EXAMINING THE ECHO CHAMBERS OF COUNTERMOVEMENTS TO

BLACK LIVES MATTER ON TWITTER

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DECLARATION OF ORIGINALITY

I, Kadir Cihan Duran, certify that

- I am the sole author of this thesis and that I have fully acknowledged and documented in my thesis all sources of ideas and words, including digital resources, which have been produced or published by another person or institution;
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ABSTRACT

Examining The Echo Chambers of Countermovements to Black Lives Matter on Twitter

This research examines the changes in echo chambers formed by individuals with similar beliefs in opposition movements from their emergence to the present day. In this context, the thesis compares the echo chambers of countermovements, including “All Lives Matter”, “Blue Lives Matter”, “Police Lives Matter”, and “White Lives Matter”, which emerged in opposition to the Black Lives Matter movement, between 2013 and 2022. Topic modeling and network analysis methods were used to define the echo chambers. With the use of these methods, the topics discussed in the echo chambers and the members belonging to these groups were easily identified. This allowed for the observation of changes in echo chambers from 2013 to 2022. In this study, changes in echo chambers were examined from two perspectives: the dominant topics in the echo chambers and the members of the echo chambers. The continuity, change, and differences between countermovements in terms of these two factors are the focal points of this study. Accordingly, the thesis demonstrates that there is an increasing trend in the number of echo chambers and their members during times of crisis. It also shows that the continuity of echo chambers differs, dominant topics have distinct seasonal trends, and the continuity of the echo chambers that contain both similar members and topics varies between countermovements.

ÖZET

Twitter'da Siyahların Hayatı Önemlidir Hareketine Yönelik Karşı Hareketlerin Yankı Odalarını İncelemek

Bu araştırma karşı hareketlerdeki benzer düşüncedeki insanların oluşturduğu yankı odalarının, sosyal hareketlerin doğuşundan günümüze kadar olan süreç içerisindeki değişimlerini incelemektedir. Buna göre tez kapsamında 2013 ve 2022 yılları arasında, Siyahların Hayatı Önemlidir hareketine karşı olarak ortaya çıkan "Tüm Hayatlar Önemlidir", "Mavilerin Hayatı Önemlidir", "Polislerin Hayatı Önemlidir", ve "Beyazların Hayatı Önemlidir" karşı hareketlerinin yankı odalarını karşılaştırmalı incelemektedir. Bu bağlamda, yankı odalarını tanımlarken konu modelleme ve ağ analizi metotları kullanılmıştır. Bu metotların kullanılmasıyla beraber yankı odalarında bahsedilen konular ve aynı zamanda bu gruplara mensup olan üyeler rahatlıkla tanımlanmıştır. Bu durumun getirdiği avantajla birlikte 2013'ten 2022'ye kadar olan süreçte yankı odalarındaki değişimi gözlemlemek mümkün olmuştur. Bu çalışmada, yankı odalarındaki değişim temel olarak iki perspektiften incelenmiştir: yankı odalarındaki baskın konu ve yankı odalarının mensupları. Bu iki unsurun zaman içerisindeki sürekliliği, değişimi, ve karşı hareketler arasındaki farklılıkları bu çalışmanın odak noktasıdır. Buna göre tez, olağan üstü zamanlarda yankı odalarının ve mensuplarının sayısında artış eğilimi göstergiğini, yankı odalarının sürekliliğin farklı olduğunu, baskın konuların dönemsel akımlarının ve hem üyelerin hem de konuları benzer olan yankı odalarının devamlılığının karşı hareketler arasında farklılık gösterdiğini ortaya koymaktadır.

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CHAPTER 1

INTRODUCTION

In recent years, there has been growing interest in social movements as a mechanism for promoting social and political change. However, social movements are not immune to the opposition and face resistance from those who are opposed to their objectives or tactics which are called countermovements. Countermovements can pose a significant challenge to social movements, as they strive to subvert their objectives and discredit their arguments (Benford & Hunt, 2003). Hence, understanding countermovements is essential for comprehending the wider context in which social movements operate and the determinants that influence their success or failure.

One key feature of countermovements is their ability to mobilize support and amplify their message through digital technologies and social media platforms (Roth, 2018, p. 541). However, countermovements can also become trapped in echo chambers, where like-minded individuals and groups reinforce each other's views and insulate themselves from opposing viewpoints (Festinger, 1957, p. 203). Therefore, in order to understand the impact of countermovements on social and political change, it is essential to examine the role of echo chambers in shaping their discourse and tactics.

To understand the impact of countermovements on social and political change, it is essential to examine the role of echo chambers in shaping their discourse and tactics. This thesis aims to conduct a comparative study of the echo chambers of four countermovements, which are All Lives Matter, Blue Lives Matter, White Lives Matter, and Police Lives Matter. By examining the formation, maintenance, and impact of echo chambers within these countermovements, this thesis seeks to provide insights into the complex dynamics that shape contemporary social and political discourse.

The Black Lives Matter movement originated in 2013 as a response to the acquittal of George Zimmerman, who was charged with the shooting of Trayvon Martin, an unarmed Black teenager (Brown, Mourao, & Sylvie, 2019). Since then, the movement has evolved into a global effort aimed at raising awareness of police brutality and systemic racism against Black individuals (Barrie, 2020). Despite its widespread support, the Black Lives Matter movement has faced significant opposition from various countermovements, including All Lives Matter, Blue Lives Matter, White Lives Matter, and Police Lives Matter.

One of the critiques to Black Lives Matter accuses the movement of being divisive and exclusionary, arguing that it prioritizes the concerns of Black people over those of other races and groups (Bennett-Swanson, 2017, p. 102). The All Lives Matter movement, in particular, has come under fire for minimizing the unique experiences and challenges faced by Black individuals, as well as for failing to address systemic racism and police brutality (Carney, 2016). On the other hand, Blue Lives Matter and Police Lives Matter emerged as a countermovement following the killing of police officers, used as a means of countering Black Lives Matter's message (Solomon & Martin, 2019). Similarly, White Lives Matter has been appropriated by white supremacists and used to advance their agenda (Stack, 2016).

Although social movements and their countermovements may have different goals and strategies, they often use social media as an effective tool to gain support and express their grievances (Sripanidkulchai, Maggs, & Zhang, 2004). Through the use of social media, we can observe the network structure and changes in these movements over time (Borge-Holthoefer, et al., 2011). The strategies employed by movements on social media provide valuable insights into their activities, including how they mobilize their supporters and spread their message (Breuer, Landman, & Farquhar, 2015). Overall, the use of social media has become a critical factor in the success or failure of social movements and their countermovements, and further analysis especially on echo chambers is needed to fully understand the dynamics of online activism.

Twitter has emerged as a platform where echo chambers can thrive, owing to its algorithmic curation and personalized feeds that often expose users to content that aligns with their beliefs and preferences. (Colleoni, Rozza, & Arvidsson, 2014)Twitter's recommendation algorithms prioritize content based on users' past behavior, interactions, and preferences, creating a filter bubble that reinforces users' existing views and opinions (Gupta, et al., 2014).

At this point, it is important to define echo chambers and where they exist. An echo chamber refers to an environment where individuals are exposed only to ideas and opinions that reinforce their pre-existing beliefs and values (Jamieson & Cappella, 2008). Such an environment discourages individuals from encountering contrasting viewpoints, leading to entrenchment in their existing beliefs (Jasny, Waggle, & Fisher, 2015). The structure of Twitter, with its emphasis on short, highly shareable messages, can also contribute to the creation of echo chambers. The platform's features, such as retweets, likes, and hashtags, can create a viral spread of information, amplifying the messages within echo chambers (Shin, Jian, Driscoll, &

Bar, 2016). Consequently, Twitter plays a significant role in the creation and maintenance of echo chambers, and understanding its dynamics is crucial.

The examination and evaluation of the structures of echo chambers are crucial for comprehending the dynamics and consequences that arise from them. Through a close analysis of the patterns of interaction and information sharing within echo chambers, we can gain a deeper understanding of how they are formed, maintained, and reinforced over time. Additionally, a detailed examination of the content and messaging that circulates within these echo chambers can provide valuable insights into the values, attitudes, and beliefs that underlie them, offering important clues to their potential impacts on society. Ultimately, a thorough understanding of the structure of echo chambers is vital for gaining insights into the characteristics and attitudes of the masses, particularly those who mobilize online.

This research aims to observe the echo chambers of the countermovements and compare their characteristics and continuity of them over time by proposing a new method to detect echo chambers on social media. In this study, I analyze the countermovements All Lives Matter, Blue Lives Matter, Police Lives Matter, and White Lives Matter on Twitter, which is one of the largest social media microblogs in the world. I collected over one million tweets using the Twitter Developer API for academics between 2013 and 2022, covering the entire lifespan of these countermovements. This is a unique feature of my study, as most previous studies have only focused on specific time periods of these movements. Prior to analysis, I preprocess the data by removing stop words, website links, and mentions, and I also introduce a new spam detection algorithm specifically tailored to my dataset to filter out irrelevant and noisy tweets.

In this research, I primarily employ topic modeling and network analysis techniques to identify echo chambers and their characteristics as mentioned above. I contend that actively writing and sharing posts on a specific topic on social media reflect a stronger commitment to a community and its values compared to other activities like liking, retweeting, or following prominent figures in the movement. By utilizing this approach, I aim to accurately determine the specific echo chambers that people are involved in.

My research aims to address gaps in literature from different perspectives. First, I seek to identify potential differences between echo chambers over time. This is facilitated by the broad coverage of the datasets, which allows me to observe potential changes in the attitudes of the echo chambers.

Second, it is important to establish a clear definition of echo chambers, and there are various strategies used in the literature to do so. One popular approach is to create echo chambers by analyzing the retweet networks of users, as demonstrated in studies by Wieringa et al. (Wieringa, van Geenen, Schäfer, & Gorzeman, 2018) and Lynch et al. (Lynch, Freelon, & Aday, 2017). Another approach is to consider parametric data related to posts, such as likes and favorites, as done by Vicario et al. (Vicario, Gaito, Quattrociocchi, Zignani, & Zollo, 2017). Following and follower networks have also been used to create echo chambers, as in the study by Hayat and Samuel-Azran (Hayat & Samuel-Azran, 2017), while Furman and Tunç (Furman & Tunç, 2019) focused on mentions of others in posts as a means of generating echo chambers. However, I contend that echo chambers are intricate structures that require more sophisticated analyses than simple text parameters. To address this issue, my study employs a combination of topic modeling and network analysis to identify echo chambers, which I propose has the potential to identify these communities more precisely.

Third, there is a lack of studies that provide a comprehensive analysis of countermovements from their inception to their dissolution. Previous research has typically focused on specific time periods, providing only snapshots of the movements. In contrast, my study examines the entire lifespan of the countermovements, providing a more holistic view.

Last, my research includes a comparative study that aims to identify potential variations between the echo chambers of different countermovements. Additionally, I have developed two algorithms, the continuity score, and the spam detection algorithm, which can be further developed and utilized by future studies.

In the first chapter of my research, I provide an overview of literature from various fields. First, I review studies on social movements and their countermovements, with a focus on the emergence conditions of countermovements. Second, I analyze the relationship between the initial movements and their countermovements. Although existing studies mainly focus on field movements, I extend the discussion to include the effects of the internet and social media on social movements, countermovements, and their relationships. Moreover, I examine the historical background of the Black Lives Matter movement and its countermovements. Subsequently, I delve into the concept of homophily, which is the core concept of my research, and its reflection on social media echo chambers and filter bubbles. Lastly, I review previous studies on echo chambers in social media.

In the second chapter, I present my data and methods. First, I explain how I collected and pre-processed my data for analysis, including the implementation of my spam detection algorithm, which successfully detected a significant number of spam tweets. Second, I introduce the statistical tools and methods that I used in my research, starting with the topic modeling and algorithms behind this technique. Then, I delve into the network structure, followed by other statistical tools such as the Jaccard similarity and continuity algorithm that I developed for this study.

In the last chapter, I present my analyses and interpret the results. Specifically, I compare the results of the four countermovements from different perspectives, focusing on the frames of the echo chambers, the members of the echo chambers, and the combination of both. I also include visualizations such as bar charts, box plots, and line charts to facilitate understanding and interpretation. Lastly, I conclude with a general discussion of the results and their implications.

CHAPTER 2

LITERATURE REVIEW

2.1 Social movements and their countermovements

Social movements have been a powerful force for social, political, and cultural change throughout history. They have challenged existing power structures, advocated for marginalized groups, and shaped public opinion on a wide range of issues, from civil rights and environmental justice to gender equality and LGBTQ+ rights. Understanding the dynamics of social movements is crucial for identifying their potential for impact and for developing effective strategies for social change. Social movements have been studied extensively by scholars from various disciplines, who have sought to understand their emergence, dynamics, and impact on society. According to Charles Tilly's conceptualization, social movements arise from the convergence of three distinct elements: the campaign, which encompasses the overarching goals and demands of the movement; the collection of actions or repertoire of participants, which includes the various tactics, strategies, and forms of protest utilized by the movement; and the representation of the participants' collective devotion, or their shared commitment to the movement's cause. (Tilly, 2004, p. 3). In other words, Tilly argues that social movements emerge when people come together to make collective claims on targeted authorities, which is defined as a campaign, using some strategies such as public meetings, rallies, or petitions, which correspond repertoire of the social movement. While doing these they also need to show their worthiness, unity, numbers, and commitment too (Tilly, 2004, p. 4).

From a broader perspective, social movement can be defined as dynamic and intricate webs of individuals who unite under a shared collective identity to actively participate in political conflicts (Diani, 2011). What sets social movements apart is their networked nature, as members connect through a web of relationships, shared values, and common goals. Furthermore, this interconnectedness allows for the mobilization of large numbers of individuals, amplifying their voices and enabling them to push for change on a broader scale (Della Porta & Diani, 2006, p. 21). By shifting our focus away from traditional notions of social movement control centered around hierarchical leadership structures and organizations, adopting a network perspective offers valuable insights into the dynamics of social movements. Examining a social movement as a network of individuals allows us to explore various aspects such as the participants' commitment to the cause, their interconnections and collaborative relationships, the coherence of their collective discourse, and the sustained efforts they exert over time. This approach proves to be fruitful in enhancing our understanding of social movements and their intricate workings.

It is a natural outcome that the existence of the movements that successfully organized, take attention of the public, and finally get power leads to the mobilization of their countermovements (Zald & Useem, 1987). Shortly, there will be the unification of the people who want to secure their position and resist change if there is a threat from the newly established social movement. From this view, countermovements can be seen as a reactionary movement, which wants to maintain its position, to the initial movement, which wants to change. Lo, on the other hand, sees countermovements as not just reactionary movements, but these movements also might be progressive another movement (Lo, 1982, p. 118). In other words, countermovements do not just resist change but also propose new arguments that make it difficult to possible future changes about what they resist.

How exactly do countermovements emerge? Meyer and Staggenborg claim three steps for the rise of the countermovements (Meyer & Staggenborg, 1996). First, there should be an initial movement that wants to change and proves its success in society. Second, the interests of some part of society, which would create countermovement later, must be threatened by that initial movement. Lastly, political allies have the opportunity to help mobilization of that threatened group (Meyer & Staggenborg, 1996, p. 1635).

Countermovements can have significant implications for both the social movements they target and the wider political and social context in which they operate. The consequences of countermovements can take various forms. Mottl identifies three possible outcomes: inequality, stabilization of the situation, and reconsolidation of bureaucratic authority (Mottl, 1980, p. 631). The first outcome refers to the ways in which countermovements can reinforce existing inequalities in society and institutions, as they pursue their specific goals through various means. The second outcome occurs when countermovements manage to neutralize some of the progress made by the initial social movement, thereby stabilizing the status quo. The third outcome is the possibility of a close relationship between government authorities and countermovements, leading to the reconsolidation of bureaucratic authority (Mottl, 1980). By examining the consequences of countermovements, we can gain insights into the ways in which social movements and countermovements interact and how they shape broader social and political dynamics.

Kenneth Andrews' study on white flight schools in Mississippi (Andrews, 2002, pp. 920-923) serves as a compelling example that vividly illustrates the reactionary nature of countermovements and the intricate outcomes that may ensue. By examining this case, we gain valuable insights into the complex dynamics that unfold when countermovements are mobilized in response to social changes. In this case, in response to the desegregation of public schools, many white families withdrew their children and enrolled them in private academies, a trend that represented a countermovement against the broader civil rights movement of the time. While this process was driven by discrimination against Black students, it also illustrates how countermovements can arise in response to movements seeking greater social justice and equality. As Black communities protested and gained organizational power, white families in Mississippi formed alliances to resist the changes being brought about by the civil rights movement. This example underscores the importance of analyzing the dynamics of social movement-countermovement interactions to better understand how networks of individuals are shaped by these processes over time. A thorough analysis of this case can provide insights into the complexities of countermovements, including the ways in which they can serve to perpetuate inequality and undermine progress toward greater social justice.

The interactions between social movements and countermovements is a complex and multifaceted phenomenon that has been extensively analyzed in the literature. The tactics used by social movements to eliminate their rivals are of particular importance in this context. In their study on the abortion movement, McCaffrey and Keys identify three strategies that are commonly employed by social movements: polarization, frame debunking, and frame saving. These strategies involve creating an "us versus them" environment, denigrating opposition, and using appropriate terminology to deal with the conflicted group (McCaffrey & Keys, 2020, p. 49). Benford and Hunt build on these concepts and introduce new ones to analyze prior movement-countermovement relations. They argue that countermovements typically deny the problems put forward by the initial movement and organize their objections in opposition to it. Countermovements propose their solutions or want to sustain the status quo by attacking the unity of the prior movement. The initial movement may respond to the countermovement by ignoring it, transforming with the critiques, or counterattacking its opponent (Benford & Hunt, 2003).

Understanding the dynamics of social movement-countermovement interactions and the strategies employed by social movements is crucial for analyzing the evolution of social movements over time. Expanding on the idea of social movement-countermovement interaction, Ayouba, and Chetaille conducted an analysis of the tactics used by the Polish LGBTI community and its conservative countermovement, utilizing the concepts of alignment, conflictualization, mirroring, and diversification (Ayouba & Chetaille, 2020). The authors observed changes in the tactics of the community over time, in response to the reaction of its countermovement (Ayouba & Chetaille, 2020). Additionally, Turner and Killian suggest that with the success of a social movement, countermovements may begin to adopt popular tactics and strategies used by the initial movement (Turner & Killian, 1987). In conclusion, the relationship between social movements and countermovements is not static, but rather characterized by a dynamic interaction between the two. While there has been ample research on offline social movements and countermovements, further analysis is needed in the realm of online social movements, especially in light of the growing importance of social media.

In the context of traditional social movements and countermovement relations, the role of government agencies in shaping policy has been widely recognized (Gale, 1986). While it is still important, the way of creating public opinion to influence these agencies changes dramatically thanks to social media platforms. Due to the higher public pressure that comes with social media and the lack of control of the state on the internet (Peckham, 1998), the direct effect of the state on social movements mitigates. This can be understood through the lens of the transformation of the public sphere with the advent of the internet. Habermas conceptualizes the public sphere as a space where individuals come together to identify and discuss societal problems, creating a powerful force in the political arena through the formation of public opinion (Habermas, 1962). Traditional media tools like newspapers and radio have historically been central to communication tools. However, the advent of social media has introduced a transformative element. Unlike the one-way communication style of traditional media, social media platforms offer a more inclusive and participatory public sphere (Gerhards & Schäfer, 2010, p. 154). This shift allows individuals to actively engage in discussions, share information, and contribute to public discourse. As a result, social media has the potential to enhance the public sphere by providing a platform for diverse voices and facilitating broader participation in shaping public opinion and democratic processes.

The emergence of social media and the increasing trend of user-generated content has transformed the public sphere by creating new opportunities for dialogue and collaboration among individuals. Despite ongoing debates regarding the potential pitfalls of social media, such as issues of censorship, the influence of private corporations over these platforms, and the proliferation of trolls and bots, I argue that social media offers at least a minimum level of public sphere engagement, while dramatically reducing the cost of participation.

2.2 Effects of the Internet on social movements

The proliferation of internet usage among the masses has significantly transformed the characteristics of social movements. As previously noted, social movement organizations have adapted their strategies by utilizing the internet to garner support from the public and raise awareness. The Internet offers numerous advantages, including accessibility, cost-effectiveness, and independence from state authorities (Castells, 2015). First, with the increase in the popularity of the internet, the autonomous communication tool emerges. In other words, the rise of social media has given communication tools greater autonomy, replacing the centrality of traditional media such as newspapers and TV channels. With social media platforms, people can easily communicate with each other and share information, thus facilitating the conversion of collective emotions into collective action (Castells, 2015). Another advantage of internet usage and participation in social networks is promoting civic participation (Earl, Maher, & Elliott, 2017). People, especially the young generation use social media platforms as a space where they can meet with people who are interested in shared topics so, they can share information and discuss with people who share the same interests and opinions (Borrero, Yousafzai, Javed, & Page, 2013). Third, no doubt one of the advantages of the internet on social movements is decreasing the problem of free riders (Leizerov, 2000). Sometimes people want to participate in campaigns or social movements, but they cannot due to the lack of time or potential risks. However, with the internet, the total number of free riders drops even if it does not solve completely (Leizerov, 2000). Each of these elements is one of the reasons why people frequently use social media platforms when they want to protest. Overall, the internet has significantly transformed the landscape of social movements, making communication faster, more accessible, and more attention-grabbing than any other tool.

The Internet has not only revolutionized the way individuals communicate and exchange information but also transformed the tactics and structures of social movement organizations. Scholars Laer and Aelst have examined this shift through the lens of Tilly's concept of the "repertoire of collective action" (Laer & Aelst, 2009). According to Tilly, this notion is tactics and strategies that are developed in time by the protest groups to influence both individuals and society (Tilly, 1984). Strikes, riots, sit-ins, or boycotts are some examples of these strategies. On the other hand, with the increase in popularity of the internet, Laer and Aelst claim that these tactics and strategies are expanded such as with the online petition, virtual sit-ins, hacktivism, or protest in social media (Laer & Aelst, 2009). On the other hand, there are some disadvantages of the internet on social movements too. For instance, it is inevitable that not everybody has internet access, even in the scenario where most of them have, not all individuals have equal access to the skills and resources necessary to participate effectively in social media-based movements. It may conclude with the over-representation of some parts of society and less representation of others (Lorenzo, 2007). To sum up, the over-representation of certain groups in online social movements may result in a skewed representation of the movement's goals and demands, leading to unintended consequences. Moreover, the use of troll and bot accounts by experts to manipulate online social movements can also result in the spread of false or misleading information, which can harm the credibility and legitimacy of the movement.

At this point, how do people unite and reach others on social media? The rise of social media has provided new avenues for individuals and organizations to reach a wider audience and mobilize support for their causes (Sripanidkulchai, Maggs, & Zhang, 2004). In order to be successful, both social movements and organizations need to establish a collective identity that resonates with their target audience. The creation of a collective identity is especially critical for social movements, as it enables individuals to shift their focus from "I" to "we" and feel a sense of belonging to a larger community (Gerbaudo & Treré, 2015, p. 865).

Social media plays an important role in creating this phenomenon of collective identity. One tool that has been instrumental in creating collective identities on social media is the hashtag. Hashtag is a word that represents a “#” sign. It is used on social media platforms, websites, and applications both to highlight and identify terms. It plays an organizer role, especially in social media. For instance, people can share their opinions by writing a hashtag before the topic, organization, or movement word such as “#BlackLivesMatter”, so, others can easily find what people say about that specific term on the platform. By engaging with the hashtag, people start to create awareness then they promote the hashtag to increase its popularity so they can reach more people. As people interact with the hashtag, they develop a collective action frame and create an echo chamber for their message (Benford & Snow, Framing Processes and Social Movements: An Overview and Assessment, 2000). In other words, as individuals engage with a hashtag and share their perspectives, they create an echo chamber in which their collective identity is reinforced and amplified. This can lead to increased awareness and support for a particular cause or movement. However, it is important to recognize that echo chambers can also contribute to polarization and the silencing of opposing viewpoints due to their nature. Therefore, it is important to approach the use of hashtags and other tools on social media with a critical lens and an awareness of their potential impact on the broader discourse.

The increasing use of social media platforms has led to the emergence of big data, which is an important resource for understanding online social movements. As millions of tweets are posted on a specific topic, it is difficult to analyze them individually. Therefore, we need to use quantitative research methods to analyze large sets of data. While qualitative research methods are widely used to analyze social movements, such as Polish lesbian and gay activism, the case of white flight schools in Mississippi, the case of Scientology, and the environmental movement as mentioned above, there are also quantitative studies that use discourse analysis and hashtags to examine online social movements (Freelon, McIlwain, & Clark, 2016; Tindall, Howe, & Mauboulès, 2020). In such studies, scholars generally focus on the discourse of the people, the connection network of the users, or metrics of the posts such as likes, reposts, or mentions. Scholars use various methods, such as topic modeling, network analysis, and inferential statistics, to analyze the data. While some articles take a snapshot of a certain period, others conduct analyses over time. It can be inferred that various perspectives can be considered, and each perspective provides additional insight into the structures and characteristics of the movements. Furthermore, on the one hand, social movements are more commonly studied due to their prevalence and impact. On the other hand, there remains a gap, especially for the countermovements in literature.

2.3 The term homophily

The concept of “Homophily” is used by Lazarsfeld and Merton first time in 1954 in the book chapter called Friendship as Social Process: A Substantive and Methodological Analysis?” (Lazarsfeld & Merton, 1954). They analyzed two housing communities in New Jersey and Pennsylvania based on the friendship of residencies. They observed friendship relations of people in these communities are affected by the values such as race, sex, or educational status. Furthermore, the authors ask the question: “When it comes to close friendship, do birds of a feather flock together?” (Lazarsfeld & Merton, 1954, p. 22). Then, due to the absence of the terminology for such a concept, they coined homophily and define it as “a tendency for friendships to form between those who are alike in some designated respect” (Lazarsfeld & Merton, 1954, p. 23). The introduction of this concept provided a new perspective on the relationships between individuals and opened up new avenues of inquiry in the academic community.

McPherson et al. are known for their famous article "Birds of a Feather: Homophily in Social Networks," in which they examine the structure and characteristics of homophily. In their study, they define homophily as the tendency for similar people to interact more with each other than with dissimilar people. (McPherson, Smith-Lovin, & Cook, 2001, p. 416). This more simple but generalizable description is used in today’s studies. Moreover, McPherson et al. distinguish between two types of homophily: status homophily, which covers factors such as sex, gender, ethnicity, race, religion, and age, and value homophily, which includes attitudes and beliefs. They also identify the sources and causes of homophily, such as geography, family ties, and organizational foci subtitles (McPherson, Smith-Lovin, & Cook, 2001). McPherson et al. characterize the existence and attributes of homophily under these scenarios. In the context of social movements, I believe that we can observe a combination of status and value homophily. While the emergence of the movement started with the status homophily, such as the unification of the black community response to the unjust acts at the beginning, with the expansion of the movement, which might gain supporters from others, including other ethnic groups, the elements from value homophily can be observed due to the merging of the people who share the same opinion, which is discrimination of the black community in our case.

2.4 Terms of the echo chamber and filter bubble

The concepts of the echo chamber and filter bubble are two of the primary concerns addressed in this research. While some scholars have used these terms interchangeably, Terren and Borge have distinguished them as separate phenomena (Terren & Borge, 2021, p. 100). Specifically, the term "filter bubble" was coined by Eli Pariser to describe a unique online environment where individuals interact with content tailored to their preferences by predictive algorithms (Pariser, 2011, p. 10). Pariser identifies three key characteristics of the filter bubble: first, users are isolated within their own bubble; second, the filter bubble is invisible to users; and third, individuals cannot select which bubble they wish to participate in. This personalized virtual sphere is both cultural and personalized, as the algorithm tailors content to each user based on their online activities (Pariser, 2011). Additionally, Thorson, Cotter, Medeiros, and Pak's survey study further supports the notion that the behaviors of users, such as following groups or liking posts, are instrumental in shaping their filter bubbles on Facebook (Thorson, Cotter, Medeiros, & Pak, 2019). In contrast, the concept of an echo chamber differs from that of a filter bubble. The term "echo" implies a sense of unity and consensus, while "chamber" refers to the transmission of information among individuals in a given location. Specifically, Jasny and colleagues' empirical examination of echo chambers in US climate policy networks highlights the ways in which like-minded individuals communicate with one another, reinforcing shared beliefs and values (Jasny, Waggle, & Fisher, 2015). The phenomenon called echo chamber is stressed from various perspectives such as political theory, psychology, or media. For instance, echo chambers can be structured from the concepts of we/they or friend/enemy. The usage of these concepts can be seen as the engagement of groups of like-minded people in the issue of democracy (Mouffe, 2005). From a psychological perspective, people want to reduce their cognitive dissonance or avoid an increase in dissonance, and to achieve it they associate with other people who have similar ideas with them (Festinger, 1957, p. 203). In social media literature, the term echo chamber is defined as the existence of an environment bordered by a common frame and tendency of the like-minded people, who share the same belief with that frame, to join this community (Jamieson & Cappella, 2008; Garimella, Gionis, Morales, & Mathioudakis, 2018).

Do echo chambers behave differently in terms of the topics? Research has suggested that the behavior of echo chambers may vary depending on the topic of discussion. Barberá, Jost, Nagler, Tucker, and Bonneau found that while echo chambers tend to communicate more frequently within their groups, their tendencies may change depending on the topic of conversation. For example, when discussing non-political events, interactions between different echo chambers may be higher. However, on political issues, people tend to communicate with others in their own echo chambers, resulting in much higher interaction (Barberá, Jost, Nagler, Tucker, & Bonneau, 2015). These findings highlight the significance of the topics that individuals engage with in shaping echo chamber behavior. Moreover, it raises the question of whether there are any divisions within the group in terms of political context. Given that countermovements are often highly concentrated in their efforts to suppress prior movements, it may be expected that there is a sense of unity within the network and echo chambers.

An important question that arises is whether the network structure of echo chambers changes over time, and if so, what impact this has on the durability of the echo chambers. According to Jasny and Fisher, people might change their opinions and echo chambers they are in over time. Their study on the opinions about climate change suggests that people change their beliefs with the impact of the views on climate change and the attitudes of the politicians in the government. Thus, the network of the people changes too (Jasny & Fisher, Echo chambers in climate science, 2019). However, in the context of countermovements, especially for the countermovements of Black Lives Matter, most of the time during the lifespan of the movements, there is no dramatic change in demands and beliefs so, is it still possible to observe durable echo chambers or there is not any unity on echo chambers? It would be interesting to explore potential differences in echo chambers across various countermovements, particularly those that offer critiques of prior movements from different perspectives. To date, there has been no comparative study of echo chambers among countermovements that share opposition but have fundamentally different arguments.

2.5 Echo chambers in social media

Echo chambers are observed on various platforms. For instance, there are studies on echo chambers and filter bubbles on Twitter (Bozdag, Gao, Houben, & Warnier, 2014), Facebook (Bode, 2012), and even YouTube (O'Callaghan, Greene, Conway, Carthy, & Cunningham, 2013). While most studies use datasets retrieved from digital sources or social media, some studies use survey data. For the latter one, the existence of echo chambers is problematic. For example, in the article of Dubois and Blank, they claim that only a small part of society is in the echo chamber. Moreover, they argue that most of the studies that just cover single social media as a source do not sustain real-world conditions (Dubois & Blank, 2018). On the other hand, most studies using social media data find the existence of echo chambers (Terren & Borge, 2021).

In my research, I aim to analyze echo chambers within countermovements on Twitter. Twitter presents itself as a suitable platform for such an investigation for several reasons. First, the Black Lives Matter movement and its countermovements are highly active on Twitter, with millions of tweets containing both #BlackLivesMatter and countermovement hashtags (Ince, Rojas, & Davis, 2017). Second, Twitter's competitive nature and high polarization levels (Garimella & Weber, 2017) make it an ideal platform for studying echo chambers. As Ray et al. suggest in their study, echo chambers on Twitter create polarized environments where dominant ideologies align with individuals' beliefs, making Twitter an optimal platform for observing such phenomena (Ray, Brown, Fraistat, & Summers, 2017, p. 1799).

2.6 Historical background of the movements

In this part of my thesis, I introduce prior movement, Black Lives Matter, and its countermovements called All Lives Matter, Blue Lives Matter, Police Lives Matter and White Lives Matter with their historical background and main characteristics.

2.6.1 Black Lives Matter

The genesis of one of the most significant online social movements can be traced back to the killing of Trayvon Martin, an unarmed 17-year-old black civilian, by George Zimmerman, a neighborhood watch volunteer, in February 2012 (Brown, Mourao, & Sylvie, 2019). The trial of Zimmerman was held in July 2013, and he was ultimately acquitted of Martin's murder (Obasogie & Newman, 2016) The unexpected verdict triggered the founding of Black Lives Matter by Alicia Garzia, Patrisse Cullors, and Opal Tometi (Black Lives Matter, 2023). Garzia's vision for the movement is rooted in the notion of "ideological and political intervention in a world where Black lives are systematically and intentionally targeted for demise" (Garza, 2014). The movement gathered momentum with the deaths of Michael Brown, Eric Garner, and Breonna Taylor, but it reached its peak following the tragic murder of George Floyd in May 2020 (Barrie, 2020). Floyd, a 46-year-old African American, was killed by a police officer in Minnesota, with footage of the last minutes of his life galvanizing the movement and sparking intense public anger. In the video, the police officer can be seen using a chokehold on Floyd as he repeatedly says, "I can't breathe" (Apata, 2020). This disproportionate use of force by the police officer was far from a justifiable act of self-defense, once again raising questions about police actions against black civilians.

Alongside physical demonstrations, online social media platforms have played a crucial role in advancing the Black Lives Matter movement. The hashtag #BlackLivesMatter has been tweeted millions of times, with its usage skyrocketing during the aftermath of the killings of Eric Garner, Michael Brown, Ahmaud Arbery, and, most significantly, George Floyd. On May 28, 2020, just three days after Floyd's death, the hashtag was tweeted 8.8 million times, highlighting its widespread appeal and resonance (Anderson, Barthel, Perrin, & Vogels, 2020). The use of the hashtag has not been confined solely to Twitter; other social media platforms such as Snapchat and Facebook have also been utilized actively during the protests (Clark, 2016).

2.6.2 Countermovements to prior movement

After a notable rise in the Black Lives Matter movement, there are various countermovements emerged to protect the values and norms that they believe and the prior movement, Black Lives Matter, try to change. Three main branches can be classified for these countermovements. First, there is the color-blind racist movement, which advocates for All Lives Matter. Second, a white nationalist movement which is White Lives Matter. Last, pro-police movements which include Blue Lives Matter and Police Lives Matter. While these four movements may espouse different arguments, they are all underpinned by the same fundamentally racist attitudes.

