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Study Opinion Dynamics of Migrated Individuals using Multi-layer Social Graphs

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By

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Study Opinion Dynamics of Migrated Individuals using Multi-layer Social Graphs

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Declaration of Co-Authorship / Previous Publication

I. Co-Authorship

I hereby declare that this thesis incorporates material that is the result of research conducted under the supervision of Dr. Pooya Moradian Zadeh (Co-Advisor), and Dr. Ziad Kobti (Co-Advisor). In all cases, the key ideas, primary contributions, experimental designs, data analysis, and interpretation were performed by the author, and the contribution of the co-author was primarily through the proofreading of the published manuscripts.

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II. Previous Publication

This thesis includes 1 original paper that have been previously published in a peer reviewed conference, as follows:

Thesis Chapter	Publication title/full citation	Publication Status
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Abstract

Human migration is one of the challenging issues facing today's world. It can happen for different reasons and at different levels, from one country to another or between societies. As a result of social collaboration and knowledge exchange, a migrant's opinion about a topic can change over time. These collaborations lead to network evolution, which affects each individual's decisions in society. In this thesis, we propose a novel computational model to study the opinion dynamics of a migrated individual in a multi-population social network.

In this model, an individual migrates from one society to another with different beliefs and values. Each individual is able to take actions and has different opinions regarding various topics. We use Social Network Analysis (SNA) to investigate the opinion evolution of the migrated individual. Two algorithms, Belief-based and Learning-based, have been proposed to consider the opinion dynamics in which the migrated individual is under the effect of their neighbors' opinions, actions, and their origin and new society's social norms. Over time, the migrated individual tries to adapt to the new society by receiving feedback from their actions and collaborating with other people.

The main objective of this thesis is to propose a new computational framework to investigate the effect of different factors on a migrated individual's opinions and actions in multi-population social networks. We define various scenarios and situations to analyze the impact of different settings in the process of opinion dynamics.

We have evaluated our proposed model by conducting several experiments on a couple of synthetic social networks. We have analyzed the impact of different selection mechanisms, the role of origin's and destination's social norms, as well as the neighbor's opinion on the opinion dynamics of the migrated node. In addition, the role of learning and observation in the decision-making process has been studied. The results show that our model is capable of tracking the opinion dynamics of the migrated node in different scenarios and situations.

Dedication

I Would Like to Dedicate This Thesis to My Beloved Parents:

Reza and Fariba

for Their Constant Support and Immense Love

In Memory of My Dear Brother

Sepanta

Acknowledgments

I would like to sincerely express my most profound gratitude towards my supervisors Dr. Pooya Moradian Zadeh and Dr. Ziad Kobti for their continuous support and invaluable advice. The completion of this thesis could not have been possible without their expertise and guidance. I would like to offer my special thanks to Dr. Pooya Moradian Zadeh for his encouragement and assistance at every stage of this research.

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Contents

Declaration of Co-Authorship / Previous Publication **III**

Abstract **V**

Dedication **VI**

Acknowledgments **VII**

List of Tables **X**

List of Figures **XI**

1 Introduction **1**
1.1 Importance 3
1.2 Social Network Analysis 5
1.2.1 Single and Multi-layer Graphs 6
1.2.2 Static and Dynamic Graphs 6
1.3 Motivation 7
1.4 Problem Statement 7
1.5 Research Objectives 10
1.6 Research Contribution 11
1.7 Thesis outline 11

2 Related Works **12**

3 Proposed Model **18**
3.1 Population Space 18
3.2 Individual's Opinion 19
3.2.1 Weight Calculation 20
3.2.2 Structure of the Population's Belief 21
3.2.3 Selection of the migrated individual 22
3.2.4 Selection of an individual to connect at the destination population 23
3.2.5 Influence Measurement 23
3.2.6 Our proposed Belief-based Algorithm 25
3.2.7 Learning Scenario 27
3.2.8 Actions 27
3.2.9 Observation 28
3.2.10 Action Selection 29

4 Evaluation **30**
4.1 Experimental Setup 30
4.2 Experiments 31
4.2.1 Analysis of Belief-based Algorithm 32

4.2.1.1 Distance of the Migrant's opinion vs. Social Norm . 32
4.2.1.2 Measuring the quality of connections 46
4.2.2 Analysis of Learning-based Algorithm 51
4.2.2.1 Effect of learning on reward values 51
4.2.2.2 The effect of learning on knowledge expansion 53
4.2.3 Discussion 54

5 Conclusion **57**
5.1 Future Work 58

References **60**

Vita Auctoris **64**

List of Tables

4.2.1 List of the scenarios for evaluation and comparison 32
4.2.2 Comparison between scenarios in terms of the number and the quality of connections 47
4.2.3 Comparison between scenarios in terms of the number and the quality of connections for scenarios S13 to S24 48
4.2.4 Comparison between scenarios in terms of the number and the quality of connections for scenarios S25 to S36 49
4.2.5 Comparison between scenarios in terms of the number and the quality of connections for scenarios S37 to S48 50
4.2.6 The number of learnt actions in the first and last 20 iterations 53

List of Figures

1.4.1 An example of an individual's opinion vector 8

1.4.2 A sample scenario for individual migration 10

3.2.1 A comparison between opinion vectors of two individuals coming from two different societies 19

3.2.2 An example of distance between a pair's opinions 21

4.2.1 Migrant's Opinion vs. destination's Social Norm (node's origin: Elite) 33

4.2.2 Average distance of a Migrant node (Elite) connecting to the community, random and most similar nodes in the social network with 230 nodes 35

4.2.3 Average distance of a Migrant node (Elite) connecting to the community, random and most similar nodes in the social network with 500 nodes 36

4.2.4 Migrant's opinion vs. destination's social norm (node's origin: Isolated) 37

4.2.5 Average distance of a Migrant node (Isolated) connecting to the community, random and most similar nodes in the social network with 230 nodes 38

4.2.6 Average distance of a Migrant node (Isolated) connecting to the community, random and most similar nodes in the social network with 500 nodes 39

4.2.7 Migrant's Opinion vs. destination's Social Norm (node's origin: Most Similar) 40

4.2.8 Average distance of a Migrant node (Most Similar) connecting to the community, random and most similar nodes in the social network with 230 nodes 42

4.2.9 Average distance of a Migrant node (Most Similar) connecting to the community, random and most similar nodes in the social network with 500 nodes 43
4.2.10 Migrant's Opinion vs. destination's Social Norm (node's origin: Random) 44
4.2.11 Average distance of a Migrant node (Random) connecting to the community, random and most similar nodes in the social network with 230 nodes 45
4.2.12 Average distance of a Migrant node (Random) connecting to the community, random and most similar nodes in the social network with 500 nodes 46
4.2.13 Average reward value gained by the migrant node compared to the other nodes in the network in the last 20 iterations 52

Chapter 1

Introduction

Migration has always been one of the most critical topics in human behavior. In most cases, people migrate to other places to live in a better situation. However, the definition of a better situation varies from one person to another as individuals have different factors and beliefs throughout their life. These differences are one of the main reasons for having a diverse world. Consequently, people of one country may think differently about a subject than another. This also can be applied to smaller networks such as cities or communities in a workplace. In fact, individuals who belong to a specific community tend to share more similar opinions, values, and tasks. Despite a small number of individuals, the majority of a society is on the same level regarding views and actions they take. Therefore, in addition to individuals, societies themselves have their own social values and norms, which can be seen as an approximate average of people's opinions living in that society.

During migration, a person moves to a new environment and faces some challenges, such as adapting to the new social norms, values, actions, and behavior. This adaptation process is a normal stage for migrants but differs from one person to another. For instance, a person who migrates to another city in their own country may be better adapted than a person moving to a new country since people of the same country share more similar values and actions.

On the other hand, humans are social creatures, and most people in a community tend to communicate with other individuals. In reality, although they can live individually, communications and relationships play an essential role in everyone's life.

These interactions can happen between friends or strangers. However, individuals often try to make a relationship with a person who has similar attitudes and behavior as their own [1].

The communication between a newcomer and other individuals can positively or negatively impact the performance of the person in the new society. If they have similar opinions, this communication may happen more frequently and make these two individuals closer. Meanwhile, if their behavior and values are contrary, it may lead to polarization and less communication in the future. In other words, it affects both individuals in a relationship. Indeed, these interactions and collaboration are essential steps in this process. Although a migrant individual is more subject to these differences, the impression of a newcomer on the new society's culture, economics, and social behavior is inevitable.

This phenomenon is the foundation of another important concept known as opinion dynamics, which can be defined as the process of opinion evolution caused by social interaction between a group of social entities where the final opinion tends to consensus, polarization, or fragmentation [2]. Meanwhile, the migration network can be seen as a social network consisting of social entities from different populations interacting with each other. Consequently, the origin and destination societies in the migration system can be mapped to social graphs. A migrating person here is a social entity moving from one place to another and will interact with many other social entities during this journey. Consequently, when people in a network are in touch with each other, they transfer their knowledge and opinions. As a result, a constant evolution happens in the network.

Studying opinion evolution in social networks is a trending and challenging topic in social network analysis. Many algorithms and methods have been proposed to investigate the opinion evolution process and its impacts during the last few decades [2]. However, only a few of them focused on the opinion evolution of a migrated individual. This problem is also related to another concept known as population adaptation. It studies how a migrated individual goes through the adaptation process when facing a new society with different values and beliefs [3]. Basically, the adaptation process can take place on population, individuals, and components. Our model is designed in a way that satisfies all three mentioned levels.

In this research, the emphasis is on proposing a new computational model for tracking the opinion dynamics of a migrant in a multi-population social network. We use computational modeling alongside social network analysis, which is a novel and practical way to study this problem. This proposed multi-population model enables us to track the opinion changes of the migrants in a new environment and analyzes their behaviors. Our proposed model can also be used to study the adaption process.

1.1 Importance

According to the United Nations International Organization for Migration (IOM), 3.6% of the global population are migrants [4]. This statistic shows that migration is a prevalent and widely accepted strategy for people to move to places aligned with their values, opinions and where they can fulfill their needs better. Although the purpose of migration is mainly to improve and amend the current situation of migrants' lives, they need to struggle with some challenges to adapt to the new society. Dealing with different opinions, tasks, and social norms are examples of social adaptation difficulties migrants encounter at the beginning of this process. However, the required amount of time for adjustment and the conformity level acquired varies between individuals.

People come from various backgrounds, cultures, and places and their expectations are different from one to another. As a result of this disparity, their reasons for immigration also differ. For instance, a person might move to a big city for more job opportunities while another prefers living in smaller cities with less traffic. This is an example of migration between cities. But it can occur on smaller or larger scales too. A person changing their group of friends is migrating as well as someone moving to a new country.

In addition to individuals' backgrounds, communications and the relationships a migrant build in the new society play a vital role in the adjustment process. As a result of social collaboration and knowledge exchange, a migrant's opinion about a topic can change over time. However, regardless of being a newcomer or an existing member of a society, the whole network interacts with each other, which leads to network evolution that affects each individual's decisions in society.

Studying opinion evolution of individuals during migration is a multidisciplinary topic that can have a considerable impact on various real-life concepts such as the following:

- **Human Behavior:** Individuals pursue different manners and strategies in certain circumstances. A better understanding and discovery of the pattern behind these behaviors help societies to tackle the social problems between their members better. On the other hand, one of the topics in sociology that has grabbed a lot of attention is discovering how society evolves during different eras, which can be achieved with the help of opinion dynamics [2],[5].

- **Policy Making:** Rules and policies are one of the tools that keep a society cohesive and arranged. However, setting appropriate policies has always been challenging for governments and policymakers. A policy would be more successful if it corresponds to the factors such as characteristics, values, opinions, and traits of the people living in that society [5].

- **Economics:** Business is another criterion that is highly dependent on the opinions and decisions of individuals. By studying the opinion dynamics, companies will be more aware of demanding products which can lead to gaining higher profit and also cause more satisfaction among their customers [5].

- **Netwrok Formation:** This is a novel sub-field in physics that studies and investigates the networks' structures, how they evolve, and the factors influencing the network [2].

The cases mentioned above refer to some of the most important applications of opinion evolution. But due to its extensive usage and high significance (high impact), there are other applications in other fields too. Studying opinion evolution of individuals during migration is vital to understand the adaptation process, network formation, and to identify the mutual impact of opinions and decisions.

1.2 Social Network Analysis

In general, a social network indicates a network containing a group of social entities or network members that are connected by one or more types of relation [3]. The difference between a social network and a regular network can be found in their members and the type of their ties and links. A key trait of a social network is the sociability of its members, which leads to interaction and building a relationship with other members. A relationship in a social network can be any social relationship such as friendship, coworkers, relatives or imply positivity/negativity of their connection such as competitiveness/cooperation. Subsequently, social network analysis is the process of investigating these ties and relations as well as their members [3].

According to [6] all social networks have specific common characteristics that make them distinguishable from other networks:

- **High cluster coefficient:** Cluster coefficient is a parameter for measuring the tendency of a network's members to form a group. The higher cluster coefficient means more sociable entities which is a reliable metric for identifying a social network.

- **Power-Law distribution:** Another distinct characteristic of a social network is that the Power-Law distribution is always true for these networks. According to this law, a social network has many members with low links. On the other hand, a random network has fewer members with high connections.

- **Small world effect:** This theory states that any two individuals in a social network can be linked together through a short path using their neighbors. It verifies that all network members are in touch with each other, which is an apparent characteristic of a social network.

- **Dynamic networks:** Interactions and communications are the factors that keep a network active. Due to these social activities, members are under the effect of others' opinions, actions, and behaviors. This is the main reason for a social network's changes and evolution which does not happen for a random network.

1.2.1 Single and Multi-layer Graphs

A social network can be represented by a graph in which nodes are the members and edges show the ties between individuals. Graphs are one of the most frequently used ways for demonstrating the abstract concepts of a social network. There are different types of graphs that each of them is suitable for a specific situation. A single layer graph can be defined as a graph with weighted edges indicating the strength or weakness of the relationship between a pair of nodes [7].

On the other hand, a multi-layer graph is made up of two or more single-layer graphs, each of them depicting nodes in a different social network or the same network in various periods [8]. In these graphs, each node in each layer is mapped to its correspondence on the other layer. Multi-layer graphs can show how nodes behave in various situations, how their relationships and ties change, and what parameters cause these changes. Moreover, it is also a helpful strategy for tracking the evolution of the whole society. Therefore, using these graphs is an intellectual method to deal with complex networks [9].

1.2.2 Static and Dynamic Graphs

Graphs can also be categorized into two types in terms of dynamicity. Static graphs are the ones that their topology and structure do not change over time. This means no relationship is being added or removed from this network. As a result, these graphs are called static. On the contrary, a dynamic graph is dependent on time. Relations are different in each time span which changes the graph's topology and causes a transition from current state of the network to the next state [10].

1.3 Motivation

Migration is a challenging and critical stage in every migrant's life. Majority's intention for migration is to build a higher quality of life. However, adjusting to a new place and people with different backgrounds, experiences, and lifestyles is not a simple task. Any social network member needs to communicate to fulfill their social desires and have their own circle of friends. Social interactions are the ways that keep people close and also make them aware of the differences between each other. However, this seems to be different for a migrated individual with little knowledge of the new society and its members. They would not be able to interact with everyone as most of their communications may lead to conflict or disagreement. Therefore, a migrant would have a small circle of friendships at the beginning. This affects both the migrant and the whole society. The migrant might have difficulty adjusting to the new environment while still bearing the values of the previous society. This is a complex situation that both sides might not know how to deal with. This is also a big challenge for the decision-makers that their communities consist of a large number of migrants.

The aim of this research is to propose a model that enables us to investigate the migration process under various conditions. It is in this context that we can identify the potential factors influencing the opinion dynamics of the migrated individual and the network evolution and also recognize its underlying patterns. It can minimize the factors causing more delay in the adaptation process and make the whole society more consistent and compatible. The results of this research can be beneficial in various fields such as computer science, sociology, recommendation, and planning systems.

