UNDERSTANDING SOCIAL MOVEMENTS THROUGH SIMULATIONS OF ANGER CONTAGION IN SOCIAL MEDIA

by

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ABSTRACT

NAZMIYE GIZEM BACAKSIZLAR. Understanding Social Movements through Simulations of Anger Contagion in Social Media. (Under the direction of DR. MIRSAD HADZIKADIC)

This dissertation investigates emotional contagion in social movements within social media platforms such as Twitter. The main research question is: How does a protest behavior spread in social networks? The following sub-questions are: (a) What is the dynamic behind the anger contagion in online social networks? (b) What are the key variables for ensuring emotional spread? We gained access to Twitter data sets on protests in Charlotte, NC (2016) and Charlottesville, VA (2017). Although these two protests differ in their triggering points, they have similarities in their macro behaviors during the peak protest times. To understand the influence of anger spread among users, we extracted user mention networks from the data sets. Most of the mentioned users are influential ones, who have a significant number of followers. This shows that influential users occur as the highest in-degree nodes in the core of the networks, and a change in these nodes affects all connected public users/nodes. Then, we examined modularity measures quite high within users own communities. After implementing the networks, we ran experiments on the anger spread according to various theories with two main assumptions: (1) Anger is the triggering emotion for protests and (2) Twitter mentions affect distribution of influence in social networks. We found that user connections with directed links are essential for the spread of influence and anger; i.e., the angriest users are the most isolated ones with less number of followers, which signifies their low impact level in the network.

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CHAPTER 1: INTRODUCTION

The collective behavior in society is a main interest of this research, especially collective decisions and actions of humans, such as in social movements and conflicts. This study aims at understanding social movements with their reflections through simulations of anger contagion in social media. What sparks protests? Why do most of them die out quickly? What is the role of emotions in starting and maintaining them? What is the role of social media in entire process? Can this social media reflect the pulse of streets? This dissertation is focused on anger contagion in social media channels, more specifically Twitter because of the availability of its data.

The ease of spreading information over the internet and the widespread use of smartphones creates an interesting research venue for scholars, allowing them to investigate thoughts, decisions, and emotions of people expressed through their social media postings and activities. This increasing spread of information and its effect on users/citizens have played a major role in protest participation, as well as influencing user decisions under alternative circumstances, such as censorship, dense or sparse online and offline social networks, and grievance distributions. Compared to this fairly new social media-enabled analysis, traditional social science studies rely on case studies such as participant observation, interviews, or the snowball sampling approach to learn about attitudes, characteristics, and aim of participants. These methods are powerful to extract real-life descriptions and information from experienced people in

social movements. However, the sample size of these traditional methods are limited, and it only considers active participants who are willing to have an interview or share information. This limitation also introduces a lag in time between an event occurrence and its observation [14].

On the other hand, there are alternative methods in computation social science for studying the dynamics of social movements and simulating the current environment, such as system dynamics, network science, and agent-based modeling.These methods aim to understand the underlying dynamics of social movements and to predict the future outcomes by defining and calibrating parameters from data sourced from Twitter and Facebook.

While some are skeptical about the validity of data gathered from social media due to the number of bots, unverified users, and duplicate posts, we argue that there are a number of ways to manipulate the data that will eliminate these concerns and maintain the advantage of having access to an instantaneous and vast pool of human emotions and thoughts. We believe that these channels offer us the potential for a much broader perspective on human behavior, especially in the context of significant sociopolitical incidences, such as protests.

The relationship between protest behaviors and sociopolitical contexts is a complex process to analyze and predict. This complexity has both macro and micro aspects from social, economical, and political perspectives [46, 52]. When human emotions, behaviors, and interactions towards these cultural perspectives are combined with contrasting governmental decisions, social conflicts may result. These conflicts, which can be defined as protests, have been witnessed in the digital-age around the world,

including protests in Cairo, Ankara, Istanbul, Athens, Madrid, New York, Ferguson, Santiago, and many other [31, 41].

The primary objective of this thesis is to understand how emotions, specifically anger, spread in digital age social networks, such as Twitter. The main research question is: How does a protest behavior spread in social networks? The following sub-questions are: (a) What is the dynamic behind the anger contagion in online social networks? (b) What are the key variables for ensuring emotional spread? The theories behind the social movements and real-world examples of collective protest behaviors, such as Arab Spring, 15M, Chilean students, and Gezi Park movements, are used to help us better understand the effect of social media on protests. The computational social science methodologies have been applied in the past to model protests and civil revolutions.

Models with an Agent-Based Modeling (ABM) methodology are analyzed in detail compared to other computational social science techniques, such as Network Science and System Dynamics, and this methodology is reviewed in terms of its benefits for understanding both micro and macro level behaviors of social systems. Also, current computational models with ABM are introduced with a comparison to our proposed model. The potential strengths and future enhancements of our proposed model are presented as well. For this dissertation, we gained access to Twitter data sets on protests in Charlotte, NC (2016) and Charlottesville, VA (2017), with specific hashtags and keywords used during the relevant protest periods. We conducted descriptive statistical analyses on these data sets in order to compare them. To investigate the influence of anger spread among users, we extracted two networks of

users from the Twitter data sets through their mentions. Most of the mentioned users are influential ones, who have a significant number of followers. Then, we examined modularity measures of these networks, which are quite high within users own networks/communities. After implementing these networks in two separate agent-based simulation models in NetLogo, we ran experiments on the anger spread according to various theories, such as the homophily effect, influential nodes impact factors, and weighted average of corresponded network nodes attributes. In these experiments, there were two main assumptions: (1) Anger is the triggering emotion for spreading influence and (2) Twitter mentions affect distribution of influence in social networks. We found that user connections with directed links are essential for the spread of influence and anger. For further research, this study can create a base line for emotion contagion algorithms with ensuing protest behaviors.

The organization of the dissertation is as follows: Chapter 2 explains a background on social movements from social sciences and on models in computational social sciences. Chapter 3 introduces the proposed approach with data analysis and agent-based model. Chapter 4 investigates the model experiments with research questions and Chapter 5 examines the model verification. Chapter 6 presents model results and Chapter 7 provides discussions. Chapter 8 emphasizes conclusions and future work implications.

CHAPTER 2: LITERATURE REVIEW

2.1   Background on Social Movements

2.1.1   Definitions and Theories

If there is an increase in societal distrust of government actions paired with a constant ignorance to people's rights, then a civilian uprising should be no surprise [15]. This ignorance creates tension in the society, and there is a societal perception about deterioration to people's dignity, which triggers emotional outrage and causes people to stand for their rights [15]. To gage the societal trust towards governments in different countries, the World Public Opinion report conducted a survey showing that most people believe their government is run by a few big interests, rather than for the benefit of the people [44]. Also, the Edelman Trust Barometer shows that, in general, people do not trust their governments. Figure 1 displays the Edalman Trust Index on a world of distrust with the average trust in institutions from sample of countries [24].

As mentioned, societal distrust creates social conflicts that can lead to protests. The difference between a social movement and a protest is ambiguous. Instead of listing their common points, their differences are explained. Social movements are peaceful demonstrations that aim to create social changes, whereas protests can be violent events that focus on forcing immediate action. The size of the crowd is also an
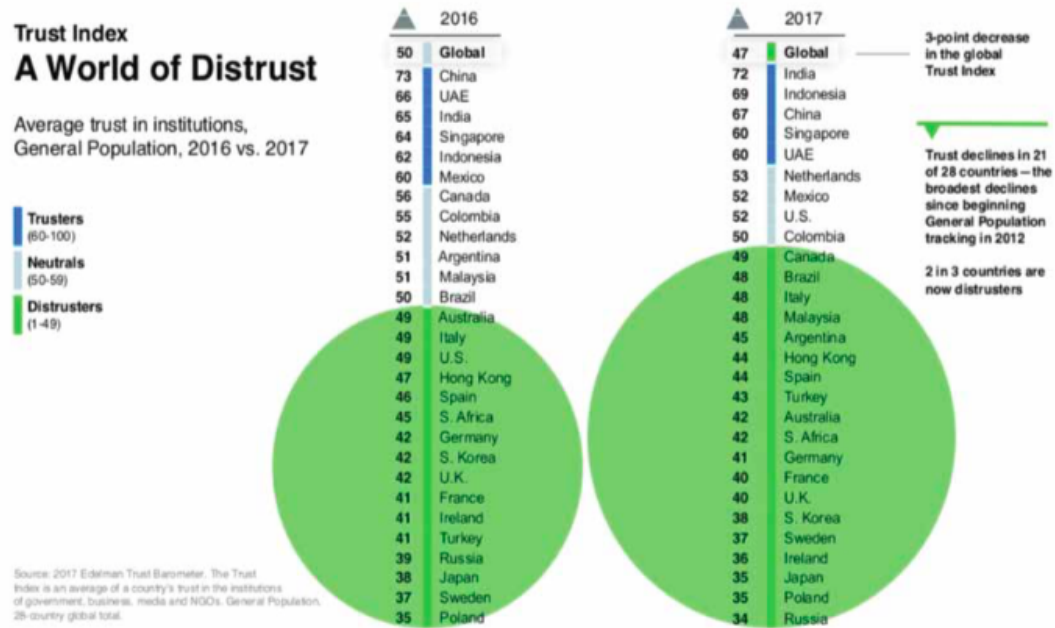
Figure 1: Edelman Trust Barometer: Distribution of Trust in Countries [24].

important differentiator between the peaceful and violent events. Social movements have a tendency to create organized, collective groups of individuals. Also, social movements do not have any institutional or political party roots. Conversely, protests can be violent, disorganized, and in varying sizes. There is a constant ambiguity in defining social movements and differentiating them from protests. This section includes introducing social scientists' definitions for social movements and protests from the literature, then a conceptual building of social movements takes place and their common themes in the digital age are listed. Castells' research [15] is essential to classify social movements for the aim of this study since he states features of social movements with the technological advancements and Internet in detail and we use his theory to build the foundation of the model base.

According to Castells, there is a new concept of social movements in our digital age,

which he calls "social movements in the Internet age." However, in the pre-Internet age literature, there are different and yet somehow similar definitions for social movements and protests. Opp has a collection of definitions from the literature in his book "Theories of Political Protest and Social Movements" and Table 1 introduces the selected of definitions [64]. Basically, these definitions from Opp's collections allow us to understand the main components of social movements as collectivity of individuals, organized efforts of individuals, and joint causal statements to social change. According to Opp, a political activity is considered as a protest, which is defined as joint action of individuals aimed at achieving their goal and goals by influencing decisions of a target [64]. Social movement is a certain type of protest group, whose motivation is to create a societal change with its peaceful ways.

In this study, social movements and protests are used interchangeably. Tarrow draws a mental diagram for the intersecting elements of social movements such as political opportunities/constraints, cultural artifacts and frames, and networks and organizations. According to Tarrow, the intersection of these three elements creates social movement campaigns [73]. He illustrates the cycle of protest beginning with a stage of heightened conflict, followed by diffusion of conflict over geographic and sectorial boundaries, the appearance of new social movements and consolidation of existing ones, the creation of new frames of interpretation and protest techniques, and finally the eventual decline of protest.

In addition to Tarrow's point with the increased conflicts creating social movements, Castells elaborates common themes or features of social movements in the digital age and his insights are inspirational for our work [15]. Social movements are

Table 1: Definitions for Protest Behaviors and Social Movements [64].

Definition	Reference
"Protest activity is defined as a mode of political action oriented toward objection to one or more policies or conditions, characterized by showmanship or display of an unconventional nature, and undertaken to obtain rewards from political or economic systems while working within the system."	Lipsky, 1968 [49]
"An act of protest includes the following elements: the action expresses a grievance, a conviction of wrong or injustice; the protesters are unable to correct the condition directly by their own efforts; the action is intended to draw attention to the grievances; the action is further meant to provoke ameliorative steps by some target group; and the protesters depend upon some combination of sympathy and fear to move the target group in their behalf."	Turner, 1969 [78]
"A social movement organization is a complex, or formal organization which identifies its goals with the preferences of a social movement or a countermovement and attempts to implement these goals."	McCarthy & Zald, 1977 [58]
"A social movement is a purposive and collective attempt of a number of people to change individuals or societal institutions and structures."	Zald & Ash, 1966 [83]
"Social movements are efforts by a large number of people to solve collectively a problem that they feel they have in common."	Toch, 2013 [74]
"Social movements are voluntary collectivities that people support in order to effect changes in society. Using the broadest and most inclusive definition, a social movement includes all who in any form support the general ideas of the movement. Social movements contain social movement organization, the carrier organizations that consciously attempt to coordinate and mobilize supporters."	McCarthy & Zald, 1973 [57]
"Social movements are better defined as collective challenges, based on common purposes and social solidarities, in sustained challenges against powerful opponents."	Tarrow, 2011 [73]
"Social movements have traditionally been defined as organized efforts to bring about social change."	Jenkins & Form, 2003 [40]

networked in multiple forms, such as online and offline network connections that can be also classified as strong and weak ties, which will be defined in detail in Chapter 3. Online network connections indicate social media links, whereas offline ones refer to friends and family, colleagues, and memberships (e.g., football teams). All Internet aged social movements occupy an urban space in addition to their online space. Also, these movements are local and global at the same time and movements around the world recognize each other. They are leaderless and timeless. They do not have any selected authority or organization behind them nor do they seek any deadlines. They are sparked by indignation from the society and they have a spontaneous spirit. In addition to this spirit, these social movements are viral in that people sharing the same fear and anger come together as a means to protect their rights and dignity. Social movements are also very self-reflective since they do not accept any formal leaders. They are non-violent, mostly non-programmatic, and fundamentally political movements. They are aimed at changing the social values [15]. If social movements respond to violence from the government forces, they do not keep their spirit for this category and with the increase of violence, peaceful protests turn to other social conflict stages that are shown in Figure 2 [46] .

2.1.2   Social Movements in Digital-Age

The attention towards social media effects on civil revolutions has increased since the Arab Spring. This subject has become a point of interest for scholars, especially those in the social sciences, who are now researching how social media brings people together and influences protest participation rates. In light of these questions, related
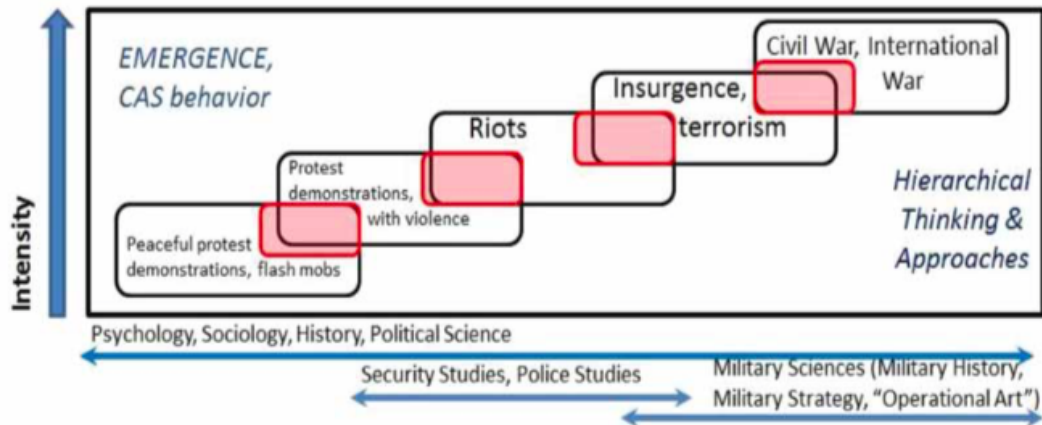
Figure 2: Classification of Social Conflict Based on Their Intensity (or Level of Violence) and the Disciplines [46].

works are introduced from network and social sciences.

Little (2015) builds models for technological information channels that impact two factors: the level of dissatisfaction with the current regime and logistical information about when, where, and how potential protests will occur [50]. According to Little (2015), public grievance levels against the regime have an ambiguous effect on protest levels [50]. There could be more or less popular effects than expected. Although sharing more complaints about the regime can increase average grievance levels against the government, there is no exact correlation between anti-regime content and protests. However, there is other research that demonstrates a relationship between opposition to the government and protest behaviors [12].

As mentioned earlier, since the Arab Spring uprisings in Tunisia and Egypt in early 2011, scholars have researched the Internet and social media contributions to political change in authoritarian regimes [43]. Tufekci and Wilson's (2012) research "Social Media and the Decision to Participate in Political Protest" shows observations from

Tahrir Square as events unfolded in real time [77]. This paper is evidence of how social media and the Internet were actively used by protesters. To better understand Egypt's conditions, Tufekci and Wilson (2012) present the timeline of the revolution. From 2005 on, there were persistent protest efforts by a small but dedicated group in Egypt. In 2009, Facebook in Arabic was introduced and this amplified communication opportunities and in 2010, Tunisian unrest broke out. Finally, in 2011, the Egyptian revolution began after 18 days of sustained protests [77].

For Tahrir, there was a new system of political communication due to technological improvements. This system involved three broad and interrelated components: (1) an independent TV channel (Al-Jazeera), (2) the rapid diffusion of the Internet and the rise of social media (Facebook and Twitter), and (3) the decreasing costs and expanding capabilities of mobile phones [77]. Tufekci and Wilson (2012) conducted a survey of media use by Egyptian protesters. A total of 1,050 people were interviewed using both random and snowball sampling approaches. They demonstrated that "people learned about the protests primarily through interpersonal communication using Facebook, phone contact, or face-to-face conversation" [77]. According to their statistical analysis, controlling for other factors, social media use had a positive impact on protest attendance on the first day and Facebook was the most common communication source among surveyed people.

The results of the Tufekci and Wilson study underline the central role of social media, particularly Facebook and Twitter, which assisted in the development of the protests leading up to the February 2011 resignation of Egyptian President Hosni Mubarak. As mentioned in the study, Facebook only became available in Arabic in

2009 but protesters quickly utilized the platform to share most of their pictures and videos about the protest. On the other hand, protesters used Twitter and blogs to communicate text about the demonstrations [77].

With the Arab Spring, protesters demonstrated that they can hear about each other through social media. To better understand this communication network, Breuer et al. conducted a preference survey among a sample of Tunisian Internet users (February May 2012) [12]. According to the study results, social media broke the elitism of mainstream media and provided a basis for intergroup communication and collaboration among protesters [12]. In addition to the creation of new digital space for the protest cycles, social media helps citizens to convey and share their emotions to the regime and this creates an "emotional mobilization" [12].

Like in Castells theory about emotional aspects of social movements, Breuer et al.'s research investigated not only the protesters opposition against the regime but also the protesters' emotions like anger, sadness, and frustration over online pictures and videos that were showing the regime's response to the protesters [12]. Breuer et al. have three questions to analyze people's freedom under the Ben Ali regime, such as how people feel about freedom of speech, freedom of the press, and general respect for people's rights [12]. According to their results, the frequency of opposition to the Ben Ali regime is very high (see Figure 3) [12]. In addition to these general levels of opposition to the regime, 59.5% of the sample expressed their trigger emotions to the protests.

Another political protest example that is introduced in order to provide a worldwide perspective is the 15M protests in Spain, which were occured on 15 May 2011 [2].
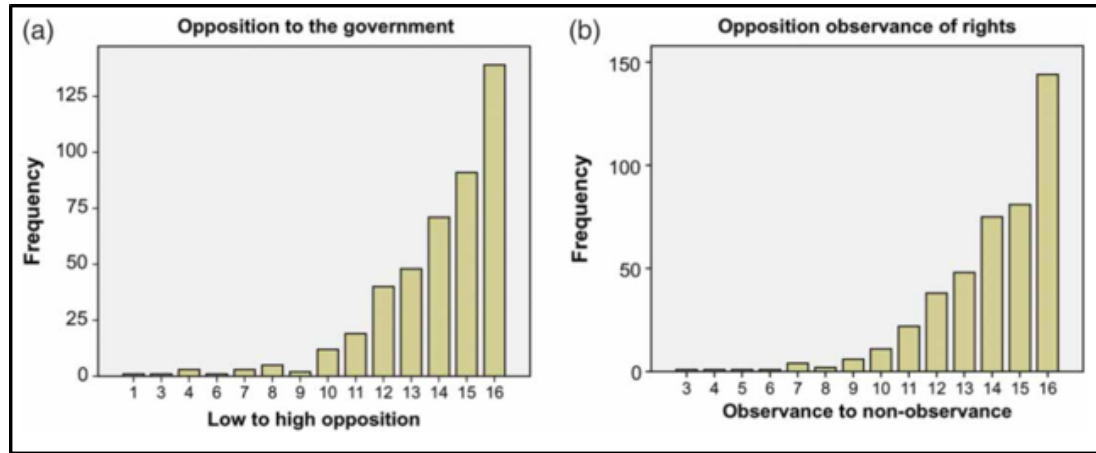
Figure 3: Levels of opposition to the Ben Ali regime. (a) Economy (economy, jobs, income distribution, and corruption) and (b) Rights and freedoms (press, speech and general state of rights) [12].