2.6.2.1 All Lives Matter as a color-blind movement

On the one hand, Black Lives Matter supports and highlights the right of black people, most basically the right to live, on the other hand, a more local movement called All Lives Matter claims that all races and living beings should be treated the same. In other words, All Lives Matter is seen as a movement that advocates for equal treatment to all individuals, regardless of their ethnicity and race, and tries to promote unity and inclusivity for all living beings. While this desire seems to be innocent, the content and arguments of the supporters are nothing more than color-blind racism (Carney, 2016, p. 185). Moreover, it is possible to match All Lives Matter's ideology with Bonilla-Silva's two of central frames of color-blind racism which are cultural racism and minimization of racism (Bonilla-Silva, 2017). The former concept claims that there is no inferior or superior ethnicity but the difference between them is based on cultural values and traditions. For instance, they claim that there is equality in the job market, but black people are lazy and do not want to work due to their inheritance so white people get the positions. On the other hand, the latter concept is about neglecting existing problems. For example, people agree that there were problems with racism in the past but today, there are not. Moreover, they claim that even though there is still a problem, a too small part of society is affected by it, and in general, there is justice among the races (Bonilla-Silva, 2017). When we observe All Lives Matter, there are effects of these two concepts on the discourse of the people. While people minimize the problems of the black community by highlighting the problems of others, they also blame supporters of the Black Lives Matter movement for their cultural norms.

2.6.2.2 Blue Lives Matter and Police Lives Matter as pro-police movements

Blue Lives Matter is a social movement that originated in the United States as a response to the escalating violence targeted at law enforcement officials. Its emergence can be attributed to the growing prominence of the Black Lives Matter movement in 2013, as a reactionary countermovement. The fundamental underpinning of Blue Lives Matter is the support for the police force, the families of police officers who have been victimized, and the advocacy for more stringent laws and harsher punishments for those who inflict harm upon police officers (Solomon & Martin, 2019).

According to Cooper, there are four elements that make Blue Lives Matter a legal and considerable movement. First, the Blue Lives Matter movement has had a fluctuating impact on legislation across the United States. While the call for Blue Lives Matter laws may have been a brief trend, most states and the federal government proposed additional protection for police officers in 2016, 2017, or 2018. Second, some states have adopted some form of extra protection for police officers, indicating that there is still significant interest in Blue Lives Matter bills across the country. Third, although most jurisdictions have declined to initiate Blue Lives Matter bills, a few may have considered them under unconventional phrasing. Lastly, despite this, the Blue Lives Matter movement is still advocating for these laws, and it is a crucial sign of their legal and social impact (Cooper, 2020).

Compared to other countermovements, Blue Lives Matter demonstrates a greater degree of mobilization and centralization. Although lacking a clear organizational center or founder, the movement has been embraced by a wide range of individuals and organizations. For instance, a registered nonprofit organization based in New York City self-identifies as a group dedicated to supporting and raising awareness for police officers and their families, operating under the name Blue Lives Matter NYC (Blue Lives Matter NYC, 2023). Unlike other countermovements, Blue Lives Matter has a symbol, namely the “thin blue line” flag, which serves to represent the movement. Additionally, the movement capitalizes on its symbol and message by marketing specialized clothing, flags, hats, and other souvenirs, both to increase solidarity among its supporters and to raise funds for the movement (Wall, 2020).

Although often used interchangeably with Blue Lives Matter, Police Lives Matter exhibits subtle differences in its focus and objectives. While Blue Lives Matter centers on advocating for law enforcement officers after they have experienced violence, Police Lives Matter expresses a more general sentiment of support for the law enforcement community, independent of any particular violent action. In this way, Police Lives Matter's claim is primarily geared toward demonstrating respect and promoting support for police officers (Police Lives Matter USA, 2023).

Similar to Blue Lives Matter, Police Lives Matter lacks a centralized organizational structure, and instead comprises several smaller groups working to sustain the movement, often relying on donations to do so. However, in terms of online presence, Police Lives Matter has garnered relatively fewer supporters, as indicated by the lower number of tweets shared under the #PoliceLivesMatter hashtag, in comparison to the volume of tweets associated with the Blue Lives Matter with an exception. It is important to mention that while Police Lives Matter is more active users at the beginning of the lifespan of these two countermovements, it slowly decades and Blue Lives Matter becomes more popular and flagship movement that protects rights of the police officers.

2.6.2.3 White Lives Matter as a white nationalist movement

White Lives Matter is a movement that emerged in 2015, in response to the Black Lives Matter movement by the white supremacist group called Aryan Renaissance Society. The movement seeks protection and advancement of the interests of the white people in society. Not just associated with this group but this movement has supporters can be seen in fascist movements and organizations (Stack, 2016). However, despite its association with these groups, White Lives Matter's activity on social media, particularly on Twitter, remains limited, as evidenced by the relatively lower number of tweets associated with the #WhiteLivesMatter hashtag.

CHAPTER 3

DATA AND METHODOLOGY

This research involves a three-step data and methodology approach, namely tweet scraping, data pre-processing, and methods and visualization. While the tweet scraping step involves the collection of Twitter data using an application programming interface (API), the remaining two steps encompass more complex quantitative methods. Data pre-processing involves the removal of spam tweets, detection of one-time participants, tokenization of tweets, and removal of stopwords. Methods and Visualization, on the other hand, entail two distinct techniques, namely topic modeling and network analysis, along with their respective visualizations. The sequence of these steps is illustrated in Figure 1 as follows:

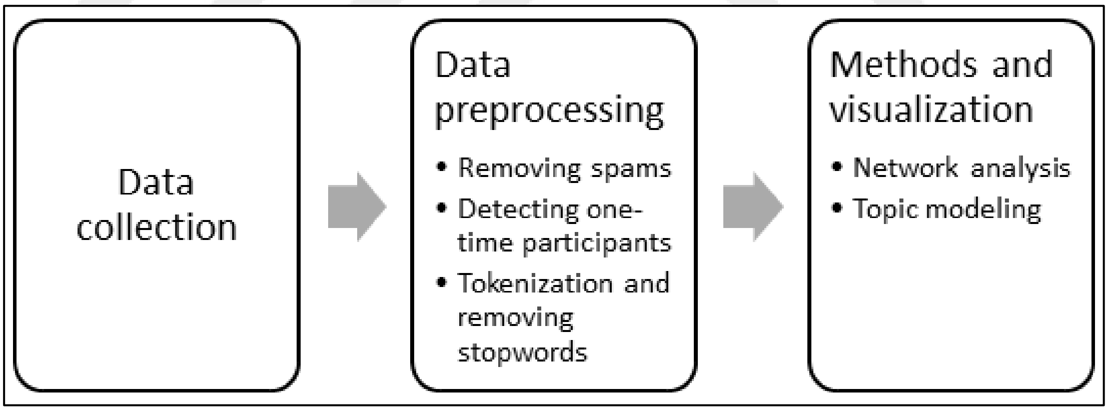

Figure 1. Steps of the data and methods

3.1 Data

In this study, I employ Python programming language version 3.9 to both obtain and analyze Twitter data. Specifically, I utilize the Twitter API V2 for Academic Research (Twitter, 2023), which requires researchers who are either academics or graduate students to apply for access. Unlike other Twitter tools, which limit the collection of tweets to the last 15 days and 500,000 tweets per month, API V2 offers the so-called full-archive search, allowing for the scraping of tweets without any time restriction. Moreover, this tool permits the collection of up to 10 million tweets per month (Twitter, 2023) enabling the gathering of big data sets related to social movements, such as the Black Lives Matter movement, without any constraints.

In order to collect data on four countermovements, namely White Lives Matter, Blue Lives Matter, Police Lives Matter, and All Lives Matter, I utilized the Twarc library in Python (Summers, Brigadir, & Hames, 2022). The query, which specifies the rules for collecting tweets that meet certain criteria, consisted of three parts. First, I included a key term that must be present in the tweets, specifically the hashtag versions of each countermovement (#WhiteLivesMatter, #BlueLivesMatter, #PoliceLivesMatter, and #AllLivesMatter). Second, to focus solely on original content, retweets were excluded from the results. Lastly, the period of interest was set to cover the entire duration of the movements, from January 1, 2013, to September 28, 2022, which corresponds to the day when the tweet collection process started. Using these criteria, a total of 157,305 tweets were collected for White Lives Matter, 672,646 tweets for Blue Lives Matter, 80,737 tweets for Police Lives Matter, and 903,029 tweets for All Lives Matter as can be seen in Figure 2.

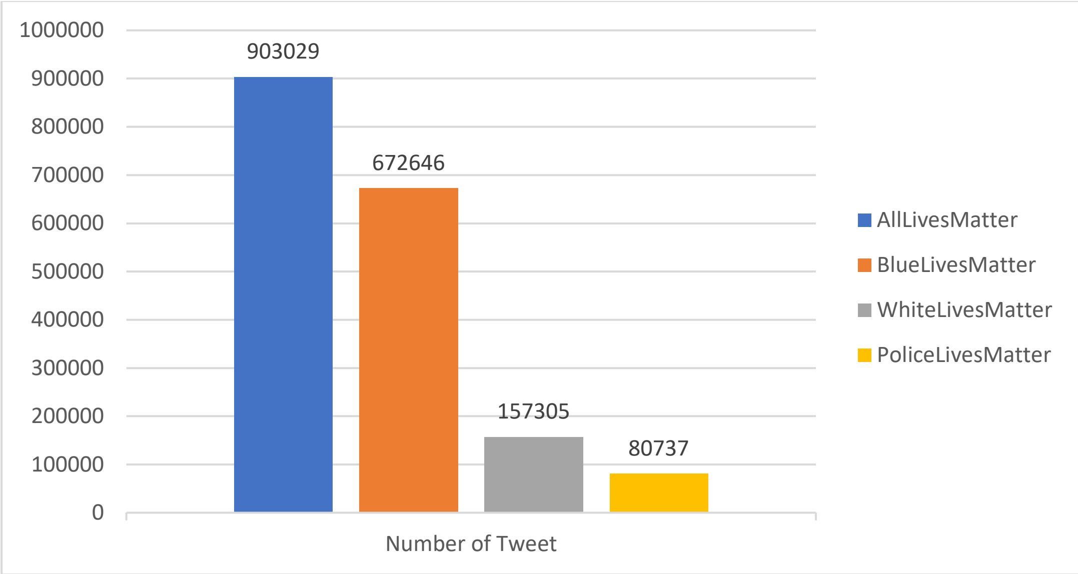

Figure 2. Total number of countermovements tweets

The differences in the number of users of the four movements can be attributed to their popularity and the extent of their scope of interest. Figure 3, represented as a bar chart, shows that All Lives Matter has the highest number of users with a total of 409,907, followed by Blue Lives Matter with 197,786 users. White Lives Matter has 72,787 users, and Police Lives Matter has 31,681 users.

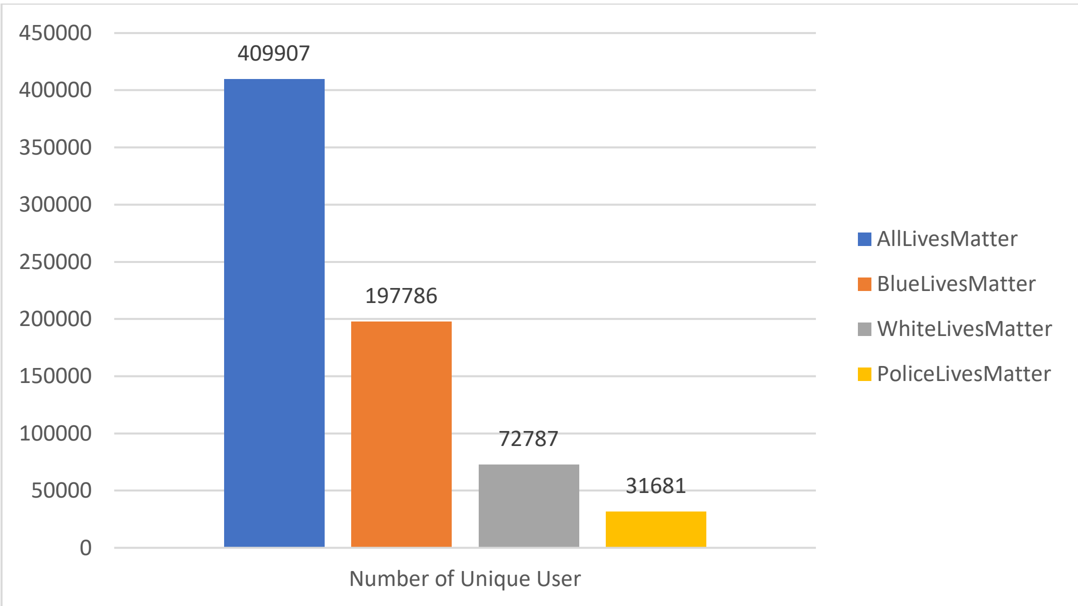

Figure 3. Total number of unique users in datasets

In order to gain a better understanding of the engagement of users in the four movements, it is useful to determine the average number of tweets sent by each user. Based on the data collected, it was found that the average number of tweets per user is 2.20 for All Lives Matter, 3.40 for Blue Lives Matter, 2.16 for White Lives Matter, and 2.55 for Police Lives Matter. This suggests that users who tweet about police-related hashtags tend to post more tweets than those who support All Lives Matter and White Lives Matter. However, before drawing any conclusions, it is important to consider the potential impact of spam and spammers on the data and eliminate them from the dataset.

3.2 Data preprocessing

In order to obtain the most reliable and impartial results, it is essential to clean the data, a process commonly referred to as data preprocessing. Neglecting this step can result in misleading outcomes due to the presence of irrelevant and erroneous information. In my study, I undertake two fundamental procedures for data preprocessing. First, I eliminate spam tweets that potentially impact the results. Second, I meticulously clean the text of the remaining tweets to enhance accuracy and minimize bias.

3.2.1 Removing spammers from the dataset

Spam tweets and bot accounts are potential sources of noise in the datasets, although scholars have not reached a consensus on their specific effects on the research results. Some scholars argue that spam tweets have limited effects on the dataset, as indicated in studies such as Colladona and Gloor (Colladona & Gloor, 2019) and

Stafford and Yu (Stafford & Yu, 2013). Conversely, other scholars attempt to identify and eliminate spammers to achieve more accurate research results such as Ferrara (Ferrara, 2018) and Haustein et al. (Haustein, et al., 2016) claim. I contend that while spammers may not significantly affect the research outcomes, they may have a limited impact on certain results, such as topic modeling results.

There are various techniques available to identify spam in datasets. These methods include user information interest-based techniques (Koggalahewa, Xu, & Foo, 2022), machine learning-based algorithms (Gao, Chen, Lee, Palsetia, & Choudhary, 2012), network-based spam detection (Shehnepoor, Salehi, Farahbakhsh, & Crespi, 2017), and sentiment-based detection (Hu, Tang, Gao, & Liu, 2014). However, there is no universally accepted technique that is considered superior to others. The effectiveness of these methods can vary depending on the dataset. Therefore, in my research, I develop a method to identify and eliminate spam in the countermovements' datasets. This is essential because it ensures that the detection of spammers in these movements is accurate and reliable.

My spam detection algorithm is designed to eliminate links in tweets, which are often used by spammers to share the same content or text with different pictures. Due to the structure of scraped tweets, including links to pictures in the text, it is difficult to label these tweets as spam without removing the links, as different URLs are often used for different pictures. To effectively detect spam in countermovement datasets, I determined two important variables: the number of tweets sent by the same users and the time of the tweets sent by those users. I set a threshold of two for both variables in my algorithm, meaning that I label tweets as spam if the same bunch of tweets are sent more than twice in more than two days. These thresholds were established to seek consistency among spammers, as there are cases where people post the same tweets repeatedly to gain attention from the community. By using these thresholds, I aim to exclude this type of behavior from the identified spammers.

In my spam detection algorithm, I identified 37,028 spam tweets for All Lives Matter, 17,266 spam tweets for Blue Lives Matter, 21,451 spam tweets for White Lives Matter, and 1,148 spam tweets for Police Lives Matter. When examining the ratio of spam tweets to the total number of tweets for each movement, the results were 0.04, 0.02, 0.13, and 0.01, respectively. While the spam tweet ratios for All Lives Matter, Blue Lives Matter, and Police Lives Matter are noteworthy, the ratio is relatively high for White Lives Matter. Figure 4 presents the percentage of spam tweets for each movement.

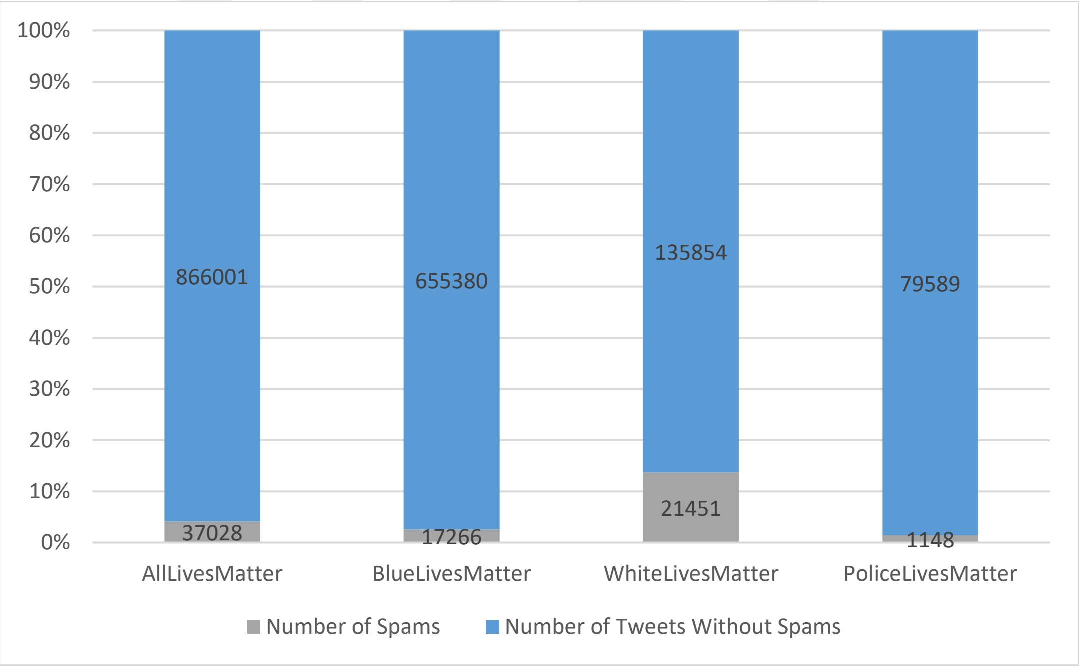

Figure 4. Total number of spam and their proportion in datasets

Remarkably, Figure 5 illustrates that less than 1 percent of the users in all countermovements engage in spamming tweets, indicating that this behavior is not widespread among the general user population.

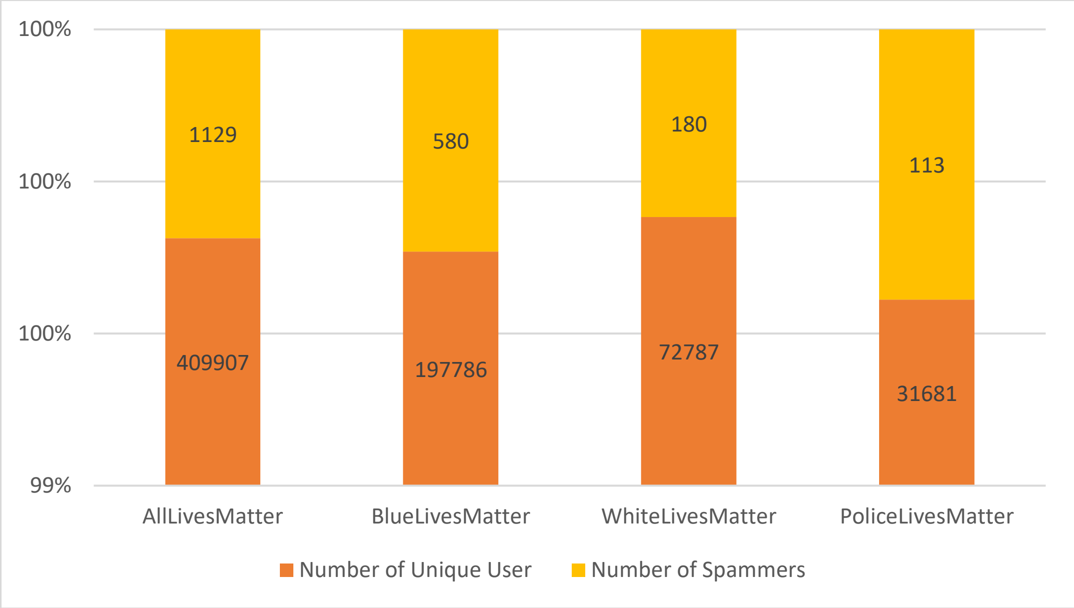

Figure 5. Total number of spammers and their proportion in datasets

Upon analyzing the average number of tweets per spammer in countermovements, it is noteworthy that White Lives Matter exhibits a significant difference compared to the other countermovements. Specifically, while the average number of tweets for each spammer is 119 for White Lives Matter, it is 32 for All Lives Matter, 29 for Blue Lives Matter, and 10 for Police Lives Matter. These findings suggest that the spammers of White Lives Matter generate more spam tweets than the spammers of other countermovements, despite the smaller number of total spammers in White Lives Matter. Consequently, the potential impact of White Lives Matter spammers on network analysis and topic modeling is relatively higher when compared to other countermovements.

3.2.2 Detecting one-time participants

Addressing users who only post one tweet during the countermovement poses a challenge. There are two approaches that can be taken: either remove these users and their tweets from the dataset or include them and measure their contribution to the analysis. Each approach has its advantages and disadvantages. For example, removing one-time participants could provide an opportunity to better observe the relationship between active users over time, allowing for an analysis of the continuity of user relationships. However, removing them would also result in data loss and could potentially affect the echo chamber effect. In my analysis, I chose to include these users and display their proportion in the dataset. The dataset includes 310,578 tweets from All Lives Matter, 142,020 tweets from Blue Lives Matter, 57,860 tweets from White Lives Matter, and 24,248 tweets from Police Lives Matter. Figure 6 presents a bar chart that shows the number of spam tweets, one-time users' tweets, and the remaining tweets.

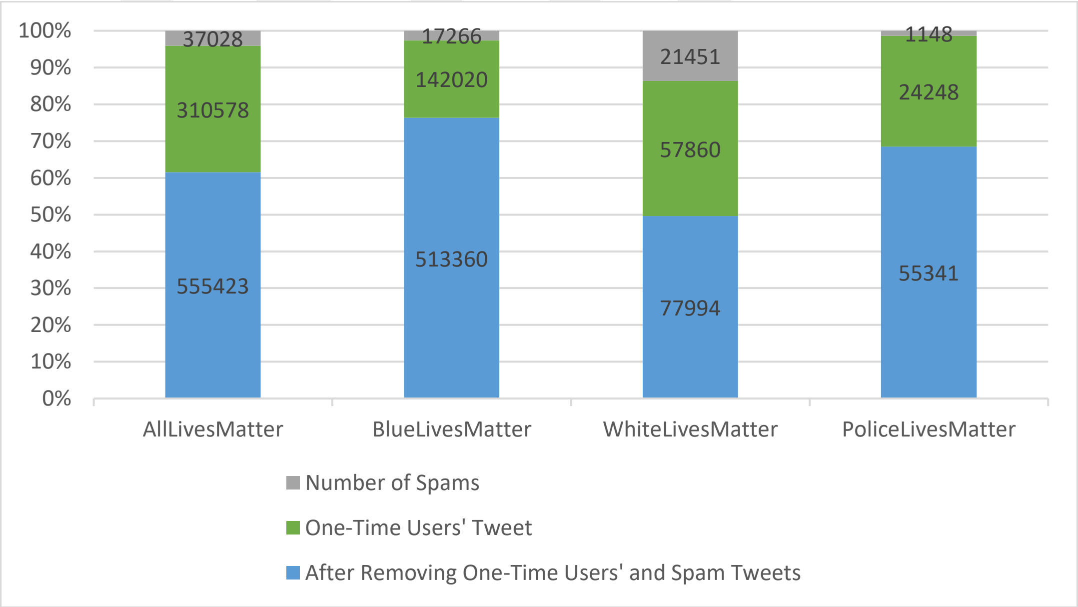

Figure 6. The proportion of the tweets belonging to spammers and one-time users

At this stage of the analysis, in order to gain insights into the tweeting behavior of users, I classify them into four distinct groups: one-time participants, less active users, active users, and highly active users. These categories respectively represent individuals who have sent one tweet, 2 - 10 tweets, 10 - 100 tweets, and more than 100 tweets. To provide a comprehensive overview of user activity, I have created pie charts for each countermovement, both before and after eliminating spammers, which illustrate the percentage of users in each category. These charts can be found in Figure 7 through Figure 10.

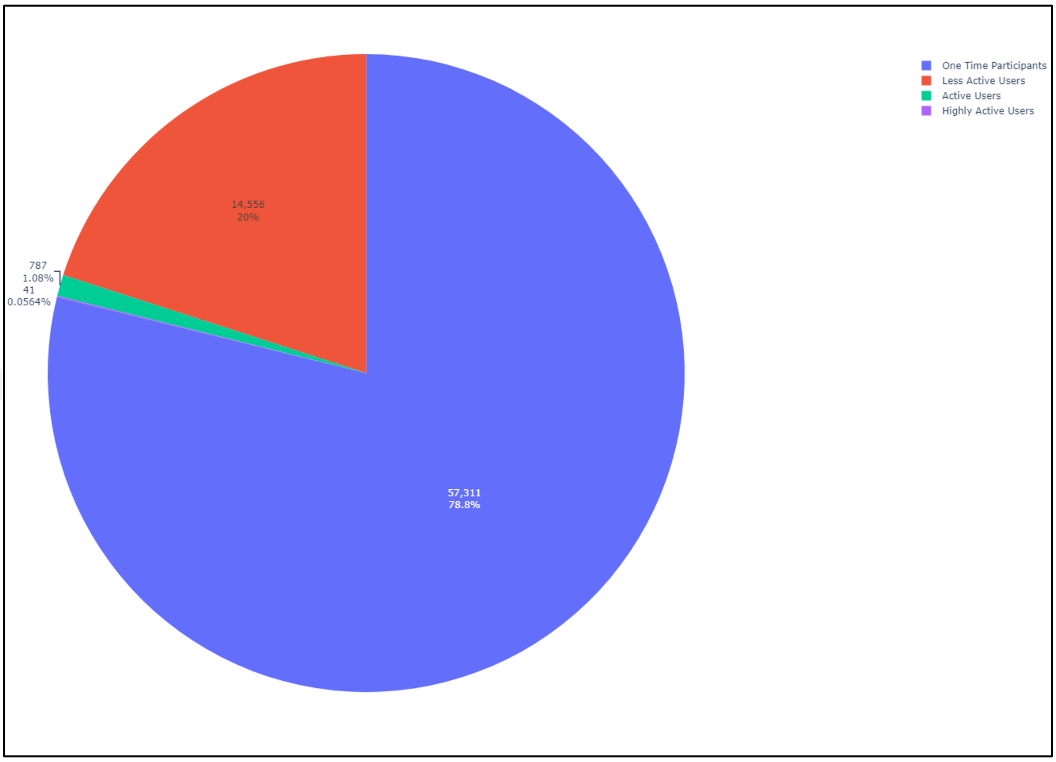

Figure 7. White Lives Matter users pie chart

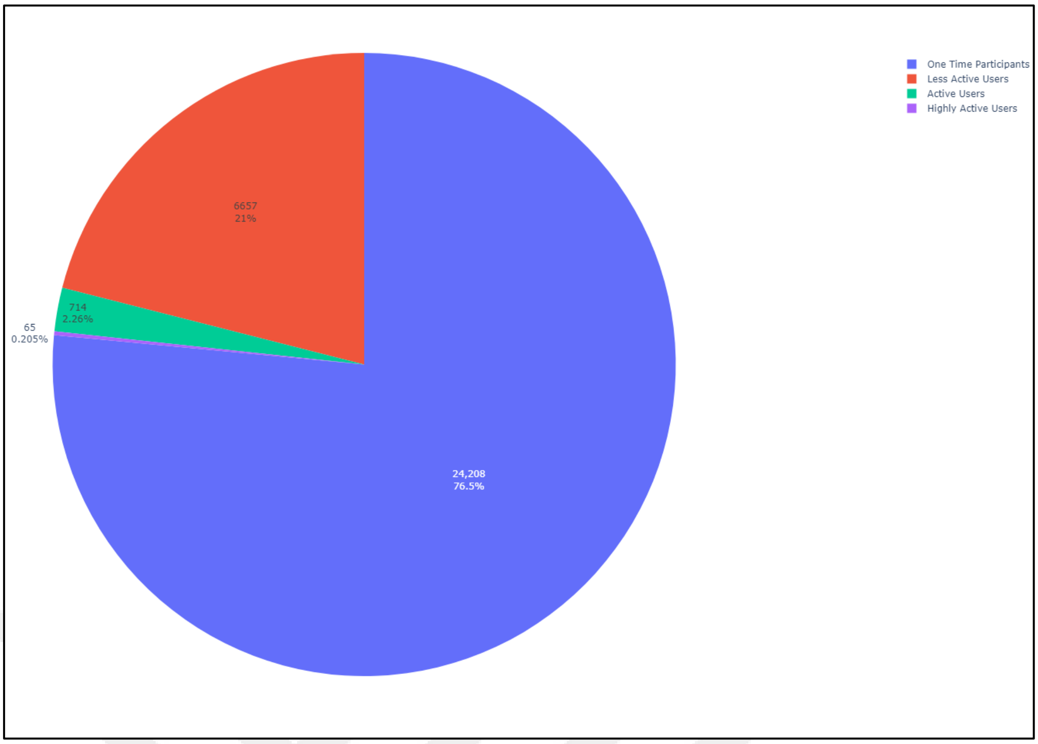

Figure 8. Police Lives Matter users pie chart

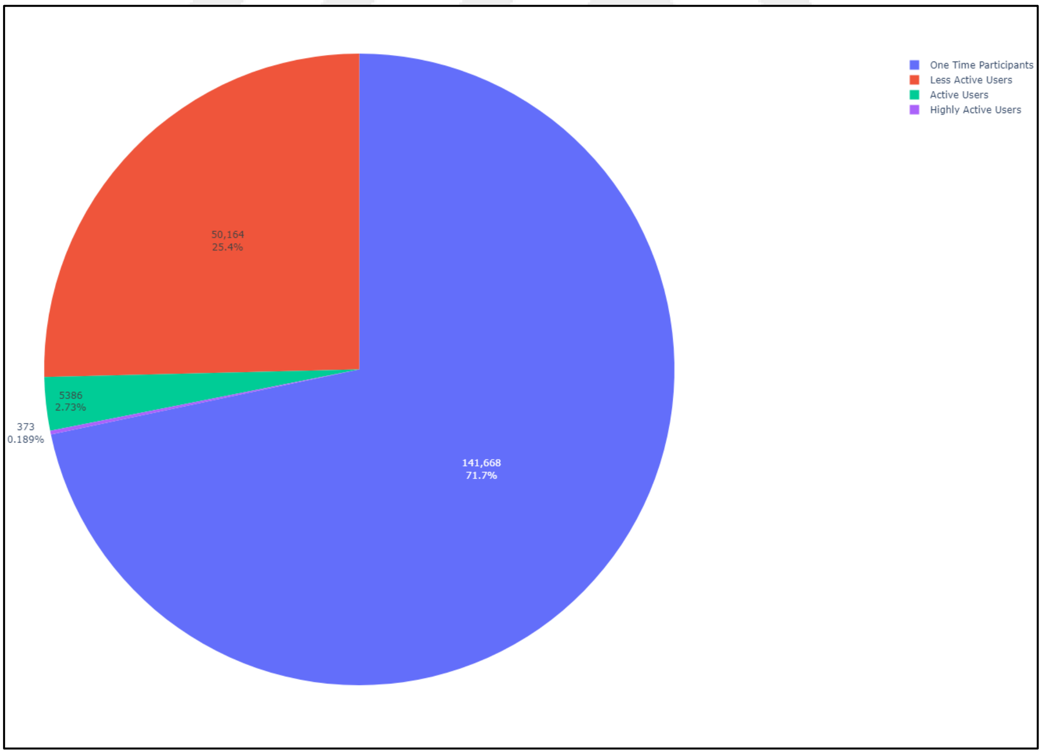

Figure 9. Blue Lives Matter users pie chart

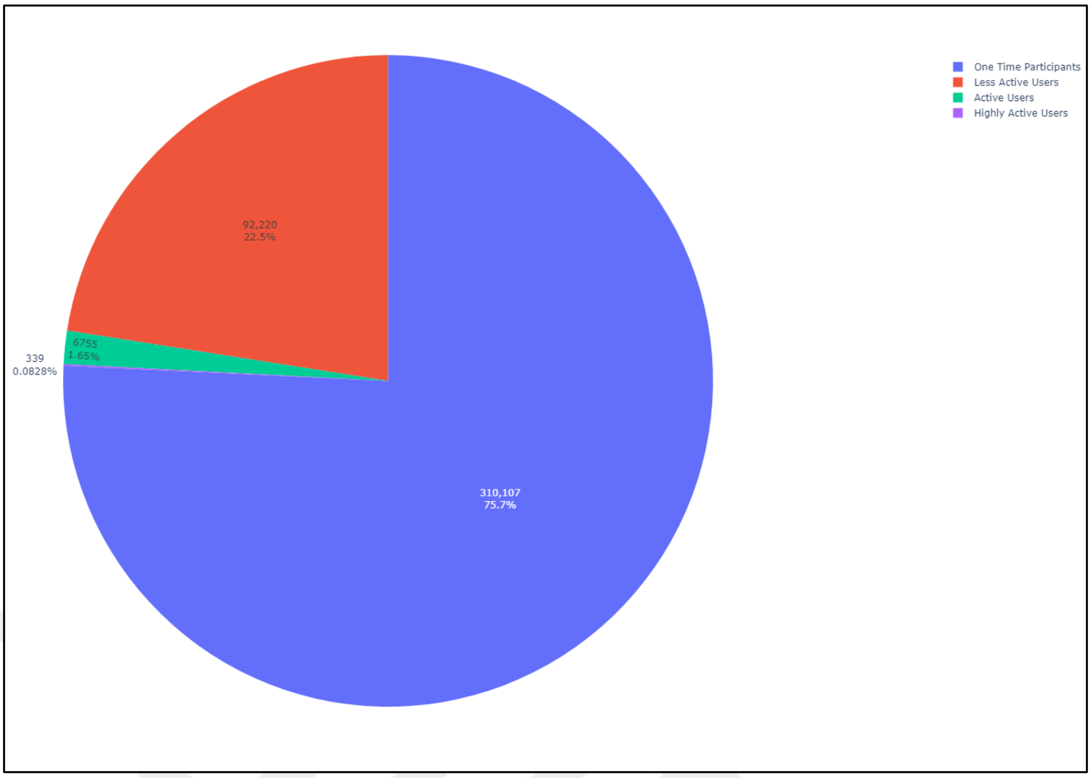

Figure 10. All Lives Matter users pie chart

These pie charts represent users, which are grouped by the number of tweets they sent, in four countermovements' datasets. In these pie charts, blue areas represent users who just sent tweets with related hashtags one time. Orange areas correspond to fewer active users who sent tweets between 2 and 10. Green areas are active users that have tweets of more than 10 to 100. Lastly, tiny purple areas show highly active users who post more than 100 tweets. All four datasets share nearly the same user activeness. While the share of one-time participants is between 71 and 79 percent. While the ratio of one-time participants of White Lives Matter is 78.8, Police Lives Matter is 76.5, All Lives Matter is 75.7, and Blue Lives Matter is 71.7 percent. For the less active users, Blue Lives Matter takes the biggest share with 25.4 percent. And the rest of them are between 20 and 22.5 percent. On the category of active users Police Lives Matter and Blue Lives Matter have more than 2 percent, respectively 2.26 and 2.73; All Lives Matter and White Lives Matter have less than 2 percent with 1.65 and 1.08 percent. Lastly, the group of highly active users takes the least share for each countermovement. While again Police Lives Matter and Blue Lives Matter have so close shares with 0.205 and 0.189, All Lives Matter and White Lives Matter have less than 0.1 percent of users in this category. In sum, from the perspective of the number of tweets sent by the users, all countermovements share nearly the same ratios. While the highest share is taken by the one-time participants, the group of less active users is the second biggest group and so little amount of the ratio is shared by the active and highly active users. When we examine pie charts of the spammers, from Figure 11 to Figure 14, results seem even more similar.