1.4 Problem Statement

In this research, we investigate the problem of opinion evolution in a social network. However, due to high significance of this subject in immigration, our main focus is on opinion dynamics of a migrated individual. Given a multi-population social network, each sub-population can be represented by a graph $G_p = (V_p, E_p, w)$, where V_p defines social entities or network members and E_p is the relations established between them. Each of these edges has a weight denoted by w that measures the strength level of the ties between two individuals. In our model, w is a real number between 0 and 1 ($0 < w \leq 1$) and is used as a metric for calculating the similarity degree of two individuals' opinions regarding particular topics. Here, a higher value of w refers to less similarity, while values close to 0 show more compatibility between opinions. The opinion of each member is defined by a fixed-size vector $O_{v_i} = [o_1, ..., o_i]$ where i is the number of topics that each individual has an opinion about. In this model, members' viewpoints about a topic are expressed by a number ranging from $-x$ to $+x$. Fig. 1.4.1 is an example of opinion structure of a random individual. As we can see, the values differ from one to another topic. For instance, his/her sight about topic 3 is 23 and 40 for topic 9.

t1	t2	t3	t4	t5	t6	t7	t8	t9	t10
45	97	23	2	14	8	36	21	40	58

Figure 1.4.1: An example of an individual's opinion vector

However, the individuals of these two sub-populations think differently. To make a distinction between their opinions, we define diverse ranges of numbers for members of each population. This ranges from 0 to 100 in population 1 and -80 to 20 for population 2. A topic that has a positive value in population 1 can have a negative value in population 2 because of disparity in their people's opinions. The positive and negative values about a topic show the agreement or disagreement level about that topic. A closer person's opinion about a topic means more compatibility between that person and the topic. On the other hand, if two people's opinions about a topic are distant from each other, it means they have different thoughts.

Members of each society form their social norms. Here, we call social norm the "Belief" of each population and represent it by B_p. This parameter is the normative knowledge of a society which is the average of individuals' opinions. Similar to opinion vector, Belief is also a fixed-size vector storing i values about i topics. Therefore, if $B_p = [Nt_1, ..., Nt_i]$ represent the Belief of population p, Nt_i corresponds to the normative knowledge of all individuals' opinions about topic i.

One important aspect of this study is to focus on the dynamic part of this process. As we mentioned before, one characteristic of a social network is its constant change over time. It means the status of the whole network varies in time 0 to time n as people might have different opinions and relations in each time span. Multiple factors such as communication, collaboration, and the social norm can be the primary reasons for these changes.

In a social network with various types of thought and backgrounds, people are constantly learning about new viewpoints and expressing their own opinion by taking different actions and interacting with their peers or strangers, which causes the network to evolve. But how do these communications and social interactions affect a migrated individual's opinion and decisions?

Assume a migrant's opinions are distant from those already living in that society, which requires more time to adjust. So how does this person act during this adaptation process? What parameters cause changes in their opinion? These are some of the primary questions we want to address in this research.

Fig. 1.4.2 depicts the whole network during a regular scenario of migration. As we can see, each society has a unique Belief or social norm indicating how individuals of that society think about 10 distinct topics. On the other hand, the opinion of each individual inherits from this Belief values as people of each network are under the effect of the values and beliefs in that society. In this scenario, individual 1 in population 1 is a person who wants to migrate to network 2. By comparing the Beliefs of these two societies and the opinion of this individual, it is clear that there is a huge difference between Belief of population 2 and that of population 1. Subsequently, this disparity would also be true for this migrant and Belief of population 2 or people's perception living in population 2. For instance, the migrant's perspective about topic 1 is 25 which is close to the society's norm. However, in society 2, the social norm for this topic is -61. This means most people in population 2 have a negative view about

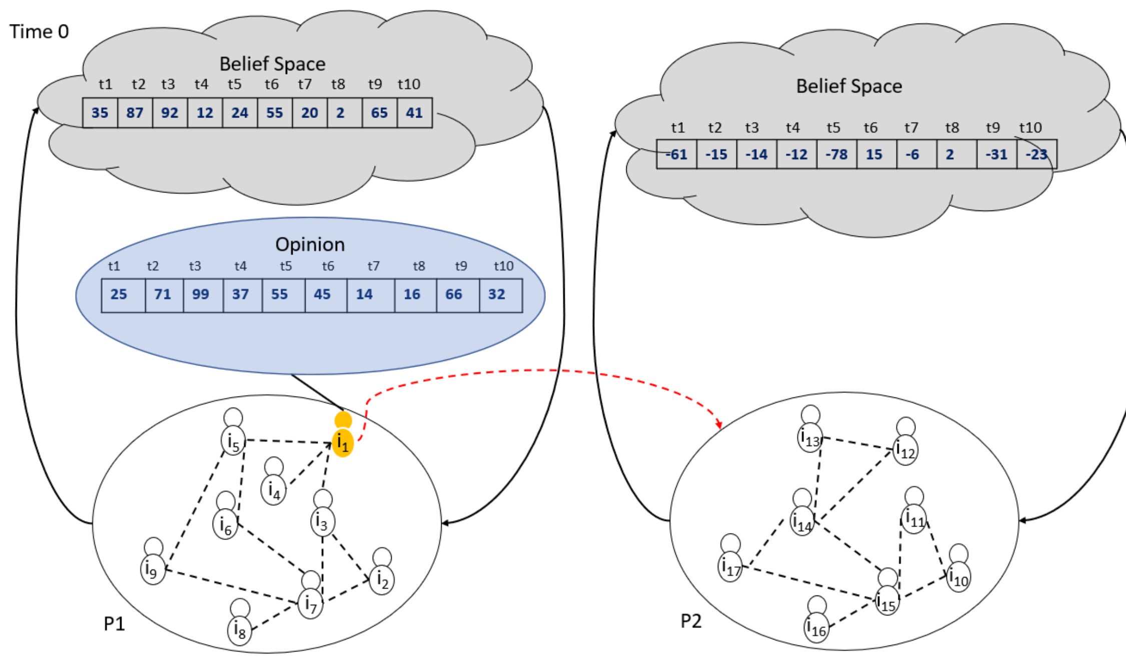


Figure 1.4.2: A sample scenario for individual migration

it while it is normally acceptable in population 1. Therefore, this person faces many social challenges when entering the new society. Despite these difficulties, how he/she is able to adjust him/herself over time? Another critical question is how the whole network leads to evolution and what is the status of it when time gets to infinity.

As a result, the main problem that we try to address in this thesis research is to track the opinion dynamics of the migrated individuals in a multi-population social network while considering various parameters affecting this process and investigating the network evolution.

1.5 Research Objectives

The main objective of this research is to propose a computational model to keep track of opinion dynamics of a migrated individual in a destination population. Various scenarios such as interactions with the neighbor nodes, the impact of destinations' social norms, and the effect of the origin's social norms are considered in our model.

The second objective is to study the role of learning and observation in the adaptation process.

Several steps are taken to attain this goal. First, a multi-population social network is defined with unique social norms and individuals to model a real network. Then, different scenarios are determined to investigate effective parameters involved in opinion dynamics of a migrant. Finally, by considering the social norms, opinions, and acceptance rate of the individuals, new algorithms are proposed to keep track of both the changes in the migrant's opinion and the network evolution in different scenarios and situations.

1.6 Research Contribution

The main contribution of this research can be summarized as follows:

- Propose a multi-population computational framework to study the opinion dynamics of a migrated individual by focusing on the role of the origin and destination's social norms in addition to the opinions' of the circle of friends and acquaintances.
- Develop a novel learning-based model to study the role of learning and observations on migrant's actions in different scenarios.

1.7 Thesis outline

The rest of this thesis is organized as follows. Related works will be reviewed in the next chapter. After that, the proposed model is presented in chapter 3. The details of implementation and evaluations are reported in chapter 4. Finally, we will have a conclusion chapter.

Chapter 2

Related Works

In this section, we briefly review some of the existing related works.

In recent years, several research works have been conducted to study the concept of knowledge migration and population adaptation in social networks. Some of these works are based on the Cultural Algorithm (CA), which is a dual inheritance evolutionary framework consists of belief and population spaces. Belief space is a knowledge repository that plays a vital role in CA and guides the search direction in the optimization process [11]. CAs are also known for their abilities in simulating multi-population systems in which each population can represent a society in real life. Thus, it is also feasible to track the evolution of communities correlated to the opinion changes in their members.

In [3], the authors proposed a novel evolutionary model based on CA to study the problem of population adaptation in social networks. They used the problem of community detection as a use case and defined multiple scenarios for transferring only a population, its knowledge, or a combination of them to a new environment with different levels of similarity. The model uses a community detection method proposed by [8] to search for communities and changes the structure of the network to investigate the role of knowledge in the adaptation process. They considered the normative knowledge matrix and the number of iterations needed in each scenario to identify the correct communities to evaluate its performance. They found that if a level of similarity between two populations is more than 25%, the previous knowledge that a migrated population has does not accelerate the adaptation process but also increases its time.

In another work, the authors in [12] proposed a multiple-population CA (MPCA) by combining a method proposed in [13] and the concept of artificial dominance, which considers the influence of dominants on other members. The fitness values of each sub-populations are computed using the benchmark functions, and their belief spaces were updated. The individuals with lower fitness values are migrated to the other sub-population where they can be affected by the other members. One common issue in those research works is that these networks become more complex to be considered for a one-by-one interaction when the population grows. As a potential solution to this problem, a novel evolutionary model [14] has been proposed. The authors presented a new mean-field game framework to consider the opinion evolution in a multi-population network. However, in this work, instead of considering each member's influence, the effect of the whole population is considered on opinion evolution. This strategy has been used in two scenarios: single population and multi-population. They defined the problem of opinion evolution as an optimization problem; the lower the cost function is, the stronger the influence. This strategy lies on Nash equilibrium, where each member's cost function is dependent on the others.

Friedkin-Johnsen (FJ) model [15, 16] is another popular strategy for opinion evolution. In this model, the opinion evolution process is based on two main matrices: the matrix of interpersonal influences, a row stochastic matrix, and a diagonal matrix representing individuals' susceptibilities to social influence. Each individual has a feature called prejudice that shows the initial opinion of that agent. Many studies used this model as the basis of their research to extend it to a more robust model.

Recently, the authors in [17], proposed an extension of the FJ model where each agent has an opinion represented by a vector. Each cell of the vector demonstrates the agent's topic-specific opinion. According to the authors, no study investigates how belief space forms and evolves through interpersonal influence in a network. To address this problem, they proposed a new model based on the FJ strategy by using the existing two main matrices of social influence and agent's susceptibility, and introducing another matrix, multi-issues dependence structure (MiDS), as an extension to the FJ. The role of this matrix is to consider the opinion dynamics on an issue that has been caused by opinion changes in another interpersonal issue. They also considered the stability and convergence of this model. Finally, their model has been created based on the idea of gossip-based communication to obtain more realistic opinion dynamics than simultaneous communication. Their results suggest that using the MiDS matrix can significantly drag in the opinion evolution of the agents compared to independent issues.

The authors in [18] focused on the problem of polar opinion evolution among individuals in social networks and proposed a general nonlinear model to address it. This model highly relies on agents' stubbornness features, and unlike other methods, the initial opinion of the agent plays a vital role. The stubbornness parameter shows how strict the agent is toward other opinions, while another parameter called averaging component pursues the agents to consensus. Three scenarios with three different rates of stubbornness have been investigated for analysis; an agent with neutral stubbornness, an agent who is only stubborn toward one side of the subject, and extremists who do not change their opinion easily.

A popular opinion dynamic model, known as DeGroot[19], considered a group of individuals to keep track of their opinion evolution until they reach a consensus. Recently, a novel opinion evolution model [20] has been proposed in which the social network was based on a signed graph. Similar to the other works in the field, a prejudice parameter has been considered for all the individuals. However, the authors of this paper used matrices that can take negative values as well as non-negative values for diagonal entries. Consequently, they could define the concept of confidence for individuals, which shows how confident each agent is in its prejudice. They categorized it into three parts: less confident, confident, and neutral. Unlike the traditional DeGroot model [19], this model considers both cooperative and competitive relationships. Negative signed edges show competition and confrontation, while positive signed edges illustrate friendly relationships. Relationships are created based on switching the signal values. Therefore, when agents are required to make a decision, they consider both their neighbors' opinions and their own opinions.

Online social networks are another significantly helpful platform for studying opinion dynamics. The authors of [21] proposed a new opinion guidance model using machine learning approach to study the evolution of public opinion in a virtual environment such as Twitter, Facebook, and email network. One fundamental difference between this model and existing models in opinion guidance is using machine learning to identify the dominant nodes in a social network. In order to do this, they used the Girvan and Newman(GN) algorithm combined with machine learning. This approach can be an intellectual replacement of fixed formulas and eliminates humans' interference in finding the leaders of a network since machine learning can easily recognize the underlying patterns in a large amount of data. The guidance process is in the form of dual communication between two agents based on dual learning, which is a sub-branch of machine learning. This is an efficient way to perform guidance and consider feedback simultaneously. The combination of Reinforcement learning for optimization and opinion guidance with the help of dual learning brought promising results. However, there is a lack of generalization in selecting the node responsible for guidance.

A recent study [22] looks at opinion dynamics from a different insight. The authors of this study proposed a mathematical framework to focus specifically on the interdependency between opinion dynamics and individuals' decision-making to identify the emergent behavior in a social network. Similar to [14], [17] [15] this model also tries to recognize the paradigm shift of individuals' opinions and see how it affects the evolution of the whole network. However, this is a two-layer network consists of two major components opinion dynamics and decision making. One layer is assigned to the knowledge exchange of the members through communication or action observation, while the other layer acts as a channel to obtain the effects of the decisions taken after opinion revision. In addition to the factors mentioned above, graph structure is also examined to see how it influences the existing and emergent social norms in a society. Two types of social norms, unpopular and popular destructive have been investigated on this network. Various scenarios were defined to capture the potential effect of each parameter. According to the authors, the results of this study show that the network structure plays a vital role in dissemination of an emergent social norm. On the other hand, individuals' susceptibility towards opinions, actions, and their rationality cause a difference in the outcome.

An agent-based model has been proposed in [23] to consider the best strategy for more cooperative relationship between newcomers and the hosts in a social network. Similar to [3], [12], [13] this is a population adaptation problem but with a different scenario. Cooperativeness here refers to prosperity improvement. In other words, the primary purpose of this model is to integrate newcomers and the hosts in a way so that the migrants would be able to enhance their socioeconomic situation and feel accepted. The authors tried to address this problem using a combination of game theory and opinion dynamics. Two important parameters that significantly affect this cooperation were introduced as adaptation time and number of migrants. According to the authors, fast adjustment leads to higher cooperation, while longer adjustment makes it more difficult since the major goal of the migrants cannot be obtained. Moreover, the ratio of migrants to the hosts is another critical factor in achieving cooperativeness.

Another study considered the similarities and differences between two popular models of opinion dynamics and language change known as Social influence and Recurrent Mobility, respectively. According to the authors, these two phenomena both show similar stochastic dynamics that happen in complex social networks. As a result, identifying their association can cause a significant advance in their models[24].

In [25] the authors investigated the association between natural phenomena and opinion dynamics. In this study, the authors used agent-based modeling to simulate the natural phenomena and consider their effects on opinion formation. According to the authors, existing studies in nature-inspired models such as the Ising model show a relation between these phenomena and opinion formation. NetLogo was used as a tool for simulating these natural events. The majority of opinion dynamic models rely on binary or continuous approaches. According to the authors, opinion dynamics and network evolution result from agreement/conflict among individuals in their circle of friendship that spreads throughout the network. Unlike most studies that focus on individuals' neighbors, this work also considers the influence of external parameters. This model was applied on an online social network and the results substantiate that external factors such as mass media, turn and the flow of events play a vital role in opinion dynamics.

A comprehensive study in [26] reviewed existing agent-based modeling methods for population migration with emphasis on the decision-making process and the factors that affect each individual to choose migration. The authors referred to geographical location, migrant's life in the origin, and similarities/differences between origin and the destination that could be attractive/unattractive to an individual as some of the primary factors that could finally lead to migration. Since immigration is the outcome of a person's action, the decision-making task here is categorized in behavioral model for migration. According to the authors, most of these models are based on uncertainty as individuals' actions and opinions depend on fixed and changing factors and vary at different times. According to the authors, ABM is a powerful method to simulate immigration and the interactions between individuals. However, there are still some challenges. For instance, ABM cannot support complex rational rules. Therefore, it relies on simple scenarios in which there is not much uncertainty or flexibility in different circumstances.

