

POSITEAMS – POSITIVE SYSTEMS INTELLIGENT TEAMS, AN AGENT-BASED SIMULATOR FOR STUDYING GROUP BEHAVIOUR

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ABSTRACT

Systems intelligence is the ability to act intelligently within complex systems involving interaction and feedback. Organizations and social groups are typical examples of everyday systems. The dynamics of social systems can be difficult to understand because of their systemic nature. This makes positively affecting the state of the system a challenging problem. The effects of positive emotions have been linked with increased performance in social groups and individuals. Thus simulating emotion dynamics can be used to better understand how to act more constructively within organizations. PoSITeams is a web-based multi-agent simulator to study the dynamics of emotions. We present a novel agent-based emotional contagion model based on psychological research to study the dynamics of positive and negative emotions in organizations. The purpose of the simulator is to let the user explore the effects of different behavioural and structural changes in organizations. This facilitates perceiving the organization as a system and also lets the user recognize the potential of changing the system from within, thus promoting systems intelligent behaviour in the organization. The presented emotional contagion model is also considered as an optimization problem to let the simulator suggest systems intelligent actions. The behaviour of the model and the optimization methods are examined with example simulations.

Keywords: systems intelligence, agent based modelling, social systems, emotional contagion

INTRODUCTION

Organizations and social groups can be naturally perceived as systems, i.e. wholes consisting of multiple mutually interacting parts, where the interactions often include non-linearities and feedback loops. Such systems are seldom observed from the outside, but rather we are surrounded within them. Acting constructively within a social system and positively affecting its state is a complex problem since the effects of the system, such as non-linearities, feedbacks and time delays, are difficult or even impossible to understand. Consequently, tools that would facilitate perceiving the systemic nature of the problem could be beneficial to our understanding of the everyday systems, ultimately leading to a more productive behaviour within them.

Although the dynamics of social systems can be difficult to understand, humans do have a remarkable capability to act intelligently within systems, a concept known as systems intelligence (Saarinen & Hämäläinen, 2007). A systems intelligent person perceives the system as a whole and recognizes herself as an active part of the system, who is both able to affect the state of the system and is reciprocally influenced herself by the system. She

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can act productively inside the system and is able to recognize and take advantage of different feedback mechanisms. Some individuals are more proficient than others in acting intelligently within systems such as different social groups, but it is a skill that can be developed. To study systems intelligence within social groups, we have developed a simulator called Positive Systems Intelligent Teams (PoSITeams). PoSITeams is a web-based multi-agent social simulator that simulates the dynamics and evolution of positive and negative affect in a team. Agent-based simulations have been used extensively to model social systems and they can provide useful insights into the underlying systems and introduce ideas to improve their performance.

We are social animals and we are greatly influenced by the emotions of others. Emotions have been widely studied in psychology (Frijda, 1986) and a lot is known about their effects on individuals and social groups. Positive emotional contagion has been linked to increased performance in social groups (Barsade, 2002). In particular, the ratio of positive and negative affect has proven to be an especially useful parameter. It has been successfully applied to predicting effective organizations and successful marriages (Losada & Heaphy, 2004; Gottman, 2002). Positive emotions have been studied in the field of positive psychology, which focuses on human flourishing and how to improve our lives contrary to the traditional fields of psychology, which concentrate on the remedies to psychological problems (Seligman & Csikszentmihalyi, 2000). Also on the individual level the characteristic difference between flourishing and non-flourishing individuals has been observed to be the ratio of experienced positive and negative emotions (Fredrickson, 2013). Positivity ratios can therefore be used as indicators of the overall performance and well-being of both social systems as well as its individuals, which has been the motivation behind PoSITeams.

The purpose of PoSITeams is to enable the user to simulate social groups of her own and explore the effects of different behavioural changes. The focus is especially in engaging the user in reflective thought-processes and facilitate seeing the system as a whole and let the user recognize herself as an active part of the system. In this sense, the simulator could be used to promote systems intelligent behaviour in a social context.

BACKGROUND

Systems Intelligence

The concept of systems intelligence was introduced by Professors Raimo P. Hämäläinen and Esa Saarinen of Aalto University in 2004. Systems intelligence can be defined as the ability to act intelligently within complex systems, i.e. wholes consisting of different parts with complicated interactions, dynamics and feedback loops (Saarinen & Hämäläinen, 2007). The conceptual basis of systems intelligence has been greatly influenced by systems thinking, especially by the highly acclaimed work of (Senge, 1990). Both of these systems approaches emphasize the holistic view of perceiving the world through interconnectivity and interdependence of its components rather than reducing the whole to its parts. They share the tenet that the whole is greater than its parts and that there are emergent phenomena that are not reducible to the properties of these parts. However, systems intelligence focuses

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on human behaviour within systems, rather than attempting to understand the system from the outside, which is characteristic for systems thinking. In systems intelligence, a person is recognized as an active part within the system with some power to affect its state, while being reciprocally influenced by the system. It is recognized that everyday systems have uncertainties, but they might still require taking action. Systems intelligence therefore strives to be an intuitive concept that brings new perspectives to everyday issues, leading to concrete actions.

Systems intelligence is conceptually related to the theory of multiple intelligences (Howard, 1983) and emotional intelligence (Goleman, 1995). Systems intelligence is, however, considered to be a higher level competence, which is not directly reducible to these forms of intelligences (Saarinen & Hämäläinen, 2010). Since systems intelligence also looks for opportunities for improvement within systems, it is also connected to positive psychology (Seligman & Csikszentmihalyi, 2000), a field of psychology focusing on how to live better rather than finding remedies to psychological problems. Systems intelligence is considered to be a combination of eight distinct capabilities: systems perception, attunement, reflection, positive engagement, spirited discovery, effective responsiveness, wise action and positive attitude (Hämäläinen, et al., 2014). These dimensions can be grouped roughly into four categories: perceiving, attitude, thinking and acting, as shown in Table 1.

Table 1. The eight dimensions of systems intelligence

Perceiving	Systems Perception	Attunement
Attitude	Positive Attitude	Spirited Discovery
Thinking	Reflection	Wise Action
Acting	Positive Engagement	Effective Responsiveness

Organizations can be naturally considered as systems, which makes systems intelligence a particularly useful concept to leadership and organizational life (Hämäläinen & Saarinen, 2008). Most organizations have a clearly defined goal, and systems intelligent behaviour in such a context is therefore finding actions within the organization that make it more effective at reaching its goals. Especially in leadership positions the potential to influence the system is large, which makes systems intelligence a key competence of a successful leader.

Organizations are examples of social groups. An important feature of social groups is that one seldom has an opportunity to view them from the outside, but rather one is an active part of the system with some power to affect its state. Social groups are therefore a great environment for the analysis of systems intelligence. For example a simple encouragement might have a surprisingly significant effect depending on the group. Humans are social

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animals, so we have a fairly developed innate ability to understand social systems. However, systemic features such as non-linear interactions, feedbacks, accumulation and time delays can be difficult to grasp intuitively. Therefore humans can have difficulties to see the potential that a simple act, such as an encouragement, might have on the group. Similarly it can be difficult to see the extent to which negative behaviour is detrimental for the group. Systems intelligence in a social context therefore requires an understanding of emotion dynamics.

Effects of positive and negative emotions

Since an encouragement or a criticism can have a great impact on individuals, and therefore on the whole group, it is no surprise that negative and positive affect may serve as an indication of how well a group of people function together.

The broaden-and-build theory in positive psychology suggests that positive emotions have a much larger role than merely to make one "feel good" or indicating emotional well-being (Fredrickson, 1998; Fredrickson, 2001). There is empirical evidence that experiencing positive emotions increases awareness and openness to consider a wider selection of thoughts and actions (Fredrickson & Branigan, 2005; Schmitz, et al., 2009). Contrary to negative emotions, that are often associated with narrow thought-action repertoires which are quite specific to cope with event that induces the negative reaction (e.g. fear tends to elicit a fight-or-flight response), positive emotions such as joy promotes playfulness, curiosity and interest, which can turn into a wide selection of different thoughts and actions. Through such positivity-induced actions, a person then builds her cognitive, social, psychological, emotional and physical resources that will be long lasting, unlike the fleeting emotions evoking this process (Fredrickson, 1998; Fredrickson, 2001).

Since experiencing positive emotions broadens one's thought-action repertoires and builds personal resources, positive emotions increase flexibility and ability to cope with adversities (Garland, et al., 2010; Fredrickson, et al., 2003). Therefore people experiencing positive emotions are more resilient against negative emotions and they are more likely to experience more positive experiences in the future, creating a positive feedback loop towards emotional well-being (Fredrickson & Joiner, 2002). Negative emotions also have a potential to turn into feedback loops, as is often observed in depression (Garland, et al., 2010).