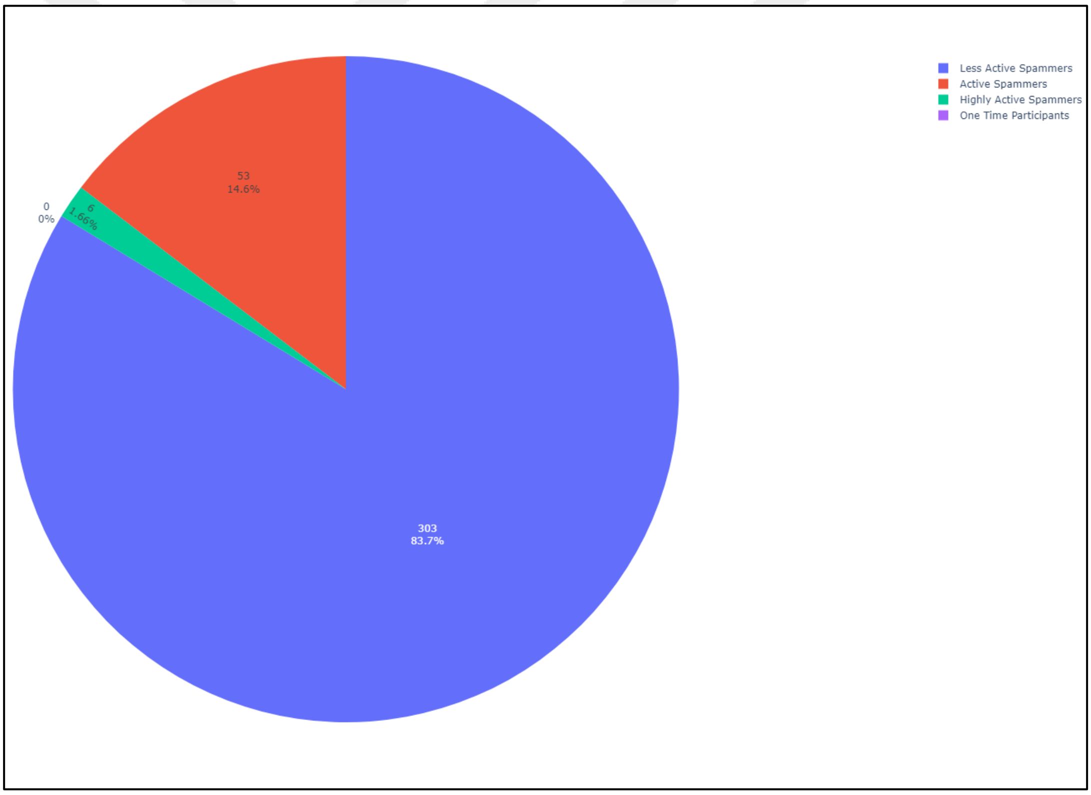

Figure 11. White Lives Matter spammers pie chart

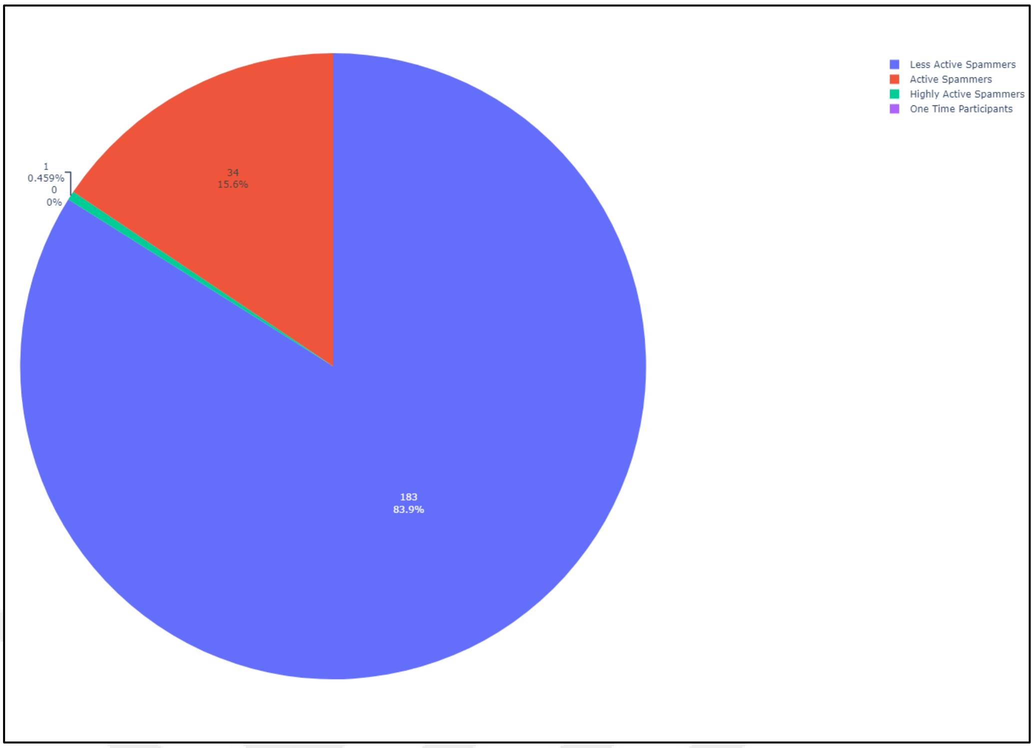

Figure 12. Police Lives Matter spammers pie chart

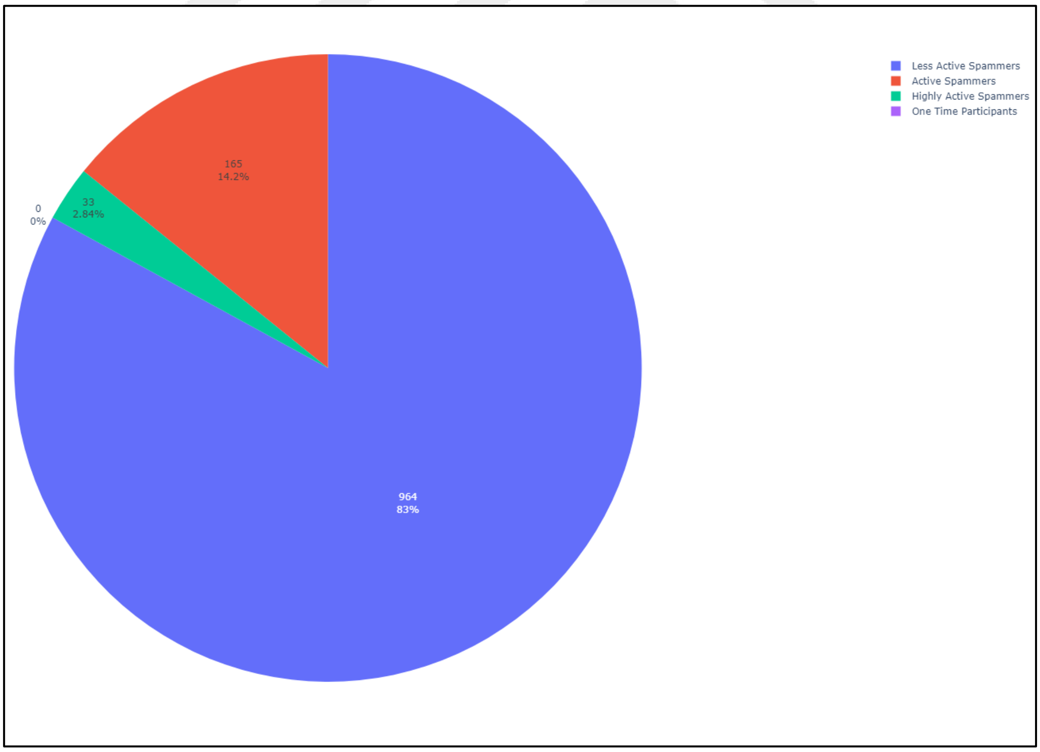

Figure 13. Blue Lives Matter spammers pie chart

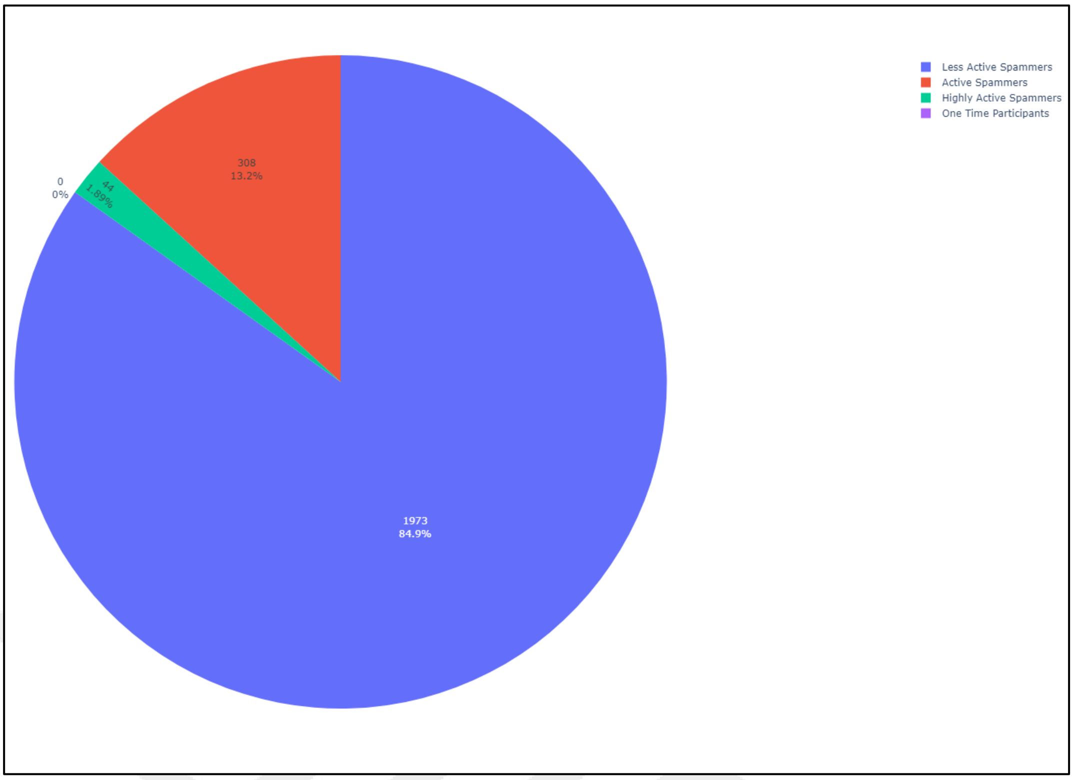

Figure 14. All Lives Matter spammers pie chart

To begin with, it is worth noting that the spammer charts do not contain any one-time participants, as the definition of the spammer concept requires that the same tweet be posted more than twice over two days. 83 percent to 85 percent of the spammers in countermovements are less active in other words they send 4 to 10 tweets in total. Active spammers, who send between 10 and 100 tweets, on the other hand, take a share between 13 to 15.6 percent. Lastly, the ratio of highly active spammers ranges from 0.5% to 3%. In conclusion, the ranking of spammer categories is consistent with the pie charts of users, and there are no significant differences in the activity levels of spammers across countermovements.

3.2.3 Removing stop words

Following the removal of spammers and detection of one-time participants from the dataset, the next step involves cleaning the remaining tweets' texts. The initial technique employed is the removal of stop words. Stop words refer to a list of words that are deemed insignificant in natural language processing and are hence eliminated from the texts. There are many popular lists of stop words such as Natural Language Toolkit (NLTK) (Natural Language Toolkit, 2023), spaCy (spaCy, 2020), or Scikit-Learn (scikit-learn, 2023). Even the total number of stop words they contain is different and most of them are the same. I prefer to create my own stop words list for this research so, I can both eliminate stop words that repeat so often and preserve important words for my datasets. I list stop words that I use in my research in Figure 15 below.

"the", "to", "and", "a", "in", "of", "for", "you", "is", "this", "i", "are", "on", "all",
"mt", "amp", "that", "with", "it", "be", "have", "who", "do", "at", "what", "no", "out",
"if", "will", "just", "was", "from", "about", "as", "when", "or", "up", "s", "more", "#",
"via", "an", "has", "t", "u", "w", "r", "m", "k", "\u200d", "re", "bio", "lets", "lot",
"ur", "liu", "al", "gt", "sh", "ng", "cg", "hr", "un", "kag", "sot", "ing", "de", "sc", "th",
"me", "myself", "you're", "you've", "you'll", "you'd", "your", "it's", "its", "itself",
"which", "whom", "that'll", "these", "those", "been", "being", "by", "against",
"between", "into", "through", "during", "before", "after", "above", "below", "off",
"over", "under", "where", "why", "how", "can", "hadn", "hadn't", "hasn", "hasn't",
"haven", "haven't", "isn", "isn't", "ma", "mightn", "mightn't", "mustn", "mustn't",
"needn", "x", "needn't", "shan", "shan't", "shouldn", "shouldn't", "wasn", "wasn't",
"weren", "weren't", "won", "won't", "wouldn", "wouldn't", "nor", "not", "only",
"own", "same", "so", "than", "too", "very", "he", "she", "her", "his", "don", "any",
"let", "did", "were", "any", "am", "could", "oh", "ones", "getting", "ppl", "got",
"had", "don't", "dont", "does"

Figure 15. Stop words list

Eliminating stop words is important but it does not make texts ready for analysis. I also apply a bunch of rules for the tweets. First, I remove website links that both start with “http” and “www”. Many tweets contain that kind of external link and pictures that exist as a link in the text. Since these are not significant, I remove all of them. Then I exclude the term “RT” which corresponds to re-tweet in most of its usage. I also exclude mentions too. Mentions are used for tagging other people and organizations, or other Twitter accounts, in that tweet and these mentions start with ‘@’. I delete all the words that start with that specific symbol. Subsequently, I eliminate special characters such as “!”, “?” or “%” to increase the accuracy of the results. Finally, I remove all numeric values from zero to nine in the text. Those are highly used insignificant characters that might lead to corruption in the results. Before moving on to the analysis, I change all the words to lowercase and tokenize them. The tokenization process is breaking sentences into words to make them ready for Natural Language Processing methods (Verma, Renu, & Gaur, 2014, p. 16). After the tokenization process, I remove stop words from the list of words and make my dataset ready for analysis.

3.3 Methodology

In this research, I have adopted a unique approach by combining two of the most widely used Natural Language Processing techniques, topic modeling and network analysis. Typically, most studies use either topic modeling or network analysis to answer specific research questions such as what people are talking about or how they are connected. However, using both techniques in conjunction allows for a more comprehensive understanding of the complex relationship between individuals and any potential echo chambers that may emerge. To this end, I begin by elaborating on the specific topic modeling technique utilized in this research and the corresponding visualization tools, before introducing the networks of individuals within the countermovements.

3.3.1 Topic modeling

Broadly, topic modeling is a statistical method that aims to find the thematic structures of the given texts. There are two types of topic modeling called supervised and unsupervised topic modeling. Supervised topic modeling is a technique that needs prior study, in this case, it is pre-defined topics, and guidance to conduct new research. Lists of words belonging to the specific topics are defined and a new corpus is analyzed based on those pre-defined topics. As a result, texts in this corpus are categorized based on the similarity of the current grouped texts (Agrawal, Fu, & Menzies, 2018). This process allows us to concentrate on more specific topics in that research and gives better results. However, preparing pre-defined topics and words needs great effort and the dataset structure must be suitable for this process which can be seen as a trade-off for this technique. There are many methods based on supervised topic modeling such as labeled or supervised LDA (sLDA) (Ramage, Hall, Nallapati, & Manning, 2009), maximum entropy discrimination latent Dirichlet allocation (MedLDA) (Zhu, Ahmed, & Xing, 2009), or Siamese Labeled Topic Model (SLTM) (Huang, Rao, Liu, Xie, & Wang, 2018) but the availability of these methods still needs re-designing and adaptation for the particular research. In contrast, for unsupervised topic modeling, there is no need for prior knowledge about the thematical structure of the documents but the algorithm that is used by the method discovers topics with the patterns of the words in the documents (Agrawal, Fu, & Menzies, 2018). While it does not allow more concentrated results like supervised learning, it gives more flexibility and generates the possibility to find topics that are not considered before the research. There are many different topic modeling methods used in NLP studies such as, most famously, Latent Dirichlet Allocation (LDA) (Blei, Ng, & Jordan, 2003), Hierarchical Dirichlet Process (HDP) (Teh, Jordan, Beal, & Blei, 2004), Bert Topic Modeling (Peinelt, Nguyen, & Liakata, 2020), or top2vec (Angelov, 2020).

When the advantages and disadvantages of both techniques are considered, it is better to choose the path of unsupervised topic modeling. There are three main reasons for this choice. First, my dataset contains more than 1.5 million tweets that correspond to that number of documents for the topic modeling. The preliminary analysis reveals that even though there is a filter for the language, English, while collecting tweets which makes the broad similarity for the texts, the dataset may contain different languages due to the imperfect algorithm of Twitter. In other words, there might be tweets that are written in different languages or mixed with English. Supervised topic modeling methods cannot differentiate these tweets and it might affect the results. On the other hand, unsupervised topic modeling methods most probably identify these tweets as a different topic. Second, the countermovement datasets contain millions of tweets. At this point, even though there are some expected topics for each countermovement, it is inevitable to not pre-define all the topics. For instance, the topic of police and their rights are expected topics for the Blue Lives Matter and Police Lives Matter movements, or topics related to problems of farmers and animal rights are in All Lives Matter. However, there are more than these topics either mentioned high or low by Twitter users. With the supervised topic modeling method, it is too difficult and nearly impossible to detect all these topics while it is much easier with the unsupervised methods. Lastly, related to the second reason, the workload of determining each topic and its keywords is nearly impossible in this kind of big dataset. When the number of documents, the unknown number of topics, and their expected keyword are considered, it takes several months of preparation for the supervised topic modeling due to the lack of this countermovement-specific method. To sum up, the unsupervised topic modeling method fits my research.

After determining the way of the method, it is time to find the best technique for my research. As mentioned above there are various unsupervised topic modeling methods such as Latent Dirichlet Allocation, Hierarchical Dirichlet Process, Bert Topic modeling, or top2vec. All these methods have both similar and different characteristics so they have various advantages and disadvantages. From this view, there is no superior method that dominates others, but the main issue is the characteristics and structures of the dataset they deal with. The number and length of texts, and the possible number of topics both for each text and in total are some of the key factors for the performance of the topic modeling. For instance, while LDA is a popular method, due to both accuracy and visualization tools, to study with this method, a total number of topics must be defined before performing analysis which is one of the key aspects of my research. Four different datasets have different numbers of documents, and it is difficult to determine the number of topics for each dataset. Even some techniques are applied to find the optimal number of topics, such as differences in the coherence and topic overlapping scores of the topics, this comes with huge computational resource needs. Not just LDA faces a lack of computational resource problems, but the Bert method and Hierarchical Dirichlet Process are also at the same point. They require a lot of computational resources both to train datasets and make inferences.

In this research, I use the Top2Vec topic modeling method due to its advantages which are mentioned below. Broadly, Top2Vec is a method for creating topic vectors from text data. Top2Vec aims to discover the sentences that most closely reflect each topic in a collection of documents and then group these topics, or vectors, by how semantically similar they are (Angelov, 2020). Prior to discussing the methodology, I would like to provide a rationale for its selection. First, unlike the other topic modeling methods, it does not require lots of computational resources for the analysis. In other words, Top2Vec is computationally efficient and can generate results quickly compared to the other methods which are crucial while more than a million tweets considered. Second, unlike other topic modeling methods, it does not require a topic number beforehand. It automatically finds the total number of topics for the documents. In this scenario, it both reduces time and resource to find an optimal number of topics and gives the best result generated by the algorithm itself. Third, Top2Vec can handle out-of-vocabulary words and misspellings. As mentioned above, even if I clean the data as much as possible in the pre-processing step, there might be some unseen and little problems that have an impact on the results. However, the performance of this method with noisy data is relatively high and I believe that it increases the accuracy of my results. Lastly, Top2Vec has a feature called hierarchical reduction. Shortly, this technique allows me to reduce the number of topics based on the closeness of the vectors of the topics, or their similarity so, without any additional statistical method, I can both reduce the number of topics and find the most similar topics in the documents. After this brief and general introduction of the Top2Vec method, I introduce detailed steps of the topic modeling process, algorithms of hdbscan and umap, and visualization of both the Top2Vec method and hierarchical reduction technique.

To understand how the Top2Vec method works, I first introduce the main characteristics of the method and its differences of it when compared to others. Then, I elaborate algorithms, which are word2vec, doc2vec, umap, and hdbscan, that are used in this method. Lastly, I give examples that I sampled from my main datasets.

Top2Vec is an NLP method that is used to classify texts according to their semantic structure (Angelov, 2020). There are three main advantages when compared to other popular topic modeling methods such as Latent Dirichlet Allocation or Probabilistic Latent Analysis. First, for these popular methods, I need to do deeper pre-processing, including steps such as stemming, lemmatization, or a broader stop-words list, to get the best results otherwise, there is a higher chance to get insignificant results due to the noisy data. On the other hand, for Top2Vec, due to the algorithms, which I introduce below, there is no need for such a pre-processing step. However, as I mentioned in the dataset and pre-processing part, I applied some of these steps to both accelerate the performance of the model and eliminate the possibility of the effect on the results. Second, most of the popular topic modeling methods use a technique called bag-of-words (Zhang, Jin, & Zhou, 2010) for the library of the corpus which neglects the semantics of the words because of ignoring their position of them in the text. In the Top2Vec, instead of using the bag-of-words technique, distributed word and document representation models called word2vec (Mikolov, Chen, Corrado, & Dean, 2013) and doc2wec (Le & Mikolov, 2014) are used. Lastly, unlike the other popular topic modeling methods which require several topics as a parameter beforehand, Top2Vec generates several topics by finding dense areas in the space.

As I mentioned above, one of the biggest differences between the Top2Vec is using a distributed representation of words and documents instead of the bag-of-words technique. At this point, two main models are used: word2vec and doc2vec.

Word2vec is an algorithm that learns vector representations of the words from the texts. It uses a neural network to learn the vector representations of these words. This neural network is trained on a large corpus of text and then the model tries to predict the context in which a word appears. The crucial point which differs from a bag of words method, the context is seen in the number of ‘k’ words that appear before and after the target word in each text (McCormick, 2016). In other words, while the bag-of-words algorithm counts the value of the words as either 0 or

1 which concludes with ignoring the semantic values of the words in the text, in the word2vec algorithm, the order of the words before and after the targeted word is important which captures the semantic meaning of the words. While there are two main approaches for the predicting algorithm called Continuous Bag of Words (Rong, 2014) and skip-gram (Goldberg & Levy, 2014), the Top2Vec method prefers to use the latter one due to the outperforming performance, even though there is not a huge difference (Angelov, 2020). Briefly, in the predicting step, Continuous Bag of Words predicts a target word based on its context. On the other hand, the skip-gram approach predicts the context words with the target word.

Doc2vec, on the other hand, can be seen as the extended version of the word2vec. It is an algorithm that creates a vector representation of the documents instead of the words (Lau & Baldwin, 2016). Similar to the word2vec approach, the model under consideration employs a neural network for training. In this model, the process begins by assigning a unique identifier to each document, after which the context is predicted based on a given target document. This approach, known as the Distributed Bag of Words model, generates document vectors as a result of these predictions. These document vectors effectively encapsulate the underlying topics present within the corpus of documents. (Le & Mikolov, 2014).

Both the skip-gram model in Word2vec and the distributed bag of words model in doc2vec exhibit notable similarities. This similarity is further evident when examining the equations that govern these algorithms and the underlying structures of the models. These equations and model structures have been detailed in Angelov's research study (Angelov, 2020). Assume that the word2vec model is shaped with a matrix $W_{n,d}$ as an input word vector and $W'_{n,d}$ for context word vectors. In these matrices, n is the size of the vocabulary generated from the documents, and d is the size of the vectors to be learned for each targeted word. Moreover, each row of these matrices is a word vector and context word vector, respectively $\vec{w} \in \mathbb{R}^d$ and $\vec{w}_c \in \mathbb{R}^d$. As mentioned above, word2vec looks ‘k’ number of words both left and right. For both these ‘k’ numbers of words, which corresponds to 2k, that are neighbors of the ‘w’, or targeted word, the input vector $\vec{w}$ is generated and it will be used for predicting $\vec{w}_c$ context vector of the context word w_c. After the choosing targeting word, for each neighbor word, ‘w’, the prediction will become softmax($\vec{w} \cdot W'_{n,d}$). It creates a probability distribution over the words of the corpus, or vocabulary, for each word that is context word w_c. This learning process is applied for each word vector, $\vec{w}$, row in $W_{n,d}$, and context word vector, $\vec{w}_c$, row in $W'_{n,d}$ so, probability of the context vector being in these surrounding, or neighbor, words, which can be formulated as $P(\vec{w}_c|\vec{w})$. After determining probability vectors for all ‘n’ words in the vocabulary, the maximum value of $P(\vec{w}_c|\vec{w})$ word pairs become semantically more similar. The reason is that in order to get highest possible the value of $P(\vec{w}_c|\vec{w})$ is possible when $\vec{w} \cdot \vec{w}_c$ is maximum in $\vec{w} \cdot W'_{n,d}$ so, vectors of $\vec{w}$ and $\vec{w}_c$ are getting closer in the space. On the other hand, while $\vec{w} \cdot \vec{w}_c$ is minimum in $\vec{w} \cdot W'_{n,d}$, this situation corresponds $\vec{w}$ and $\vec{w}_c$ are moving away in the space and it means these word pairs are semantically irrelevant and they belong to different topics (Angelov, 2020).

Distributed bag of words model of doc2vec is fundamentally very similar to word2vec’s skip-gram. The model is built on the matrix $D_{c,d}$. While c corresponds to the number of documents in the corpus, d is the size of the vectors that will be learned for each document. For the rows of doc2vec’s matrix, we define the document vector of $\vec{d} \in D_{c,d}$. In the Top2Vec method, the required context word matrix, that defined as a $W'_{n,d}$ before, is pre-trained by the word2vec beforehand. Afterward, the context vector of each word in the document, $\vec{w}_c \in W'_{n,d}$, is utilized for predicting the document's vector $\vec{d} \in D_{c,d}$. Again, same as word2vec, the prediction is created as softmax($\vec{w}_c \cdot D_{c,d}$). This prediction process is repeated for each document. In the end, the probability of the document given the word, or $P(\vec{d}|\vec{w})$, is obtained. When this value is high, it means that the word vector, or simply a word, occurs in the document vector, or document and does not occur when vice versa (Angelov, 2020). In sum, different word vectors generated by the word vectors and the document they belong to will be on one side of the space, and semantically different document vectors with their word vectors will be on another side of the space. At this point, the problem emerged. How can we represent these vectors in the two-dimensional space?

As mentioned above, one of the advantages of Top2Vec is analyzing words with respecting their surrounding words or neighbor words so, it gives semantically meaningful results when compared to the other topic modeling methods. The source of this result is models called word2vec and doc2vec. When we want to visualize vectors that are generated by these two methods in two-dimensional space, no doubt, it can be called semantic space due to the characteristics of these methods. Angelov also calls this "continuous representation of topics" (Angelov, 2020, p. 5). However, the problem occurs when these vectors are taken by the context matrices. The main issue is that $W'_{n,d}$ matrix generates 'd' dimensional space over the 'n' number of vocabulary (Angelov, 2020). To solve this problem, there is a need for dimension reduction. The Top2Vec method uses Uniform Manifold Approximation and Projection for Dimension Reduction (UMAP) (Leland, Healy, & Melville, 2018) to perform this task. With UMAP, that ‘d’ dimensional space can be represented in the plane. Here is the example of the UMAP on the sample of 200 documents, which are grouped as 50 from each dataset in Figure 16.

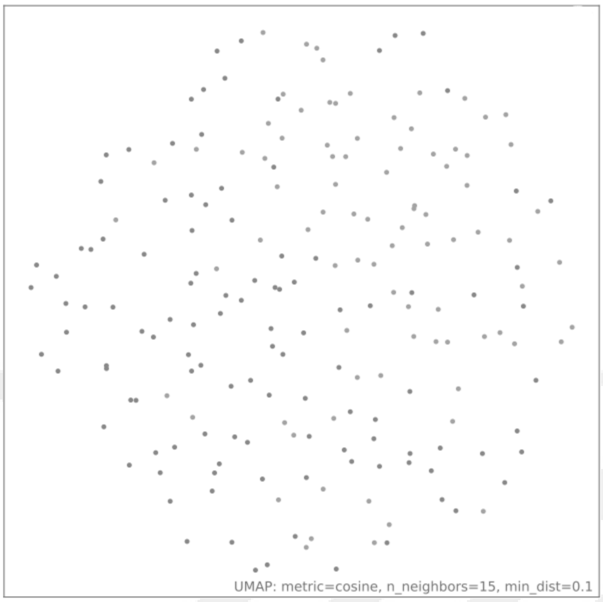

Figure 16. Application of UMAP to the sample dataset

This representation has 200 hundred document vectors and unseen words around them. In normal conditions, if there are significantly different topics, we expect to see semantically the same topics together, far away from the other topics. However, at this point, another problem emerges, how can we define topic similarity in this two-dimensional semantic space? We use another algorithm called Hierarchical Density-Based Spatial Clustering Application with Noise (HDBSCAN) (Campello, Moulavi, & Sander, 2017) to solve this question. To apply this method, the first need is two-dimensional space which is already done by the UMAP. HDBSCAN finds dense areas of the document vectors on the plane, and it performs with the most basic method, taking the arithmetic mean of the document vectors in the dense areas which are also called the arithmetic centroid. In the graph below, we can see how topics are distributed to the vectors which are gray after UMAP is applied. In our 200 documents sample, there are two different topics. While these documents look mixed, most of the blue-colored documents, which are classified as topic 1, are at the right top side and red-colored documents, which are classified as topic 0, are at the left bottom side in Figure 17.

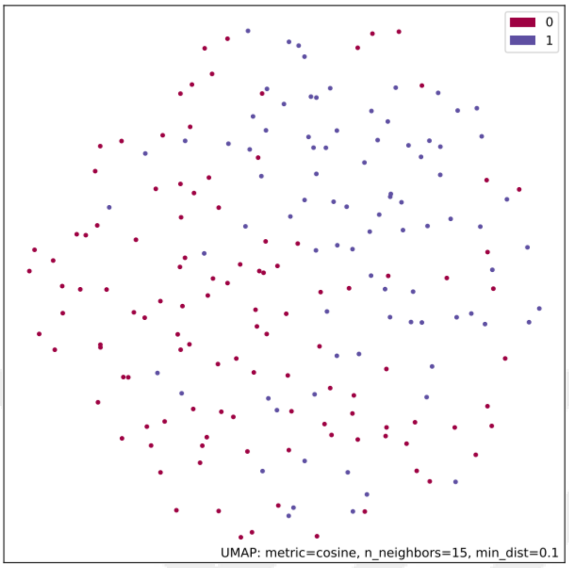

Figure 17. Application of UMAP and HDBSCAN to the sample dataset

We can see the performance of the HDBSCAN on bigger clusters. For instance, the graph at the bottom contains 4,000 document vectors and 1,000 documents from each countermovement dataset. After applying the Top2Vec method, 24 topics emerged and they take place on the plane as follows in Figure 18:

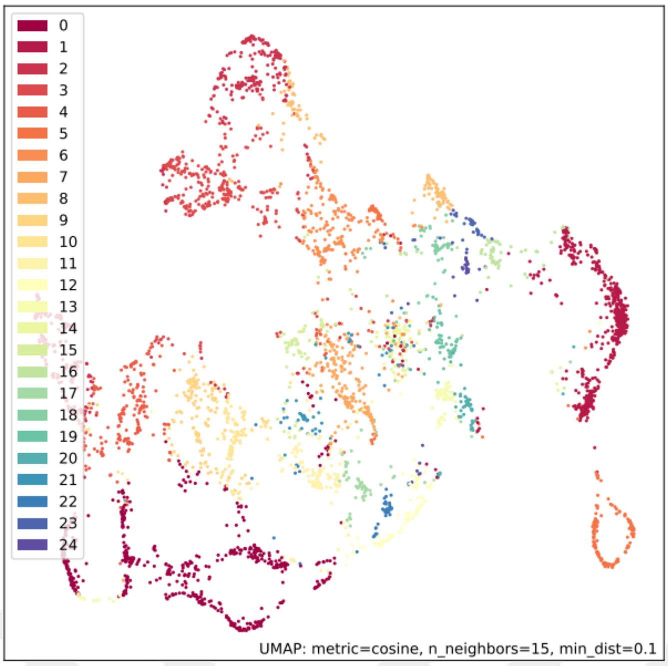

Figure 18. Application of the HDBSCAN to the larger dataset

As can be seen, while various colored document vectors represent different topics, semantically similar documents are closer to each other and identically colored.

3.3.2 Network analysis

Following the identification of topics within the text and their assignment to individual users, the subsequent step involves analyzing echo chambers through network analysis. In this section, I provide an in-depth examination of the overall structure of the networks under investigation. Additionally, I introduce the Louvain community detection algorithm, a specialized tool utilized for the purpose of delineating echo chambers within countermovements.

3.3.2.1 The general structure of the networks.

To observe possible attitude change in echo chambers, I divide datasets into monthly periods. While this step makes it possible to find changes in communities over time, it also makes it easier to observe the structure of the echo chambers and the attitudes of their members. After applying this to the datasets of four countermovements, there are 96 numbers of monthly periods that start in October 2014 and end in September 2022. I apply network analysis for each month and finally, I get 384 networks in total.

This study adopts a network-based approach, where nodes correspond to users who actively engage with specific hashtags associated with countermovements during predetermined monthly intervals. Edges within the network indicate instances where users write about the same topic within the corresponding month. Alternatively, scholars have structured networks in various ways such as creating hashtag co-occurrence network where users are nodes and common hashtags usage is edge (Wang, Liu, & Gao, 2016) or network structure based on manually labeled tweets of the users (Milani, Weitkamp, & Webb, 2020). However, with the capability of the top2vec topic modeling method which gives results based on the usage of the words and documents with their semantic similarity, defining edges as writing about the same topics, or implementing top2vec results to the network, is better in terms of the definition of the echo chamber and capability to observe in big data.

