Protest Participation in a Networked Society: Unraveling the Dynamics Through Agent-Based Modeling

Muhammad Rizki Duwinanto (s564971)
Daan Kaasjager (s3905845)
Kyriakos Antoniou (s5715881)
Pedro Lavin (S5509025)

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Abstract

The impact of social networks and interpersonal relationships on an individual's tendency to participate in protests is a widely researched topic. This report proposes a multi-agent system model designed to simulate the dynamics among three distinct types of social groups within a population (close friends, acquaintances, and network connections) and their influence on the emergence of protests. We define the concept of level of dissatisfaction, a metric that gives a notion of how likely an agent is to become actively involved in a protest. The experiment involves running multiple simulations with different relationship configurations and event types, focusing on statistical measures like average dissatisfaction. We conducted experiments to model Black Lives Matter historical events, purely random events and without any events. The results are that the dissatisfaction of agents with Black Lives Matter protests and random events can be accurately illustrated through the graph, demonstrating how close friends, networks and acquaintances combined significantly influence an agent's dissatisfaction and that with sufficient time for events, dissatisfaction among agents tends to increase. In contrast, a lack of dissatisfaction events results in dissatisfaction averaging out on the agents and then slowly decreasing with time.

1 Introduction

Protests are a powerful way for citizens to raise awareness or speak up about societal issues. People often come together in peaceful protests, which can become violent and chaotic but also disperse. Protests in recent years, such as the protests in Hong Kong, Iran, COVID-19 protests, and the BLM movement in the United States, raise questions about how these protests begin and what keeps them alive. The study of protests is not only of academic interest but also holds critical implications for policymakers, law enforcement agencies, and social activists striving for a more fair world.

Numerous factors contribute to what can only be described as a very complex social system. Social media has become increasingly important in spreading protests in the last decade. Using Agent-Based Modeling (ABM), scientists have attempted to model protests to determine which factors contribute the most to their instigation. Understanding the impact of protesters' different social networks on their eagerness to join a protest can contribute to answering what instigates and sustains protests.

1.1 State of the art

Protests occur when the social context leads to significant levels of grievance in a large proportion of the population.

People may become aware of the protest from several sources, and the decision to join the protest can be viewed as a contagion process [Eps02]. In other words, people may inspire other people around them to join a protest. Once assembled, the protest may remain peaceful, or part of the crowd may engage in violent confrontations with police forces. Depending on the intensity of the social conflict, the protests may persist in time or repeat cyclically, changing the social context.

Much research has been done on what instigates protests and how they escalate from peaceful protests to violent protests, riots, and even civil war. These factors depend on what drives people to join a protest. People's close network seems to have a major motivational impact. [OG93] has found that people are more likely to protest if their friends also protest. Furthermore, [Lar+19] has found through connection strengths on social media that online connection strength positively influences the likelihood of attending a protest. Also, research on the Arab Spring in Egypt has found that social media played a crucial role in the lead-up to the revolution [TW12].

1.2 New idea

While the importance of networks for the mobilization of protests is a well-established fact [OG93] [Lar+19], very little work has been done on applying this information in the context of ABM.

By examining the decisions of individuals and the micro-level interactions between protesters in a broader macro-level context within a simulated environment, we aim to uncover the hidden drivers of protest instigation and escalation. Using an ABM approach, we can model the importance of social networks in protests. Specifically, we can see the impact of close friends, acquaintances, and online communities on the probability of participating in a protest.

2 Method

2.1 Simulation model

We are mainly basing our model on the framework provided by a state-of-the-art paper on modelling protests using an ABM approach [Eps02], such as ideas about the macro and micro level interactions between agents in protest. We are then incorporating some missing aspects of the model created by [MR11] into our model, such as the different relationships between agents and a more realistic topology of agents' networks. This allows us to take a closer look at the effects of social networks on instigating, prolonging, and escalating protests. We will also include random events that can occur to simulate random occurrences that can happen on different scopes of a person's network (explained in more detail in section 2.1.2.

2.1.1 Citizens

Our model includes one type of agent, citizens, each having four types of relationships with each other: close friends, acquaintances, social network, and overall population. Our focus will be on how the relationships of agents affect the dissatisfaction of each agent and thus model protests and the effect that the relationships of agents will have on them. In addition, we explore how events such as government interference will affect the dissatisfaction of agents and, thus, the protest overall.

Dissatisfaction of citizens

Research has shown that people with lower trust in the government are very often more *dissatisfied* with the current political climate [WWP23]. Furthermore, grievance theory assumes that particular modes of political participation are stimulated by feelings of dissatisfaction or grievances [CM81] [Gam71] [AJJ71]. For these reasons, *level of dissatisfaction* (or simply *dissatisfaction* has been chosen as a metric for the probability of an agent joining a protest.

An agent's level of dissatisfaction represents how (dis)content they are with the current political situation. This number can range from 0 to 100, where 0 is an agent that is not dissatisfied with the current political situation, and 100 is where an agent is highly dissatisfied with the current political situation. The level is capped within this range to formulate a scale for our model's dissatisfaction level.

This influences agents in their network and can influence the probability of occurring events (more detail in section 2.1.2). For every iteration of the simulation, each agent will have its level of dissatisfaction affected by the agents connected to them and random events that will affect the dissatisfaction of agents. The dissatisfaction of each agent for the next iteration is affected by several factors, some of which are global, some shared between the agent's connections, and others specific to each agent. These elements are:

1. Current personal level of dissatisfaction (aka dissatisfaction)
2. The quality of a connection between two agents multiplied by the difference between each agent's dissatisfaction.
3. Events, which can occur on both local and global scales.

Each citizen has an innate value of dissatisfaction, which reflects each individual's susceptibility to protest. The values of each agent will be on a normal distribution, with the average value of all agents combined representing the global mean dissatisfaction of agents in the current political climate.

Relationships between agents

The relationship quality between two agents will determine the rate of change of the level of dissatisfaction. The higher the strength of an agent's relationship to another agent, the higher its effect on an agent. These effect rates will be summed and divided by the total effect rate that an agent can have so that there is a controlled change of dissatisfaction per agent per turn.

There will be multiple relationships between the agents, each affecting the dissatisfaction of one agent more than the other. The number of close friends, acquaintances, and social networks is based on a survey from [Pew23], an American research center. Stronger relationships will have fewer agents, while weaker ones will have more agents. The strength of the relationships will differ between agents. Stronger relationships between agents influence each other's dissatisfaction more than weaker relationships. In descending order of strength, the relationships an agent can have are the following:

1. Close-friend relationship (3 connections to other agents, which are interconnected)
2. Acquaintance relationship (10 connections to other agents)
3. Network relationship (50 connections to other agents)

The close-friend relationships will be the main factor of change in the dissatisfaction of an agent. The agents in these relationships will all be connected as close friends; in other words, agents will share friend groups. Because of the nature of the relationship, only a few agents will be grouped up per group. For example, In a 5-person close-friend relationship, each agent will have the other four as close friends. This is to model a family and best friend groups.

The acquaintance relationship will be the second most vital relationship. Each agent will have a group of agents as acquaintances, and all its acquaintances will have him as an acquaintance as well. For example, one agent will have ten acquaintances, and those ten acquaintances will have that one agent as an acquaintance. This is to model friend groups or befriend colleagues.