An important concept in positive psychology is *flourishing*, which is "*to live within an optimal range of human functioning, one that connotes goodness, generativity, growth, and resilience*" (Fredrickson & Losada, 2005). The characteristic difference between flourishing and non-flourishing individuals appears to be the ratio of experienced positive and negative emotions (Fredrickson & Losada, 2005). A commonly used estimate for this tipping point has been 3:1, although it might not be universally applicable to all demographics (Fredrickson, 2013). People have a tendency to experience negative emotions more strongly than positive ones (Baumeister, et al., 2001; Rozin & Royzman, 2001), which might explain the asymmetry seen in the positivity ratio. This negativity bias

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seems to be relatively weaker for the flourishing individuals, who have a stronger reaction to positive everyday events (Catalino & Fredrickson, 2011). Another asymmetry between positive and negative emotions is the positivity offset, which is tendency to experience most neutral situations as mildly positive (Cacioppo, et al., 1999).

People have a tendency to be influenced by the emotions of others, known as emotional contagion, which has been defined by (Hatfield & Cacioppo, 1994) as:

"a tendency to automatically mimic and synchronize expressions, vocalizations, postures, and movements with those of another person's and, consequently, to converge emotionally"

That is, people do not experience emotions and moods in isolation, but they are largely affected by the surrounding people, often unknowingly. Groups can experience collective emotional states, which are not directly reducible to the individuals of the group. This is referred to as the "top-down" view of group emotions, where the group is seen as an emotional entity that shapes the emotional responses of its individuals (Barsade & Gibson, 1998). However, it is argued that group emotions should also be viewed from a "bottom-up" perspective, where the composition of the individuals construct the emotional state of the group (Barsade & Gibson, 1998).

Positive emotional contagion has been linked to increased performance in social groups (Barsade, 2002). For example successful marriages tend to have a ratio of positive and negative interactions around 5:1 (Gottman, 2002). Similarly high performance business teams seem to have a positivity ratio of 5:1 (Losada & Heaphy, 2004). Thus the positivity ratio is a useful concept also in social groups. High positivity ratio also increases the number of strong connections in the group, referred to as *connectivity* (Losada & Heaphy, 2004). Similar observation has also been noted in (Waugh & Fredrickson, 2006), where positive emotions were shown to increase the feeling of "oneness" in the group, which could be interpreted as a form of connectivity. There is also empirical evidence that positive emotions increase sociability (Whelan & Zelenski, 2012), also a means to increase connectivity of the group.

Modelling the effects of emotions

Representing emotions

Computational processing and simulation of human emotion has been studied in the field of *affective computing* (Picard, 1997). There have been several attempts to identify a discrete set of fundamental basic emotions that are cross-culturally recognized and that can explain more complicated emotions (see e.g. (Ekman & Friesen, 1971; Jack, et al., 2014; Plutchik, 2001)). Although there is no consensus on the number of basic emotions (Ortony & Turner, 1990), one approach to modelling emotions could be to select a subset of them to be represented separately. Emotional contagion of different basic emotions has been studied in (Doherty, 1997). However, it is more common to represent emotions with different dimensional models, which usually have two to three different dimensions to

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describe the emotions (Marsella, et al., 2010). Typical parameters for these models are valence, which represents emotion in the negativity-positivity continuum, and arousal, which indicates the intensity of the subjective emotion parameters. For example, hate is a highly aroused state with negative valence, whereas boredom would be a state with negative valence and low level of arousal. Examples of dimensional models of emotion are, for example, the circumplex model (Russell, 1980), which uses valence and arousal dimensions, and the PAD model (Mehrabian, 1980), which also incorporates dominance-submissiveness dimension. For instance, hate and fear are examples of dominant and submissive emotions.

The dimensional models of emotions are mostly concerned with representing different emotions. However, the interest of this work is the effects of positivity and negativity in social groups, so there is no need to represent different emotions and it is natural to model them only in terms of their impact on positivity and negativity. This also greatly simplifies the model since the complex interplay of different emotions and also their arousal/dominance aspect can be omitted. Therefore only models that concentrate on positivity and negativity are considered in this work.

One interesting note is that it is common to represent mood by its positivity, so the simplification of modelling emotions by classifying them into positive and negative might capture some other affective phenomena such as mood. The main distinctive difference between mood and emotion is that mood is generally a much longer lasting phenomenon, whereas emotions usually only last at most a couple of hours (Frijda, 1993).

Emotional contagion models

Although John M. Gottman does not use the term "emotional contagion", his research on marital happiness is highly relevant (Gottman, 2002). Gottman models the interaction between husband and wife with equations

$$W_{t+1} = I_{HW}(H_t) + r_1 W_t + a \quad (1)$$

$$H_{t+1} = I_{WH}(W_t) + r_2 H_t + b, \quad (2)$$

where W_t and H_t represent the emotional states of the wife and the husband respectively at time t . Husband and wife affect each other through their influence function I_{HW} and I_{WH} , which are bilinear functions of the influencing partner's current emotional state. The rest of the equation represents the uninfluenced part, which describes the behaviour of the spouse when there is no interaction between the partners. Parameters r_1 and r_2 are called emotional inertia that describe how quickly the emotional states approach their steady states. The parameters a and b do not have an intuitive interpretation, but they affect the dynamics of the model. Gottman has also extended the model with additional correction terms (Gottman, 2002).

Agent-based simulations have been used extensively to model phenomena in social sciences (see e.g. (Gilbert, 2004)), so it is no surprise that agent-based modelling has been

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used to model emotional contagion. (Bosse, et al., 2009a) suggest a model where the emotional contagion strength between agents i and j is represented by

$$\gamma_{i,j} = \varepsilon_i \alpha_{i,j} \delta_j, \quad (3)$$

where ε_i is the strength by which the agent i expresses its level of emotion. This can be understood as the degree of introversion/extroversion of the agent. Parameters $\alpha_{i,j}$ represent the connection strength between agents i and j , which can be understood as how close the social relationship between the agents is and how much they are interacting with each other. δ_j represents how easily the emotions of agent j are affected by the emotions of others, which can be interpreted as emotional sensitivity.

The overall emotional impact directed towards agent j is then

$$q_j^* = \sum_{i \neq j} \frac{\gamma_{i,j} q_i}{\gamma_j}, \quad (4)$$

where q_i is the emotion level of agent i and

$$\gamma_j = \sum_{i \neq j} \gamma_{i,j} \quad (5)$$

is the overall emotional contagion strength. The interaction model in (Bosse, et al., 2009a) is then

$$q_j(t + \Delta t) = q_j(t) + \gamma_j (q_j^*(t) - q_j(t)) \Delta t. \quad (6)$$

In this model the emotional level of agent j is updated towards the overall emotional impact directed at the agent. The magnitude of the update depends on the overall emotional contagion strength of the agent.

(Bosse, et al., 2009b) extends the model by introducing a bias term β_j representing whether the agent is more susceptible to positive or negative emotional impacts. The interaction formula of this model is then

$$q_j(t + \Delta t) = q_j(t) + \gamma_j (\beta_j PI(t) + (1 - \beta_j) NI(t) - q_j(t)) \Delta t. \quad (7)$$

This has again been extended in (Hoogendoorn, et al., 2011), where the parameter η_j was introduced, representing the tendency of agent j to amplify or absorb the received emotion impacts, leading to an equation

$$q_j(t + \Delta t) = q_j(t) + \gamma_j \left[\eta_j (\beta_j PI(t) + (1 - \beta_j) NI(t)) + (1 - \eta_j) q_j^*(t) - q_j(t) \right] \Delta t. \quad (8)$$

MODELLING THE CONTAGION OF EMOTIONS

A new model is proposed to capture the essential dynamics of emotional contagion in groups. Since this work focuses on positivity ratios and its effects on organizations and social groups, elaborate models aiming to accurately reproduce the variety of different emotions are not considered. The model focuses only on the level of positivity and negativity of emotions. However, since there are some qualitative differences between positive and negative emotions, such as broadening and narrowing of awareness and the negativity bias, positive and negative emotions are represented as separate variables. Similarly to Gottman’s model in (1) and (2), the proposed model is of the form

$$P_j(t + 1) = a_j P_j(t) + b_j + \sum_{i \neq j} I_{i,j}^P(t) \tag{9}$$

$$N_j(t + 1) = c_j N_j(t) + d_j + \sum_{i \neq j} I_{i,j}^N(t). \tag{10}$$

As in Gottman’s model, the positive and negative states can be separated into the influenced and uninfluenced components. The influenced components are represented by the influence functions $I_{i,j}^P$ and $I_{i,j}^N$, which characterize the interaction and emotional contagion between the agents i and j , whereas the remaining terms of the model represent the uninfluenced part of the emotional state of agent j . That is, the uninfluenced part represents the emotional state of the agent when there is no interaction between any other agents. When the influence functions are set to zero and the agents are only affected by the uninfluenced component of the model, then

$$P_j(t + 1) = a_j P_j(t) + b_j \tag{11}$$

$$N_j(t + 1) = c_j N_j(t) + d_j. \tag{12}$$

From this we get the following stable steady states for the model

$$P_j = \frac{b_j}{1 - a_j} \tag{13}$$

$$N_j = \frac{d_j}{1 - c_j}. \tag{14}$$

Therefore it follows, that the stable steady state for the positivity ratio in the uninfluenced case is

$$\frac{P_j}{N_j} = \frac{b_j(1 - c_j)}{d_j(1 - a_j)}. \tag{15}$$

The general positivity of the agent can be characterized by setting proper values for these parameters, e.g. a flourishing person might have the ratio $(b_j(1 - c_j))/(d_j(1 - a_j))$ of 3:1. Gottman calls a_j and c_j emotional inertia parameters (Gottman, 2002), which indicate how quickly the agent returns to its steady state. Positive emotions tend to be more fleeting and short-lasting than negative emotions (Baumeister, et al., 2001), so for most people it

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would be expected that $a_j > c_j$. It is also worth noting, that the uninfluenced case in (11) and (12) have solutions

$$P_j(t) = a_j^t P_j(0) + \frac{b_j(1 - a_j^t)}{1 - a_j} \quad (16)$$

$$N_j(t) = c_j^t N_j(0) + \frac{d_j(1 - c_j^t)}{1 - c_j}. \quad (17)$$

Therefore $\frac{P_j}{N_j} \rightarrow \frac{b_j(1-c_j)}{a_j(1-a_j)}$ when $t \rightarrow \infty$, only if $|a_j| < 1$ and $|c_j| < 1$.