In the graph below, Figure 19, the network of the people who use the #PoliceLivesMatter hashtag in their tweets that were sent in May 2018, can be seen. In this network, there are 94 nodes and 23 edges. In the middle of the graph, there are many nodes without edges, and outside of them, few of the nodes are connected and some of them create cliques. As a result of these, the density of the graph is too low, 0.005.

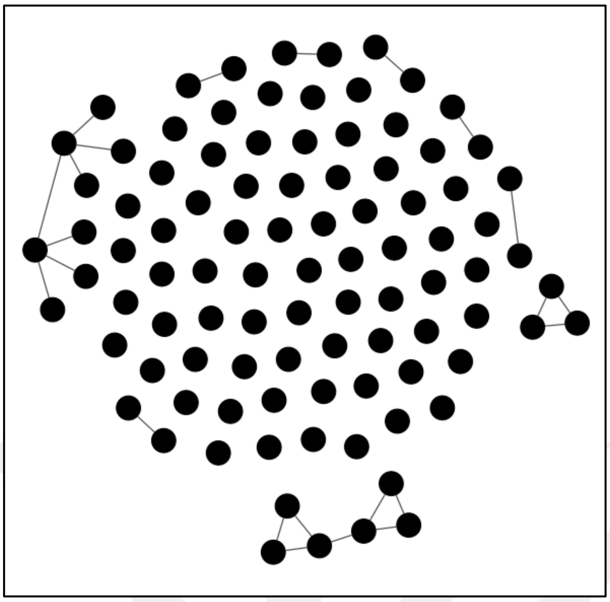

Figure 19. Graph of the sample dataset

It is natural that users talk about more than one topic in a month. For instance, users can talk about both problems of the farmers and racial equality under the hashtag of the All Lives Matter movement. In this scenario, this user should have an edge between nodes of the users who talk about either problem of the farmers, racial equality, or both. When there are more than two users who share more than two topics, the linkage between their nodes should be different than the others such as with users who share just one common topic. In another example, people who talk about the same topic more than once, in other words, they post tweets that contain the same content, should have a different level of linkage between people who send just a tweet about the same topic. At this point, edge weight is equally important in determining echo chambers in the community detection algorithm process. As the examples above show, edge weight can be defined as an attribute that corresponds dense of the relationship between nodes. In my research, I also respect edge weight between nodes.

When we consider edge weight, changes in the graph above can be observed on the next graph. As can be seen, some linkages between nodes are thicker than others which means that the relationship between these nodes is denser than their relation with other linked nodes in the network which is shown in Figure 20.

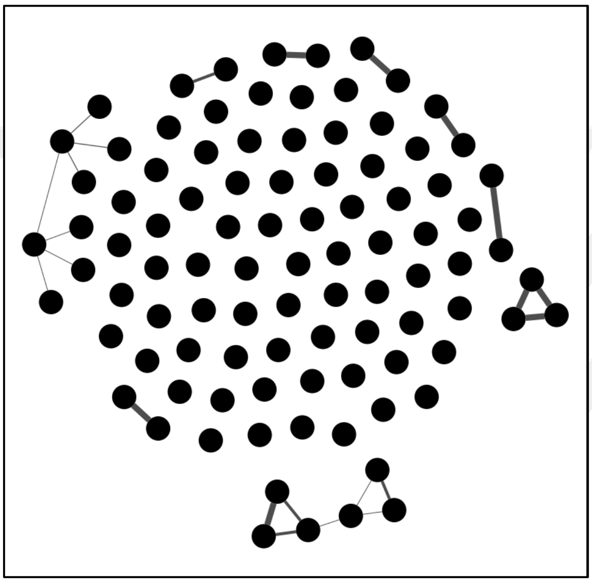

Figure 20. Graph of the dataset respecting edge weight

The weight of edges in a network is not only relevant for visualization purposes but also holds significance in the process of community detection. When identifying communities within the network, the edge weight is considered as a factor. The subsequent section will delve into the impact of edge weight on community detection and elaborate on its effects.

3.3.2.2 Louvain community detection algorithm

The Louvain community detection algorithm is one of the popular algorithms used to detect communities in a network. The main reason why this algorithm is popular is its speed when it is applied to large communities (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008). This algorithm works by optimizing a modularity function that finds the degree of the connected communities in the network. The algorithm contains two main phases which can be defined as initialization and iteration.

The initialization process is short but needs to start the algorithm. In this process, initial communities are defined. These prior communities are defined by assigning each node to its own community in the network so, at the end of this step there are several communities that equal the total number of nodes in the community (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008).

In the second phase, on the other hand, the main purpose is maximizing the modularity score. Before elaborating on this step, it is better to introduce modularity. Modularity is a measure that quantifies the density of the connection of the nodes in the community compared to the other nodes (Newman, 2006). The density of the connection of the nodes is determined by the edges between the nodes. From this view, the modularity score is the difference between the number of edges of the nodes and the expected number of edges if the nodes are connected randomly (Newman & Girvan, 2004). Mathematically, the modularity score ranges from 1 to -1, where a higher score corresponds more modular or dense community and a lower value means a sparse and less modular community (Newman, 2006).

Modularity is a measure of the quality of a network partition into communities. It is a single scalar value that represents how well a given partition of the network captures the underlying community structure (Newman & Girvan, 2004). The modularity score is defined as the difference between the actual number of edges within communities and the expected number of edges if the network were randomly connected, normalized by the total number of edges in the network (Newman & Girvan, 2004). In my research, I use an equation that belongs to the NetworkX Python package (NetworkX Developers, 2023) that can be seen in Figure 21.

$$\Delta Q = \frac{k_{i,in}}{2m} - \gamma \frac{\Sigma_{tot} \cdot k_i}{2m^2}$$

Figure 21. Equation of modularity

m on the left-hand side of this equation represents the size of the graph, while $k_{i,in}$ is the sum of the weights of the edges from node i in community C. On the right-hand side, k_i corresponds to the sum of the weights of the edges linked to the node i, and Σ_{tot} denotes the sum of the weights of the links go to the nodes in community C. Lastly, γ is the resolution parameter which is a constant value and determines which communities will be determined in the process. While a higher value of resolution includes more communities and a lower value lead to fewer communities (Traag, Waltman, & Van Eck, 2019). It is noteworthy to say that in both parts, since my networks are undirected graphs, equations do not divide to the m but $2m$, so the modularity equation differs for the directed graphs. Finally, the importance of the weight, which is mentioned above, for maximizing modularity is also seen in the equation.

The first step of the iteration process is that a random node is chosen, and it moves to a neighbor community that maximizes the modularity score. Then this process is applied to the rest of the nodes in the network. After this iteration process is finished, all communities are transformed into nodes, and a new network is created. In other words, communities become a single node again and they are treated as nodes again. In this new network, the random node is chosen, and it joins the neighbor community if the new modularity score is greater than the actual score. These steps are repeated until there is no increase in modularity score. In the final network node communities are labeled with community numbers. Nodes in these communities expanded with their edges in the original network, and in the final product, we get communities of the network (NetworkX Developers, 2023).

3.3.2.3 Observing echo chambers in networks

As I mentioned above, an echo chamber in social media is defined as the existence of an environment bordered by a common frame and tendency of the like-minded people, who share the same belief with that frame, to join this community. I match important parts of this definition with all the elements that I use to make it appropriate for studying.

In this definition, two crucial aspects and characteristics are emphasized: the presence of a conducive environment and the presence of like-minded individuals. In this study, a diverse set of methods is employed to achieve the most robust outcomes. Before introducing the metrics, it is essential to provide a comprehensive explanation of the computational definition of echo chambers.

It is crucial to recognize the concept of an environment's existence at both macro and micro levels. On the macro level, the presence of a countermovement's hashtag establishes a broad boundary within which individuals engage. Hashtags, operating as collective action frames within social media, serve as fundamental elements for the movement's functioning. Nonetheless, these hashtags can also attract individuals who may either undermine the movement or express specific and dissenting views contrary to the mainstream discourse. Social movements in the realm of social media, encompassing countermovements, are intricate entities that cannot be reduced to a singular, unified entity but should rather be viewed as an amalgamation of diverse perspectives held by individuals. At this juncture, it becomes imperative to examine the environment at the micro level, characterized by the discourse shaped by individuals, which in turn contributes to the framing of the social movement. To accomplish this, the focus is directed toward the monthly discussions undertaken by individuals, which are analyzed using topic modeling techniques. The outcomes of this analysis, encompassing the topics discussed within a given month, reveal a shared framework within the environment as outlined in the definition of an echo chamber.

On the other hand, there is a part of like-minded people and their tendency to join the community. For this section, parallel to the section above, I find these people with their discourse in a particular month. After finding topic modeling results, I assign the topics to each user so, I can label people as like-minded and share the same belief. After then, I assign linkage between people who share the same discourse or topic in the network analysis part so, this creates a community that has a common topic and frame with the people.

One approach to an echo chamber focuses on likes and retweets of the people and creating a network based on these tweets' parameters (Vicario, Gaito, Quattrociocchi, Zignani, & Zollo, 2017; Wieringa, van Geenen, Schäfer, & Gorzeman, 2018). However, this research uses what people say independently from their interactions because writing about something is a much stronger attitude compared to liking or re-posting others' comments. This more intentional act of the people, or writing instead of liking, has a chance to give more accurate results.

Despite the presence of vulnerabilities, such as hashtag hijacking and conflicting opinions expressed in tweets, the research employs several algorithms and methods to mitigate these issues. For instance, an algorithm was developed specifically to filter out spam tweets prior to the analysis phase. Additionally, the semantic insights derived from the topic model are expected to distinguish individuals who hold dissenting views from the majority or others within the dataset.

I also use this two-part based echo chamber analysis in my analysis part. I start with the topic-based analysis and user-based analysis and lastly, I combine these two parts to observe results while these are bound. I use various metrics to find continuity and differences between themes expressed in echo chambers. While most of them are mentioned in detail below, in the findings part, there is an algorithm that I created to observe the continuity of the topics over time.

Finally, I utilize the following algorithm to find the durability of the echo chambers and their changes over time. In this context, the existence of the echo chamber in a given period becomes important. The term continuity can be observed in various contexts, but in this study, the focus is specifically on investigating the continuity of dominant topics within communities in the network. By examining the persistence of these dominant topics, it becomes possible to gain insights into the role of topics within echo chambers. In this concept, the most important aspects are how many months these dominant topics emerged and are these occurrences consecutive. By answering these questions, we can solve the problem of finding continuity.

In the realm of time series analysis, a wide range of statistical metrics are employed. Nevertheless, to the best knowledge, most of these metrics are insufficient for capturing the desired notion of continuity as required by this research. One particular statistical concept worth mentioning is auto-correlation, which assesses the similarity between a time series and a lagged version of itself (Papoulis & Pillai, 2002). Auto-correlation serves to quantify the linear relationship between observations at different time points within a time series. However, there is a bad side to this tool. In auto correlation, the continuity of the specific element in the series is correlated with the other elements which are located before and after that chosen element. From the view of my research, the existence of the topic in t_2 period is correlated with the possible existence of it former, t_0 and t_1, and following, t_3 and t_4, months. While this looks good in my context, because of the structure of my series, which contain 1s when there is the occurrence of the topic and 0s when the topic does not exist in that month, auto correlation does not fit perfectly. The main reason is that auto correlation also sees 0s as an independent value which affects the result. To clarify, the primary focus of the analysis is to examine the continuity and correlation specifically within the series of 1s, based on the defined criteria for assigning 1s and 0s. However, it should be noted that the technique employed in the study also considers the presence of 0s in the series. Despite this inclusion, the preliminary findings indicate that the results are not statistically significant.

The other statistical metric that I try for my research is the Runs Test. The Runs Test is a procedure that finds whether series in the elements are randomly distributed or not (Gibbons & Chakraborti, 2003). While this technique also uses a way like what I want, comparing the results of this tool, which is about the randomness of the series, does not exactly answer the questions of this research. It also suffers the same problem, which is counting 0s as another important variable, as auto correlation does.

3.3.3 Continuity function

Due to these problems that I faced with the statistical tools mentioned above, I created my own algorithm to find continuity for the topics. There are two main advantages to this technique. First, I designed it solely to answer my questions, so it satisfies the requirements that I want. Second, it makes it possible to compare the results of the two series when the continuity score is got. The employed technique, although not solely reliant on statistical methods, provides a comprehensive overview of the continuity of the significant element, represented by the value of 1, or the presence of the topic in the list. This approach offers a broader understanding of the topic's continuity. Moreover, it is worth noting that the technique can be refined and enhanced in future studies, allowing for further improvements and advancements in the analysis.

I look for two important aspects of the occurrence of the topics over time: the count of the appearance and consecutiveness of them over time. To study this equation, a series of all the topics are created based on time intervals. In other words, the list which contains 0s and 1s based on the occurrence of the month is generated and the function works on that list. Hence the following equation can be seen in Figure 22.

$$\frac{\sum_{i}^{n} \delta_{i1} \times \mathrm{maxc}(1)}{\dim(v)^2}$$

Figure 22. Equation of contunity function

In this equation, at the left-hand side, the values in the series are iterated and it sums each i, or element of the list, if it equals t which is operated with the Kronecker delta function (Arfken & Weber, 2005). In other words, it counts whether a topic is occurred in that month or not. On the right-hand side, on the other hand, $\mathrm{maxc}\,(1)$ function finds the highest value of consecutive 1s in the series. Lastly, to get a score between 0 and 1 which makes it easier for comparison, I divide the square of the dimension of the series that I represent as $\dim(\mathrm{v})$.

This equation computes the continuity score of any series. The result ranges between 0 and 1. Where 0 means all the elements in a given list are 0, 1 corresponds to all the elements in the list being 1. Even though this equation does not directly say whether there is continuity or not, it makes it possible to compare each topic and make relative assumptions.

Before moving on to the next section, I want to give some examples to clarify how the continuity function works. Assume that there are six different topic series that contain 0s and 1s for the existence of the topic in a month. In this example, I create lists for each topic for a year period and these are as follows in Figure 23:

A = [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]

B = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]

C = [1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0]

D = [1, 1, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0]

E = [1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1]

F = [1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0]

Figure 23. Continuity function example lists

In this example, broadly there are three types of lists. First, there is a list that just contains 1s; second, the list which does not have any 1s and just has 0s; lastly, the rest of the lists contain the same number of 1s, six times, with different patterns. From the view of our case, while topic A appears in all the months of a given period, B is not mentioned at the same time. Topics of C, D, E, and F on the other hand, occurred the same amount of time at different times.

When we apply our continuity function to these series, a score of topic A is 1 due to the 1s for each element in a list as mentioned above. On the other hand, it is not surprising that the score of topic B is 0 since it has not any 1 on the list. While these results are expected, it becomes complicated for the rest of the topics. At first glance, it is expected that C has a higher score compared to the other because of the six consecutive 1s and F has the least score in that group due to the discontiguous of 1s. The result of the continuity function proves this claim too. While the score of topic C is 0.25, score of topic F is 0.006. For the rest of the topics which are topics D and E, their continuity scores are respectively 0.125 and 0.083 so, in the end, the continuity score order of this example is 1 > 0.25 > 0.125 > 0.083 > 0.006 > 0 which corresponds to A > C > D > E > F > B for the topics. This procedure allows comparing these topics in terms of their continuity over time. While topic A is the most continuous topic, B is not continuous at all. Respectively, topics C, D, E, and F follow topic A.

While this result can be predicted due to the few number of topics and months, I deal with nearly a thousand topics in some countermovements with more than 90 months in my study so, it makes it impossible to create such rank order without any quantitative method.

3.3.4 Jaccard similarity

The last statistical method I want to introduce is the Jaccard similarity. The Jaccard similarity is a technique to compare the similarity and diversity between two groups.

It is calculated by dividing the number of intersections of these groups' elements by their union of them. The result takes a value between 0 and 1 where 0 corresponds to there is no similarity among the elements of the groups and 1 means that those groups are identical (Jaccard, 1912). The equation of the Jaccard similarity is shown in Figure 24:

$$\frac{A \cap B}{A \cup B}$$

Figure 24. Equation of Jaccard similarity

3.3.5 Echo chamber function

After introducing various method tools, algorithms, and statistical metrics, before moving on to the findings part, I elaborate on how I analyze all these with computational methods. I prepare an echo chamber function that generates most of the information that I need for my analysis. I designed this function as follows:

Let P be the collection of posts of a specific countermovement, which contains tweet text, user id, and time of the tweet. When we give P as an input, the function gives first, community, which has more than one member, taken from community detection algorithm results of network analysis, which is mentioned above, based on monthly intervals with the users along with their topics of tweets for that month. In light of these, echo chamber function can be seen in Figure 25 below.

$$\text{compute\_}\mathcal{ec}(\text{P}) =$$

$$\left(\begin{array}{c} \text{EC}_1\text{:} < \text{time of echo chamber} >,\ \{\text{users: [list of topics they talk in that month]}\} \\ \text{EC}_2\text{:} < \text{time of echo chamber} >,\ \{\text{users: [list of topics they talk in that month]}\} \\ \text{EC}_3\text{:} < \text{time of echo chamber} >,\ \{\text{users: [list of topics they talk in that month]}\} \\ \dots \end{array}\right)$$

Figure 25. Echo chamber function

As can be seen in the equation, the compute_ec function takes P as an input then it gives an echo chamber, or $\mathrm{EC_n}$, as an output with its details. This information mainly includes the time interval of the network and users' list with the topics they talk about in that period. While the information on time is stored as year and month, users' lists are community members with their tweets' topics. The number of echo chambers, or n in $\mathrm{EC_n}$, is determined by the total number of communities, which contain more than two nodes, in the whole lifespan of the countermovement.

3.3.6 Time series composition

In this research, I employ the time series decomposition technique to examine the temporal trends of the topics under investigation. This approach involves breaking down a time series into distinct components, enabling the analysis of potential patterns and dynamics within the series (Cleveland, Cleveland, Mc Rae, & Terpenning, 1990). Specifically, I utilize the seasonal decomposition of time series by employing the Loess method. The primary rationale behind selecting this method is its versatility, as it allows for the application of various statistical techniques. By utilizing this decomposition technique, I aim to gain deeper insights into the temporal patterns and fluctuations of the topics in question.

The seasonal decomposition of time series by the Loess method is a non-parametric approach that aims to analyze and understand the different patterns and variations present in the data (Cleveland, Cleveland, Mc Rae, & Terpenning, 1990). By adopting a non-parametric approach, this method avoids making any assumptions regarding the underlying distribution of the time series. Instead, it provides a valuable means of visualizing trends over time. The Loess method employs a locally weighted regression technique known as Loess to identify and extract underlying trends in the data (Cleveland, Cleveland, Mc Rae, & Terpenning, 1990, p. 3). By applying this method, it becomes possible to gain insights into the temporal patterns and fluctuations present in the time series data. There are three different approaches to observing changes in this method called trend, seasonal, and residual. Seasonal components were found by computing the moving averages of the time series in a fixed length, which is a month in my research. The trend component, on the other hand, is found by applying the Loess method to the time series after estimating the seasonal component. Lastly, the residual component is got by subtracting the estimated trend and seasonal parts from the original time series (Cleveland, Cleveland, Mc Rae, & Terpenning, 1990).

CHAPTER 4

FINDINGS

This section discusses findings of the topic-based analysis, user-based analysis, and a combination of them. I argue that with this new perspective, observation of the echo chambers gives more accurate results compared to the existing literature.

4.1 Findings based on frames of the echo chambers

In this part, I introduce my topic modeling results and observe the continuity of them over time. First, I perform pre-processing on the texts of the tweets and the top2vec topic modeling algorithm to these pre-processed texts. Although the top2vec model claims that it does not need any pre-processing, I applied it to get faster and more precise results. As a result of this algorithm, I get 8,578 dense areas for All Lives Matter, 6,907 number for Blue Lives Matter, 413 for Police Lives Matter, and lastly, 1,122 for White Lives Matter. A bar chart of the results can be seen in Figure 26 below.

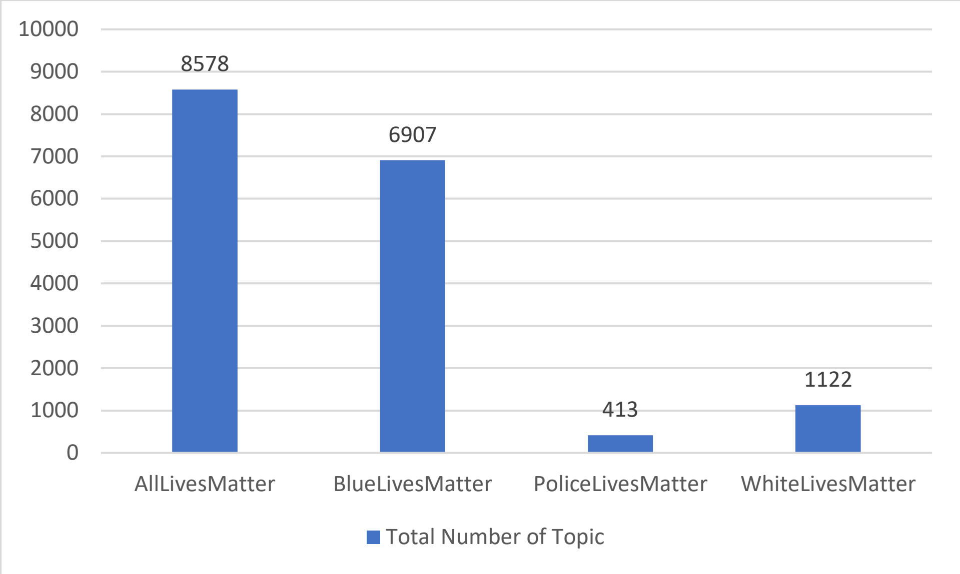

Figure 26. Total number of topics for each dataset

It is not surprising that the number of dense areas is much higher for All Lives Matter and Blue Lives Matter due to the higher number of tweets they contain. However, when we perform Uniform Manifold Approximation and Projection for Dimension Reduction and Hierarchical Density-Based Spatial Clustering Application with Noise techniques on countermovements datasets to see structural variations in datasets, we can see differences. Figures 27 and Figure 28 present the two-dimensional document vectors of the White Lives Matter and Police Lives Matter datasets[1].

[1] Due to the lack of computational resources, I cannot visualize two-dimensional representation of the All Lives Matter and Blue Lives Matter countermovements.

Figure 27. Top2Vec results of Police Lives Matter

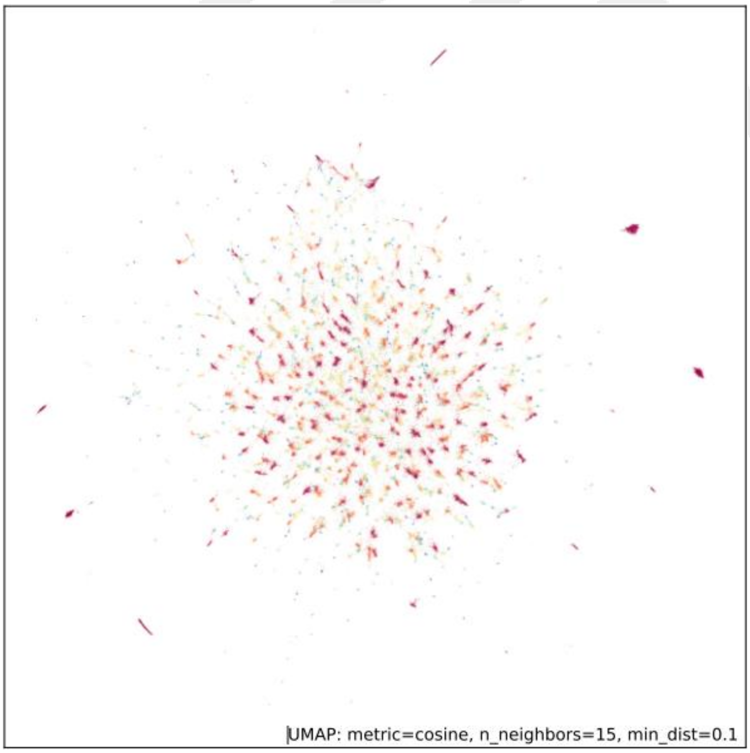

Figure 28. Top2Vec results of White Lives Matter

Figures 27 and 28 visually illustrate the distribution of document vectors for Police Lives Matter and White Lives Matter, respectively. These preliminary findings provide an initial understanding of the expected outcomes from the subsequent topic modeling analysis. Both charts exhibit similar characteristics in terms of the distribution of document vectors. In the center of each chart, there are clusters of document vectors that are closely positioned, indicating a higher degree of similarity among the corresponding documents. However, there are also outlier groups scattered around the central clusters, representing documents that deviate from the dominant topics or themes. This observation suggests that the topic modeling results for both countermovements are likely to exhibit similar patterns, with some cohesive clusters of documents and potential variations or outliers within the broader discourse.

After determining topics for each document, or tweet's texts, I associate topic numbers with each corresponding tweet. Next, I create networks for the tweets on a monthly basis. In these networks nodes are users, and edges represent the posting of tweets about the same topics. I also respect the amount of mentioning the same topics with the edge weight. I apply the Louvain community detection algorithm for each network belong the countermovements and take communities that have more than just one node due to the requirement of the echo chamber which needs a community from the view of social science but not network analysis.

From the result of the community detection algorithm, there are 41,587 communities for All Lives Matter, 24,546 communities for Blue Lives Matter 2,578 for Police Lives Matter, and 5,221 for White Lives Matter. Figure 29 represents these results with a bar chart.

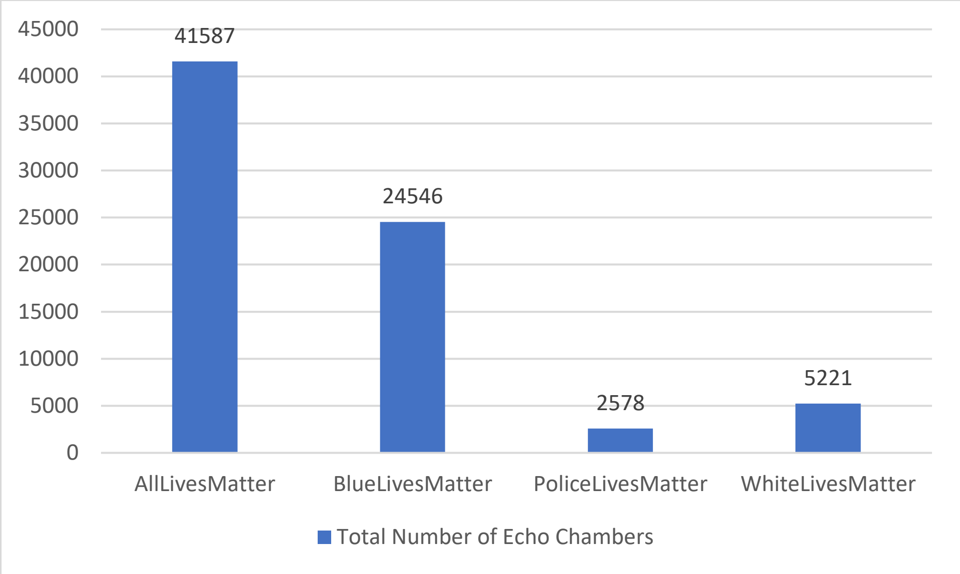

Figure 29. Total number of echo chambers for each dataset

In this context, comparing ratios of the total number of tweets and a total number of echo chambers indicates to understand if there is a significant difference. As mentioned at the beginning there are 903,029 tweets for All Lives Matter, 672,646 tweets for Blue Lives Matter, and 80,737 tweets for Police Lives Matter, 157,305 tweets for White Lives Matter. After removing spam from these datasets respectively, I get 866,601, 655,380, 79,589, and 135,854. The ratios of the number of tweets are 10.89 / 8.23 / 1 / 1.7. From this perspective, for each Police Lives Matter tweet there are 1.7 White Lives Matter tweets, 8.23 Blue Lives Matter tweets, and 10.89 All Lives Matter tweets. We expect to see nearly similar ratios if there were the same structure of dense areas for all countermovements. However, the ratios of the total number of echo chambers are 16.13 / 9.52 / 1 / 2.02, which means that for each echo chamber of Police Lives Matter, there are 2.02 echo chambers for White Lives Matter, 9.52 echo chambers for Blue Lives Matter but 16.13 echo chambers for All Lives Matter. While the ratios of Blue Lives Matter and White Lives Matter remains nearly the same and little increase, there is a more significant change for All Lives Matter. From this view, it is possible to say that it is expected to observe more echo chambers on bigger countermovements in terms of the number of tweets sent during their lifespan. However, the total number of echo chambers of All Lives Matter is much higher than expected.

After identifying an anomaly concerning the overall count of echo chambers for countermovements, particularly for All Lives Matter, I proceed to generate bar charts which are Figure 30 to Figure 33 that illustrate the variations in the number of communities over time for each countermovement. This comparative analysis enables the identification of potentially notable discrepancies among them.

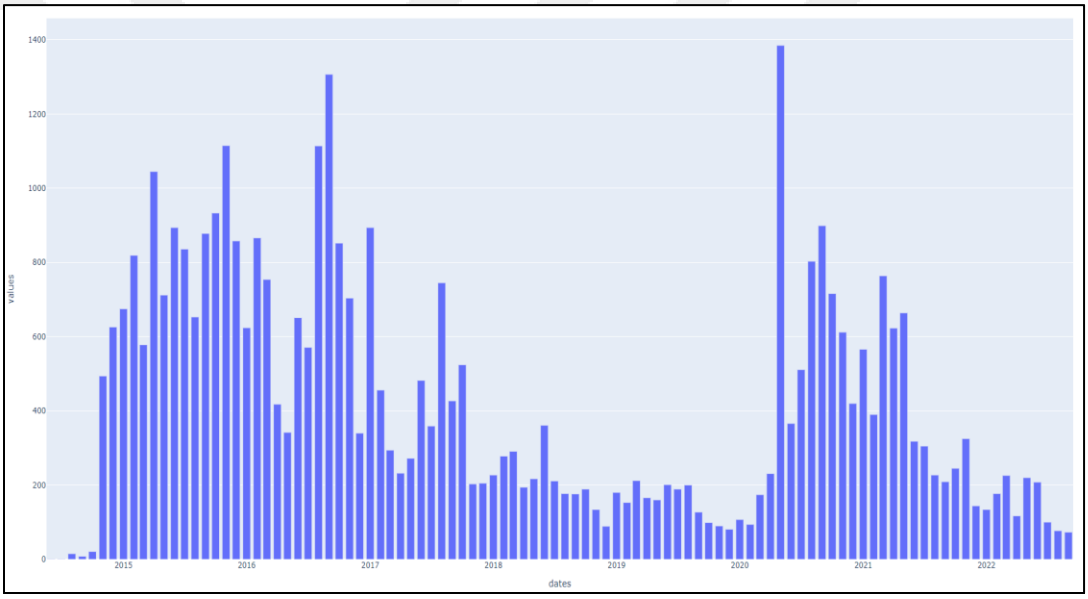

Figure 30. Total number of echo chambers over time - All Lives Matter

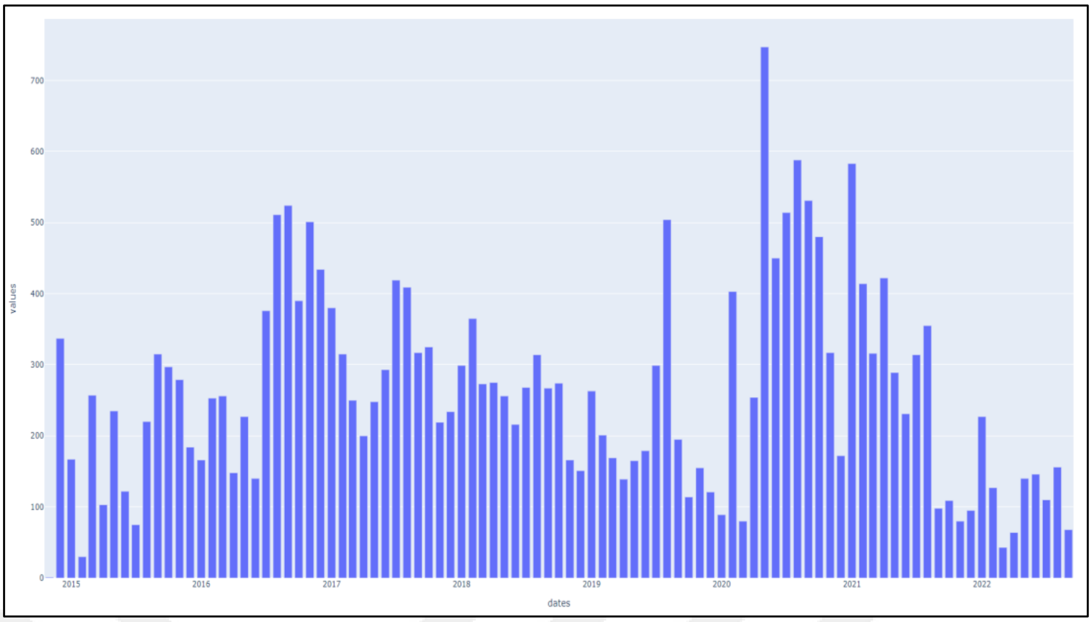

Figure 31. Total number of echo chambers over time - Blue Lives Matter

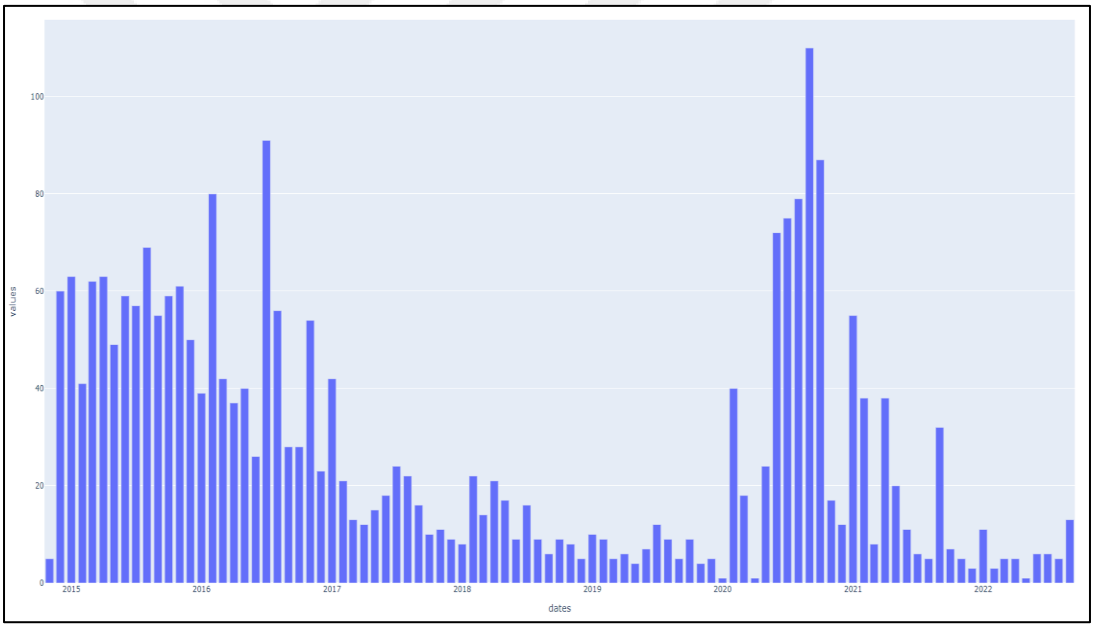

Figure 32. Total number of echo chambers over time - Police Lives Matter

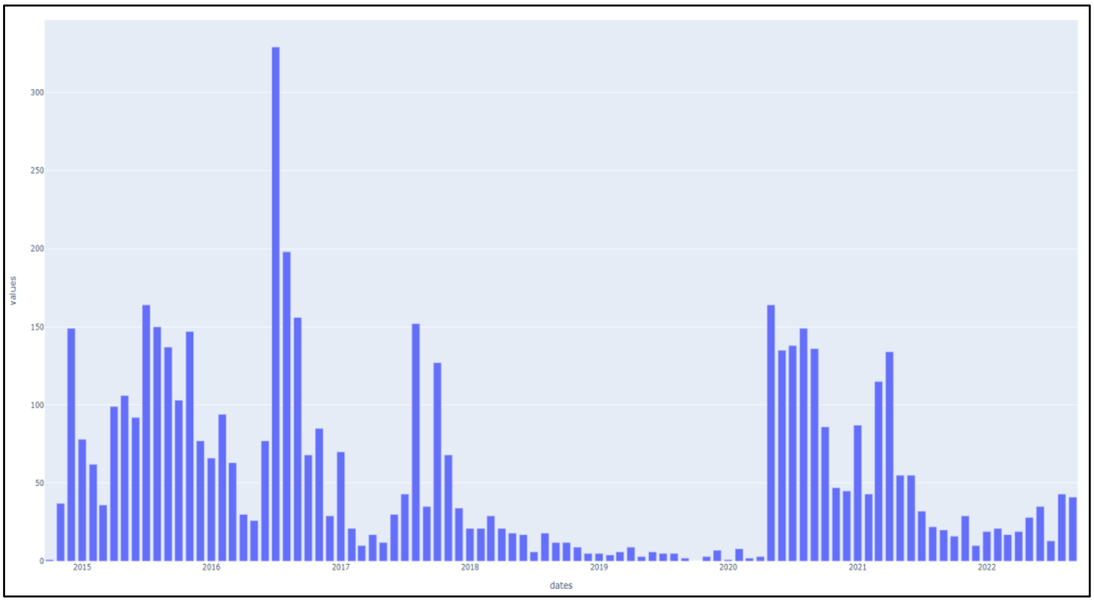

Figure 33. Total number of echo chambers over time - White Lives Matter

There are some important outputs from the distribution of the echo chambers over time. First, there are some peak periods which are mid-2016 and mid-2020 for all countermovements. The reason for the peak in mid-2016 is police killings and the protests of them that were held in various areas in the US. For instance, Alton Sterling was killed by a police officer in Baton Rouge, Louisiana, and Philando Castile was killed by a police officer in Saint Paul, Minnesota. After these police officers were killed in Dallas, Texas, and Baton Rouge, Louisiana. The result of these total number of tweets sent with #BlackLivesMatter raised drastically as well as #AllLivesMatter and #BlueLivesMatter (Anderson, Toor, Olmstead, Rainie, & Smith, 2018). While the total number of echo chambers belong those two countermovements are raised with the increase in the total number of tweets, as it can be seen it is not limited to All Lives Matter and Blue Lives Matter, but White Lives Matter and Police Lives Matter are also raised during these periods. No doubt that the reason for increasing in mid-2020 is the death of George Floyd and the protest of it. From this perspective, the total number of echo chambers is increasing during extraordinary periods, and it is applicable to all countermovements.

