The Influence of Psychological Processes on the Structure of Social Networks: An Agent-Based Simulation

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Abstract

The topic of social network analysis pervades many fields of science. The field of social psychology, however, has been remarkably absent in the various accounts of network dynamics. This thesis argues that unconscious, automatic social behaviours have the potential to affect the structure of social networks. First, it discusses the social-cognitive theory of assimilation and contrast and summarizes it using the Inclusion/Exclusion Model (Bless & Schwarz, 2010). Second, it presents the typical structural characteristics of social networks. Then, a computational model is devised based on artificial agents that exhibit realistic social behaviours. The results show that the behaviours of these agents have an impact on the global structure of their network. The influence is most profound on the degree of assortativity, one of the distinguishing characteristics of real-world social networks. The discussion explains these findings and presents directions for further research.

Contents

Preface

This is the master's thesis for my study in Human Aspects of Information Technology (HAIT), a track of the Master in Communication and Information Sciences.

During my study, I have had the privilege to become acquainted with the excellent researchers of the Creative Computing research program, most notably my thesis supervisors Dr. Ir. Pieter Spronck and Prof. Dr. Eric Postma. They introduced me to the fascinating field that combines artificial intelligence with human cognition. Combined with my own background in social psychology, this formed the breeding ground for the idea to use artificial intelligent agents to simulate the theories of social psychology. I am both of my supervisors very grateful for their guidance and support in my pursuit of this interest.

I believe that humanity is at the dawn of an age of intelligent systems, and that a thorough education in this field is the best long-term investment any student can make. The makers of the HAIT program understand this, and have provided me with the coolest curriculum of psychology, language, philosophy, and computer science subjects I could dream of. Thank you all very much.

Finally, I greatly thank my beloved girlfriend Jolanda for her support in writing my thesis.

Jaap Joris Vens,

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Chapter 1

Introduction

The structure of social relations, traditionally a research topic of sociologists, is increasingly receiving attention from fields outside the social sciences such as computer science (e.g., McCallum, Wang, & Corrada-Emmanuel, 2007), social robotics (e.g., Duffy, 2008), statistical physics (e.g., Albert & Barabási, 2002; Newman, 2003), and medicine, especially epidemiology (e.g., Shirley & Rushton, 2005). The resulting new field of network science and in particular the topic of *social network analysis* is becoming a multidisciplinary research area that combines the sociological elements of the social sciences with the topological elements of the natural sciences. Remarkable, however, is that the science of psychology, and in particular the field of *social psychology* that studies social interactions, has been largely ignored in the scientific accounts of social networks (Kalish & Robins, 2006). Therefore, the goal of this thesis is to investigate how the cognitive processes of individual human agents affect the general structure of a social network.

Section 1.1 provides the motivation for this goal. Section 1.2 introduces the field of social psychology and its sub-field *social cognition*. Section 1.3 introduces the structural properties of realistic social networks. Section 1.4 states the problem statement and the research questions. This chapter ends with an overview of the thesis in Section 1.5.

1.1 Motivation

The goal of social network research is to give a coherent account of both the dynamics of a social network as a whole and of the behaviour of the individual members of a social network. The challenge is to explain how the structure of a social network determines the outcomes of the indivuals it comprises and, at the same time, how these individuals influence the network that they constitute. The importance of this challenge is signified by the classic debate on *structure versus agency* (Hays, 1994). On the one hand there is the view that the structures within a society fully determine the behaviour and even the consciousness of individual humans. On the other hand there is the view that social structures are fully constructed by the autonomous actions of individuals. Of course, these views are not mutually exclusive, and both are generally regarded to be true. The network determines certain aspects of what people can do and people determine certain aspects of the structure of their network. Both directions of causality should therefore be part of a complete scientific account of social networks.

However, according to Kalish and Robins (2006), the current state of research fails to provide such a complete account of social networks. They claim that social network research has largely ignored the influence of individual psychological characteristics on the structure of social networks, and overly focuses on the structural understanding of networks. These criticisms have been repeated by Totterdell, Holman, and Hukin (2008), who assert that contemporary social network research is still too concerned with the structure and effects of relations between people, rather than understanding how this structure might emerge out of the social interactions between individual actors.

The underlying problem that is adressed by these critics is the lack of a psychological perspective on the formation of social networks. Of the many sciences that participate in the field of social network research, the science of psychology has so far been absent. Social psychologists have, however, conducted a myriad of studies that investigate the nature of human social behaviour. The main tenet of their findings is that both conscious and unconscious behaviour are fundamentally social (Fiske, 2004). Humans are psychologically geared towards creating, modifying and sustaining social networks. The goal of this thesis is to combine findings of social psychology with the network-level perspective of social network analysis to investigate the process by which individual psychological processes affect the emergence of social networks.

1.2 Social Psychology

Social psychology is the scientific study of the effects of social and cognitive processes on the way individuals perceive, influence, and relate to others

(Smith & Mackie, 2007). The term 'social processes' in this definition refers to a variety of mechanisms by which social influence can take place. The more specific term 'cognitive processes' refers to the ways in which the human brain processes social information. The study of cognitive processes attempts to explain the mechanisms by which social processes come about. It is generally studied by a sub-field of social psychology called *social cognition*.

1.2.1 Social Cognition

Social cognition is the field in social psychology that tries to explain the social behaviour of human beings by investigating the cognitive processes that underly the perceptions, inferences, and judgments people make about others and themselves (Bless, Fiedler, & Strack, 2004). Using an information-processing paradigm, social cognitive research treats brain processes similar to the way a computer program processes information, namely by *a)* perceiving and encoding sensory input; *b)* retrieving, organizing, and storing knowledge; *c)* making inferences based on comparative processing; and *d)* generating judgments, decisions, and behavioural responses (Bless et al., 2004). One of the basic assumptions in social cognition is that these processes are largely unconscious, which means people are unaware of their existence and influence (Bargh, 2007).

Many findings of social psychology can be related to the notions of psychological *assimilation* and *contrast*. The concept of assimilation in social psychology refers to the shift in perceptions or judgments towards some contextual anchor. Contrast refers to the opposite phenomenon: situations whereby perceptions or judgments are displaced away from the context. (Suls & Wheeler, 2007). Chapter 2 elaborates upon this definition. It describes and relates several research findings and uses them to model the influence of cognitive processes on the structure of social networks.

1.3 Social Networks

The central assumption of this thesis is that people's individual psychological tendencies collectively influence the structural properties of the social networks they inhabit. These properties have been extensively studied by network scientists, who have identified which features separate social networks from other types of networks.

According to Hamill and Gilbert (2009), a realistic social network is characterized by *a)* a low global density; *b)* a fat-tailed distribution of connectivity; *c)* a positive assortativity of connectivity; *d)* high clustering; and *e)* short path lengths. The explanation and operationalization of these features is the topic of Chapter 3.