The positivity ratio of the model in (9) and (10) increases, when

$$\frac{P_j(t)}{N_j(t)} < \frac{P_j(t+1)}{N_j(t+1)} = \frac{a_j P_j(t) + b_j + \sum_{i \neq j} I_{i,j}^P(t)}{c_j N_j(t) + d_j + \sum_{i \neq j} I_{i,j}^N(t)} \quad (18)$$

$$\Rightarrow \frac{P_j(t)}{N_j(t)} \left[c_j N_j(t) + d_j + \sum_{i \neq j} I_{i,j}^N(t) \right] < a_j P_j(t) + b_j + \sum_{i \neq j} I_{i,j}^P(t) \quad (19)$$

$$\Rightarrow \frac{P_j(t)}{N_j(t)} < \frac{(a_j - c_j) P_j(t) + b_j + \sum_{i \neq j} I_{i,j}^P(t)}{d_j + \sum_{i \neq j} I_{i,j}^N(t)}. \quad (20)$$

Assuming $a_j = c_j$, the inequality is further simplified to

$$\frac{P_j(t)}{N_j(t)} < \frac{b_j + \sum_{i \neq j} I_{i,j}^P(t)}{d_j + \sum_{i \neq j} I_{i,j}^N(t)}. \quad (21)$$

This shows that the change of P/N depends both on the agent's personal characteristics of b_j and d_j and the external influences determined by the influence functions. Since it is assumed that $a_j = c_j$, the uninfluenced steady state of the agent is simply b_j/d_j as seen from the equation (15). Therefore if the values of b_j and d_j are large compared to the influence functions, P/N converges towards the uninfluenced steady state of the agent. In other words, by changing the absolute values of b_j and d_j the behaviour of the model can be adjusted to either emphasize the impact of the influence functions or the agent's general positivity determined by the uninfluenced steady state. This is analogous to the "top-down" and "bottom-up" view of group emotions in (Barsade & Gibson, 1998). The parameters b_j and d_j also keep P/N within a finite positive range, avoiding both zero and infinity. This suggests that adjusting the b_j and d_j parameters also affects how volatile the behaviour of P/N is.

Influence functions

The proposed form for the influence functions is

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$$I_{i,j}^P(t) = \gamma_{i,j}(1 - \beta_j)P_i^{rel}(t) \quad (22)$$

$$I_{i,j}^N(t) = \gamma_{i,j}\beta_jN_i^{rel}(t). \quad (23)$$

It is known that the ratio of positive and negative emotions is the distinctive difference between flourishing and non-flourishing individuals (Fredrickson, 2013; Fredrickson & Losada, 2005), so it is assumed that the agents interact with the other agents according to their positivity ratios. Instead of directly using the positivity ratio P/N , relative positivity and negativity ratios are used, defined as

$$P_j^{rel}(t) = \frac{P_j(t)}{P_j(t) + N_j(t)} \quad (24)$$

$$N_j^{rel}(t) = \frac{N_j(t)}{P_j(t) + N_j(t)} \quad (25)$$

to limit the interaction values within the range $[0,1]$ and to avoid issues caused by the singularity of P/N when $N \rightarrow 0$.

The parameter β_j describes the negativity bias effect, i.e. a negative event has more impact than a corresponding positive effect (Rozin & Royzman, 2001). Accordingly, the effects of negative events are emphasized when $\beta_j > 1 - \beta_j$. Negativity bias can be also interpreted as the different slope parameters in the bilinear influence function of Gottman's model in (1) and (2). The models (7) and (8) also take the negativity bias into account by weighting the positive and negative emotional impacts with β_j and $1 - \beta_j$. Parameter $\gamma_{i,j}$ describes the strength of emotional contagion. As in (3), it is expressed as

$$\gamma_{i,j} = \varepsilon_i \alpha_{i,j} \delta_j. \quad (26)$$

Here ε_i describes how strongly agent i expresses her emotional state to the other agents, $\alpha_{i,j}$ represents the level of interaction between agents i and j and δ_j describes how greatly the emotional level of agent j is affected by the emotional influence of other agents.

Broaden-and-build extension

The broadening effect of positivity is one of the main tenets of the broaden-and-build theory (Fredrickson, 2001). This is implemented by increasing both δ_j , which represents the emotional sensitivity of the agent, and ε_i representing extroversion. Increasing either of these parameters also increases the total emotional contagion strength and thus increases the connectivity of the group as stated in (Losada & Heaphy, 2004). As the value of δ_j is increased, the effect of the group on the emotional state of the agent also increases. Thus the coupling between the agent and the whole group becomes stronger. This is consistent with the results of (Waugh & Fredrickson, 2006), which states that increased positivity affects the feeling of "oneness" in the group. Increasing the extroversion parameter ε_j as the positivity ratio increases is also consistent with (Whelan & Zelenski, 2012), which states that positivity has a favourable effect on sociability.

The increase of δ_j and ε_j is implemented with simple linear models

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$$\delta_j(t) = P_j^{rel}(t-1)(\delta_j^{MAX} - \delta_j^{MIN}) + \delta_j^{MIN} \quad (27)$$

$$\varepsilon_j(t) = P_j^{rel}(t-1)(\varepsilon_j^{MAX} - \varepsilon_j^{MIN}) + \varepsilon_j^{MIN}. \quad (28)$$

It is assumed that $\delta_j^{MIN} < \delta_j^{MAX}$ and $\varepsilon_j^{MIN} < \varepsilon_j^{MAX}$ to ensure that δ_j and ε_j increase as the positivity ratio of the agent increases.

The broaden-and-build theory states that experiencing positive emotions facilitates coping with adversity (Fredrickson, et al., 2003; Garland, et al., 2010). Using the same approach as with δ_j and ε_j parameters, the parameter β_j is modelled with a linear model depending on the level of relative positivity P_j^{rel} . That is

$$\beta_j(t) = P_j^{rel}(t-1)(\beta_j^{MIN} - \beta_j^{MAX}) - \beta_j^{MIN} + 1. \quad (29)$$

This makes the agent less susceptible to negativity when its positivity ratio increases. Again it is assumed that $0 \leq \beta_j^{MIN} < \beta_j^{MAX} \leq 1$ so that the negativity bias decreases as the positivity ratio increases. This also ensures that β_j and $1 - \beta_j$ are non-negative.

Selecting the model parameters

The presented emotional contagion model has several free parameters, and some choices were made regarding which of these should be adjustable by the user and which of them should be given a fixed value. Granting the user too much freedom can be overwhelming and make it more difficult to obtain insights from the application. Therefore the following choices have been made.