On the contrary, there is a noticeable decline in the number of echo chambers for all countermovements, with some minor fluctuations, between these two peak periods. However, this decline is relatively less pronounced for Blue Lives Matter compared to the other countermovements. In other words, the total number of echo chambers associated with Blue Lives Matter demonstrates greater consistency over time when compared to the other countermovements. In summary, there is a tendency for an increase in the number of echo chambers during extraordinary times or significant events, while the number decreases during other periods. It is plausible to suggest that there may be greater unity among activists during times of crisis. However, contrary to this assumption, the emergence of more cliques within the networks of people is observed.

Figures 34 to 37 depict the average number of users in communities for each month, providing insights into the user density within these communities. By examining these figures, it becomes possible to make comprehensive assertions about the specific time periods during which individuals gather together.

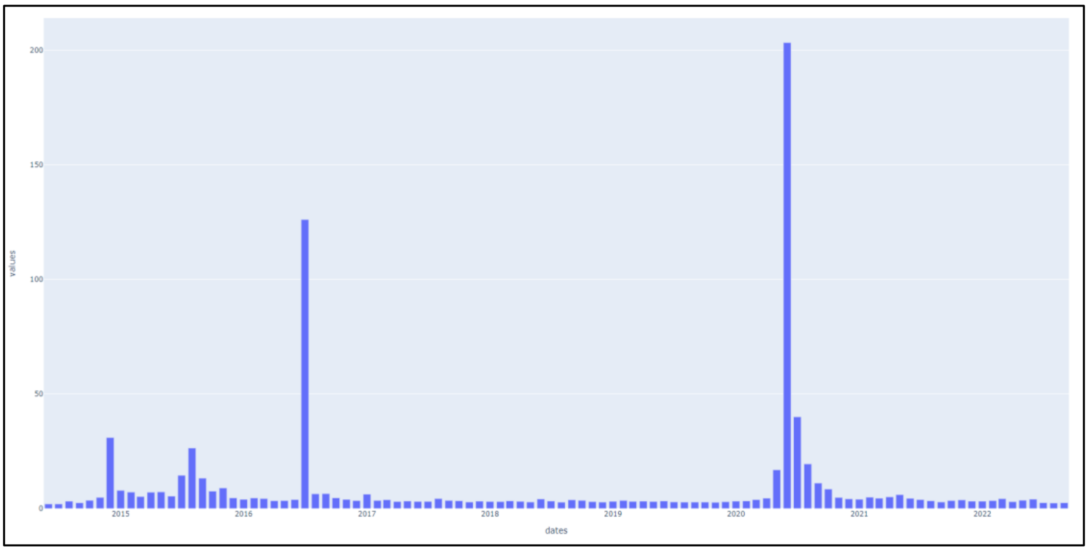

Figure 34. The average number of users in communities over time - All Lives Matter

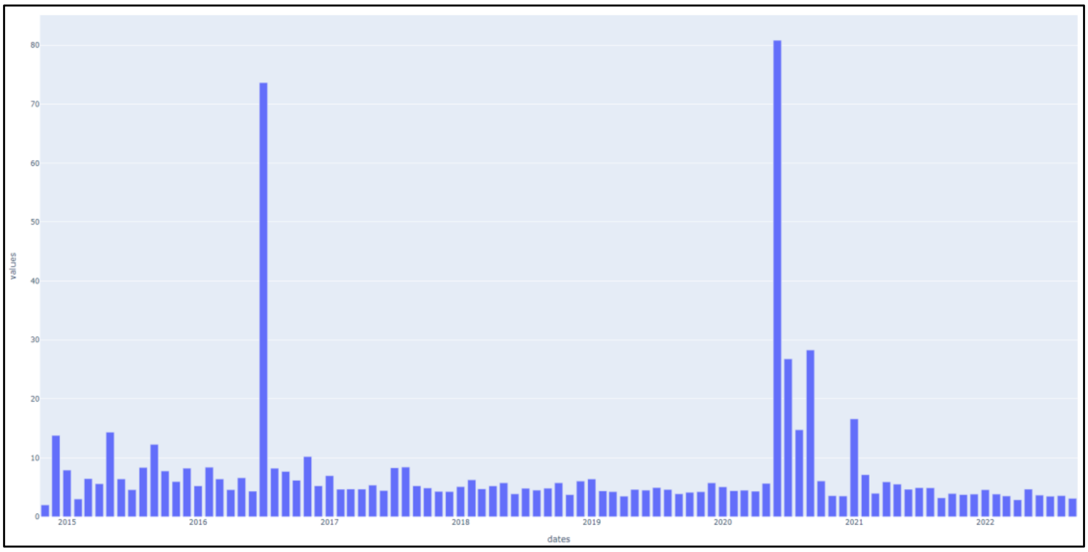

Figure 35. The average number of users in communities over time - Blue Lives Matter

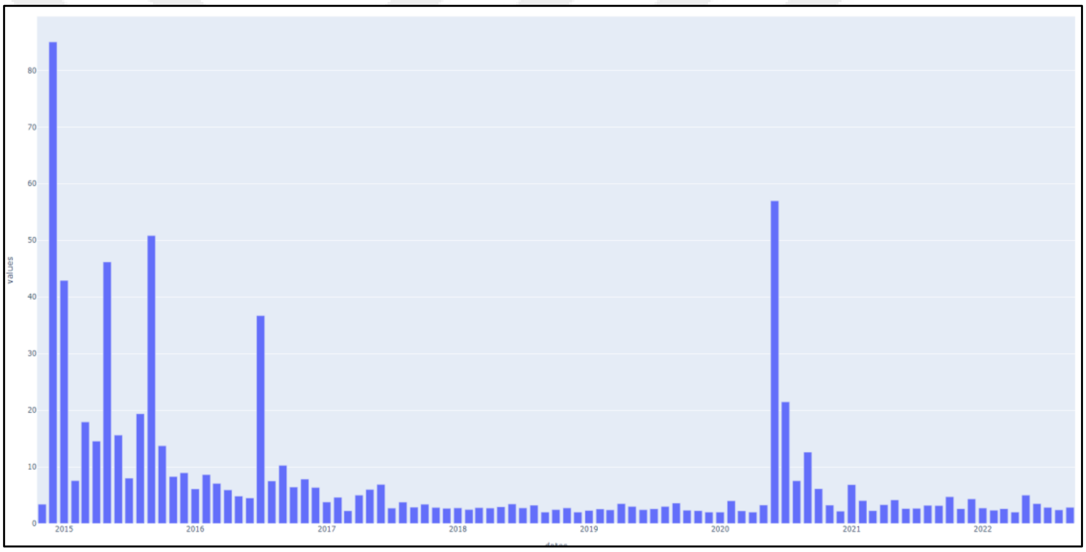

Figure 36. The average number of users in communities over time - Police Lives Matter

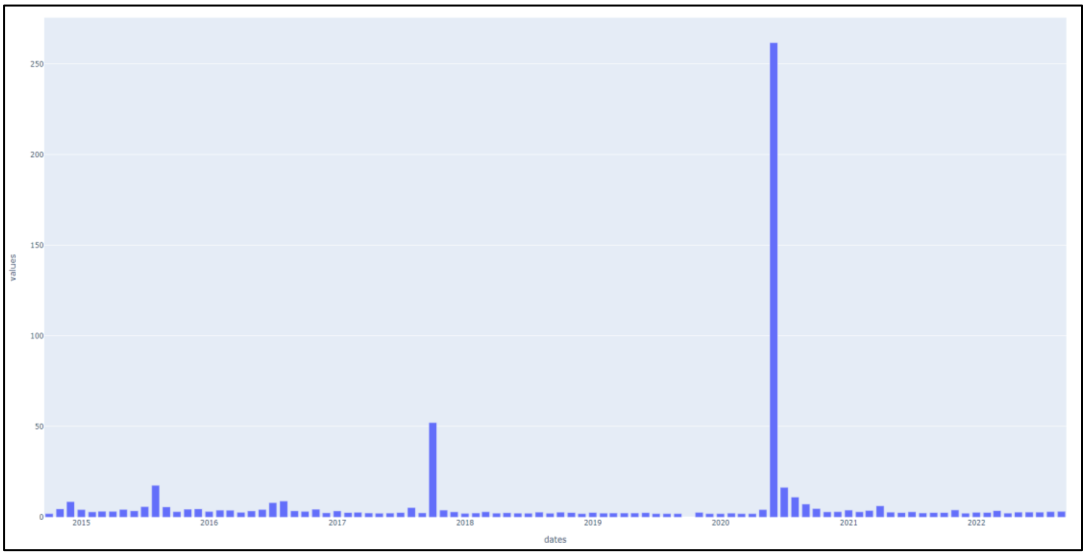

Figure 37. The average number of users in communities over time - White Lives Matter

The impact of periods marked by events such as the killing of Alton Sterling and George Floyd is evident in the average number of users within communities for each month, with a few notable exceptions. First, there is a notable peak in mid-2020 for all countermovements. However, while there are distinct surges in mid-2016, the same cannot be observed for White Lives Matter. Second, apart from these outliers and some exceptional cases, there are no significantly high values for the remaining months. Notably, Police Lives Matter stands out with a high average number of users at the end of 2014, distinguishing itself from the other countermovements in this aspect. The emergence of Police Lives Matter with the killing of police officers in Brooklyn, New York, and the protests that followed against it (Mueller & Baker, 2014) can be identified as the primary reason behind the difference. It is noteworthy that supporters of Police Lives Matter have reacted strongly to this event, while no such reaction has been observed from the supporters of other countermovements.

As can be seen in Figures 24 through 27, the total number of echo chambers over time, there are more cliques during important events. With the charts of the average number of users in communities, this claim goes one step further and we can observe that communities, or cliques, in the networks, also contain more users compared to the rest of the time. On the other hand, we can also see that except during these peak periods, the average number of users in the echo chambers is stable most of the time. This trend shows similarity with the total number of echo chambers too. Especially when we compare charts of the Police Lives Matter, at the beginning of the movement both the total number of echo chambers and the average of users belong them are high then nearly all the time these values go parallel. Lastly, inclines on the echo chambers between peak periods generally do not have an impact on the average number of users in communities but mostly it is affected when there are only important events and sharp raises connected to those events.

The next step is assigning a topic to them and computing their continuity. First, I find the dominant topic for each echo chamber. In this context, the dominant topic means the most mentioned topic in the echo chambers, and I assume that this dominant topic is comprehensive for all the members of the community.

To analyze the continuity of topics within countermovements over time, I generated time series data for each topic. In these time series, a value of 1 is assigned if the topic is present in a given month, and a value of 0 indicates its absence. These time series serve as input for my continuity algorithm, which calculates a continuity score for each topic in the countermovements. I then collected and stored the continuity scores obtained for each topic.

To compare the continuity scores across different countermovements, I constructed box plots for each countermovement. These box plots, represented in Figure 38 to Figure 41, provide a visual representation of the distribution and variability of continuity scores for the topics within each countermovement. By examining these box plots, we can gain insights into the level of continuity exhibited by the topics associated with each countermovement.

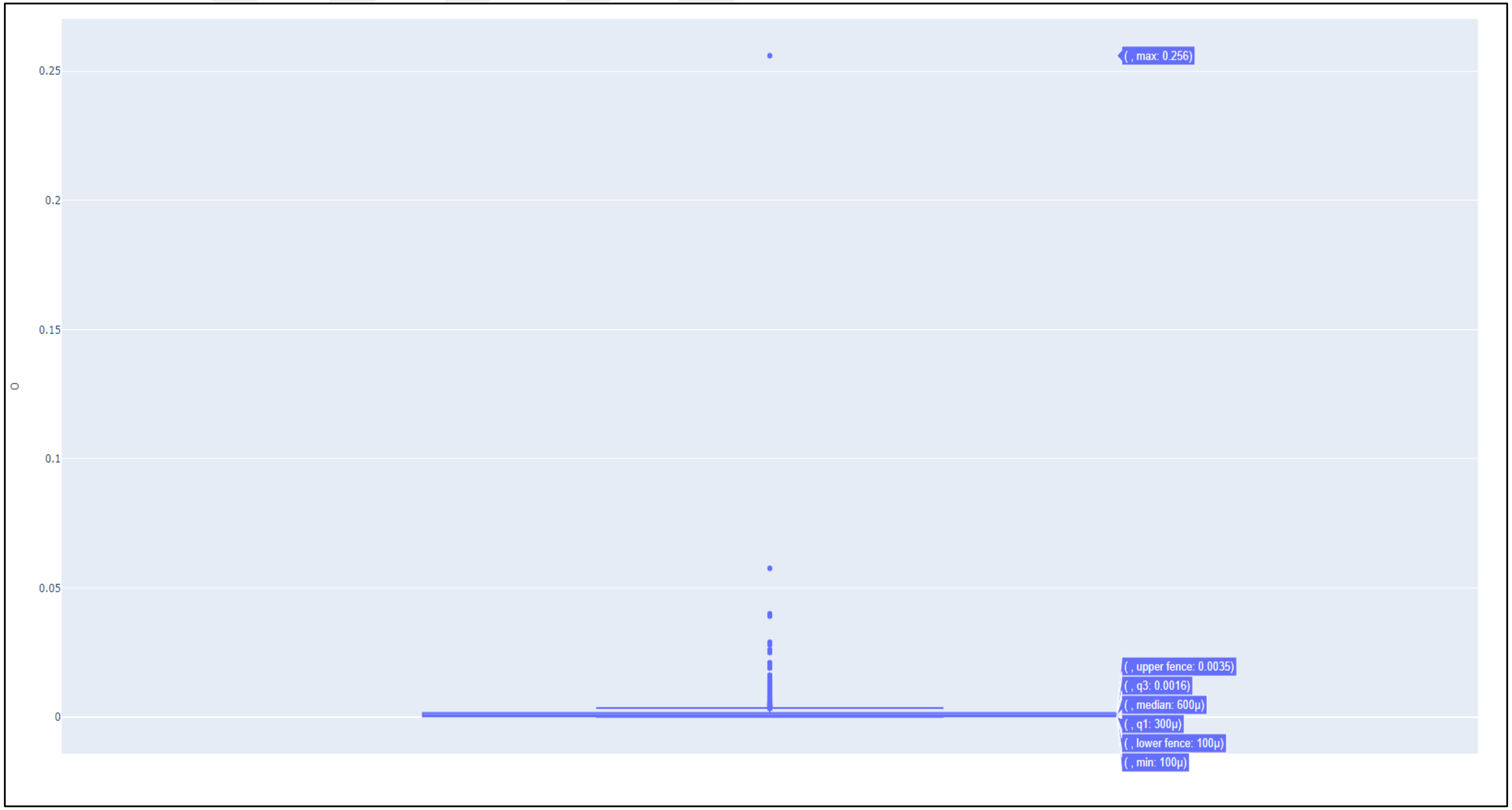

Figure 38. Box plot of continuity score of the topics - All Lives Matter

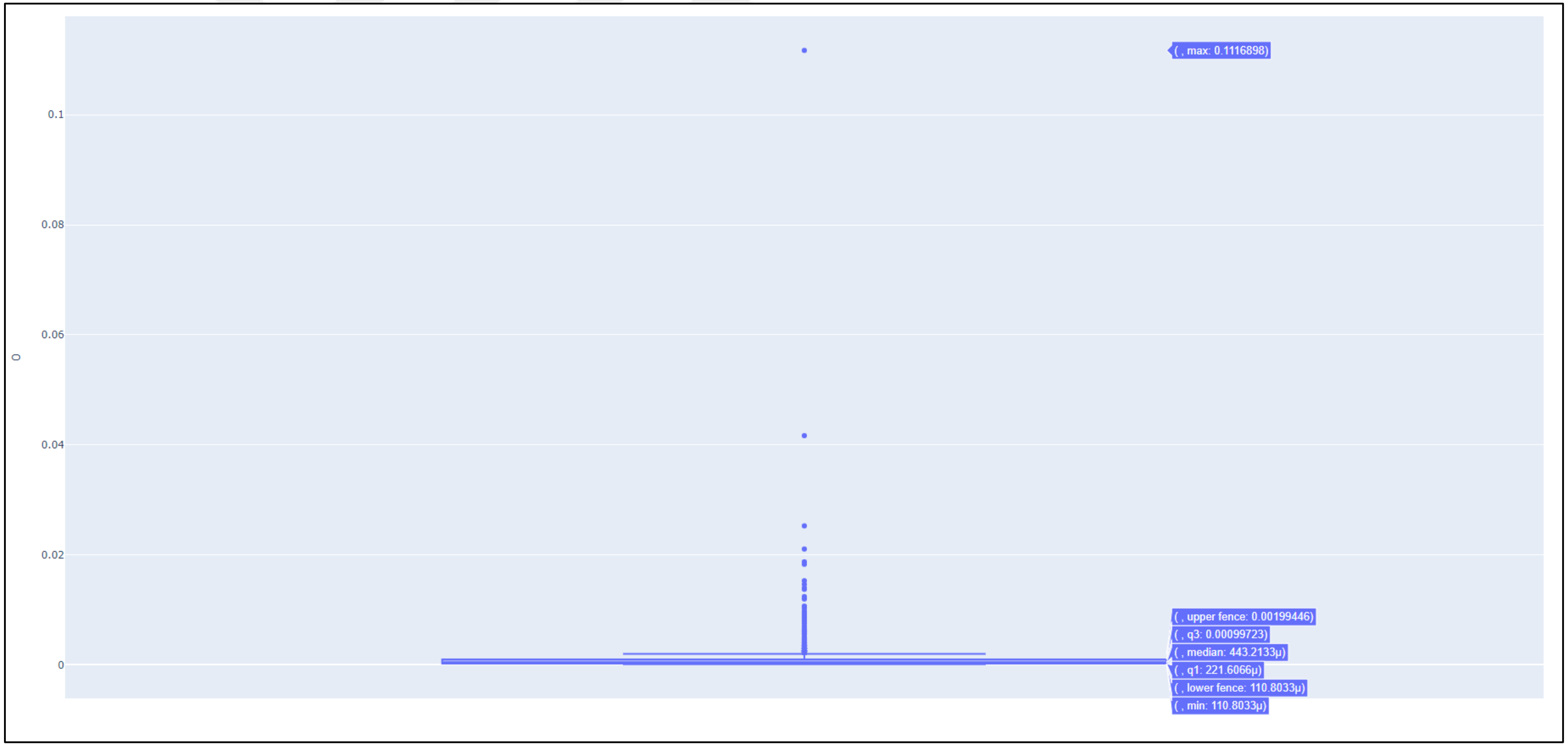

Figure 39. Box plot of continuity score of the topics - Blue Lives Matter

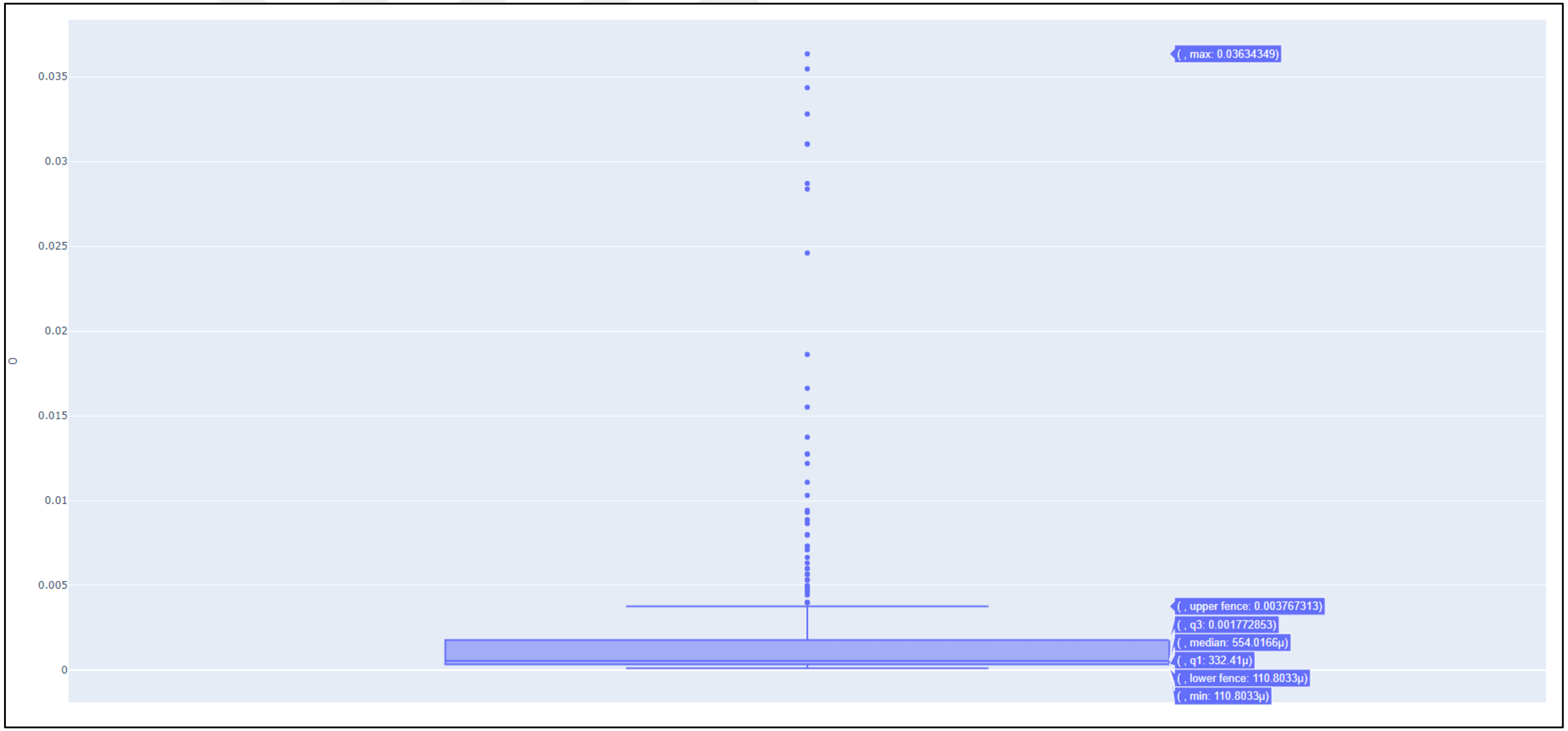

Figure 40. Box plot of continuity score of the topics - Police Lives Matter

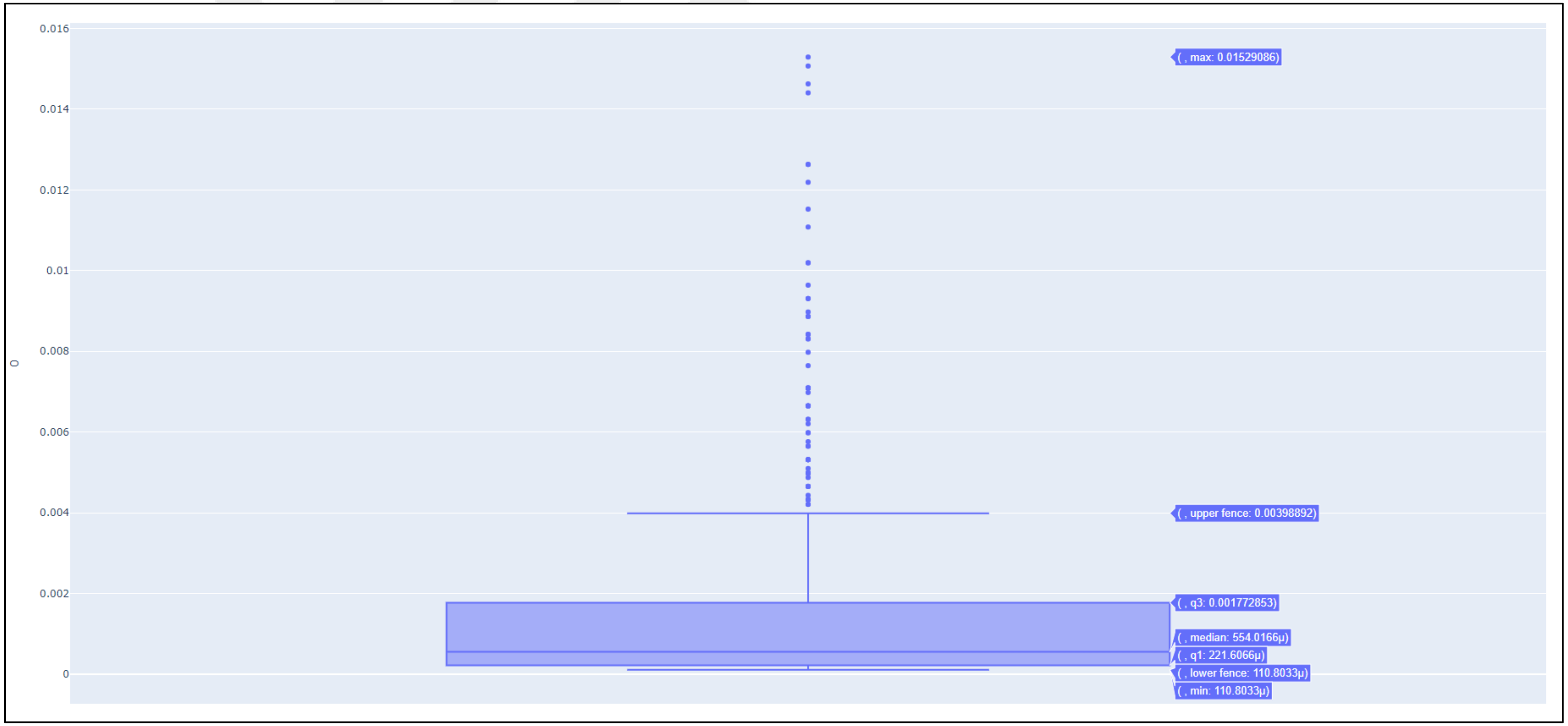

Figure 41. Box plot of continuity score of the topics - White Lives Matter

Prior to comparing the results depicted in the box plot that illustrates the persistence of dominant topics within echo chambers, it is good to compile the relevant data into Table 1. This will provide a clear overview of the key findings and facilitate their analysis.

Table 1. Continuity Score of the Topics – Summary

Countermovement	Minimum Value	First Quartile	Median	Third Quartile	Maximum Value
All Lives Matter	100μ	100μ	600μ	0.0016	0.256
Blue Lives Matter	110μ	221μ	443μ	0.0009	0.111
Police Lives Matter	110μ	332μ	554μ	0.0017	0.036
White Lives Matter	110μ	221μ	554μ	0.0017	0.015

First, it is not surprising to see that nearly all results are too close to 0, which is around 100 μ[2], due to the high number of months in the series and the low level of existence of the topics. Rather than proposing statistically significant results, this method helps me to compare the countermovements. From this view, nearly all scores are very similar and there are minimal differences. For instance, while the first quartile scores of Blue Lives Matter and White Lives Matter are the same, All Lives Matter has the least score, and Police Lives Matter has the biggest one. On the other hand, All Lives Matter has the largest value of median while Blue Lives Matter least for this one. Police Lives Matter and White Lives Matter share the same score which is between the others. Furthermore, for the third quartile score, All Lives Matter, Police Lives Matter, and White Lives Matter have nearly the same scores, but Blue Lives Matter has the least value which is nearly half of the others. To sum up, from the perspective of continuity of the dominant topics of the echo chambers, the range

[2] μ (Mu) represents the prefix multiplier 0.000001 or 10^{-6}.

of All Lives Matter is broader while Blue Lives Matter has a narrower range compared to others. However, as mentioned above, the differences are too minimal.

I go one step further and before moving on to user-based analysis, I want to introduce time series decomposition of the topics. Due to the high number of topics for each countermovement, rather than a particular analysis, it is better to interpret the cumulative trends of the topics over time.

First, time series decomposition line charts are a trend approach. We get general information about the long-term patterns of the existence of the topics over time. In other words, this method captures the overall direction of the existence of the topics in the long term. This helps me to observe if there is increasing, decreasing, or remaining stable over time. Charts are represented below from Figure 42 to Figure 45.

