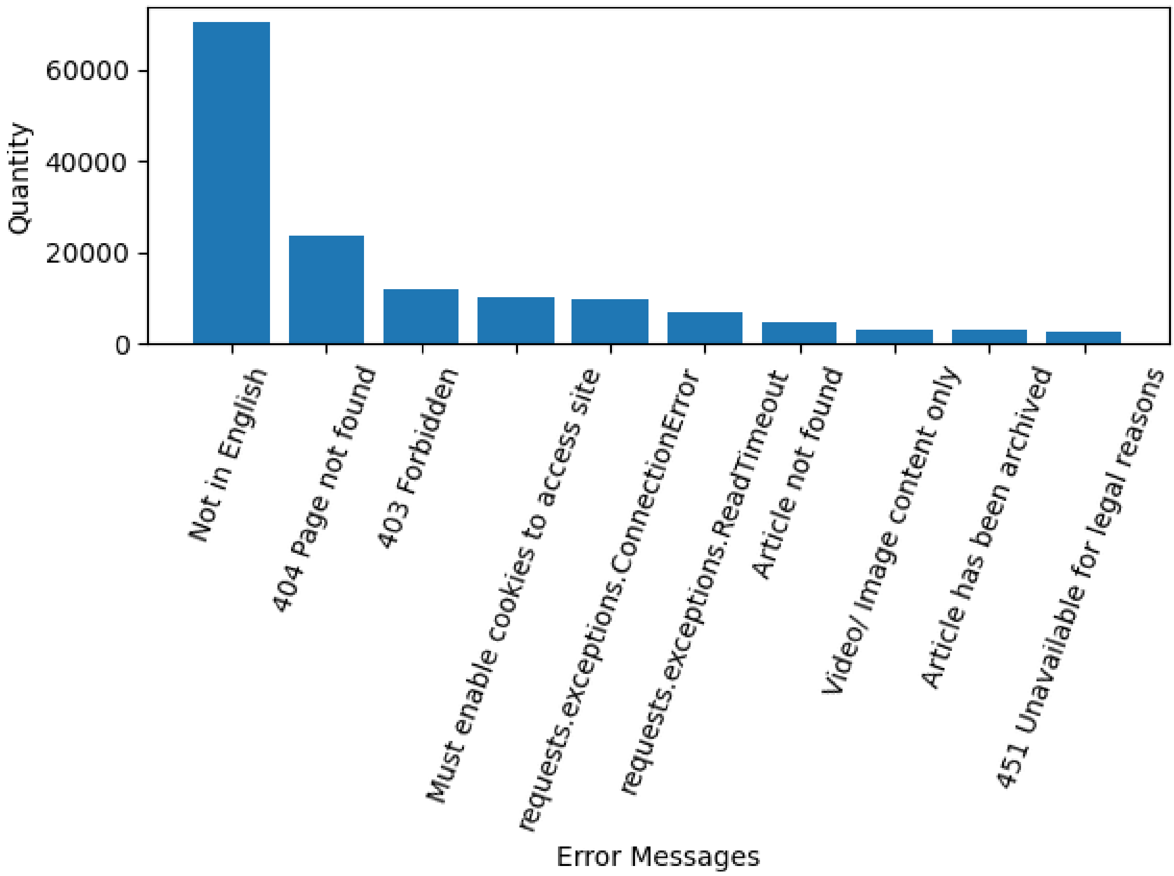

Figure 4 Top Ten Most Common Errors

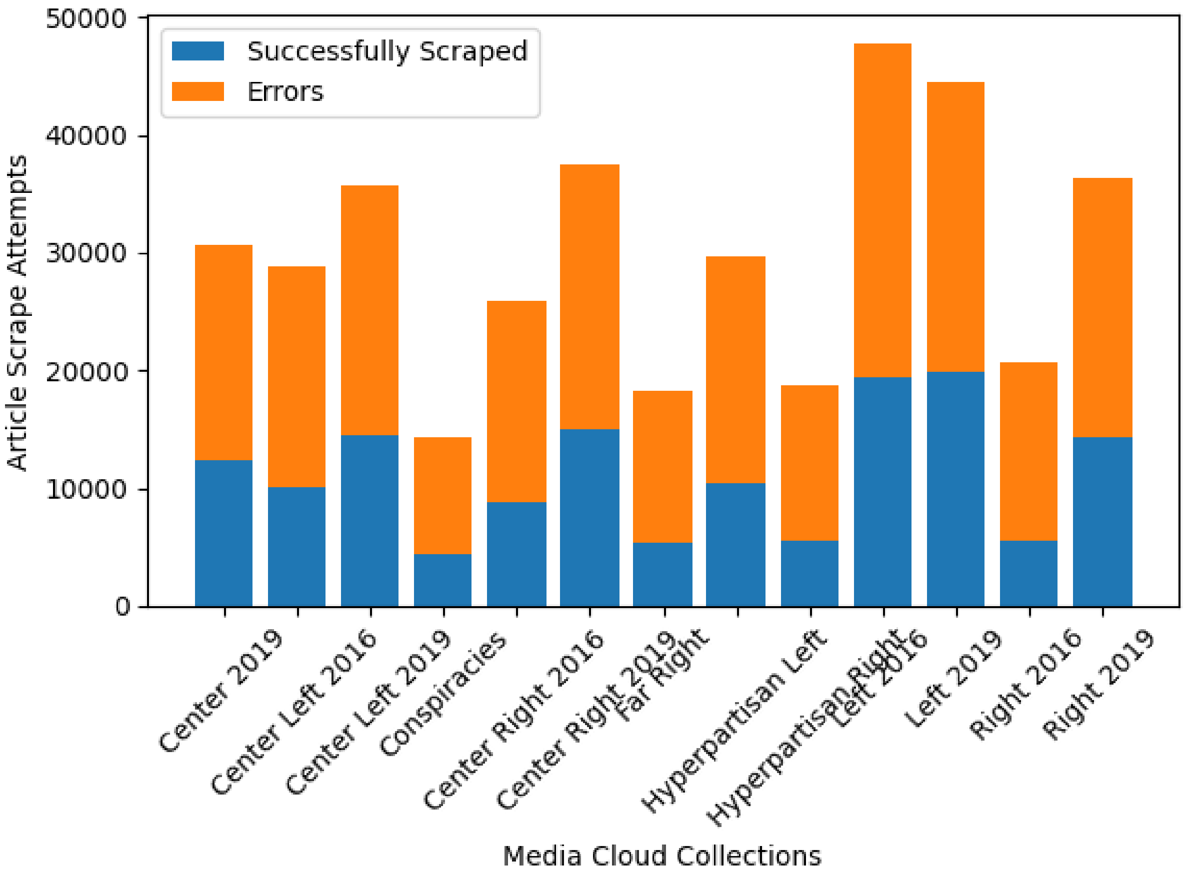

Figure 5 Scrape Success Rate per Media Cloud collection

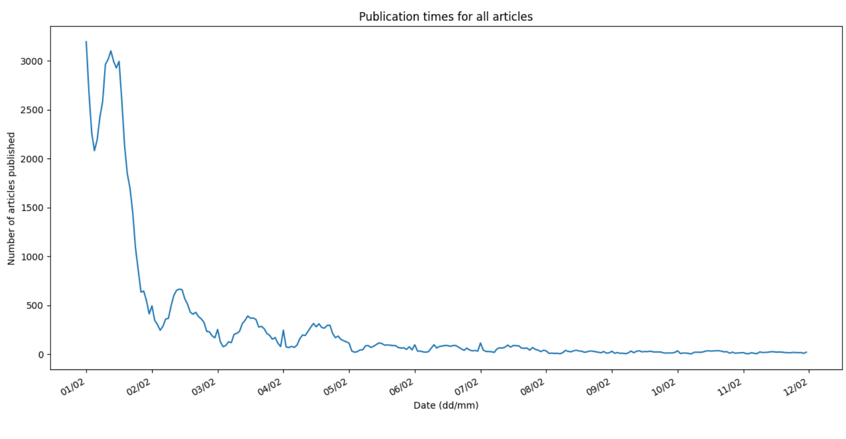

Figure 6 Publication Times for All Articles by Frequency

```
{
    subject: str
    subjectSpan: List[int]
    relation: str
    relationSpan: List[int]
    object: str
    objectSpan: List[int]
    tokenized_sentence: List[str]
    sentence_id: int
    article_id: str
    entity_location: dict
}
```