As stated before, other international uprisings such as the Occupy Movements, the protests in Greece, the Arab Spring, and the Egyptian Revolution happened at a similar time as 15M. Around 130,000 people gathered to demand democracy in Spain using the slogan "Real Democracy Now!" The protesters' grievance levels against the government had increased due to the national economic crisis, the high unemployment rate, and the government cutbacks in health care and education. These protests were different than the others that happened in Spain because of their self- organized nature. There were no political parties, unions, or large organizations behind the protests.

The 15M demonstrations could be considered an instance of a "self-organized connective action network with significant differences" as compared to other collective action events in Spain [2]. Anduiza et al. conducted interviews and postal surveys with protesters [2]. In each demonstration, the researchers contacted the protesters randomly and interviewed them face-to-face. Afterwards, they handed out a postal

questionnaire. Response rates to the postal questionnaire ranged from 18% to 33%, and reached 35% for the 15M demonstration. Anduiza et al. had 2,265 protesters complete the postal survey [2].

As mentioned before, 15M was structured differently with respect to its mobilization processes. Almost 55% of the participants heard about the demonstration through social media and alternative media sources, and 49% of them were informed specifically through personal connections in their social networks. In other protests, these percentages were 26% and 17%, respectively [2]. The role of traditional media as an information channel was very limited.

Anduiza et al. (2014) show, with their comprehensive comparative study on the Spain demonstrations, the traditional intermediary structures, such as unions, parties and traditional news are still important for large-scale political mobilizations. However, in the 15M case, the researchers claim that union, party, and traditional media involvement were no longer a necessary initial condition for generating high turnouts at protests because the social media network had an enormous role.

Around the similar time as Arab Spring and 15M, student demonstrations in Chile were sparked due to the increase in tuition fees. There was again a relationship between social media use and protest behavior among the young Chilean student population [79]. Valenzuela et al. (2014) used propensity score matching to analyze data from a repeated cross-sectional survey taken before, during, and after the 2011 student demonstrations in Chile. According to their results, Facebook and Twitter have significant effects on "the likelihood of protesting" (see Figure 4) [79].

Again, around the similar time as the social movements above, the Gezi Park
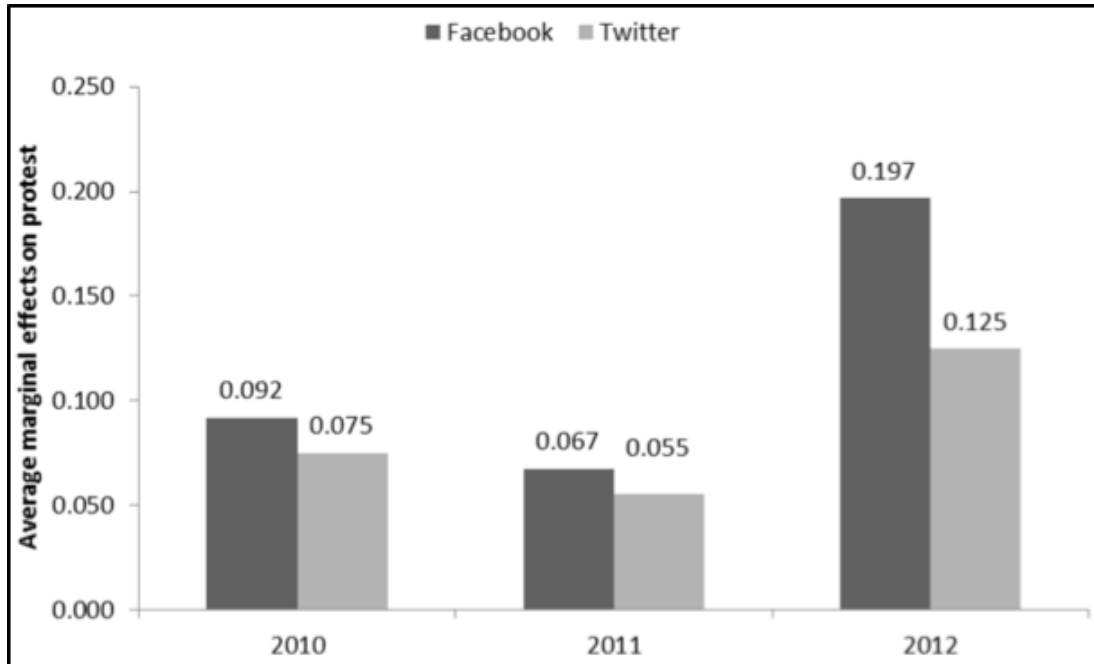
Figure 4: The Average Marginal Effects of Facebook and Twitter on the Likelihood of Protesting among Chilean Youth [79].

movements in Istanbul, Turkey arose on May 28, 2013. A small group of 50 environmentalists occupied Gezi Park near Taksim Square, which is one of the main squares in Istanbul, to demonstrate their opposition to the decision made by the Turkish government to replace the park with a shopping mall [14]. A violent police officers attempt after this small group's demonstration triggered much larger protests in Gezi Park, Taksim Square and other parts of Istanbul. Also, outrage spread to other cities across the country which incited a continuous cycle of police repression and further protests at various levels of intensity during the summer of 2013 (May 28 - Aug 1, 2013). The Gezi Park movements are a great example of Castells' theory of social movements due to their leaderless and timeless nature [15]. Also, the movements do not have any selected authority or organization behind them. All the movements that arose from the Gezi Park demonstrations went viral through social

media, especially with Twitter. These movements were mostly non-programmatic, fundamentally political, and non-violent even though there were some attempts to turn these demonstrations into violent protests.

The protest related incidents occurred around a similar time, and we can use these works to derive theories about technological advancements, focusing on their huge impact on the structure of social movements. In our research community, scholars are still learning how social media affects political participation in areas such as voting or demonstrating for or against a given cause or regime [41]. According to Jost et al., "isolating direct and specific causes and consequences of social media use remains tremendously challenging, and acute theoretical and methodological problems have yet to be solved" [41]. We consulted these studies in order to improve our theoretical and practical background in the field, and to determine the essential parameters for joining protest behaviors, such as network and agent types, and emotion distributions.

2.2   Background on Computational Models

2.2.1   General Introduction to Computational Models

There are three quantitative approaches that can be used to examine social movements within computational social science: Network Science, Complex Adaptive Systems: Agent-Based Modeling (ABM), and System Dynamics (SD). First, there is a joint introduction for the three methods to better understand how they can be implemented to better understand social movements in the digital age. Then, benefits of ABM with human systems are introduced. Finally, the comparison of computational model examples for civil revolutions and emotion contagion models take places [51].

In ABM, there are micro and macro level dynamics. Each agent has its own attributes that determine its actions, which create interactions in both space and time [60]. The agent's interactions have a one-to-one relationship in the model and create micro level dynamics. Agent-based interactions might lead to a global emergent behavior that can affect the macro level dynamics, such as a social context with socio-economic conditions, power dynamics in the country, and political situations. In turn, these macro level dynamics also have an effect on micro level dynamics. It can be fair to call this a "bottom-up approach" meaning interactions happening at the bottom level impact the interactions at the top.

On the other hand, the System Dynamics approach can be applied understanding the greater implications of a problem. This approach helps us to link together subparts of the problem and their relationships to better understand the system dynamics (see 5). Each arrow represents causal relationships that mean a variable in the beginning of the arrow has an influence on other variable in the end of the arrow [71]. This influence can be positive (+) or negative (-). A positive influence means that an increase in the variable at the beginning of the arrow can lead to an increase in the variable at the end of the arrow. On the other hand, a negative influence indicates that an increase in the variable at the beginning of the arrow can lead to a decrease in the variable at the end of the arrow. If there is an ambiguity in a relationship, the arrow's sign will remain blank.

There is a feedback loop dynamics between micro and macro level relationships in social systems. Micro level dynamics can create emergent behaviors, which develop macro level dynamics to influence agent's interactions (see Figure 5).
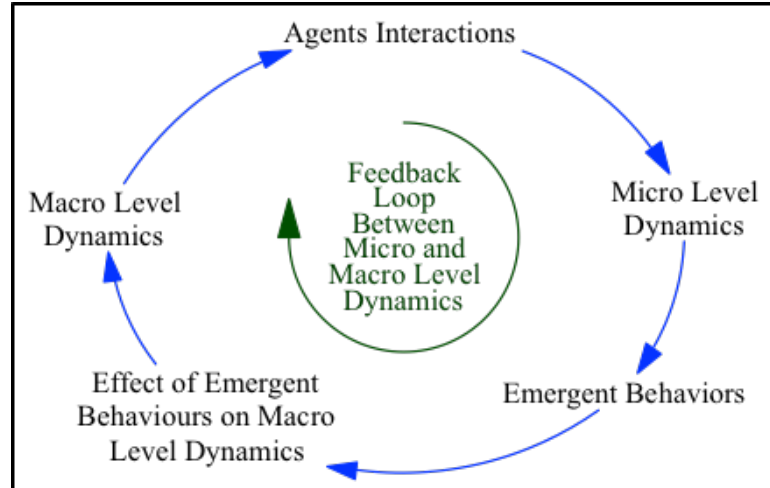
Figure 5: Feedback Loop between Micro and Macro Level Dynamics of the ABM.

2.2.2 Introduction to Relevant Computational Models

2.2.2.1 Network Science

Social movements as a collective behavior of humans can be investigated by two different hypothesis on people's network structures that affect the dynamics of protester's actions [79, 10]. The first hypothesis is known as strength of weak ties, which means that heterogeneous networks are more effective at social contagion and information spread compared to homogeneous networks. Weak ties connect social networks that are sometimes called bridges, which indicate relationships among people who are not daily base, densely connected [34, 35]. Therefore, with weak ties, people whose friends do not know each other can become connected. Among social media channels, Twitter can be a good example for weak-tie networks.

On the other hand, the second hypothesis is known as "strength of strong ties" and addresses the importance of homophily for spreading behavior [16, 79]. Homophily means the tendency for people to have social connections with people who are similar

to the, and this refers to the close relationships with people requiring social rein-forcement to adopt the behavior of their peers [17]. Strong ties create homogeneous environments and Centola (2013) suggests that in large groups, it is hard to find the initial source of power or specific contributor that serves as the catalyst to start action [17]. However, there can be a "bandwagon" effect that increases group co-operation. This means that when the first wagon starts to move, the others follow its lead. He provides examples of mass actions displaying this effect, such as large strikes, political protests, and violent revolutions. Centola's point of view is helpful in constructing one of the feedback loops in this research, which is the effect of social media on protester interactions (see Figure 6).
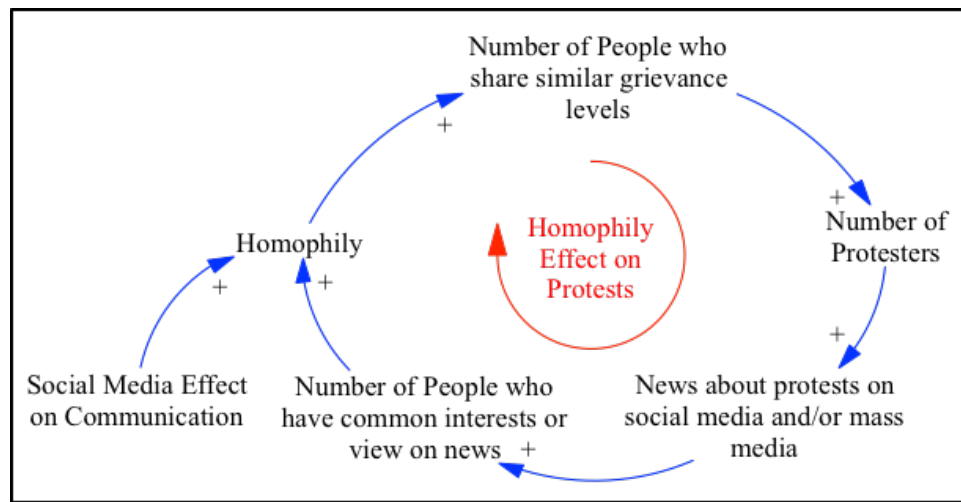
Figure 6: Feedback Loop for Homophily Effect on Protests.

Figure 6 shows the feedback loop for the Homophily Effect on Protests. If the number of people who share a similar level of grievance against the current regime increases, then the number of protesters will increase. Their posts and/or tweets will increase the awareness on communication channels. People with similar interests might also start following or mentioning each other on social media [59]. Therefore,

there will be more news about protests in social and mass media. With the help of this increase in communication channels through social media, more people with common interests or views about news can be more active and engaged. This process can create increased homophily in society, and there is a positive feedback loop for the effect of homophily on the number of people who share a similar level of grievance against the current regime and government.

2.2.2.2   Agent-Based Modeling

Agent-Based Modeling (ABM) helps construct an artificial environment for modeling problems with complicated behaviors. This simulated environment can refer to the society, nature, and any type of relationships among their agents. For example, people, viruses, cars, and roads can each be defined as an agent in the ABM. Users decide on the agent's behaviors, agent's degree of rationalities, and rules of agent's interactions with other agents, who have memory, can learn, and can evolve [28].

There are benefits of applying Agent-Based Modeling in simulating human systems. According to Bonabeau (2002), there are three main benefits of ABM [7]. First, "ABM captures emergent phenomena", which is created by the interactions of agents. Second, "ABM provides a natural description of the system." This simulation method makes the model closer to the real world, making it easier to interpret its dynamics compared to other traditional modeling approaches. Also, ABM can run data-driven simulations. No matter the size of the data, users can implement the data into their model. Third, ABM is flexible in terms of changing the agent's attributes and framework in the model. In other words, it is faster to create experimental results

with scenarios and policy analysis in ABM [7].

This section is introduced the literature review on computational modeling of the civil revolutions and emotional contagion. Civil revolutions, also referred to as protests or demonstrations, come from citizens who believe their actions are for the common good. For our research, it is important to understand the dynamics of the protests before, during, and after their occurrences.

There is a growing literature on ABM simulations of civil revolutions. The first published paper about ABM of civil riots is from Epstein [29], who developed a rebellion model that considers simple threshold-based rules to represent collective behavior and contagion effects. There is a threshold for agents to join a protest or riot. If other agents join the protests, its grievance level exceeds the threshold, and it turns to an active one. The active agents are in interaction with policemen, who serve the government. The policemen can arrest the protesters, who may face jail terms.

There is another parameter called government legitimacy in Epstein's model, which reflects the agents' trust of their government and its rules. Every agent wants to maximize her utility function according to her internal state, agent interactions, and environment. When her grievance level is higher than her threshold and assuming her grievance level exceeds her net risk perception, the agent wants to move and protest [46].

After Epstein's main contribution to the field, there are some variations of his model. Lemos et al. has a wide survey paper on civil revolutions models. Therefore, we would like to cite their work in order to show all of the former papers on civil

revolts until 2012 [46].

Here, civil revolutions papers, published after 2012, are introduced. A new way for agent's actions is suggested by Comer and Loerch [19]. In their model, agents are not moving uniformly as they were in Epstein's model. In Comer and Loerch's model, agents move either asynchronously or randomly [19]. For the asynchronous, agents' neighbors influence agents' attributes. At first, an agent moves to a state and checks its conditions by counting the numbers of active agents and cops in its vision radius. Then, according to its neighborhood, it looks at its own threshold and decides whether or not to act. This action is dependent on the agent's neighborhood. For the random, an agent makes decisions on whether or not its next action is active. This paper opens an additional discussion for our research: If we have a social media effect on our agents, then there will be no constraint on their visions; therefore, it can be stated that the social media effect will enlarge the agent's vision.

New types of agents and their roles listed correspondingly by Lemos et al. [47]. Here, the number of previously active protesters who are in jail affects an agent's grievance level [47]. There is a feedback process in this model. If the number of jailed active agents increases, then government legitimacy decreases, and the agent's grievance level subsequently increases. Lemos et al.'s point is more realistic than Epstein's model in that there exists an internal dynamic for an agents activation processes instead of there being a random distribution of grievance levels for the agents [47].

Compared to others, Moro (2016) offers the greatest contribution to the literature with his model, as it can generate real world examples of civil revolutions like the

Arab Spring [62]. His model predicted several rebellions that arose in similar ways with different scenarios. Outcomes of his model show different political conditions, such as the successful revolution in Tunisia, the failed protests in Saudi Arabia and Bahrain, and the civil wars in Syria and Libya. His model has the ability to create similar dynamics to these real civil revolutions.

In his model, there are three types of agents to characterize citizens: active (A), jailed (J), and revolutionary (R). Also, there are policemen (P) who fight with the active citizens, who turn into active revolutionary citizens if they intend to kill policemen in their vision radius. Moro suggests three scenarios with different parameters for the probability of killing police: successful revolution, anarchy, and failed revolution. When a revolutionary citizen is active, he kills a randomly selected policeman in his vision radius with a probability equal to r. For the policemen, if the randomly selected agent is a citizen, he arrests him; if he is a revolutionary citizen, he kills him with a probability equal to p [62]. These probabilities are given in Table 2.

Table 2: Probabilities in Different Scenarios of Moro' s Model [62].