- *Emotional inertia.* This is denoted by parameters a_j and c_j , which are given a fixed value of 0.9. Although negative emotions tend to be longer lasting than positive ones, these parameters are given the same value since the impact of negative emotions is already emphasized by the negativity bias parameters. A shared value also facilitates the reasoning of the model behaviour as shown in (21).
- *General positivity.* This corresponds to the positivity ratio in the uninfluenced steady state of the agent given by equation $P_j/N_j = (b_j(1 - c_j))/(d_j(1 - a_j))$. That is, how positive the agent is when there is no interaction with any other agents in the system. Since $a_j = c_j$, the general positivity is determined by the parameters b_j and d_j . The sum of b_j and d_j is given a fixed value of 0.1 and this is divided between the parameters so that the agent will have the general positivity level set by the user. Also the initial P_j and N_j levels are determined so that their sum is 10, which is divided between P_j and N_j so that the P_j/N_j equals to the given general positivity value.
- *Extroversion.* This is the parameter ε_j and can be interpreted as the tendency to express one's emotional level to others. In the simulator this is implemented as a linear function as defined by equation (28) to take into account the increase in connectivity as the positivity ratio increases. The user is allowed to adjust ε_j^{MIN} between $[0, 0.8]$ and ε_j^{MAX} is fixed at $\varepsilon_j^{MIN} + 0.2$. That is, the extroversion parameter is determined by

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$$\varepsilon_j(t) = 0.2P_j^{rel}(t-1) + \varepsilon_j^{MIN}, \quad \varepsilon_j^{MIN} \in [0,0.8]. \quad (30)$$

- *Emotional sensitivity.* This corresponds to δ_j , the tendency of agent's own emotional level being affected by the emotions of others. This is implemented similarly to extroversion using the linear equation (27) and the user is allowed to change δ_j^{MIN} within range $[0, 0.8]$ and δ_j^{MAX} is fixed at $\delta_j^{MIN} + 0.2$. This corresponds to equation

$$\delta_j(t) = 0.2P_j^{rel}(t-1) + \delta_j^{MIN}, \quad \delta_j^{MIN} \in [0, 0.8]. \quad (31)$$

- *Connection strength.* Determined by parameters $\alpha_{i,j}$, which represents how strong the social relationship is between the agents i and j . The user is allowed to change this parameter between $[0, 1]$.
- *Negativity bias.* As stated in the broaden-and-build theory, experiencing positive emotions increases the capability to cope with negative emotions and therefore the negativity bias is changed according to the equation (29). The user is allowed to change β_j^{MIN} between $[0, 0.5]$ and β_j^{MAX} is set to $\beta_j^{MIN} + 0.5$. Negativity bias is therefore determined by

$$\beta_j(t) = -0.5P_j^{rel}(t-1) + 1 - \beta_j^{MIN}, \quad \beta_j^{MIN} \in [0, 0.5]. \quad (32)$$

PoSITeams presents these parameter ranges as sliders with values between $[0, 1]$ and they are internally mapped to the aforementioned ranges. This makes the user interface more consistent for the user. The only exception to this is the general positivity parameter, since it has a direct interpretation as a positivity ratio.

HOW TO BEST IMPROVE TEAM BEHAVIOUR

Considering the emotional contagion model as an optimization problem, there are a number of interesting problems to investigate, such as

- find the optimal behaviour that maximizes the individual or collective positivity ratio
- find the optimal structure of the organization
- what kind of a team member would be the best addition to the team in terms of maximizing the positivity ratio of the team

Simulated annealing

The optimization of the emotional contagion model is performed with simulated annealing for its simplicity. Simulated annealing is an approximate global optimization technique that emulates the process of slowly cooling a heated metal and thus minimizing its thermodynamic free energy (Kirkpatrick, et al., 1983). A typical example of its application is the traveling salesman problem, a classic NP-hard problem (Černý, 1985).

To use simulated annealing, each value combination of free parameters of the system is defined as a state. For simplicity, all the parameters are considered to be discrete values within a predefined interval. A neighbouring state is obtained from the current state by randomly changing the value of each parameter p with a probability of

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$$P(|\Delta p| > 0) = \min\left(\frac{1}{2}, 1 - \frac{S-2}{S}\right), \quad (33)$$

where S is the number of parameters in the state. The expected number of parameters to be changed is therefore 2, when $S \geq 4$. This is motivated by the assumption that good solutions are located near other good solutions. After a number of iterations the current solution is presumably better than a randomly selected state and by doing a minor change in the current state, the obtained neighbouring state is also likely to be good. Minor alterations to the current state hopefully improve the poor parts of the solution while keeping the good parts mostly unchanged.

If a parameter value p is changed, its new value p' is selected uniformly from range

$$p' \in [\max(l, p - 0.1N), \min(u, p + 0.1N)]. \quad (34)$$

where l and u define the lower and upper bound of the parameter interval of length N . Each state s has an associated energy defined by the energy function $E(s)$. The algorithm attempts to find the state with the lowest energy. The transition from state s to its neighbouring state s' is accepted with probability

$$P(e, e', T) = \begin{cases} 1 & \text{if } e' \leq e \\ \exp(-(e' - e)/T) & \text{if } e' > e, \end{cases} \quad (35)$$

where e and e' are the energies of the states s and s' respectively. T is the temperature parameter, which is initially set to $T_0 = 10^{10}$ and cooled according to $T_{n+1} = 0.999T_n$ until $T < 0.01$. This corresponds to 27618 iterations, which has been found out to be sufficiently quick and accurate in practice.

The energy function can be chosen rather freely. It can be for example the negative P/N of a single agent or the negative mean P/N of all the agents. The P/N value can be evaluated by performing simulations for each parameter combination until convergence. However, reaching convergence can be slow in practice, so a predefined number of simulations is used to evaluate P/N approximately. A value of 100 is used to provide satisfactory results in reasonable time. Other interesting energy functions could be negative of the minimum P/N of the group, so that the objective is to maximize the lowest P/N in the group.

The energy functions can incorporate costs associated with changing a parameter value. The motivation behind this is that there is always some effort required in changing one's behaviour or social connections. Also some changes are easier than others, for example increasing extroversion can be easier for someone than decreasing negativity bias.

The actual cost functions for Δp are unknown, so it is assumed that each parameter p has a cost c^- for a negative change of one unit and a cost c^+ for a positive change of one unit. This corresponds to a bilinear cost function g_p as shown in Figure 1.

Including the costs in the optimization turns the problem into a multi-objective optimization problem. A common approach to multi-objective optimization is to optimize a weighted sum of all the objectives (Marler & Arora, 2004). The costs are therefore combined with an energy function $E(s)$ by

$$E'(s) = (1 - w)E(s) + \frac{w}{M} \sum_{p \in s} g_p(\Delta p), \quad (36)$$

where $w \in [0, 1]$ is the trade-off between minimizing the original energy function and minimizing the costs associated with changing any of the parameters. M is the number of agents in the system, hence the total cost is divided between all the agents (i.e. it is easier for two agents to do one behavioural change each than for one agent to do two changes).

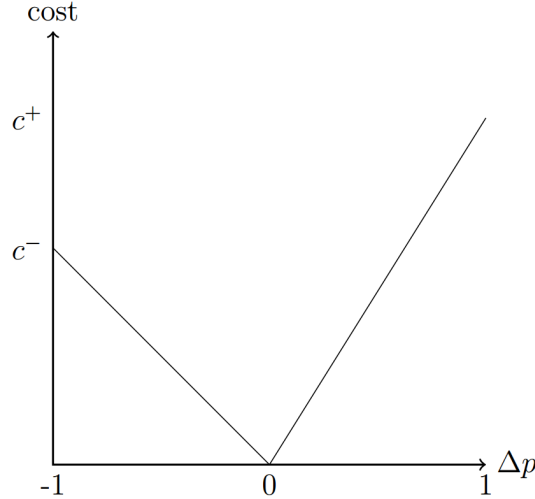


Figure 1. An example of a bilinear cost function g_p of changing the value of parameter p .

EXAMPLE SIMULATIONS

The following examples simulations are performed with the PoSITeams simulator, which can be found at <http://systemsintelligence.aalto.fi/positeams>. Most of the simulator view is dedicated for visualizing the agents and their connections as seen in the figures of the example simulations. The agents change their color from deep blue to bright yellow depending on their positivity ratio. Similarly the facial expression of the agent varies dynamically from sad to happy depending on its current positivity ratio. The positivity ratios are also drawn as a function of iterations next to the agent graph. The connections between the agents are shown as links in the directed graph and their opacity is directly proportional to the total emotional contagion strength $\gamma_{i,j}$ between the agents. The length of the links also indicates the level of interaction and the strength of the social relationship between the agents described by the parameters $\alpha_{i,j}$, which enforces clustering of socially connected groups.

A simple group

The first simulation example consists of three agents, one positive and two negative. The agent parameters of the example are shown in Table 2. The agent parameters of the first simulation example. All the connections have a strength of 1, except there is no connection from Cecilia to Bob. Figure 2 shows the simulation at its steady state after around 200 iterations. The average positivity ratio in this steady state is only 0.14, which is much lower

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than the general positivity of any of the agents. Similar behaviour can be observed in (Bosse, et al., 2009b) using the model (7), where the authors model emotion contagion spirals inspired by the broaden-and-build theory. The behaviour in this simulation example can be considered an example of a negativity spiral and it is also an example of a collective emotional state, which is not a sum of its parts, consistent with the "top-down" view in (Barsade & Gibson, 1998). This is a consequence of fixing $b_j + d_j$ to a small value of 0.1. The agents are affected both by their individual characteristics and their neighbouring agents. This balance can be adjusted by the b_j and d_j parameters of the model as shown in (21). When this sum is set to a larger value, the behaviour of the agents is largely determined by their general positivity rather than their environment. The sum of these parameters is therefore set to a small value in the simulator, since it shows more interesting behaviour by incorporating both the "top-down" and "bottom-views" of collective emotions as stated (Barsade & Gibson, 1998). This also allows the model to describe behaviour analogous with emotional contagion spirals.

Table 2. The agent parameters of the first simulation example.