1.4 Problem Statement and Research Questions

This introduction argued that social psychology could provide valuable insight into the formation of social networks. Section 1.1 argued that the current state of social network research lacked this kind of psychological approach, which is the motivation for this thesis. Section 1.2 introduced the notion of unconscious cognitive processes as an explanation for human behaviour. Section 1.3 hypothesized that these processes ultimately affect the structure of a social network. Consequently, the problem statement that guides the research of this thesis is the following:

> **Problem statement**: To what extent do realistic social networks emerge from unconscious cognitive processes?

To provide specific answers, this problem statement breaks down into the following research questions:

> **Research question 1**: What cognitive processes cause assimilation and contrast effects?

> **Research question 2**: What are the typical properties of realistic social networks?

> **Research question 3**: How can psychological assimilation and contrast affect the structure of social networks?

> **Research question 4**: To what extent can psychological assimilation and contrast produce realistic social networks?

1.5 Thesis Outline

Chapter 2 and Chapter 3 will provide the theoretical background needed to answer the first two research questions. Chapter 4 outlines a computational model that simulates the emergence of social network structure from psychological assimilation and contrast in attempt to answer the third research question. Chapter 5 presents the results of this simulation and Chapter 6 discusses them in order to answer the fourth research question. Chapter 7 formulates the conclusion of this thesis, its shortcomings, and directions for further research.

Chapter 2

Assimilation and Contrast

Peoples' judgment of the same target can be different depending on the context in which the judgment is made. For an example of this phenomenon on a physiological level, submerge for a few minutes your left hand in a bucket of cold water and your right hand in a bucket of hot water. Then place both hands in a third bucket filled with water of an intermediate temperature. The same objective temperature is now perceived as warm by your left hand but feels cold to your right hand (Boring, 1942).

Context effects in psychology can be classified as either *assimilation* or *contrast* effects (Stapel & Suls, 2007). An assimilation effect occurs when perceptions or judgments are displaced towards a contextual anchor. A contrast effect occurs when perceptions or judgments are shifted away from a contextual anchor (Suls & Wheeler, 2007). By this definition, the above example demonstrates a physiological contrast effect. The perception of the temperature of the final bucket of water is displaced away from the temperature of the previous bucket (the context). Note that this classification only describes the direction of contextual influences; it makes no claim about the underlying process by which this influence is accomplished (Bless & Schwarz, 2010).

According to social psychologists, context-dependency and hence potential assimilation and contrast effects can also occur in social rather than physiological contexts. For example, Asch (1951) showed in a classic experiment that subjects' judgments of the length of a line converged towards the answers that were given by the other participants. The other participants were really confederates of the experimenter that were instructed to deliberately give faulty answers. Another example is that people regard their partner as less attractive after watching a television show with highly attractive actors (Kenrick & Gutierres, 1980).

According to social cognition researchers, social contexts never directly influence observable behaviours. One of the premises of the field of social cognition is that the influence of social stimuli is mediated by an internal mental representation of those stimuli (Bless et al., 2004). The term context has thus adapted the new meaning of *cognitive context*. In that capacity is has been shown to interact—often outside the awareness of participants—with other mental representations of, for instance, feelings, motivations, opinions, and even behaviours.

One famous demonstration of the influence of an internal mental represention on observable behaviour was given by Bargh, Chen, and Burrows (1996). They used a lexical decision task to subliminally prime participants with words related to the social category of elderly people. The prime of the elderly stereotype caused the participants to walk slower to the elevator after the task had ended, compared to a control group that did not receive the prime. Numerous follow-up studies have replicated this assimilation effect, for a review see Wheeler and Petty (2001).

Section 2.1 explains some possible mechanisms that account for assimilation and contrast effects. The *Inclusion/Exclusion Model* (IEM) integrates these mechanisms into a coherent framework that serves as a reference point for the computational model that underlies this thesis. It is discussed in Section 2.2. Section 2.3 hypothesizes the implications of this model for the dynamics of social networks.

2.1 Mechanisms

A recurring type of process in social cognition that explains assimilation effects is that the heightened accessibility of a mental representation of behaviour increases the probability of that behaviour occuring (Wheeler & Petty, 2001). This process explains why participants walk slower after they have been primed with elderly-related words (Mussweiler & Strack, 2000): The priming of the elderly stereotype causes a heightened accessibility of its associated traits (slow walking) which leads to a heightened probability of this behaviour occuring. The outcome is an observable assimilation effect.

However, contrast effects are also observed in social cognition. When participants are primed with a specific exemplar of a social category, they often contrast their behaviour. Dijksterhuis et al. (1998) showed that, compared to an unprimed control group, participants performed better in a game of Trivial

Pursuit after they were primed with the category of professors (assimilation), but worse after a prime of the specific exemplar Albert Einstein (contrast). The mechanism proposed by Dijksterhuis et al. is that comparing oneself with the target is facilitated when the target is a specific exemplar rather than an abstract category. The outcome of this comparison seems to negatively impact the self-image and subsequent motivation of participants to exert cognitive effort in answering the Trivial Pursuit questions.

A follow-up study by LeBoeuf and Estes (2004) further demonstrated the influence of a comparison with the target on the direction of context effects. They increased the relevance of making a comparison by inducing participants to feel similar to Einstein by listing similarities with him. This indeed resulted in a contrast effect. The participants acted less intelligent on the Trivial Pursuit test than those who had listed dissimilarities with Albert Einstein. A similar but weaker result was found for primes of the category of professors: listing differences produced a lower comparison relevance and higher intelligence scores. In conclusion, the presence of a comparison with the target increases the likelihood of a contrast effect.

2.2 Inclusion/Exclusion Model

The Inclusion/Exclusion Model (Bless & Schwarz, 2010; Schwarz & Bless, 2007; Bless & Schwarz, 1998; Schwarz & Bless, 1992) integrates the various findings on the mechanisms by which assimilation or contrast can occur. This model assumes two mental representations in every social situation that requires a target to be judged. The first is a mental representation of the target. The second is a mental representation of the comparison standard. Both representations are constructed on the spot, drawing on contextual information that is accessible at the time of judgment (Bless & Schwarz, 2010).

Whether contextual information will result in an assimilation or contrast effect depends on how the information is used. Information that is used in constructing the mental representation of the target results in an assimilation effect (Bless & Schwarz, 2010). This explains the results of Dijksterhuis et al. (1998), where participants put more ingenuity into answering Trivial Pursuit questions after a prime of the category of professors. Here, the contextual information consisted of the activated concept of professors. This information was included in their mental representation of the target: the task of answering

Trivial Pursuit questions. This resulted in an increased ability to answer these questions—similar to the way the participants of Bargh et al. (1996) walked slower to the elevator when the behavioural traits of the elderly were included in their mental representation of walking behaviour. In conclusion, inclusion of contextual information into the mental representation of a target results in assimilation effects.

On the other hand, when contextual information is included into the mental representation of the comparison standard, contrast effects occur (Bless & Schwarz, 2010). When the participants in the study of Dijksterhuis et al. (1998) were primed with the exemplar Albert Einstein, they excluded this contextual information from the mental representation of their own behaviour, and instead they used it to form a mental representation of a comparison standard. After explicitly comparing their own ability to that of Albert Einstein, they scored significantly lower on the subsequent task of answering Trivial Pursuit questions than the unprimed participants.