Network relationships are the weakest; this relationship will have a one-way connection where agents can connect to multiple other agents while the other agents do not need to follow them back; this simulates media and influencers.

As mentioned in section 1.1, [Lar+19] has found that social media (which would be on the social network scope) positively influences the likelihood of attending a protest. People who lack trust in the government (in other words, have a higher level of dissatisfaction) are also prone to be more active on non-institutional methods, such as social media, to voice their political views [WWP23]. Therefore, we can confidently say that agents with a higher level of dissatisfaction should be more likely to spread their dissatisfaction through their social network. Furthermore, According to [OG93], social networks (read: acquaintances and close friends) seem to have a major motivational impact on joining a protest. For these reasons, when agents interact in their network, the difference in the level of dissatisfaction affects both agents. However, agents that are more dissatisfied than other agents are not as affected by their level of dissatisfaction as the other way around. In other words, more dissatisfied agents 'pull harder.' This ratio is set to 2/3 (e.g., when agent 1 has dissatisfaction 100 and agent 2 has level 0, after their interaction, agent 1 has dissatisfaction 66 and agent 2 has dissatisfaction 33)

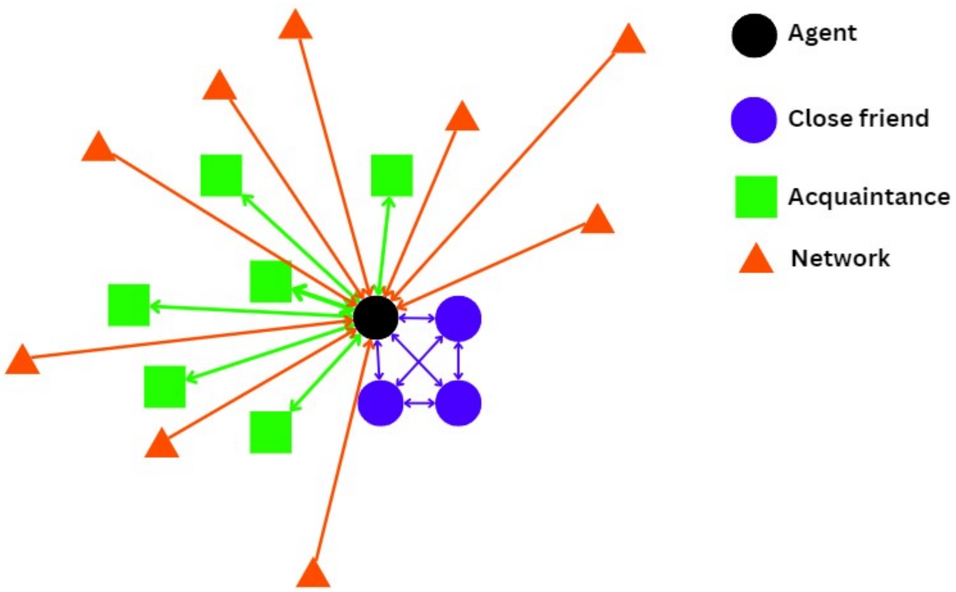

Figure 1: Image showing the different types of possible connections an agent (black) can have with other agents: close friends (blue), acquaintances (green), and network (red). Note that in the actual model, the number of agents in the network social group is much bigger than the number of acquaintances. labelfig:enter-label

2.1.2 Events

Events have a probability of occurring in each iteration of the simulation. Events can affect four scopes of agents. Events always affect the dissatisfaction level of the scope equally. It is essential to remember that the probability of an event occurring depends on many complex factors and has a significant variance. The probability of an event occurring can depend on time (in iterations, which represent days), dissatisfaction levels, or both simultaneously.

Events are an essential part of the model, as they create randomness. This is important because finding an equilibrium would not be realistic when modelling protests. Protests are chaotic; real-life events can disrupt the balance at any time. Pent-up frustrations are usually ignited into outrage due to a single event (e.g., George Floyd in the BLM protests and a newly presented nitrogen reduction plan for the Dutch farmers' protest).

There isn't a specific average number of large protest instigations in the world that can be readily quantified. The frequency of large protests, demonstrations, or social movements can vary widely yearly and from one region to another. It also depends on the social, political, and economic climate and the specific events or issues that prompt people to organize large protests. All the events can either increase or decrease the dissatisfaction level of agents on that scope. This list of events is not meant to be exhaustive; it is used to disrupt the model's equilibrium.

Events can occur on a:

1. **Global scope**. The event affects all agents in the simulation. Represents an event where something in a country occurs that increases the dissatisfaction of the entire population, instigating protests (e.g., George Floyd killing, the government passing an unpopular law, etc.).
   When the model starts running, a global event that increases dissatisfaction starts off the model, leading to protests around the country. The probability of such an event is low, as a significant global increase in dissatisfaction is the cause of a major outrage. Events where the global level of dissatisfaction decreases increase with the probability of occurring when the level of dissatisfaction has been high for a long time. As this is often a direct result of the protests, the more influential the protest, the more chance there will be some form of systemic change.

2. **Network relationship scope**. This event affects the entire network of a single agent. Represents an event where something occurs that increases the dissatisfaction of everyone on that person's network (e.g., the agent posts a politically charged Instagram story).

3. **Acquaintance relationship scope**. This event affects all of the acquaintances of a single agent. Represents an event where something in occurs that increases the dissatisfaction of each acquaintance of that person (e.g., the agents raise awareness for a subject at work)

4. **Close friends relationship scope**. This event affects all of the close friends of a single agent. Represents an event where something occurs that increases the dissatisfaction of each close friend of that person (e.g., The agent has been arrested by the police during a protest).

The events are implemented through a function with different parameters controlling the various events. First, the scope parameter determines how many citizens are affected by that event (close friends, acquaintances, network, or global). Secondly, a parameter controls whether the event will increase or decrease the dissatisfaction of the selected group. This parameter is related to the next one, the event's impact, which ranges from 0 to 100. For events that increase the dissatisfaction, the average dissatisfaction of the group affected by the event is calculated. Then, the dissatisfaction of the affected group is increased depending on the impact parameter (if the impact is 100, the dissatisfaction will be increased up to 100; if it is 50, it will increase up to a midpoint between the current value and 100). A similar approach happens in the events that decrease dissatisfaction (a 100 impact will lower the dissatisfaction to 0, while an impact of 50 will set the dissatisfaction between the current level and 0). The last parameter that needs to be specified in the event function is the probability. This refers to how probable an event is for each iteration to happen. A probability of 1 indicates that it will happen in every iteration of the simulation, while a probability of 0.5 means that it will only happen in half of the iterations. Following the construction of our model from real-life social group dynamics, close friends' events will be more common and happen more often than network events.

2.1.3 Model Progression

In the initialization process of the model, several variable numbers will be requested from the tester; these are the average affect rates of each scope, the minimum amount of agents in each relationship, and the average dissatisfaction of the entire population. The variables will create a pool of agents with their affect rates and dissatisfaction normally distributed according to the inputs. The testers then set the model to have random events and the strength of those events or leave it random.

Once the model is initialized, it runs for a set amount of time; at the start of each turn in the time frame, the possibility of a random event or a scripted event depending on the turn and dissatisfaction of the population happens. A random number of agents selected at random have their scopes affected according to the event; no agent is affected twice by the same event, but multiple events can also take place in one turn. Here *PullRatio* is determined by which of the two agents interacting has the higher level of dissatisfaction.