To the best of our knowledge, none of the existing studies have considered the problem of opinion evolution for a migrated individual by considering the impact of the origin and destination's societies' norms and belief spaces as well as the person's individual opinion and its circle of friends in the new society.

Chapter 3

Proposed Model

In this section, we discuss our proposed model for the problem of tracking the evolution of opinions of a migrated individual in a multi-population social network.

Since our model is applied to a multi-population network, the first step is to define the population space, which incorporates a collection of individuals as members and their ties.

3.1 Population Space

To represent our network system, each sub-population has been defined by an attributed weighted graph consists of a set of nodes and their established edges. Each node demonstrates a member of society and their edges is a representation of their relations with other members. Each edge has a weight which is a metric for opinion similarity of the two members. Here we assume that the individuals of the same society have closer opinions than those living outside of this environment. We use an adjacency list to store the structure of each population. The list size is equal to the size of the population, and an entry list[a] retrieves the list of nodes adjacent to the ath node in the graph.

3.2 Individual's Opinion

The next important concept in our model is individuals' opinions. Here, we assign opinions as attributes for each member of the society, which is a fixed-size vector consists of i elements demonstrating the perspective of a person about i different topics. These perspectives are represented by numbers ranging from x to y where $-\infty < x, y < \infty$. As a result, members would have disparate viewpoints about the i subjects. However, as the members of the same society think more closely, these numbers are closer among individuals within a society. Conversely, higher differences between these numbers are an indication of disparate and less matching ideas. Therefore, by comparing the opinion values, we can discover the compatibility between two individuals.

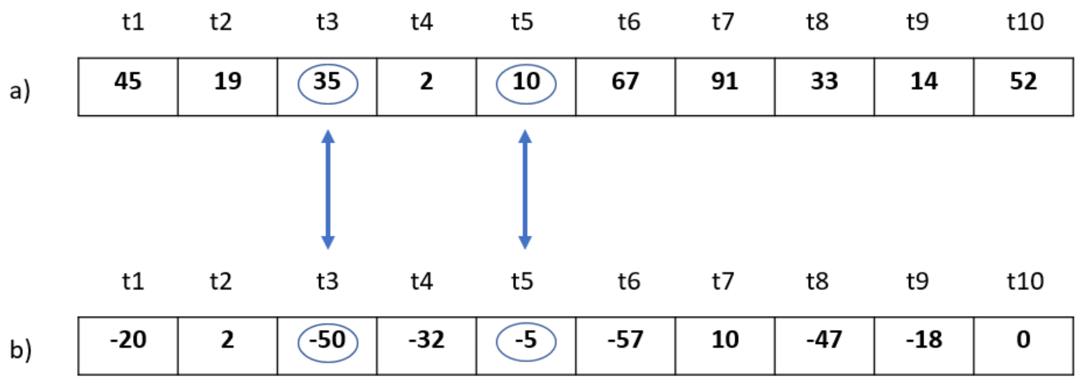


Figure 3.2.1: A comparison between opinion vectors of two individuals coming from two different societies

Fig. 3.2.1 shows an example of two individuals' opinions who have different ideas regarding 10 various topics. As we can see, the values are entirely disparate as individual a has more positive views while individual b has a negative perspective toward specific subjects. We considered negative and positive values to be able to represent how different two individuals can think regarding the same topics. For instance, in Fig. 3.2.1, individual a's opinion about topic 3 is 35 while it is -50 for individual b. As a result, we can conclude their opinions about topic 3 are incompatible. On the other hand, Their opinions regarding topic 5 are 10 and -5 for individuals a and b, respectively. Although individual a's positive insight and individual b's negative opinion about this topic show some level of incompatibility, the distance between their opinions is not considerable, meaning they do not show strong positiveness/negativeness. Therefore, their opinions are closer regarding topic 5 compared to those for topic 3.

3.2.1 Weight Calculation

One of the most crucial characteristics of this system is its weighted graphs. As we mentioned before, this parameter is an implication of the strength level between two individuals and in this model, relation strength refers to the opinions similarity. The level of strength varies from 0 to 1. We define more closeness with lower weight and more distance with an edge weight closer to 1. The following formula calculates the weight between a pair of nodes:

$$w_{(v_a,v_b)} = \frac{k * \sum_{j=1}^{i} |O_{v_a}[j] - O_{v_b}[j]|}{i^2 * (y - x)} \tag{1}$$

where $O_{v_a}\&O_{v_b}$ are the opinions of individuals v_a, and v_b respectively. x and y specify the range of values for each element in opinion vector ($x < O_{v_a}, O_{v_b} < y$). i refers to the number of topics and k is the number of topics in which the pair's opinions are not the same. This formula is based on the hamming distance, which is one of the best approaches to calculate the similarity between the different data.

As shown in Fig. 3.2.2, the distance compares the data to find the differences. Generally, this method adds one unit to the distance when it finds a dissimilarity between two values. In this model however, two data points are compared and in case of dissimilarity, their absolute subtraction will be added to the overall distance. The final value is then multiplied by the number of topics that two nodes think differently about. At the end, this value will be normalized according to the number of topics and their range of value. In our case, this is one of the most useful strategies to investigate the similarity degree of opinions in a diverse network.

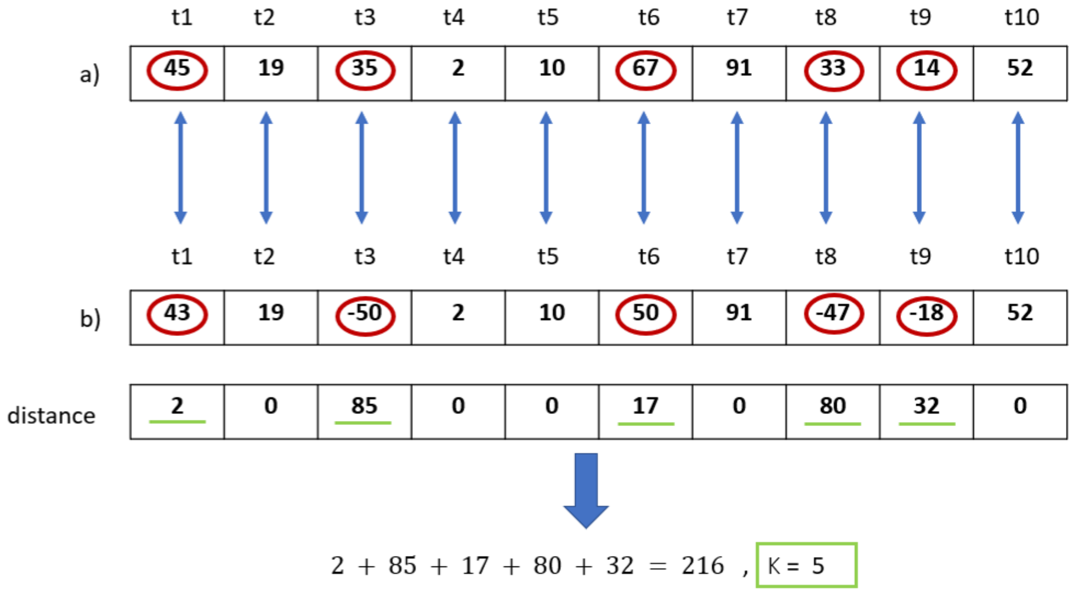


Figure 3.2.2: An example of distance between a pair's opinions

3.2.2 Structure of the Population's Belief

This parameter is defined as the social norm of each society. In most cases, the individuals' opinions of a network form its social norm, which we also call here as "Belief". Similar to opinion, Belief is also made up of a fixed-size vector with i elements demonstrating the whole society's approximate opinion toward 10 topics. So assume $B_P = [b_1, ..., b_i]$, B_P is the social norm of population P. The social norm of each society here is the average of opinions.

$$b_j = \frac{\sum_{v_j \in P} O_{v_j}[j]}{|P|}, 1 \leq j \leq i \tag{2}$$

Where P is the total number of members in that society. Since members' opinions values vary from one to another network, their social norm is also within their own range. Derived from this concept, another parameter, "Distance_in", is introduced to capture the distance between a member's opinion and the social norm of their society. In other words, this is a metric that considers how much someone's opinion belongs to their own society and accepts its norms. This attribute is calculated using the following formula:

$$V_n^{distance\_in} = \frac{k * \sum_{j=1}^{i} |O_{v_n}[j] - B_{P_O}[j]|}{i} \tag{3}$$

Where O_{v_n} is the opinion of individual v_n, and B_{P_O} is the norm of its own original population, and k is the number of topics in the individual's opinion that are different from society's norm.

Another attribute called "Distance_out" is also defined to measure the similarity between someone's opinion and the social norm of another society. In contrary to the distance_in this one shows compatibility between an individual and another society. This attribute can be a helpful measurement to consider whether someone would be a suitable member for an arbitrary external network or not.

$$V_n^{distance\_Out} = \frac{k * \sum_{j=1}^{i} |O_{v_n}[j] - B_{P_D}[j]|}{i} \tag{4}$$

Where B_{P_D} is the norm of the destination population.

In addition to the mentioned attributes, an acceptance_rate has been defined for each person. Acceptance_rate is a random number between 0 and 1 assigned to members, which is used to show an individual's sensitivity toward a new opinion and value. This model is designed in a way to simulate the characteristics of a real world and in reality, individuals have different acceptance_rate when they face a new perspective. Accordingly, this parameter shows the possibility of an individual accepting a new idea. More acceptance_rate means more sensitivity and leads to opinion change.

3.2.3 Selection of the migrated individual

In our model, an individual can be selected from four different types of groups to be transferred to the new society:

- Elite: This group is the top 20% of the individuals whose opinions are the most similar to the norm of their society. This means they have the least Distance_in in their network.

- Similar to destination: This group of individuals is the top 20% whose opinions are more compatible with the social norm of the destination society but not their own network. This group has the least Distance_out but may not have the highest Distance_in.
- Isolated: This group is the top 20% of individuals with the least similarity with the social norm of their own society. This means they have the highest value of Distance_in, but their Distance_out values are not necessarily low.
- Random: This group of individuals is some random nodes not included in the other three groups. In other words, these types of people are some regular individuals.

3.2.4 Selection of an individual to connect at the destination population

As we mentioned before, like other members of a society, a migrant also needs to communicate and engage in social activities. Therefore, we defined another scenario after the migration, which considers the person the migrated individual connects to immediately when they enter the new environment. The first connection in an unfamiliar community plays an important role and can significantly affect a newcomer, which makes this scenario an important aspect of immigration. We assume that the first connection of a migrant can be a random person or someone who has the most similar opinion to the migrant. The aim of these two scenarios is to investigate what could be the difference in a migrant's opinion evolution according to their first connection.

3.2.5 Influence Measurement

This part explains how the opinion of the migrant after immigration and also opinions of the other members of society 2 changes and evolve over time. In our model, individuals are influenced by three major factors: their neighbors' opinions and the social norm of the origin and destination. The first factor that we consider is the neighbors' opinions. Each member of a social network needs to communicate and as a result of this interaction, their perspective can change about various topics. To measure this influence, we introduced the following formula:

$$I_{(v_a,v_b)}[j] = (O_{v_b}[j]) * (1 - w_{(v_a,v_b)}) \tag{5}$$

where v_b is a neighbour of the node v_a in the destination population and and $O_{v_b}[j]$ is its opinion about the topic j. $I_{(v_a,v_b)}[j]$ measures the impact of its opinion about topic j on node v_a based on the weight of their connection. The next parameter that can cause a change in opinions is the influence of the destination population's social norm or belief. This factor plays a vital role for a migrant and is considered as the inner social norm for other members. The following formula is introduced to calculate the influence of the destination's social norm on the opinion of an individual:

$$I_{(v_a,P_D)}[j] = B_{P_D}[j] * (1 - \frac{v_a^{distance\_in}}{i * (y - x)}) \tag{6}$$

where $I_{(v_a,P_D)}[j]$ measures the impact of the destination population's norm about topic j on node v_a. The third and the last factor is the influence of the origin's social norm on individuals' opinions which can be calculated by the following formula:

$$I_{(v_a,P_O)}[j] = B_{P_O}[j] * (1 - \frac{v_a^{distance\_out}}{i * (y - x)}) \tag{7}$$

where $I_{(v_a,P_O)}[j]$ measures the impact of the original population's norm about topic j on node v_a.

Finally, using a combination of the three aforementioned factors we come up with the following equation for influence measurement $O_{v_a}[j] = O_{v_a}[j]+$

$$\begin{cases} A_{v_a} * (\frac{I_{(v_a,v_b)}[j] + I_{(v_a,P_D)}[j]}{2}) & \text{if } v_a \neq S\_ind \\ A_{v_a} * (\frac{I_{(v_a,v_b)}[j] + I_{(v_a,P_D)}[j] + 2 * I_{(v_a,P_O)}[j]}{4} & \text{if } v_a = S\_ind \end{cases} \tag{8}$$

where A_{v_a} denotes the acceptance rate of the node v_a, and S_ind is the migrant node. In fact, in this model, the opinion of a person is a function of their friends' ideas, the norm of the destination societies, the norm of the origin society, and their own beliefs. However, this function differs for a migrated individual and other members of the society. As shown in the above equation, migrated individuals are still affected by their origin society's belief while living in another society. This is because most migrants are still connected to their family or friends in origin, but the influence of that social norm might vary compared to the time when this person lived in their own society.

3.2.6 Our proposed Belief-based Algorithm

Algorithm 3.2.1 The proposed Algorithm

Input: A multi-population social network
Output: Opinion Dynamics of a migrated node
Start
Initialize(Populations)
Update(Belief Spaces)
Calculate(weights, Distance_In, Distance_Out)
Select(S_Ind) ▷ Select the migrant individual based on the scenarios in (3.2.3)
Migration(S_Ind) ▷ Based on the Scenarios in (3.2.4)
for $it \leftarrow 1$ to t **do**
    Update($O_{\forall V_a \in P_D}$) ▷ Update all the individuals' opinions in P_D using (8)
    Update(weights) ▷ Update the weights using (1)
    Update(B_{P_D}) ▷ Update the belief space using (2)
    Friend(S_Ind) ▷ Expand the neighbors of the migrant node
    Store($Network\_State$) ▷ Store all weights, number of friends, opinions, P_{B_D}, distances, and edge lists
end for
Return ($Network\_States$)
End

The algorithm starts by initializing the populations and reading the values. After that, the belief spaces are formed according to the method described in section 3.2.2. Moreover, other attributes such as edge weights (equation 1), Distance_In (equation 3), and Distance_Out (equation 4) are calculated and assigned to each node in the graph.

In the next step, the selected individual for the migration, S_Ind, is chosen based on the scenarios defined in section 3.2.3. Then, the function $Migration$ is executed to identify a node in the destination population to link to the $S\_Individual$. The function works according to the methods described in section 3.2.4.

After transferring the node to the destination population and linking it to another node in that society, a loop starts and continues for t iterations. In each iteration, a series of activities are performed to capture the changes in opinions. As mentioned before, in this model, the evolution of a node's opinion depends on the node itself, its neighbors, its acceptance rate, and the norms of the destination and original populations. Therefore, the opinions of the nodes and their weights of the connections are updated based on the equations defined in section 3.2.5 and (1). Due to these changes, the belief space of the society should be recalculated.

In addition, as a natural reaction to the new environment, the migrant node tries to broaden its connection and make new friends. Consequently, to make the system closer to reality, we have considered that the migrated node can expand its circle of friends during each iteration. Therefore, a function called $Friend()$ is defined to add new nodes to the list of migrated node's neighbors in the destination population. The node is selected from the neighbors of the migrant node's neighbors if the distance between itself and such node is less than its weight with the common neighbor. In other words, the migrant node does not choose its new friends randomly, but it tries to find the best individual as its new friend based on the weights of the edges between itself and its neighbors. Accordingly, the weights between the neighbors of the neighbors are compared to the weights of the neighbors. Since the weight shows the distance between opinions, the migrant node makes a new connection with a node whose opinion is closer to it rather than its current neighbors. As a result, the migrant would be surrounded by members who have the most similarity to itself.