Figure 7 JSON Object Output from CoreNLP

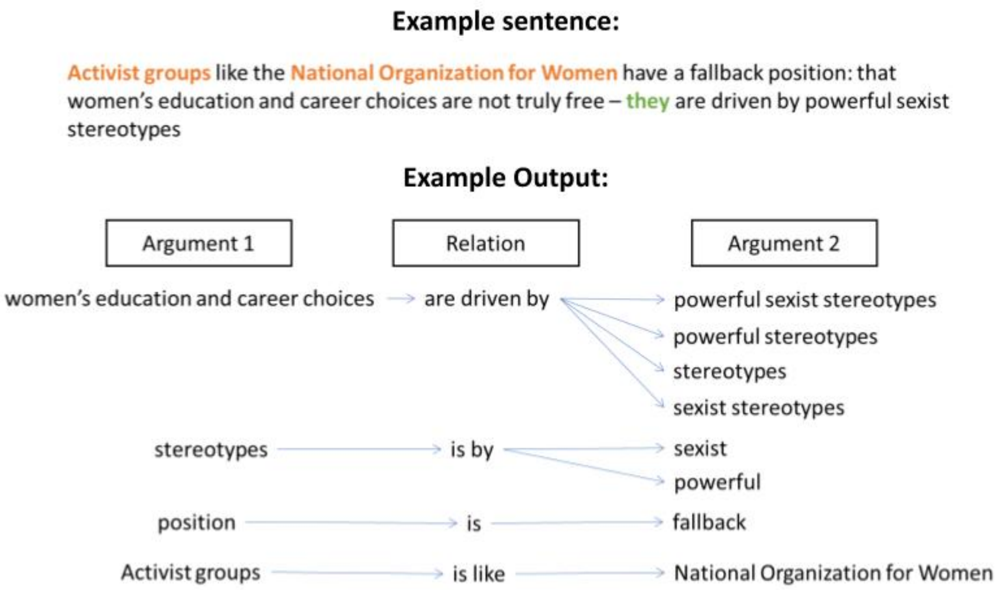

Figure 8 Example of the StanfordCoreNLP model

1. Immigration
    a) Discusses immigration or asylum processes or people moving across borders
    b) Discusses immigration policy, like building a wall or legalizing immigration
    c) A story in about immigrants where that identity is a relevant fact
2. Transphobia
    a) Discusses gender-enforced separation, like in bathroom separation policies
    b) Discusses trans identity, including medically assisted transition and words for trans people
    c) Explicitly reference biological sex distinctly from gender identity, like referring to people as "biologically" men or women
3. Islamophobia
    a) Discusses Islam or Muslim identity
    b) Discusses usage of hijab or other muslim head coverings
4. Antisemitism
    a) Labels people or organizations as antisemitic
    b) Discusses Judaism or jewish people and identity

Figure 9 Manual Classification Rules

Figure 10 Data Breakdown after Clustering

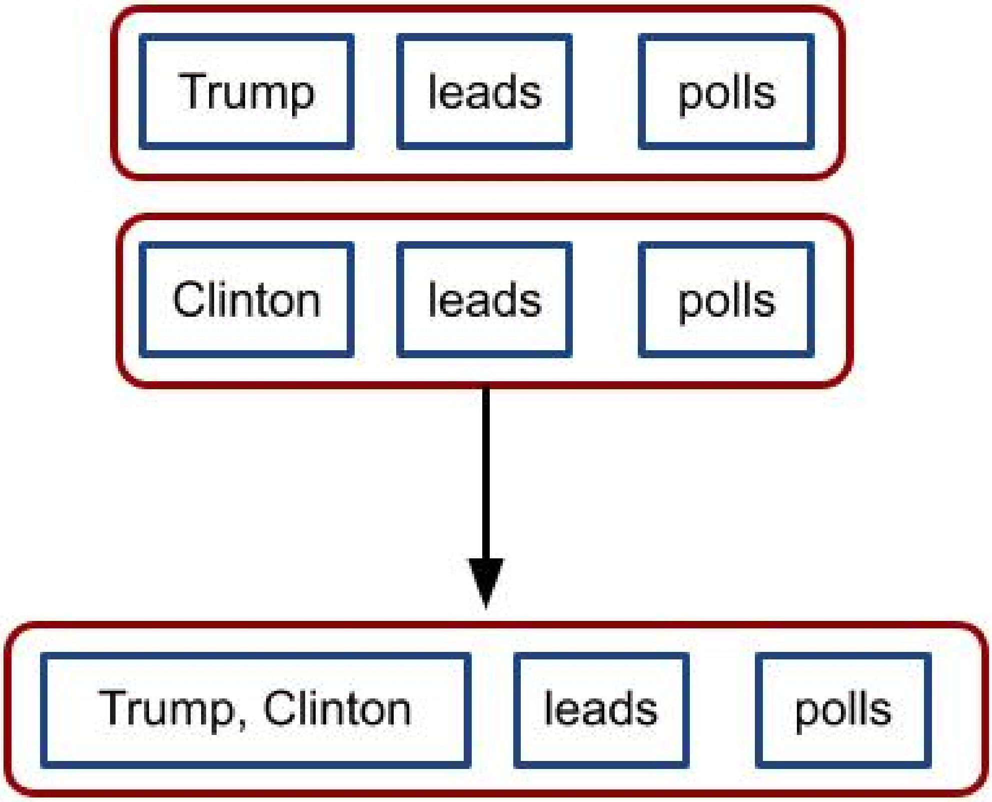

Figure 11 Example of how the Ceran algorithm creates initial concepts

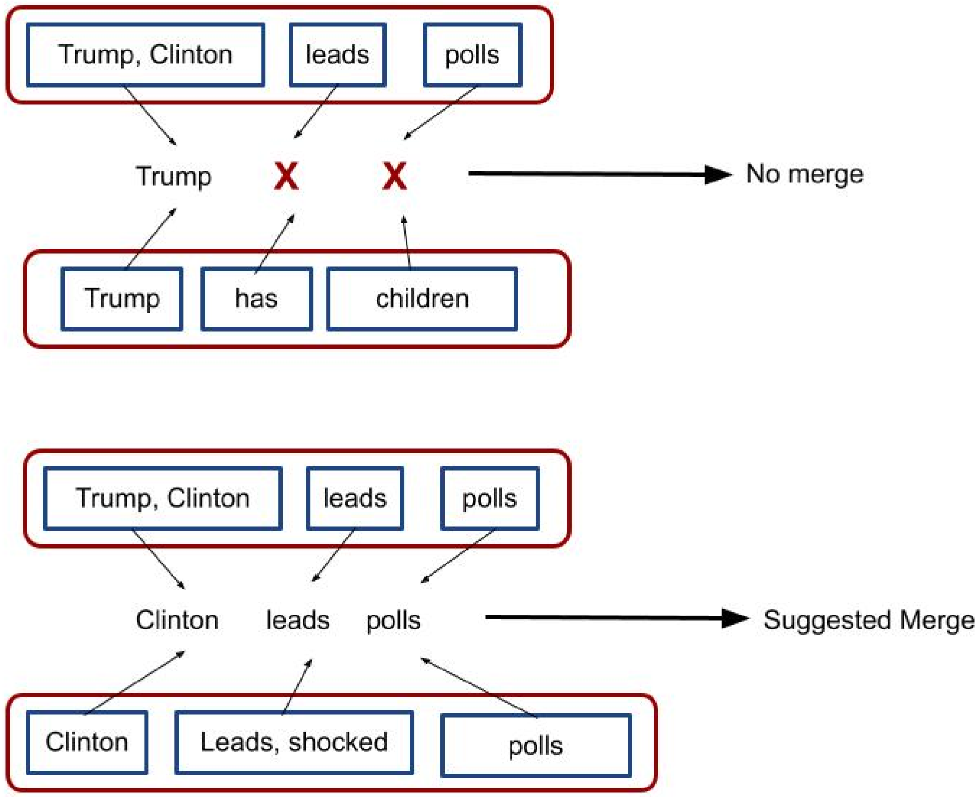

Figure 12 Example of how the Ceran algorithm matches concepts based on syntactic criterion