Name	General positivity	Extroversion	Emotional sensitivity	Negativity bias
Adam	5	1	1	0.6
Bob	1	0.8	0.8	0.7
Cecilia	1	0.8	0.8	0.7

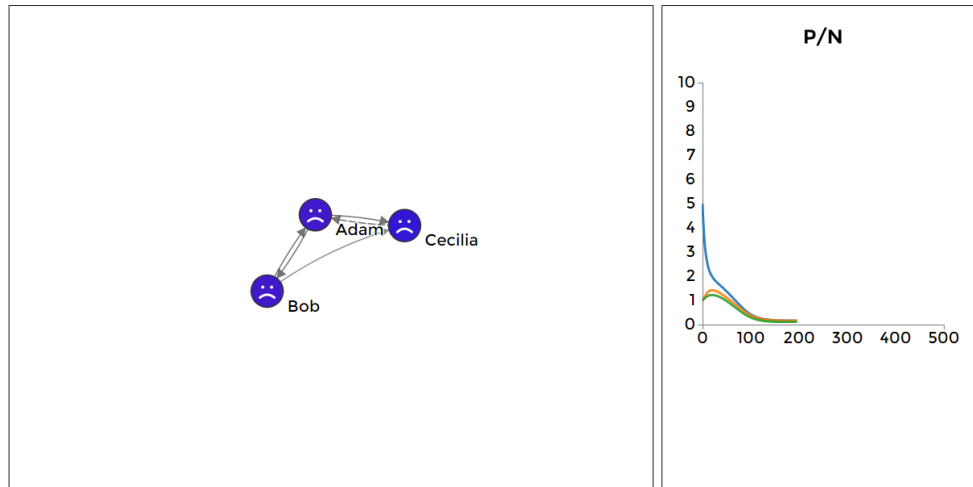


Figure 2. The first simulation example after reaching its steady state.

The behaviour of Adam is then optimized, restricting the optimization only to adjustment of emotional sensitivity and extroversion. This leads to a change in emotional sensitivity from 1 to 0, whereas the level of extroversion stays unchanged. Since Adam is the most positive of the three agents with general positivity of 5, it is natural to adjust the emotional sensitivity to a low value to self-generate positivity and increase resistance to external negativity. Also having a high level of extroversion is beneficial to spread positivity in the system. This adjustment leads to an average P/N of 5.53 as shown in Figure 3.

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Now the average positivity ratio is larger than the general positivity of any of the agents. Again, this is similar to the model in (Bosse, et al., 2009b) being an example of a positive spiral. The main difference is that (Bosse, et al., 2009b) have a stricter interpretation of the emotional contagion as converging to the same shared emotional state. In the example shown in Figure 3, the agents have different steady states caused by individual differences, but they still represent a collective emotional state and an example of a positive spiral. This is also consistent with the view in (Barsade & Gibson, 1998), where the authors argue that studying group emotion should include both views, the "top-down" view where the emotions of the individuals arise from the group and the "bottom-up" view, where the group emotion is determined by a composition of the emotions of the individuals.

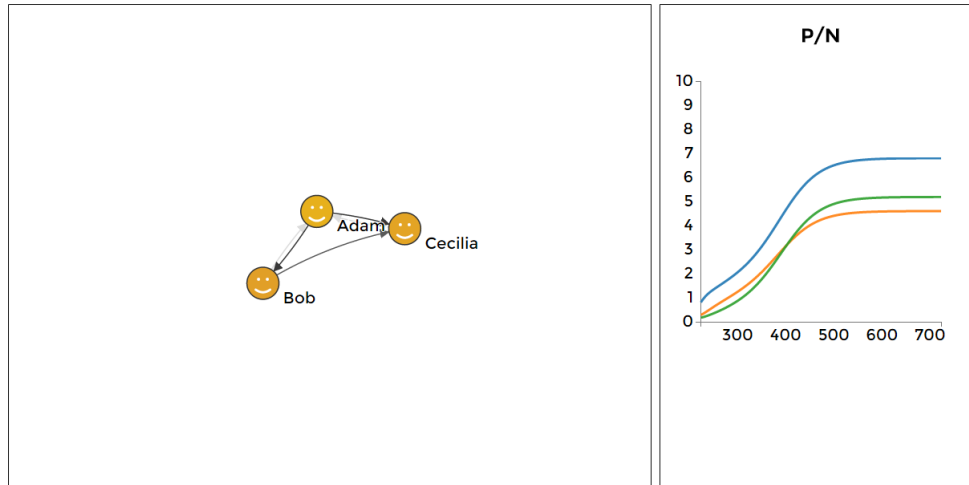


Figure 3. The state of the system after optimizing the emotional sensitivity and extroversion parameters of Adam.

An interesting behaviour happens when the emotional sensitivity and extroversion parameters of Adam are optimized again, starting from the state shown in Figure 3. As a result of this, the emotional sensitivity is set from 0 to 1, which increases the average P/N to 8.22 as shown in Figure 4. Interestingly, the emotional sensitivity and the extroversion parameters of Adam are exactly the same as in the initial negative steady state. One might expect that setting the parameters to their original values would have a negative effect, returning the system to its original state. However, the difference is that the system is not the same anymore and whereas in the beginning Adam was surrounded by negative agents, now he is surrounded by positive ones. Being emotionally sensitive is a positive quality in a positive environment since it lets one be influenced by the surrounding positivity. Conversely, being emotionally stoic is beneficial in a negative environment. This example also demonstrates that it is not necessarily possible to reach the global optimum of the system using a single optimization step, since the optimal behaviour in the global optimum might not suffice to escape the initial negative steady state.

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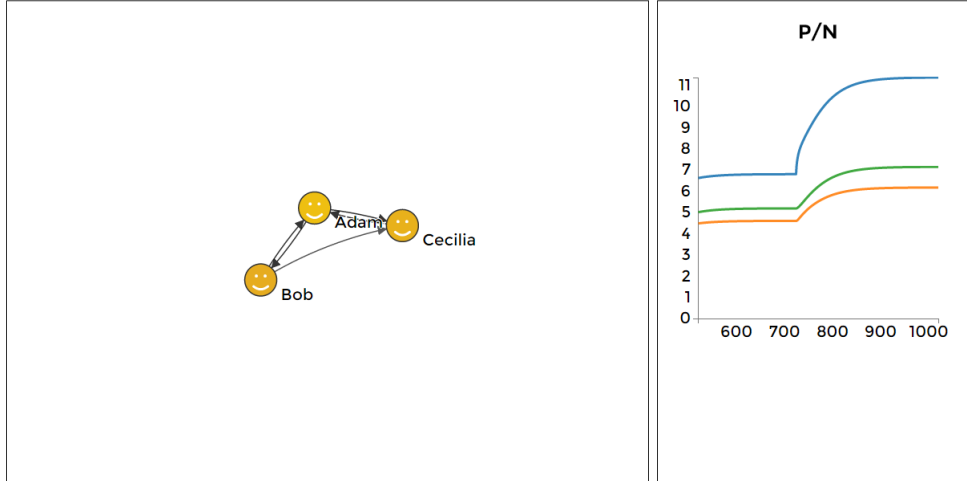


Figure 4. The state of the system after optimizing the emotional sensitivity and extroversion of Adam for the second time starting from the state shown in Figure 3. This demonstrates that it can be impossible to reach the global optimum of the system with a single optimization. Also, changing the parameters to their original values does not necessarily return the system to its original state.

A small organization

Optimization with zero costs

A more complicated example is shown in Figure 5, which consists of two small teams with a shared supervisor. The agent parameters of the example are shown in Table 3. All the connections shown in the figure have a strength of 1. Team A consists of Adam, Albert and Anna, whereas team B is formed by Barbara and Bob. Cecilia is the supervisor of the two teams. To enforce the team structure in the simulation, the parameter limits are set so that connections within each team must be in range $[0.5, 1]$ and between the teams within $[0, 0.1]$. Cecilia must have connection strengths in the range $[0.2, 1]$ with all the members in the organization. The general positivity of all the agents is also constrained between $[0, 5]$ and the negativity bias must be within $[0.5, 1]$. The whole group is then optimized without parameter costs, which leads to a steady state shown in Figure 6 with an average positivity ratio of 34.66. Detailed optimization results can be found in the Appendix.

Table 3. The agent parameters of the organization simulation example.