The inclusion of information into a mental representation of a target is facilitated by the mental accessibility of differences between the contextual information and the target, as demonstrated by the studies of LeBoeuf and Estes (2004). As the perceived distance between the available information and the target of judgment increases, making a comparison becomes less relevant and the probability that the information is used in constructing a comparison standard decreases. Likewise, when the perceived distance between the available information and the target of judgment decreases, this makes a comparison more likely, and hence the probability of constructing a comparison standard increases. This result is somewhat counterintuitive. As it becomes easier to include contextual information into the mental representation of a judgment target because of less peceived differences, the probability of inclusion actually decreases, making contrast effects more likely.

To summarize, the IEM predicts an assimilation effect when contextual information is included into the mental representation of a target, which is more likely when the perceived difference between the context and the target is large. The IEM predicts a contrast effect when contextual information is excluded from the mental representation of the target, which is more likely when the perceived difference between the context and the target is small.

2.3 Implications for Social Networks

The possibility of assimilation or contrast at each social interaction between individuals could ultimately affect the large-scale structure of a social network. When assimilation occurs at a social encounter between two persons, their judgments or behavioural tendencies regarding a communal target become slightly more similar, which heightens the possibility of future encounters as well the relevance of making comparisons at those encounters. On the one hand, this increased relevance of a comparison is more likely to lead to contrast effects in the future. On the other hand, when a contrast effect occurs, both persons become slightly more dissimilar with regard to a communal target. This lowers the relevance of making a comparison the next time they meet, which increases the probability for assimilation in the future. It seems that the forces of assimiliation and contrast act as the pushing and pulling forces that balance the structure of a social network.

In terms of the IEM, each social interaction that involves behaviour towards some target will have the participants either include or exclude the contextual information into or from their mental representation of the target. On inclusion, an assimilation process occurs that heightens the possibility for future exclusion of the same information. On exclusion, a contrast process occurs that heightens the possibility for future inclusion.

The remainder of this thesis will attempt to demonstrate this influence of assimilation and contrast effects on the structure of a social network. This demonstration involves a simulation of these effects in a large population of computer agents. For this simulation an understanding of the structural properties of social networks is required. This is the topic of the next chapter.

Chapter 3

Social Networks

Social networks, like any other network, are best represented by a *graph*, a collection of *vertices* (also called *nodes*) connected by *edges*. Depending on the application, the vertices can refer to anything from countries or families to web pages or neurons. In social network analysis the vertices often represent individual human *agents* and the edges represent the social relationships or *links* between them. Let $N = \{1, 2, \ldots, n\}$ denote a set of agents, then a social network g can be represented by an $n \times n$ matrix with values g_{ij} between 0 and 1 that represent the *weight* of a link between the agents i and j. A positive value implies some sort of connection between two agents, of which the exact meaning depends on the type of behaviour under investigation. The value 0 means two agents are not connected. The links between agents can be *directed* or *undirected*, again depending on the specific type of behaviour. Handshaking, for example, is a necessarily undirected behaviour, while a money transaction is necessarily directed. If a graph is undirected, then $g_{ij} = g_{ji}$ for all pairs of agents. When no self-referencing links are present, the diagonal of matrix g contains only zeros.

Social networks have certain characteristics that distinguish them from other types of networks. This chapter describes the key properties of social networks according to (Hamill & Gilbert, 2009). They are are *density* (Section 3.1), *connectivity* (Section 3.2), *assortativity* (Section 3.3), *clustering* (Section 3.4), and *path lengths* (Section 3.5).

3.1 Density

Network density is the proportion of existing links relative to the total number of possible links. With the exception of small, closed networks, social networks are generally sparse. Of the $n(n-1)/2$ links that can exist in an undirected social network, or $n(n-1)$ in a directed social network, only very few actually exist. Most social networks exhibit a density of 1% or less (Hamill & Gilbert, 2009).

3.2 Connectivity

An agent's *degree of connectivity* is the number of agents that are linked with it. The maintenance of a social link usually comes with a certain cost, depending on the type of links. Hence, there is an upper limit to the number of links an agent can have. A commonly cited upper limit to the degree of connectivity in friendship networks is 150 (Dunbar, 1992).

The degree of connectivity of each agent follows a positively skewed distribution: few agents have many links and most agents have few links. However, there are more agents with a relatively high connectivity than would be expected if the degree of connectivity followed a Poisson distribution. This means the distribution of connectivity is fat-tailed, and the cumulative distribution tends to follow a power law.

3.3 Assortativity

In real-world social networks, agents with many links tend to be linked to agents that also have many links, or in Hamill and Gilbert's (2009) words: "well-connected individuals tend to be connected to each other". This is known as a positive *assortativity by degree of connectivity*, or assortativity for short). An operationalization of assortativity is Pearson's r correlation between the degrees of connectivity j_i and k_i for m pairs of linked agents (Hetman, Magnuszewski, Stefanska, Bujkiewicz, & Ostasiewicz, 2008):

$$r = \frac{\sum_{i=1}^{m} z_{j_i} z_{k_i}}{m-1}$$

where z is a standardized degree computed as the deviation of the degree from the mean degree, divided by the standard deviation of degrees:

$$z_{j_i} = \frac{j_i - j_i}{s_{j_i}}$$

By combining the above, one gets the following single formula for calculating Pearson's r correlation between degrees (Hinkle, Wiersma, & Jurs, 2003):

$$r = \frac{m\sum_{i=1}^{m} j_i k_i - \sum_{i=1}^{m} j_i \sum_{i=1}^{m} k_i}{\sqrt{[m\sum_{i=1}^{m} j_i^2 - (\sum_{i=1}^{m} j_i)^2\,]\,[m\sum_{i=1}^{m} k_i^2 - (\sum_{i=1}^{m} k_i)^2\,]}}$$

3.4 Clustering

Social networks consist of multiple tightly knit groups that share a relatively high density of links. This results in a high[1] *local clustering coefficient* for each agent as well as a high *global clustering coefficient*. The local clustering coefficient indicates for each agent the clustering of the agent's *personal network*, which is the network that consists of those agents it links to (its *neighbours*). It is defined as the ratio of existing links between an agent's neighbours to the number of possible links between its neighbours. Let d_i be number of neighbours of agent i and e_i the number of undirected[2] links that exist between them. The clustering coefficient of agent i is then given by:

$$C_i = \frac{e_i}{d_i(d_i - 1)/2}$$

The global clustering coefficient is simply the average of all the local coefficients:

$$C = \frac{1}{n}\sum_{i=1}^{n} C_i$$

Combined, this gives:

$$C = \frac{1}{n}\sum_{i=1}^{n} \frac{e_i}{d_i(d_i - 1)/2}$$

3.5 Path lengths

A network's mean or median *path length* indicates how many intermediate agents are needed on average for one agent to reach another. Social networks

[1]High in this context means higher than would be expected if the links were created randomly (Watts & Strogatz, 1998).