The whole process continues for t iterations, and after that, the results will be stored for analysis.

3.2.7 Learning Scenario

In the previous section, we introduced our model for tracking the opinion dynamics and the network evolution of a multi-population social network. However, in reality, when someone moves to a new place, they usually try to observe new behaviors and actions at first to increase their knowledge about the new society so that the migrant becomes familiar with the people and learns about acceptable actions and the kind of behavior that leads them to receive more pleasant feedback and finally will become significantly adapted to the new place.

On the other hand, if this person would not be able to learn about the new actions they may receive negative feedback from society since their behavior may not be acceptable by the social norms. Additionally, learning here is an essential key for adaptability. Therefore, a person who does not learn or observe is less likely to adapt to the new situation.

Because of its high significance during the migration, we also define another scenario in which the migrant can observe and learn new social norms. Here, in addition to communication, all network members can learn, choose an action, and get rewards.

3.2.8 Actions

Actions are one of the most important factors in the learning scenario. In this model, we suppose that each society has its own actions. It means the actions that individuals can take in each community is different since their social norm and characteristics are disparate. These actions are represented by a $m \times n$ matrix where m is the number of actions and n is its characteristics.

We consider three main characteristics for each action: name, requirement, and reward. Name here is an indicator of real-world actions. The second one is the minimum opinion needed for an individual to be able to take that action. This is the main reason that members choose various actions since they have different opinions. This is also true for a real-world scenario as people with the same mindset usually take more similar actions compared to the others. In order for an individual to be able to choose a specific action, their opinion is compared to this requirement element-wise. If all elements are equal or more than the minimum opinion, then the person is eligible to take that action.

The third attribute is the reward assigned to each action in that society. As a result, if a person takes an action, they receive its reward. We define an attribute for each population as "action_table" to store the set of acceptable actions of each society. The number of actions considered for each society is the same, but their nature differs.

Furthermore, to make our model closer to reality, some actions are acceptable in both societies. However, their reward is different, which means the same actions can have various outcomes in different societies.

The rewards of each action are correlated to their minimum required opinion; Actions with higher rewards seek higher opinion requirements. Therefore, only those with more consistent opinions to the social norm can take those actions. However, to make the model more realistic, we considered 10% of actions with no minimum requirement and 20% with low requirement. It means that 10% of the actions can be taken by any person regardless of their opinions.

3.2.9 Observation

Observation is a critical component of the learning process. In our case, an individual enters a new society without prior knowledge of their social norms and acceptable actions. Observation can help a person become adapted to the new situation by familiarizing the person with new opinions, actions, and their rewards. As we mentioned before, each action contains a value that shows its feedback reward in society. During the observation, a migrated individual tries to observe the actions taken by their neighbors and increases their knowledge about the rewards of those actions. As a result, we define a knowledge history for the migrant, which is a $m \times n$ matrix where m is the number of actions observed by the migrant and n is the number of characteristics of each action which is 3 in our model (name, minimum requirement, reward).

In each iteration, the whole network members choose a set of actions from which are available. Then each person tries to maximize their value by choosing the best 5 actions among eligible actions for each individual. The best actions here are the positive ones with the highest values. Since members of a society are familiar with all the rules and feedback of different actions of their own society, they can easily choose the top 5 actions in each iteration.

On the other hand, the migrant observes this process from their neighbors and learns how to react better in the future. Therefore, a copy of the neighbors' selected actions, their requirements, and rewards is copied into the migrant's knowledge space during the observation.

3.2.10 Action Selection

This stage is a reflection of the migrant's knowledge about the new environment and usually happens after the observation. Here, in addition to the members of the destination's society, the migrated individual also starts taking actions. Similar to the previous section, this step first checks the opinion of the migrant to find the eligible actions for them. Then, the top 5 actions are selected by the migrant and their value is given as a reward.

In this stage, in addition to learning from the neighbors, the migrant also learns from its own list of selected actions. Therefore, a copy of its selected actions along with their rewards values is copied to its knowledge.

Since this newcomer thinks different from the social norm, it is most likely that the majority of their actions are among the ones with no requirement or minimum requirement, which gives them a low value.

Meanwhile, due to the fact that some of the actions are shared between the origin and the destination's population, it is very likely that the migrant chooses an action that is already aware of it from its origin society. However, the value and the requirement of that action is different in the new society. As a result, it may receive negative feedback if it takes that action. To encourage the migrant to maximize their action value, the migrant can broaden their friendship circle if its value is more than 0.

Chapter 4

Evaluation

In this chapter, we evaluate our proposed models by comparing the results gained in different scenarios. Various tests are conducted to review and analyze the effect of different selection strategies, origin and destinations' beliefs, and the opinion of the neighbor nodes in the process of opinion dynamics of a migrated individual.

4.1 Experimental Setup

To form a synthetic multi-population social network, we have first created a synthetic weighted social graph for each population. Graphs have been generated using LFR Benchmark [27] which is a widely used method for creating synthetic social networks.

Two synthetic multi-population social networks with different sizes have been generated to conduct the experiments. In the first network, population 1 (i.e., the origin population) and population 2 (i.e., the destination population) consist of 200 and 230 nodes respectively. In another network, we increased the size of the population 2 from 230 to 500 nodes. The number of edges in the first network for population 1 and population 2 is 1883 and 2140, respectively. The number of edges in population 2 of the second network with 500 nodes is 4993.

Minimum community size is set to 20 for the first network and 40 for the second network. We increased the community size to 45 for the network with 500 nodes. The average degree of all nodes is set to 15 for all graphs and mu is equal to 0.3, which shows the fraction of inter-community edges to the whole edges of the network.

The belief and opinions of each individual consist of 10 elements. The values of each element ranges from 0 to 100 for population 1 and -80 to 20 for population 2. Python has been used as our programming language and libraries such as Networkx [28], Numpy and Pandas were used for development of this framework and to analyze the experiments. All experiments have been conducted on a PC with AMD Ryzen 5 4500U, 6 Core CPU, and 12 GB RAM. Each experiment has been performed for 50 iterations and the results are based on the average of 50 independent experiments.

4.2 Experiments

We have conducted several experiments using our two proposed algorithms, the Belief-based model and the Learning-based model. To complete the experiments and perform a comparison between various situations, we have defined 48 scenarios. Table 4.2.1 summarizes these scenarios.

The Origin column shows the group of nodes a migrated individual has been selected from. As discussed before, the node can be selected from the Elite, Isolated, Most similar, or Random groups. The Destination column refers to the group a migrant connects to after migration. These groups are Random, Community, or Most similar. The last two columns show the beliefs involved in opinion dynamics of a migrant. Belief1 refers to the social norms of the origin population, and Belief2 indicates the destination population's social norms. Scenarios S1 to S12 represent situations in which, in addition to the neighbors' opinions, Belief1 and Belief2 are also taken into account. On the other hand, scenarios S13 to S24 indicate scenarios in which neighbors' opinions are the only factors that can influence the migrant.

Scenarios $S25$ to $S36$ refer to the situations where the belief or social norm of the origin society is not considered during the opinion evolution. In fact, we want to measure how a migrant node acts in the absence of its origin social norms. These scenarios will help us determine the impact of the origin's network on the opinion dynamics of the migrant node.

Similarly, scenarios $S37$ to $S48$ show the situations that the effect of the destination's social norm is eliminated. These scenarios have been defined to give us some insight into the role of the destination's norm on the opinion change process.

In total, 48 different scenarios have been defined for each network, one with 230 nodes and the other with 500 nodes.

Table 4.2.1: List of the scenarios for evaluation and comparison

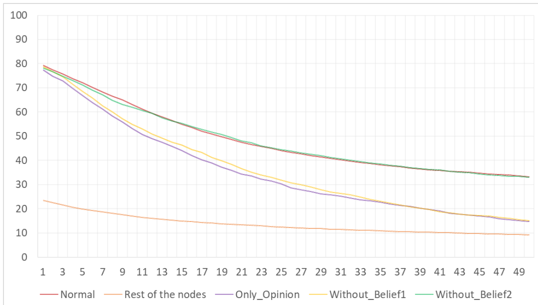
Scenarios	Origin	Destination	Belief1	Belief2
S1	Elite	Community	✓	✓
S2	Elite	Most similar	✓	✓
S3	Elite	Random	✓	✓
S4	Isolated	Community	✓	✓
S5	Isolated	Most Similar	✓	✓
S6	Isolated	Random	✓	✓
S7	Random	Community	✓	✓
S8	Random	Most Similar	✓	✓
S9	Random	Random	✓	✓
S10	Similar	Community	✓	✓
S11	Similar	Most Similar	✓	✓
S12	Similar	Random	✓	✓
S13	Elite	Community	X	X
S14	Elite	Most Similar	X	X
S15	Elite	Random	X	X
S16	Isolated	Community	X	X
S17	Isolated	Most Similar	X	X
S18	Isolated	Random	X	X
S19	Random	Community	X	X
S20	Random	Most Similar	X	X
S21	Random	Random	X	X
S22	Similar	Community	X	X
S23	Similar	Most Similar	X	X
S24	Similar	Random	X	X
S25	Elite	Community	X	✓
S26	Elite	Most Similar	X	✓
S27	Elite	Random	X	✓
S28	Isolated	Community	X	✓
S29	Isolated	Most Similar	X	✓
S30	Isolated	Random	X	✓
S31	Random	Community	X	✓
S32	Random	Most Similar	X	✓
S33	Random	Random	X	✓
S34	Similar	Community	X	✓
S35	Similar	Most Similar	X	✓
S36	Similar	Random	X	✓
S37	Elite	Community	✓	X
S38	Elite	Most Similar	✓	X
S39	Elite	Random	✓	X
S40	Isolated	Community	✓	X
S41	Isolated	Most Similar	✓	X
S42	Isolated	Random	✓	X
S43	Random	Community	✓	X
S44	Random	Most Similar	✓	X
S45	Random	Random	✓	X
S46	Similar	Community	✓	X
S47	Similar	Most Similar	✓	X
S48	Similar	Random	✓	X

4.2.1 Analysis of Belief-based Algorithm

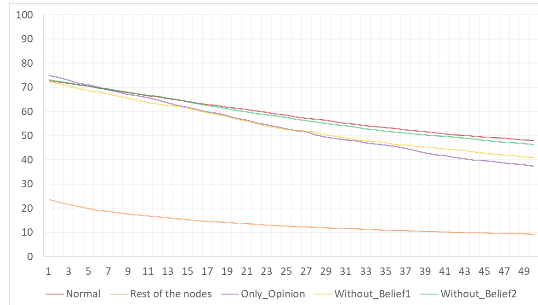
In this section, we discuss the details of the experiments conducted on our Belief-based algorithm and review the results gained by our experiments.

4.2.1.1 Distance of the Migrant's opinion vs. Social Norm

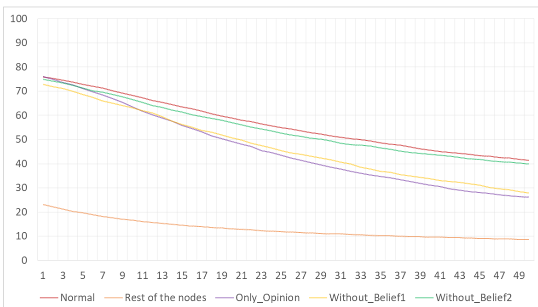
The first experiment has been defined to measure the average distance between the migrated node's opinion and the belief or social norm of the new society. The aim of this experiment is to measure how different parameters in our predefined scenarios affect the adaptation process and opinion dynamics.



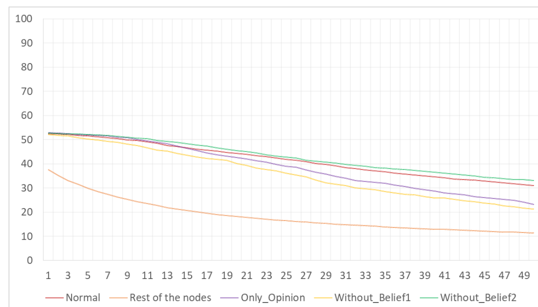
(a) Scenario S1 (Network with 230 nodes)



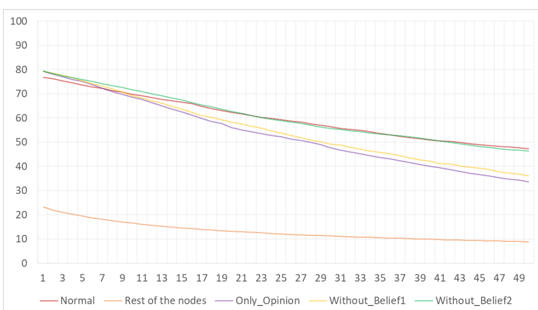
(b) Scenario S2 (Network with 230 nodes)



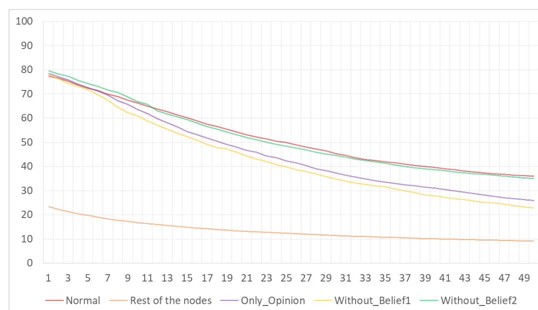
(c) Scenario S3 (Network with 230 nodes)



(d) Scenario S1 (Network with 500 nodes)



(e) Scenario S2 (Network with 500 nodes)



(f) Scenario S3 (Network with 500 nodes)

Figure 4.2.1: Migrant's Opinion vs. destination's Social Norm (node's origin: Elite)

Elite node: Fig. 4.2.1, shows the distance of the migrant's opinion to the social norm when the migrant is selected from the Elite group after 50 iterations. According to the result, the migrant's opinion's distance to the social norm decreases from 80 to 37 when it is connected to a community. Meanwhile, this rate drops by 5% if this node is connected to a random node and nearly 15% if it is connected to the most similar node. The changes in scenario S1 occur at a sharper rate compared to the scenarios S2 and S3. However, in all three cases, the rate of changes in the first 30 iterations is higher than iterations 30 to 50.

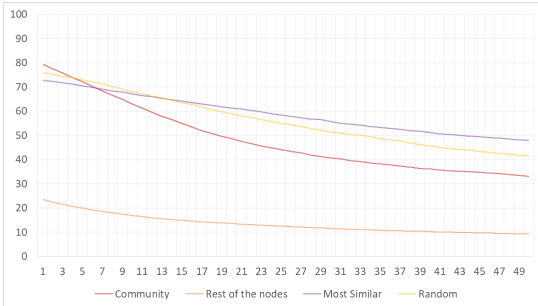
The same trend is seen when we increase the size of the graph to 500 nodes. In fact, there is a gap of approximately 20% between migrant and the social norm, which is nearly the same amount as the network with 200 nodes. However, in this situation, the migrant's distance starts from 50, which is significantly lower than in the smaller network.

Additionally, we have analyzed the role of origin's belief and the destination's social norm in the opinion dynamics process. By comparing the results, it seems that the origin's belief plays a significant role in this process. Consequently, the rate of the change in the migrant's opinion is dramatically different when Belief1 (i.e., the origin's social norm) is not considered.

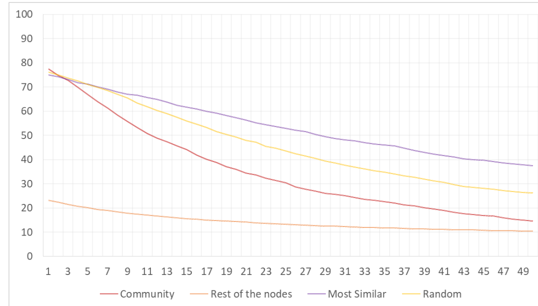
The results also suggest that the effect of Belief2 (i.e., the destination's social norm) on the migrant is insignificant compared to its neighbors nodes. In all three scenarios, the trend of opinion changes shows very similar characteristics in cases of not considering the origin population's belief and the case of counting only the neighbors' opinions. However, the changes in scenario S1 happen at the beginning of the migration while it takes around 5 iterations to have a visible change when the migrant is connected to the random node in scenario S3 and it takes around 11 iterations when it is connected to the most similar node in scenario S2.