Name	General positivity	Extroversion	Emotional sensitivity	Negativity bias
Adam	2	0.2	0.2	0.6
Albert	5	0.8	0.8	0.6
Anna	3	0.2	0.8	0.6
Barbara	2	0.3	0.3	0.6
Bob	2	0.3	0.3	0.6
Cecilia	1	0.9	0.4	0.8

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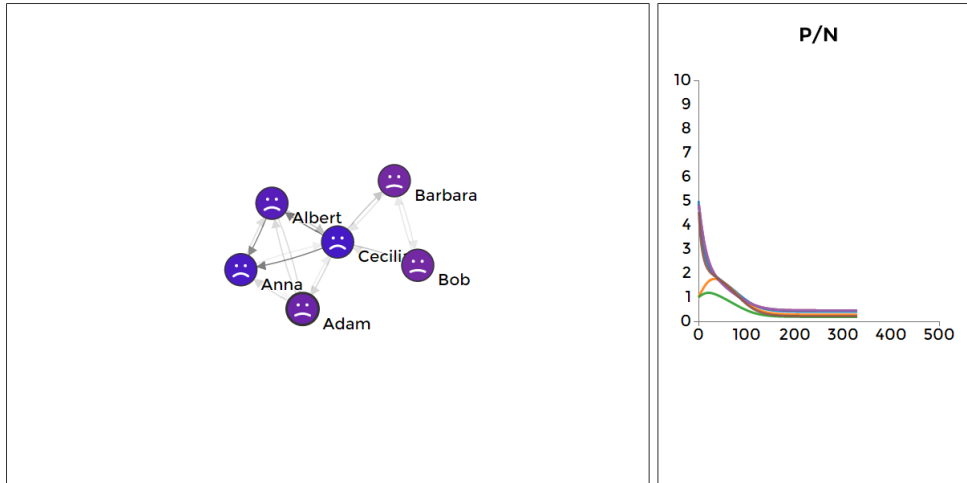


Figure 5. Steady state of the small team before optimization.

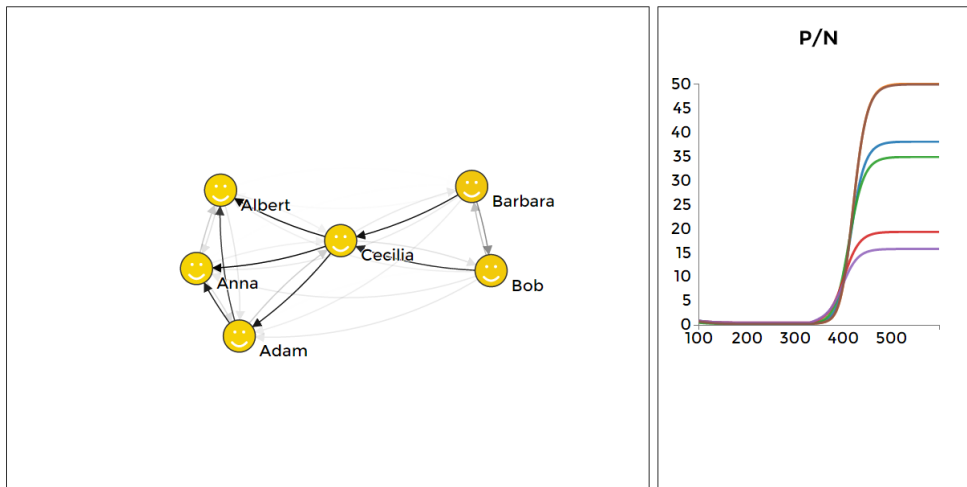


Figure 6. The result of optimization with no parameter costs.

Although the exact solution varies between subsequent runs, since simulated annealing is an approximate global optimization method, the general trend is minimizing negativity bias, maximizing general positivity and strong emotional connection strengths. However, the "trivial solution" of setting extroversion, emotional sensitivity and general positivity to maximum and negativity bias to minimum fails to escape the negative steady state, eventually reaching a steady state with an average P/N of 0.12. In the solution Cecilia draws positivity from team B and spreads it to team A, which seems to enable escaping the negative steady state, while keeping a fairly strong level of connectivity.

Optimizing connection strengths

Another type of solution can be obtained by only optimizing the connection strengths, attempting to find an optimal organizational structure. Again no parameter costs are used and the limits are kept the same as for the previous example. This leads to a solution in Figure 7 with an average P/N of 3.37. Detailed optimization results can be found in the Appendix.

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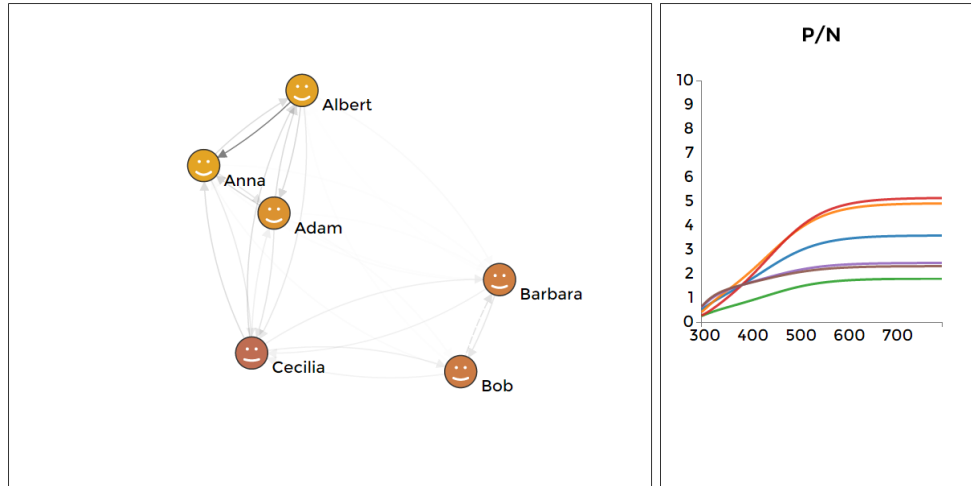


Figure 7. The results of optimizing the connection strengths of the group.

The main characteristic of the obtained solution is that the connection strengths from Cecilia to other agents are minimized. According to the general positivity parameter, Cecilia is the most negative person in the group. Thus the solution is to restrict the flow of negativity originating from her by decreasing emotional contagion strengths.

Optimization with costs

PoSITeams allows assigning costs for changing each of the agent and connection parameters. This takes into account the effort associated with changing one's behaviour or social relationships. For the following simulation example, these costs (both c^+ and c^-), are assigned so that for each agent the cost of changing general positivity or negativity bias is set to 10 and the cost of changing any of the other parameters is set to 1. Since the solution of the optimization without costs invariably maximizes general positivity and minimizes negativity biases, large costs are assigned to these parameters to moderate their effect. The trade-off parameter w in equation (36) is set to 0.5. The solution with an average P/N of 12.46 is shown in Figure 8. Detailed results can be found in the Appendix.

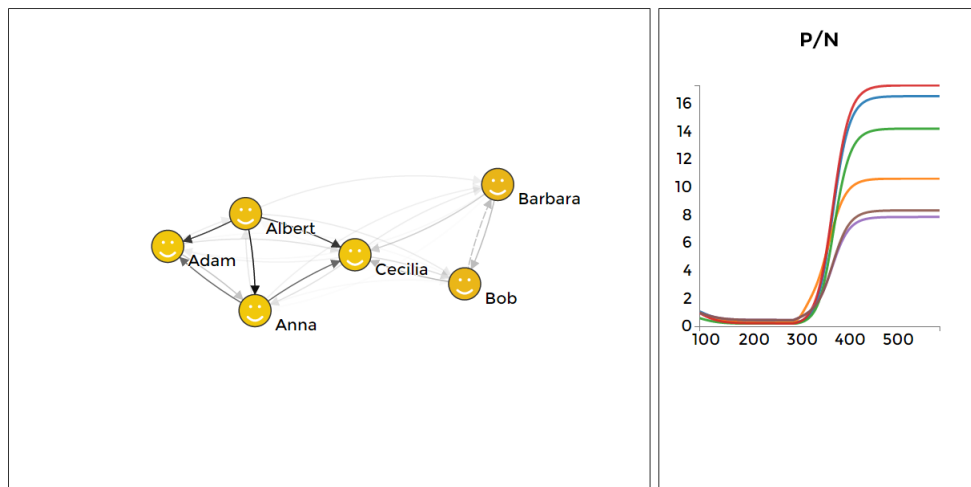


Figure 8. The solution of the optimization with costs.

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Two interesting aspects of the obtained solution is the weak connection strengths from Cecilia and strong connection strengths from Albert, who is the most positive agent based on general positivity. Albert is given a more central role to benefit from his positivity, while Cecilia's role is diminished.

Adding a new team member

The last example examines the possibility of adding a new member, Brian, to the team B. The question is, what kind of person Brian should be and what should be his role so that the average positivity ratio of the group is maximized? The connection strengths between Brian and team A are limited within range $[0, 0.1]$ to enforce the structure of two separate teams. Other connections are left unconstrained. All the parameters are given zero costs to give different solutions equal weights. In this example, Brian is to be considered a pseudo member rather than an actual team member with personal characteristics. Thus changing the parameter values does not correspond to changing the behaviour of an actual team member and there is no cost associated with changing one's behaviour. Instead, we are interested in the characteristics that an optimal team member would have. The solution of the optimization is shown in Figure 9, with an average P/N of 7.82. Detailed optimization results are found in the Appendix.