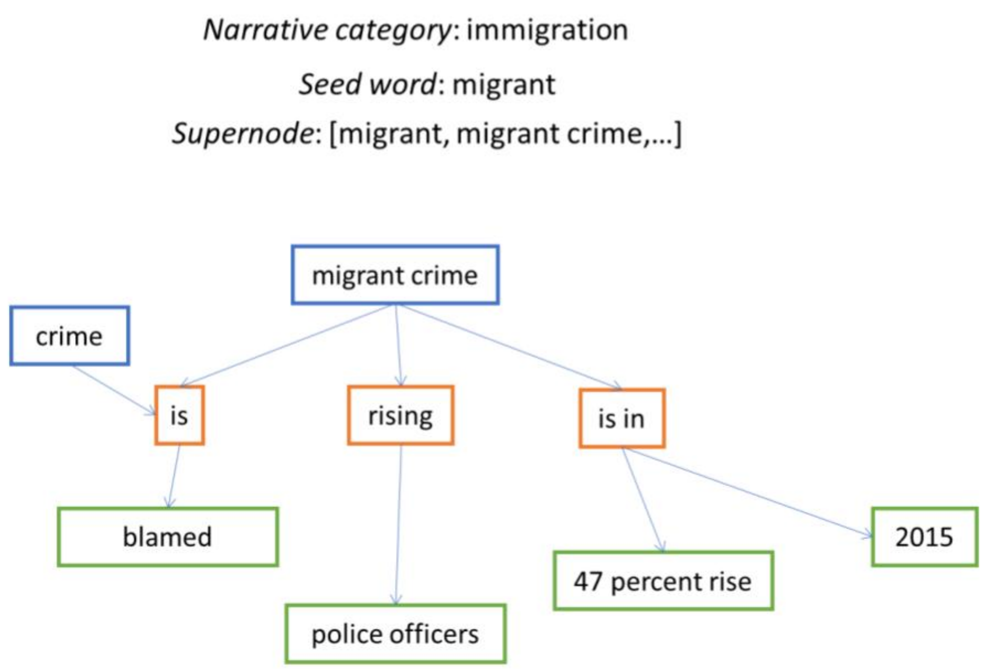

Figure 13 Example of a portion of a concept network

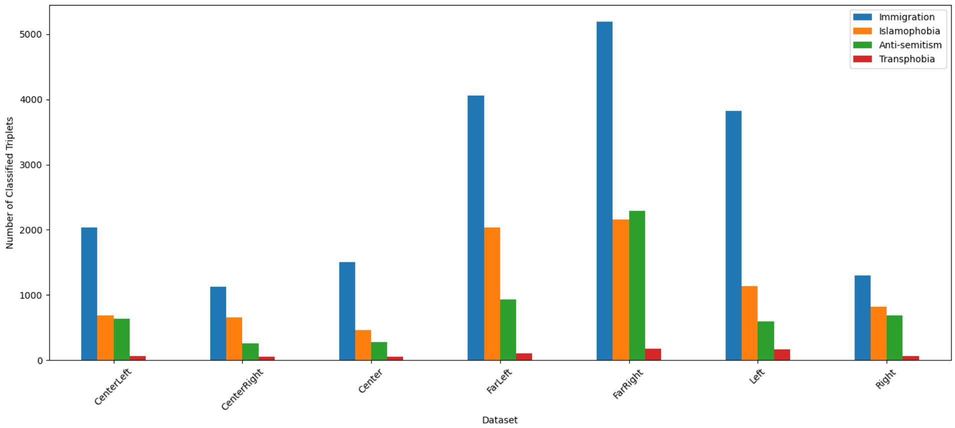

Figure 14 Number of Triplets Classified through Keyword Matching

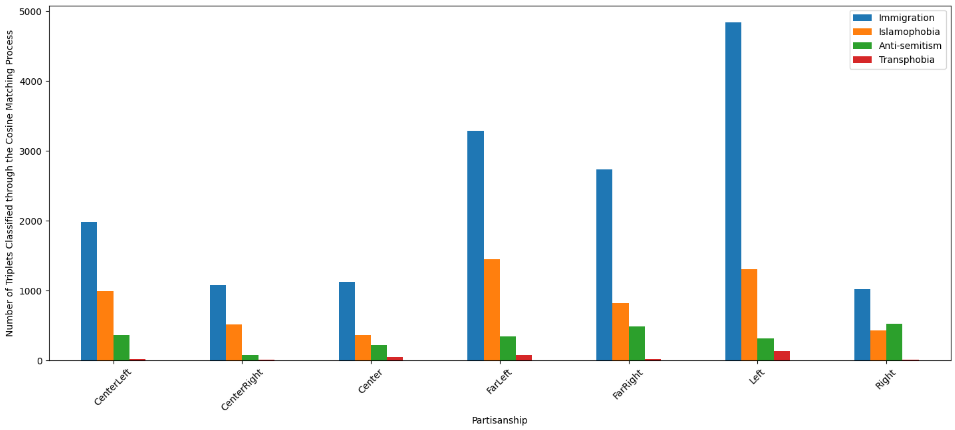

Figure 15 Number of Triplets Classified through Cosine Matching, t=0.97

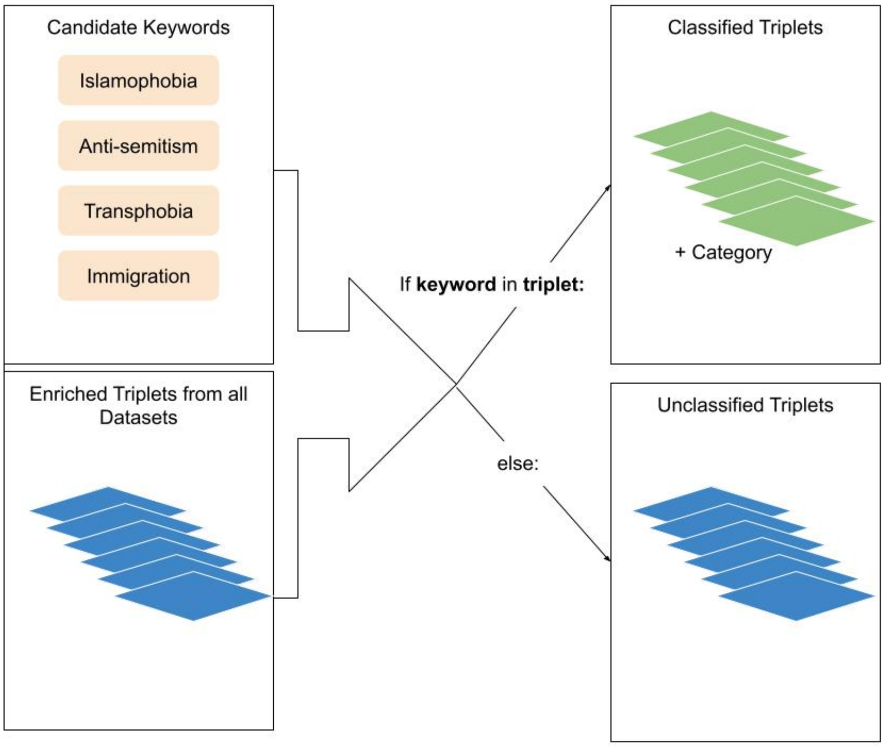

Figure 16 Keyword Matching Process

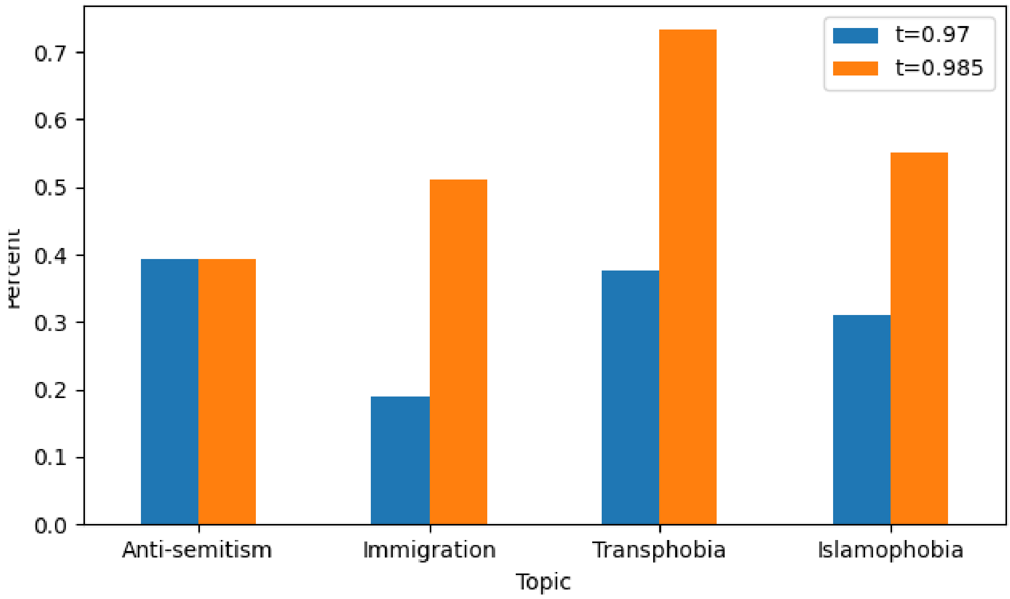

Figure 17 Percentage of Classified Triplets with a Keyword in the Source Sentence for Cosine Similarity Threshold t

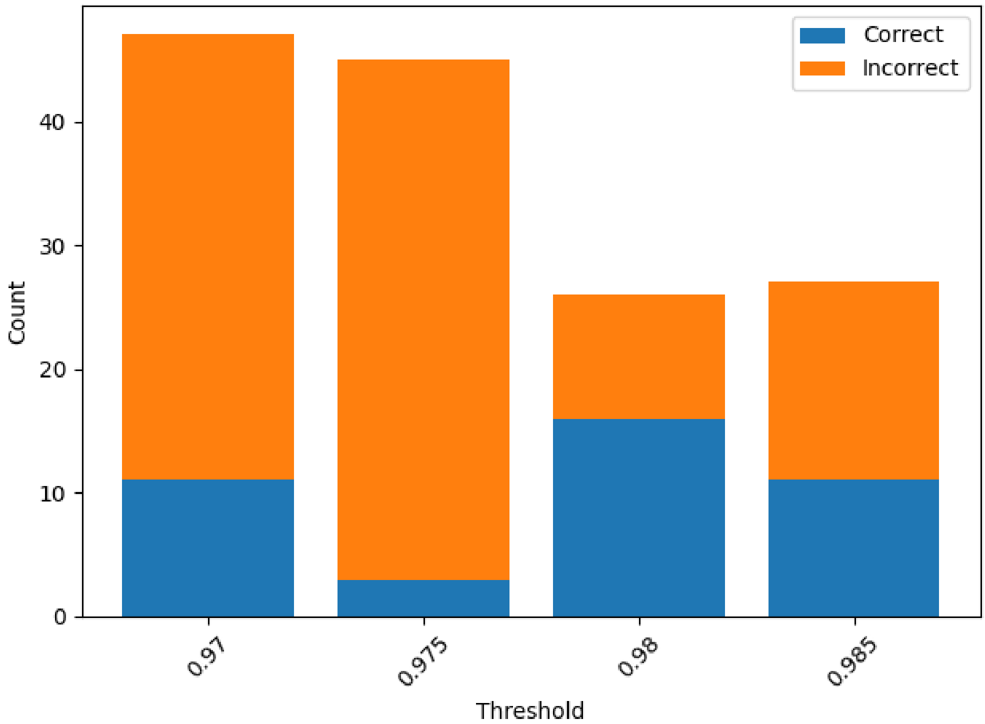

Figure 18 Manual Evaluation: Number of Correctly vs. Incorrectly Classified Triplets by Threshold