Scenario	p	r
Successful Revolution	0.4	0.3
Anarchy	0.9	0.3
Failed Revolution	0.9	0.1

Figure 7 illustrates the possible outcomes of the three scenarios. In the successful revolution (p=0.4, r=0.3), after time step 40, the number of active agents is higher than the number of jailed ones, and there is an exponential decrease in the jailed ones. For the policemen and revolutionary citizens' dynamics, initially the number of policemen is higher than the number of revolutionary users. However, after ap-

proximately time step 40, the number of policemen decreases exponentially. On the contrary, in the failed revolution scenario (p=0.9, r=0.1), the number of jailed users is higher than the active ones. Eventually, the active users become zero. Policemen kill most of the revolutionary ones where there are not many active ones. Interestingly, the civil revolution dynamics in the case of anarchy show complex behavior. Active and jailed ones create a different pattern compared to the failed revolution scenario.
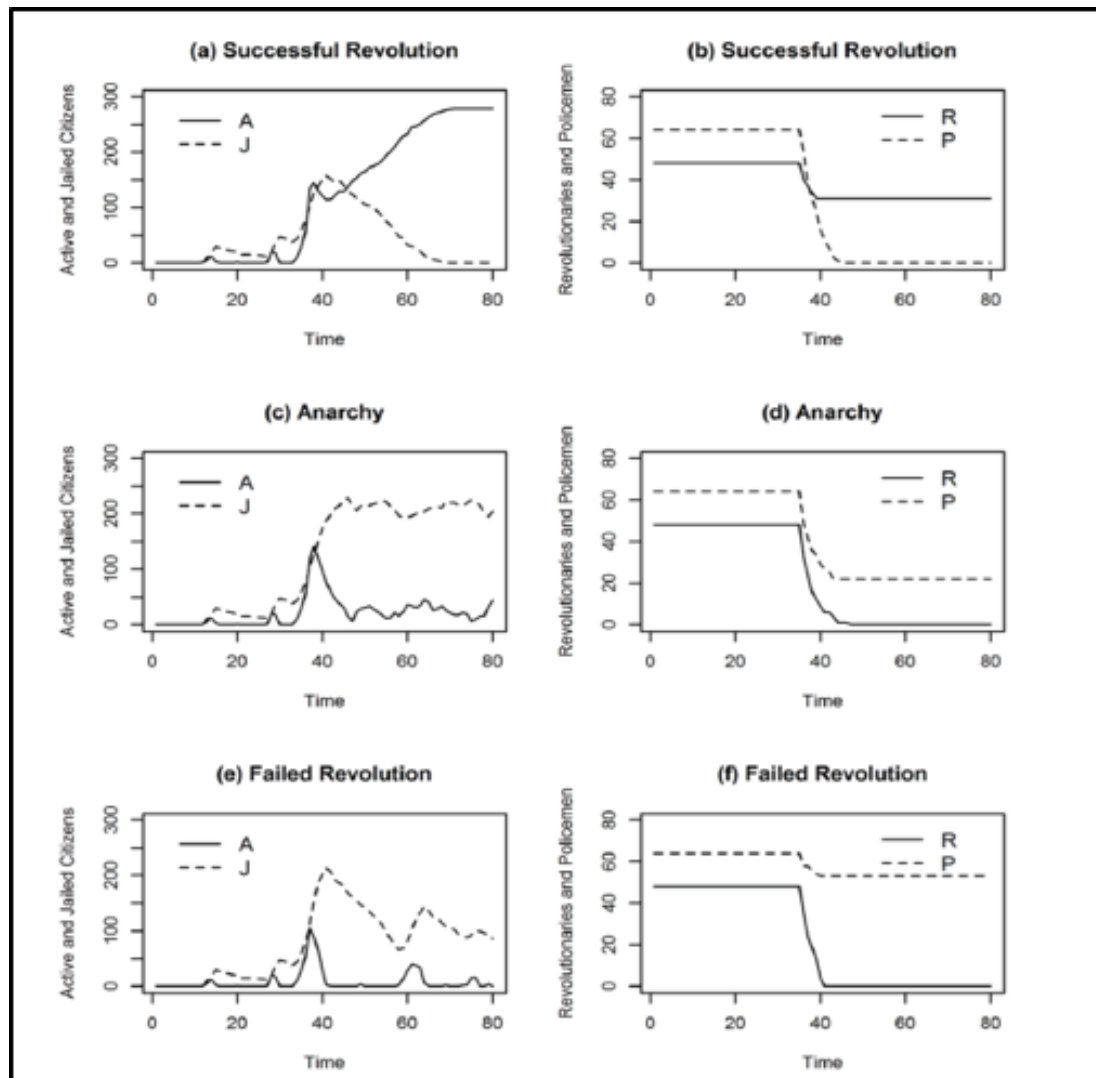
Figure 7: Time Series Graph for the Different Model Scenarios of Moro' s Model [62].

The comparison of civil revolutions models with ABM after 2012 is introduced in

Table 3.

Table 3: Comparison of Civil Revolutions with ABM after 2012.

Author	Paper	Contribution
Epstein (2002) [29]	Modeling Civil Violence: an Agent-Based Computational Approach	The first agent-based model for civil revolutions. Agents are moving according to their grievance levels and risk thresholds.
Comer et al. (2013) [19]	The Impact of Agent Activation on Population Behavior in an Agent-Based Model of Civil Revolt	Technical improvements on agents' actions are introduced.
Lemos et al. (2016) [47]	On Legitimacy Feedback Mechanisms in Agent-Based Modeling of Civil Violence	Agent's grievance level is dependent on jailed citizens.
Moro (2016) [62]	Understanding the Dynamics of Violent Political Revolutions in an Agent-Based Framework	Replications of real cases form the civil revolutions are applied.
Lemos et al. (2016) [48]	ProtestLab: A Computational Laboratory for Studying Street Protests	Real cases form the protest environments are applied in an interactive simulation setting.

CHAPTER 3: PROPOSED APPROACH

3.1 Data Analysis

Social movements have become digital-age social movements due in most part to the increase in technological opportunities for communication channels, such as social media. As mentioned in Chapter 2, actual and potential protesters use Twitter and/or Facebook to connect with each other, communicate about the protests, and plan and organize their activities. As seen in digital-age social movements, such as Black Lives Matter protests in Charlotte, North Carolina and Charlottesville, Virgina, people reacted on social media about these incidences. There are two data-sets collected from Twitter for the Charlotte and Charlotessville protests with specific hashtags and keywords during the protest time periods.

For preprocessing the data sets, three stages are implemented, such as filtering out non-English tweets and dropping duplicated tweets. Details of these two protests are introduced with descriptive statistics in the following subsection.

3.1.1 Descriptive Statistics

There is a data collection process through Twitter' s proprietary firehose (Gnip Historical PowerTrack) for the two protests related to Black Lives Matter, which occurred in Charlotte, NC (2016) [45] and Charlottesville, VA (2017) [5], with specific hashtags and keywords used during the relevant protest periods. We conducted

descriptive statistical analyses on these data sets in order to compare them. For Charlotte and Charlottesville protest data sets, 1.36 million and 390,915 posted tweets have been extracted from Twitter, respectively. These data sets have 430,260 (Charlotte) and 188,516 (Charlottesville) unique users. The details are given in the following subsections.

3.1.1.1 Charlotte Protests

In September 2016 in Charlotte, NC, the police shooting of Keith Lamont Scott, who was African American, triggered the Black Lives Matter protests which came be to known as the Charlotte uprisings or Charlotte riots [45]. Twitter users expressed their thoughts and emotions through tweets as users were activated by the proximity of the protests and ties to the Charlotte community. Posted between September 20 - 26, 2016, 1.36 million posted tweets were extracted from the social media platform. To identify Charlotte protests related tweets, only tweets with at least one of seven protest-related hashtags (e.g., #KeithLamontScott, #CharlotteProtest) are included in the data analysis. The detailed explanation of the Charlotte data set is listed in Table 4.

Table 4: Details of Twitter Data for Charlotte.

Start Date	09/20/2016
End Date	09/26/2016
Total Number of Tweets	1,358,469
Total Number of Retweets	1,171,723 (86%)
Total Number Users	430,260
Hashtags	#keithscott, #charlotteprotest, #keithlamontscott, #prayersforcharlotte, #justincarr, #charlotteuprising, #charlotteriots

Before running the data analysis on the Twitter data sets, two data preparation tasks are performed: Text preparation and exclusions. Figure 8 shows the number of tweets per day from Charlotte' s Twitter data. During the first two days of the protests, users actively tweeted about the incident and the number of tweets started declining until the fifth day (September 25) of the protests. On September 25, 2016, the victim's wife shared the video that she took when the incident took place which increased the number of tweets.
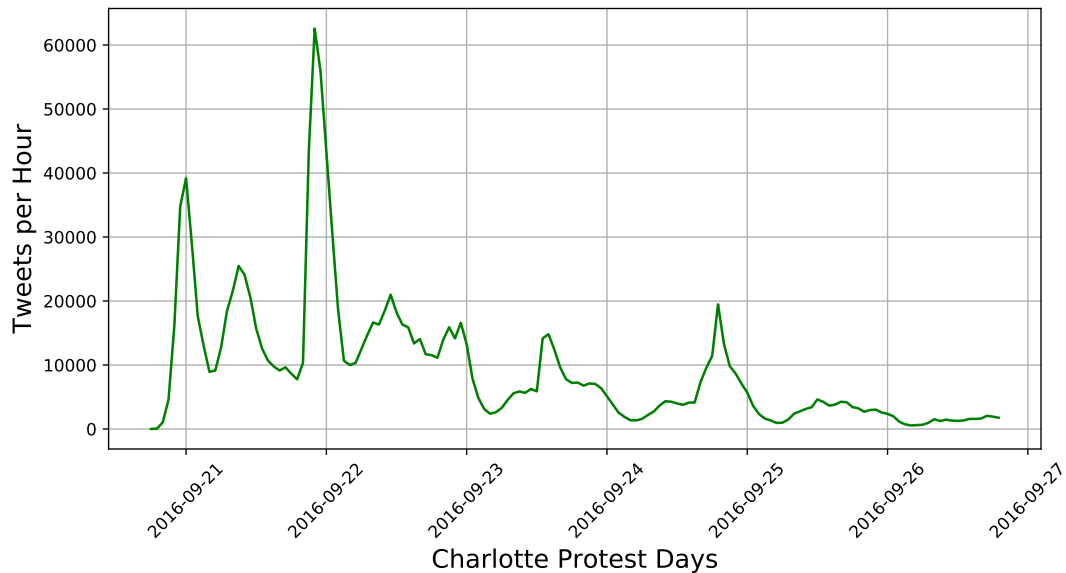
Figure 8: Number of Tweets Count for Charlotte.

As mentioned before, Twitter users (public and influential ones) expressed their thoughts and emotions through tweets; however, this expressiveness is quite subjective. Figure 9 shows the number of tweets per user from Charlotte' s Twitter data with a power law distribution. A limited number of users tweet more than average (typically 10-20), and a significant number of users tweet less than 50.
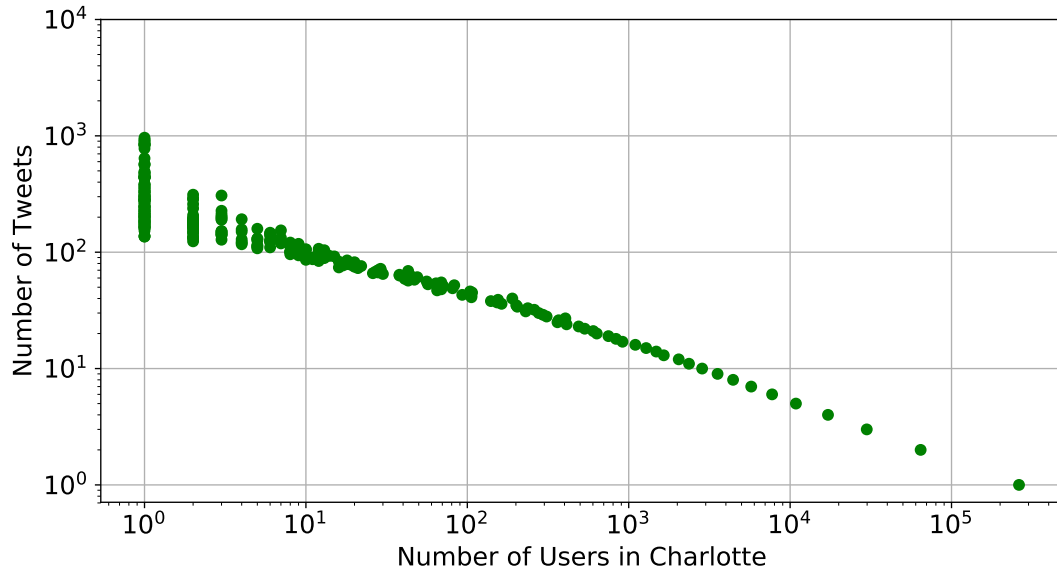
Figure 9: The Number of Tweets per User for the Charlotte Protest Data Set.

3.1.1.2 Charlottesville Protests

In 2017, the Unite the Right rally, also known as the Charlottesville rally or Charlottesville riots, was a white supremacist rally that occurred in Charlottesville, VA [5]. Twitter users (public and influential ones) posted tweets about the Charlottesville protests to express their thoughts and emotions. Those tweets with hashtags and keywords (e.g, #standwithcharlottesville, #HeatherHeyer) are extracted between February - October, 2017 from the social media channel; however, the actual protests were held between August 11 - 18, 2017. The data extraction process took longer than the actual protest dates in order to have analysis before, during, and after the protest time-lines. The detailed explanation of the Charlottesville data set is listed in Table 5.

Figure 10 shows the number of tweets per day from Charlottesville' s Twitter data for eight months. As it is seen, there was a huge increase in the number of tweets on

Table 5: Details of Twitter Data for Charlottesville.

Start Date	02/07/2017
End Date	10/11/2017
Total Number of Tweets	807,954
Total Number of English Tweets (defined by Twitter)	706,233
Total Number of Users	335,183
Selected Hashtags	#unitycville,#defendcville #cvillestrong, #standwithcharlottesville, #invisiblecville, #HeatherHeyer, #DeAndreHarris

August 11, 2017; the time of actual protests started after Heather Heyer struck by the car attack.
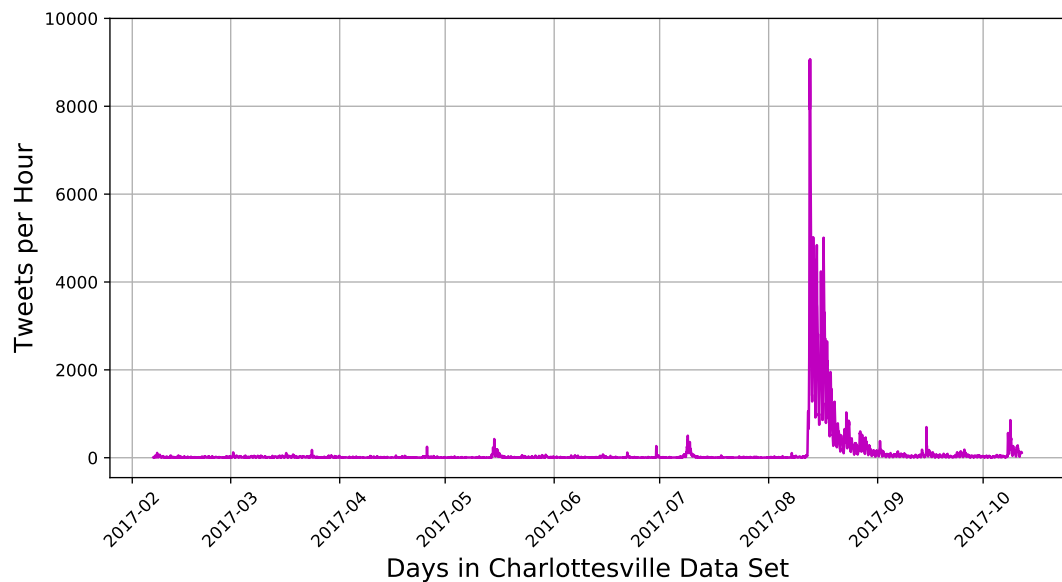
Figure 10: The Number of Tweets in the Charlottesville Data Set.

We conducted a comparative analysis for Charlotte and Charlottesville' s protests. To be consistent with our analysis, even though there are differences between the Charlotte and Charlottesville data sets, such as the latter data set having a longer time period (8 months, see Figure 10) of tweets, it is similar to the Charlottesville

protest time because its peak period lasted for one week.

To illustrate actual protest data set dynamics, which were held between August 11 - 18, 2017 are plotted in Figure 11. During the first two days of the protest, users actively tweeted about the incident and the number of tweets declined after the sixth day (August 17) of the protest; however the number of tweets about this incident did not decrease even though the protest ended.
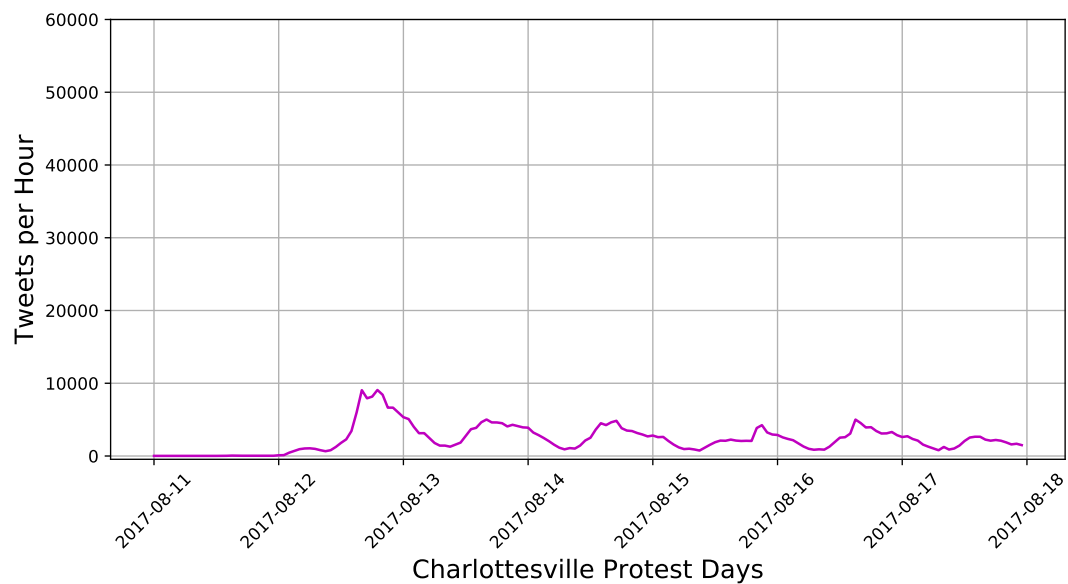
Figure 11: The Number of Tweets in the Charlottesville Data Set during Actual Protests.

Twitter users expressed their thoughts and emotions through tweets; however, this expressiveness is quite subjective. Figure 12 shows the number of tweets per user from Charlottesville' s Twitter data with a power law distribution. As our comparative studies shows, even though Charlotte and Charlottesville protests happened by different causes, there exist similar patterns of macro behaviors.
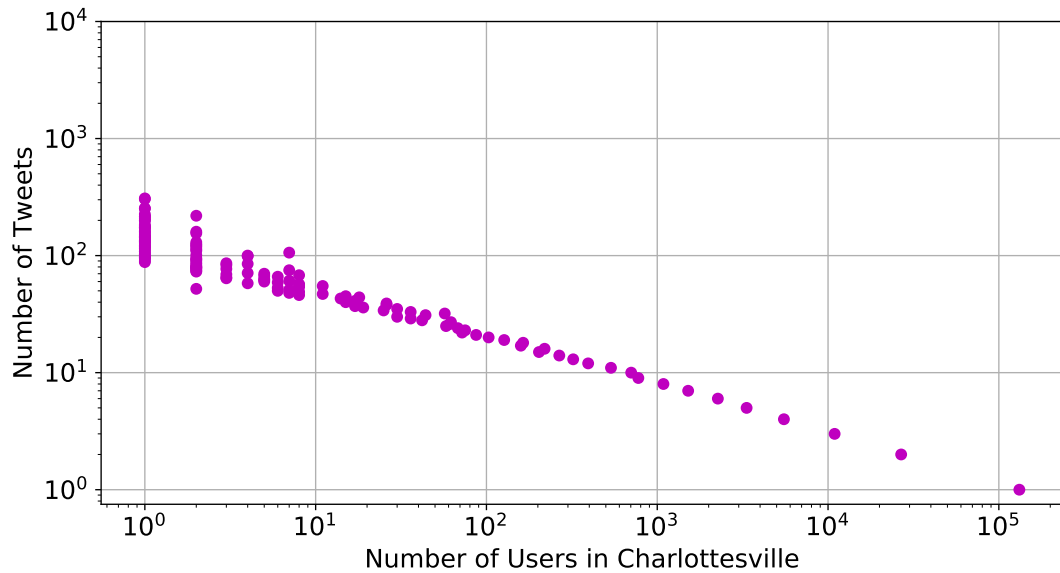
Figure 12: The Number of Tweets per User for the Charlottesville Data Set.

3.1.2   Emotion Analysis

Psychologists and other behavioral scientists have conducted numerous studies and in-person experiments investigating human emotion and facial expressions [4, 26, 27]. Several theories have formed a list of basic emotions; Ekman identified six of them as anger, disgust, fear, happiness, sadness, and surprise [25]. Other researchers have extended these six basic emotions to eleven emotions anger, aversion, courage, dejection, desire, despair, fear, hate, hope, love, and sadness [4].

With the increase in the number of microblogging channels, people have found a platform to express their emotions and opinions on a daily basis. As these channels are rising and diversifying, researchers are becoming interested in sentiment analysis and emotion detection algorithms in natural language processing and other fields that include political science, marketing, communication, social sciences, and psychology [1, 18, 61]. Sentiment analysis refers to classifying a subjective text as positive,

neutral, or negative, whereas emotion analysis detects types of feelings through the expression of texts, such as anger, joy, fear, and sadness [1]. Twitter plays an essential role in spreading information and emotion. Researchers have shown that tracking and analyzing public opinions from social media can help to predict certain events, such as elections [30, 76].