Then, the dissatisfaction of each agent is updated by the following function.

$$\begin{gathered} DissatisfactionChange = MaximumEffectRatePerTurnOfAgent* \\ ((CloseFriendsEffectRate * (CloseFriendsAverageDissatisfaction- \\ AgentDissatisfaction) * PullRatio + AcquaintanceEffectRate* \\ (AcquaintanceAverageDissatisfaction- \\ AgentDissatisfaction) * PullRatio + NetworkEffectRate * (NetworkAverageDissatisfaction- \\ AgentDissatisfaction) * PullRatio)/TotalEffectRate) \end{gathered}$$

Which gives a weighted dissatisfaction change towards the direction in which the agent is most affected.

Then, data is collected about the dissatisfaction of specific agents, their scopes, and averages of different agent scopes and the entire population. There is also a constant global decrease in each agent's level of dissatisfaction, as shown in Equation 1. This is implemented in the model to represent the protests slowly dying out over time.

$$\text{affected\_dissatisfaction} = \text{affected\_dissatisfaction} - 0.04 \times \frac{j}{iterations} \tag{1}$$

2.2 Implementation details

We use the Python programming language to implement the models as it has many libraries and frameworks that support agent-based models. Python has high readability and can be used as a procedural and object-oriented language. Using Python Object Oriented Programming, we can create classes to define agents as shown in Figure 2. Also, Python is usually a great language for data analysis to help process our findings based on the data generated from the experiments. Additionally, Python can be utilized for data visualization from models and agents with many available libraries, for example, Matplotlib [Hun07] and Seaborn [Was21]. We can implement a user interface based on the Jupyter Notebook with the given libraries without difficulties. We also use Numpy Library [Har+20] to help assign and process the array of the objects.

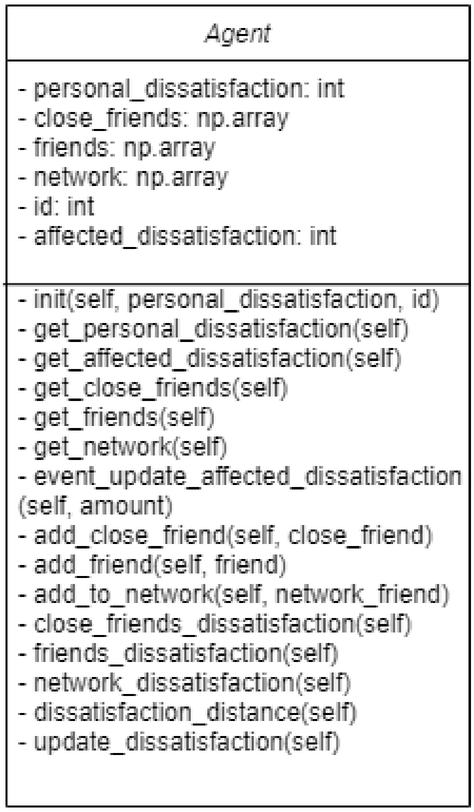

Figure 2: Class Diagram of the Implementation of the Agent-Based Models

We have selected both Matplotlib and Seaborn as libraries to visualize our model. With these libraries, we can process and analyze the data generated from multiple runs of the model and visualize using the plot function to create a line graph. We chose to run it on Jupyter Notebook because it can give better data analysis and visualization of each experiment.

2.3 Experiment design

As stated in the introduction, this research aims to see the impact of close friends, acquaintances, and online communities on the probability of getting involved in a protest. The previous sections of this methods section have defined the different levels of relationships, the level of dissatisfaction has been defined as a metric to measure this probability, and the model progression has also been defined.

Based on the literature from[Eps02] [OG93] and [Lar+19] the following to hypotheses have been constructed:

1. Each relationship type affects the dissatisfaction of the agents in a different way.
2. Combination of relationships has a similar effect on the dissatisfaction of the agents as the relationships that were used in the combination.

To test the first hypothesis, we ran our model in 8 different settings for the first experiment, plotting a graph of the level of dissatisfaction over time for each experiment setting. Therefore, each graph will represent a different experiment setting for the first experiment. The first graph is our baseline, where no relationships exist in the agents and are only affected by the events in the timeline. The agents have different relationships in the following three graphs, allowing us to compare each relationship with the baseline. Furthermore, we plot four additional graphs with all the possible combinations of relationships. On each graph, only the relationships plotted have an affect rate, setting the rest to 0 and removing all the other relationship connections.

For this experiment, we ran each scenario on a seeded event list. The Black Lives Matter historical events were used to create a similar to real-life event list. The event list was created to be semi-randomized; it is split into years where the probability for an event to occur in a specific year is the amount of events that happened in that year divided by 365 (leap years are not simulated).In addition, certain events do happen at specific times in the event list; for example, the major increase followed by the major decrease in dissatisfaction are both scripted events. After that, we collect the distribution of each agent's dissatisfaction and plot the data into line diagrams. We calculate the statistical measures for each scenario and analyze the data for each scenario to understand better how each agent's dissatisfaction is influenced. The statistical measure we focus on for this experiment is the average dissatisfaction of all agents. Each event has an effect rate on how much each relationship group will be affected. Each event affects a random agent's relationships; these events are trying to model real-life events of police brutality that lead to deaths. In addition, there are also global events where these are trying to model real-life events, such as protests, which spread awareness of police brutality. Below are the events in the Black Lives Matter event list in iteration order. As time iterations pass, the effect each event has on the entire population increases, simulating how people get more and more angry the more an event happens.

- In the first 365 iterations (first year), 12 events increase the dissatisfaction of a random agent's relationships: 100 for himself,100 for his close friends,70 for his acquaintances,10 for his network, and 0.5 for the entire population. These events try to simulate the change in dissatisfaction from the 12 deaths between 2014-2015 due to police brutality. In addition, one event models a protest, increasing the dissatisfaction of the entire population by 1.
- In the next 365 days (second year), 15 events increase the dissatisfaction of a random agent's relationships to 100 for himself,100 for his close friends,70 for his acquaintances,10 for his network, and 1 for the entire population. These events try to simulate the change in dissatisfaction from the 15 deaths between 2015-2016 due to police brutality. In addition, 10 events model protests, increasing the dissatisfaction of the entire population by one each.
- In the next 365 days (third year), 15 events increase the dissatisfaction of a random agent's relationships; to 100 for himself,100 for his close friends,70 for his acquaintances,10 for his network, and 1.5 for the entire population. These events try to simulate the change in dissatisfaction from the 15 deaths between 2016-2017 due to police brutality. In addition, there is one event that tries to model the hundreds of protests that happened in January 2016, increasing the dissatisfaction of the entire population by 5.
- In the next 365 days (fourth year), there is only one event that increases the dissatisfaction of a random agent's relationships to 100 for himself,100 for his close friends,70 for his acquaintances,10 for his network, and 2 for the entire population. These event tries to simulate the change in dissatisfaction from the death of a person between 2017-2018 due to police brutality. In addition, there is one event that tries to model the month-long BLM art exhibition and one event simulating a major protest, increasing the dissatisfaction of the entire population by 11 together.
- In the next 365 days (fifth year), two events increase the dissatisfaction of a random agent's relationships: 100 for himself,100 for his close friends,70 for his acquaintances,10 for his network, and 5 for the entire population. These event tries to simulate the change in dissatisfaction from

the death of a person between 2018-2019 due to police brutality. In addition, there is one event that tries to model the BLM Facebook page scam where it decreases the dissatisfaction of the entire population by 5.