As shown in Figs. 4.2.2 and 4.2.3, in order to investigate the impact of the selection on the opinion's dynamic, we have compared the effect of the migrant's first connection in its adaptation process for both social networks.

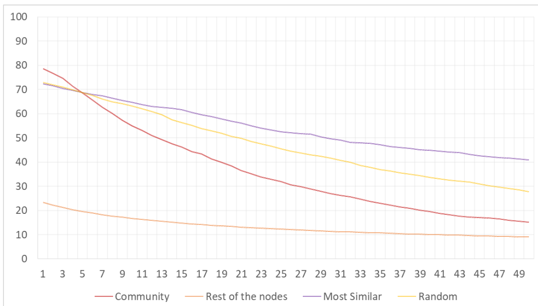
In all situations, the migrant's distance is almost similar when it is first connected to a community, a random node, or the most similar node. However, there is a sudden drop during the first 10 iterations that causes the migrant connected to the community to have the closest opinion to the social norm. Meanwhile, in the "only opinion" situation, when the node is only affected by its neighbor nodes, this decline happens in the first iteration, while for other three situations, it is almost in iterations 5 to 7. A migrant connecting to the most similar node shows a linear rate of change



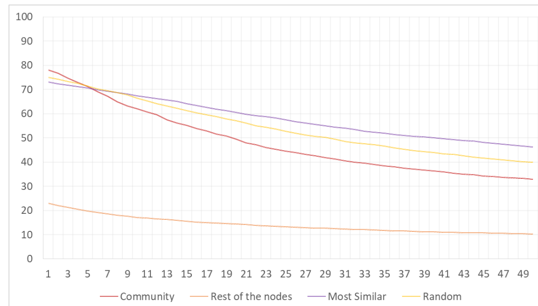
(a) Normal



(b) Only Neighbor's Opinion



(c) Without the Origin's population belief



(d) Without the destination's population belief

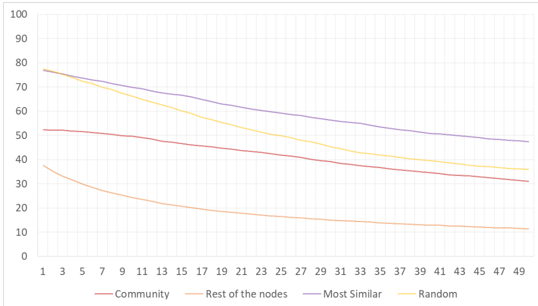
Figure 4.2.2: Average distance of a Migrant node (Elite) connecting to the community, random and most similar nodes in the social network with 230 nodes

and causes the slightest change among other situations.

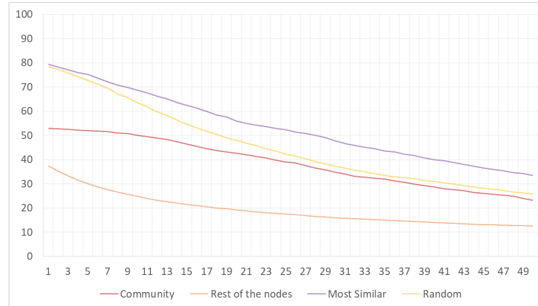
Fig. 4.2.3 demonstrates the results of the same experiment on a network with 500 nodes. Unlike the smaller network, here, the migrant's opinion connected to a community is the closest to the social norm with a gap of around 15 and a distance of 25 units compared to the situations when the migrant is connected to the most similar or the random node. Despite this closeness, at the end of the 50 iterations, the migrant's distance to the social norm is higher than that in the smaller network.

The migrant's distance reaches the same amount when it is connected to the community or a random node. In a Normal situation, the migrant's distance is the same when it is connected to the most similar node or a random node. But this similarity ends after iteration 5, where the migrant connected to a random node witnesses a higher decrement.

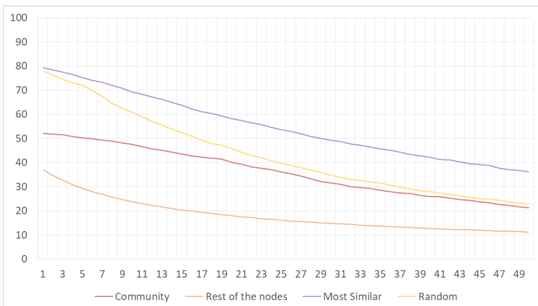
Isolated node: Fig. 4.2.4 demonstrates the average distance between the migrant's opinion and the social norm when the migrant is selected from the isolated



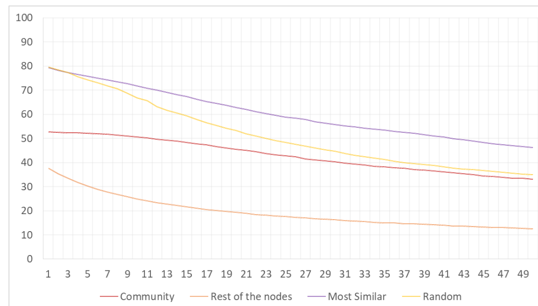
(a) Normal



(b) Only Neighbor's Opinion



(c) Without the Origin's population belief



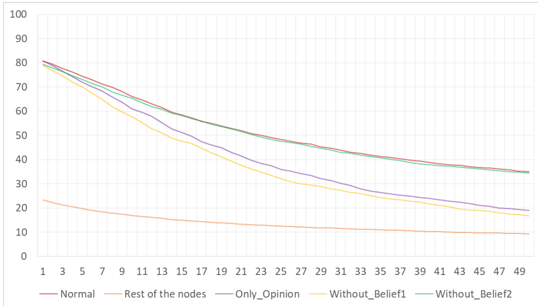
(d) Without the destination's population belief

Figure 4.2.3: Average distance of a Migrant node (Elite) connecting to the community, random and most similar nodes in the social network with 500 nodes

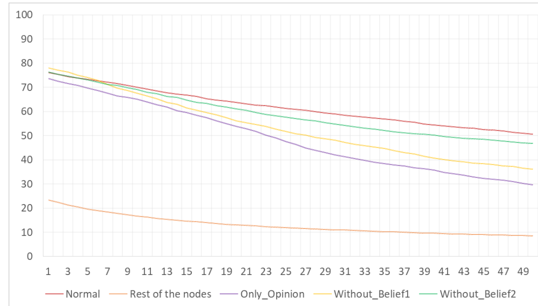
group. Accordingly, at the beginning, S4 has the highest distance to the social norm at around 81. Meanwhile, this value in S6 is 74, which is the lowest. However, the migrant's distance in S4 starts declining from the first iteration, while in scenario S6, this decrement happens with a milder slope and starts from iteration 3. The results also show that the migrant's distance in S4 declines from 80 to 35 when it is connected to a community, while in S6, its distance is 75 at the beginning and reduces by 37 units until the end of the experiment.

This indicates that, similar to the Elite node, connection to the community has the highest influence on the migrant's opinion to become closer to the social norm.

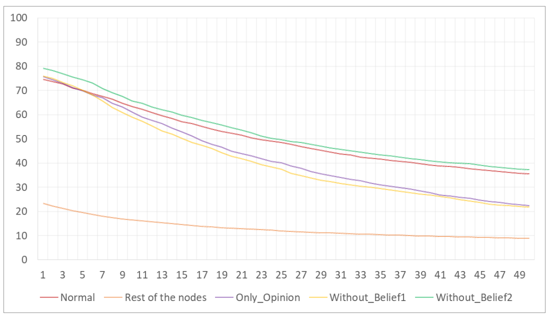
When we increase the size of the network, the migrant's distance starts from 60, which is 25% less than that of in the smaller network. In other two situations, the distance begins at 80. The distance of the migrant increases by 10 units if the migrant connects to a random node instead of a community (Figs. 4.2.4(d) and (f)) which is negligible for situations in Figs. 4.2.4(a) and (c)). Fig. 4.2.4(e) however, shows that



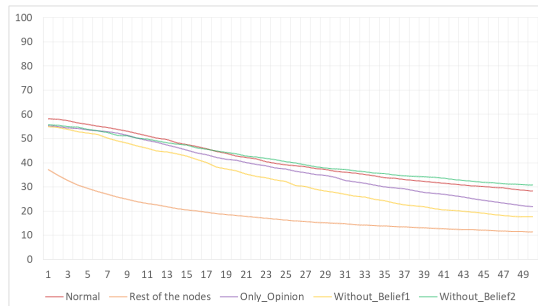
(a) Scenario S4 (Network with 230 nodes)



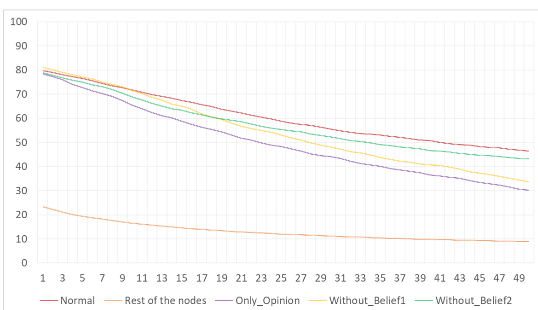
(b) Scenario S5 (Network with 230 nodes)



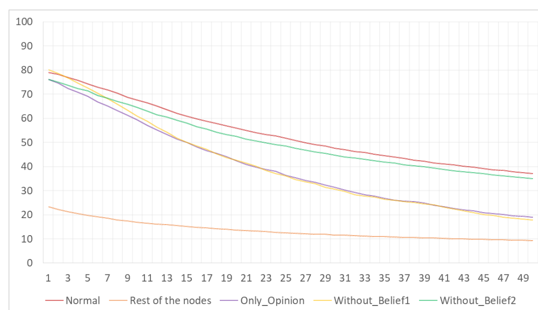
(c) Scenario S6 (Network with 230 nodes)



(d) Scenario S4 (Network with 500 nodes)



(e) Scenario S5 (Network with 500 nodes)



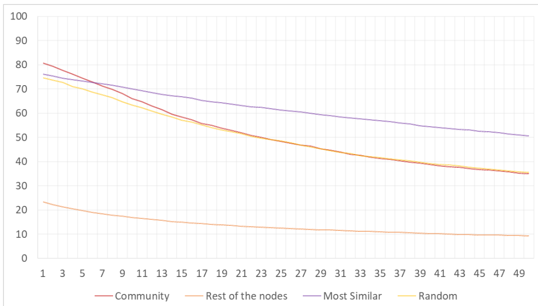
(f) Scenario S6 (Network with 500 nodes)

Figure 4.2.4: Migrant's opinion vs. destination's social norm (node's origin: Isolated)

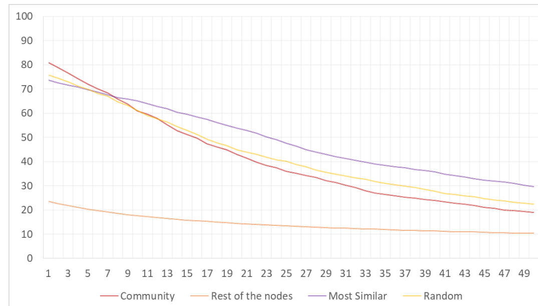
in the larger network, the migrant's distance decreases by 8% when it is connected to the most similar node compared to Fig. 4.2.4(b).

In terms of the impact of beliefs on the opinion dynamics, we can observe that in Figs. 4.2.4(a) and (c), the migrant's distance becomes less when Belief1 is not in effect. On the other hand, when this node connects to the most similar person, the highest change is seen when it is only affected by its neighbors' opinions by nearly around 20% difference compared to the situation without Belief1.

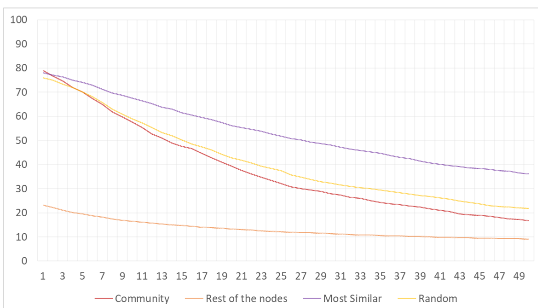
According to the results, although the migrant's opinion is closer to the social norm when it is connected to a community, there is not much difference between its distance to the social norm in Figs. 4.2.4(d) and (f) when Belief1 is not considered. Fig. 4.2.4(f) shows that this distance reaches 20 in both cases of "only opinion" and "without Belief1" when it is connected to the random node.



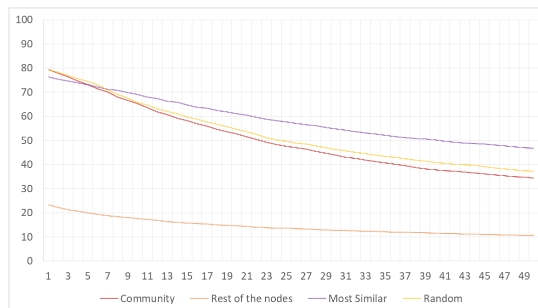
(a) Normal



(b) Only Neighbor's Opinion



(c) Without the origin's population belief



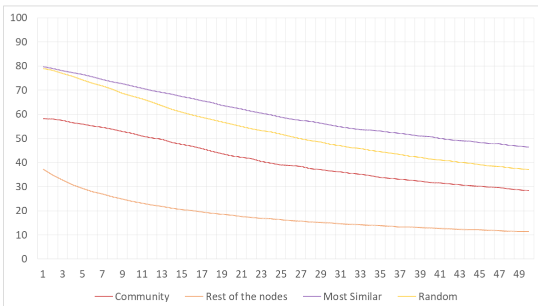
(d) Without the destination's population belief

Figure 4.2.5: Average distance of a Migrant node (Isolated) connecting to the community, random and most similar nodes in the social network with 230 nodes

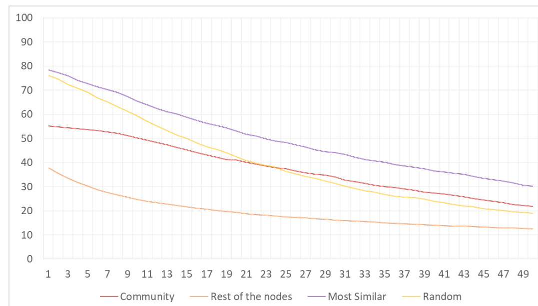
Fig. 4.2.5(a) demonstrates that the migrant's distance starts with around 6% less value when it is connected to the Random node compared to when it is connected to a community in a normal situation. Until iteration 17, the migrant's distance has a better improvement when connected to a random node. However, since then, both community and the random node have the same effect on the migrant's distance.

When we consider only the neighbors' opinion, the opinion of the migrant connected to the community becomes significantly closer to the social norm with a 10% gap. Here we can see that the migrant's distance has a sharper drop when it is connected to the community compared to the time connected to a random node. However, during the first 11 iterations, they have the same impact, but since then, the community causes a better adaptation which makes the distance reaches 20 (20% more change than the random node).

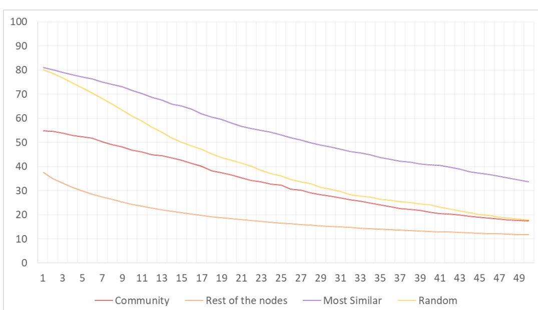
When the origin networks' belief is not considered, the migrant's opinion becomes closer when it is connected to a community. However, when it is connected to a random or the most similar node, the only opinion situation has a higher change. The distance does not make much difference to the normal situation when the destination's network belief is not considered.