[2]In directed networks, there are twice as many possible links so the denominator of the equation should then be multiplied by two.

display short path lengths, which is the result of a high degree of clustering and the presence of *weak ties* (Granovetter, 1973): the links that interconnect the clusters.

The term *small world* to describe this type of network was coined in 1967 by the psychologist Stanley Milgram (Travers & Milgram, 1969) and has gained widespread popularity (Schnettler, 2009). The notion that there are only "six degrees of separation" between any two people in the world illustrates the extremely short path lengths of small world social networks.

"In a random network with symmetric ties and a homogeneous degree distribution [...], holding vertice degree k constant, the average geodesic d increases only linearly with exponential increases of the population size N ($d \log N / \log k$)." (Schnettler, 2009)

Chapter 4

Computational Model

This chapter will combine the individual-level theory of assimilation and contrast effects with the group-level characteristics of social networks in order to produce a computational model that is able to demonstrate the influence of the aggrerate of individual assimilation and contrast effects on the structure of the social network that connects these individuals. For this demonstration, a computer program simulates a population of interacting agents that assimilate or contrast a unidimensional attribute value at each interaction. This attribute can represent an individual characteristic, opinion, behavioural tendency, perception, or judgment, since assimilation and contrast studies show similar predictions for all these attributes. The result is a generic computational model of social network dynamics that encompasses a wide range of possible applications.

Section 4.1 presents the rationale for the computational model. Section 4.2 explains the flow of the simulation. Section 4.3 informs about the parameters that govern the simulation.

4.1 Rationale

Recall from Chapter 2 that the context of a judgment is either included in the mental representation of the judgment target, or excluded from it and used to form a comparison standard. Contexts that are very dissimilar to the target at hand are more likely to be included while contexts that are very dissimilar to the target are more likely to be used as comparison standards. Inclusion leads to a shift in judgment towards the contextual standard—assimilation. Exclusion leads to a shift in judgment away from the contextual standard—contrast.

By assuming that two people in a social interaction form eachother's context in making judgments, it is possible for these individual psychological processes to have an impact on the dynamics of a social network. Let's imagine a social interaction between Alice and Bob, where Bob's behaviour prompts Alice to judge a certain target. For instance, Bob could ask Alice for an opinion on a political issue. In doing so, Bob undoubtedly provides Alice with an abundance of explicit and implicit social cues that form the context of Alice's judgment process. When these cues match Alice's a priori mental representation of the target, she will deem Bob's cues relevant to the judgment task and use them to construct a standard of comparison, thereby excluding them from her representation of the target. This leads her to contrast her judgment away from the contextual information given to her by Bob. The result of the social interaction is that Alice takes a different stance on the political issue than Bob and the two remain a little more dissimilar after the interaction than before.

By the same inclusion/exlusion process, the opposite effect can also come about, given a high enough a priori difference between Alice's and Bob's mental representations of the target. When Bob prompts Alice to form a judgment and the contextual information he provides is dissimilar enough from Alice's mental representation of the target, Alice will no longer regard a comparison relevant. She will then unknowingly shift her judgment towards the context provided to her by Bob, leading her judgment to become slightly more similar to Bob's.

By this reasoning, the occurence of an assimilation or contrast effect is dependent on a critical difference between two persons' mental representations of a target. Let's call this critical difference the *assimilation threshold*. Differences that exceed the assimilation threshold lead to an assimilation effect, because the contextual information is deemed too irrelevant to make a comparison. Differences that do not exceed the assimilation threshold lead to a contrast effect, because then the contextual information is relevant enough to construct a comparison standard from it.

4.2 Simulation flow

The simulation starts with a network 1000 agents randomly connected by 5000 links, following the Erdős-Rényi (1959, in Albert & Barabási, 2002) model. The resulting density is $(1000 \times 999)/2 = .01\overline{001}$ or approximately 1%, comparable to real-world social networks (Hamill & Gilbert, 2009). Each agent is assigned a random attribute value between 0 and 1 from a uniform probability distribution.

Then, at every iteration, every agent has one interaction with every agent in its personal network (i.e., with every agent that is directly connected to it). This interaction consists of a comparison of both agents' attribute values. Depending on the value of the first parameter in the model, *assimilation threshold*, either an assimilation or a contrast effect will change the value of the agent's attribute by the amount specified by the second paramater, *assimilation step*. If the resulting difference between the attribute values is more than the value of the third parameter, *link threshold*, the link between the agents is removed. The role of these parameters is further discussed in section 4.3.

In this study this process iterates 100 times.[1] That means that at every iteration, each agent interacts with all the agents that are currently part of its personal network. After every iteration, the network's characteristics are calculated and recorded in a data file.

4.3 Parameters

This section discusses the parameters that determine the outcome of the simulation. They are the assimilation threshold (section 4.3.1), the assimilation step (section 4.3.2), and the link threshold (section 4.3.3).

4.3.1 Assimilation threshold

The value of the assimilation threshold, the first parameter of the model, determines whether assimilation or contrast occurs at an interaction between two agents. At every interaction, one agent compares its attribute value with the attribute value of another agent, by calculating the absolute value of the difference between both attributes. Since attribute values range from 0 to 1, the absolute value of their difference also ranges from 0 to 1.

If the difference exceeds the value of the assimilation threshold, the agent displays an assimilation effect by adjusting its attribute value towards the other agent's attribute value, decreasing the difference between both agents' attributes. If the difference does not exceed the assimilation threshold, the agent displays a contrast effect by adjusting its attribute value in the opposite

[1]Initially, the simulation was supposed to stop after the network structure converged to a stable state. However, as the results will show, in most cases this stable state was attained almost immediately and the extra iterations were added to provide extra reliability.

direction, increasing the difference between both agents. The amount by which the attribute value is increased or decreased is specified by the second parameter, assimilation step.

4.3.2 Assimilation step

The assimilation step specifies how much the value of an agent changes at interactions with other agents. It does not specify in which direction an attribute may change, this is determined by the value of the assimilation threshold (see above). The result is that the change is always symmetrical; both assimilation and contrast effects will change the value of an agent's attribute by the same amount.

4.3.3 Link threshold

After an agent has adjusted its attribute value according to the rules outlined above, the difference in attribute values between two interacting agents is calculated a second time. This time, it is compared to the link threshold, the third and final parameter of the model. If the absolute value of the difference exceeds the value of the link threshold, the link between two agents is removed. Then, a new link is created between two random agents to ensure that the global network density remains constant. This excludes any variation in network density as an explanation for the results of the simulation. It also introduces a source of randomness throughout the simulation. Without it, two equal initial networks would always evolve in exactly the same way.

4.4 Implementation

The simulation program was written in the object-oriented programming language C++. The source code of this program is freely available at `http://github.com/r2src/unet/`. The social network it generates is stored as an *incidence list* (Goodrich & Tamassia, 2002), a set of agent objects that each contain references to the link objects that link them to other agents. The member methods of the agent class model the psychological processes of assimilation and contrast. For the exact workings of this program, please see the annotated source code at the aforementioned location. For an understanding of this study, however, the previously outlined higher level description of the computational model should suffice.