- They were no events in the next 365 days (sixth year) 2019-2020
- In the next 365 days (seventh year), 2 events increase the dissatisfaction of a random agent's relationships; to 100 for himself,100 for his close friends,70 for his acquaintances,10 for his network, and 5 for the entire population. These events try to simulate the change in dissatisfaction from the two deaths between 2020-2021 due to police brutality. In addition, this event sparked 450 major protests known as the George Floyd protests. These protests increased the dissatisfaction of the entire population by 40. Following these protests the government intervened in reallocating budgets towards violence prevention pilot programs and other ways to make the people feel heard, this is simulated as an event that decrease the entire population's dissatisfaction by 60.
- In the next 1095 days (next three years 2021-late 2023) 2 events decrease the dissatisfaction of a random agent's relationships to 100 for himself,100 for his close friends,70 for his acquaintances,10 for his network, and 1 for the entire population, these events try to model the court case settlements of death's from previous police brutality, showing that police brutality is not tolerated.

We also designed an experiment with random events with no seed. In this case, for the random events, there were close friends events, acquaintances events, and network events. The different parameters used in these groups are discussed in the following paragraphs. Two types of events were defined for the random events: weak and strong. Weak events have an impact of 50, so the dissatisfaction of the affected group increases to a midpoint between its current level and 100 or 0, depending on whether it is an increasing or decreasing event. Secondly, strong events are only for increasing events, and when they occur, they increase the dissatisfaction of the affected group up to 100. These can be viewed as highly triggering events. In short, there are weak increasing and decreasing events and strong increasing events.

Depending on the social group affected (close friends, acquaintances, or network), and whether the event is weak or strong, the event probability changes. It was set for all three social group events that weak increasing and weak decreasing events would have the same probability and happen 5 times more often than strong events. For close friend events, the probability that a weak event occurs was set to 33%, so for 3000 iterations, weak events happen on 1000 of those iterations, and strong events, 6.6%. For acquaintances events, weak events happen with a probability of 13.3% and strong events, 2.6%.

Finally, network weak events happen with a probability of 4.5% and strong events with a 0.9% chance. The respective values between the 3 social group events were defined so that the ratio between them is indirectly proportional to the number of agents they affect (close friends affect 4 citizens, acquaintances 10, and network 30). We constructed several experiments with different combinations of the previously defined events: First, the effect of a single event is analyzed for each social group. Then, a simulation is run where only one event type is allowed (close friend, acquaintance or network). After this, the results of running the simulations with all the possible combinations of the 3 event types are shown.

3 Results

3.1 Black Lives Matter Event list

The figures below are based on an event list of real-life events that affected people's dissatisfaction with the Black Lives Matter protests. The event list begins with events such as police brutality, protests, and deaths, each event randomly affecting an agent and an agent's connected agents through his relationships. More substantial events are later shown from large protests and other social gatherings spreading awareness of the discrimination and racism shown by police brutality and racially motivated violence against black people. In later stages, events such as government intervention, subsidies, and court settlements decrease the dissatisfaction of agents. Each iteration represents one day from 2013 until 2022 in a total of 3285 iterations, plotted against the average dissatisfaction of the 2000 agents. The amount of events is similar to the amount of real-life events, and the time of the events are close to the times the real-life events happened but are not the same.

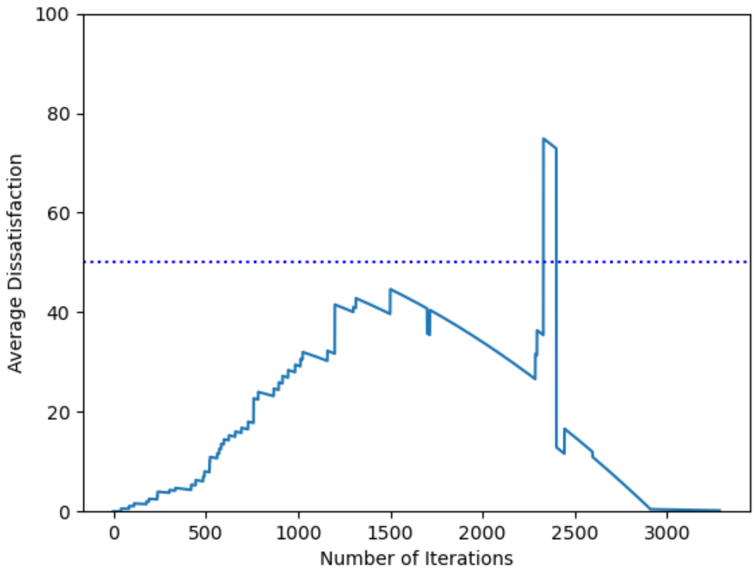

Figure 3: Baseline graph

The baseline graph, figure 3, shows how the BLM events affect the average dissatisfaction when the agents have no relationships. In addition to the events, the decay also decreases the dissatisfaction of the agents. The graph is plotted over 3285 iterations. The graph shows that the average dissatisfaction slowly increases before the decrease from the decay starts having a strong effect.

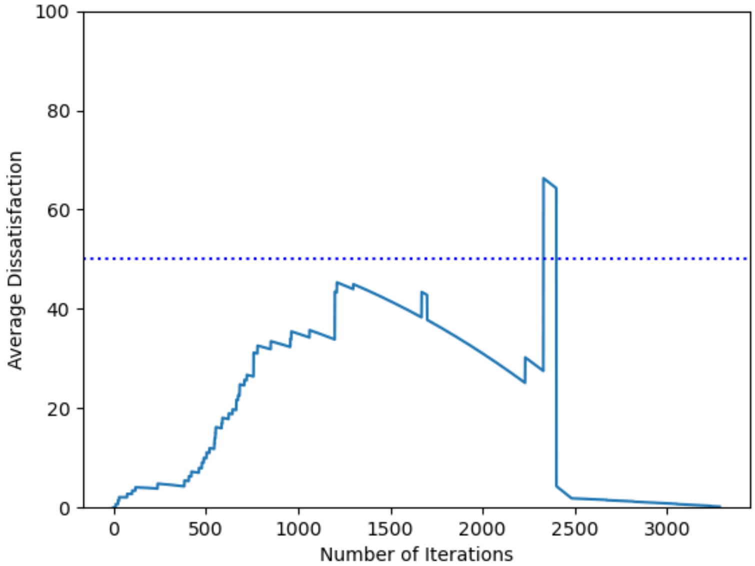

Figure 4: Close friends relationship graph

The close friends' relationship graph, figure 4, shows the effect the close friends' relationship has on the dissatisfaction of the agents when affected by the BLM events. In addition to the events, the decay also decreases the dissatisfaction of the agents. The graph is plotted over 3285 iterations. The graph shows that the close friends relationship creates sudden increases in addition to the slow increases of the entire population showing how each closed group affects the average dissatisfaction. It can also be observed that the average dissatisfaction is higher than the baseline graph.