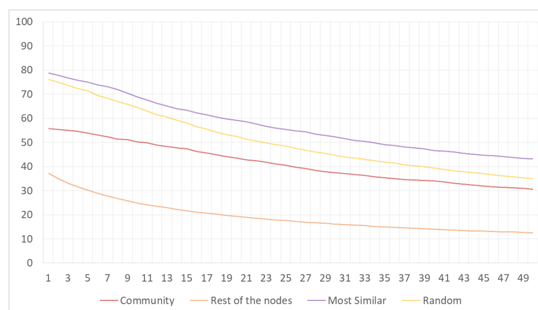
(a) Normal



(b) Only Neighbor's Opinion



(c) Without the origin's population belief

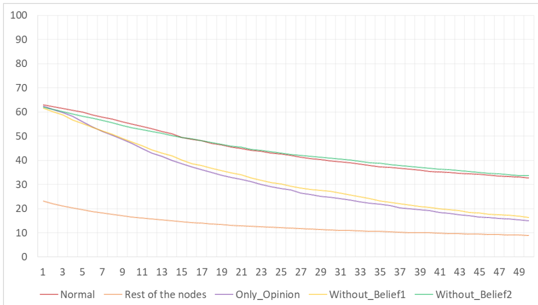


(d) Without the destination's population belief

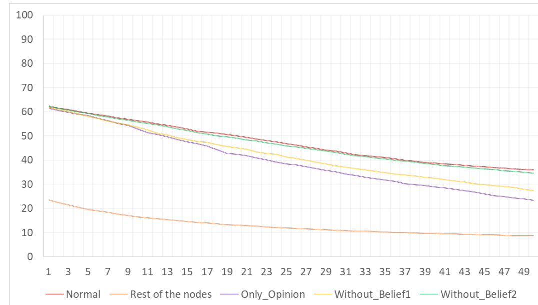
Figure 4.2.6: Average distance of a Migrant node (Isolated) connecting to the community, random and most similar nodes in the social network with 500 nodes

When we increase the size of the network, we notice some changes in these trends. In Fig. 4.2.6(a), there is a gap of 10% between the migrant's distance at the end of 50 iterations when it is connected to a community compared to the time that it is connected to random and the most similar nodes. However, in the network with 230 nodes, the migrant's distance becomes equal when it is connected to a random or a community in a normal situation.

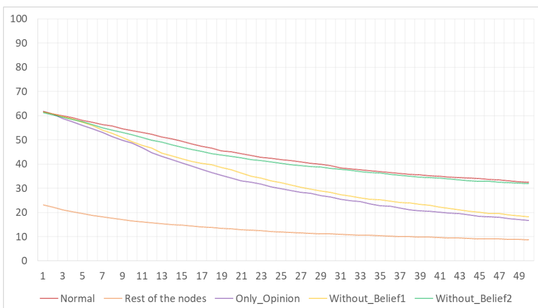
Overall, by comparing the results of these changes for both networks, it seems that the migrant's distance connected to a random node can be changed more if the size of the network increases.



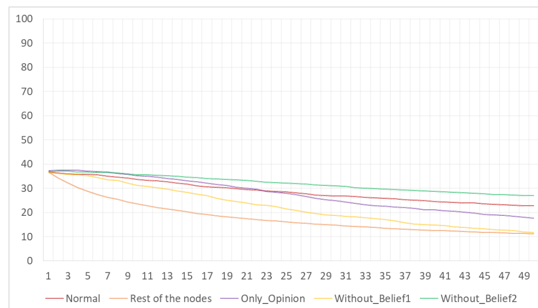
(a) Scenario S10 (Network with 230 nodes)



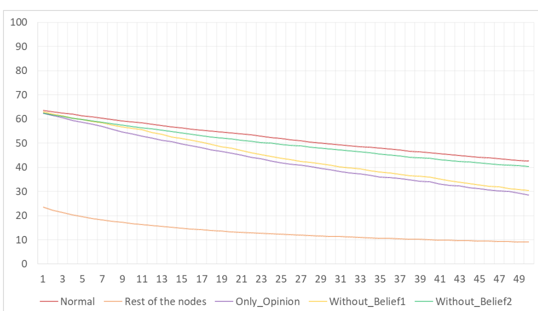
(b) Scenario S11 (Network with 230 nodes)



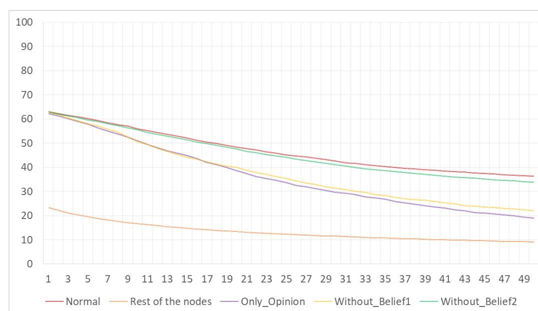
(c) Scenario S12 (Network with 230 nodes)



(d) Scenario S10 (Network with 500 nodes)



(e) Scenario S11 (Network with 500 nodes)



(f) Scenario S12 (Network with 500 nodes)

Figure 4.2.7: Migrant's Opinion vs. destination's Social Norm (node's origin: Most Similar)

Most similar node: As shown in Fig. 4.2.7, unlike other situations, the migrant's distance starts from 60 when it is selected from the most similar group. Accordingly, the distance declines from 60 to 30 when it is connected to a community or a random node. It also shows that after 50 iterations, the migrant's opinion still has 20% difference to the social norm and although it has been selected from the most similar group, there is not much difference between the opinion distance of this node and other types of nodes after 50 iterations. In other situations, when the migrant node is connected to the most similar node, the average distance decrease was around 30 units. However, here the distance declines from 60 to 40, which is about 30% less change.

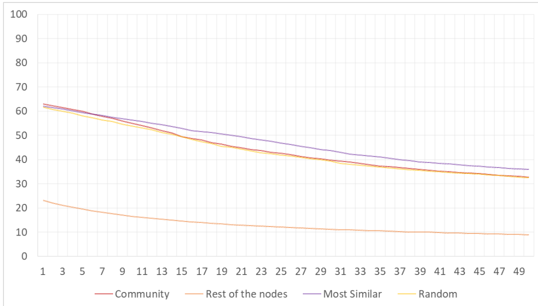
In the network with 500 nodes, there is not much difference between the initial opinion of the migrant and the social norm of the society when it is connected to the community. However, because of the network evolution and social interaction, both social norm and migrant's opinion change. Fig. 4.2.7(d) shows that this distance decreases from 40 to 23 and stabilizes at this value after iteration 40. In Fig. 4.2.7(e), however, there was a slight improvement in the migrant's opinion distance compared to the smaller network (42 to 38 units). Fig. 4.2.7(f) shows that the opinion is closer to the social norm when the size of the network is smaller. Furthermore, we can see that there is not much difference between this distance after 50 iterations when the node is selected from Elite, Isolated, or the most similar.

Figs. 4.2.7(a) and (c) show a similar trend of this distance change in the "only opinion" and "without Belief1" situations during the first 11 iterations. However, the changes in "only opinion" become more intense than after iteration 11.

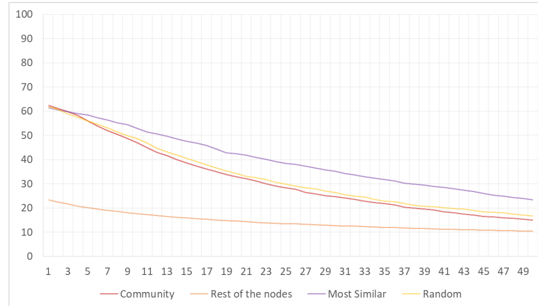
Generally, similar to the other situations, belief of the origin society and the neighbors' opinions play the most significant roles in the adaptation and opinion dynamic process.

According to the Fig. 4.2.8(a), in a normal situation, the migrant's distance is similar for the three types of connections until iteration 9. After that, the migrant connected to the community or a random node shows a similar trend reducing from 50 to 32. Fig. 4.2.8(d) also shows the same behavior, but here the migrant node which is connecting to the random node has slightly higher changes compared to the one which is connected to the community. Generally, similar to the other situations, belief of the origin society and the neighbors' opinions play the most significant roles in the adaptation and opinion dynamic process.

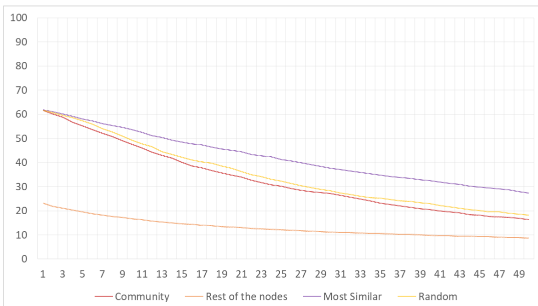
As shown in Fig. 4.2.9, by increasing the size of the network, in all four situations, the migrant's opinion connected to the most similar node is very close to the social



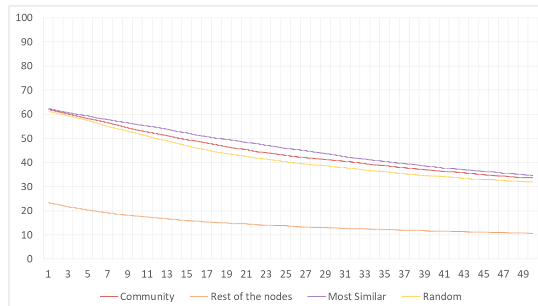
(a) Normal



(b) Only Neighbor's Opinion



(c) Without the origin's population belief



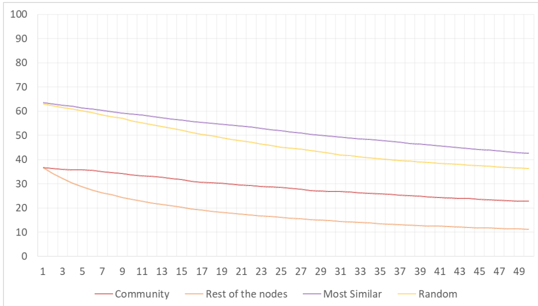
(d) Without the destination's population belief

Figure 4.2.8: Average distance of a Migrant node (Most Similar) connecting to the community, random and most similar nodes in the social network with 230 nodes

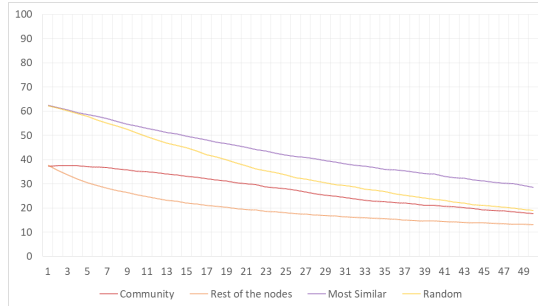
norm at the beginning. In a normal situation, the migrant's distance connected to a random node or the most similar node starts from 62 and they tend to have approximately the same value until iteration 5. Since then, the random connection causes a gentle decline in the migrant's distance while the migrant's distance connected to the most similar node has a linear behavior. At the end, the migrant's distance reaches 21 when it is connected to a community and 38 and 41 when it is connected to a random and the most similar node, respectively.

It is noticeable that in all four situations, most of the changes happen during the first 30 iterations. After that, the changes are gradual.

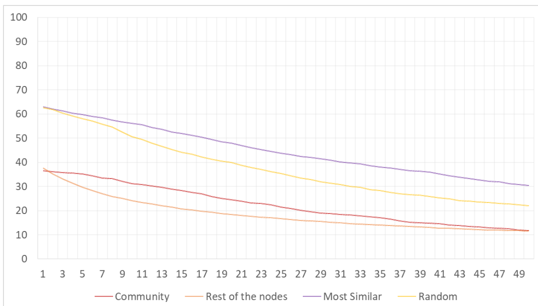
Random node: Fig. 4.2.10 shows the results when the migrant is selected from a random group. According to the results, the rate of changes in both S10 and S12 follows the same trend and it is almost the same. So for a random node, unlike other scenarios, the connection to a community does not have any remarkable impact on the opinion dynamics of the migrant node. However, similar to the other experiments,



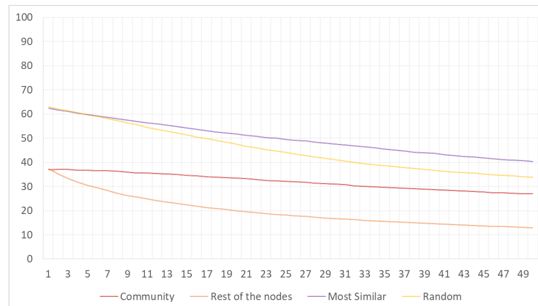
(a) Normal



(b) Only Neighbor's Opinion



(c) Without the origin's population belief



(d) Without the destination's population belief

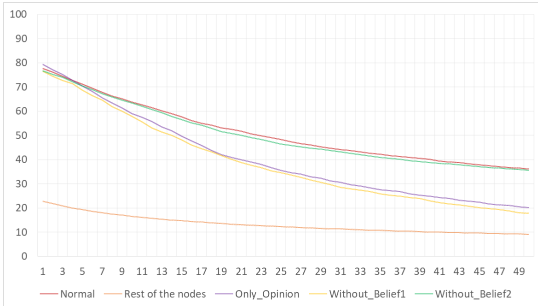
Figure 4.2.9: Average distance of a Migrant node (Most Similar) connecting to the community, random and most similar nodes in the social network with 500 nodes

the social norms of the origin community still have a significant effect on the opinion dynamics of the node in the new environment.

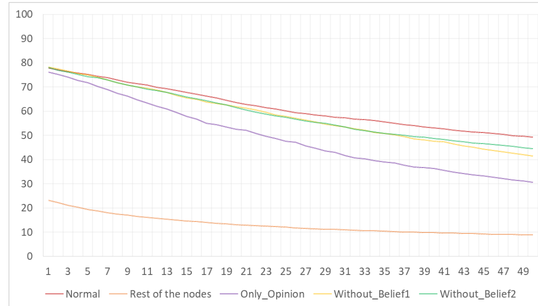
In the larger network, the initial distance is significantly closer to the social norm when it is connected to a community (around 10% gap). Also, there is more difference between distances in the "only opinion" and "without Belief1", while in the smaller network, they were approximately equal. In all situations, the first 30 iterations were the most effective period for changing the migrant's opinion.

Fig. 4.2.11(a) shows that the migrant's distance started from 80 for all three connection types. During the first 15 iterations migrant's distance connected to the community or a random node declined to 55 while this change was around 10 units for the migrant connected to the most similar node. In a normal situation, the migrant's distance reaches 38 at the end of the experiment when it is connected to a community or a random node.