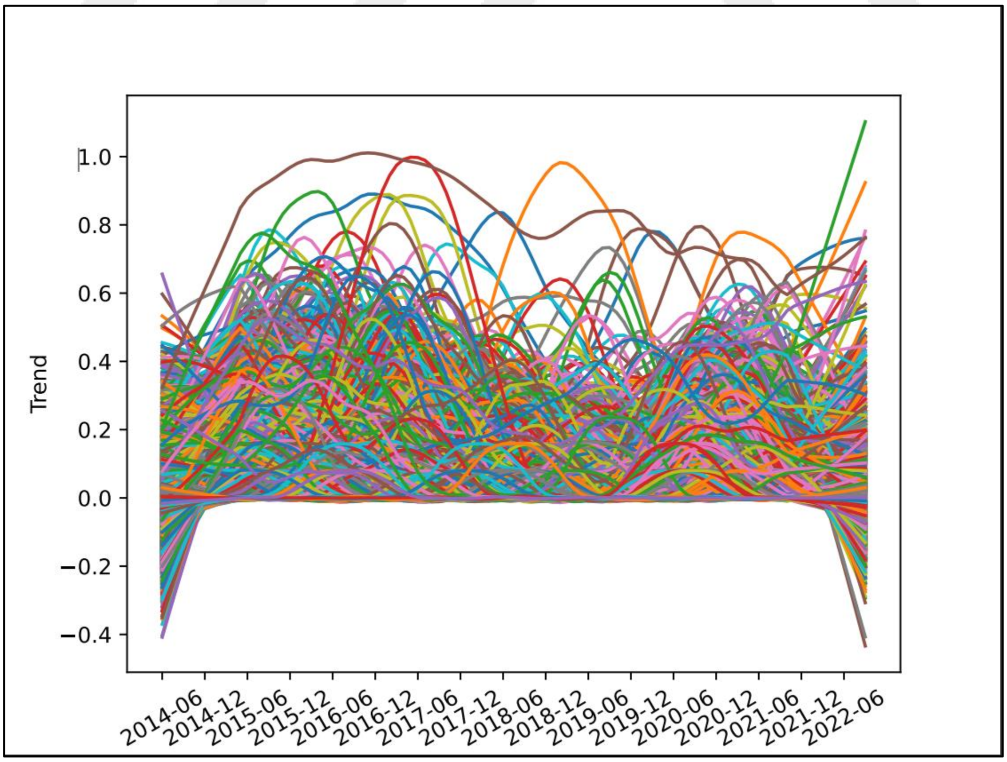

Figure 42. Time series decomposition (Trend) - All Lives Matter

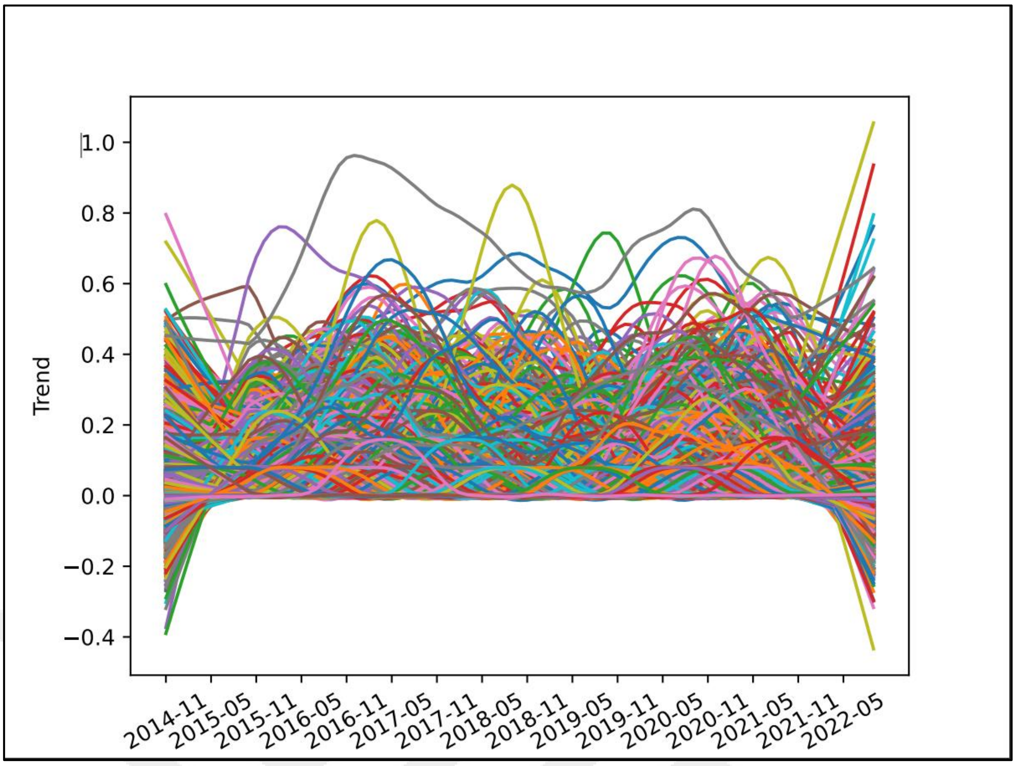

Figure 43. Time series decomposition (Trend) - Blue Lives Matter

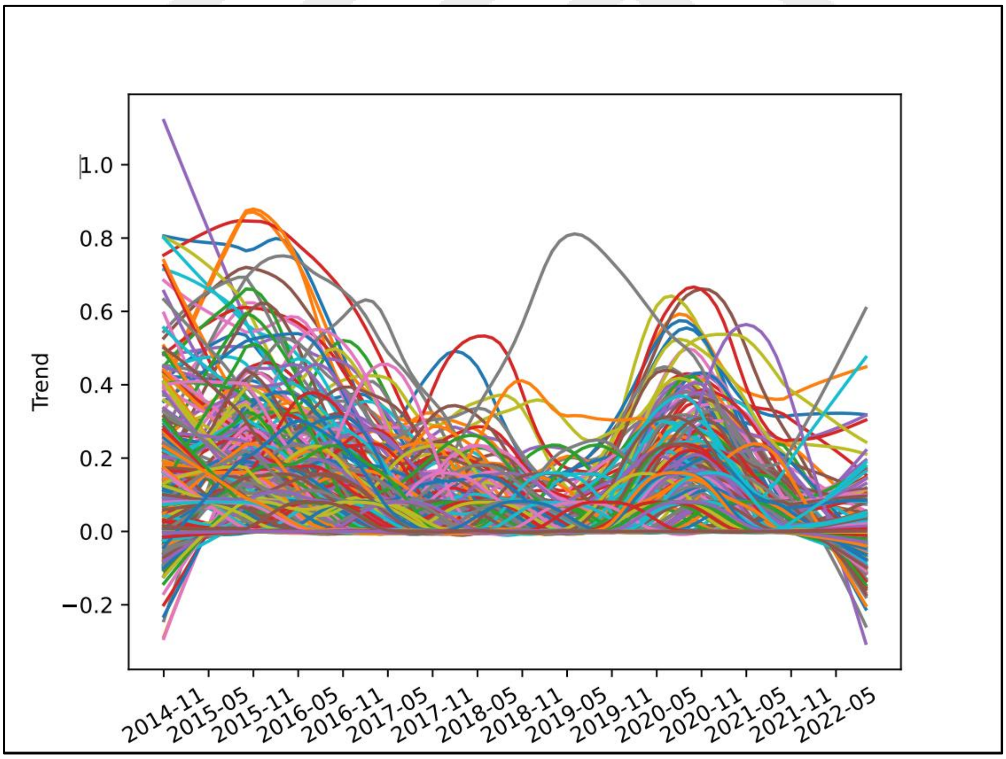

Figure 44. Time series decomposition (Trend) - Police Lives Matter

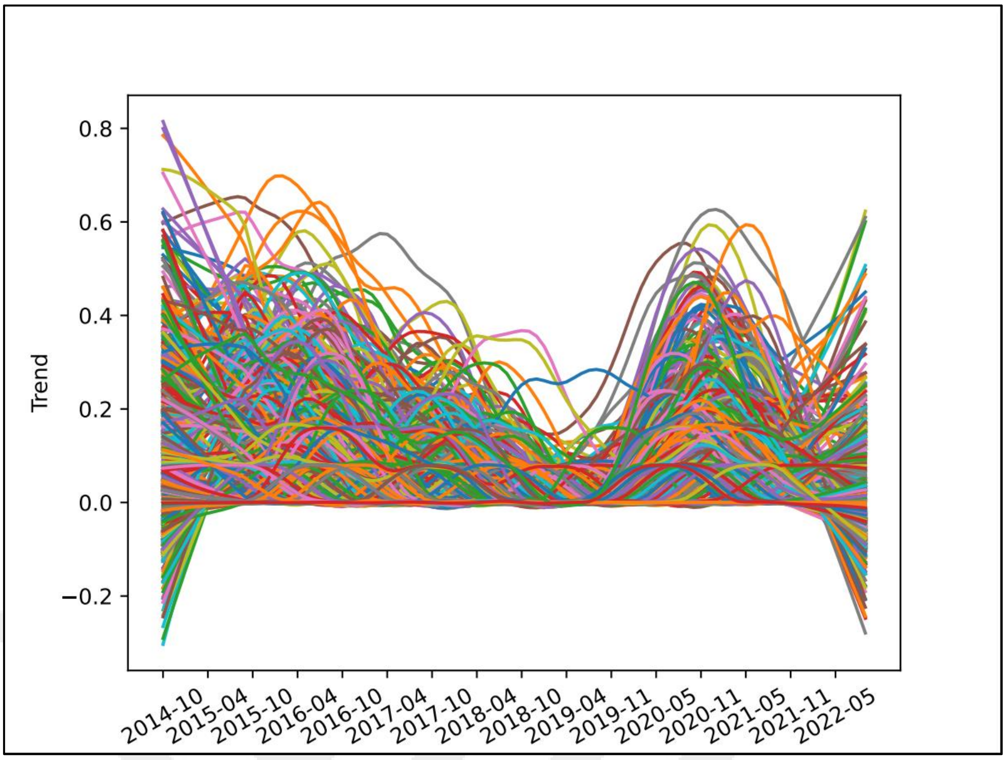

Figure 45. Time series decomposition (Trend) - White Lives Matter

These findings highlight that countermovements can be categorized into 2 groups as larger ones and smaller ones. For the former one, which includes All Lives Matter and Blue Lives Matter, there are fluctuations over all the lifespans of the countermovements. There is no significant trend for the existence of the topics. On the other hand, for the latter one which is Police Lives Matter and White Lives Matter, trends of the topics, except for some outliers, have a tendency of decreasing until mid-2020 and then increase afterward.

Compared to the former charts, it is expected to see a decline before mid-2020, especially for White Lives Matter and Blue Lives Matter. On the other hand, there are more stable trends for Blue Lives Matter and relatively stable trends for All Lives Matter. A higher number of echo chambers belonging to Blue Lives Matter over time might lead to this result. In other words, the existence of more groups and communities leads to stable trends for the topics. However, it is highly probable that these dominant topics of the echo chambers are not similar to the dominant topics of former and latter echo chambers due to the relatively lower continuity score of Blue Lives Matter. To sum up, while Blue Lives Matter looks more stable in terms of the number of echo chambers and their dominant topics, their frames are different and relatively more discontinuous compared to the other countermovements.

Second, I use the seasonal approach of the time series decomposition. As mentioned above, for this type of analysis, averages between fixed periods are calculated so it allows us to observe whether there is a trend between constant time intervals. In other words, I will identify regular or repeating patterns of the existence of the topics in the countermovements. Between Figure 46 and Figure 49, seasonal time series decomposition charts can be seen.

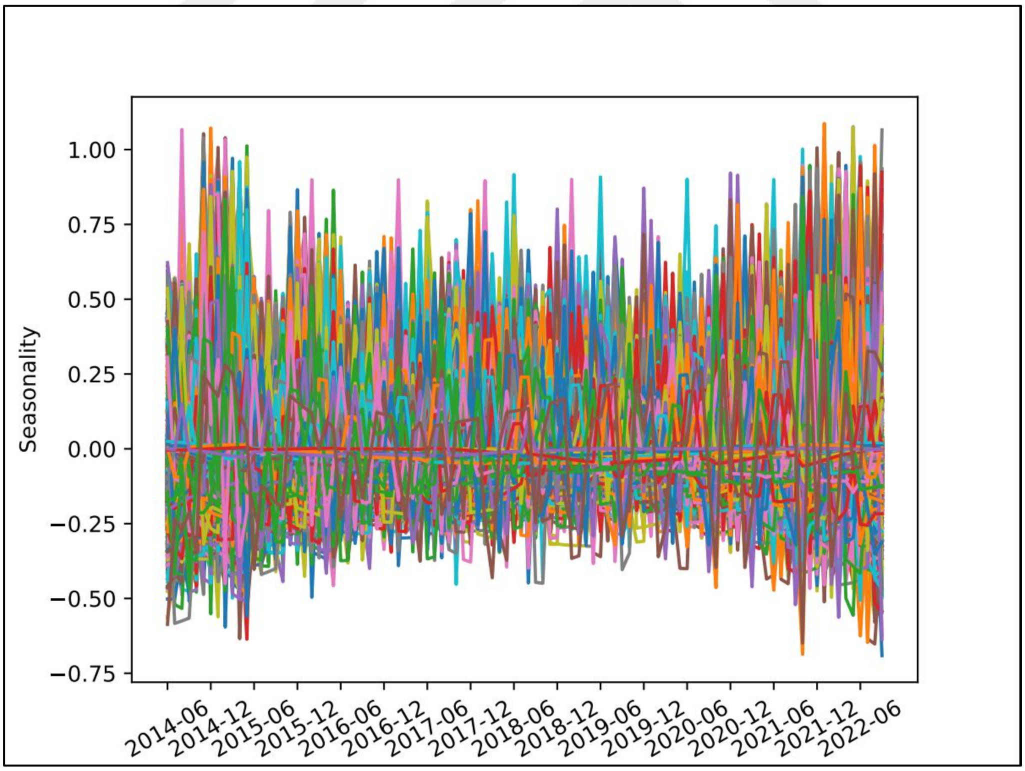

Figure 46. Time series decomposition (Seasonal) - All Lives Matter

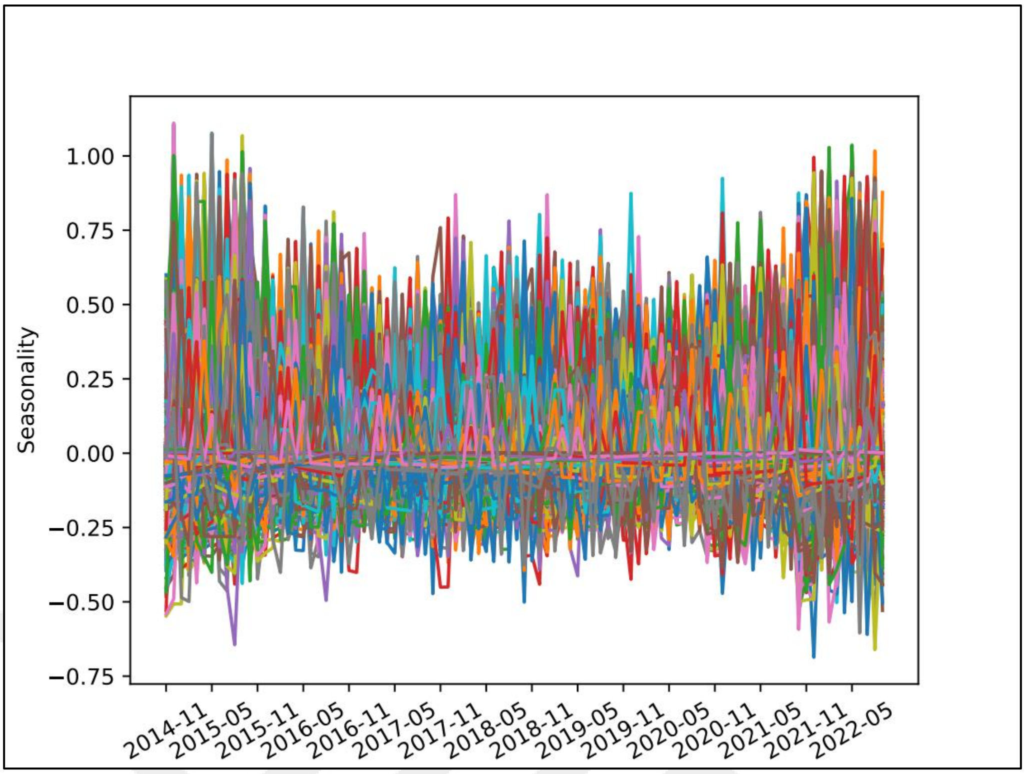

Figure 47. Time series decomposition (Seasonal) - Blue Lives Matter

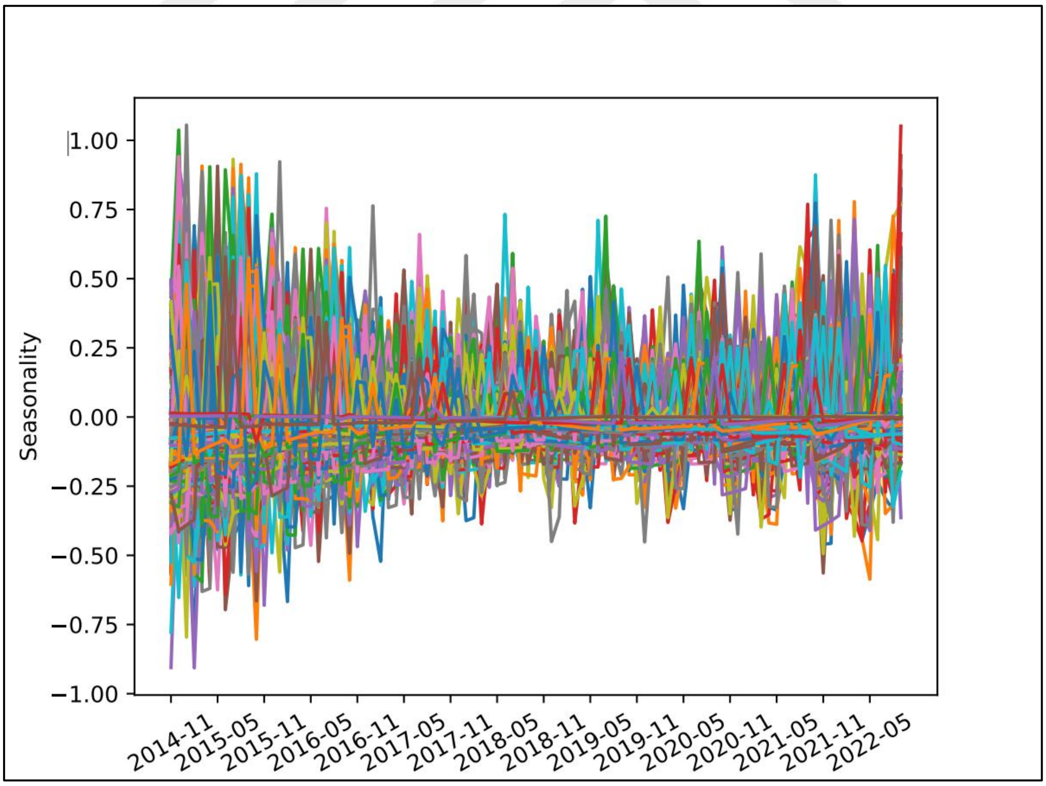

Figure 48. Time series decomposition (Seasonal) - Police Lives Matter

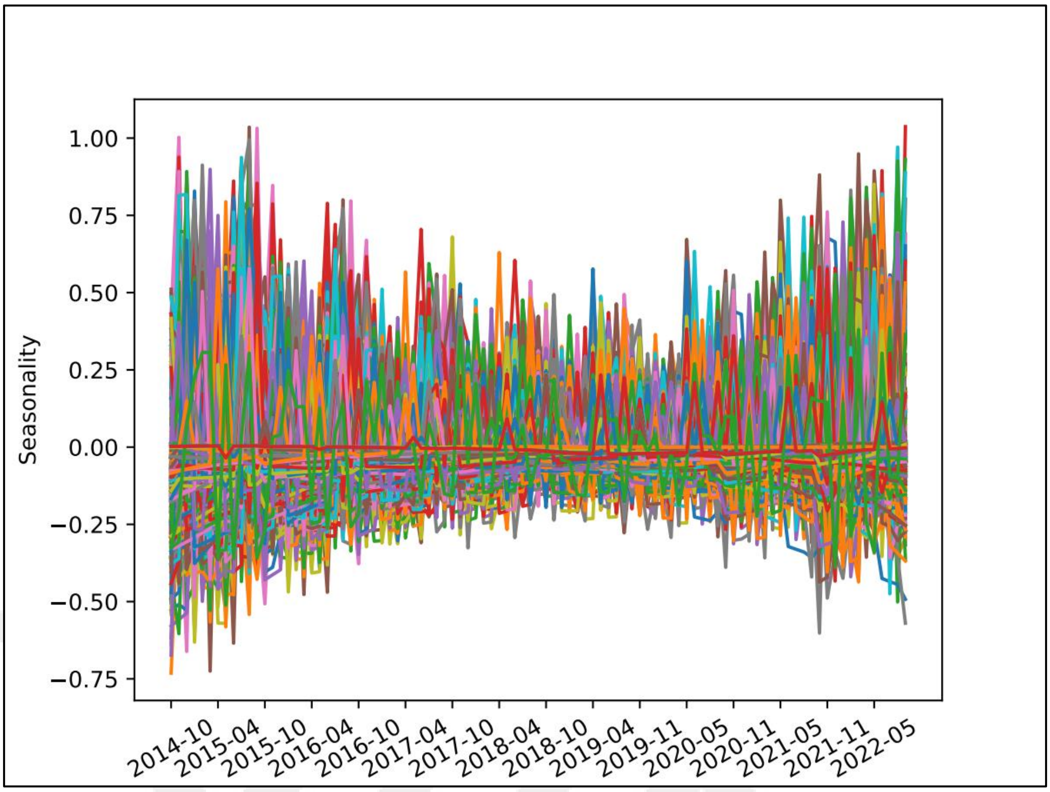

Figure 49. Time series decomposition (Seasonal) - White Lives Matter

For the seasonal time series decomposition, there are two main patterns for all countermovements. First, seasonal trends are increasing both at the beginning and end of the countermovements' lifespans. It is also possible to say that this rising trend for the tail of the datasets starts in mid-2020. These results indicate similarity with the average number of members in the echo chambers. The second outcome is that for all countermovements there are peaks for some topics in every three to four months period. Between these sharp incline points, seasonal trends show a tendency to decline.

Groupings between All Lives Matter and Blue Lives Matter, and White Lives Matter and Police Lives Matter continue for the seasonal trend charts. The total number of different topics that seasonally become trends is much higher for the former group. On the other hand, there is no difference between trends of the Police Lives Matter and White Lives Matter at the beginning of the time series so from this view, there is no effect of a high number of an average number of users at the beginning of the time series on the seasonal trends when the charts of White Lives Matter and Police Lives Matter compared. In other words, even for that short period members of the Police Lives Matter fail to generate seasonal trend topics.

Lastly, I analyze the results obtained with the residual approach. Considering the residual perspective, we can observe random fluctuations or noise in our data that are not explained by any trend or seasonal changes in Figure 50 through Figure 53.

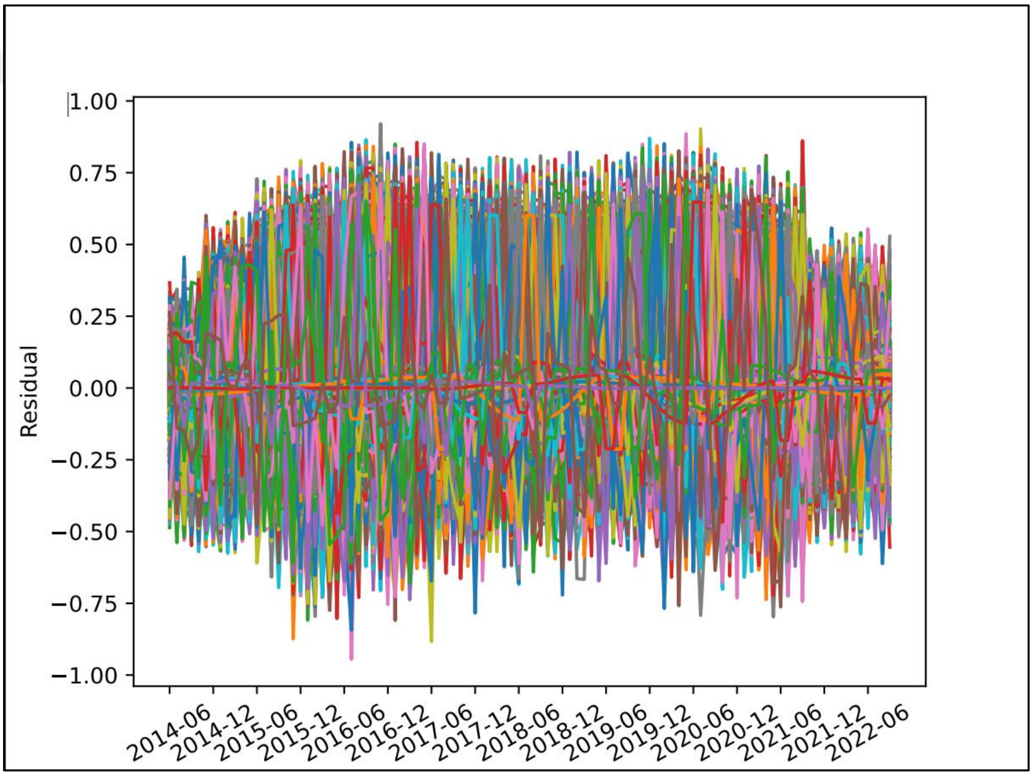

Figure 50. Time series decomposition (Residual) - All Lives Matter

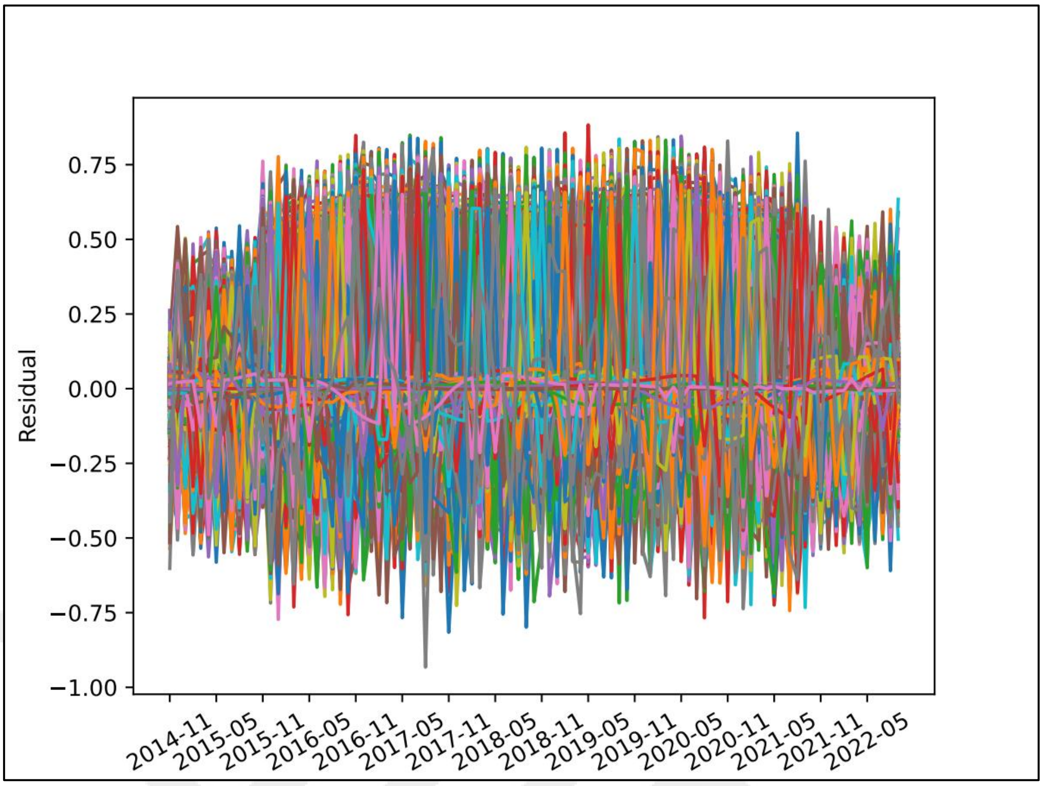

Figure 51. Time series decomposition (Residual) - Blue Lives Matter

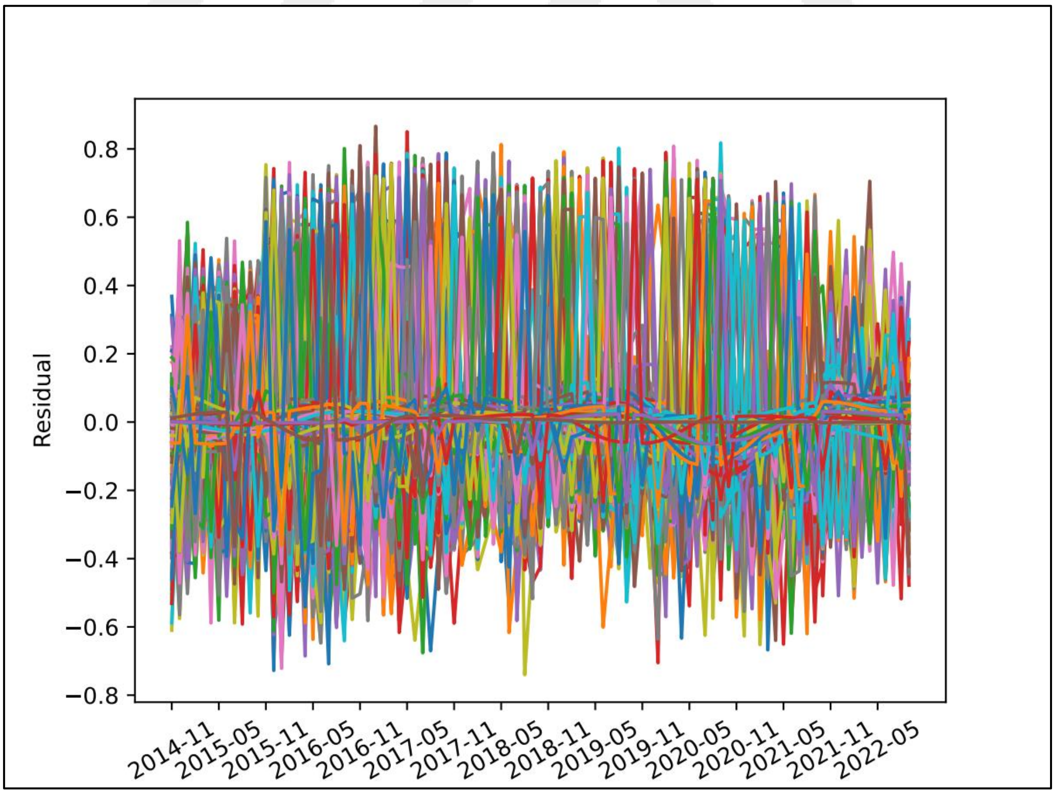

Figure 52. Time series decomposition (Residual) - Police Lives Matter

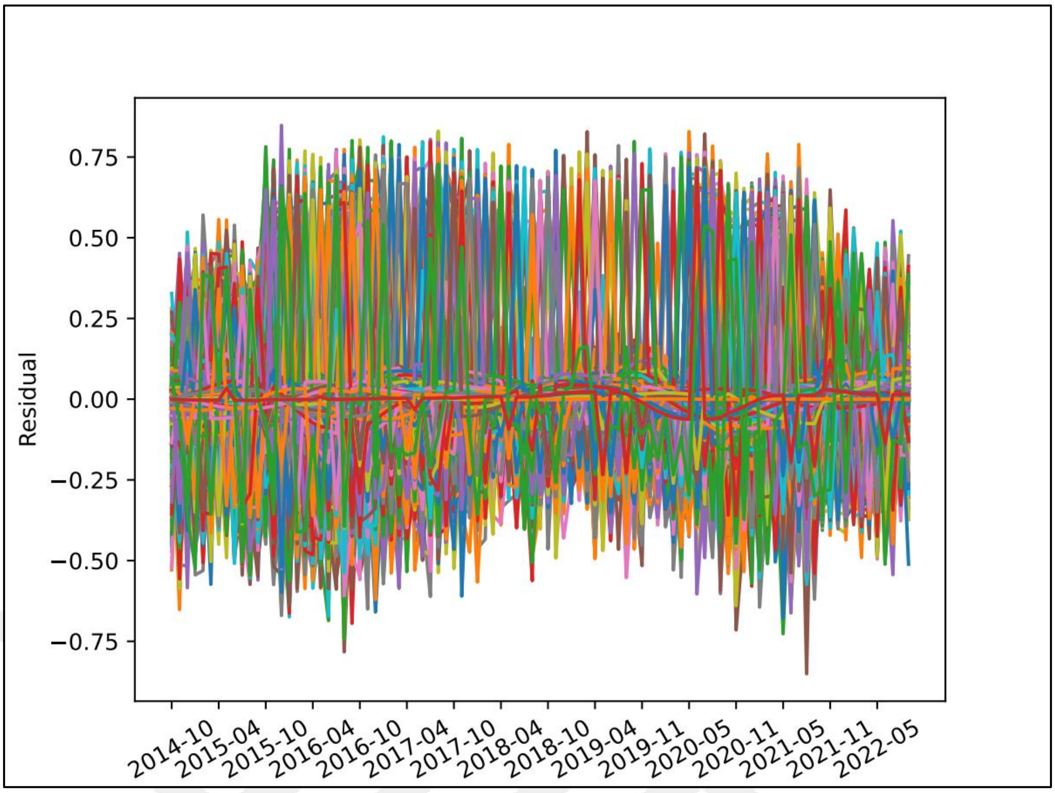

Figure 53. Time series decomposition (Residual) - White Lives Matter

Like the results of the seasonal trends, there are common outcomes for the residual analyses of the countermovements. Noise and random fluctuations are low for the beginning and end of the series. On the other hand, especially for the periods between early 2015 and mid-2021, the possibility of unexpected or unusual fluctuations that cannot be explained with trends is increasing which also supports former time series decomposition charts.

4.2 Findings based on members of the echo chambers

This section pertains to the second element of echo chambers, namely their members. Change in the existence of the users is one of the issues along with the frame of the echo chamber. In an ideal scenario, we would observe a strong relationship between topics and users, implying that certain individuals tend to discuss specific topics while others rarely mention them. This phenomenon suggests a pattern of topic ownership or specialization among users, wherein certain topics are consistently associated with particular individuals or groups, while other topics remain relatively unexplored by them. However, in practice, the attitudes of the people are more complex than expected. As can be seen in the previous part, the continuity and existence of the topics are too complicated for such a perfect scenario. Moreover, the number of one-time users is also high which possibly affects the similarity of the echo chamber members.

For the analyses of this section, I applied the Jaccard similarity to the users of each echo chamber so, I get the similarity matrix of the echo chambers' members. It is important to mention that I only compare echo chambers that share at least one similar user to accelerate computation time. From this matrix, I prepared two box plots which are about first the Jaccard similarity scores and second month interval between chosen echo chambers. Lastly, I look for a correlation coefficient and p-value to find whether is there any statistically significant relationship between the similarity of the echo chambers' users and their existence time. In other words, I want to check whether users in the echo chambers are more similar when the echo chambers are created at the closer time. First, I want to introduce box plots of the Jaccard similarity in Figure 54 through Figure 57 and the summary of the results in Table 2.