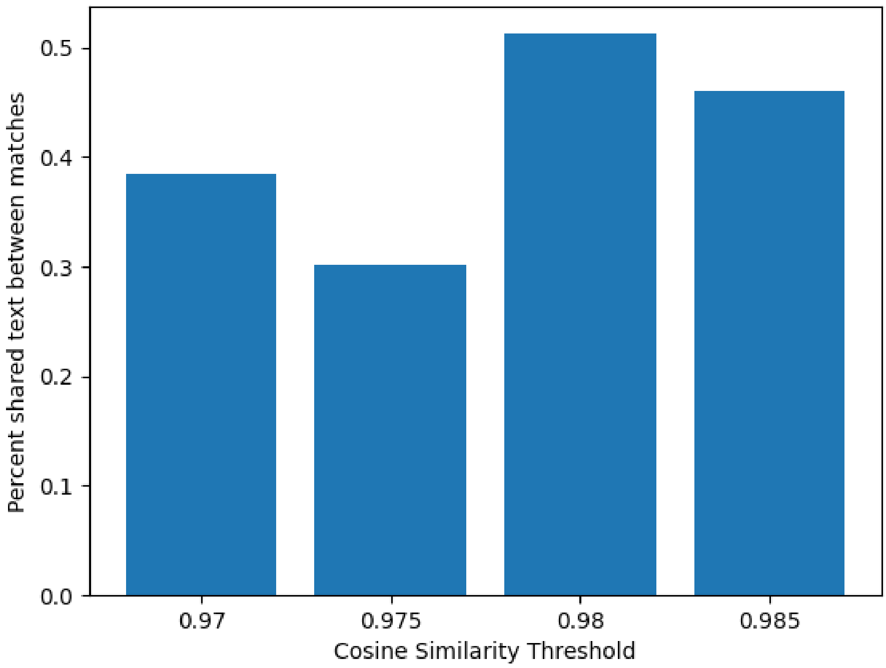

Figure 19 Percent Exact Text Matched between Matched Triplets for Cosine Similarity Threshold t

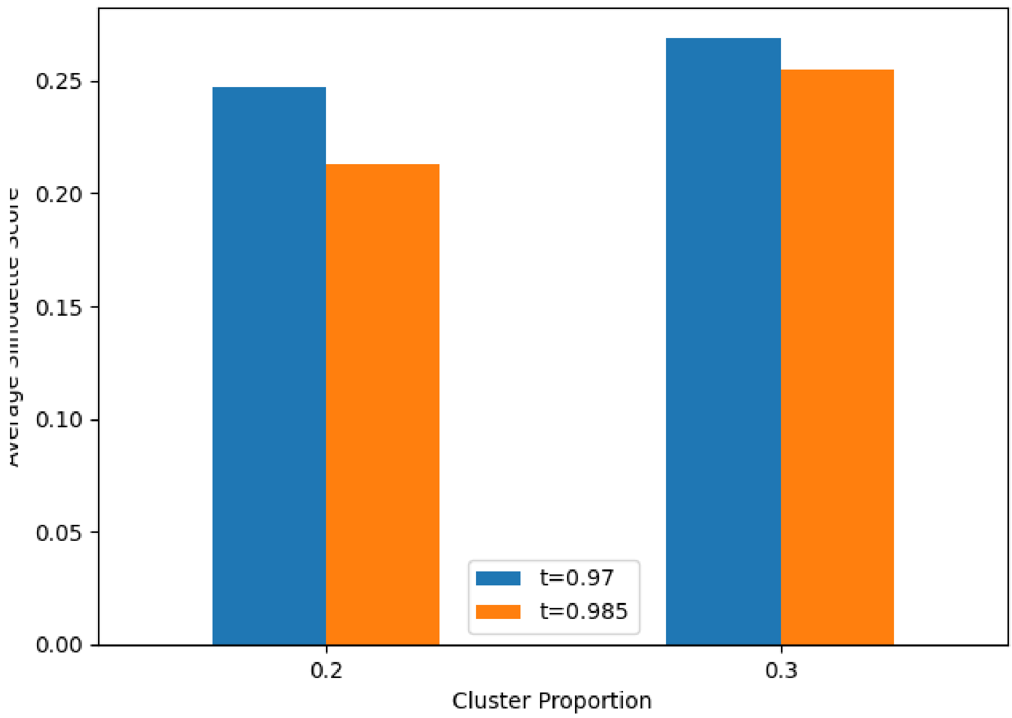

Figure 20 Clustering Silhouette Score by Cosine Similarity Threshold and Topic

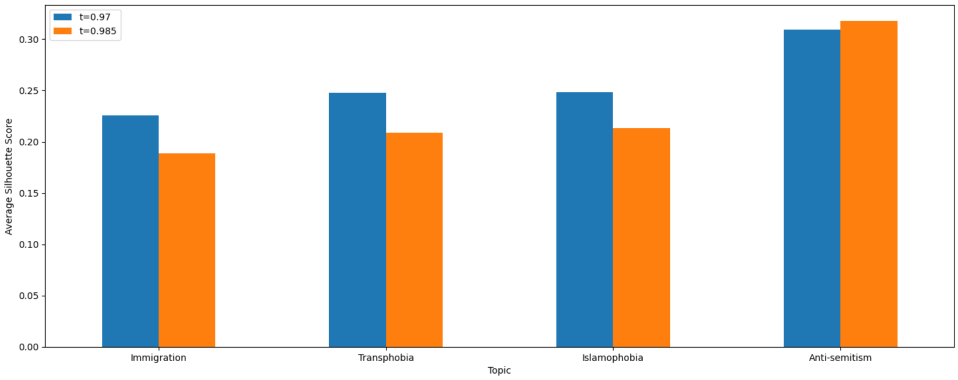

Figure 21 Clustering Silhouette Score by Cosine Similarity Threshold

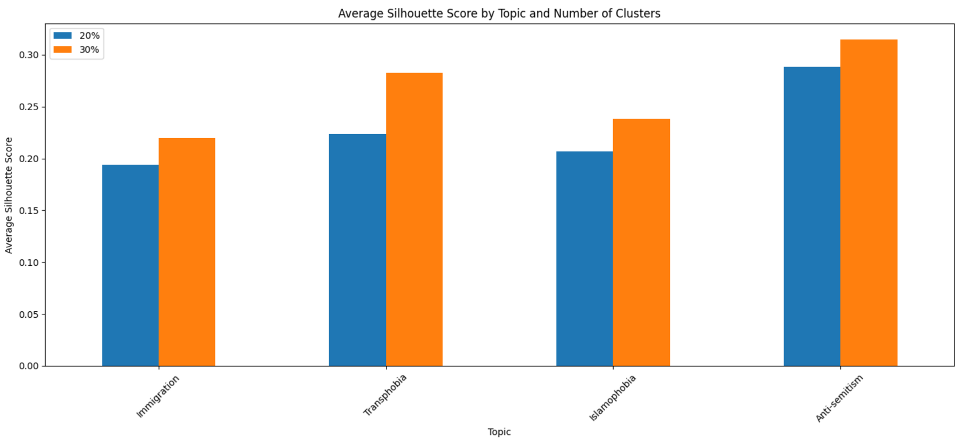

Figure 22 Average Silhouette Score Across Datasets by Topic and Number of Clusters