This particular research is aimed at understanding human behaviors in social movements, so Twitter users and their emotions are analyzed to reveal an indicator of actual protester emotion levels. Specifically, anger is considered as a key emotion. To detect anger, the Linguistic Inquiry and Word Count, or LIWC, analysis is applied on each data point [65]. This analysis was developed to provide "an efficient and effective method for studying the various emotional, cognitive, and structural components present in individuals verbal and written speech samples" [65]. LIWC is a text analysis application for language and disclosure studies, explorations with an expanded dictionary and a modern software designed in 2015. In the LIWC dictionary, words are categorized in positive or negative emotion and compared with overall number of words. According to the level of anger in each tweet and the number of tweets that the user posted, his or her mean anger is calculated.

3.1.2.1 Anger Distributions across Charlotte Protest Data Sets

When applying the LIWC emotion detection method to the Charlotte Twitter data set, Figure 13 shows the mean of the top ten angriest users, mean anger with non-zero values, and mean anger per hour. 32 % of tweets in the Charlotte data set contain anger emotion; that is why the mean anger with non-zero values is calculated.
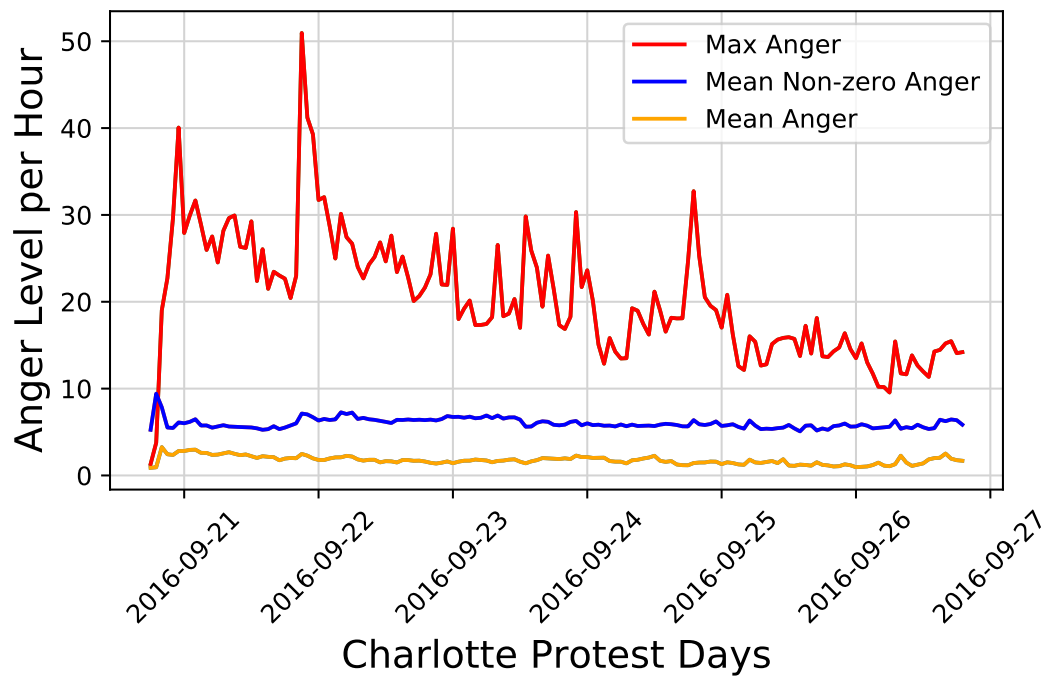
Figure 13: Anger Level Distributions of Tweets per Hour for the Charlotte Protest Data Set.

During the second day of the Charlotte protests, the angry values peaked which was likely due to the announcement that the Charlotte-Mecklenburg Police Depart chose not to release the video of the shooting.

From tweets, we calculated that the percentage of users with anger in the Charlotte data set is 47 %. Most of the users in this data set have anger levels that are lower than 30 out of 100; a limited amount of users have significantly higher levels of anger (e.g., 60 or 70) as it is shown in Figure 14. The number of users over anger levels in the Charlotte protest Twitter data set follows a power law distribution with a heavy tail.
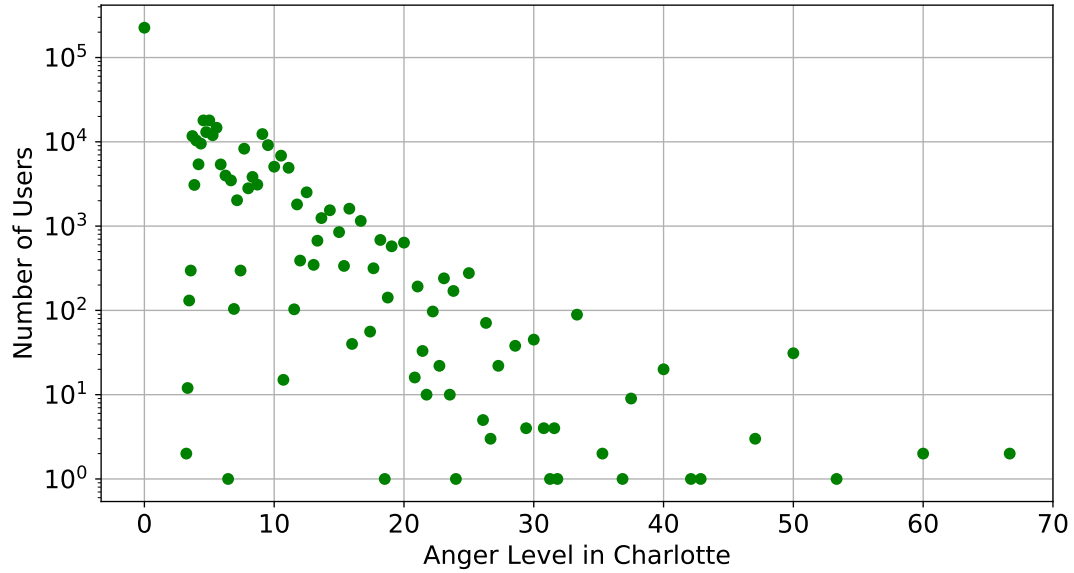
Figure 14: The Number of Users over Anger Level Distributions in the Charlotte Protest Data Set.

3.1.2.2   Anger Distributions across Charlottesville Protest Data Sets

When applying the LIWC emotion detection method, Figure 15 illustrates the mean of the top 10 angriest users, mean anger with non-zero values, and mean anger per hour. 34% of tweets in the Charlottesville data set contain anger emotion; that is why the mean anger with non-zero values is calculated. During the third day of protests in Charlottesville, the angriest values peak which likely stemmed from an appearance of the victims mother in the media (see Figure15).

From tweets of Charlottesville data set, the percentage of users with anger is 45% of tweeters, who are detected with emotions of anger (see Figure 16). Users in this data set show anger levels from 0 - 30; a limited number of users have the highest anger levels from 50 - 60 out of 100.
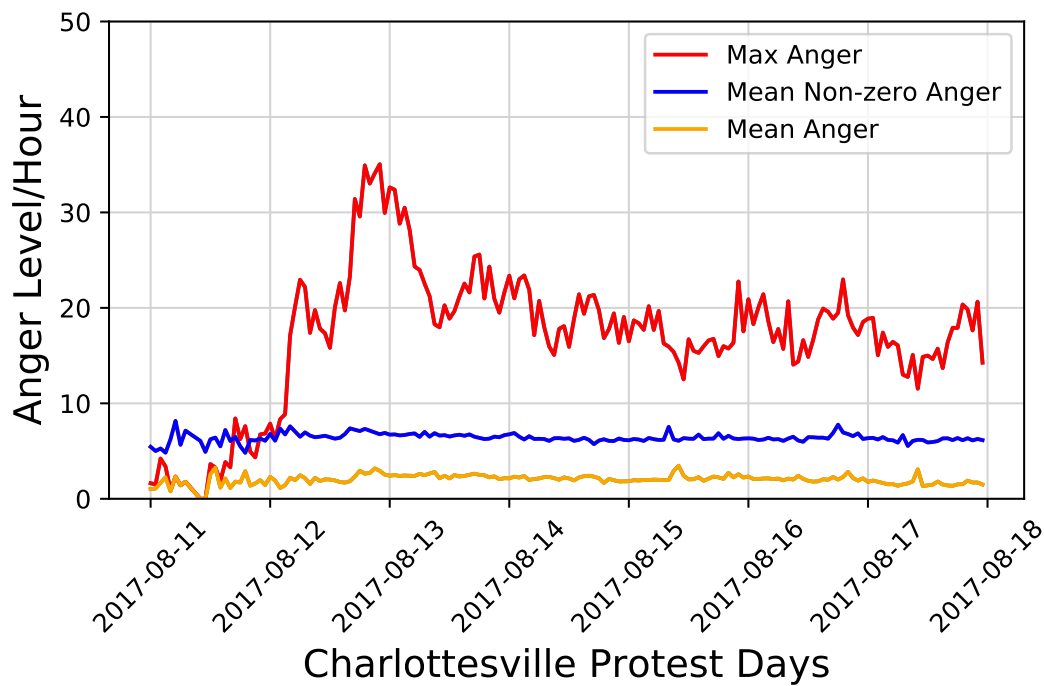
Figure 15: Anger Level Distributions of Tweets per Hour for the Charlottesville Protest Data Set.
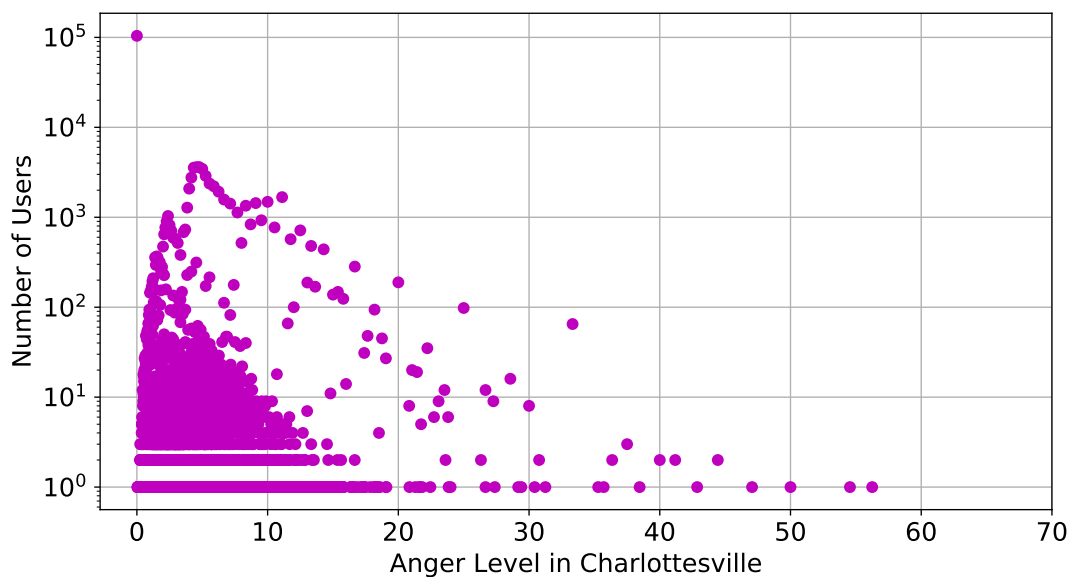
Figure 16: The Number of Users over Anger Level Distributions in the Charlottesville Protest Data Set.

3.1.3   Network Analysis

Twitter users are classified as public and influential users based on their number of followers [3]. Influential users are media channels, politicians, and celebrities, such as singers, actors/actresses, anchorwomen/anchormen, reporters, journalists, comedians, and authors.

Users can mention other users while posting their tweets. The user who mentions another user is called the source user, and the user who is mentioned by the source user is called the target user in this analysis. In addition, users can retweet other users' tweets. With retweeting, users simply copy the posted tweet from the target user. These processes build a mention network graph that shows connections among all users. This network graph can indicate the influence level distribution between source and target users. It is a directed network graph because it illustrates a link, which is created by mentioning, from the source user to the target user. To quantify the density of a relationship, the number of mentions from the same source user to the same target user is calculated. This density is called the weight of the link, and it creates a weighted directed network graph for mentions of Twitter data sets. Directed networks have "a rich topology" with containing a complex set of concentrating giant components [23].

The sample size and extraction process of the network are critical concepts. To be consistent and accurate; we select active users, non-duplicated tweets, and mentions with other users who did not mention themselves. We do not ignore these sensitivities to have larger data sets instead we carefully analyze meaningful data sets [13]. The

network graph visualizations are created with the Gephi software [6, 37].

3.1.3.1   Network from Charlotte Protest Data Set

For the Charlotte Protest Network, there are 430,260 users and 1,358,469 tweets. This data set includes duplicated tweets. To have better understanding, we removed duplicated tweets and the number of tweets, which are considered for the network, is 1,356,906. In other words, 0.12% of tweets are duplicated in the Charlotte data set.

To be consistent with the network size of the data sets, 5,000 tweets are randomly sampled out of the Charlotte data set, and from those tweets, users and their mentions are extracted. In this extracted network, there are 6,259 nodes and 5,656 edges. For visualization purposes, Figure 17 shows users/nodes who mention at least one user, meaning that having at least one link to a target user. The colors with the scale of pink show the highest modules in the network. The larger network visualization includes users without links on the outside of the network, and one can find this visualization in Appendix B.

In the Charlotte data set, most of the mentioned users are considered influential, which shows that influential users occur as the highest in-degree nodes in the core of the network [63]. For instance, users in the Charlotte network mentioned the Charlotte Mecklenburg Police Department, media channel (e.g., CNN), and the Black Lives Matter activist the most. We examined modularity measures of these network structures, which are quite high among users own networks/communities with a level of 97%.

Figure 17: Network Sample for the Charlotte Protest Data Set.

3.1.3.2   Network from Charlottesville Protest Data Set

The number of tweets for Charlottesville during the duration of the protest is 390,915; this data set also includes duplicated tweets. To get better understanding of the data, we removed duplicated tweets, which resulted in there being 389,524 valid tweets. In other words, 0.36% of tweets are duplicated in Charlottesville data set. In addition, there are 188,516 users in this data set.

As mentioned, to be consistent with the network size of the data sets, 5,000 tweets are also randomly sampled out of the Charlottesville Twitter data set, and from those tweets, users and their mentions are extracted. In this extracted network, there are 5,981 nodes and 5,719 edges. For visualization purposes, Figure 18 shows users/nodes

who mention at least one user, meaning that having at least one link to a target user. The colors with the scale of pink show the highest modules in the network. The larger network visualization includes users without links on the outside of the network, and one can find this visualization in Appendix B.
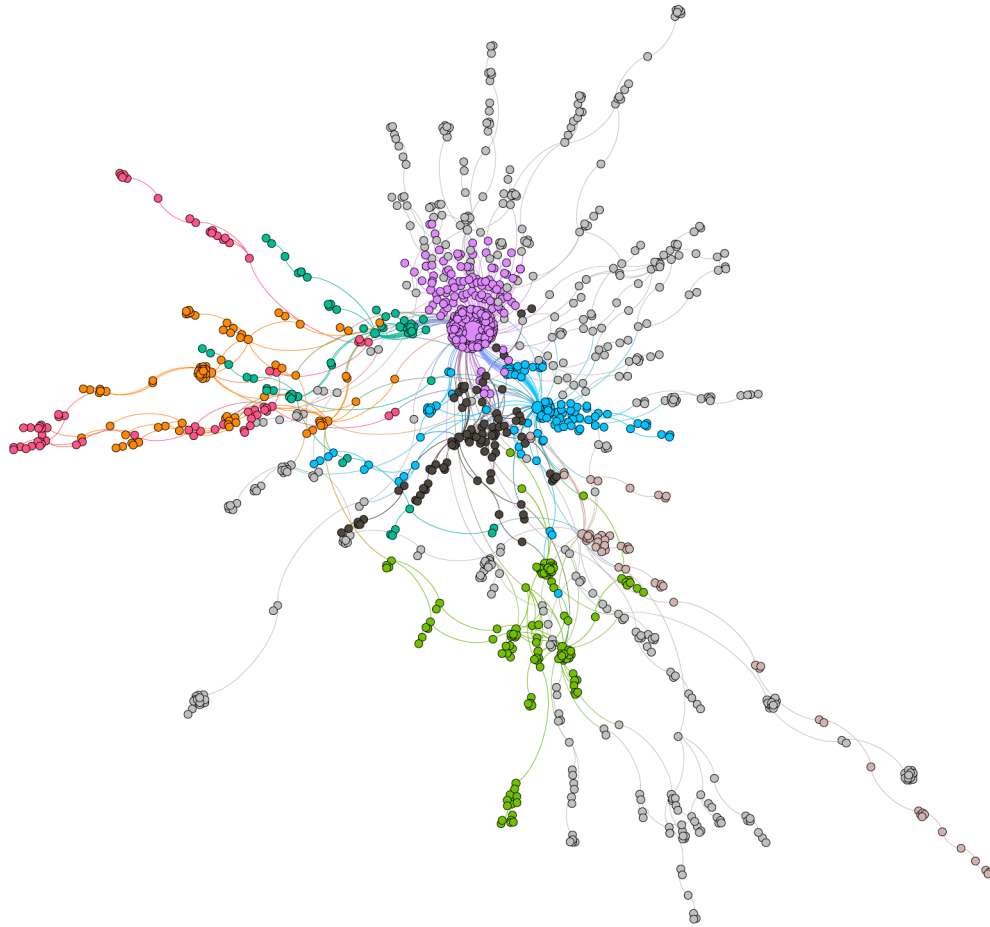
Figure 18: Network Sample for the Charlottesville Protest Data Set.

In the same fashion as the Charlotte Twitter data set, most of the mentioned users in Charlottesville are also influential. This shows that influential users, such as Donald Trump and social media platforms (e.g., Facebook and Instagram), occur as the highest in-degree nodes in the core of the Charlottesville network. This might indicate that Twitter users aimed at taking the government attention and sharing

the protest environment on social media. To better understand network structures, we examined modularity measures of the networks, which are high within users own networks/communities with a degree of 90 %.

3.2   Agent-Based Model

Gilbert [32] classifies ABMs in three forms, such as 'abstract', 'facsimile', and 'middle-range' models. Abstract models demonstrate a basic social process that may emphasize social life. Facsimile models attempt to reproduce a specific phenomenon as precisely as possible. These models are useful when predicting the future state of a phenomenon or when forecasting the effects of a policy [48]. Middle-range models fall between the abstract and facsimile ones with describing characteristics of social phenomenon. Our proposed model with ABM can be classified as middle-range in its nature and aim. Our goals are to investigate dynamics of anger spread in social media during protests through simulations.

Our proposed model has a directed network, which is created from mentions on Twitter protests data; users are nodes, and mentions are links in the network model environment. In this directed network, there are two types of nodes: influential and public users. According to our Twitter data analysis, influential users are the users who have the highest number of followers (e.g., 10,000) and public ones are the users who mentioned these influential and/or public users depending on the selected network structure.

Through mentions, users relate to one and other on Twitter; therefore, if there is a link between two users, it means that the source user connects himself to the target

user by mentioning her in his tweet. Each agent has an anger level and a directed link, which connects her to another agent. These directed links are weighted by the number of mentions on the correspondent link. Our model is constructed to answer two questions: What is the dynamic behind the anger spread in a protest network? What is the impact of the initial anger distribution of media and celebrities on social networks?

This simulation experiment of the ABM is built with a software, which is free and accessible, NetLogo [80]. The global variable is the expected level of similarities among users, and this variable, difference-level, is presented with a slider in the model environment. The model has two main procedures: setup and go. Steps for these procedures are introduced in Table 6. In this model, there are two agent breeds of users: public and influential users. Blue stars indicate influential users and agents appear as circular shape of varying colors according to their anger levels. Nodes/users have two attributes anger and updated anger according to anger of his or her connections. Connections are introduced by a directed link between a source and target node/user from their mentions. The directed links have a weight as an attribute and these links are fixed.