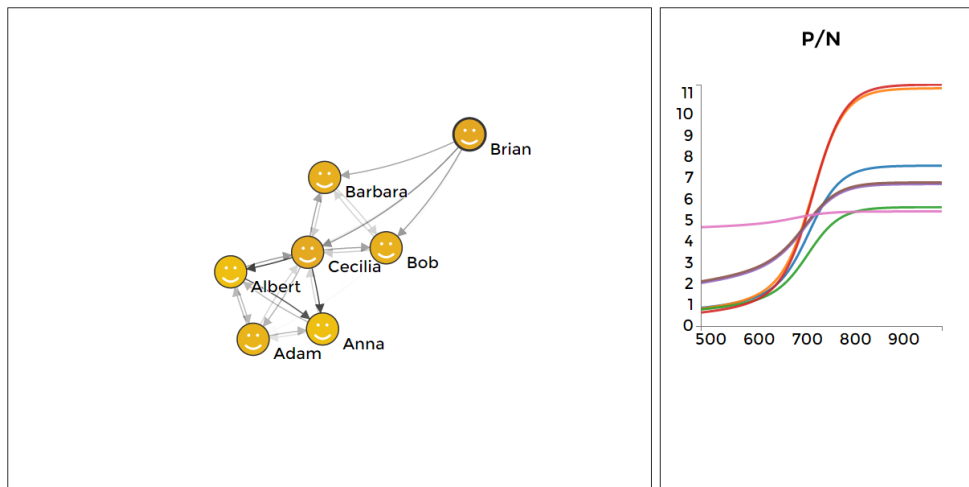


Figure 9. The solution of adding an optimal team member, Brian, to the group.

The solution is to give Brian a role where he strongly communicates towards his team members, while keeping a certain distance so that he is not himself affected by the negativity of the group. This rather one-sided communication channel might not be especially realistic in practice, but alternative solutions can be found by adjusting the costs and parameters limits and exploring different outcomes. One possibility is to set the lower bound of the total incoming connections to 1. This leads to a solution shown in Figure 10. The solution takes hundreds of iterations to escape the negative steady state, but eventually a steady state with a mean P/N of 8.85 is reached. This is even higher than in the previous example, but qualitatively the solutions are quite similar. Detailed results can be found in the Appendix. The incoming connections are divided between Bob and Barbara since they are more positive than Cecilia. However, the emotional sensitivity of Brian is set to zero

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and therefore hardly any emotional contagion occurs, allowing Brian to spread positivity in the network without being affected by the negativity of the organization.

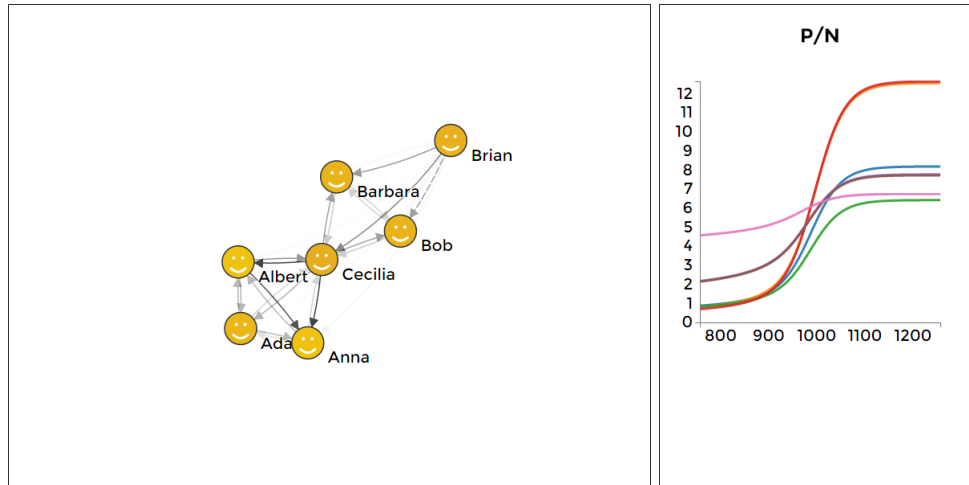


Figure 10. The solution after optimizing Brian with the lower bound of the total incoming connection strengths set to 1.

DISCUSSION

The simulation examples demonstrate how PoSITeams can introduce ideas for a more constructive behaviour in social systems, such as when being emotionally sensitive can be beneficial and when not, or what kind of interventions and structural changes might improve effectiveness of organizations. Obviously, the underlying model described in this work has not been yet validated with any real world data, so any predictions and quantitative values that the model gives remain theoretical. Nevertheless, we consider that there are still several potential applications for PoSITeams.

For example, PoSITeams could be used to facilitate perceiving organizations as systems and demonstrate plausible systemic effects that can occur within them. Exploration of different behavioural and structural changes may promote reflective thinking, allowing the user recognize herself as an active part of the system with potential to change the system from within. Therefore PoSITeams could be used as a tool to promote systems intelligence. Considering the eight dimensions of systems intelligence (Hämäläinen, et al., 2014), we can reflect on how well each of these dimensions is accounted for in PoSITeams:

- *Systems perception:* the simulator presents the organization as a graph, which draws the attention to the relationships between the members of the organization. The graph presentation also focuses on the holistic view of the organization by providing a view of the whole organization at once.
- *Attunement:* The simulator draws attention to how our own behaviour can affect the whole organization. Therefore it encourages the user to be more aware of her behaviour. Also the simulations themselves can be rather engaging and perceiving oneself visually as a part of the whole can increase awareness of the systemic nature of social groups and possibilities that may ensue.

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- *Reflection:* The user is encouraged to reflect on her own behaviour and relationships with others as she provides parameter values to the model.
- *Positive engagement:* Since the application simulates emotional contagion and focuses on the positivity ratios and their effects on organizational performance, the user is encouraged to interact positively with other people.
- *Spirited discovery:* The simulator offers possible scenarios, promoting "what-if" thinking and providing food for thought. The focus is also on embracing change and finding concrete actions to change the system for the better.
- *Effective responsiveness:* The simulator can identify leverage points in the organization either by letting the user to explore various behavioural and structural changes or by using the optimization functionality provided by the simulator.
- *Wise action:* By using the simulator, the user hopefully obtains a better understanding of the organization as a whole and how it can be affected by our own behaviour. The systems perspective also attempts to demonstrate typical features of systems, which ideally transforms into deeper understanding of systems and therefore wiser actions.
- *Positive attitude:* Again, the simulator focuses on the effects of positivity, which encourages an overall positive attitude.

It would be therefore an interesting direction for future research to evaluate whether using PoSITeams leads to more systems intelligent behaviour. This relates to a growing interest of developing technology to promote well-being (see e.g. "positive computing" by (Calvo & Peters, 2014)). Instead of promoting mental faculties such as mindfulness, empathy or compassion, it would be interesting to develop ways to improve systems intelligence. Applications that focus on increasing mental well-being are often designed to resemble games (see e.g. (McCallum, 2012)), a concept known as gamification, which aims at making the application highly engaging and fun. Perhaps a potential use case for PoSITeams would be to make it more game-like. For example the user could be given different social groups and corresponding tasks, such as maximizing the overall positivity of the given group. The approach of posing the user problems that she must solve could be more beneficial in terms of promoting systems intelligence. Also the user would be dealing with "imaginary" social groups, which might make it easier to consider actions that do not come naturally to the user. In actual social groups there can be reservations, e.g. "my workplace does not allow me to be more introverted", which might make the user more reluctant to consider alternative behavioural modes.

Another interesting question is whether using the simulator actually leads to better actions at the organizational level. Peter Senge identifies five key features of learning organizations in his book *The Fifth Discipline* (Senge, 1990): personal mastery, mental models, shared vision, team learning and systems thinking. These disciplines are promoted in PoSITeams in following ways:

- *Personal Mastery:* The simulator promotes personal growth by demonstrating how changing each of the personal characteristics can improve both personal well-being and organizational performance.

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- *Mental models*: The systems perspective presents a new way to visualize and think about the organization, which can challenge old ways of thinking and acting.
- *Shared vision*: Improving positivity ratios provides a shared goal for the organization. Since improving the positivity ratio within the organization has also individual benefits, it is an easy goal to commit to.
- *Team learning*: Using the simulator in collaboration can promote discussion and challenge old assumptions about the organization.
- *Systems thinking*: The systems philosophy is deeply ingrained within the simulator and using the simulator highly promotes thinking about the organization as a system. The simulator can even be considered to be a tool to promote systems thinking itself.

Using PoSITeams in organizations would be highly interesting to see whether it can generate change and support organizational decision making. Also designing better organizations could be also one potential direction for research. Perhaps organizations that are robust to adversities share some structural characteristics that can be explored with the simulator. Most organizations are not designed to support individual well-being. However, since positivity and effective organizations are connected, designing the organizations to embrace the effects of positivity seems like a worthwhile endeavour.

In (Bosse, et al., 2009b) an ambient agent model is proposed for an emotional contagion model, where the model would be given emotional level inputs from a group, for example by analysing facial images, and it would give action proposals to the team leader in case group emotion level drops below a certain level. That is, the emotional contagion models could be utilized to help regulate emotions in organizations. In a similar manner the emotional contagion model could be combined with sentiment analysis, which would make information channels such as e-mail and social media attainable for emotional contagion modelling. Emotional contagion has been observed in social media (see e.g. (Kramer, et al., 2014)) and by modelling and simulating the phenomenon it could be possible to design social media platforms to better support mental well-being. For example the visibility of content that promotes contagion of positive emotions could be adjusted.