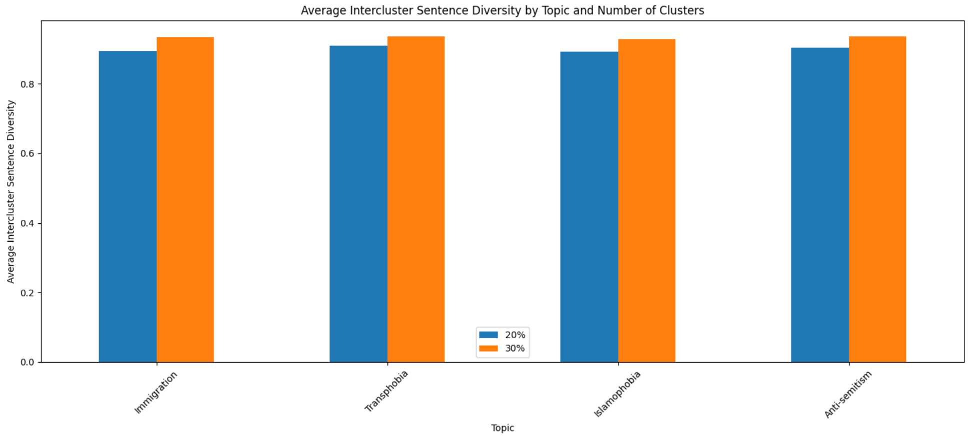

Figure 23 Average Intercluster Sentence Diversity

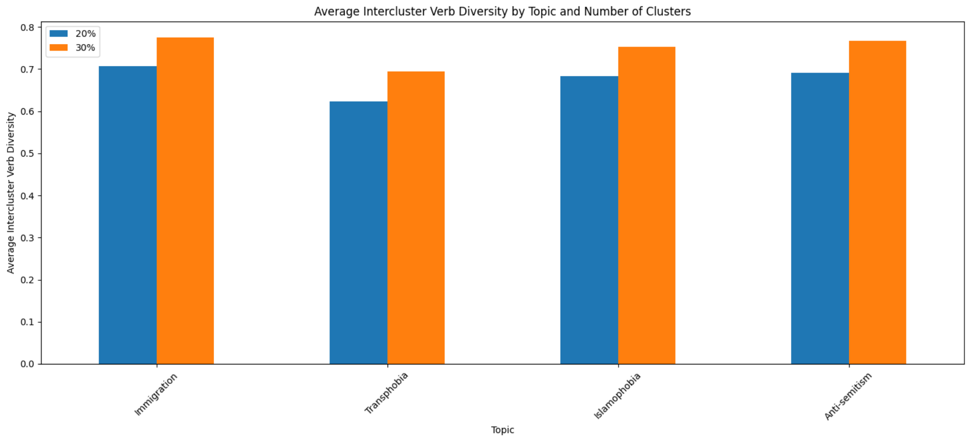

Figure 24 Average Intercluster Verb Diversity

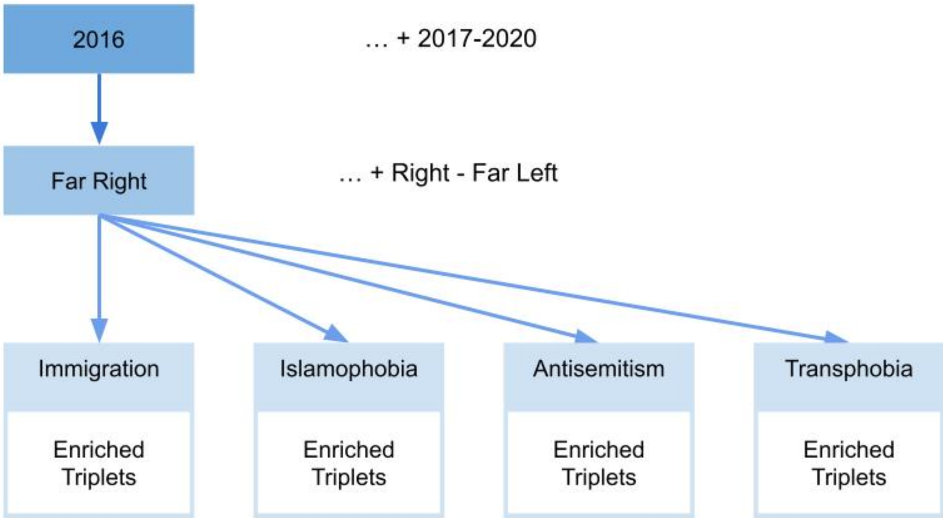

Figure 25 Data Breakdown After Classification

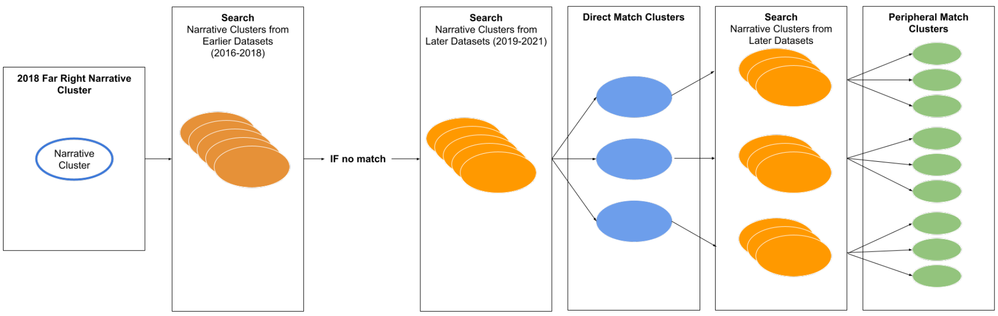

Figure 26 Tracking Procedure

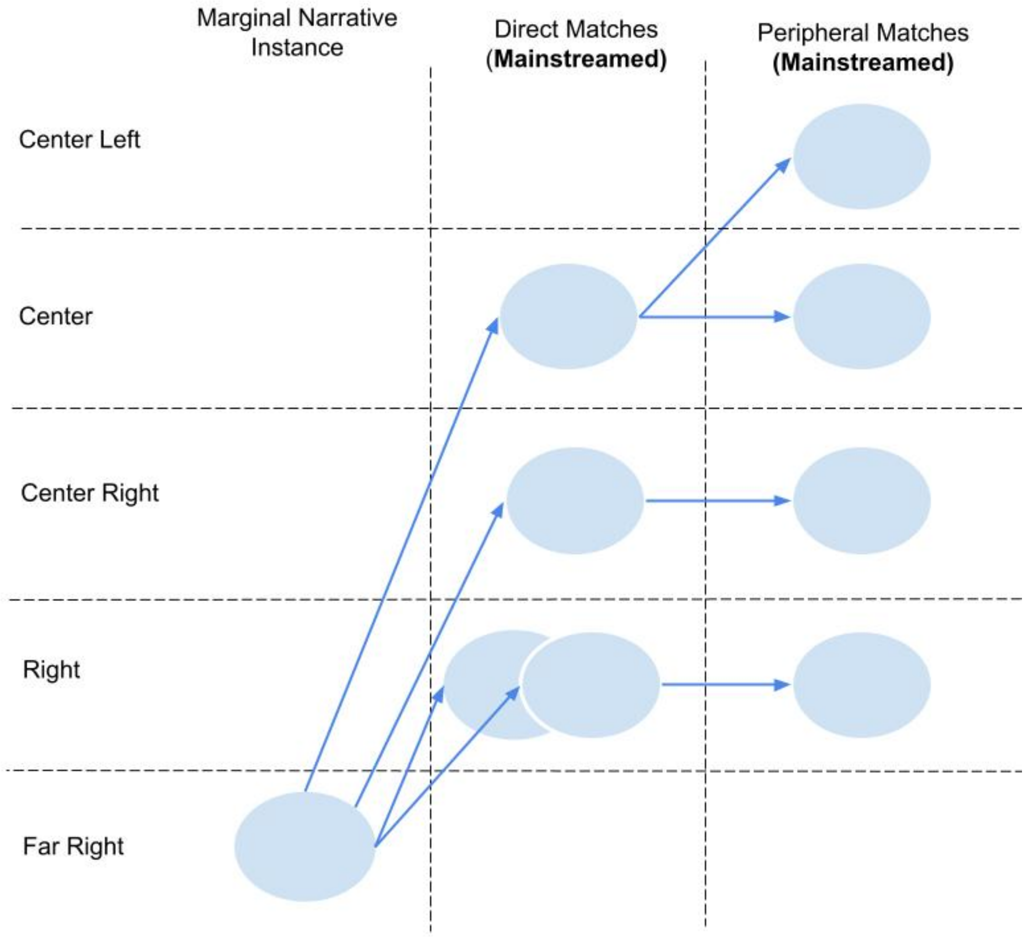

Figure 27 Example of a Marginal Narrative Mainstreamed in the Direct and Peripheral Steps