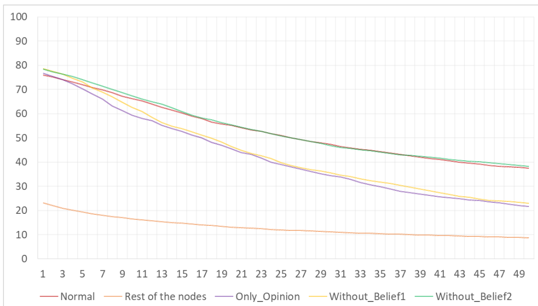
In the "only opinion" scenario, the migrant's distance in all three situations de-



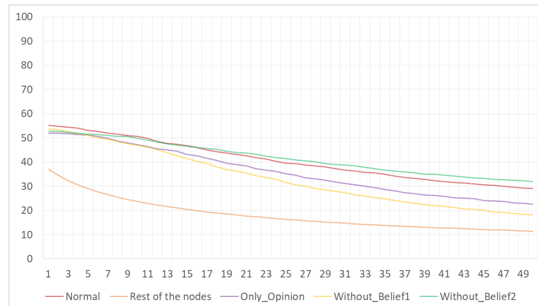
(a) Scenario S7 (Network with 230 nodes)



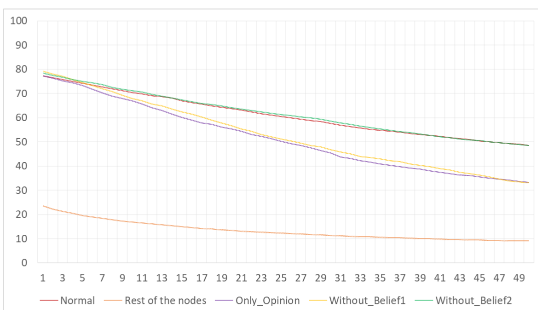
(b) Scenario S8 (Network with 230 nodes)



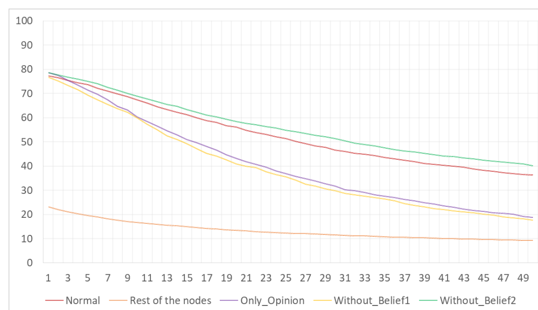
(c) Scenario S9 (Network with 230 nodes)



(d) Scenario S7 (Network with 500 nodes)



(e) Scenario S8 (Network with 500 nodes)

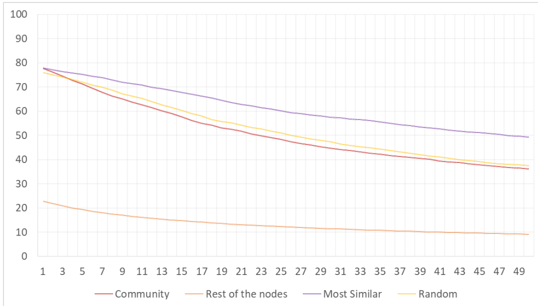


(f) Scenario S9 (Network with 500 nodes)

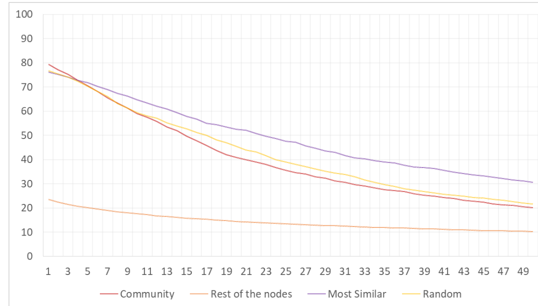
Figure 4.2.10: Migrant's Opinion vs. destination's Social Norm (node's origin: Random)

creases with a sharper trend reaching 20 at the end of 50 iterations for random and community connection, which is 10% difference from the social norm. Accordingly, it causes a change rate of nearly 2 times that of a normal situation. Similar to the previous scenarios, this clearly demonstrates the role of the social norms of the origin population in the opinion dynamics of the migrated node.

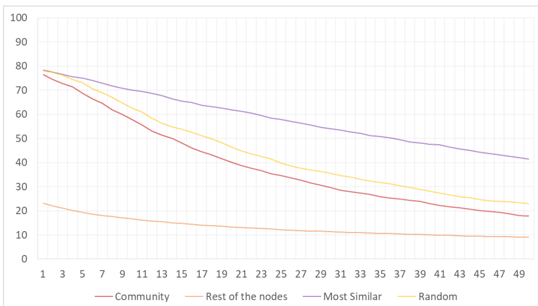
Fig. 4.2.11(c) shows that the migrant connected to a community has a better improvement to become closer to the social norm compared to the only opinion situation. The role of the social norms of the destination scenario is not very significant



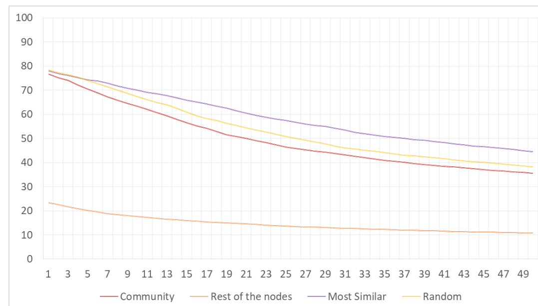
(a) Normal



(b) Only Neighbor's opinion



(c) Without the origin's population belief



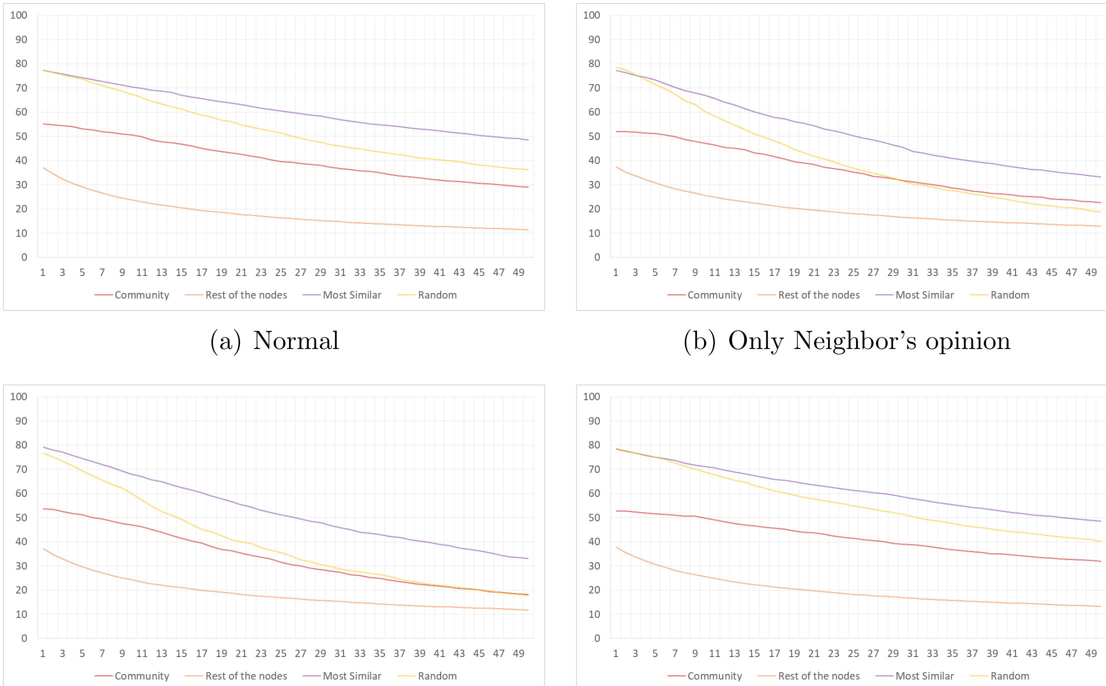
(d) Without the destination's population belief

Figure 4.2.11: Average distance of a Migrant node (Random) connecting to the community, random and most similar nodes in the social network with 230 nodes

in commission with the impact of the neighbor's opinion or the social norms of the origin's population.

As shown in Fig. 4.2.12, in a network with 500 nodes, the migrant's distance connected to a community starts from nearly 50 in all four scenarios. In a normal situation, the migrant's distance connected to a community or a random node starts from 80 and shows the same amount of decrement until iteration 5. Since then, the distance has witnessed a sharper decline when it is connected to a random node compared to connecting to the most similar node.

In the normal scenarios, when the migrant node is under the influence of both populations' norms and its neighbors, the results suggest that the changes are more visible when it is connected to a random node compared to the other two situations.



(a) Normal

(b) Only Neighbor's opinion

(c) Without the origin's population belief

(d) Without the destination's population belief

Figure 4.2.12: Average distance of a Migrant node (Random) connecting to the community, random and most similar nodes in the social network with 500 nodes

At the end, the role of the destination's belief space is not significant in the process. Meanwhile, in all cases, the migrant's distance connected to a community improves slower than others.

4.2.1.2 Measuring the quality of connections

The next experiment we conducted was to measure the average number of friends and the weight of their relations for the migrant and the rest of the nodes in all 48 scenarios. Table 4.2.2 shows the results of this experiment in different scenarios in a normal situation.

By comparing scenarios S1, S2, and S3, we can see that the migrant finds the highest number of friends (around 38) when it is connected to a community with an average weight of 0.2, which indicates a stronger relationship compared to S2 and S3. After S1, S3 has the highest number of friends, which is two times more than that of S2, with nearly 10% stronger relations compared to S2. In the best scenario (S1),

Scenarios	ave_weight_mig	ave_weight_rest	mig_sd	rest_sd	mig_ave_fr	rest_ave_fr	mig_fr_sd	rest_fr_sd
S1	2.87E-01	1.30E-01	3.01E-02	4.60E-02	3.80E+01	1.81E+01	4.94E+00	9.87E+00
S2	4.18E-01	1.26E-01	1.44E-02	4.41E-02	1.67E+01	1.83E+01	1.20E+01	1.10E+01
S3	3.72E-01	1.24E-01	2.37E-02	4.68E-02	3.13E+01	1.83E+01	9.61E+00	1.01E+01
S4	3.12E-01	1.34E-01	3.04E-02	4.82E-02	3.91E+01	1.84E+01	4.14E+00	1.10E+01
S5	4.45E-01	1.22E-01	1.53E-02	4.45E-02	1.44E+01	1.90E+01	1.19E+01	1.17E+01
S6	3.13E-01	1.24E-01	2.18E-02	4.41E-02	3.14E+01	1.89E+01	7.89E+00	1.19E+01
S7	3.19E-01	1.31E-01	2.78E-02	4.74E-02	3.67E+01	1.82E+01	5.34E+00	1.02E+01
S8	4.28E-01	1.24E-01	1.31E-02	4.43E-02	1.38E+01	1.86E+01	1.19E+01	1.16E+01
S9	3.34E-01	1.25E-01	2.30E-02	4.54E-02	3.24E+01	1.87E+01	8.71E+00	1.13E+01
S10	2.90E-01	1.30E-01	2.97E-02	4.73E-02	3.79E+01	1.91E+01	4.06E+00	1.28E+01
S11	3.08E-01	1.22E-01	1.54E-02	4.32E-02	2.13E+01	1.93E+01	1.17E+01	1.20E+01
S12	2.87E-01	1.23E-01	2.10E-02	4.42E-02	3.25E+01	1.84E+01	8.43E+00	1.01E+01

Table 4.2.2: Comparison between scenarios in terms of the number and the quality of connections

the migrant can find 2 times more friends than the average of the other nodes, but the level of strength is still around 16% lower than others.

When the migrant is selected from the Isolated group (S4, S5, and S6), the highest number of friends belong to the S4, in which the migrant is connected to a community. This number is 2 times the number of friends of the rest of the nodes, but its relations are around 18% weaker. Similar to the Elite node, when the isolated node is connected to the random node, it has the second highest number of friends with a strength level of around 0.31, which is the same as in S4. S5, however, shows approximately the same values as S2.

Among S7, S8, and S9 average number of friends when the migrant is connected to the community or a random node is closer to each other compared to the other scenarios. The strength of the relations differs 2% with S7 having stronger links than S9. S8 is the scenario where the migrant finds the least number of friends (around 13). When the node is similar to the destination (S10, S11, and S12), the highest number of friends belongs to S10, but the best strength level can be found in S12 at 0.28, which is 1% stronger than those in S10.

It is noticeable that S11 is the only scenario that achieves the strongest relations among the other scenarios in a normal situation when the migrant is connected to the most similar node, which is 0.3 and is only 1-2% weaker than being connected to a community or a random node.

By comparing all scenarios in a normal situation, S1 is the scenario where a migrant finds a high number of friends with the best level of strength. Connecting to a community or the most similar node can have the same impact on the migrant's relation strength except when the node is an Elite.

Scenarios	ave_weight_mig	ave_weight_rest	mig_sd	rest_sd	mig_ave_fr	rest_ave_fr	mig_fr_sd	rest_fr_sd
S13	1.39E-01	1.40E-01	3.38E-02	4.07E-02	3.91E+01	1.84E+01	3.53E+00	1.05E+01
S14	3.11E-01	1.35E-01	2.04E-02	4.13E-02	1.93E+01	1.82E+01	1.29E+01	9.64E+00
S15	2.24E-01	1.34E-01	2.84E-02	4.00E-02	3.30E+01	1.84E+01	6.85E+00	1.05E+01
S16	1.66E-01	1.41E-01	3.45E-02	4.15E-02	3.89E+01	1.82E+01	3.50E+00	9.56E+00
S17	2.47E-01	1.33E-01	2.26E-02	3.98E-02	2.24E+01	1.80E+01	1.20E+01	9.85E+00
S18	1.91E-01	1.36E-01	2.70E-02	3.86E-02	3.22E+01	1.89E+01	8.49E+00	1.24E+01
S19	1.80E-01	1.40E-01	3.50E-02	4.15E-02	3.87E+01	1.84E+01	3.18E+00	1.03E+01
S20	2.52E-01	1.32E-01	2.18E-02	3.90E-02	2.06E+01	1.82E+01	1.31E+01	9.60E+00
S21	1.92E-01	1.36E-01	2.84E-02	3.93E-02	3.37E+01	1.86E+01	6.84E+00	1.15E+01
S22	1.40E-01	1.39E-01	3.45E-02	4.11E-02	3.92E+01	1.80E+01	3.55E+00	1.01E+01
S23	1.90E-01	1.32E-01	2.28E-02	3.86E-02	2.47E+01	1.89E+01	1.23E+01	1.21E+01
S24	1.49E-01	1.33E-01	2.72E-02	3.86E-02	3.18E+01	1.78E+01	8.50E+00	8.71E+00

Table 4.2.3: Comparison between scenarios in terms of the number and the quality of connections for scenarios S13 to S24

Table 4.2.3 shows the results of the average weight and the average number of friends when only the neighbors' opinions are considered. In all scenarios, when the node is selected from the Elite, Isolated, most similar, or the random group, the highest number of friends is when the migrant is connected to a community which also has the strongest relations.

In S13, the migrant finds the highest number of friends and also can achieve the same level of strength in its relations as the rest of the nodes, which is 0.13. S14 shows the migrant cannot find as much as friends and closeness when it is connected to the most similar node, while in S15, the migrant finds nearly as many friends as in S13 but not strong relations.

When the node is Isolated, it can find the same number of friends as an Elite when it is connected to a community or a random node, but its relations are stronger when it is connected to a random node. On the other hand, in S17, the migrant can find a reasonable number of friends and level of strength compared to the rest of the nodes, which are on average 22 and 0.24 respectively.

By comparing S19, s20, and S21, the number of friends that a migrant finds is highest in S19, which is 38 friends on average, while it finds around 32 when it is connected to a random node. The level of strength does not have much difference, with both having a strength level of about 0.18. When the migrant is a random node connected to the community, its number of friends and the strength level are exactly the same as that of an Elite node. Although in S24, the migrant has the same number of friends as in S15, its strength is significantly higher than that in S15. The results of scenario S23 also show that when the migrant is a similar node, it can have the highest number of friends and the strongest relations compared to the other nodes connected to the most similar node.

Overall, the number of friends is higher in only opinion situation, and the relations are considerably stronger compared to the normal situation.

Scenarios	ave_weight_mig	ave_weight_rest	mig_sd	rest_sd	mig_ave_fr	rest_ave_fr	mig_fr_sd	rest_fr_sd
S25	1.40E-01	1.27E-01	3.30E-02	4.39E-02	3.85E+01	1.92E+01	4.21E+00	1.17E+01
S26	3.56E-01	1.23E-01	1.57E-02	4.36E-02	1.45E+01	1.84E+01	1.31E+01	1.06E+01
S27	2.45E-01	1.24E-01	2.24E-02	4.29E-02	3.19E+01	1.80E+01	9.15E+00	9.60E+00
S28	1.52E-01	1.30E-01	3.26E-02	4.46E-02	3.85E+01	1.85E+01	4.61E+00	1.07E+01
S29	3.14E-01	1.25E-01	1.73E-02	4.27E-02	1.89E+01	1.88E+01	1.29E+01	1.13E+01
S30	1.94E-01	1.20E-01	2.20E-02	4.22E-02	3.12E+01	1.88E+01	1.03E+01	1.03E+01
S31	1.64E-01	1.29E-01	3.24E-02	4.50E-02	3.85E+01	1.88E+01	5.50E+00	1.20E+01
S32	3.56E-01	1.24E-01	1.31E-02	4.35E-02	1.15E+01	1.90E+01	1.11E+01	1.21E+01
S33	2.04E-01	1.24E-01	2.40E-02	4.15E-02	3.18E+01	1.90E+01	1.10E+01	1.25E+01
S34	1.50E-01	1.26E-01	3.31E-02	4.46E-02	3.97E+01	1.87E+01	3.62E+00	1.13E+01
S35	2.28E-01	1.25E-01	1.60E-02	4.18E-02	1.76E+01	1.81E+01	1.39E+01	9.52E+00
S36	1.60E-01	1.23E-01	2.42E-02	4.19E-02	3.32E+01	1.93E+01	7.54E+00	1.35E+01

Table 4.2.4: Comparison between scenarios in terms of the number and the quality of connections for scenarios S25 to S36

Table 4.2.4 represents the results of the average weights and friends of the migrant and the other nodes when Belief1 is not in effect. By comparing the Elite, Isolated, and the random node scenarios, we can see the migrant finds the same number of friends when connected to a community in all three situations (38 friends).