Figure 19 demonstrates the simulation interface for the user network. On the interface, you can import the network and set up agent attributes clicking the import-network button. This button also initializes the system. You can select how strong homophily is tested, using the difference-level slider. A network structure is imported from the Twitter data sets through csv import extensions on NetLogo [80]. When you click the import-network button, the system is initialized to the imported network's

Table 6: Main Procedures in the Proposed Model.

Procedure	Steps in the Respective Procedure
Setup	• Import network with nodes and links from the correspondent data set. • Clear all results from the previous run. • Set up users.
Go	• Ask public users: To update their anger according to their out-link neighbor. • Ask influential users: To update their anger with the current one.

initial conditions. Next, you can have options for observing your simulations with two run buttons: Click the run button and the program will update agents anger levels for the protest duration, which is 7 days or 168 hours. In this model, simulation ticks indicate hours in real life. Also, you can click the run-once button to observe model behaviors in each tick.

On the interface, there are five output graphs, which visualize the dynamics of the model. First, there is a histogram of the anger distribution in the population. Second, a graph shows the development of the range of the anger distribution (max[anger] - min[anger]). Third, a graph illustrates the dynamics of mean anger change over time for public and influential users. Fourth, a graph depicts the development of the variance of the anger distribution. Fifth, a graph reports changes in the selected
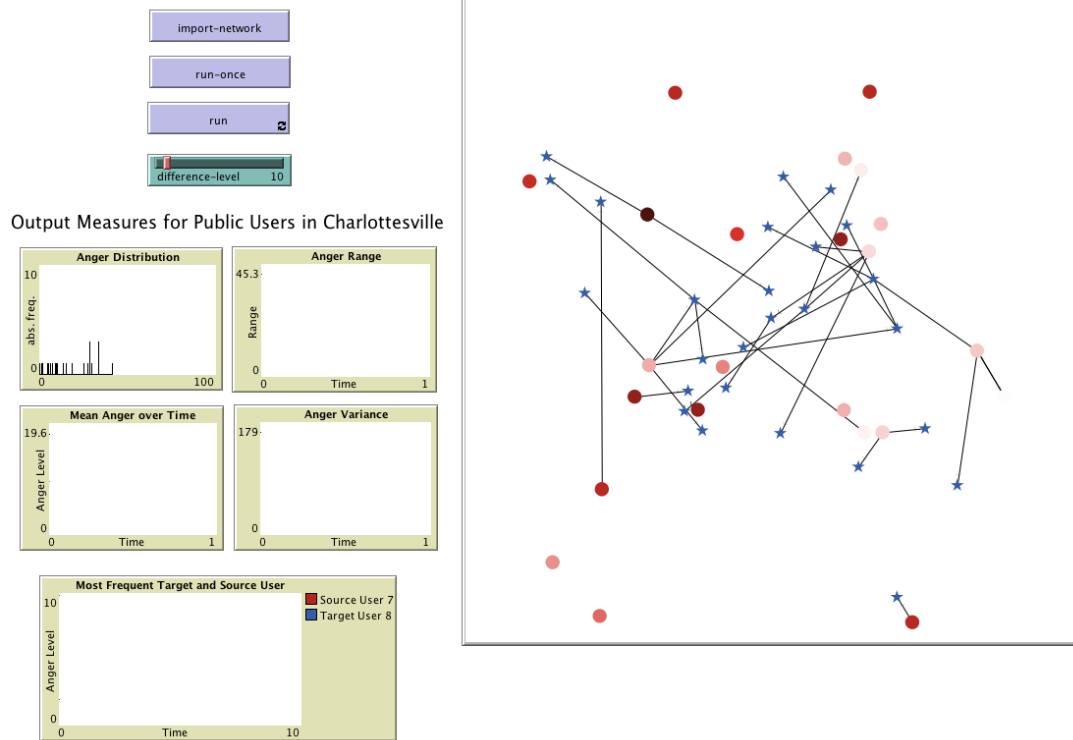
Figure 19: Proposed ABM environment.

source and target user anger levels over time. Our model is inspired by Michael Ms and Andreas Flache's model of the Social Influence, which has been implemented in NetLogo [56, 55].

The further model procedures for public and influential users are presented in Chapter 4, the following chapter, which introduces various experiments with different procedures.

CHAPTER 4: EXPERIMENTS

4.1   Model Assumptions

To understand social movements and their roots in protests, this study ran simulations through anger contagion in social media, specifically Twitter. Chapter 3 introduced how social media networks were extracted for general research purposes. In addition, this chapter will present various network structures with different anger spread algorithms with which to analyze distinct simulation experiments on these network structures. Before introducing the model experiments, six underlying assumptions for all experiments are stated:

1. Anger is the essential emotion that ignites protests. Other emotions, such as aversion, fear, or disgust, are excluded.

2. Twitter users are indicators of potential protesters, and there are two types of users based on their number of followers: influential and public users.

3. There is no difference between agents with pro- or anti-protest beliefs. All anger emotions arise due to the incident itself.

4. Links between agents are only from online connections through Twitter mentions. We are aware of the offline networks' effect on agent behaviors; however, due to the lack of personal information of Twitter users, offline networks are

not modeled.

5. The influence spreads with links trough Twitter mentions, and this influence only affects public user anger levels. The influence comes from the mentioned user; therefore, if there are no links to a target user, then the anger level stays stable. Influential users do not change their anger levels, except in extreme condition test models.

6. We examine network nodes with available data from Twitter. The users/nodes without anger or number of follower information are excluded from the networks.

4.2   Extracted Network Models

Three network structures are extracted from the Charlotte and Charlottesville data sets: (1) Top Active Public Users with All Mentioned Users (2) Top Active Public Users only with Influential Mentioned Users, and (3) Top Angriest Users with All Mentioned Users. All network structures are extended networks with extracting nodes for mentioned users' mentions as well. Also, active public users indicate the top 50 public users who tweet the most per hour.

4.2.1   Network 1: Active Public Users with Mentioned Users

The first network has nodes from the top 50 active public users, who tweet the most per hour. As mentioned before, public users are the ones whose number of followers is lower than 10,000. We extract mentioned users from these active public users and connect them with the directed and weighted links through their number of mentions. Target users in this network are public and influential ones, according

to the available data points in the data sets.

4.2.2   Network 2: Active Public Users with Influential Users

The second network differs from the first one only in excluding mentioned public users, which means it considers only mentioned users who are influential ones for the spread of anger. Therefore, there is a link between only public and influential users in this scenario. To test the anger spread from only influential users, the goal of this network is to examine the difference between the first and second networks for anger spread.

4.2.3   Network 3: The Angriest Users with Mentioned Users

The third network observes behaviors of the top 200 angriest users with their mentioned users. The aim of this network is to display the positions of the angriest users in the network and to analyze their behaviors under different scenarios.

4.3   Model Scenarios

Each network structure is run with parameters from the Twitter data sets over four scenarios for both Charlotte and Charlottesville: (1) Anger Spread with the Weighted Average of Anger Levels, (2) Homophily Desire Effect on Anger Spread, (3) Change in Anger of the Highest In-degree Node, and (4) Add a Link to the Angriest Users from the Highest In-degree Node. In total, 30 experiments are analyzed, and the most stimulating ones are represented in Chapter 5.

There are two main procedures, which are labeled as Import Network and Go, in Table 7 and Table 8 for the first two scenarios: the Anger Spread with the Weighted Average (weighted average scenario) and the Homophily Desire Effect on Anger

Spread (homophily scenario). The two tables have the same Import Network and Go procedures; however, they have different agent action rules that are shown with mathematical functions. In the Import Network procedure, all parameters and links in the model are imported from Twitter data analyses. The Go procedure is effective for public users because there is an assumption that influential users anger levels are not effected by their interactions for protest behaviors.

Table 7 shows the weighted average scenario, which investigates that the public user is impacted by her all linked user anger levels. As each link has a weight indicating a number of mentions, with these link weights, the public user updates his anger based on the weighted average. The second scenario explores the homophily effect, meaning that the public user is influenced only by those with similar anger level as him. This similarity level can be tested with various difference-level values by a slider for this global variable in the model environment. Table 8 shows the procedure for the second scenario. For instance, when you set the difference-level slider to a value of zero in the homophily scenario, agents are influenced only by their link neighbors that are perfectly similar to their anger level in their network. On the other hand, a difference-level of 100, assumes that agents are influenced by all link neighbors in their network. The values 0 to 100 of the difference-level are given to infer the agents empirical anger levels.

The final two scenarios further analyze the first two scenarios under different conditions. The third scenario, Change in Anger of the Highest In-degree Node, explores this node's effect on the entire network anger spread; the fourth scenario, Add a Link to the Angriest Users from the Highest In-degree Node, considers altering the directed

Table 7: Procedures for Agents in the Anger Spread with the Weighted Average of Anger Levels Scenario.

Procedure	Steps in the Weighted Average Scenario
Import Network	• Create the agents with importing agent attributes. • Color agents based on the agent type, such as for influential users color blue and for public users color red. • Scale color of public users according to their anger level. • Layout agents with spring-layout steps.

Updating public agents' anger

IF (# neighbors > 0):

$$\alpha(t+1) = \frac{\alpha(t) + \sum_i w_i \alpha_i(t)}{1 + \sum_i w_i}$$

ELSE:

$$\alpha(t+1) = \alpha(t)$$

$\alpha(t)$ - agent's anger level at time t

$\alpha_i(t)$ - i-th neighbor's anger level at time t

w_i - i-th neighbor's weight in weighted average (influence on the agent)

Procedure	Steps in the Weighted Average Scenario
Go	• Update the anger and change the look of public users if the condition is hold. • Stop after a week of the protest where every tick represents an hour.

links to undirected ones to analyze the change in the angriest user's impact on the entire network, where the highest in-degree node is connected to this angriest user.

Table 8: Procedures for Agents in the Homophily Desire Effect on Anger Spread Scenario.

Procedure	Steps in the Homophily Scenario
Import Network	• Create the agents with importing agent attributes. • Color agents based on the agent type, such as for influential users color blue and for public users color red. • Scale color of public users according to their anger level. • Layout agents with spring-layout steps.

Updating public agents' anger

IF (# neighbors > 0):

$$\alpha(t+1) = \frac{\alpha(t) + \sum_i \{\alpha_i(t) : \ |\alpha_i(t) - \alpha(t)| \leq \Delta\alpha_{th}\}}{1 + \#\{\alpha_i(t) : \ |\alpha_i(t) - \overline{\alpha(t)}| \leq \Delta\alpha_{th}\}}$$

ELSE:

$$\alpha(t+1) = \alpha(t)$$

$\alpha(t)$ - agent's anger level at time t

$\alpha_i(t)$ - i-th neighbor's anger level at time t

$\Delta\alpha_{th}$ - anger difference threshold (similarity measure)

Go	• Update the anger and change the look of public users if the condition holds. • Stop after a week of the protest where every tick represents an hour.

CHAPTER 5: MODEL VERIFICATION AND VALIDATION

A good Agent-Based model (ABM) should be "simple, valid, and robust" [67]. Sayama (2015) states that in order to have a scientifically meaningful ABM, "It has to be built and used in either of the following two complementary approaches: (1) Build an ABM using model assumptions that are derived from empirically observed phenomena, and then produce previously unknown collective behaviors by simulation. (2) Build an ABM using hypothetical model assumptions, and then reproduce empirically observed collective phenomena by simulation."[67]. Our proposed ABM is in the second category with understanding and observing collective behaviors of agents in protests.

Model verification is a process to make sure that our implemented model corresponds to our conceptual model in scientifically meaningful ways. In addition, model validation is a tool used to verify that our model shows realistic results as we see in the real world [81]. Both model verification and validation processes are for determining whether a model is a reasonable representation of reality. With comparing the model actions and data that are available for a related phenomenon, we determine whether the model has a valid background. As mentioned in Chapter 2, ABMs are built from agents; this can give an intuitive understanding of the agent definition and behaviors in the real world. We can directly compare the agents that exist in our model, Twitter users as public and influential ones, with those exist in Twitter social

networks today.

According to Wilensky and Rand (2015), there are two types of validation, such as "Face" and Empirical validation [81]. The first one helps convincing someone without any detailed information on the model. By looking at the simulated environment, one can understand the elements and components, which are related to agents and mechanisms in the real world. Our model, with its real representations for Twitter users and their networks, is one the audience can easily relate the model environment with the real world. Therefore, we expect to convince our audience with the "Face validation." The second type of validation, Empirical validation, is a process of comparing the data produced by the model to the empirical data derived from the real world. This comparison with the real data sets is based on the measures, macro and micro behaviors, and numerical data generated by the model results. Empirical validation shows us similarities between the model results and data sets.

For the model verification process, there are ways to explain our model with drawing the flowchart diagram and/or rewriting it in pseudo-code. To have better conceptual descriptions, Figure 20 displays the flowchart diagram of the proposed ABM. This diagram shows the model steps and agent roles until the decision making process through arrows. Our proposed model time period is 7 weeks, which is equal to 168 hours to match with the actual protest times according to the Twitter data sets.

On the other hand, the model validation process with the empirical validation has three rules to test on our models: (1) Set influential users anger levels to zero after a day of simulations, (2) Change in initial anger values of users while starting simulation, and (3) Compare changes in the most active user's anger levels in simulations
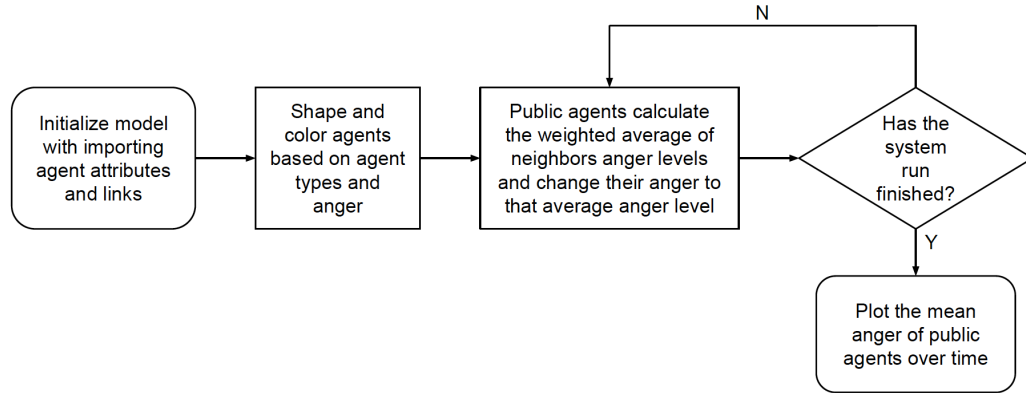
Figure 20: Flow Chart of the Model.

with the data sets. These rules applied to the Anger Spread with the Weighted Average of Anger Levels scenario as it is our base scenario. Also, they are run on the Charlottesville Twitter data set for this chapter. The similar results are observed for the Charlotte Twitter data set and included in Appendix C.

To validate the model with the first rule, we set influential user anger levels to zero after a day of simulations with a result of an expected decrease in the mean anger of public users over time. Figure 21 is a reference figure for the rest of the results analysis with its subplots. It shows the anger distribution, anger range, mean anger over time, and anger variance for public users. With the validation test of decreasing the influential users' anger level to zero after a day of simulation (equals to 24 ticks or time steps), 358 public users have an anger level of zero. Also, to analyze the individual user behaviors, the users who most frequently mention and who are the most frequently mentioned are selected. Figure 21 has a subplot for this analysis as well. The source user is a public user, and the target user is an influential user in the last subplot, which shows the influential user anger at level zero after a day of simulation runs.
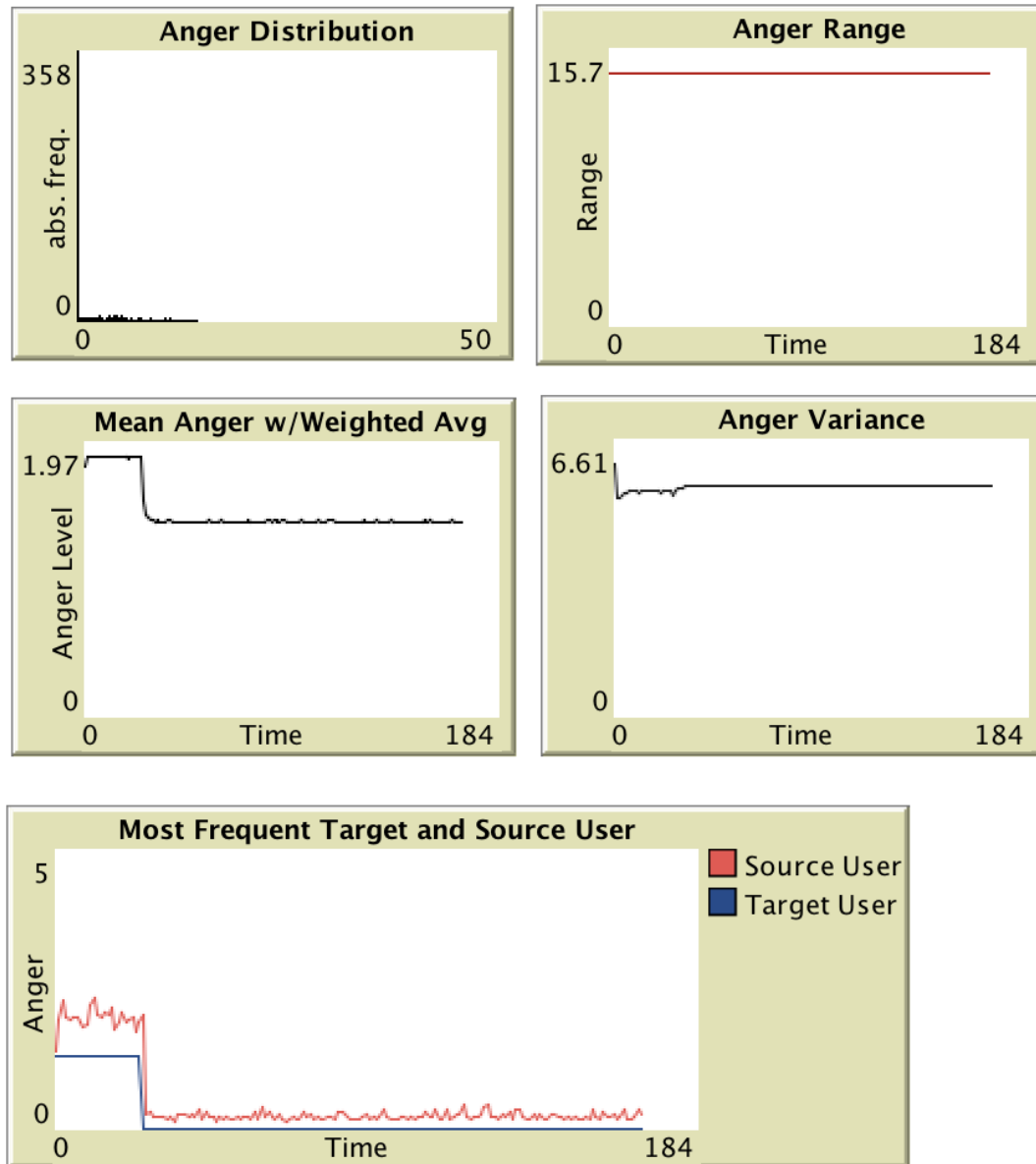
Figure 21: Validation Rule 1 for the Charlottesville Twitter Data Set: Change in Anger Values of Influential Users to Zero after a Day of Simulation.