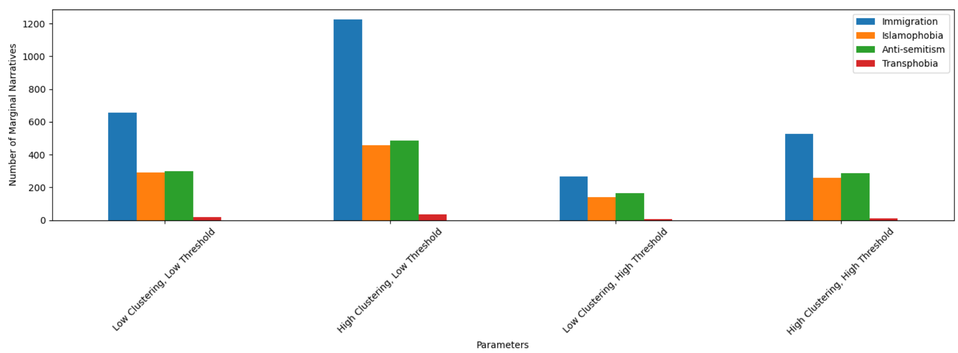

Figure 28 Number of Marginal Narratives by Parameter Modification and Topic

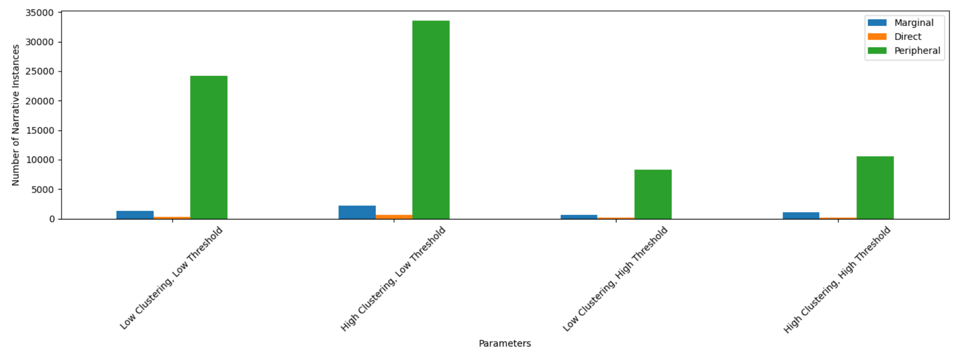

Figure 29 Number of Marginal, Direct, and Peripheral Narrative Instances per Pipeline Modification

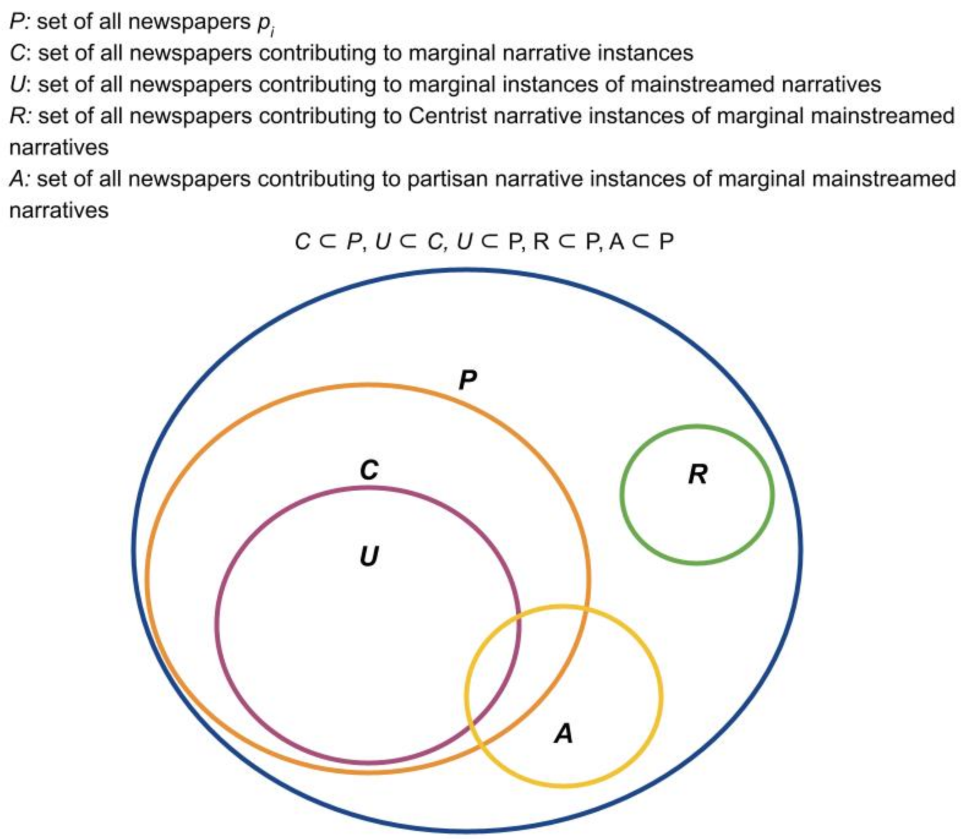

Figure 30 Subsets of Newspapers

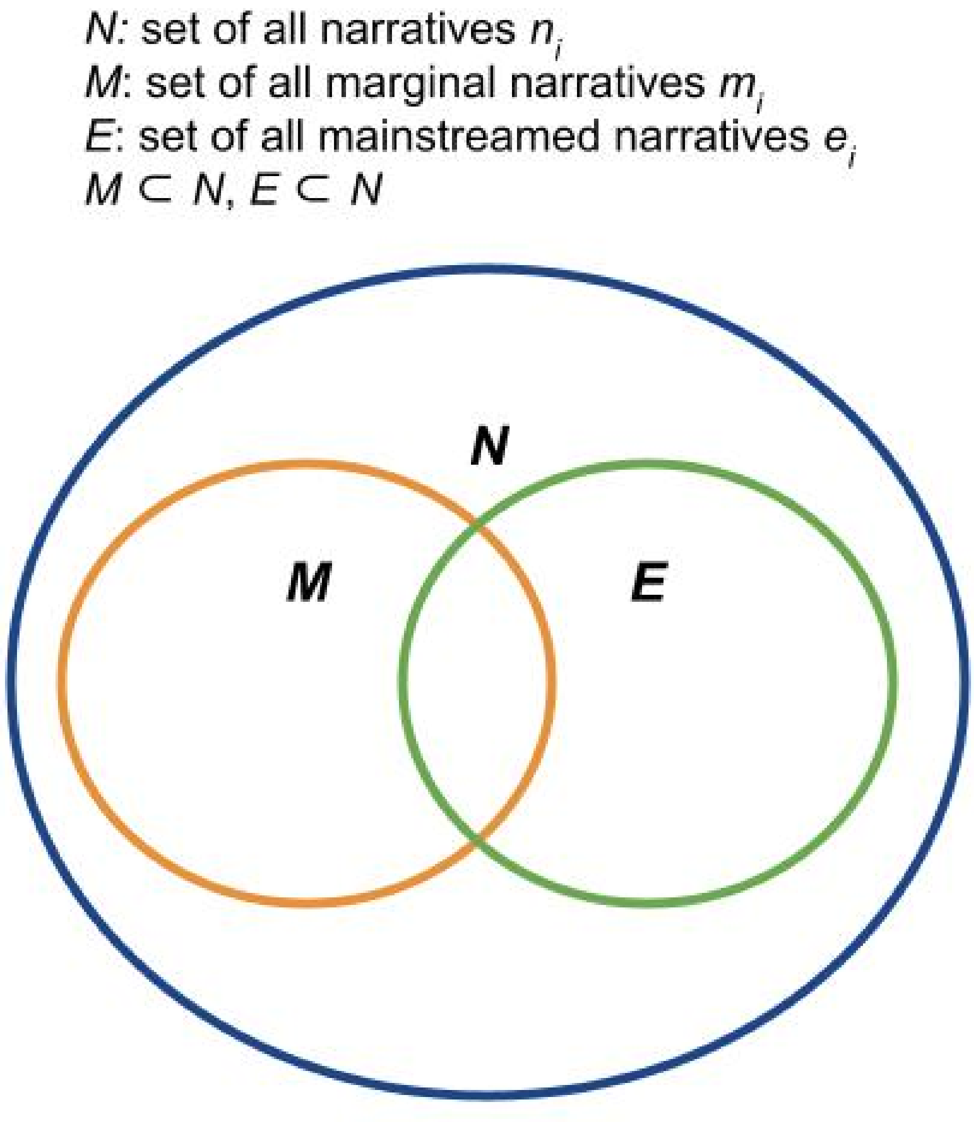

Figure 31 Subsets of Narratives

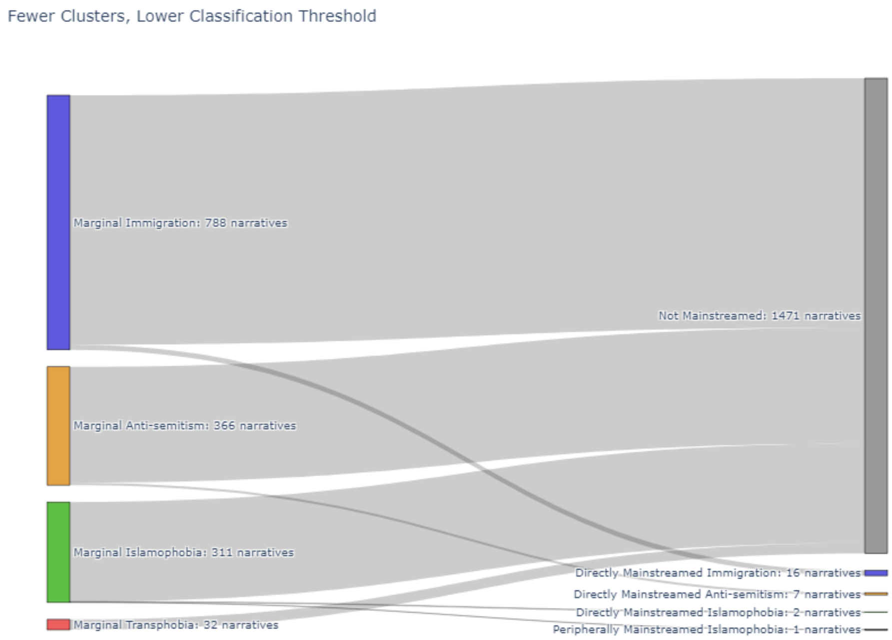

Figure 32 Fewer Clusters, Lower Classification Threshold: Marginal to Mainstreamed Narratives by Topic