Similarly, they have the same number of friends when they are connected to the most similar node, which is around 31 friends. However, the level of strength differs in these scenarios. When connected to a community, the Elite node can have stronger relations compared to other nodes. S28 and S34 have the same level of strength, with S34 having 1 to 2 more friends on average.

Finally, a random node connected to a community has the weakest relations with 0.16, which is 4% more than that of the average strength in society. By comparing S27, S30, and S33, we can see connecting to a random node has a better influence on the Isolated node and the Random node, which causes an average weight of 0.19 to 0.20.

A random node, however, has the weakest relation when connected to a random node. S36 shows that the most similar node connecting to a random node has a considerable effect on this node by causing a number of friends around 33 and a level of strength of 0.16, which is at least 3% stronger than other nodes. When the migrant is connected to the most similar node, the most similar node would have the best relationship strength compared to the other nodes with 0.22 average weight (10% gap with the average weight of other nodes) and average 17 friends, which is nearly the same number as other nodes.

By comparing S26, S29, and S32, we can see that as the number of friends increases, the level of strength also improves. Generally, when Belief1 is not in effect, the most similar node can achieve a higher number of friends with more strength.

Scenarios	ave_weight_mig	ave_weight_rest	mig_sd	rest_sd	mig_ave_fr	rest_ave_fr	mig_fr_sd	rest_fr_sd
S37	2.82E-01	1.42E-01	3.37E-02	4.27E-02	3.69E+01	1.84E+01	4.33E+00	1.08E+01
S38	3.89E-01	1.36E-01	2.10E-02	4.09E-02	1.86E+01	1.78E+01	1.27E+01	8.14E+00
S39	3.41E-01	1.36E-01	2.79E-02	4.22E-02	3.15E+01	1.89E+01	8.00E+00	1.19E+01
S40	2.95E-01	1.45E-01	3.35E-02	4.35E-02	3.71E+01	1.84E+01	3.38E+00	1.11E+01
S41	3.97E-01	1.36E-01	2.06E-02	4.19E-02	1.97E+01	1.86E+01	1.29E+01	1.12E+01
S42	3.19E-01	1.35E-01	2.88E-02	4.08E-02	3.26E+01	1.80E+01	6.57E+00	9.94E+00
S43	3.07E-01	1.45E-01	3.54E-02	4.33E-02	3.79E+01	1.81E+01	4.16E+00	9.04E+00
S44	3.77E-01	1.35E-01	2.29E-02	4.11E-02	2.01E+01	1.84E+01	1.19E+01	9.91E+00
S45	3.26E-01	1.36E-01	2.79E-02	4.14E-02	3.01E+01	1.90E+01	9.23E+00	1.06E+01
S46	2.88E-01	1.45E-01	3.34E-02	4.33E-02	3.72E+01	1.81E+01	3.98E+00	1.10E+01
S47	2.88E-01	1.35E-01	2.26E-02	4.03E-02	2.38E+01	1.86E+01	9.09E+00	1.14E+01
S48	2.71E-01	1.34E-01	2.66E-02	4.00E-02	3.30E+01	1.82E+01	7.17E+00	1.03E+01

Table 4.2.5: Comparison between scenarios in terms of the number and the quality of connections for scenarios S37 to S48

Table 4.2.5 shows the results of the same experiment when the effect of Belief2 is not considered. By considering the scenarios by the type of the migrant node, we can see the number of friends is approximately in the same range for all three connections. However, when the node is a similar node, the level of strength is significantly higher than other three types of nodes (at least 9% stronger).

By comparing the values for the most similar node (S46, S47, and S48), we can see the level of strength for all these three scenarios are the same, while in S46, the migrant can find the highest number of friends. When the migrant is a random node, its connections are stronger when it is connected to the community and are the weakest when it is connected to the most similar node. The Elite and Isolated nodes have the strongest relations when connected to a community, a random node, and the most similar node, respectively.

According to the results, similar to the normal situation, most similar would have the highest number of friends and the highest strength level when Belief2 is not in effect.

4.2.2 Analysis of Learning-based Algorithm

In this section, we discuss the results of the proposed Learning-based Algorithm. To evaluate the learning-based algorithm, we conducted a couple of major experiments for the scenarios $S1$, $S3$, $S4$, $S6$, $S10$, and $S12$.

4.2.2.1 Effect of learning on reward values

The first experiment was to measure the changes in values gained by the migrant node in different scenarios. The aim of this experiment is to identify the impact of learning on the migrant's decision by considering its action selection in the new society.

The test consists of the following steps: a set of 50 actions have been created for each population in our first generated social network. The actions have been generated using the method described in section 3.2.10, and each consists of a name, a required opinion, and the value. 25 of these actions are shared between the populations, however, their minimum requirements and their reward values are different. The values are calculated based on the level of the difficulty of that action in terms of the number and the values of the required opinions.

In each iteration, a set of 20 actions are available for the whole population. Each individual then will select the five best actions in a way that maximizes its gain reward value. However, due to the minimum requirement of each action, not all the 20 actions can be taken by the individual. Therefore, the level of gained values is different person by person.

On the other hand, the migrated individual does not have access to the details of these actions in the new society. However, it has full knowledge of the actions of its own origin population. As mentioned in the section 3.2.9, the migrant node then tries to learn the new actions either by observing the actions that itself or its circle of neighbors select in each iteration. To conduct this test, we considered $0, 5$, and 10 iterations for the observations period. However, we have noticed that the results obtained by 5 iterations are very similar to the non-observation state, so in this report, we just focus on 0 and 10 iterations.

The amount of values gained by the migrant node throughout 100 iterations has been collected and reported. This experiment demonstrates how a new node in a society can learn from the environment and its own actions to optimize its value in a new society.

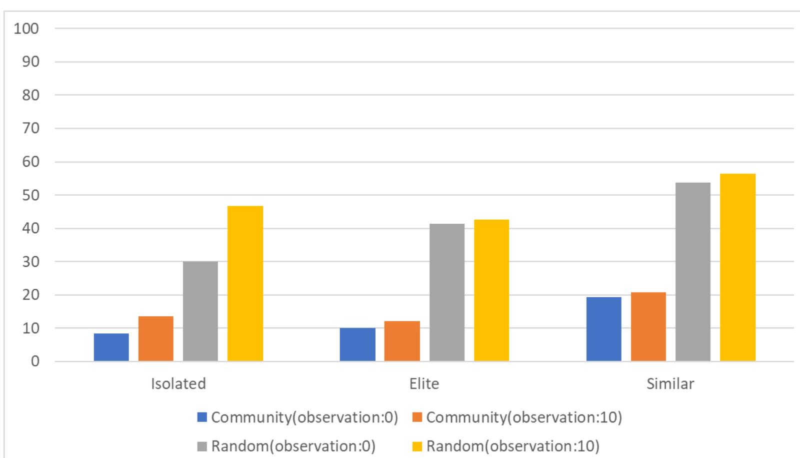


Figure 4.2.13: Average reward value gained by the migrant node compared to the other nodes in the network in the last 20 iterations

Fig. 4.2.13 represents the percentage of the values gained by the migrant to the whole network in the last 20 iterations of the experiment with 0 and 10 observations. This is the average of 10 independent experiments. As the results show, connection

	Isolated		Elite		Similar	
	First	Last	First	Last	First	Last
Community(observation:0)	5	31	4	28	6	31
Community(observation:10)	7	32	5	29	7	32
Random(observation:0)	13	34	14	33	13	35
Random(observation:10)	19	35	18	34	20	36

Table 4.2.6: The number of learnt actions in the first and last 20 iterations

to the most similar community generally provides the node's least level of rewards value. On the other hand, if a node connects to a node with different characteristics even randomly, overall can get more values during the iterations.

As shown in this figure, the isolated node achieves the highest value when it is connected to the random node with 10 iterations of observation (nearly half of the value taken by the whole network). The second highest value for this node happens when it is connected to a random node with no observation. However, when it is connected to a community, it gains lower values which range from 8 to 12 percent of the whole value gained by the network.

Similarly, the Elite node also receives the lowest values when it is connected to the community. However, there is not much difference between the values taken by this node when it is connected to a random node with 0 or 10 observations (about 40% of the network). The similar node receives approximately the same value in both 0 and 10 observations when it is connected to the random and a community. However, the values taken when connected to the random node are at least 2 times more than those connected to the community.

Overall, the node with the most similar characteristics to the norm of the new society can gain higher values than the isolated or elite nodes.

4.2.2.2 The effect of learning on knowledge expansion

The next experiment was conducted to measure the average number of the actions the migrant learned in each scenario. The aim of this experiment is to investigate the impact of observation and the type of nodes and their connections on a migrant's knowledge. As shown in Table 4.2.6, when the migrant is linked to a community, the impact of initial observation is between 2% to 4% on learning the new knowledge. This impact is between 8% to 14% in other cases. It shows the observation has a lower impact on the learning process when a node is connected to the most similar community.

On the other hand, in all three cases, the migrant's knowledge reaches the same approximate value in the last iteration whether there are 0 or 10 observations. When the migrant is connected to a random node, we can see that in all three cases, the migrant's knowledge improves by more than 8% when there are 10 iterations for observation. Meanwhile, the difference in the last 20 iterations with and without observation is from 33 to 35 in all three cases (i.e., Isolated, Elite, and Similar), which is equal to a 2% improvement.

By comparing the scenarios where the migrant is connected to a community or a random node, we can see the Elite node can learn less than other 2 nodes when it is connected to a community, while its knowledge is the same as other nodes when it is connected to a random node. When the migrant is connected to the random node, the similar node learns around 35 actions at the end, which is 70% of the whole actions.

According to this table, we can see that observation can increase the knowledge of the migrant at the beginning and the end by approximately 10% and 2%, respectively.

4.2.3 Discussion

In this research, we proposed a new computational model for opinion dynamics of a migrated individual. Our model consists of two algorithms Belief-based and Learning-based. In the Belief-based approach, the migrant's opinion changes due to social interaction with other nodes. In the Learning-based approach, the migrant can also observe and learn to choose the best actions, which can cause progress in the adaptation process. At the end, we have compared these two algorithms to identify the impact of different factors in opinion dynamics and adaptation of a migrated node.

According to the results gained by our experiments, when the migrant's opinion is only affected by its neighbors' opinions or in a situation when the origin's belief is not in effect, the fastest adaptation progress occurs. This is also true when the size of the network increases.

Additionally, the opinion of all types of node become closer to the social norm when it is connected to a community or a random node meaning there is a better chance for the migrant to become adjusted to the new society if it is connected to a community similar to itself or a random node. In the network with 500 nodes still, the migrant who is connected to the community shows better progress, but its opinion changes slower, while when it is connected to a random node, the changes are significant and fast. In all cases, connecting to the most similar node is less helpful for the migrant to become adapted. Except for the situations where the migrant is connected to the community in a graph with 230 nodes and connected to a random node in a graph with 500 nodes, all nodes reach the same closeness value to the social norm. In that case, the most similar node has the closest opinion to the social norm.

Overall, the effect of the node's origin's social norms and belief is significant on opinion dynamics of the migrant. Additionally, the results of the Tables 4.2.2 to 4.2.5 show that in most cases, the migrant connecting to a community finds 2 times more friends than the average of the network, which are also stronger than being connected to the most similar or a random. Also, when we eliminate the effect of the origin's social norm or both social norms, the average weight of the migrant node increases by at least 12%.

According to the results gained by evaluating the Learning-based algorithm, observation causes a 2% overall increase in learning new actions. However, when the migrant connects to a community, it learns less than 10% of the time connected to a no-community situation. In this case, the actions that a migrant learns are not necessarily high-value ones but are more general, which causes the migrant to select actions that have a high value in its community but not in the whole network. Meanwhile, the learning rate becomes slower when the most similar node is connected to a community.

The highest knowledge difference between connecting to a community and a non-community happens when the migrant is an Elite node which is more than a 15% gap.

The results also suggest that at least 70% knowledge of the new society is needed for the migrant to have a constant reward value gain and effectively participate in the new population.

Chapter 5

Conclusion

Immigration has become more widespread over time. It can be defined as a movement from one place or a community to another in order to improve the quality of life. Migrants, however, face many challenges since their values and beliefs differ from those in the new society, which causes some difficulties in the adaptation process. In this thesis, we proposed a computational model to track the opinion dynamics of a migrant based on several parameters such as origin's and destination's social norms, neighbors' opinions, the type of the migrant, and its connections in the new society. This model is based on two different algorithms Belief-based and Learning-based. The Belief-based algorithm focuses on the impact of the origin and destination network's beliefs and opinions, while in the Learning-based approach, in addition to the beliefs, the impact of knowledge is also considered.

In this research, we defined a multi-population social network by a weighted graph in which the nodes represent members, edges are the relationships, and weights indicate the strength of these relations. We proposed two algorithms that can track the opinion dynamics of a migrant by considering the impact of different parameters on the migrant's opinion. Here, we have two populations and the migrant is selected from population 1 and enters population 2, which is an entirely different place compared to its origin. Each member has their own opinion, which is a vector of i elements expressing their opinion regarding i topics. The social norm of each society is an average of opinions of all the members. Therefore, we proposed several formulas for calculating the distance between social norms and opinions and the weights. Then, a set of scenarios have been defined for selecting the migrant according to its opinion and distance to its origin's social norm.

Furthermore, different scenarios have been defined for the migrant's connection after the migration to measure the impact of its new relations in the new society on its opinion. Then, we proposed our Belief-based algorithm based on individuals' acceptance rate, the impact of the origin's and destination's social norms, and neighbors' opinions. In this model, the migrant can broaden its connections if its opinion is close enough to that person.

In the Learning-based algorithm, individuals can take actions and each action has a value and a minimum opinion requirement. Actions containing higher values have a higher requirement. In this algorithm, the migrant is able to observe the actions taken by its neighbors and store them in its knowledge history. As a result, it can learn which actions are more acceptable and have better values in the new society. Here, in addition to the opinion distances between a pair, finding new friends is also dependent on the migrant's value.

We have evaluated our proposed model by conducting several experiments on a couple of synthetic networks based on the scenarios that we defined and compared the results. The main objective of this evaluation was to identify the impact of social norms and opinions of individuals and learning in the adaptation process. Our results show that observation can have a 2% effect on the migrant's adaptation and the impact of the origin's social norm on the migrant is significant. The results also show that a migrant node can consistently gain high reward values in the new society, which means making better decisions when it learns around 70% of the rules and knowledge of that society.

5.1 Future Work

As future work, we aim to improve this model from different aspects. In terms of evaluation, the experiments have been conducted on a synthetic network which might show different results compared to a real network. As a result, one of the main future works is to conduct these experiments on a real dataset to investigate the performance of our model.

In this work, our parameters are limited. However, in the real world, other factors such as age, gender, and other characteristics of an individual can impact the adaptation process. Therefore, considering more characteristics for an individual is another aspect of this future work. Connecting to a community was one of the scenarios in our model. In this model, the community was similar to the migrant. We aim to consider the influence of different types of communities on a migrant in the destination.

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