For the second rule of our validation process, the model is initialized with the mean anger and maximum anger levels of users, which are extracted from Twitter data sets for users. Figure 22 has two parts from these simulations with two different initial values. The first part (a, on the left-hand side) shows the mean anger over time for all users in each tick/time step with the initial values of the mean anger of each user. The

second part has the same mechanism with the initial values of the maximum anger of each user. As the initial values are increased with the maximum anger levels, one can expect to see an increase in the anger range, anger variance, and the mean anger over time.
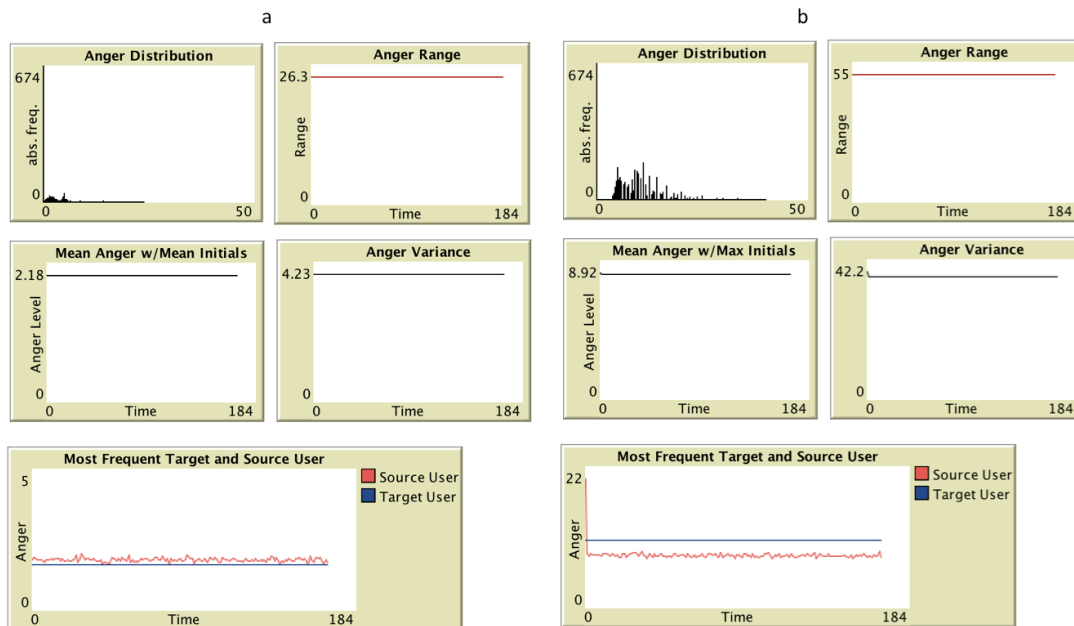
Figure 22: Validation Rule 2 for the Charlottesville Twitter Data Set: Change in Initial Anger Values of Users in the Initialization. (a) With Mean Anger Initial Values. (b) With Maximum Anger Initial Values.

The third step of our validation is to compare our model results for a specific public user, who frequently mentions other users most, to the empirical data analysis. There is a difference in these two behaviors. Before going into details, it should be clearly emphasized algorithms aim to quantify the spread of anger with mathematical functions in the simulation runs that we do not have calculations for in the real world. Therefore, our model does not follow exact anger level values but can have the similar pattern of the specific user; however, the simulation results closely match with the average anger level of the user, which is 1.38.
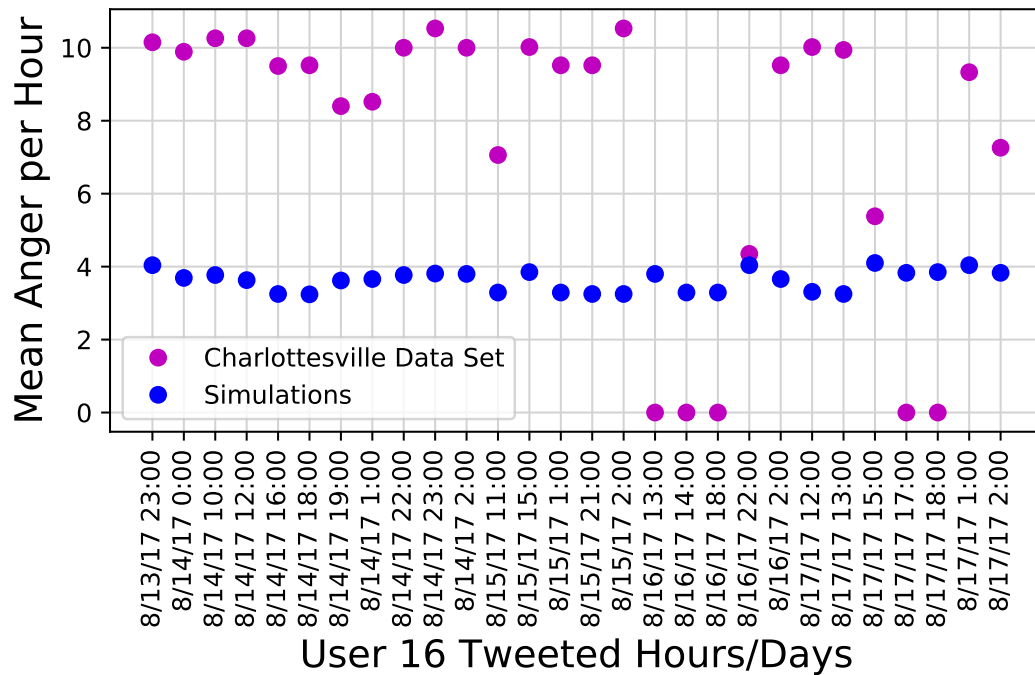
Figure 23: Validation Rule 3 for the Charlottesville Twitter Data Set: Compare a Specific User Anger Levels with the Simulation Results.

During our validation process, one challenge that we faced and that was understanding the one specific user behavior that is generated by the model comparing to the data itself. As we do not have a computational calculation for the spread of anger in real life, user behaviors can have different dynamics based on the distinct anger spread algorithms. Wilensky and Rand explain the challenge in running the empirical validation that "Inputs and outputs in the real world are often poorly defined or nebulous. The real world is not a computational machine with precise inputs and outputs." [81].

CHAPTER 6: RESULTS

Four scenarios were applied to three different network structures: (1) Spread of Anger with the Weighted Average of Anger Levels, (2) Homophily Desire Effect on the Spread of Anger, (3) Change in Anger of the Highest In-degree Nodes, and (4) Adjust the Network Structure with Undirected Links. For the network structures, we extracted three networks from Twitter data sets. The first network is with active public users and all their mentioned users. For the purpose of this research, we have defined public users as those who mention other people the most and whose number of followers is less than 10,000 in the Twitter data sets. The second network differs from the first one with mentioned users, who are the most active influential users with the number of followers more than 10,000. The third network is built for the top 200 angriest users and their mentioned users to investigate the angriest users, who are public and influential ones in the data sets.

Results of all experiments are presented to show the productions of our simulations on each network. The simulation results are exported from the NetLogo environment and plotted with Python in one graph for the results' comparisons in this chapter to have a better understanding [36, 39].

Figure 24 displays the comparison of the mean anger level among all users between the model experiment results and the Charlotte data set. In the first experiment, we consider anger spread algorithms as calculating the weighted average of the agent

out-link neighbors, and for the second experiment, we only consider the spread of anger among the agents who have similar anger levels. We have not seen significant differences in these two experiments because the influence in the mention network is one way (directed) and the network itself has limited connections with mentions. Therefore, the agent's anger level stays in her own community network and does not spread among the entire network.

If the model assumptions are changed to the undirected influence through mentions and all agents are influenced by their link neighbors, then the model results show similar patterns with the empirical data. In other words, our simulations and sample networks emphasized that the influence should be bidirectional, and there should be exogenous variables to shock the system during the protest times as we experienced in real life with news from the media channels and reactions of politicians or governors. In the first extracted network from the Charlotte Twitter data set, the most frequent user is a public user, and the most frequently mentioned user is a media channel, CNN. Therefore, we ran our third and fourth experiments on those users with adding a link to them and changing the link directions to undirected ones. The fourth experiment had a decreasing pattern as the empirical data follows in the Charlotte Twitter data set.

To compare our experiments in the Charlotte data set with the Charlottesville data set, a similar approach of the experiment analysis is conducted. Figure 25 displays the comparison of the mean anger level among all users between the model experiment results and the Charlottesville data set. In the first experiment, we consider anger spread algorithms as calculating the weighted average of the agent out-link neighbors,
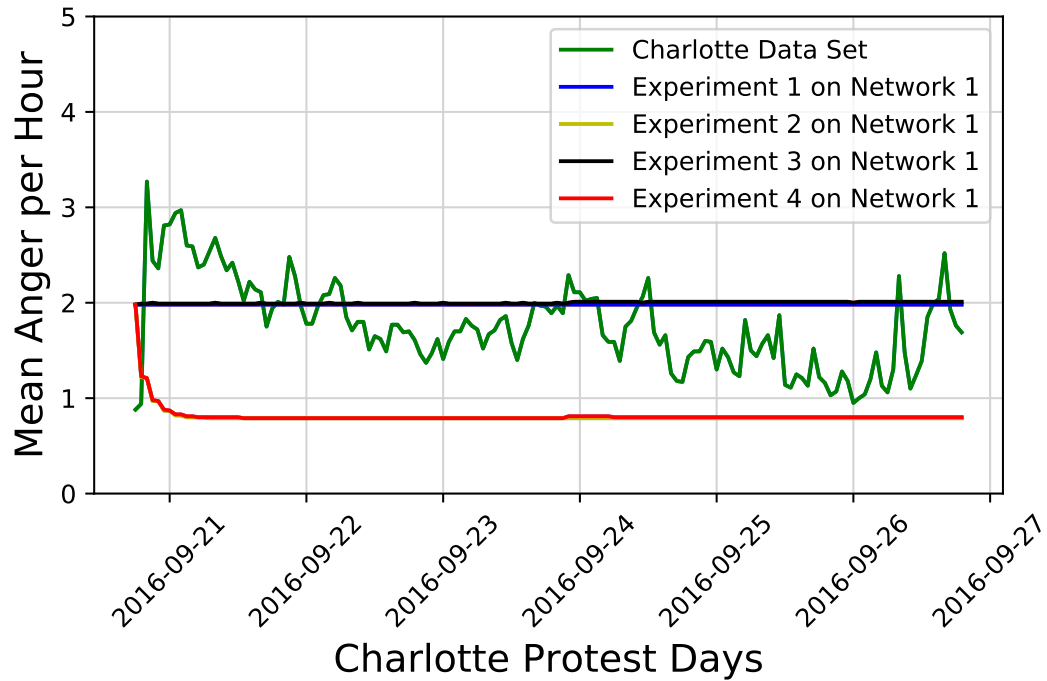
Figure 24: Experiments on Network 1 from the Charlotte Data Set: Active Public Users with Mentioned Users.

and for the second experiment, we only consider the spread of anger among the agents who have similar anger levels. We also have not seen significant differences in these two experiments due to the influence in the mention network's one-way (directed) nature. The network itself has limited connections with mentions as the Charlotte data set experiments depicted the similar results. The agent's anger level stays in her own community network and does not spread among the entire network. On the other hand, compared to the third and fourth experiments on the Charlotte Twitter data set, we observed nonlinear behaviors as the Charlottesville data set empirically shows oscillations in anger levels. Even though the oscillations' amplitudes are not exactly the same, the first sample of the network with active public users and all mentioned users from the Charlottesville data set still illustrates a similar pattern with the

empirical data along exogenous variables, such as an increase in the highest in-degree nodes anger and an additional influence from the inverse direction of mentions.
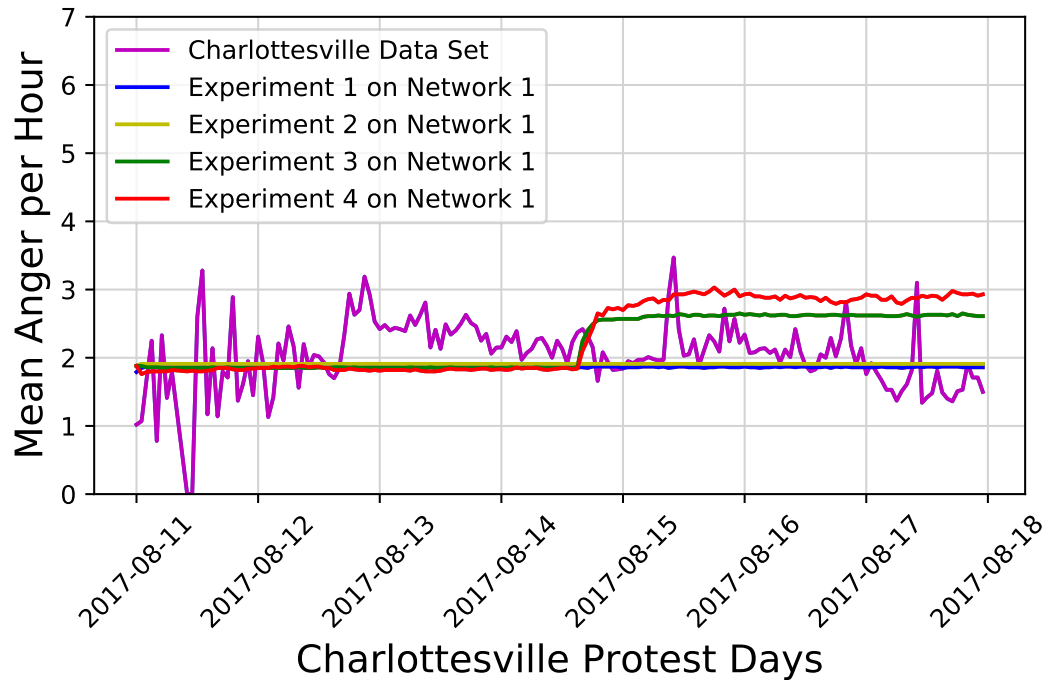
Figure 25: Experiments on Network 1 from the Charlottesville Data Set: Active Public Users with Mentioned Users.

The second network has only influential users as mentioned users to analyze the effect of the highest in-degree nodes (influential users). The experiments indicated no significant difference between the first and second networks, and a great number of mentioned users in the first network is influential users. Therefore, we do not include the second network results in the documentation. However, the third and fourth experiments have a similar interpretation behind the second network, and these experiments are displayed in the graphs.

For the third network, we consider only angry users and their mentioned users in the network structure. In the Charlotte Twitter data set, 33% of the tweets

with mentions are detected as angry tweets. Of the angriest users in the Charlotte

data set, out of the 100 angriest users, only three of them have more than 10,000

followers. The angriest users mention not only other random public users, but also

six influential users, who are an activist, a journalist, a comedian, a news channel, a

political figure, and one suspended account user. In addition, these angry users do

not have a significant number of followers, which indicates that they do not impact

spreading emotions and opinions on social media. In the data analysis, we show that

users who have the highest anger levels have a lower number of followers compared

to the lower anger level users.

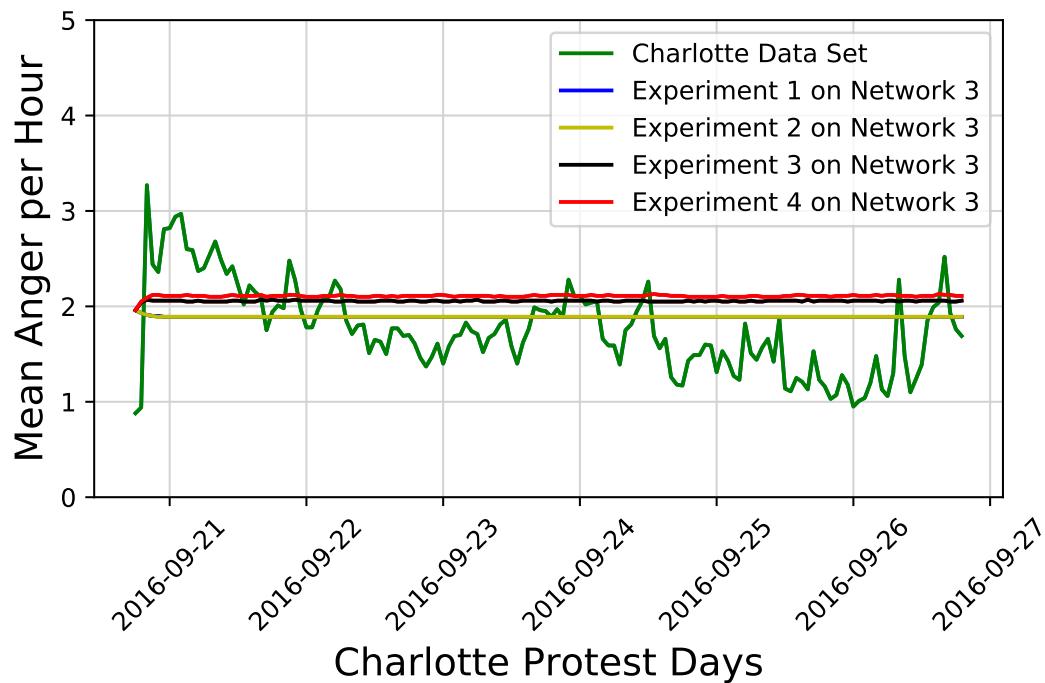

Figure 26: Experiments on Network 3 from the Charlotte Data Set: Active Public
Users with Influential Users.

The results of the third network analyses are compelling to better understand the

spread of anger among the users, but especially among the angriest user network.

Out of the top 100 angriest users in the Charlottesville data set, only six of them mentioned other users, who were a journalist, a commentator, a politician, a film producer, a news channel, and a public user. In addition, these angry users do not have a significant number of followers, which indicates that they do not impact spreading emotions and opinions on social media. In the data analysis, we show that the number of followers and the anger level of a user has a reverse relationship. Users who have higher followers are not angry. However, the angriest ones do not have a significant number of followers; therefore, their influence in the network is insignificant without any connections.

In our simulation results for the third network from the Charlottesville data set, there are 44 public and 43 influential users with a balanced structure. The most mentioned user did not tweet about the protests. Therefore, we do not have any information about his anger and his number of followers during that time. Because of this constraint, the specific user is not included in the network for Experiments 1 and 2 (see Figure 27). The angriest users are not the most active ones in mentioning other users; therefore, we have not seen any anger change according to our anger spread algorithms in the simulations. However, these results open us another research question with what happens if these angry users are well connected and affect the influential users? To answer this question, Experiments 3 and 4 are conducted. We could only observe an increase in anger levels only if the highest in-degree nodes and public users are connected, and their anger levels are not zero.

To summarize our results in this chapter before the discussion section, the significance of the network structure is an important element to explain. If it is a sparse
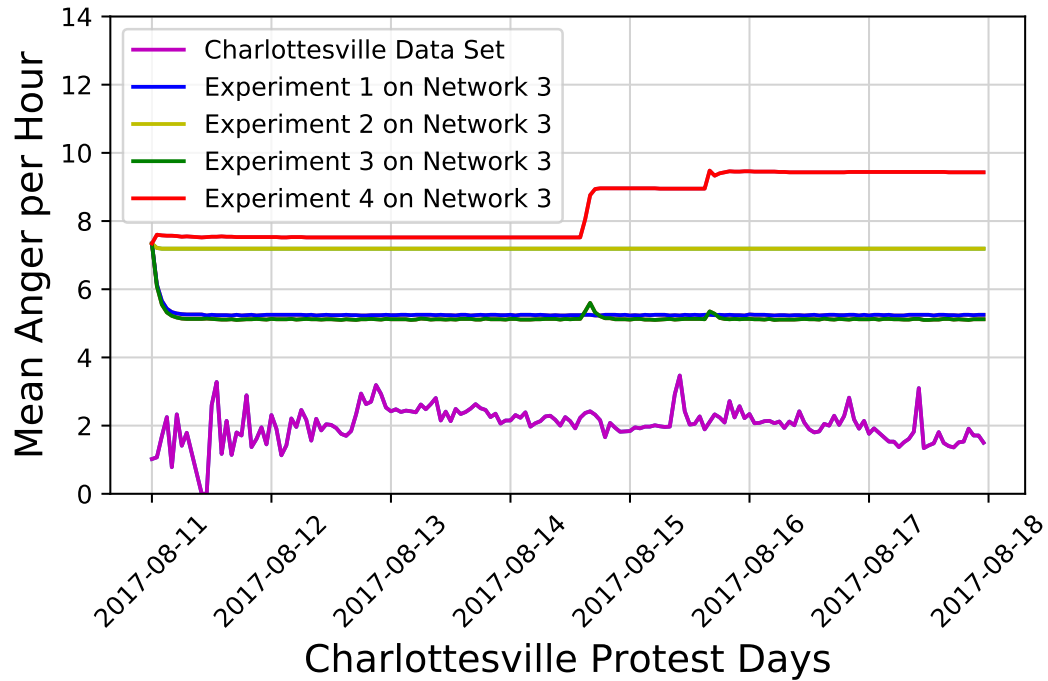
Figure 27: Experiments on Network 3 from the Charlottesville Data Set: The Angriest Users with Mentioned Users.

network, then agents are not highly connected to each other. Public users mostly mention influential users; therefore, according to our assumptions, there are no connections through their social network links among public users. However, the emotions of public users might be affected by offline links outside of their online networks. Also, as we considered only anger levels in our simulations, the neighbors' anger levels and the algorithm to calculate their anger levels are critical. If we combine the angry and isolated users together and connect them to the highest in-degree node, then the scenario of the politicians and/or media broadcasting about the protest is replicated. The effect of news and politicians' reactions should be considered in scenarios for the spread of anger as we see in real-world incidents, such as protest news from different locations.