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The acquaintance relationship graph, figure 5, shows the effect the acquaintance relationship has on the dissatisfaction of the agents when affected by the BLM events. In addition to the events, the decay also decreases the dissatisfaction of the agents. The graph is plotted over 3285 iterations. The graph shows a slow, smooth increase and then a slow, smooth decrease, showing how agents affect each other over time. In addition, it can be seen that the average dissatisfaction is higher than the only close friends graph

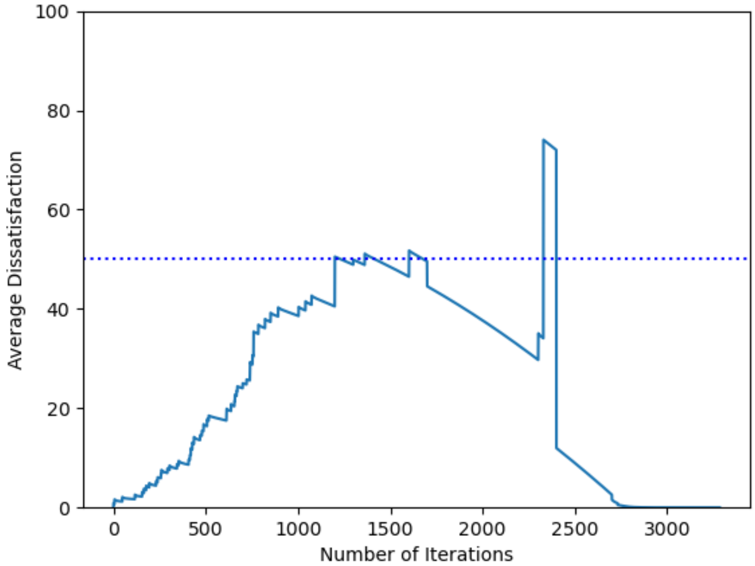


Figure 5: Acquaintance relationship graph

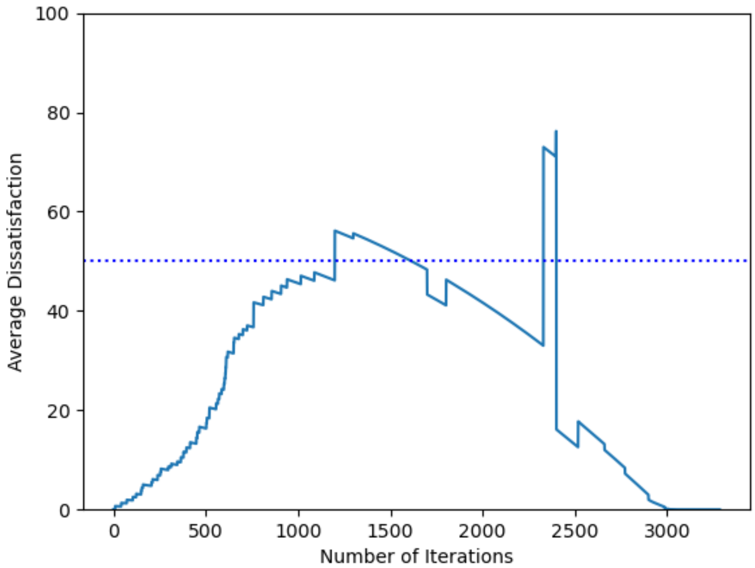


Figure 6: Network relationship graph

The network relationship graph, figure 6, shows the effect the network relationship has on the dissatisfaction of the agents when affected by the BLM events. In addition to the events, the decay also decreases the dissatisfaction of the agents. The graph is plotted over 3285 iterations. The graph shows a slow smooth increase and then a slow smooth decrease, similar to the acquaintance graph showing how agents affect each other over time. In addition, it can be seen that the average dissatisfaction is higher than the acquaintance graph

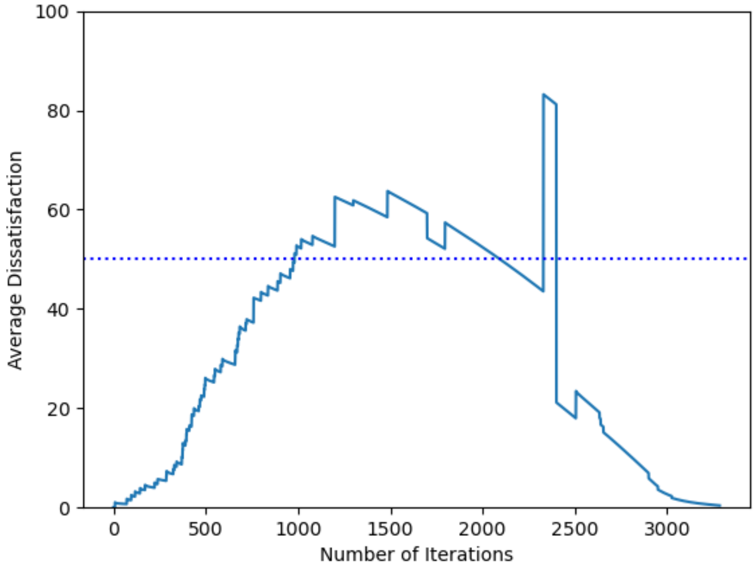


Figure 7: Close friends and Acquaintance relationship graph

The Close Friends and Acquaintances relationship graph, figure 7, shows how close friends and acquaintances relationships affect the agents' dissatisfaction when affected by the BLM events. In addition to the events, the decay also decreases the dissatisfaction of the agents. The graph is plotted over 3285 iterations. The graph shows a smooth increase and then a smooth decrease, similar to the acquaintance graph, showing how agents affect each other over time, as well as the spiky increases similar to the close friends graph. In addition, it can be seen that the average dissatisfaction is higher than all the previous graphs

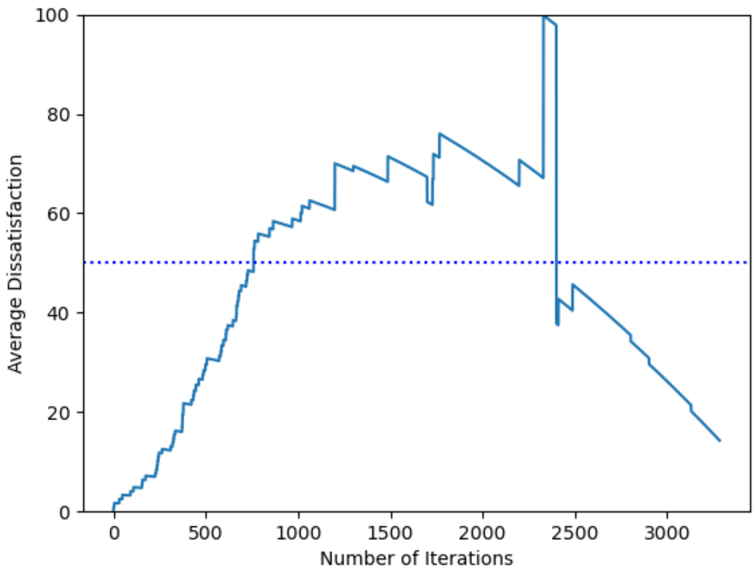


Figure 8: Close friends and Network relationship graph

The Close friends and Network relationship graph, figure 8, shows how close friends and network relationships affect the agents' dissatisfaction when affected by the BLM events. In addition to the events, the decay also decreases the dissatisfaction of the agents. The graph is plotted over 3285 iterations. The graph shows a fast smooth increase and then a fast smooth decrease, similar to the network graph, showing how agents affect each other over time, as well as the spiky increases similar to the close friend's graph. In addition, it can be seen that the average dissatisfaction is higher than all the previous graph