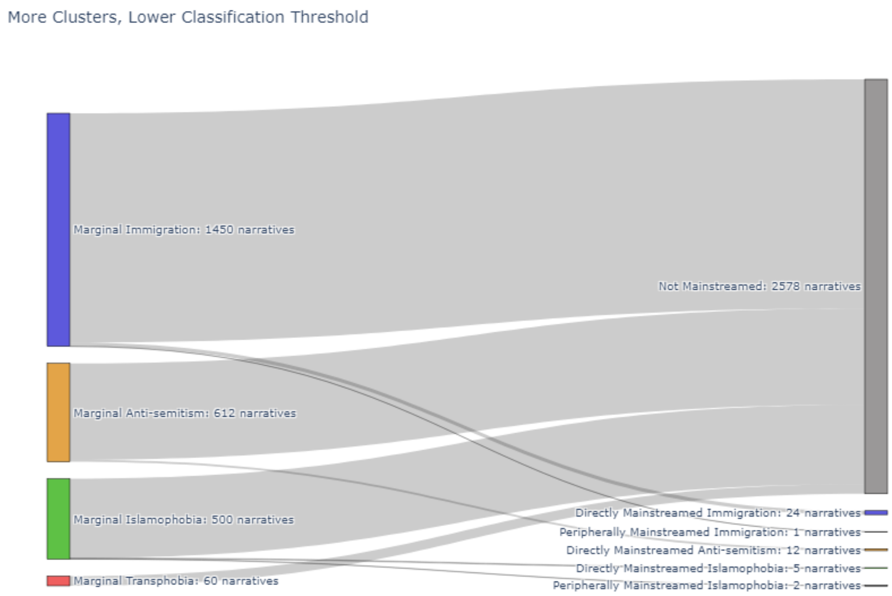

Figure 33 More Clusters, Lower Classification Threshold: Marginal to Mainstreamed Narratives by Topic

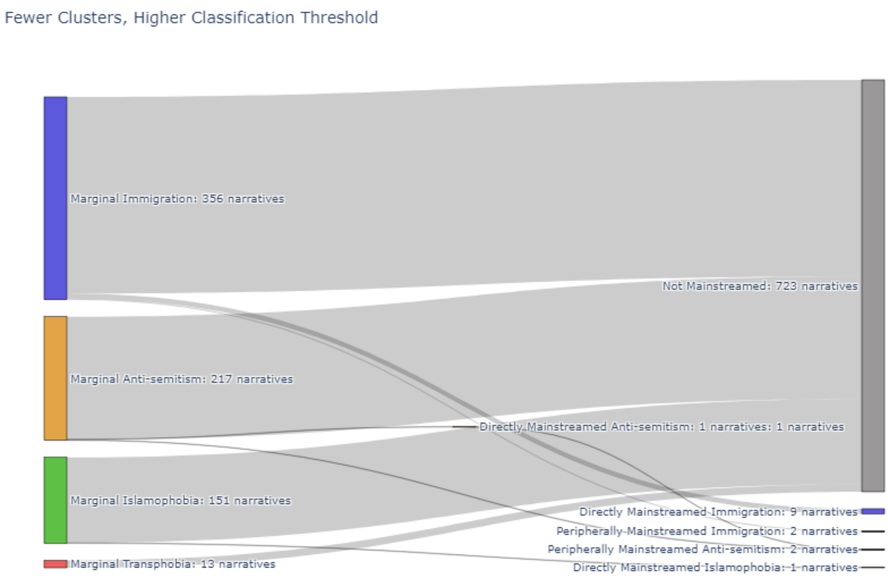

Figure 34 Fewer Clusters, Higher Classification Threshold: Marginal to Mainstreamed Narratives by Topic

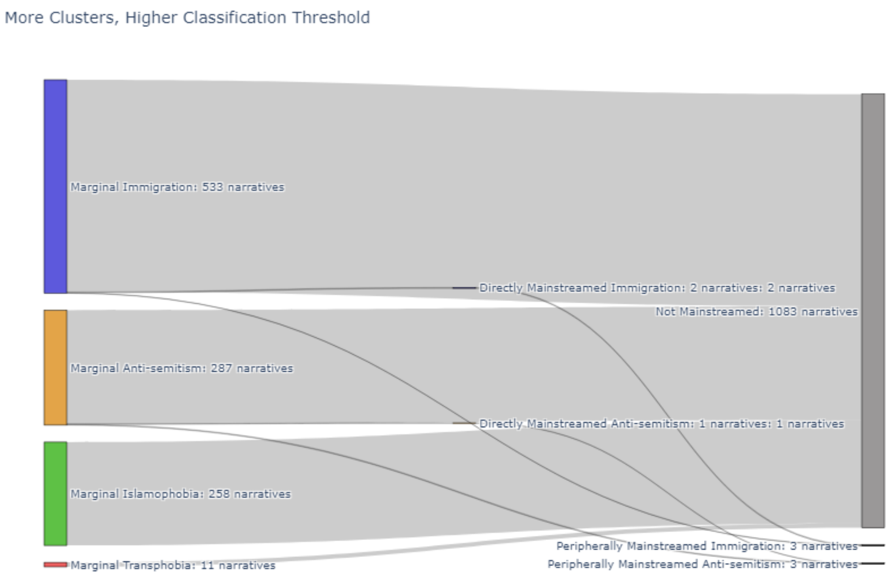

Figure 35 More Clusters, Higher Classification Threshold: Marginal to Mainstreamed Narratives by Topic

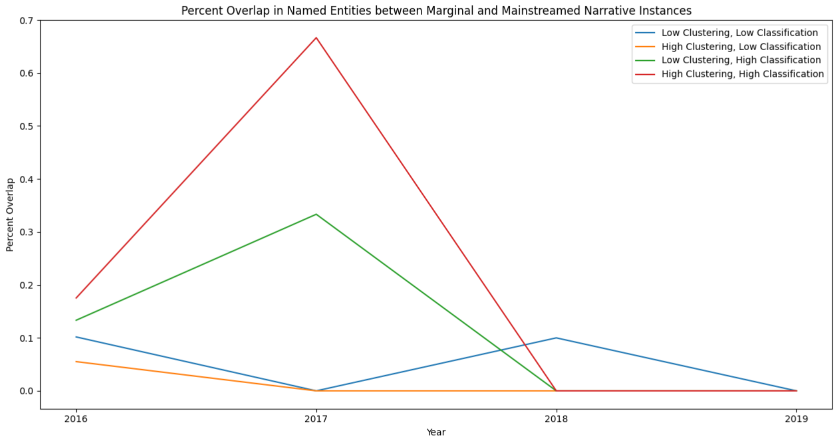

Figure 36 Percent Overlap in Named Entities between Marginal and Mainstreamed Narratives by year

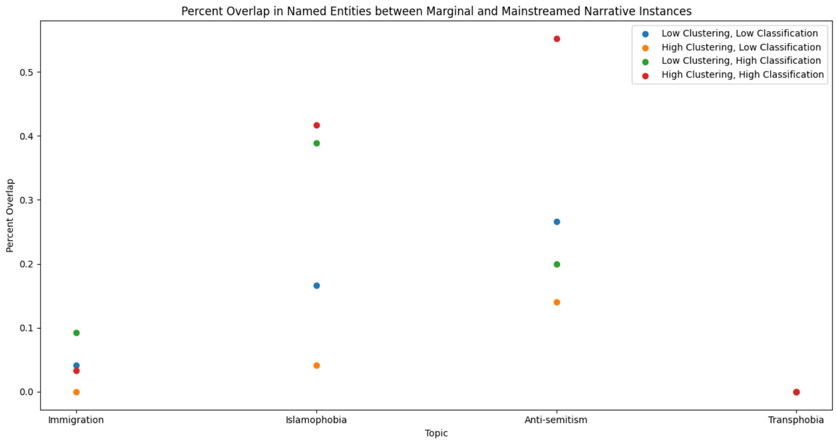

Figure 37 Percent Overlap in Named Entities between Marginal and Mainstreamed Narratives by Topic