4.5 Execution

The simulation was performed multiple times, once for each combination of parameter values. The following values for each parameter were used:

assimilation threshold: .1, .2, .3, .4, .5, .6, .7, .8 and .9

assimilation step: .1, .2, .3, .4, .5, .6, .7, .8 and .9

link threshold: .1, .2, .3, .4, .5, .6, .7, .8 and .9

This resulted in a total of $9^3 = 729$ simulations of 100 iterations each, which took an AMD Athlon 4600+ 64 bit dual core processor 35 hours to complete.

Chapter 5

Results

This chapter describes the results obtained by running the simulation program that implements the model outlined in the previous chapter. Section 5.1 reports the characteristics of the initial, random networks. The remaining sections deal with each of these characteristics in the resulting networks after the simulation program had finished. Section 5.2 discusses the model's influence on the degree of assortativity. Section 5.3 present the finding on clustering coefficients. Section 5.4 calculates the mean path lengths for a subset of the final networks.

5.1 Initial Characteristics

The initial network of 1000 agents connected by 5000 links was generated randomly for each run of the simulation. It possesed the following characteristics.

Density. $(1000 \times 999)/2 = .01\overline{001} \approx 1\%$.

Degree of connectivity. Since each link connects two agents, and there are 5000 links in total, the sum of degrees equals $2 \times 5000 = 10000$ and the mean degree equals $10000/1000 = 10$. By holding the number of links constant throughout the simulation, this mean degree remained constant as well. The distribution of these degrees in a random network follows a Poisson distribution (Albert & Barabási, 2002).

Degree of assortativity. In a random network each agent's degree of connectivity is established randomly. Hence, one expects no relationship between degrees of connectivity of pairs of agents (Albert & Barabási, 2002). The degree of assortativity was indeed zero or very close to zero in all initial networks.

Clustering coefficient . The probability that two agents in an agent's personal network are connected is, for a random network, equal to the probability that two randomly selected agents are connected (Albert & Barabási, 2002). Therefore, the initial clustering coefficient was expected to be, and indeed was, roughly equal to the network density for all generated networks ($.01\overline{001}$).

Mean path length According to Fronczak, Fronczak, and Hołyst (2004), the mean path length of a random network is $\frac{\ln(N)-\gamma}{\ln\langle k\rangle} + \frac{1}{2}$ where $\langle k\rangle$ is the mean degree of connectivity and γ the Euler–Mascheroni constant of approximately .5772. The expected mean path length for the each initial network is therefore $\frac{\ln(1000)-.5772}{\ln(10)} + \frac{1}{2} \approx 3.249$. The observed mean path lengths of the initial networks all approximated this prediction.

The following sections will report the change in all but one[1] of these characteristics after 100 iterations of the assimilation/contrast algorithm. It is hypothesized that their values will approach the typical values for social networks as laid out in Chapter 3.

5.2 Degrees of Assortativity

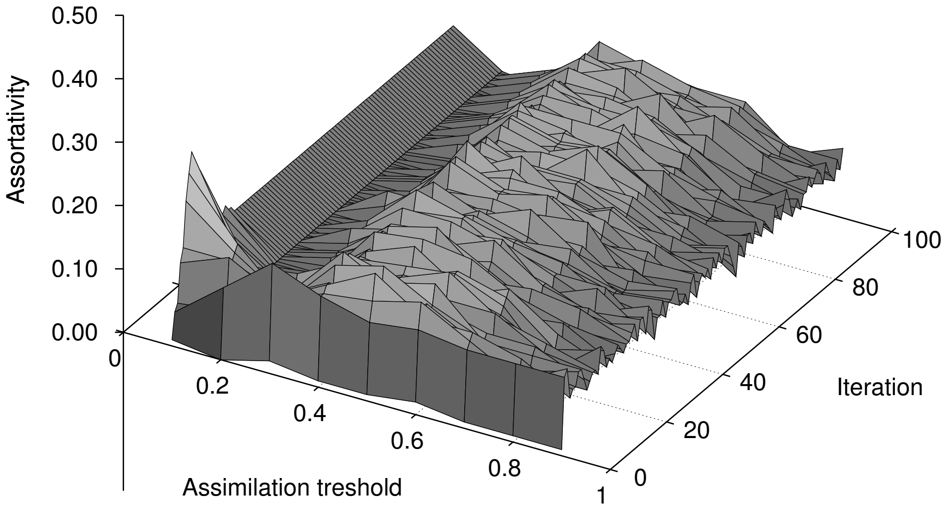
Some combinations of parameters led to an increase of the network's degree of assortativity. The following subsections will discuss various aspects of this increased assortativity. Section 5.2.1 shows how the assortativity developed across the iterations of the simulation. Section 5.2.2 reports the results of a grid search to determine the combination of parameters that maximizes the degree of assortativity. Section 5.2.3 visualizes the results space in a series of plots that relate the parameters values to the observed degree of assortativity. Finally, Section 5.2.4 determines the reliability of these results by repeating the simulation multiple times.

[1] The first characteristic – density – is omitted from the results because it remained constant throughout the simulation.

5.2.1 Procession of Assortativity

With certain parameter combinations, the assortativity of the network increased after only a few iterations and then remained more or less constant, as illustrated by Figure 5.1. The original intent for the simulation program was to make the number of iterations dependent on the variation of assortativity degrees, such that when these degrees approached more or less stable values, the simulation program would record the final results and move on to a next combination of parameters. However, as Figure 5.1 shows, this stable state was attained almost immediately, and so the simulation program was changed to always complete 100 iterations.

Figure 5.1: Procession of assortativity at various assimilation thresholds



Note. Assimilation step and link threshold were held constant at .2 and .2, respectively.

5.2.2 Maximizing Assortativity

To determine which combination of parameters resulted in the highest assortativity, a grid search algorithm explored the results space. Table 5.1 shows the combinations of parameters that were associated with the ten highest degrees of assortativity.