Our findings show that, if the influence is directed, then the spread of anger is limited by this direction. However, if an assumption on the spread of influence with directed links changes to the undirected ones, then we would see dramatic changes in the spread of anger. The ratio of public users over influential users is also an important element; however, the numbers of public and influential users are not given randomly in the model. To be consistent with the empirical data, the percentages of public and influential users in the model environment are from Twitter data sets, and these numbers are set according to the networks in the scenarios.

The Charlotte data set has more angry users than the Charlottesville data set, and the nature of Charlottes network became more sparse as we ran experiments on the third networks extracted from Twitter data sets. Changing the anger levels of the top three highest in-degree nodes increases the mean anger level of the entire network. However, the total behavior is not realistic according to the data sets. Therefore, we applied the fifth scenario by adding a link to the angriest users from the highest in-degree node and changing the influence for both influential and public users. We have not seen significant changes; therefore, additional graphs are represented in Appendix C.

CHAPTER 7: DISCUSSION

Twitter is a micro-blogging platform that plays the role of "an electronic word of mouth" [38], and this function has an influence on people's emotions and opinions. Twitter data has been used to predict human behaviors in political manners, such as investigating political tendencies and voting paradigms [21, 20, 72, 70]. Also, Twitter social networks are analyzed with out-degree and in-degree centrality measures to investigate the influence within the network [75]. With the growing research area in the computational social science studies, agent-based modeling (ABM) is considered as a new approach for theory building in the social sciences [68]. For instance, modeling studies on the spread of ideas among groups have found the threshold for consensus [82]. However, the spread of ideas and emotions have a significant difference with the subject of spread. For models in the spread of ideas, researchers consider binary values to assign a citizen's preference for an idea or a political group. On the other hand, when it comes to emotional contagion, a spectrum of emotion is under consideration [9, 8]. Therefore, finding a specific threshold for emotion spread is more complicated than finding a threshold for the opinion change. When opinions and emotions vary constantly, the clustering of opinions in human populations is a complex phenomenon [56].

To build and/or test the social science theories on the spread of opinions and emotions among agents, social media platforms create a wide area for data collections

and parameter estimations for agent-based models. Since the combination with social media analysis and ABM has been augmented, the researchers have started working on emotional agents and the spread of emotions within the agents' network [11, 53]. Through our simulations, we sought to find the best fit from our sample networks to explain the macro behaviors from Twitter data sets on Charlotte and Charlottesville protests. To reach the similar patterns that are empirically observed, we need to shock the system at some points of the simulation runs. This shows that we need to have exogenous variables in our model to mimic news' and fake news' effects on human emotions and opinions and to reproduce politicians' and/or governors' emotional reactions. Also, one might argue to include offline network effects on human emotions and opinions in the model. Due to the lack of empirical information, we considered only online networks in our study. Keijzer et al.'s research (2018) can support this assumption with their new claim on the role of online social networks in communication between friends, colleagues, business partners, and family members [42]. Keijzer et al. show that "the online communication fosters cultural diversity to a larger degree than offline communication"[42].

Social science theories on a threshold for political protest participation are helpful to define important network structures for users. According to our data sets, the most active Twitter users are media channels, politicians, journalists, celebrities, singers, comedians, actors/actresses, and such individuals as those considered influential. Therefore, if one aims to investigate the protest network and anger spread in this corresponding network, then our model results show that the angry users' network should be built up with online and offline links. Based on different algorithms, the

anger spread benchmarks different values, such as the average of the neighbor anger levels. In the voting model algorithms, we see that decision updates happen based on the majority. On the other hand, people may care for the users that have similar anger levels as them. However, who we are connected to becomes very important for the spread of higher levels of anger. Angry users are not generally connected to the highest in-degree nodes and, if there are not enough media channels broadcasting this event, then the anger does not spread around.

The network science theories emphasize the importance of weak ties, which is a critical notion for our Twitter protest data sets. Twitter users mention the same influential user, but this user does not have any link to them. Granovetter (1978) demonstrated the relevance of this concept for groups [33]. Similarly, the researchers worked on the importance of linkage strength and breadth for social movement group [66]. In our simulation networks, the users who have the most followers are not angry, which shows that the users with a significant number of followers might have a tendency to show less extreme emotions as they are more careful with their reputation [54]. To understand the dynamics behind the collective behaviors, we should pay attention to thresholds for people to join collective behaviors [33]. With the spread of anger in online social networks, we investigate this threshold through mentions. However, for individual levels, users with online links should pair with other links representing offline networks, such as friends and family members.

With extracted networks, we investigated and compared the macro and micro pictures of protests across Twitter data sets. Our sample networks with different algorithms were extracted to represent reality. According to our findings, the network

with the active users and their mentioned users are the best-fit indicators for the re-production of the empirical data sets. The model findings also indicate that a protest organization's network attributes are an important determinant with the anger spread algorithms for an increase in mean anger levels [69, 22]. If one considers a scene with a real-world extreme experience of a protest behavior with a self-immolation, then he expects to observe a reaction from the crowd after the incident. To replicate the real-world cases and test different theories in the simulation model, there should be a combination of scenarios and underlying assumptions. Human behavior and emotional spread among their networks is a complicated phenomenon. Also, the network itself is a critical element of the research question. We noticed that, despite being two distinct events, the Charlotte and Charlottesville protests follow similar patterns with originating and spreading anger based on their different network structures. However, we noticed that this spread of anger may also depend on the agent susceptibility with how quickly she adopts or updates her anger level according to her neighbors.

CHAPTER 8: SUMMARY AND FUTURE WORK

This study has three goals. The first is to introduce literature on protest behaviors and social movements. Theories behind the common features of social movements and worldwide examples are emphasized. The second goal is to discuss current computational studies about protests represented in the literature, which is vast and growing. It helps to investigate other studies and to understand the ways for modeling social media's effect on social movements with the ABM approach. The third goal is to model spread of anger in a protest network structure through social media connections and capturing parameters from Twitter data of various protests.

Epstein's model continues to play a significant role in civil revolution modeling in ABM literature [29]. Other variations of Epstein's model are useful in improving the literature and investigating the missing aspects of collective behavior models. These aspects change over time because of the unpredictable and complex nature of humans and the continual rise of technological improvements. Lemos et al. have contributed to the protest modeling with ABM methodology especially with their ProtestLab model [48]. This dissertation aims to add value to the computational modeling area of social movements. The social media's effect on the relationship between agent emotions and network structures is modeled to analyze how anger emotions change over time. Our analysis can indicate possible protest behaviors under extreme changes and various conditions in agent emotions with understanding how emotions, specifically anger,

spreads in digital age social networks such as Twitter.

For this dissertation, we gained access to Twitter data sets on protests in Charlotte, NC (2016) and Charlottesville, VA (2017) with specific hashtags and keywords used during the relevant protest periods [45, 5]. Although these two protests differ in their triggering points, they have similarities in their macro behaviors during the seven days of peak protest time. We conducted descriptive statistical analyses on these data sets in order to compare them. For Charlotte and Charlottesville protest data sets, 1.36 million and 390,915 posted tweets have been extracted from Twitter, respectively. These data sets have 430,260 (Charlotte) and 188,516 (Charlottesville) unique users. Since our main research goal has been the understanding of social movements through anger contagion in social networks, we identified the anger level of these unique Twitter users from their posts with the Linguistic Inquiry Word Count (LIWC) method, which is a dictionary based approach to detecting emotions [65].

After applying this emotion detection method, we found that 32% of tweets in the Charlotte data set contain anger emotions. Similarly, 34% of tweets in the Charlottesville data set contain anger. From tweets, we calculated that the percentage of users with anger in the Charlotte data set is 47%, while 45% of tweeters in the Charlottesville data set contain emotions of anger. Therefore, we see similar distributions of anger in tweets and users in both cases despite differences in reasons behind the protests and the total number of tweets in these data sets within the same protest duration. Then, the obtained information about the number of followers for each user potentially indicates the influence level that each user has on others. Based on that, we classified users as public and influential ones. Most of the influential users,

those with more than 10,000 followers, are media channels, politicians, journalists, celebrities, singers, comedians, and actor/actresses.

In order to compute the degree of activity for public and influential users, as an indicator of their expressiveness, we consider the number of tweets posted per hour and per day by a particular user. A limited number of users tweet more than 10-20 tweets per day, while a significant number of users tweet less than that. These user behaviors demonstrate a heavy-tailed distribution, i.e., a power law. User anger distributions have a power law nature as well, with a few users who have strong anger levels. Among the users who are detected with anger, the top angriest users are public ones, and they have fewer followers compared to the influential ones, as one might expect.

The public and influential users on Twitter mention each other in their posts, which makes an impact on the source user from the target user (mentioned one/ones). We assigned a weight to a link based on the number of mentions. In other words, if a user mentions another user/users, then there is a weighted link between them, inferring a directed social network. We extracted two mention networks of influential and public users from the Charlotte and Charlottesville Twitter data sets. Most of the mentioned users are influential ones, which shows that influential users occur as the highest in-degree nodes in the core of these networks. To better understand network structures, we examined modularity measures of these networks, which are quite high within the user's own networks/communities. After implementing these networks in two separate agent-based simulation models in NetLogo, we ran experiments on the anger spread according to various theories, such as the homophily effect, the most influential

one effect, and the weighted average of corresponded network nodes [80]. In these experiments, there were two main assumptions: (1) Anger is the triggering emotion for spreading influence and (2) Twitter mentions affect distribution of influence in social networks.

By creating Twitter influence networks, we displayed various dynamics of anger spread among users. We found that user connections are essential for the spread of influence. For instance, the angriest users are the most isolated ones, with zero or less number of followers, which signifies their low impact level. Most of the users mention influential users, and even the influential users mention each other. Therefore, we cannot obtain a network only for public users as they do not often mention each other. However, this behavior of public users shows that if there is a change in the highest in-degree influential node, then this affects all public users' emotions and/or opinions.

We examined two protest Twitter data sets from different time periods in Charlotte and Charlottesville, which occurred for various reasons. The model verification process stems from these differences as they lead to similar patterns. In addition, we extracted specific user behaviors during the protest time to compare with our simulation results. Our findings showed that if the influence is considered a two-way relationship, then anger spread dynamics depict more realistic results with an impact on target users from source users. We also know that protesters have an effect on media-channels and politicians, who are influential users in our model. Therefore, another influence linkage in the social network, in addition to mentions in social media, should be taken into account. We would like to also further investigate the effect of

fake news on the spread of anger during protests with various agent types, such as media channels and bots to verify whether anger detection algorithm is crucial in the context of protests.

As mentioned, we used the LIWC methodology to detect anger emotion in tweets. However, we can create a context-specific protest dictionary to analyze posts. It would be worthwhile to compare our results with other protests overseas. We are interested in extending this research by analyzing larger texts and user behaviors from social media corpora other than Twitter. There is a novel research area to explore natural language processing algorithms in order to augment the existing agent-based models. In addition, it would be interesting to create links of mentions at the time that they happened and to analyze simulations of anger contagion with the dynamic network to refine a protest as an advocacy for change.

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APPENDIX A: ADDITIONAL TWITTER DATA ANALYSIS

This is the first appendix for additional data analyses of the Charlotte and Charlottesville Twitter data sets. The visualization graphs are shown in order according to the analysis and correspondent data set.
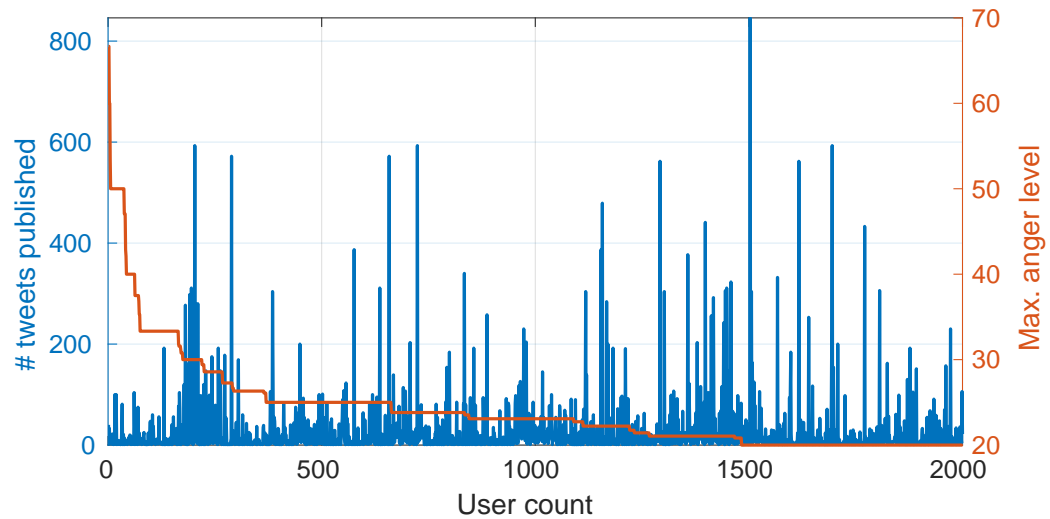
Figure 28: Number of Tweets and Maximum Anger Relationship in the Charlotte Twitter Data Set.
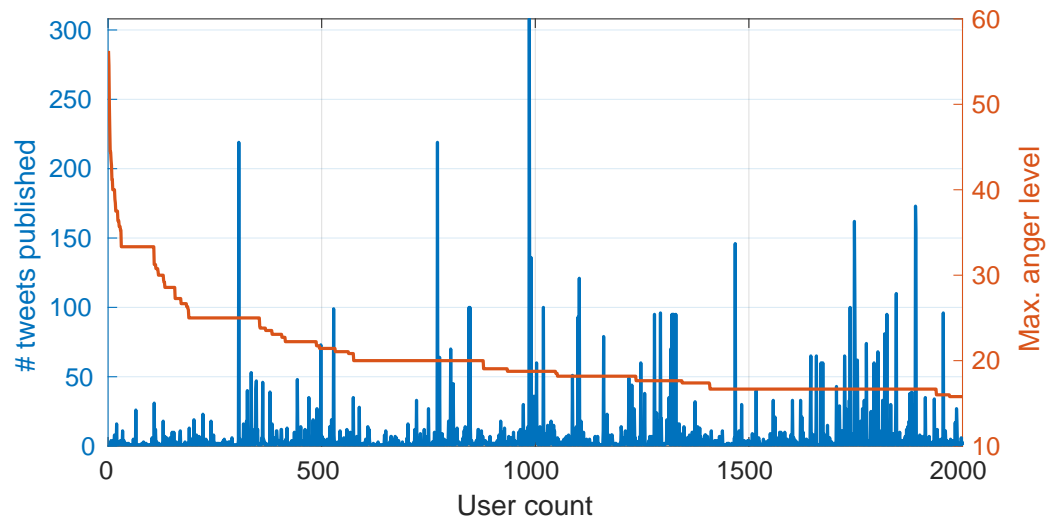
Figure 29: Number of Tweets and Maximum Anger Relationship in the Charlottesville Twitter Data Set.
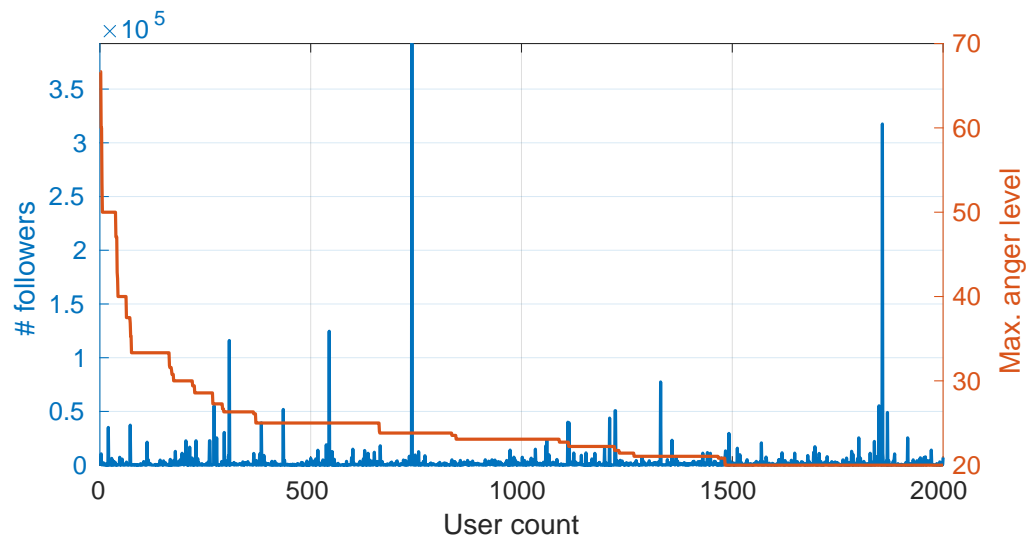
Figure 30: Number of Followers and Maximum Anger Relationship in the Charlotte Twitter Data Set.
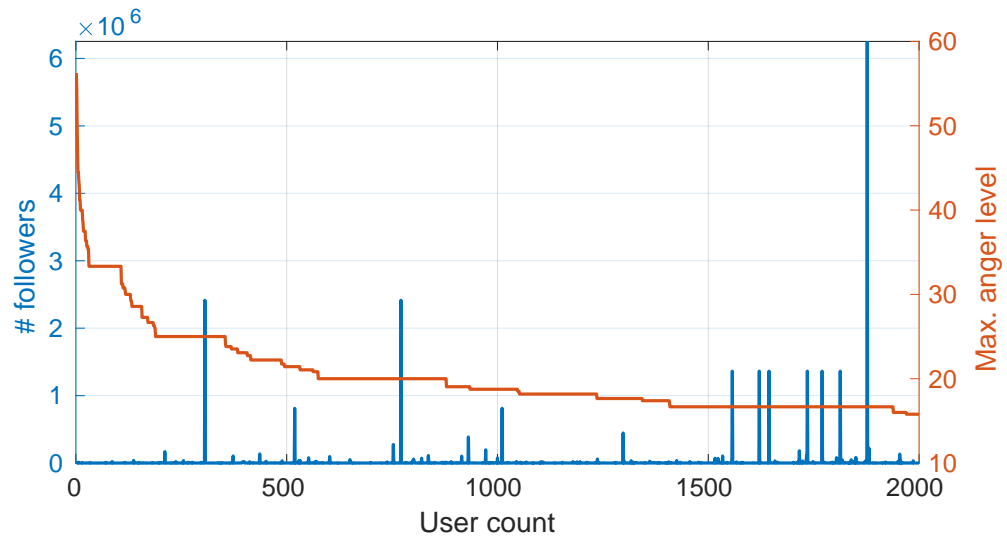
Figure 31: Number of Followers and Maximum Anger Relationship in the Charlottesville Twitter Data Set.
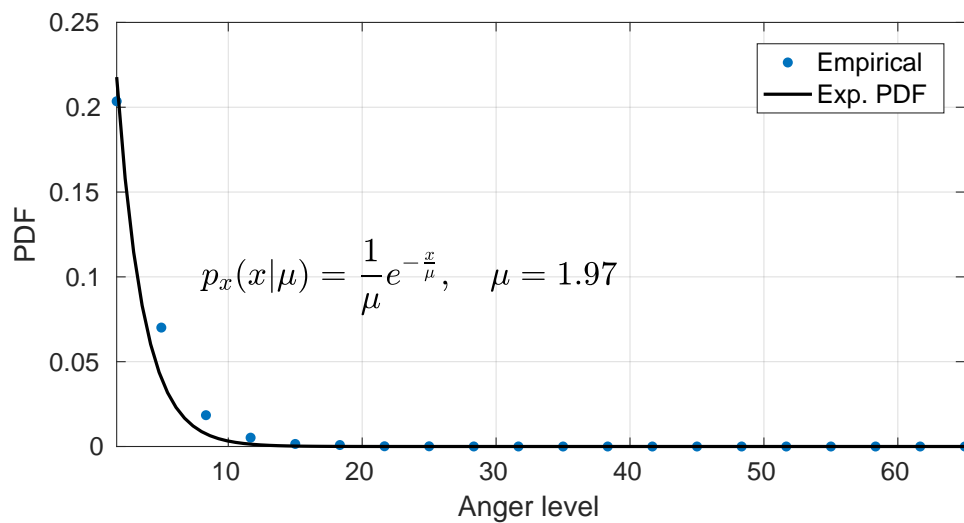
Figure 32: Probability Distribution Function for Anger in the Charlotte Twitter Data Set.
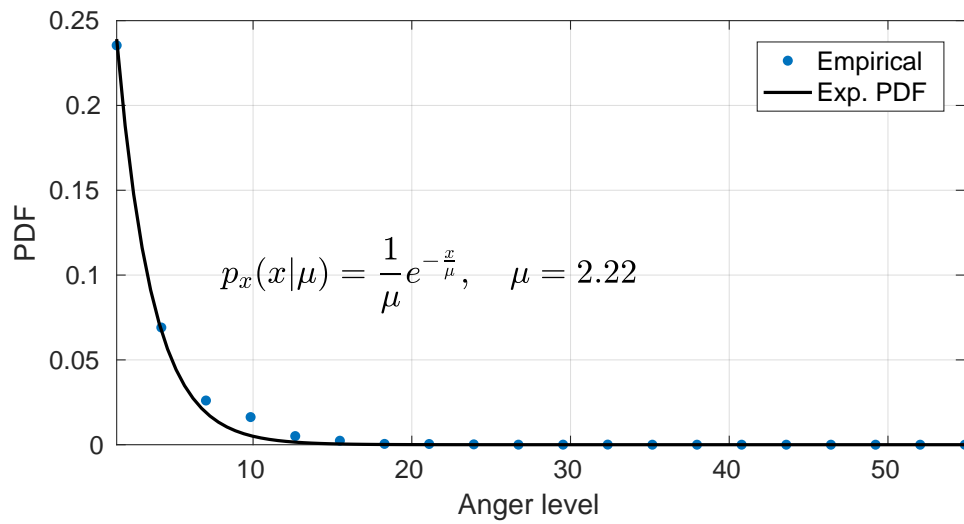
Figure 33: Probability Distribution Function for Anger in the Charlottesville Twitter Data Set.
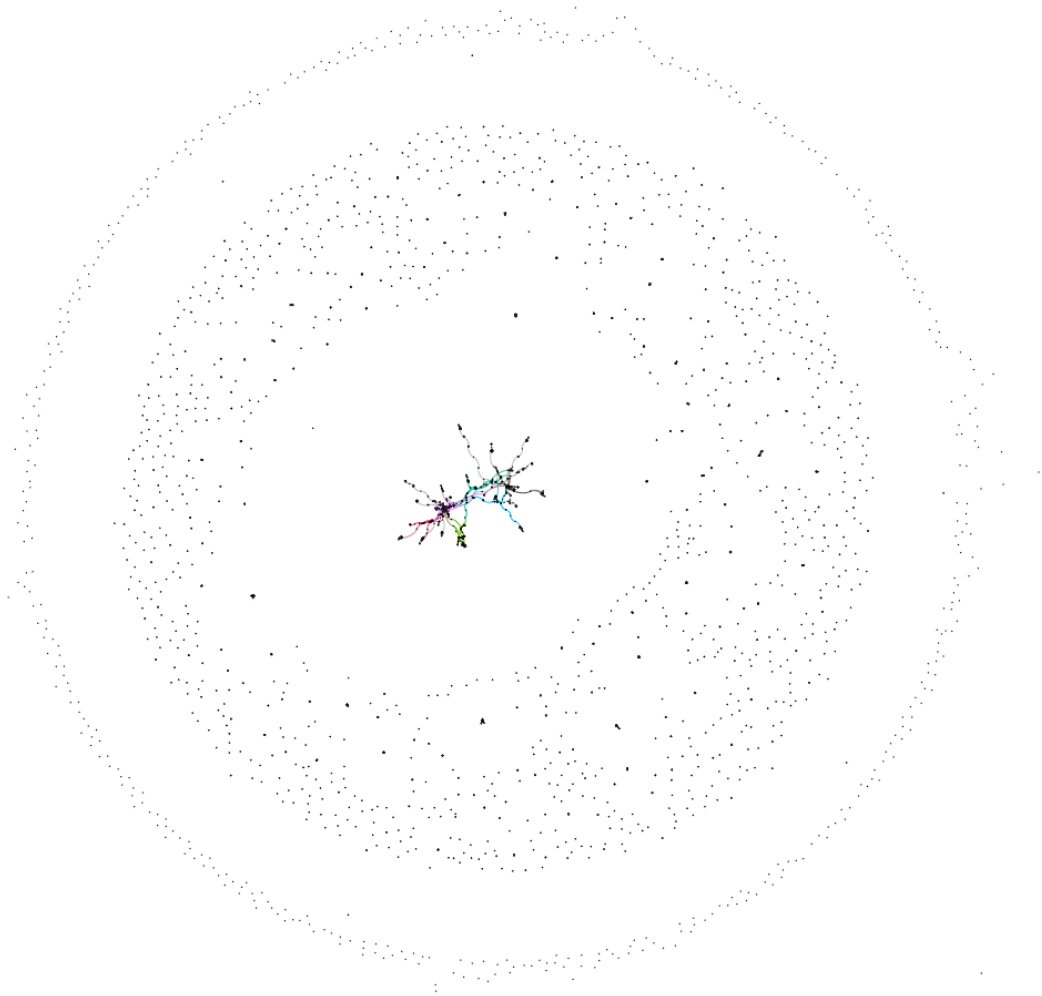
Figure 35: Charlottesville Network Graph Visualization for All Sample Nodes.