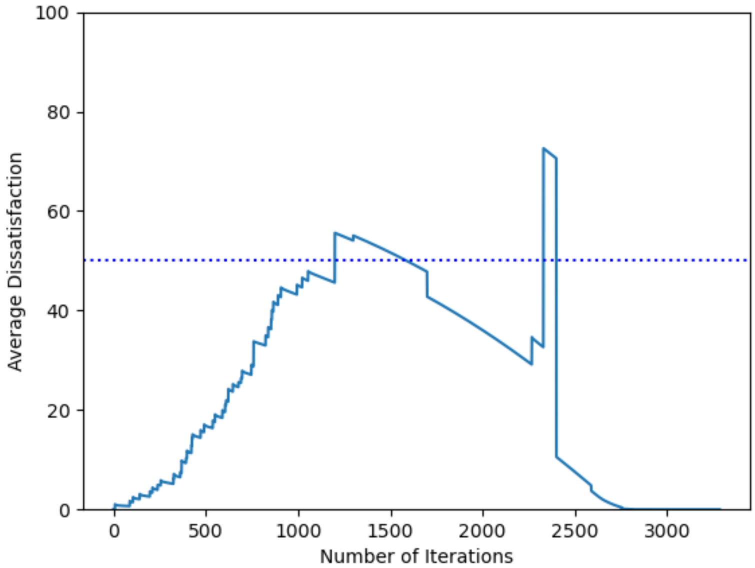


Figure 9: Acquaintance and Network relationship graph

The Acquaintance and Network relationship graph, figure 9, shows the effect the acquaintance and network relationships have on the agents' dissatisfaction when affected by the BLM events. In addition to the events, the decay also decreases the dissatisfaction of the agents. The graph is plotted over 3285 iterations. The graph shows a smooth increase and then a smooth decrease similar to the network graph showing how agents affect each other over time as well as the spiky increases similar to the close friends graph. In addition, it can be seen that the average dissatisfaction is similar to the network graph but is slightly more smooth than both the acquaintance and network graph

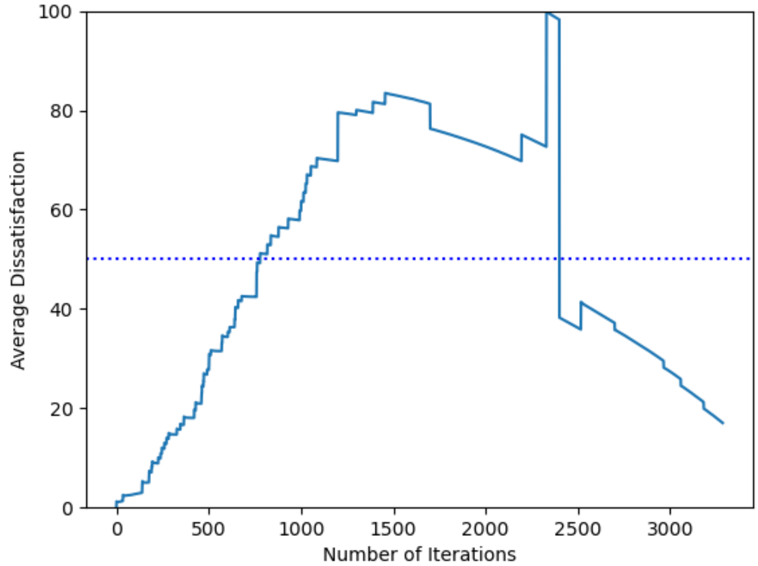
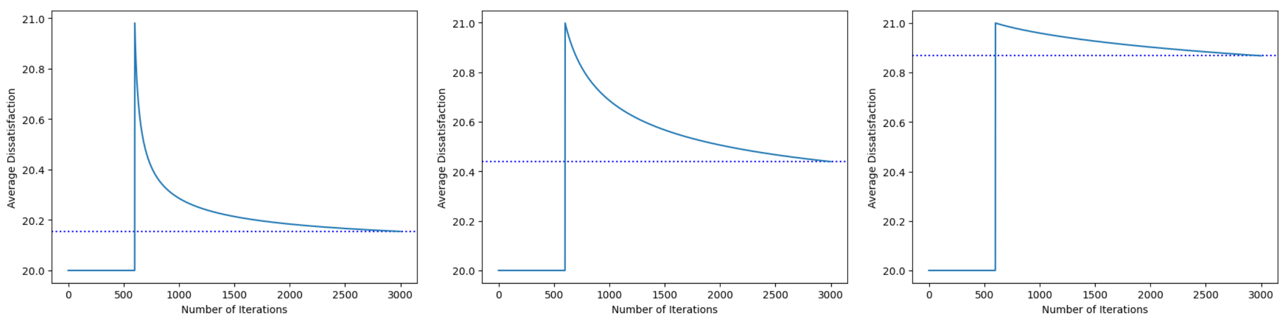


Figure 10: Close friends, Acquaintance and Network graph, Close friends relationship graph

The Close friends, Acquaintance, and Network relationship graph, figure 10, shows how all three relationships affect the agents' dissatisfaction when affected by the BLM events. In addition to the events, the decay also decreases the dissatisfaction of the agents. The graph is plotted over 3285 iterations. The graph shows a fast, smooth increase and then a fast, smooth decrease, similar to the acquaintance and network graph showing how agents affect each other over time, and the spiky increases similar to the close friend's graph. In addition, it can be seen that the average dissatisfaction is similar to the close friends and network graph but is as smooth as the acquaintance and network relationship graph

3.2 Random Events

Figure 11 shows how different events affect the overall dissatisfaction. The total change in dissatisfaction is the same in the three cases (dissatisfaction changes by 1), but it is spread in different agents. More specifically, there were four agents in the close friend event, ten in the acquaintance event, and 30 in the network event.



(a) A single close friends-scope event. Dissatisfaction levels at 20.19

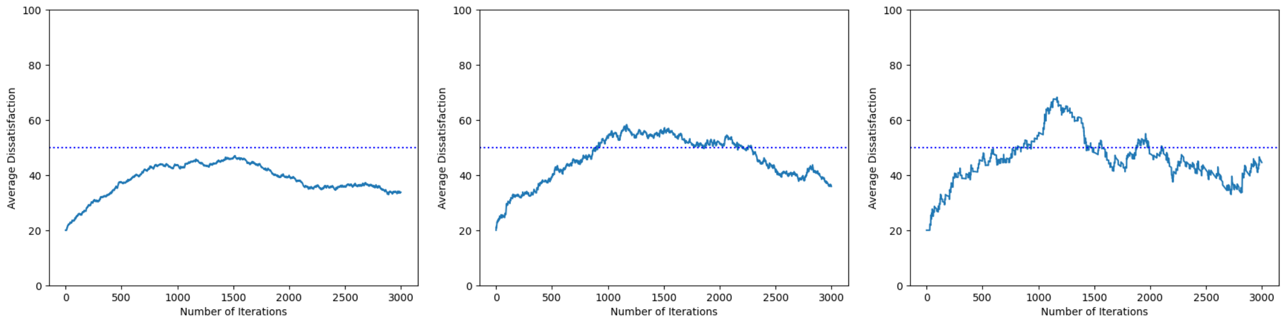
(b) A single acquaintance-scope event. Dissatisfaction levels at 20.45

(c) A single network-scope event. Dissatisfaction levels at 20.86

Figure 11: Comparison of the effect of each different event on the overall dissatisfaction.