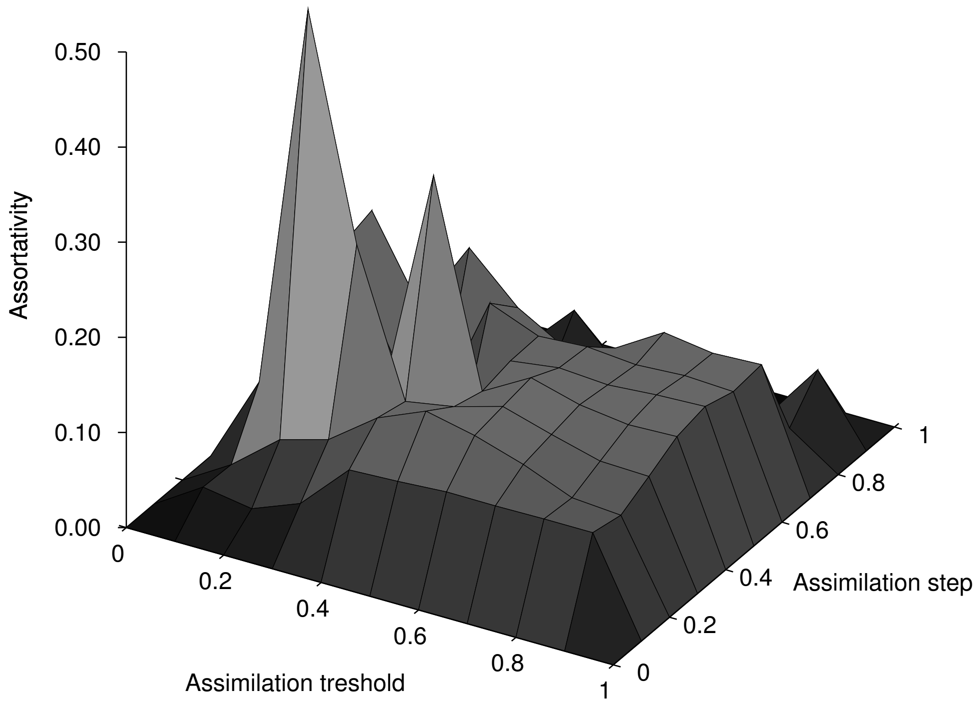
Table 5.1: Combinations of parameters that maximize assortativity

Combination of parameters			
Assimilation threshold	Assimilation step	Link threshold	Assortativity
.2	.2	.1	.255
.3	.3	.3	.266
.4	.4	.3	.328
.3	.4	.4	.357
.3	.4	.5	.357
.4	.4	.2	.378
.4	.4	.4	.378
.4	.4	.5	.388
.3	.3	.2	.398
.2	.3	.3	.499

5.2.3 Visualization of Assortativity

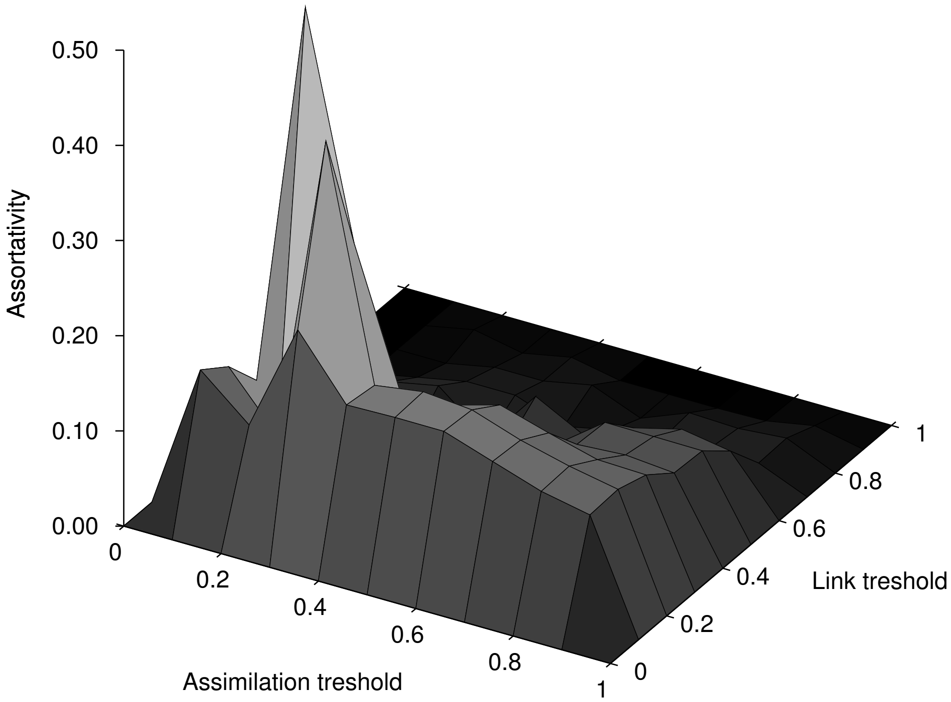
An attempt to visualize the results space is presented by Figures 5.2, 5.3, and 5.4. Each figure varies two parameters while keeping the remaining parameter constant at .3, a value that is for all parameters associated with a heightened assortativity, according to Table 5.1.

Figure 5.2: Assortativity as a function of assimilation threshold and assimilation step



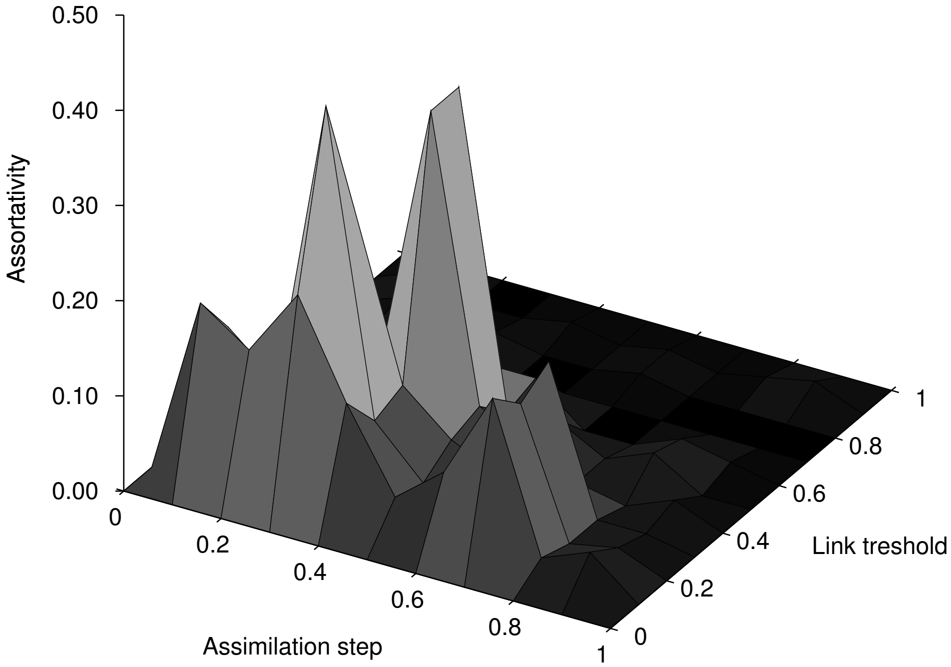
Note. Link threshold held constant at .3

Figure 5.3: Assortativity as a function of assimilation threshold and link threshold