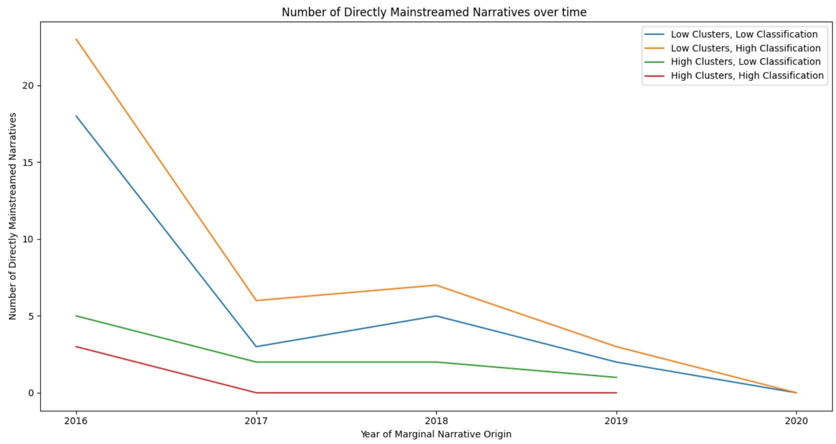

Figure 38 Number of Directly Mainstreamed Narratives by Year

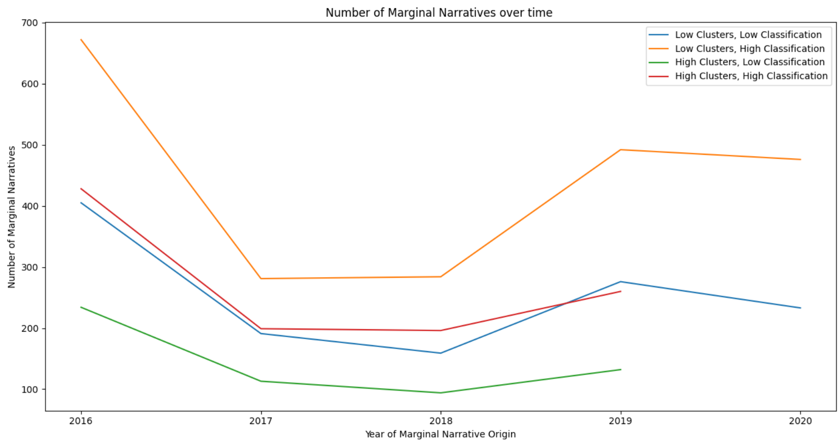

Figure 39 Number of Marginal Narratives by Year

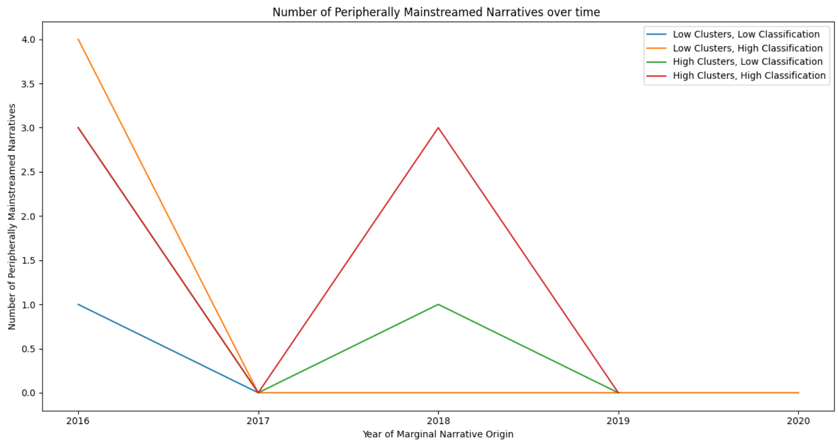

Figure 40 Number of Peripherally Mainstreamed Narratives by Year

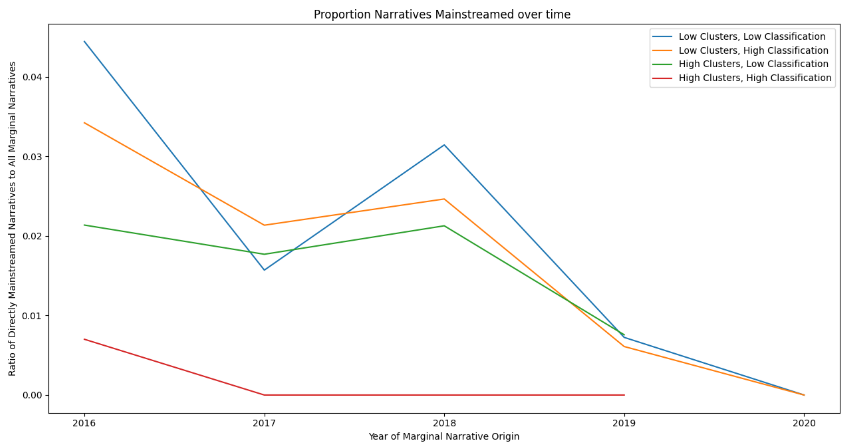

Figure 41 Proportion of Narratives Mainstreamed out of all Marginal Narratives by Year

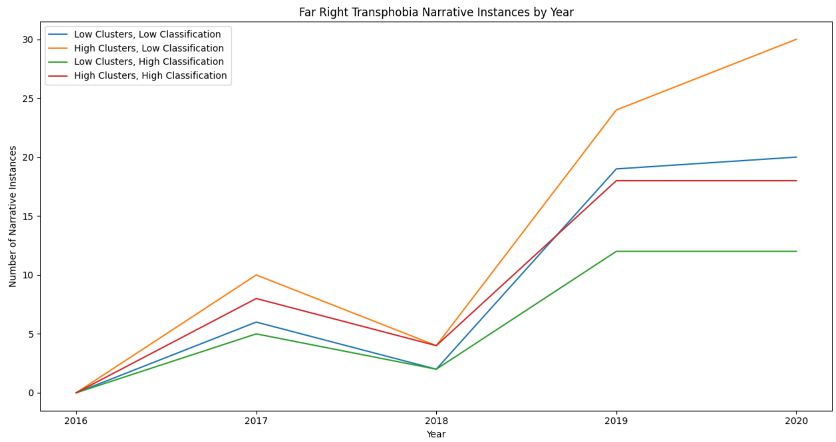

Figure 42 Number of Narrative Instances in the Transphobia Category in the Far Right over time

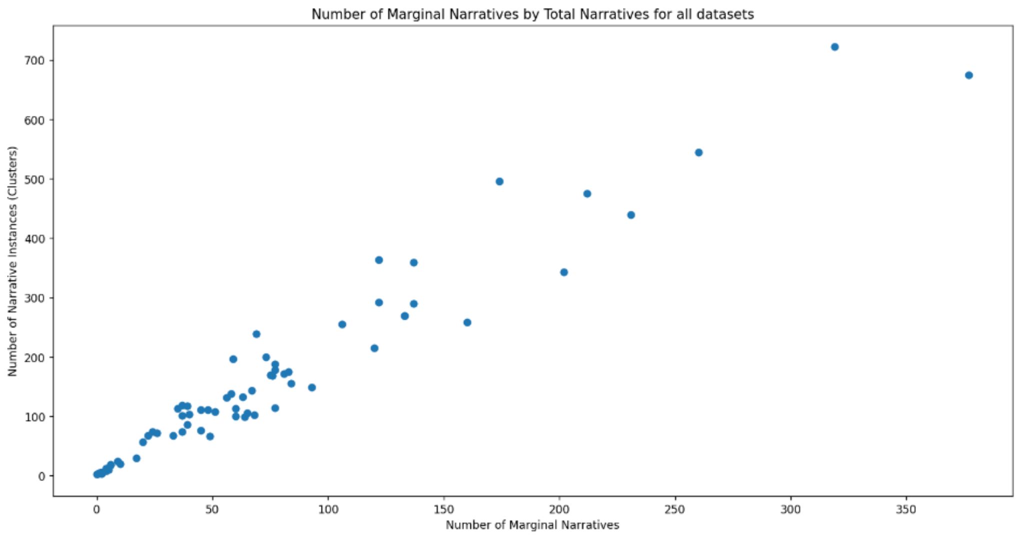

Figure 43 Number of Marginal Narratives by Number of Total Narrative Instances

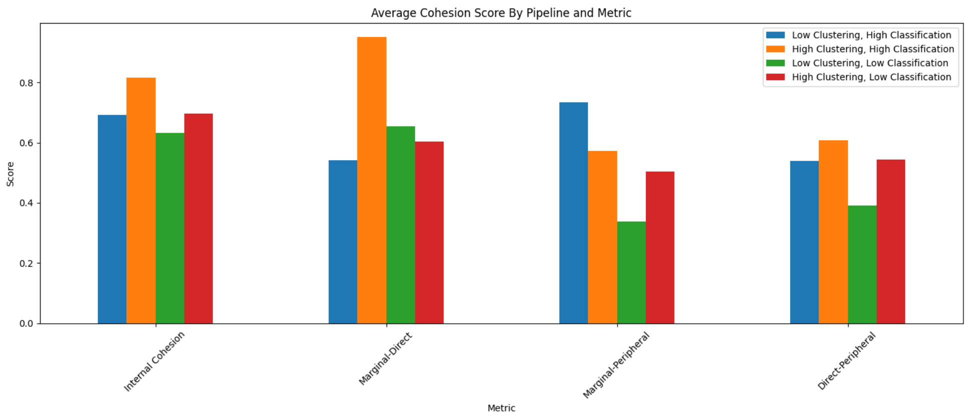

Figure 44 Average Cohesion Score by Pipeline and Cohesion Metric

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