For the rest of the simulation runs, it was run for 3000 iterations. The probabilities used in each of the events are the ones defined previously in the section of the experiment design. Figure 12 shows the cases when there are only close friends, acquaintances, or network events for each scenario. The blue dotted line indicates the point at which the dissatisfaction is 50. Each scenario was run ten times, and the number of times the overall reached a certain level was recorded.

- When only close friends' events were allowed, 0% of the times the dissatisfaction reached 50 or more.
- When only acquaintances events were allowed, 100% of the times the dissatisfaction was over 50, and 30% over 60.
- When only network events were allowed, 100% of the times the dissatisfaction reached 60, and 40% of the times it went above 70.



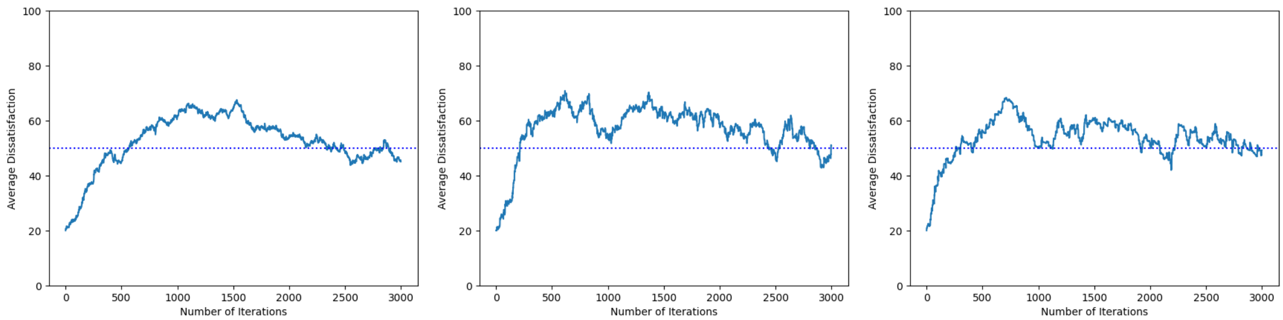
(a) Overall dissatisfaction evolution with only close friends events

(b) Overall dissatisfaction evolution with only acquaintances events

(c) Overall dissatisfaction evolution with only network events

Figure 12: Overall dissatisfaction evolution when different event types are allowed.

Then, the three different combinations of events (close friends-acquaintance, close friends-network, and acquaintance-network) were tried in the simulation runs.



(a) Dissatisfaction change with close friends and acquaintances events.

(b) Dissatisfaction change with network and acquaintances events.

(c) Dissatisfaction change with close friends and network events.

Figure 13: Graph showing how dissatisfaction changes for every possible combination of 2 event types

Finally, the three different events were included in a single run. The result is shown in figure 14

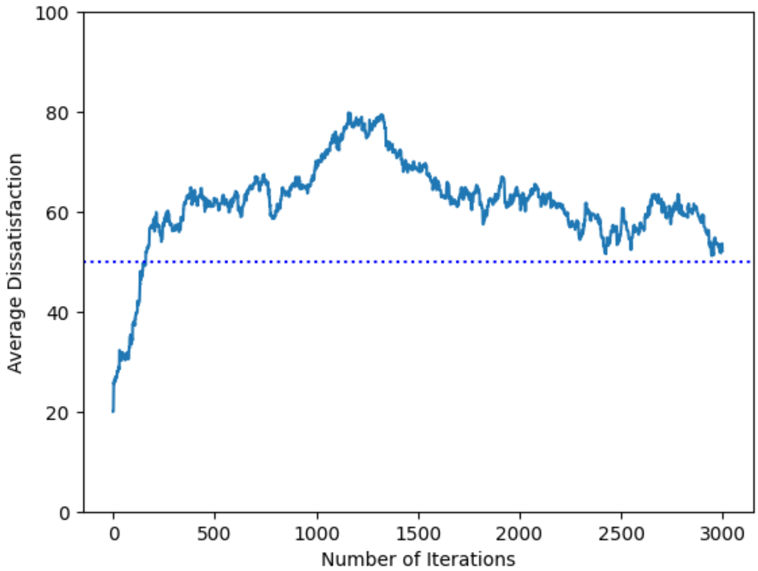


Figure 14: Plot showing how dissatisfaction changes when all three events are included in the simulation.

3.3 Global Decay

Figure 15 shows the global decay without all events. The graph illustrates that average dissatisfaction takes approximately 7000 iterations to decrease to zero from maximum dissatisfaction of 100 without any events occurring. Dissatisfaction is not added to each agent in the events that are occurring. it shows a steady decrease that is consistent with a polynomial decay function.

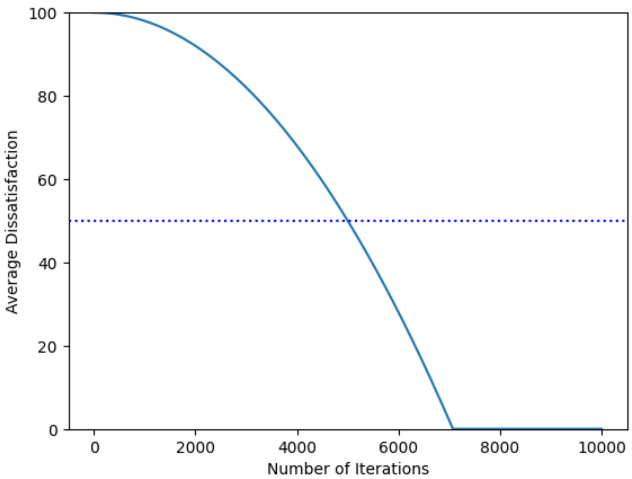


Figure 15: Plot showing the global decay without all of the events.

4 Conclusion

In conclusion, the dissatisfaction with the protest of Black Lives Matter Events with different relationships and Random Events themselves can be illustrated in the graphs. It can be shown that all relationships affect an agent's dissatisfaction differently, but the effect on the overall dissatisfaction is similar. There is an increase in dissatisfaction among agents when events are left unchecked by the government. If there are no events, the dissatisfaction of the agents seems to average out, and they begin to be affected by the decay of dissatisfaction more strongly as time passes.

The BLM results, from figure 4 to figure 10, show similar patterns that impact the overall dissatisfaction. We can see that no matter the relation, average dissatisfaction will increase in the middle, fluctuate, and decrease moderately at the end, similar to the true BLM events. The graph with the highest fluctuation is the close friends, acquaintance, and network relationship graph as shown by figure 10, followed by figure 8 of The Close friends and Network relationship graph. This shows that acquaintances only add minimal dissatisfaction compared to close friends and network relationships, showing how middle-level relationships are less effective than relationships of a large population and close relationships. We can see that when only a single relationship either close friends, network or acquaintances, as shown from figure 4, 5 and 6 does not affect the dissatisfaction of all the agents enough to be more wanting to get in a protest themselves compared to the baseline graph of figure 3 but when all relationships are combined are giving similar levels of dissatisfaction as the BLM events that happened, as shown in figure 8. We can observe from all the graphs related to the Black Lives Matter movement that as time passes, the impact of the events on the average dissatisfaction level decreases, indicating that people become less sensitive to these issues and get drained. This effect is particularly noticeable after the government takes action in response to public outcry.