Note. Assimilation step held constant at .3

Figure 5.4: Assortativity as a function of assimilation step and link threshold

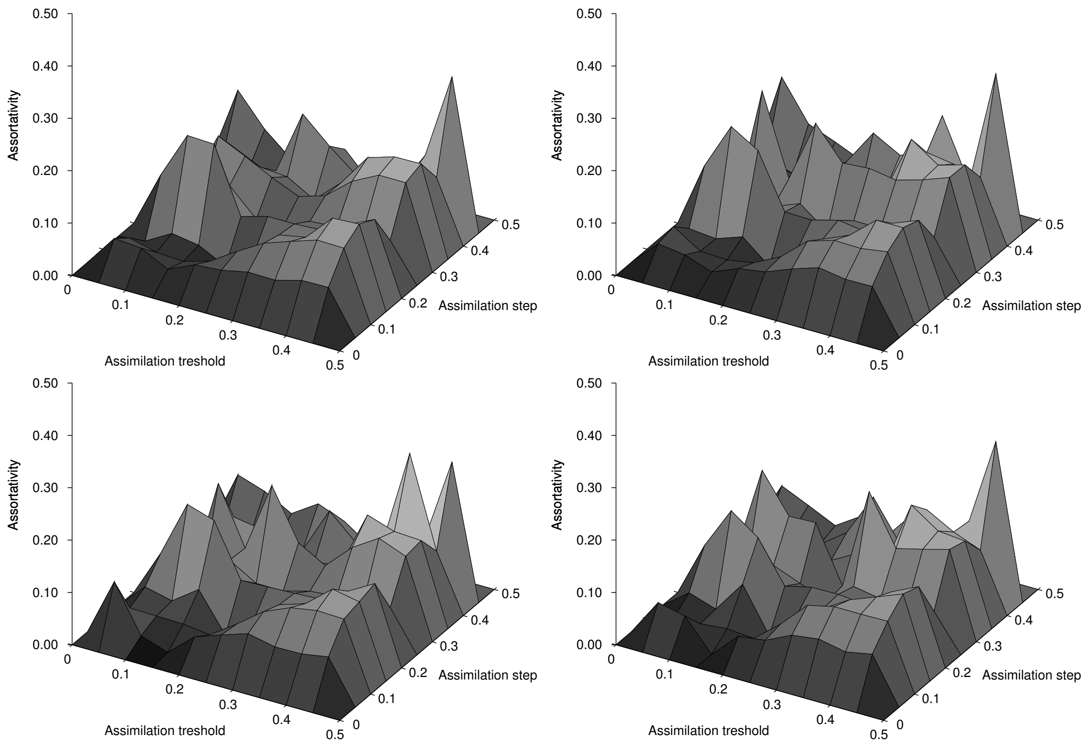


Note. Assimilation threshold held constant at .3

5.2.4 Reliability

To assess the reliability of these results, as well as establish a more fine-grained indication of the parameter values that lead to an increased degree of assortativity, the simulation was repeated four times with smaller parameter intervals. Each simulation run produced almost the exact same assortativity values for each combination of parameters, indicating that the final structure of the network was determined by the agents' assimilation/contrast processes rather than by random fluctuations. This is illustrated by the resemblence of the space plots shown in Figure 5.5 that each visualize the same portion of the results space. Also note that the parameters assimilation threshold and assimilation step in these plots range from 0 to .5 with steps of .05, while in the previous figures the parameters ranged from 0 to 1 with intervals of .1.

Figure 5.5: Assortativity as a function of assimilation threshold and assimilation step, repeated four times



Note. Link threshold held constant at .25

5.3 Clustering Coefficients

The clustering coefficients of all networks were roughly equal to their density. That is, no clustering was observed for any combination of parameters.

5.4 Mean Path Lenghts

The mean path length was calculated for the subset of parameter combinations that indicated realistic social networks according to Table 5.1. The simulation program re-run these simulations with the option to calculate mean path lengths enabled. This option was originally disabled to save time in running the simulations, as the mean path length calculation adds another 5-10 minutes to each simulation run. Another reason for not calculating the path lengths of all networks was that the calculation could crash the simulation program in networks that consisted of two or more separate clusters with no interconnections. (These types of networks were sometimes observed following extreme values for parameters.) A nice side-effect of re-running these simulations is that they replicate the findings of Table 5.1. The resulting mean path lengths are presented by Table 5.2.

From these results one can not reliably predict whether the assimilation/contrast process will increase or decrease the initial mean path length of approximately $\frac{\ln(1000)-.5772}{\ln(10)} + \frac{1}{2} \approx 3.249$ (Fronczak et al., 2004). However, when comparing the standard deviations of the 10 initial random networks (.002) and the 10 resulting networks (.858) one can certainly conclude that the mean path lengths are affected by the simulated processes.

Table 5.2: Mean path lengths of networks with high assortativity degrees

Combination of parameters				
Assimilation threshold	Assimilation step	Link threshold	Assortativity	Mean path length
.2	.2	.1	.35	3.327
.3	.3	.3	.26	1.939
.4	.4	.3	.10	3.231
.3	.4	.4	.31	4.060
.3	.4	.5	.31	4.210
.4	.4	.2	.22	3.247
.4	.4	.4	.39	1.819
.4	.4	.5	.37	3.901
.3	.3	.2	.33	4.204
.2	.3	.3	.14	3.301
				$\overline{X} = 3.324$
				$s_X = .858$

Chapter 6

Discussion

The goal of this study is to show how subtle psychological processes can influence the general structure of a social network. The approach to accomplish this goal involved a computer simulation of psychological assimilation and contrast effects in an artificial society of computer agents. The results of this simulation show several interesting findings. First, the initial networks characteristics indicate correct behaviour of the simulation program. This is discussed by Section 6.1. Second, the networks's structure was affected by the assimilating and contrasting agents. This is discussed by Section 6.2. Third, under some combinations of parameters, networks emerged that displayed some of the features that characterize realistic social networks. This is further discussed by Section 6.3.

6.1 Validity of the Computational Model

This research made, to the knowledge of the author, an unprecedented attempt to simulate unconscious, inter-human psychological processes with an agent-based computational model. Before it is possible to draw any meaningful conclusions from the results, it is important to assess the the validity of the computational model and the correctness of the computer program that implements it.

The downside of investigations of a complex system using computational models is that it is hard—often impossible—to mathematically prove the correct behaviour of the simulation program. The upside of this particular investigation is that the characteristics of the initial random networks have been proven mathematically. The match between the recorded metrics of the initial networks (see Section 5.1) and the predictions made by the Erdős-Rényi model (1959, in Albert & Barabási, 2002) assure at least the correctness of the data structure and its related algorithms. Since the assimilation/contrast algorithm is a relatively simple addition to this basic data structure, it should be assumed that the simulation program behaved correctly.

That the program behaved as intended does not mean it has not caused side effects. A notable side effect of running the simulation with discrete values for the assimilation step parameter meant that it was impossible for agents to obtain certain values for their attributes, while in reality agents should theoretically be able to make any kind of judgment about a target. For example, in simulations where the assimilation step was .5, all agents ended up having an attribute value of either 0, .5, or 1. Replications of this study should prevent this by avoiding fixed values for a parameter across a population, for instance by allowing random deviations from each parameter value.

The computational model of this thesis made an important assumption. It assumes that a person's mental representation of a target of judgment forms the context of the judgment of another person. This seems reasonable, although in reality the context of a judgment involves a lot more than just one bystander's mental representation. For the computational model to be valid, future research should to confirm the validity of this assumption. If it can be refuted that mental representations can 'transfer' between people and become a contextual influence, the model loses its validity.