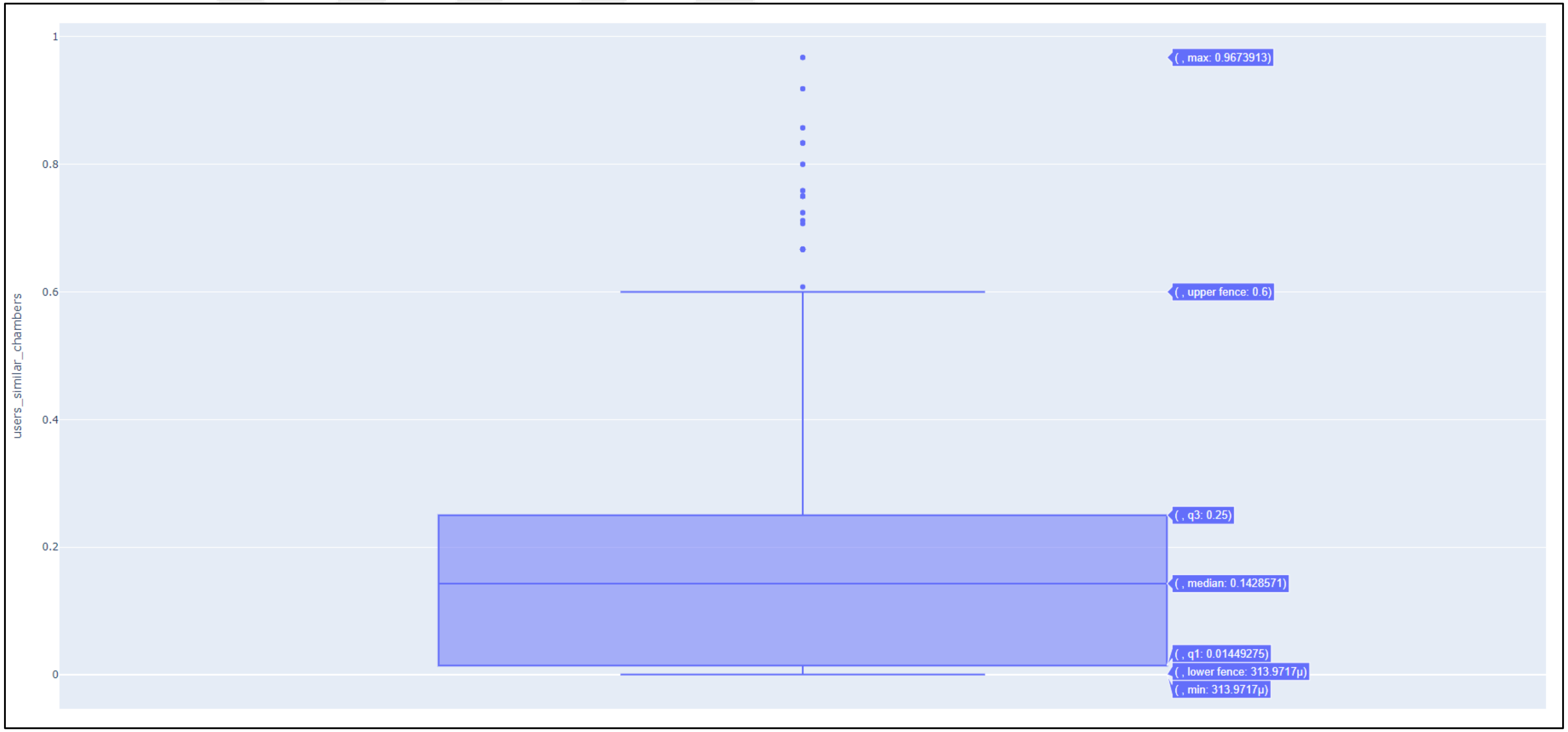

Figure 54. Box plot of the Jaccard similarity scores of the echo chambers' users - All Lives Matter

Figure 55. Box plot of the Jaccard similarity scores of the echo chambers' users - Blue Lives Matter

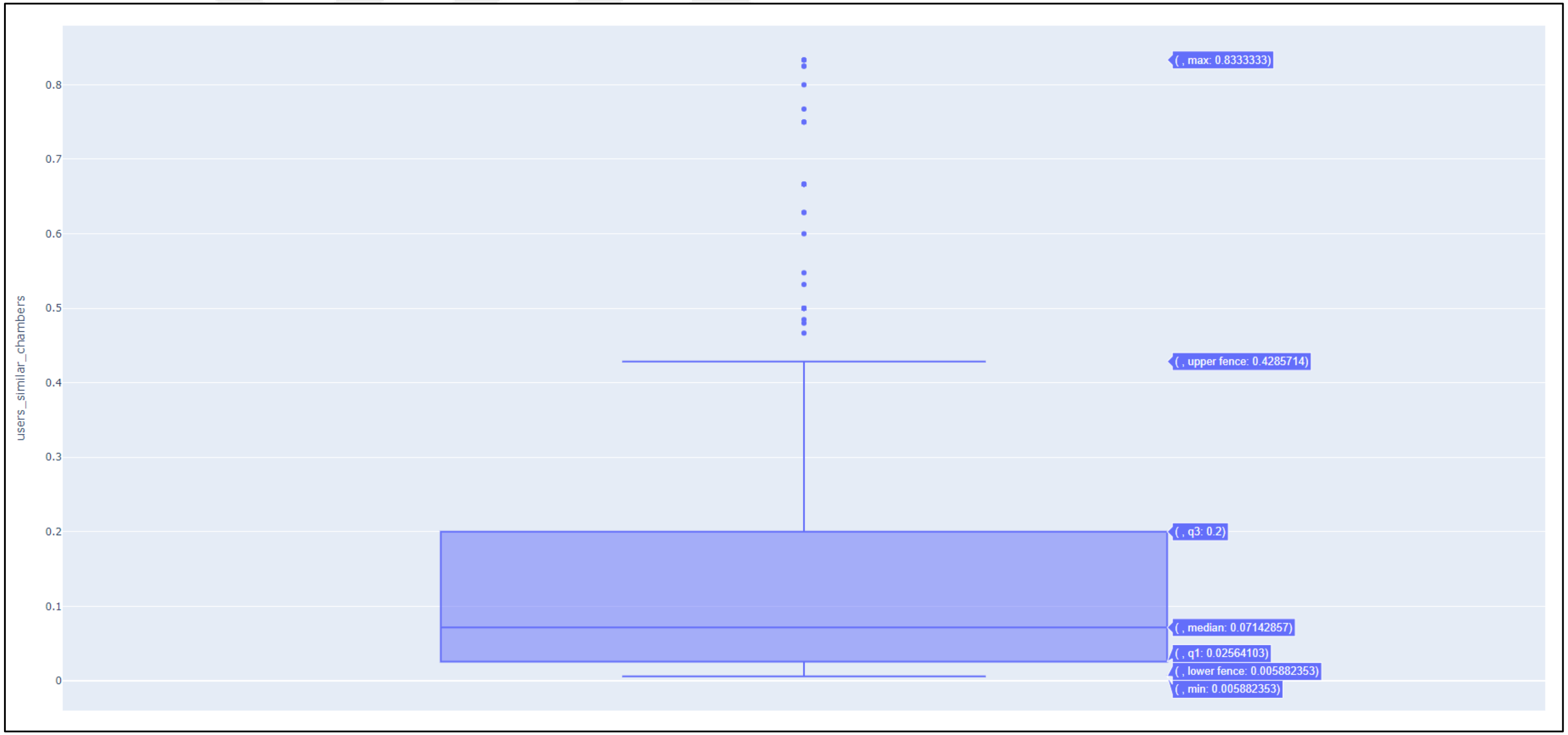

Figure 56. Box plot of the Jaccard similarity scores of the echo chambers' users - Police Lives Matter

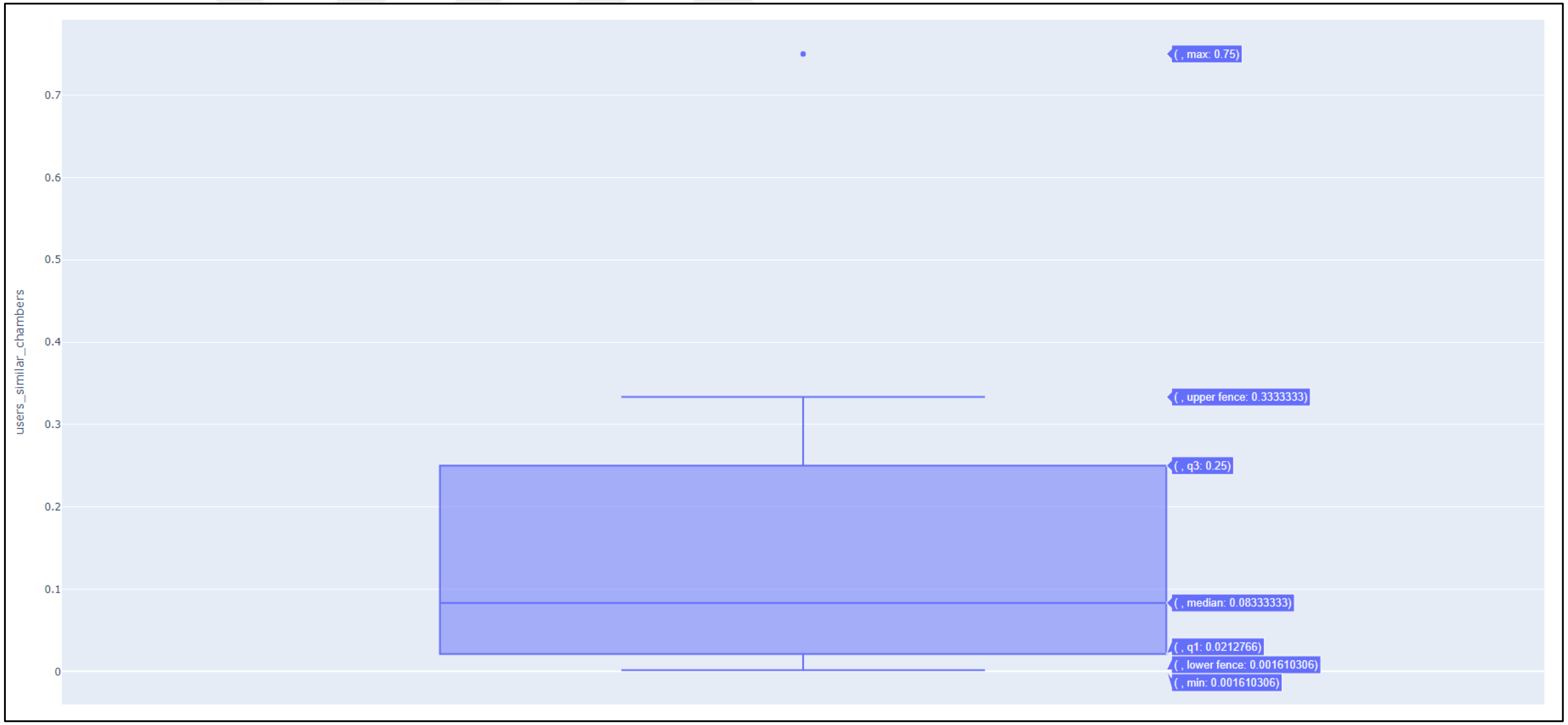

Figure 57. Box plot of the Jaccard similarity scores of the echo chambers' users - White Lives Matter

Table 2. Jaccard Similarity Scores of the Echo Chambers' Users - Summary

Countermovement	Minimum Value	First Quartile	Median	Third Quartile	Maximum Value
All Lives Matter	313µ	0.014	0.14	0.25	0.96
Blue Lives Matter	871µ	0.04	0.2	0.33	0.83
Police Lives Matter	0.005	0.025	0.071	0.2	0.83
White Lives Matter	0.001	0.021	0.083	0.25	0.75

When we analyze the Jaccard similarity of the members of the echo chambers who have at least one common member, similar to the continuity results there are minimal differences between countermovements. First of all, the widest range belongs to All Lives Matter which has the least minimum value and highest maximum value. On the other hand, Blue Lives Matter has the highest first and third quartiles as well as the median. From this perspective, members of the echo chambers in Blue Lives Matter have more tendency to be together in the same echo chamber over time when compared to the other countermovements. On the other hand, there is no distinctive difference between members of the echo chambers of the rest of the countermovements.

While the results of All Lives Matter, Police Lives Matter, and White Lives Matter are the same, Blue Lives Matter differentiates from others and gains relatively more scores compared to others. From this view, the trend of the echo chambers' frames continues for their members too.

The box plots below, from Figure 58 to Figure 61, on the other hand, represent the number of months between the existence of the echo chambers which have at least one common member. Following these figures, I summarize the overall results in Table 3.

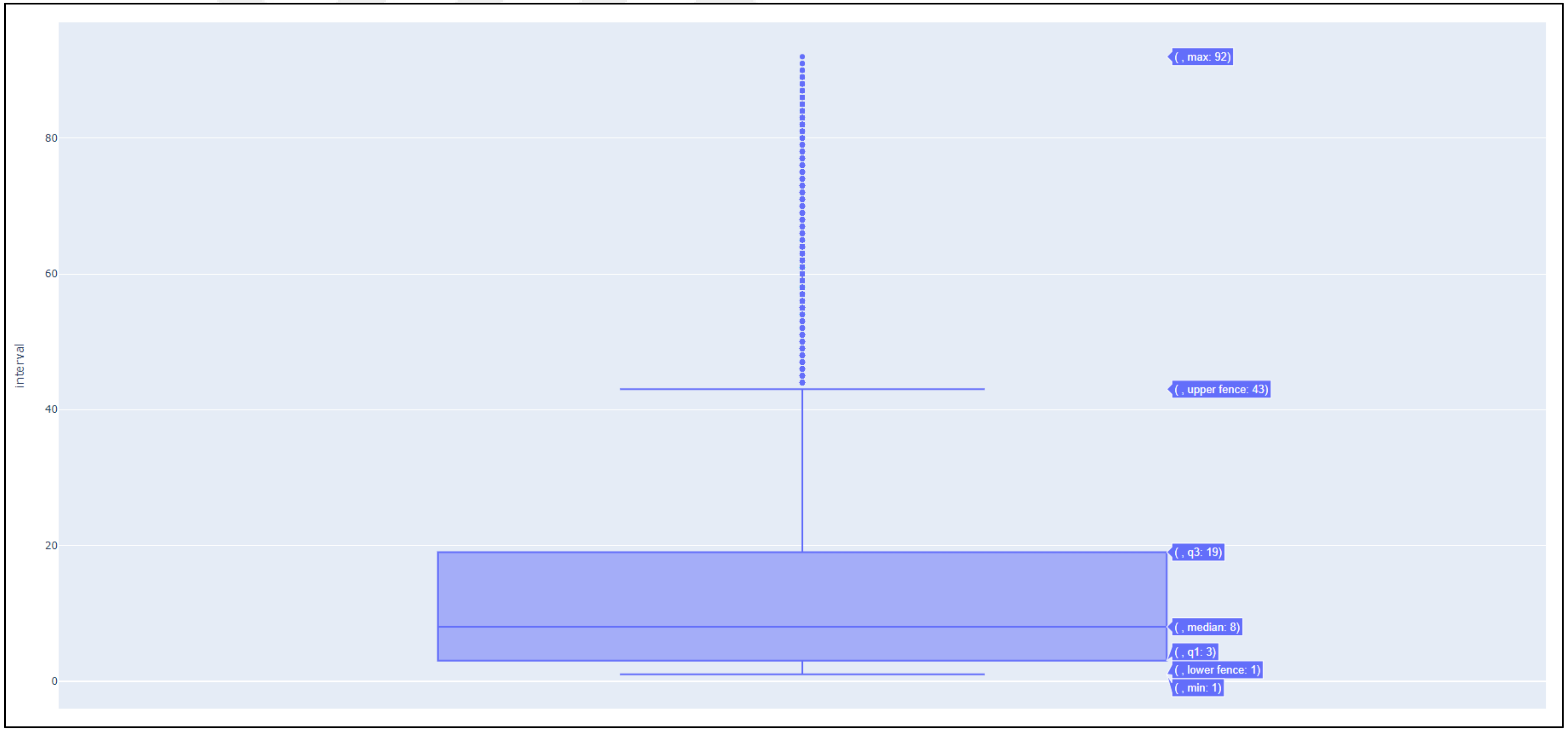

Figure 58. Box plot of month intervals between echo chambers that have common members - All Lives Matter

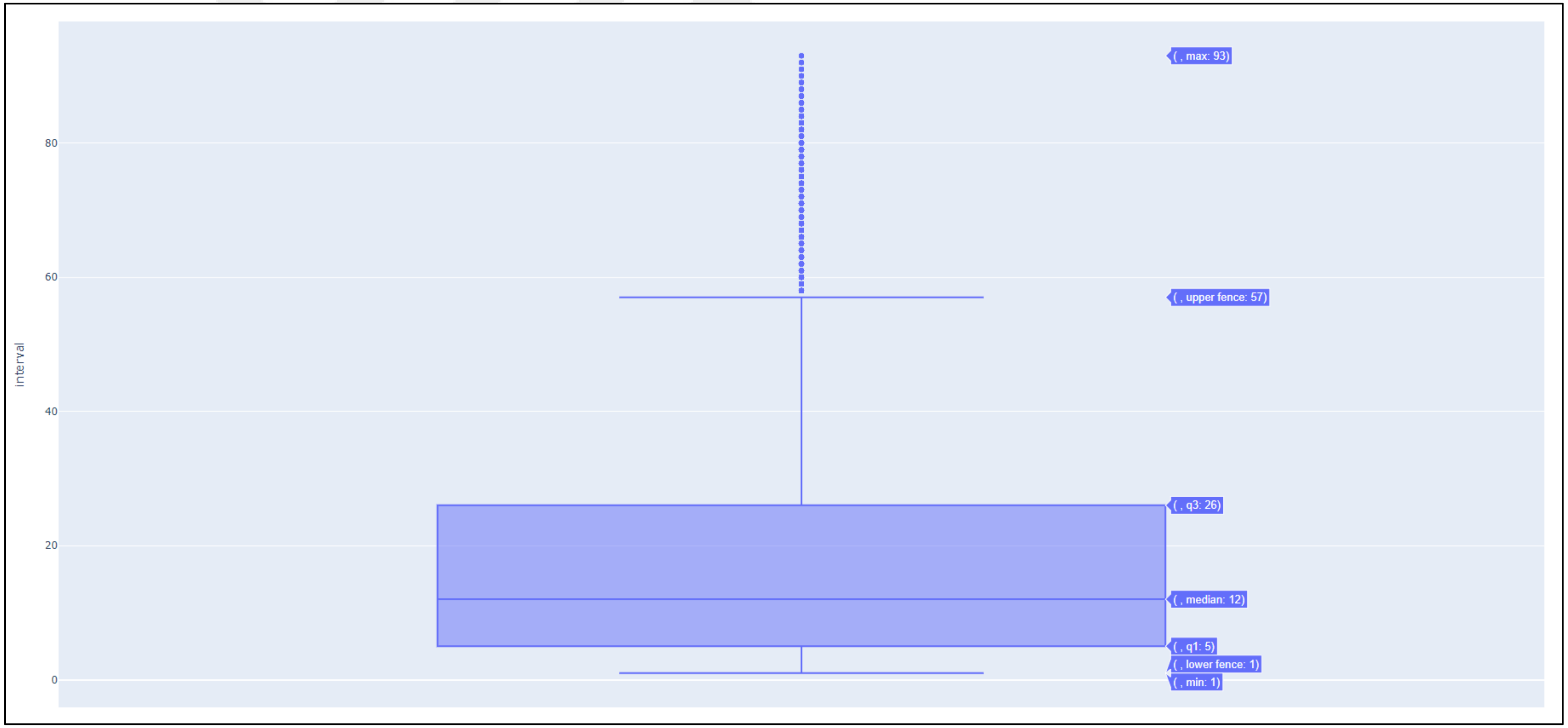

Figure 59. Box plot of month intervals between echo chambers that have common members - Blue Lives Matter

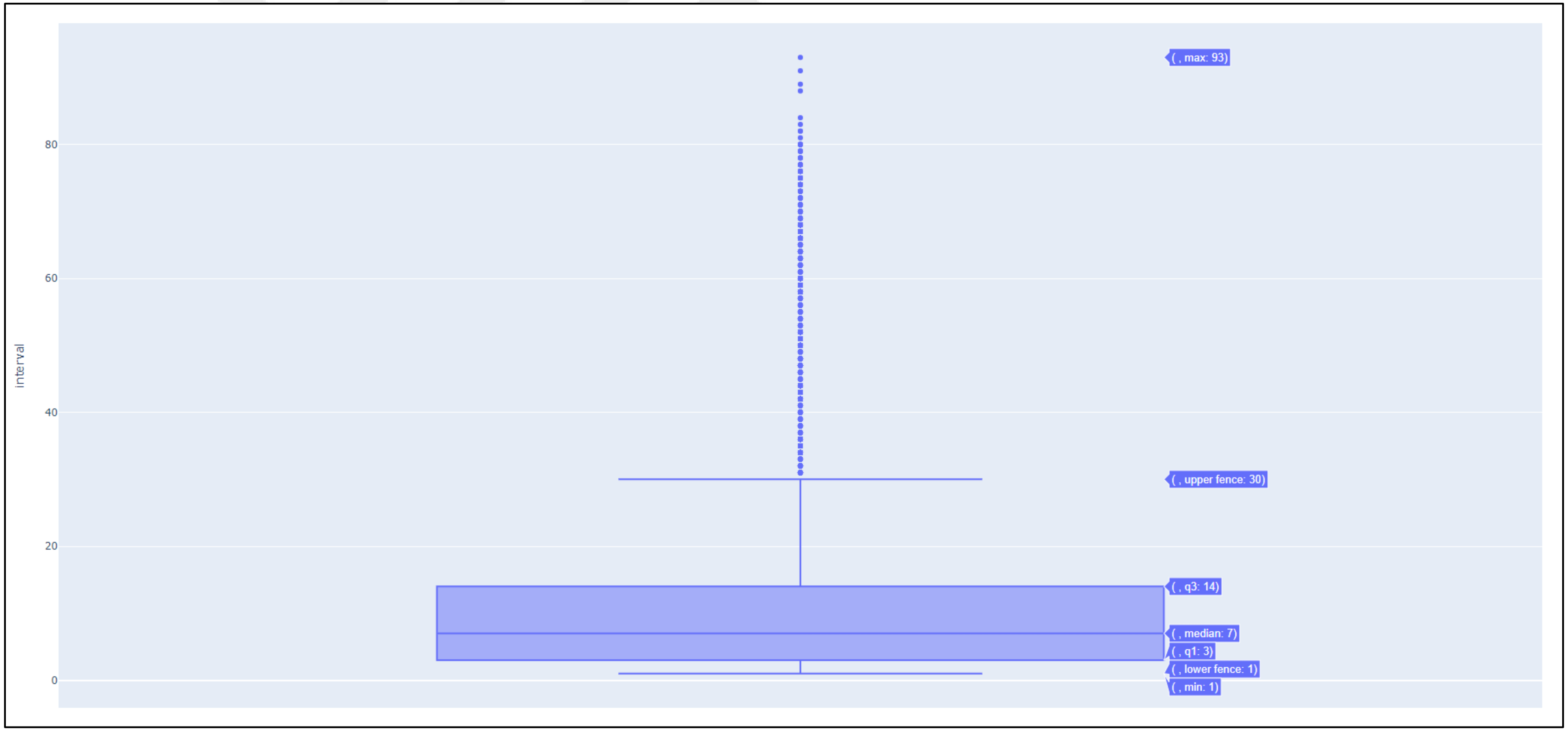

Figure 60. Box plot of month intervals between echo chambers which have common members - Police Lives Matter

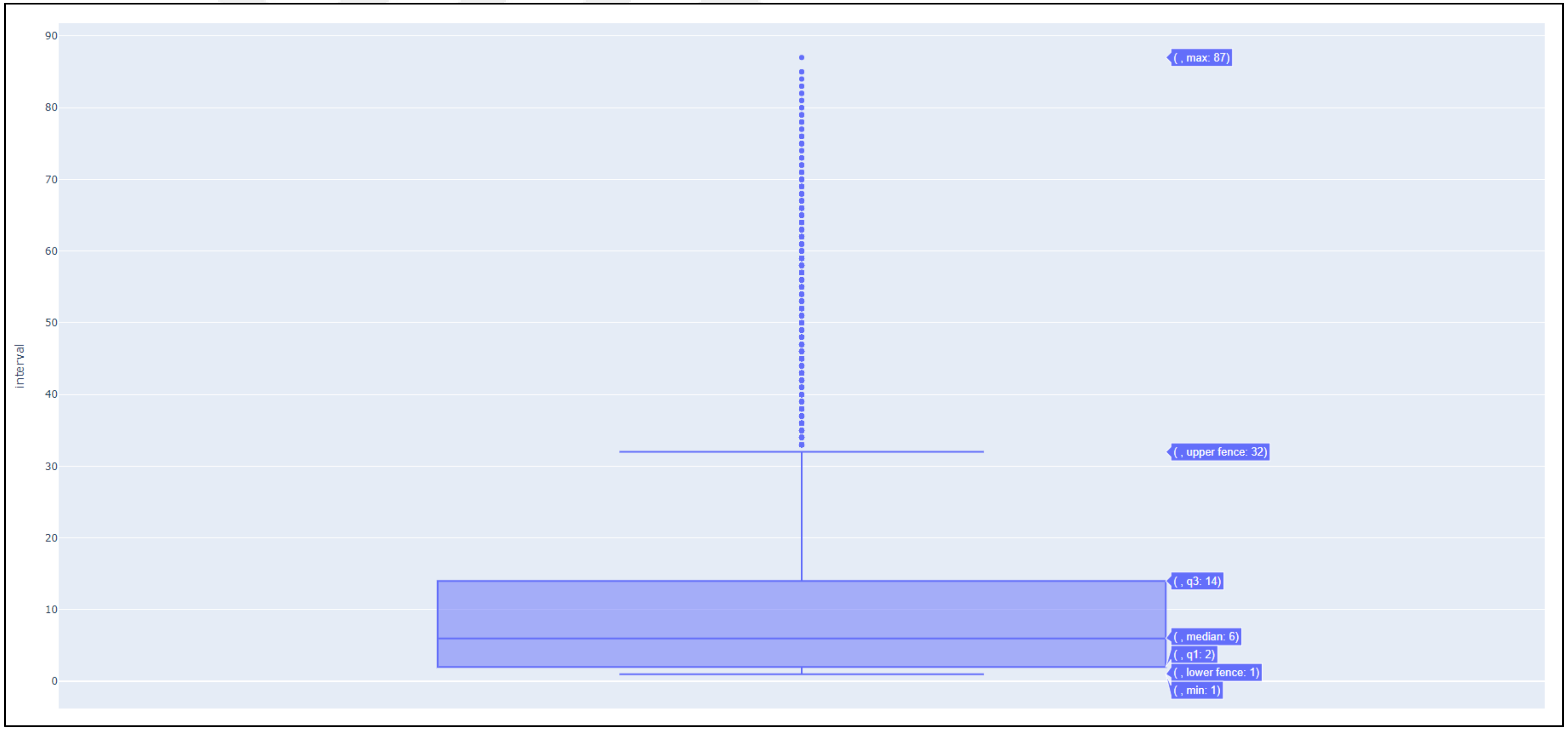

Figure 61. Box plot of month intervals between echo chambers that have common members - White Lives Matter

Table 3. Month Intervals Between Echo Chambers That Have Common Members - Summary

Countermovement	Minimum Value	First Quartile	Median	Third Quartile	Maximum Value
All Lives Matter	1	3	8	19	92
Blue Lives Matter	1	5	12	26	93
Police Lives Matter	1	3	7	14	93
White Lives Matter	1	2	6	14	87

For this observation, it is surprising to see that at least one member from each countermovement actively uses Twitter both at the beginning and end of the lifespan of the movement. However, most of echo chambers that share at least one common member, existed for consecutive months or too close a period. For this analysis, it has much clearer results compared to the others. Echo chambers belong to White Lives Matter has the lowest value which means that members of the echo chambers in that movement post closer periods compared to the members of the other countermovements. Members of the Police Lives Matter and All Lives Matter movements follow them with a little gap. On the other hand, the difference is higher for the Blue Lives Matter. In other words, members of the echo chambers are more discontinuous and there are months between similar echo chambers in terms of their members.

Same to the former results, Blue Lives Matter differentiates from others. As mentioned above, Blue Lives Matter has more continuous echo chambers' frames with more similar members. However, when the time differences between these echo chambers are considered, existence of the similarity of the users is possible with broader periods for Blue Lives Matter compared to other countermovements.

Lastly, I want to introduce the correlation coefficient and p-value results of each countermovement and compare them to find whether there is a relationship between similarities of the echo chambers' users and month intervals between these echo chambers in Table 4.

Table 4. Correlation Coefficient and P-value Table of Countermovements

countermovements	coefficient	p-value
All Lives Matter	-0.055360958	2.4E-265
Blue Lives Matter	-0.042352241	7.3E-217
Police Lives Matter	-0.10169939	5E-104
White Lives Matter	-0.033656416	1.2E-06

Based on the results of the correlation analysis, it appears that there is a very weak negative correlation between the Jaccard similarity scores of the groups and their time differences. Coefficient results are -0.05 for All Lives Matter, -0.04 for Blue Lives Matter, -0.1 for Police Lives Matter, and -0.03 for White Lives Matter. The most differentiated result belongs to Police Lives Matter. While others get results between -0.03 and -0.05, this movement doubles it with a score of -0.1. Even with this difference, still it is not quite a strong level. The correlation coefficient results suggest that there is a slight tendency for groups that have larger time differences to have slightly lower Jaccard similarity scores, although this relationship is not particularly strong. Furthermore, the extremely low p-values of the countermovements that range between 2.39E-06 and 4.9E-265 indicate that these correlations are highly statistically significant, meaning that it is very unlikely that this relationship is simply due to chance. Overall, these results suggest that there may be some meaningful relationship between group members similarity and time differences, although the strength of this relationship is quite weak.

4.3 Observations based on both users and topics

After elaborating on results based on members and frames of the echo chambers. The last analyses of my research are based on observing and comparing countermovements with combining frames and users of the echo chambers. In this part I bind members of the echo chambers with the dominant topic of the echo chambers they belong to then I prepare box plots and customized parabolic line charts to observe attitudes of echo chambers framed by the same topic also contain similar users.

First, box plots, which are displayed below in Figure 62 to Figure 65, represent the number of months that are between the specified echo chambers above and lastly, Table 5 shows a summary of these plots.

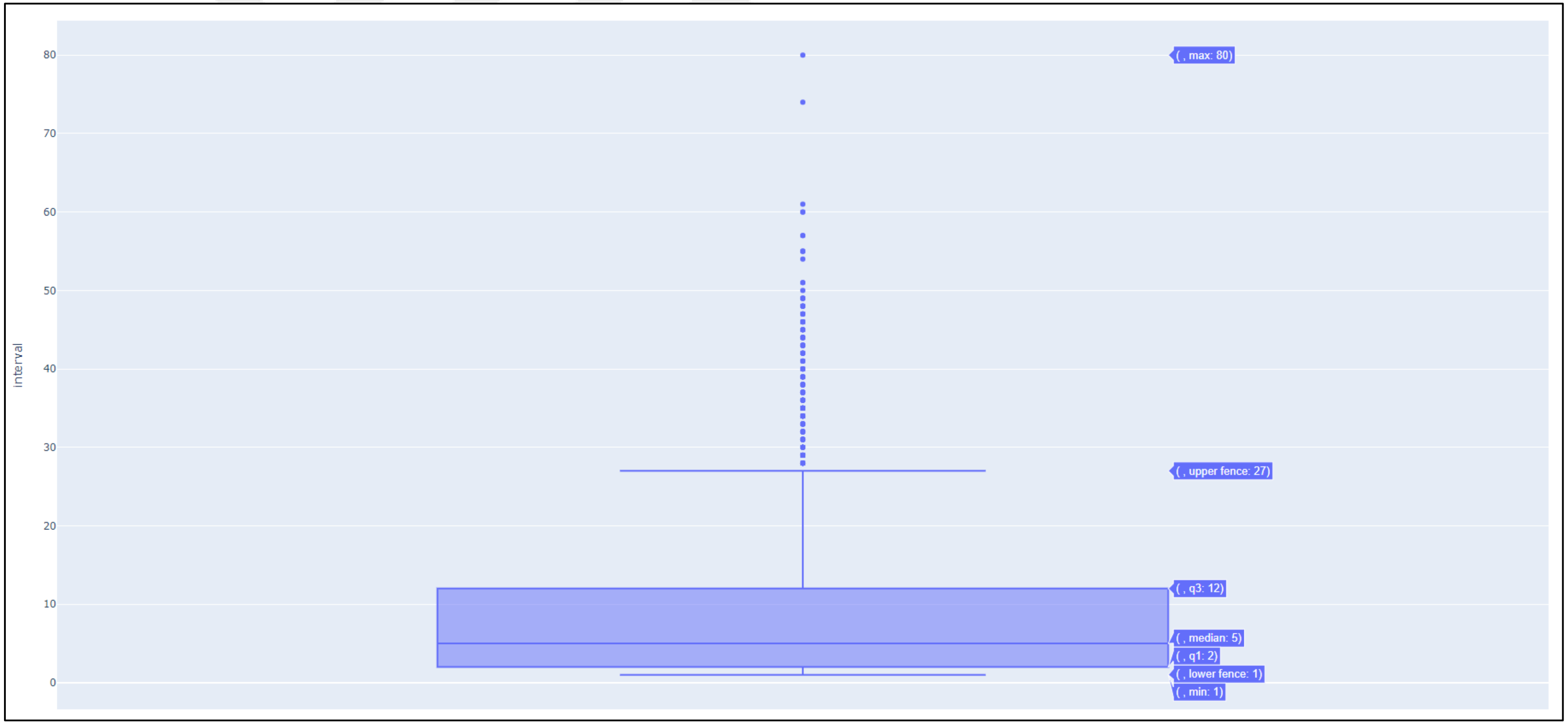

Figure 62. Box plot of month intervals between echo chambers which have common members and dominant topic - All Lives Matter

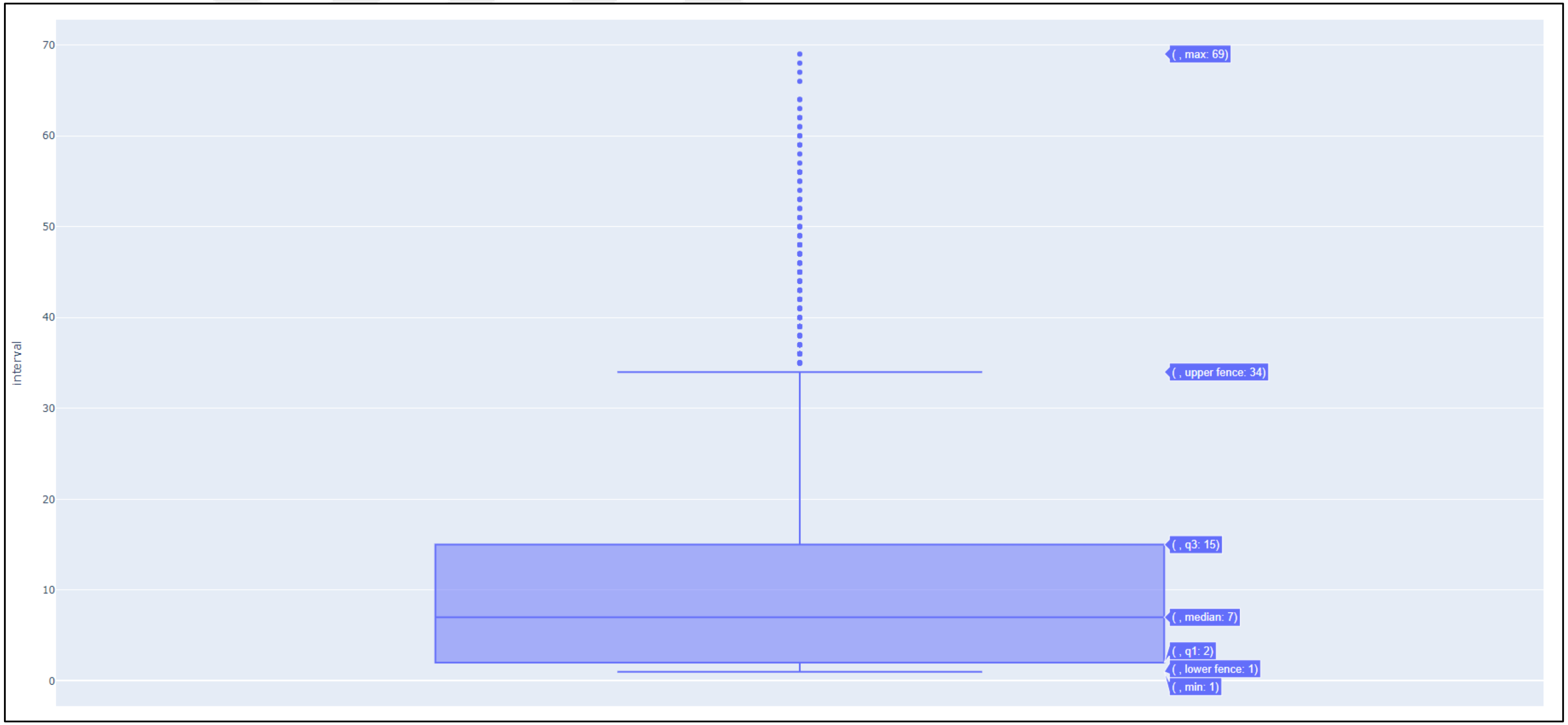

Figure 63. Box plot of month intervals between echo chambers which have common members and dominant topic - Blue Lives Matter