APPENDIX C: ADDITIONAL MODEL ANALYSIS

This is the third appendix for additional simulation model analyses on Charlotte

data set.
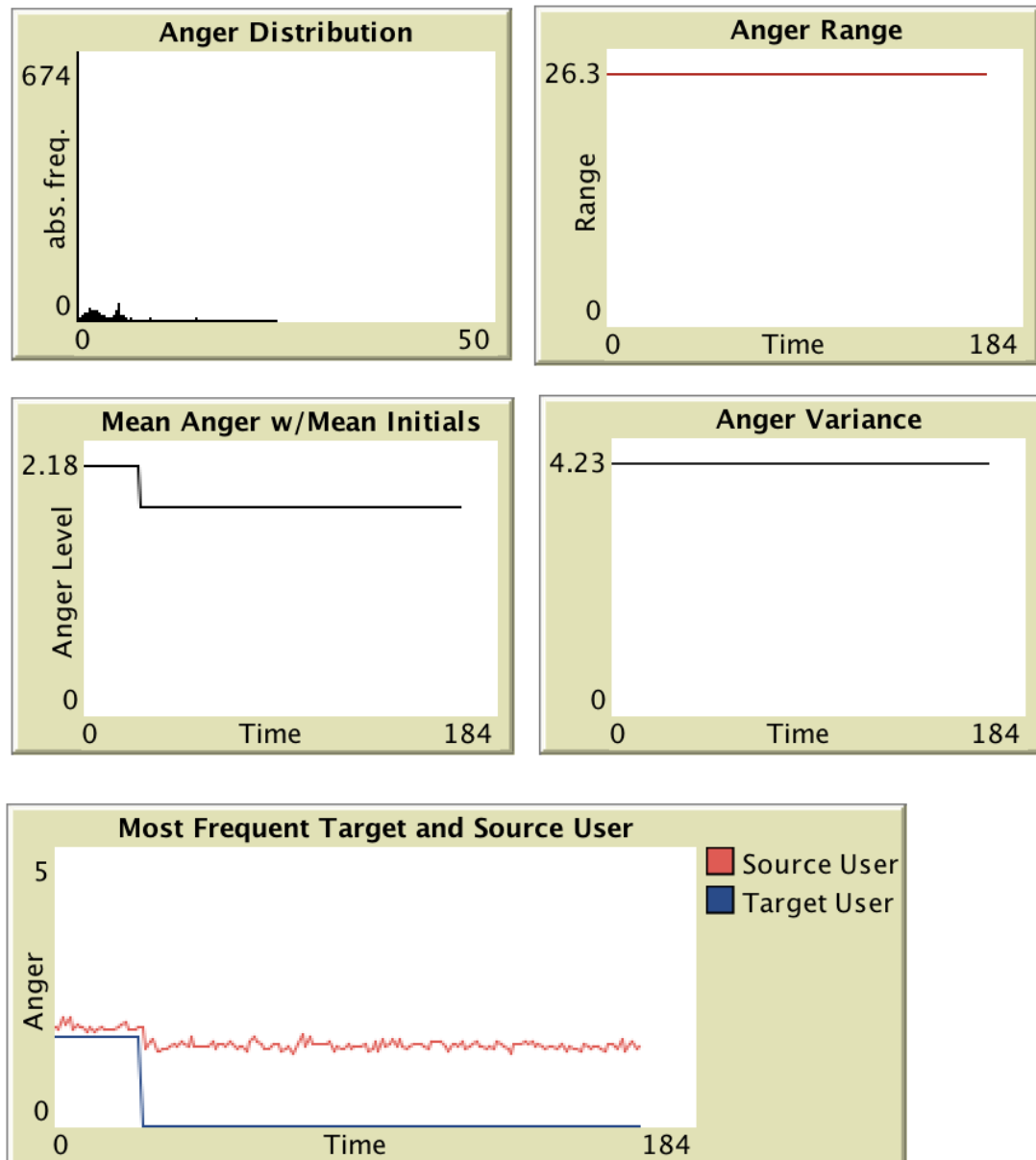
Figure 36: Validation Rule 1 for the Charlotte Twitter Data Set: Change in Anger Values of Influential Users to Zero after a Day of Simulation.
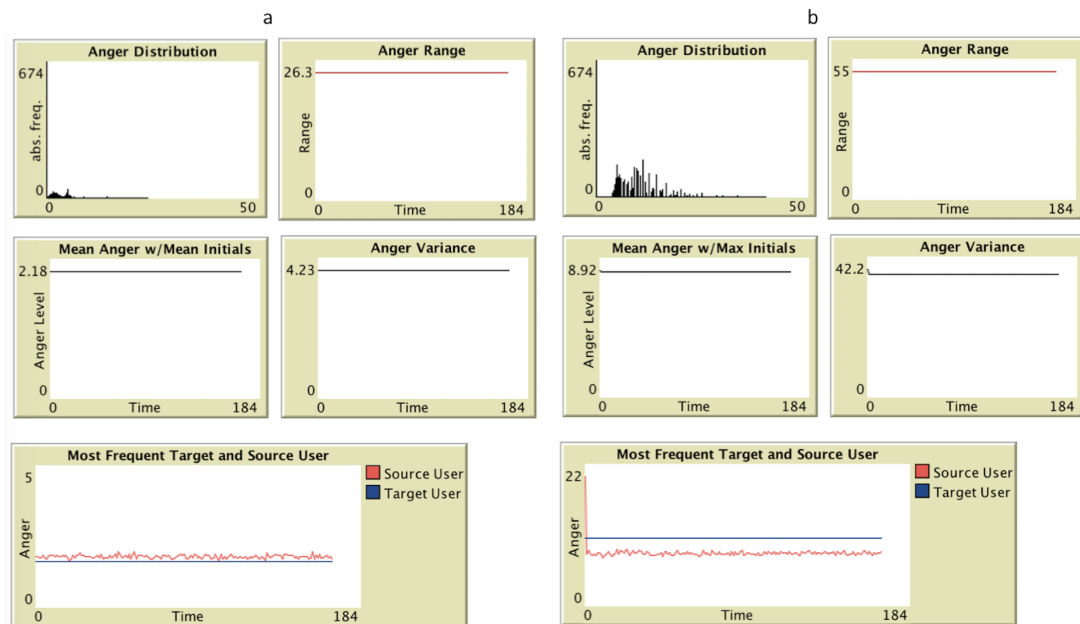
Figure 37: Validation Rule 2 for the Charlotte Twitter Data Set: Change in Initial Anger Values of Users in the Initialization. (a) With Mean Anger Initial Values. (b) With Maximum Anger Initial Values.
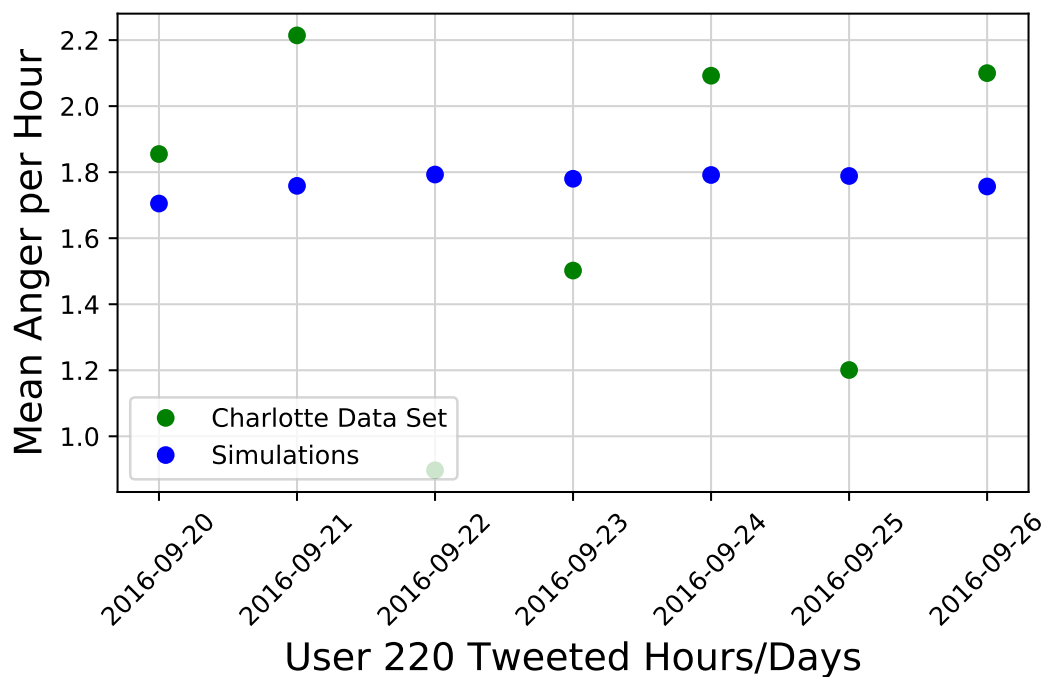

Figure 38: Validation Rule 3 for the Charlotte Twitter Data Set: Compare a Specific User Anger Levels with the Simulation Results.
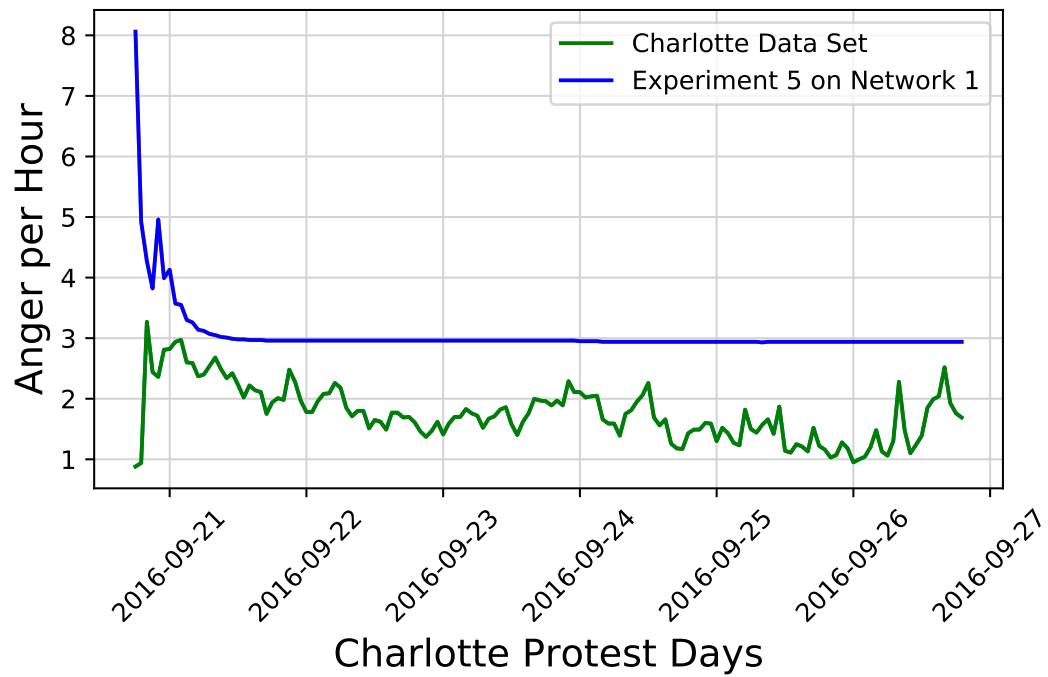
Figure 39: Maximum Anger Effect on Network 1 from the Charlotte Data Set: Active Public Users with Mentioned Users.
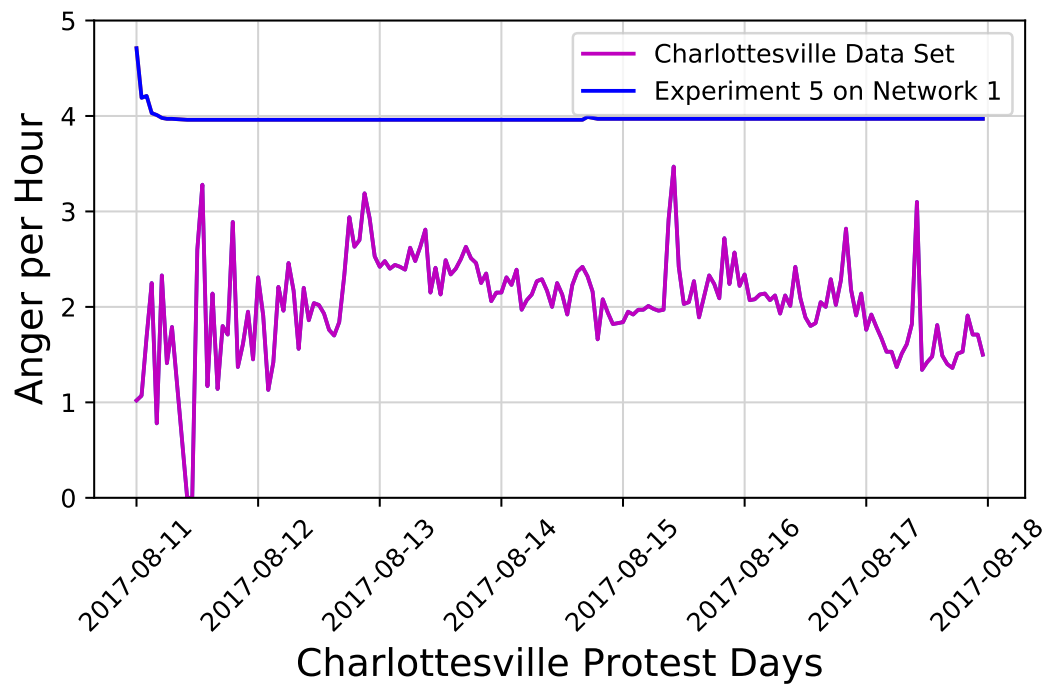

Figure 40: Maximum Anger Effect on Network 1 from the Charlottesville Data Set: Active Public Users with Mentioned Users.