6.2 Impact on Network Structure

The most prominent influence of the assimilation and contrast effects was on the degree of assortativity of the agents' network structure. The assortativity was operationalized in Chapter 3 as the correlation between the degrees of connectivity of all pairs of connected agents. So, in a network with a high degree of assortativity, agents with a high degree of connectivity tend to be connected to agents that also have a high degree of connectivity. Likewise, agents with few connections are linked to agents that also have few connections.

All initial random networks had an assortativity degree of zero. When the simulation started, the assortativity of the network increased starting the first iteration and remained more or less stable after only a few iterations (see the Results Section 5.2.1). Although is is theoretically possible, there was no combination of parameters that led to a negative assortativity. This means that some aspect of assimilation and contrast theory makes an increased assortativity very likely.

The explanation is that when the simulation started removing links between agents, it always removed the links of the agents that differ more in their attribute value than the value of the simulation parameter link threshold. The agents that remained connected therefore possesed similar attribute values. In other words, once the simulation started iterating, agents were always connected to relatively similar agents. Just by random fluctuation, some attribute values were more prevalent than others. Agents with these values had many connections to other agents, and these other agents also had many connections among eachother. Agents with rare attribute values also tended to be connected to eachother, but their degree of connectivity had to be lower because, by definition, there are fewer agents with a rare attribute value than with a widespread attribute value. The end result is a network where agents with many connections are connected to agents with many connections, and agents with few connections are connected to agents with few connections.

This also explains why the peak of the increase in assortativity is at the start of the simulation. The initial network is composed of agents that all have a random value for their personal attribute as well as links to random other agents. In this situation it is possible that they are connected to agents with largely different attribute values. The first iteration of the simulation procedure therefore encountered many links that exceeded the link threshold and removed them. The remaining links then only connect relatively similar agents, explaining the pattern of increased assortativity explained in the previous paragraph.

6.3 Realism of Network Structure

Chapter 3 argued that an increased assortativity is characteristic of human social networks. This study's computational model produces, under the right circumstances, an increased assortativity. Let's assume for the moment that a higher degree of assortativity is indicative of a more realistic social network. The questions is, then, under what circumstances the model produces the most realistic social networks.

The grid search performed in Section 5.2.2 answers this question: The highest assortativity is attained when the assimilation threshold is .2, the assimilation step is .3, and the link threshold is .3. This, and the other results from the grid search, indicate that the highest assortativity is attained with modest values for each of the parameters, which can all theoretically range from 0 to 1. This means that more realistic social networks emerge under the following circumstances:

1. Agents contrast their attributes when the difference between them is less than about .2. Any encounters between agents that differ more in their attribute values leads to assimilation.

2. Agents adjust their attribute in steps of .3, which is larger than the assimilation threshold. This makes it possible for agents to fall below the assimilation threshold after only one encounter, so they will adjust their attribute at the next encounter in the opposite direction (with the same step of .3).

3. Agents remove their link if, after the assimilation or contrast adjustment, their attribute difference is more than .3.

6.4 The Inclusion/Exclusion Model

According to its creators, (Schwarz & Bless, 1992), the Inclusion/Exclusion Model explains the mechanism behind the context-dependency of human judgment. With the growing popularity of priming studies in social psychology from researchers like Bargh et al., 1996, Dijksterhuis et al., 1998 and LeBoeuf & Estes, 2004, the IEM gradually surfaced as one the main conceptual frameworks for explaining assimilation and contrast of human behaviour in general.

It should be noted, however, that the particular use of the IEM as a theoretical model in this study makes no assumptions about the validity of the IEM's mechanisms. The core constructs of the IEM—mental representations of the target and standard of a comparison—are not part of the computational model and were not implemented in the simulation program. Therefore, it could be argued that the use of the IEM in this study is superfluous and a simpler model of assimilation and contrast theory would have sufficed. However, the IEM offers a convenient way of predicting when people assimilate or contrast, and it is widely known within the social psychological community. It was for these merits only, not for its explanatory value, that the IEM formed the basis of the computational model of this study.

Since the IEM was only used in this study for its descriptive value, there is no point in interpreting the results of this study as evidence for the validity of the psychological processes that cause assimilation and contrast. Rather, this study set out to prove that the unconscious behaviour caused by these processes influences the structure of social networks. Even if social psychologists are unsure about the exact nature about these hard-to-observe unconscious psychological processes, they have to agree about the easy-to-observe behavioural outcomes of these processes. Only these behavioural outcomes were modeled in this study, demonstrating an effect of individual assimilative and contrastive behaviours on the structure of the social network that connects these individuals, without making assumptions about the cause of these behaviours.

6.5 Directions for further research

This study provided the first exploration of an uncharted area of social science: agent-based simuations of social cognition. The outcomes suggest various interesting directions for further research. The following sections discuss each of them.

6.5.1 Group membership

The computational model used in this paper focused only on individual interactions. An extension of this model could take into account the influence that group membership has on the outcomes of a social interaction (e.g., Pettit & Lount, 2010).

6.5.2 Multiple attributes

This research failed to establish a clustering effect in the social networks it generated. This is possibly due to the use of only a single psychological attribute that the computer agents employed in their social comparisons. Further research could extend the model of this thesis with multiple attributes to compare, in an attempt to produce social networks with several clusters of like-minded agents that agree on one of these attributes.

6.5.3 Network evolution algorithms

The initial networks in this research all evolved according to the Erdős-Rényi model. Stronger support for the conclusions of this research could be drawn if further research replicated these results using other types of network evolution, for instance the preferential attachment method of Albert and Barabási (2002) that produces scale-free networks.

6.5.4 Social psychological theories

The theory of assimilation and contrast is only one of the many candidates for an agent-based social simulation. Implementing other social psychological theories in agent-based models will expose a myriad of knowledge about both the dynamics of social networks and the intricacies of social psychology. The present research has only uncovered the tip of the iceberg.

Chapter 7

Conclusion

This research was motivated by the belief that social psychology is unjustly left out of the emerging field of network science and social network analysis. At the root of this exclusion is the disproportional focus of social network scientists on network structure as the cause of social phenomena, as opposed to treating this structure as the result of individual behaviours. In the philosophical debate of structure versus agency, this reflects the structural stance.

This thesis has provided a conclusive argument that shows the importance of the agency stance of this debate. The argument can be summarized as follows. First, this thesis has argued how social psychological assimilation and contrast effects can affect the structure of a social network. Second, this thesis has proposed a computational model for assimilative and contrastive behaviours. Third, this thesis has shown an influence of the agents behaving according to this model on the global structure of their network. Finally, this thesis has shown—given the right parameters to this model—that the network these agents produce shares some characteristics with real-world social networks.

Taken together, this thesis has demonstrated that subtle behaviours of individual agents can ultimately affect the global structure of a social network. In doing so, it has provided a counterweight to the predominatly structure-oriented approach of social network research, as well as uncovered the new and interesting domain of using agent simulations as a tool for investigating the implications of social psychological theories.

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