As for the random events results, figure 11 demonstrates how each event impacts the overall dissatisfaction. Every event changes the total dissatisfaction by 1, but the drop that follows the peak gives insight into what is happening to the rest of the agents. In 13a, the drop is sharp, and the overall dissatisfaction levels out in a very similar value as its initial value. In figure 13b, there is a much smoother fall, and in figure 13c, the dissatisfaction almost stays at the same level after the event. This shows that for the close friends event, the rest of the population pull is more substantial, so there is not much of an impact. However, the larger the number of people affected, the more influence they will have on the rest of the population.

In figure 12, it can be observed how the presence of each event changes the way the dissatisfaction behaves with time. When only close friends events are allowed, figure 12a, the rise of dissatisfaction is very slow and soft, there are no statistical fluctuations, and the level of dissatisfaction barely reaches 50. When only acquaintances events are enabled, figure 12b, the dissatisfaction rises higher, and the effect of strong events can be perceived. Nonetheless, it eventually surrenders to the strength of the decay and begins to decrease. Network events, figure 12c, produce large waves of rising dissatisfaction. They have a significant impact on the rest of the population, and the dissatisfaction is much more unstable and prone to peaks.

Figure 13 presents how different event combinations influence the evolution of overall dissatisfaction over time. The features of each of the events can be inferred from the graphs. Generally, close friends' events introduce a smoothing factor in dissatisfaction. They control that the dissatisfaction of every agent is more or less within a certain level, as groups of close friends tend to level themselves out. On the other hand, network events make dissatisfaction jump to very high levels. They are responsible for the sudden peaks and decreases in overall dissatisfaction. This view can be directly linked to a simplistic real-life representation. Large protests and social movements need to involve events or triggers that affect a large part of the population and big networks to have a sizeable general impact.

In figure 14, the effect of every event is reflected. It shows how sudden increases can lead to a dissatisfaction peak. It is likely for this peak to be then suppressed by weak decreasing events or the force of the decay, which grows stronger the longer the simulation is run. It can be taken to be a broad representation of general protests.

Figure 15 shows that protests will eventually wear out if there are no events that affect the average public dissatisfaction. This shows that if the government does not act violently or the source of dissatisfaction stops the average public dissatisfaction will eventually go down, and protests will wear out.

4.1 Discussion

Modelling how networks influence a person's actions and beliefs is complex and intricate. In our model, we implemented these connections through weights that determine the level of affection for different people. Intending to model how a person's group of connections can influence them to change their current state of dissatisfaction, we found that creating a simplistic model of these connections was necessary. Even though it may be less realistic, it allows us to have more control and better understand the direct influences of different connection groups. As a result, in our initial model, where only the connections determine the change in dissatisfaction (without external events that decrease or increase dissatisfaction), the agents averaged each other's dissatisfaction out. In real life, connections wouldn't have such a strong influence on individual feelings. The events we aim to include in our model have been chosen to realistically represent how arbitrary circumstances arise in society and affect people and their social bubbles.

4.1.1 Limitations of the model

Due to the inherent complexity of real-world protests, including the social, economic, and political factors that contribute to their existence, creating a realistic agent-based model is challenging. One of the main limitations of this model is that it is an oversimplification of reality. While this does allow us to narrow down the effects of social networks and analyze some of the underlying dynamics, it assumes that there is no correlation between social networks and other factors that contribute to participating in a protest. Ideally, a model would consider the interplay between social, economic, and political factors simultaneously. However, this dramatically increases the complexity, requiring more research-driven data and making it more challenging to attribute influence to these different factors.

Another limitation of the model is that many hyperparameters of our model are a bit arbitrary. For example, many of the probabilities we have chosen for our model, such as the probability of an event occurring that increases the dissatisfaction in a close friend scope, are difficult to back up with actual data. Our model, therefore, can tell us more about how dissatisfaction spreads and moves in a population but less about how impactful each scope of relationship is, as it is hard to find a research-based, realistic, and representative effect rate.

Furthermore, our model faced scalability issues. Due to the limited computational resources available for our research, running the model took a considerable amount of time. Therefore, it was not feasible to include more connections in the network relationship scope, which would have been more realistic. Furthermore, protests exhibit a broad spectrum regarding the number of participants, ranging from small gatherings to large-scale demonstrations involving tens of thousands of individuals. As a result, characterizing the relationship between one agent in our model and 100 people in reality as a simple multiplication factor oversimplifies the complexity of this phenomenon. Another limitation of representing the number of agents in our model as a multiplication factor is that events affecting individual agents would be uniformly applied to all represented agents, not accounting for real-world variations.

4.2 Relevance

Protests are complex social phenomena that are driven by a multitude of factors. Understanding what instigates protests can improve conflict resolution and prevent escalation for future occurrences. An Agent-Based Modeling approach helps explore multiple factors, such as the influence of different levels of social networks, individual motivations, and external events. ABM can test different scenarios with different conditions, which helps understand which factors are most influential. Using different parameters in the model, policies and solutions can be found to stop protests from escalating. In other words, the model can be used as an educational tool to provide insights into the dynamics of protests and social movements.

The model presented in this paper mainly focuses on the effects of social networks, from close friends to social media connections. Through this, we gain information on the interpersonal interactions of agents. We can assess how individuals influence and are influenced by their friends and social media connections over time. It also helps us understand how information about protests spreads. The inherent agent heterogeneity allows for a representation of diverse agents with different motivations and behaviours (dependent on the level of dissatisfaction). Furthermore, by basing our model on real-world data, we can validate our model, increasing accuracy and predictive power.

Another benefit of focusing on social networks is that it helps identify key influencers for protests. People or groups that have a disproportionate impact on protest participation. It can help understand how echo chambers and social media bubbles can contribute to radicalization or polarization within protest movements. While this information is interesting, it is also sensitive information as it could aid in any undemocratic parties shutting down protests or help groups with malicious intentions effectively spread misinformation. By targeting the networks that are most prone to polarization, parties can disrupt the harmony of a society. Agent-based modelling could help analyze the resilience of protest networks by modelling how networks adapt to disruptions or attempts at suppression.

In summary, using an ABM approach allows for the exploration of essential factors that contribute to protests, precisely what the underlying dynamics are of different levels of social networks. An ABM approach gives a deeper of understanding of how protests spread and how they can be manipulated from the outside.

4.3 Team Work

We contribute equally to the report and the implementation as we work together on every section and create the Python implementation. Daan focuses on the introduction, method, conclusion of the report, and Python implementation of the formula. Pedro works on the methods, results, conclusion of the report, and helping experiments. Kyriakos focuses on the introduction and method and Python implementation, as well as BLM results and visualization, and grammatical mistake checking. Rizki works on the methods, results, conclusion, and python experiments, analysis, and visualization.

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