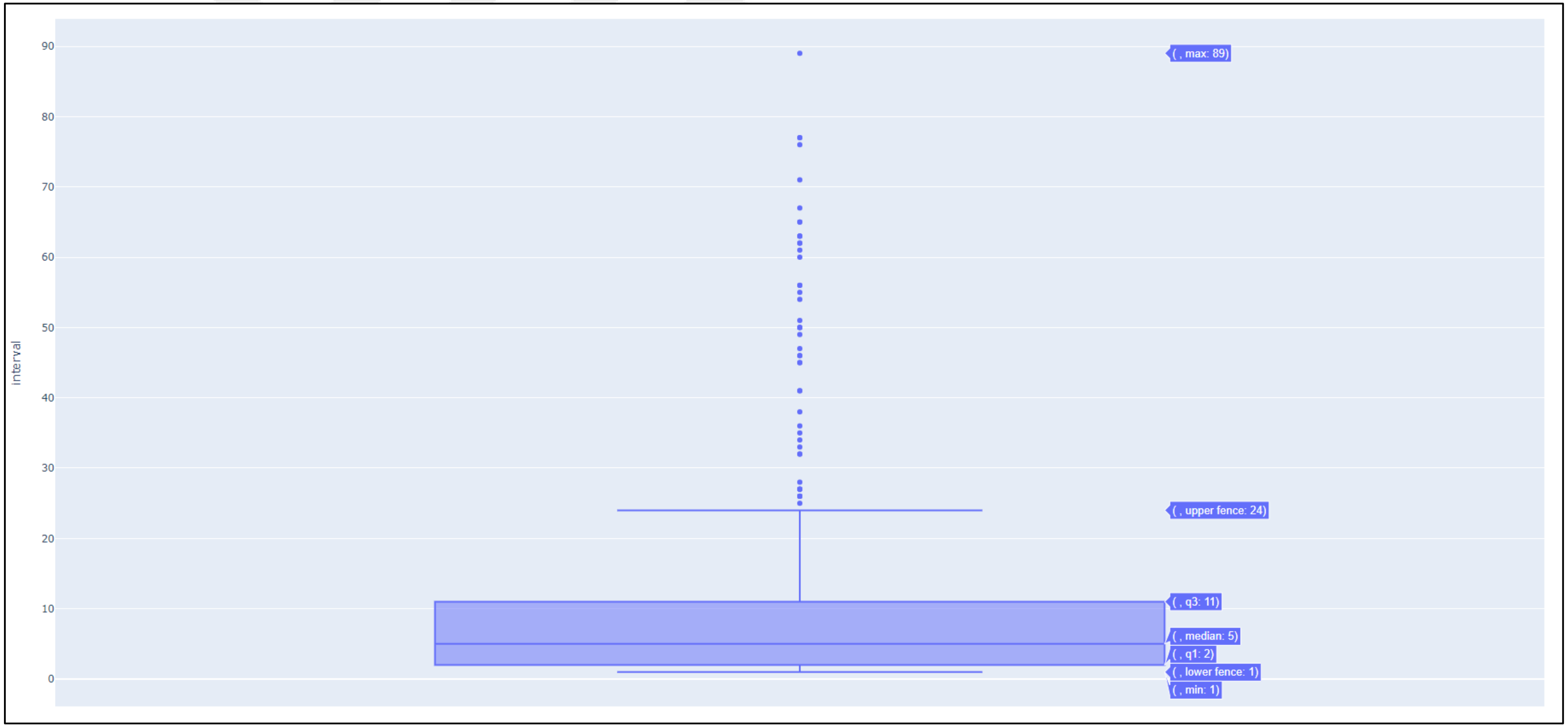

Figure 64. Box plot of month intervals between echo chambers which have common members and dominant topic - Police Lives Matter

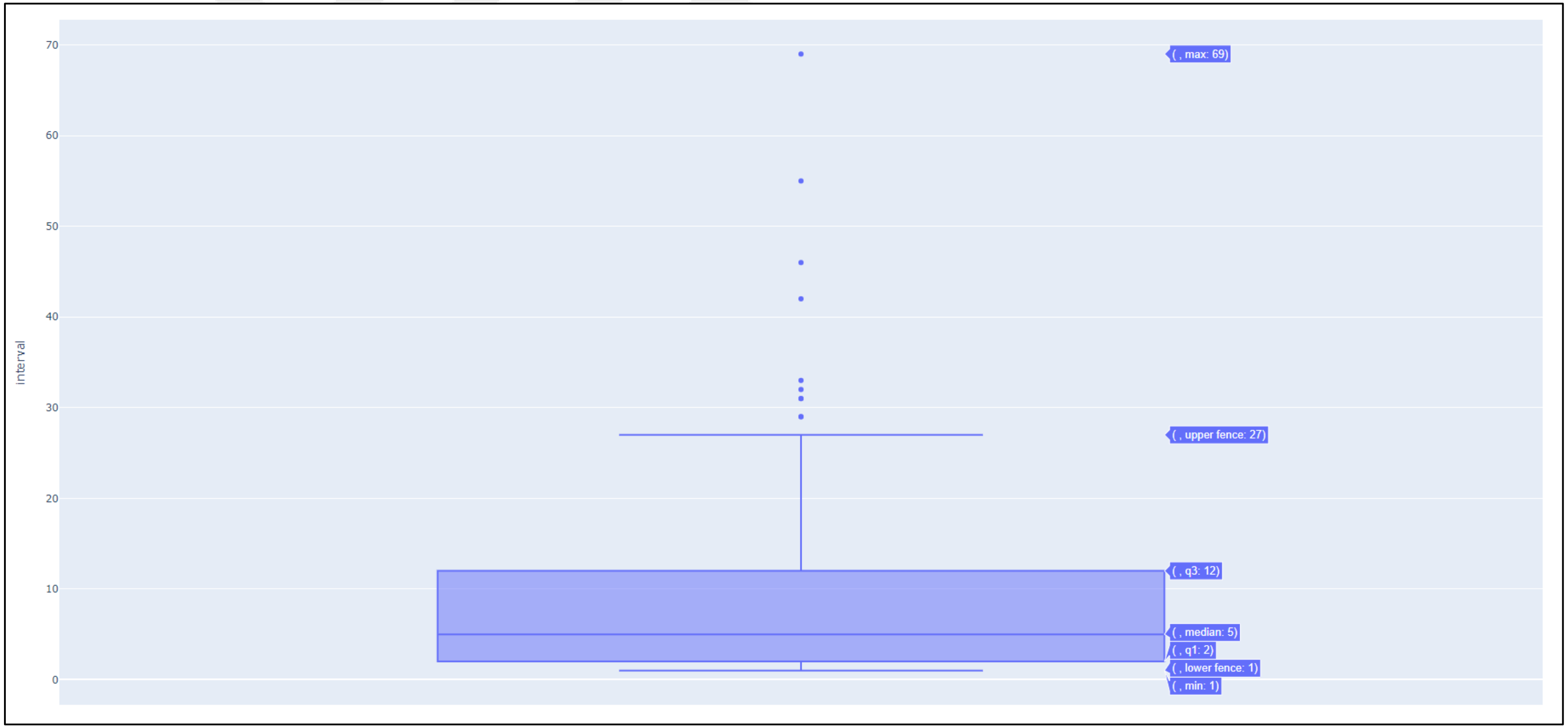

Figure 65. Box plot of month intervals between echo chambers which have common members and dominant topic - White Lives Matter

Table 5. Month Intervals between Echo Chambers Which Have Common Members and Dominant Topic - Summary

Countermovement	Minimum Value	First Quartile	Median	Third Quartile	Maximum Value
All Lives Matter	1	2	5	12	80
Blue Lives Matter	1	2	7	15	69
Police Lives Matter	1	2	5	11	89
White Lives Matter	1	2	5	12	69

It is surprising to see that the results of monthly intervals between echo chambers are very similar. First, minimum value and first quartile scores for all countermovements are the same, relatively one and two. Furthermore, median scores are the same for All Lives Matter, Police Lives Matter, and White Lives Matter, which is five, while it is seven for Blue Lives Matter. This trend differentiates with third quartile scores. Police Lives Matter has 11 third quartile scores. All Lives Matter and White Lives Matter follow with a 12 third quartile score and lastly, Blue Lives Matter has a 15 third quartile score. The maximum values of the series, which can be seen as outliers, range between 69 to 80. When we compare these results with the outcomes of the boxplots which just display month intervals of echo chambers without common frames, the difference between Blue Lives Matter and the rest of the countermovements decreases.

From the results of boxplots, we get a notion like nearly all echo chambers in countermovements behave similarly. However, it is not possible to determine exactly when these similar echo chambers follow each other. To solve this issue, I prepared customized charts. In these charts, there are points on the x-axis that represent echo chambers in a month. zero in the x-axis represents the starting month of my datasets and it increases with the time passed. In other words, zero represents January 2013, one corresponds to February 2013, and so on. I linked the points with parabolic lines on the charts below named between Figure 66 and Figure 69 if there are echo chambers framed with similar topics and containing similar users.

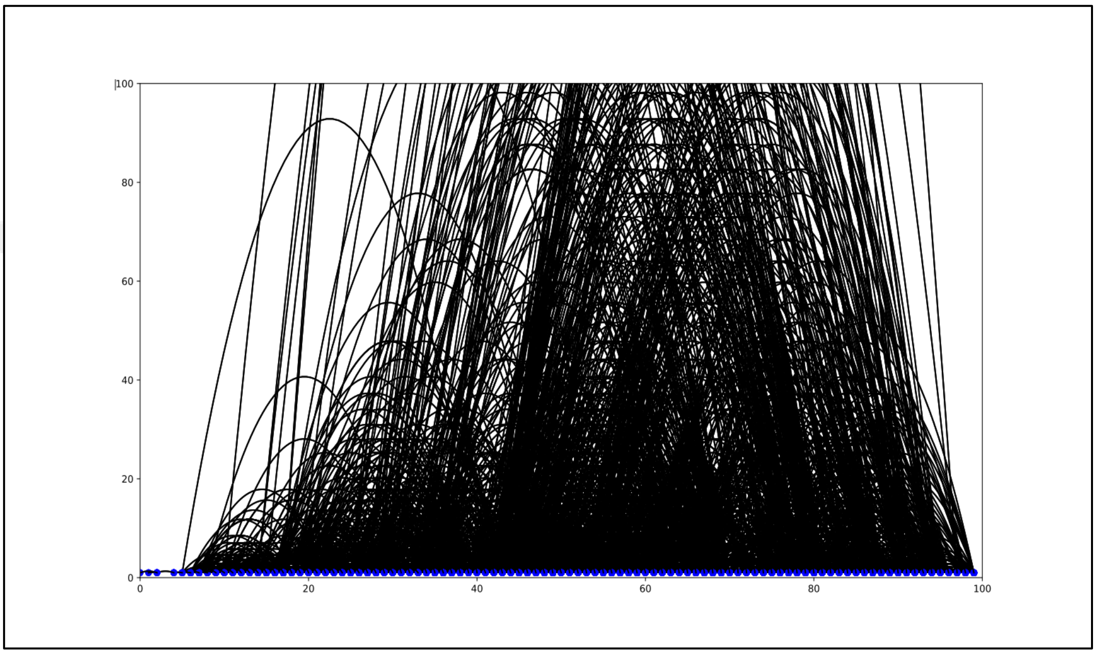

Figure 66. Linkage of the echo chambers - All Lives Matter

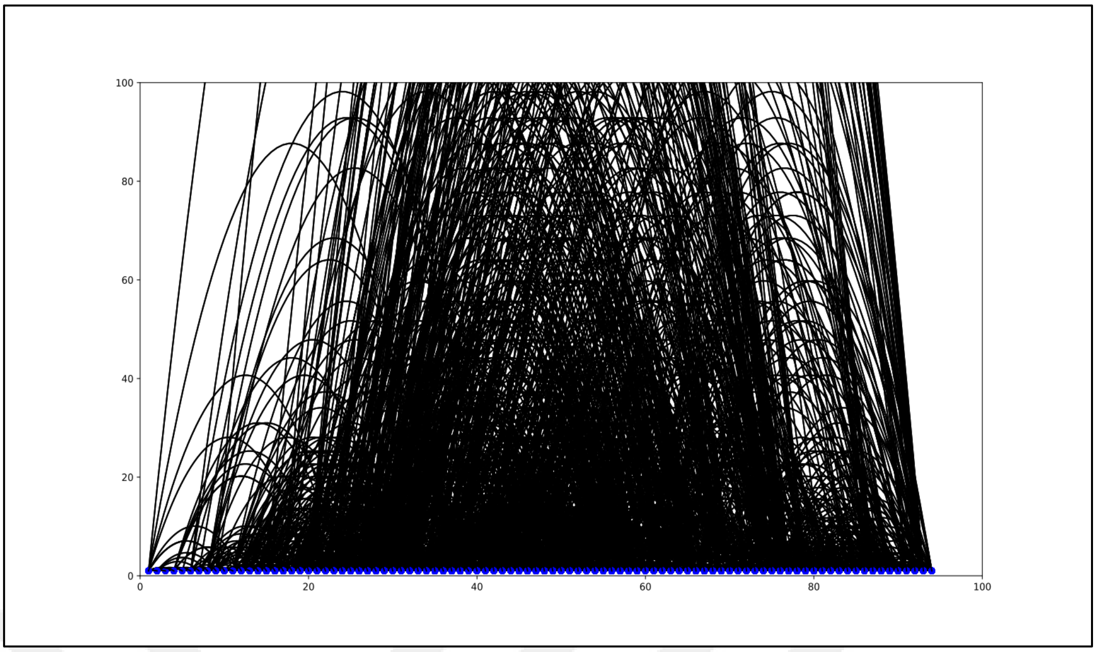

Figure 67. Linkage of the echo chambers - Blue Lives Matter

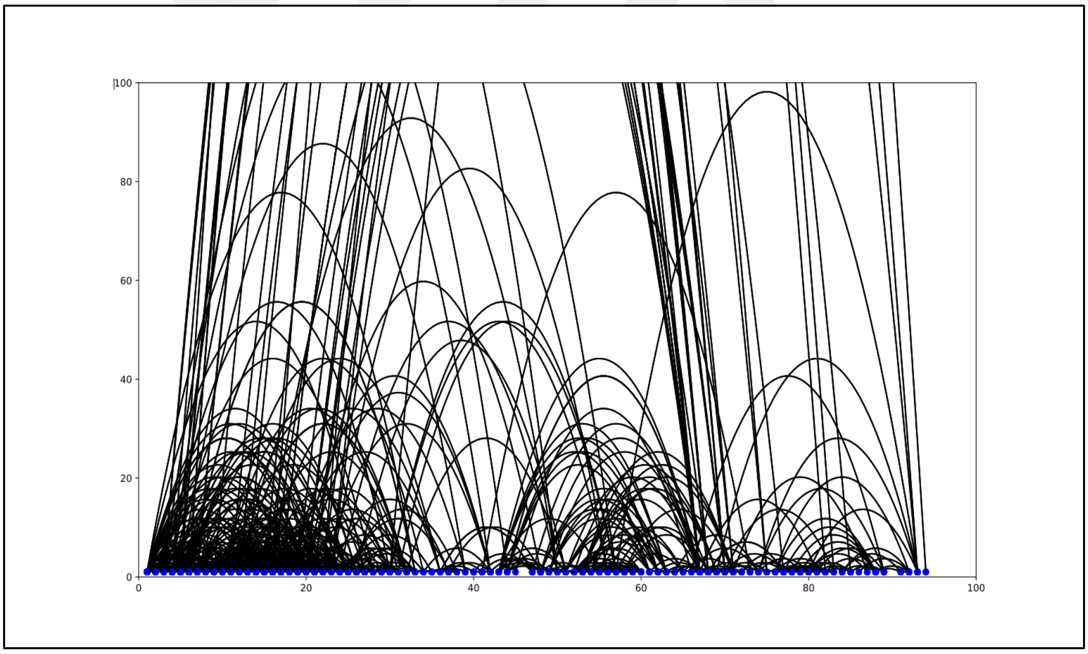

Figure 68. Linkage of the echo chambers - Police Lives Matter

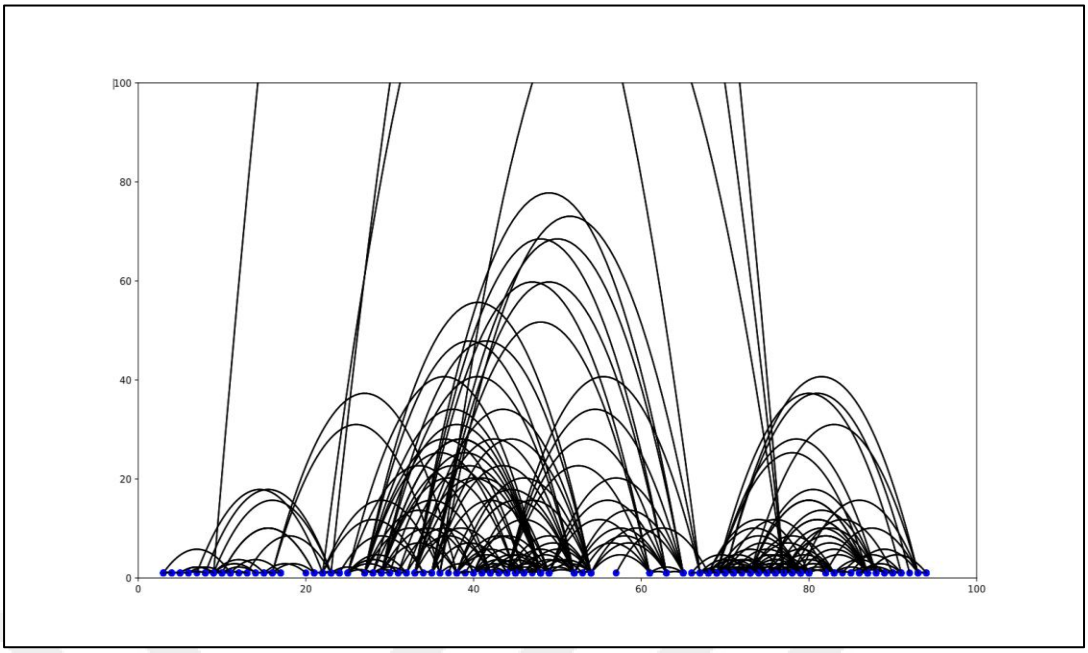

Figure 69. Linkage of the echo chambers - White Lives Matter

Countermovements can be categorized into two based on their density. On the one hand, there are more dense movements, which are All Lives Matter and Blue Lives Matter, on the other hand, there are sparser groups which are Police Lives Matter and White Lives Matter. For the former ones, echo chambers at the starting times of the movements are less connected compared to the echo chambers that emerged later on. After then, echo chambers start to connect each other too densely. The difference between those two countermovements is while echo chambers, which existed in 2017, of All Lives Matter, generally connected with the echo chambers in 2021; this mid-run connection trend starts in 2015 and creates connections up until 2019.

For the latter group, on the other hand, connections between echo chambers are less dense. For Police Lives Matter, echo chambers of the first two years gain most of the connections. then there are periodically connected echo chambers in the time series. However, for White Lives Matter, while there are no connected dense areas at the beginning of the series, there are two dense areas that cover from mid-

2015 to mid-2017 and mid-2019 to 2022. To sum up, echo chambers of the countermovements show different attitudes from the view of continuity over time.

CHAPTER 5

DISCUSSION

The study of countermovements, particularly within the context of the internet era, has been largely overlooked within academia. While foundational works by scholars such as Tilly (1984), Gale (1986), and Mottl (1980) have extensively examined the relationship and interaction between social movements and countermovements, they may not adequately explain the dynamics and complexities that arise from the interactions of twenty-first century movements in the realm of online hashtag activism.

Despite the abundance of studies focusing on the structure and dynamics of online social movements, countermovements, if acknowledged at all, are often given minimal attention. This scholarly gap presents a vulnerability within the social movement literature, as countermovements play a significant role in shaping the strategies and discourse of preceding movements (Zald & Useem, 1987) Therefore, the primary objective of my thesis is to address this gap and contribute to the existing literature by conducting an in-depth examination of countermovements from the view of its echo chambers.

The scarcity of research solely dedicated to countermovements represents an opportunity to enhance our understanding of social movements. By enriching the existing body of knowledge with insights into countermovements, we can gain a more comprehensive understanding of the intricate dynamics at play within social movements as a whole. This research endeavor aims to bridge this gap in the literature and shed light on the important role that countermovements play in shaping strategies and discourse within the broader social movement landscape.

The concept of echo chambers has gained increasing importance in the context of social media and the existence of filter bubbles. This novel concept offers a fresh perspective on the study of social movements and possesses a high level of explanatory power. However, I contend that the detection of echo chambers in the existing social media literature is a challenging task.

Various approaches have been employed to detect echo chambers, which can generally be categorized into two main approaches: human-based and context-based. The human-based approach focuses on analyzing interactions between individuals. For example, Furman and Tunç (2019) utilize mention networks, Hayat and Samuel-Azran (2017) construct following and follower networks, Vicario et al. (2017) employ tweet parametrics, and Wieringa et al. (2018) and Lynch et al. (2017) investigate retweet networks to detect echo chambers. In these studies, echo chambers are identified based solely on the relationships among the owners of the posts, independent of the specific contexts.

In contrast, the context-based approach primarily focuses on the content and context of the tweets. For instance, Aydin, Förster, and Sunier create a hashtag co-occurrence network to detect echo chambers (Aydin, Förster, & Sunier, 2022). In such studies, echo chambers are identified based solely on the content and themes of the tweets, without considering the individuals who posted them. However, I argue that these approaches, which solely focus on either context or individuals to detect echo chambers, are problematic as they underestimate the combined effect of both the context and the individuals.

In light of these limitations, my thesis proposes a novel approach to detect echo chambers by integrating network analysis and topic modeling methods. By considering both the frames and the individuals involved, this approach aims to provide a more comprehensive understanding of echo chambers in social media discourse.

One of the contributions of my research is a new and simplified perspective on spam detection algorithms. While there are various existing spam detection algorithms, many of them are based on machine learning techniques, as demonstrated in studies by Wang (Wang A. H., 2010) and McCord and Chuah (McCord & Chuah, 2011). These algorithms typically consider several factors related to user behavior, such as follower and following metrics, replies and mentions, text context, and even the timing of tweet posts. However, I argue that these approaches often conflate the concepts of bot accounts and spammers.

While characteristics like low follower and following numbers, specific text contents, or patterns can be indicative of bot accounts, spamming is a distinct concept. Real users can also engage in spamming activities to gain public attention, which sets them apart from bot accounts. Additionally, these techniques often label accounts as spammers, which may result in the misclassification of real users as well. In contrast, my algorithm focuses solely on the text content of users and identifies spam tweets based on specific patterns. This approach allows for the exclusion of spam tweets while preserving the other non-spam tweets generated by genuine activists.

It is noteworthy that the existing literature lacks a dedicated investigation into the phenomenon of echo chambers within countermovements. This absence is unsurprising given the limited attention afforded to this specific aspect. Moreover, my thesis not only examines the echo chambers within countermovements but also undertakes a comparative study to identify any notable distinctions among these countermovements. In doing so, I summarize my findings and draw attention to novel issues that set my research apart from existing scholarly works.

In the realm of countermovements, an intriguing observation emerges when examining the correlation between the overall number of topics and the prevalence of echo chambers. Generally, a proportional relationship can be identified between these two factors. However, a notable exception arises in the case of the All Lives Matter movement. This disparity can be attributed to the distinct characteristics inherent to this movement, namely its expansive scope and decentralized leadership structure, which distinguish it from other countermovements. While other countermovements often benefit from varying degrees of organizational support, the All Lives Matter movement lacks centralized backing. Consequently, a higher occurrence of echo chambers is observed within this movement, which is not commensurate with the total number of topics and tweets observed over time.

It is anticipated to observe a surge in the total number of activists discussing a specific topic during extraordinary events, as exemplified by the Arab Spring (Howard, et al., 2011).. However, existing literature does not provide insight into whether a similar pattern emerges in relation to the total number of echo chambers. Through trend analysis of echo chamber counts within countermovements, discernible patterns come to light, particularly during significant occurrences. Notably, several peaks are evident, notably in mid-2016 and mid-2020, coinciding with widespread protests and the tragic death of George Floyd in the United States. While these periods exhibit heightened activity, countermovements such as All Lives

Matter, White Lives Matter, and Police Lives Matter demonstrate varying fluctuations in the prevalence of echo chambers over time. Conversely, the Blue Lives Matter movement exhibits a more consistent and stable presence of echo chambers throughout the analyzed period.

Another significant contribution of this research lies in its examination of echo chambers through a time series analysis. While many studies focus on echo chambers through isolated snapshots or limited time periods, my thesis centers on the evolution of echo chambers in terms of their members and frames over the entire lifespan of the respective movements. For instance, Bessi et al. analyze comments and various parameters such as likes or shares on posts and videos within YouTube and Facebook (Bessi, et al., 2016). Although they analyze a dataset comprising 12 million posts, they do not categorize or observe them based on their temporal occurrence. Similarly, Batorski and Grzywińska study the activities of users affiliated with official political party pages on Facebook (Batorski & Grzywińska, 2017). Their research covers a two-year period from 2013 to 2015, dividing each year into four-month intervals. In contrast, this thesis conducts a comprehensive time series analysis of social movements on online social media platforms, enabling precise observation of changes occurring over time. Consequently, my research distinguishes itself from previous studies in the literature by providing a detailed examination of the dynamics of social movements in online social media platforms through a comprehensive time series analysis.

This observation suggests that the Blue Lives Matter movement has demonstrated relatively greater success in sustaining its mobilization efforts compared to other countermovements that encountered challenges in maintaining their echo chambers. However, it is important to highlight that the average number of users participating in these echo chambers tends to increase during the aforementioned periods. While there are some exceptions to this trend, it is notable that the Police Lives Matter countermovement exhibits distinct behavior compared to other countermovements. This discrepancy may be attributed to its early engagement and subsequent transition to the more popular Blue Lives Matter movement. The shift in activity and increased popularity could have influenced the level of engagement and overall activity within the echo chambers associated with Police Lives Matter.

The majority of studies in the literature primarily focus on analyzing frames and polarization within communities. However, Tilly argues that sustained campaigns are vital for the existence and success of social movements (Tilly, 2004, p. 3). While continuous movements are crucial for achieving success, to the best of my knowledge, there is a lack of research on the continuity of echo chambers, which are one of the main components of online social movements for mobilization. For example, in Merry's study on echo chambers of gun policy organizations, echo chambers are constructed based on people's opinions regarding gun ownership and related policies (Merry, 2016). While the analysis is centered around polarization in that particular case, the persistence of echo chambers is overlooked. Although it can be argued that this perspective may be beyond the scope of such studies, I contend that this approach neglects the significance of echo chamber durability, which is critical for the success of social movements. In contrast, my study aims to examine the continuity of echo chambers and fill this gap in the existing literature. From this standpoint, I intend to compare the echo chambers present within countermovements, considering their dominant frames and members. Investigating these characteristics of echo chambers sheds light on the relationship between a movement's success and its persistence over time.

In terms of the continuity score of the topic, it is notable that Blue Lives Matter distinguishes itself from other countermovements by displaying relatively lower values. When considering this finding alongside the number of echo chambers over time, we can deduce that while the distribution of echo chambers appears more stable for Blue Lives Matter, the main themes discussed within these echo chambers are not continuous. This assertion is further supported by time series decomposition based on trends. While All Lives Matter, White Lives Matter, and Police Lives Matter exhibit similar trends, the trend lines of topics related to Blue Lives Matter exhibit greater complexity.

Regarding seasonal and residual time series decomposition, there are commonalities observed among all countermovements. Seasonal trends tend to peak prior to mid-2016 and after mid-2020, with identifiable seasonal peak points for nearly all countermovements. Conversely, residual scores tend to be higher between these two significant dates.

In terms of the similarity among members within echo chambers, Blue Lives Matter demonstrates higher Jaccard coefficient scores in comparison to other countermovements. This implies that the members of echo chambers within Blue Lives Matter exhibit a higher degree of similarity among themselves compared to members of echo chambers within other countermovements. However, this similarity extends over a longer time period when considering monthly intervals between these echo chambers. On the other hand, other countermovements exhibit lower scores when considering differences in months. This suggests that while there may be fewer echo chambers with shared members in these countermovements, the occurrences of these echo chambers are much closer in time to each other.

The analysis of the correlation between the Jaccard similarity coefficients and the time differences of the echo chambers provides valuable insights into the relationship between member similarity and temporal proximity within countermovements. The results show that, for all countermovements, there is a statistically significant negative correlation between the time difference and the Jaccard coefficient score of echo chambers that share common members. This means that if there is a larger time difference between the echo chambers that have common members, their Jaccard coefficient score would be slightly lower. Although coefficient values for all countermovements are low, except for Police Lives Matter, their p-values indicate that these correlations are highly statistically significant. The higher coefficient value for Police Lives Matter may be due to the agglomeration of echo chambers at the starting time of the movement.

When considering month intervals between echo chambers that share common frames and members, the results are similar for All Lives Matter, Police Lives Matter, and White Lives Matter. However, Blue Lives Matter differs from them in terms of its median and third quartile scores. This finding suggests that the echo chambers belonging to Blue Lives Matter have a more stable continuity. Unlike the other countermovements, Blue Lives Matter has both short and long linkages between its echo chambers, which supports the stable continuity of these echo chambers.

The parabolic charts reveal the connectivity patterns of the echo chambers for each countermovement. In the case of Blue Lives Matter, there is a high density of connections between the echo chambers, except for the beginning of the movement. Conversely, this area is highly connected in Police Lives Matter, which supports the previous argument about the relationship between Police Lives Matter and Blue Lives Matter. It is surprising to note that the echo chambers in mid-2016 have a linkage between echo chambers located in mid-2020. These links are also observed in White Lives Matter. This indicates that the number of echo chambers and an average number of members of the echo chambers not only increase during these periods but also share the same frames and members. Furthermore, even though the chart for White Lives Matter is the sparsest, the echo chambers are spread over the lifespan of the movement rather than being concentrated in a specific period. As for All Lives Matter, the echo chambers at the beginning of the movement have fewer connections and are mostly linked to the nearby echo chambers. However, the chart becomes more complex over time, and linkages evolve over a longer term.

By consolidating the findings, several generalizable conclusions can be drawn. First, the dataset predominantly revolves around significant events, particularly the death of George Floyd and other incidents that had nationwide repercussions. Each of the four countermovements displays distinct peaks at different time points, yet they collectively share these two crucial periods. During these periods, there is a notable surge in both the overall number of echo chambers and the average number of users within them. Furthermore, these echo chambers exhibit interconnectedness through shared frames and overlapping membership, indicating a level of interconnected discourse and engagement among countermovement supporters.

Furthermore, it is noteworthy that Blue Lives Matter distinguishes itself from the other countermovements. Unlike the relatively rapid fluctuations observed in the total count of echo chambers associated with the other countermovements, Blue Lives Matter exhibits a higher number of echo chambers, particularly during the period spanning 2016 to 2020. This disparity is further evident through the outcomes of time series decomposition and the examination of additional box plots, effectively highlighting the unique characteristics of Blue Lives Matter in comparison to the other countermovements. As previously discussed, this divergence is likely attributed to the stronger organizational structure underlying the Blue Lives Matter movement.

Third, it is generally observed that a higher number of participants in a social movement corresponds to an increased presence of echo chambers. However, in the case of All Lives Matter, there are more echo chambers than expected, even when considering the larger dataset. Additionally, no discernible correlation is found between the number of echo chambers and their persistence or similarity to one another.

Lastly, the countermovements of Blue Lives Matter and Police Lives Matter, which share similar ideologies and scopes, demonstrate a striking symbiotic relationship. While Police Lives Matter exhibits heightened activity during its early stages, gradually tapering off, Blue Lives Matter experiences an inverse pattern, initially displaying relatively subdued levels of engagement before witnessing a subsequent upsurge in participation over time. This dynamic interplay between the two countermovements underscores their interdependence and interconnectedness.

In conclusion, the findings of this dissertation contribute to a deeper understanding of countermovements in the context of their echo chambers. The rising trend of both the total number of echo chambers and members inside of them during the significant events, the identification of shared periods of attention, the distinct characteristics of Blue Lives Matter, the unexpected presence of echo chambers in All Lives Matter, and the interdependence of Blue Lives Matter and Police Lives Matter highlight the nuanced dynamics within countermovements. These insights can inform future research and enhance our comprehension of the complexities surrounding these movements in the digital era.

CHAPTER 6

CONCLUSION

The concept of echo chambers has gained significant importance in the context of the rise of social media and online social movements. However, the prevailing focus on one-way observations, primarily analyzing the framing and polarization effects, limits the potential of this concept. The main objective of my thesis was to delve into the characteristics and continuity of echo chambers associated with countermovements to the Black Lives Matter movement. To achieve this objective, I specifically selected four countermovements: All Lives Matter, Blue Lives Matter, White Lives Matter, and Police Lives Matter. These countermovements were chosen based on their shared initial movement, their overlapping and distinct ideologies, and their comparable lifespans, all of which were conducive to the research being conducted.

The concept of echo chambers has received considerable attention from scholars. However, existing definitions of echo chambers have not yet integrated topic modeling and network analysis to identify and understand them comprehensively. I argue that analyzing people's written content is the most effective approach for capturing their attitudes, as it allows for the detection of echo chambers with the strongest attitudes among individuals. The integration of topic modeling and network analysis proves to be a powerful tool for comprehending the dynamics of echo chambers and their influence on social and political discourse.

By examining the structure, dynamics, and temporal changes of echo chambers, we can gain insights into the factors that contribute to the formation and mobilization of countermovements, as well as their impact on social and political change. Additionally, through a comparative analysis of echo chambers among countermovements, we can shed light on the mobilization and organizational strategies employed by these movements and the extent to which they generate echo chambers of like-minded individuals. Such comparative analyses provide valuable insights into the factors that determine the success or failure of countermovements and can inform strategies for enacting social and political change in the digital age.

Ultimately, conducting a comparative study of countermovements' echo chambers not only enhances our understanding of the complex landscape of digital communication and social movements in the twenty-first century but also informs effective strategies for social change and political action.

This thesis represents the pioneering effort to examine the persistence and continuity of both activists and frames within movements, a novel area of research in the existing literature. By focusing on the success and consistency of social movements, this study introduces a new approach to analyzing online social movements. The combination of sophisticated methods such as network analysis and natural language processing techniques, along with the utilization of both new and traditional algorithms like the continuity algorithm and time series decomposition, are notable aspects of this research contribution. These innovative methodologies enhance our understanding of the complex dynamics of online social movements and provide valuable insights into their long-term patterns and evolution.

In conclusion, this thesis opens up several promising avenues for future research based on the approaches employed in this study. Firstly, to explore the direct interactions between echo chambers or prior movements and countermovements, it would be valuable to incorporate the initial movement as part of the analysis. Although limitations in computational power and dataset size prevented its inclusion in this research focused on the Black Lives Matter movement, future studies could undertake comparative analyses to examine the effects of online social movements on each other.

Secondly, the continuity algorithm used in this thesis has the potential for further improvement. Modifications could be made to allow for the comparison of datasets with uneven lengths. Additionally, rather than analyzing the entire lifespan of movements, datasets could be divided into smaller periods, such as yearly segments, to observe the continuity of echo chambers within these intervals. Applying the algorithm to other cases where the demands of autocorrelation and random tests are not met, as was the case in this study, would also be worthwhile.

Thirdly, while this thesis identified two prominent peaks that significantly impacted the entire dataset, future studies could focus on detecting smaller-scale fluctuations and conduct comparative analyses based on these peak points. This would provide a more nuanced understanding of the dynamics and effects of countermovements within specific time periods.

Lastly, the basic spam detection algorithm developed in this thesis could be enhanced with additional capabilities. While the most repetitive patterns used by spammers were identified, there may be other patterns that could be uncovered using advanced computational methods. Improving spam detection algorithms for social media studies would contribute to more accurate data analysis and interpretation.

In summary, future research directions based on the approaches used in this thesis include exploring the interactions between echo chambers and initial movements, improving and expanding the continuity algorithm, analyzing smaller-scale fluctuations within countermovements, and enhancing spam detection algorithms for social media studies. Pursuing these avenues would further advance our understanding of online social movements and their impact on society.

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