CONCLUSIONS

We all live in a world of systems. In this work we have explored the possibility of using interactive agent-based emotional contagion simulations to support systems intelligent behaviour in social systems. By emphasizing the systemic view of social groups and by providing a means to explore different behavioural and structural changes, we hope to engage the user in reflective, more holistic way of thinking to obtain insights of more constructive ways of acting. We have presented a novel mathematical model for emotional contagion based on psychological research. The model can incorporate individual characteristics, such as general positivity, extroversion, emotional sensitivity, negativity bias and strength of social connections. The model is also capable of reproducing phenomena such as collective emotional states. The example simulations show potential use cases for PoSITeams and how optimization can be used to provide ideas and insights for a more productive behaviour within social systems. However, PoSITeams still lacks

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user experiences in the real-world and it would be interesting to see the actual effects of using the simulator in organizations. It would be also interesting to test whether using the simulator can actually increase systems intelligence. Validation and further development of the emotional contagion model are also subjects of future research.

APPENDIX: OPTIMIZATION RESULTS

The optimization results of the small organization examples are presented here in detail.

Optimization with zero costs

The results of the example shown in Figure 6.

Adam: Emotional sensitivity set from 0.20 to 0.93
Adam: Extroversion set from 0.20 to 0.98
Adam: Negativity bias set from 0.60 to 0.50
Adam: General positivity set from 2.00 to 5.00
Connection between Adam and Albert set from 1.00 to 0.80
Connection between Adam and Cecilia set from 1.00 to 0.20
Connection between Adam and Barbara set from 0.00 to 0.02
Connection between Adam and Anna set from 1.00 to 0.92
Albert: Emotional sensitivity set from 0.80 to 1.00
Albert: Extroversion set from 0.80 to 0.01
Albert: Negativity bias set from 0.60 to 0.50
Connection between Albert and Adam set from 1.00 to 0.52
Connection between Albert and Cecilia set from 1.00 to 0.29
Connection between Albert and Barbara set from 0.00 to 0.07
Connection between Albert and Anna set from 1.00 to 0.58
Cecilia: Emotional sensitivity set from 0.40 to 0.98
Cecilia: Extroversion set from 0.90 to 1.00
Cecilia: Negativity bias set from 0.80 to 0.50
Cecilia: General positivity set from 1.00 to 5.00
Connection between Cecilia and Adam set from 1.00 to 0.97
Connection between Cecilia and Albert set from 1.00 to 0.98
Connection between Cecilia and Bob set from 1.00 to 0.23
Connection between Cecilia and Barbara set from 1.00 to 0.29
Connection between Cecilia and Anna set from 1.00 to 0.99
Bob: Emotional sensitivity set from 0.30 to 0.37
Bob: Extroversion set from 0.30 to 0.99
Bob: Negativity bias set from 0.60 to 0.50
Bob: General positivity set from 2.00 to 5.00
Connection between Bob and Adam set from 0.00 to 0.10
Connection between Bob and Albert set from 0.00 to 0.07
Connection between Bob and Cecilia set from 1.00 to 0.88
Connection between Bob and Barbara set from 1.00 to 0.91
Connection between Bob and Anna set from 0.00 to 0.09
Barbara: Emotional sensitivity set from 0.30 to 0.13
Barbara: Extroversion set from 0.30 to 1.00

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Barbara: Negativity bias set from 0.60 to 0.50
Barbara: General positivity set from 2.00 to 5.00
Connection between Barbara and Adam set from 0.00 to 0.08
Connection between Barbara and Albert set from 0.00 to 0.02
Connection between Barbara and Cecilia set from 1.00 to 0.96
Connection between Barbara and Bob set from 1.00 to 0.96
Connection between Barbara and Anna set from 0.00 to 0.09
Anna: Emotional sensitivity set from 0.80 to 0.99
Anna: Extroversion set from 0.20 to 0.03
Anna: Negativity bias set from 0.60 to 0.50
Anna: General positivity set from 3.00 to 5.00
Connection between Anna and Adam set from 1.00 to 0.69
Connection between Anna and Albert set from 1.00 to 0.96
Connection between Anna and Cecilia set from 1.00 to 0.28
Connection between Anna and Bob set from 0.00 to 0.07
Connection between Anna and Barbara set from 0.00 to 0.07

Optimizing connection strengths

The results of the example shown in Figure 7.

Connection between Adam and Albert set from 1.00 to 0.56
Connection between Adam and Cecilia set from 1.00 to 0.72
Connection between Adam and Anna set from 1.00 to 0.59
Connection between Adam and Barbara set from 0.00 to 0.08
Connection between Adam and Bob set from 0.00 to 0.10
Connection between Albert and Adam set from 1.00 to 0.59
Connection between Albert and Cecilia set from 1.00 to 0.24
Connection between Albert and Anna set from 1.00 to 0.77
Connection between Albert and Barbara set from 0.00 to 0.07
Connection between Cecilia and Adam set from 1.00 to 0.23
Connection between Cecilia and Albert set from 1.00 to 0.20
Connection between Cecilia and Anna set from 1.00 to 0.20
Connection between Cecilia and Barbara set from 1.00 to 0.20
Connection between Cecilia and Bob set from 1.00 to 0.20
Connection between Anna and Adam set from 1.00 to 0.95
Connection between Anna and Albert set from 1.00 to 0.53
Connection between Anna and Cecilia set from 1.00 to 0.58
Connection between Anna and Barbara set from 0.00 to 0.07
Connection between Barbara and Adam set from 0.00 to 0.09
Connection between Barbara and Albert set from 0.00 to 0.02
Connection between Barbara and Cecilia set from 1.00 to 0.34
Connection between Barbara and Anna set from 0.00 to 0.05
Connection between Barbara and Bob set from 1.00 to 0.67
Connection between Bob and Albert set from 0.00 to 0.03
Connection between Bob and Cecilia set from 1.00 to 0.30
Connection between Bob and Anna set from 0.00 to 0.06
Connection between Bob and Barbara set from 1.00 to 0.79

Optimization with costs

The results of the example shown in Figure 8.

Adam: Emotional sensitivity set from 0.20 to 0.84
Adam: Extroversion set from 0.20 to 0.28
Adam: Negativity bias set from 0.60 to 0.50
Connection between Adam and Albert set from 1.00 to 0.94
Connection between Adam and Cecilia set from 1.00 to 0.33
Connection between Adam and Anna set from 1.00 to 0.58
Connection between Adam and Bob set from 0.00 to 0.06
Albert: Emotional sensitivity set from 0.80 to 0.00
Albert: Extroversion set from 0.80 to 1.00
Albert: Negativity bias set from 0.60 to 0.50
Connection between Albert and Adam set from 1.00 to 0.93
Connection between Albert and Cecilia set from 1.00 to 0.93
Connection between Albert and Anna set from 1.00 to 0.99
Connection between Albert and Barbara set from 0.00 to 0.08
Connection between Albert and Bob set from 0.00 to 0.10
Cecilia: Emotional sensitivity set from 0.40 to 0.84
Cecilia: Extroversion set from 0.90 to 0.01
Cecilia: Negativity bias set from 0.80 to 0.50
Connection between Cecilia and Adam set from 1.00 to 0.32
Connection between Cecilia and Albert set from 1.00 to 0.64
Connection between Cecilia and Anna set from 1.00 to 0.62
Connection between Cecilia and Barbara set from 1.00 to 0.44
Connection between Cecilia and Bob set from 1.00 to 0.82
Anna: Emotional sensitivity set from 0.80 to 0.98
Anna: Extroversion set from 0.20 to 0.76
Anna: Negativity bias set from 0.60 to 0.51
Connection between Anna and Adam set from 1.00 to 0.86
Connection between Anna and Albert set from 1.00 to 0.63
Connection between Anna and Cecilia set from 1.00 to 0.87
Connection between Anna and Barbara set from 0.00 to 0.09
Connection between Anna and Bob set from 0.00 to 0.04
Barbara: Emotional sensitivity set from 0.30 to 0.91
Barbara: Extroversion set from 0.30 to 0.27
Barbara: Negativity bias set from 0.60 to 0.50
Connection between Barbara and Adam set from 0.00 to 0.08
Connection between Barbara and Albert set from 0.00 to 0.03
Connection between Barbara and Cecilia set from 1.00 to 0.56
Connection between Barbara and Anna set from 0.00 to 0.04
Connection between Barbara and Bob set from 1.00 to 0.82
Bob: Emotional sensitivity set from 0.30 to 0.81
Bob: Extroversion set from 0.30 to 0.29
Bob: Negativity bias set from 0.60 to 0.50
Connection between Bob and Albert set from 0.00 to 0.09

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Connection between Bob and Cecilia set from 1.00 to 0.77
Connection between Bob and Barbara set from 1.00 to 0.69

Adding a new team member with no constraints

The results of the example shown in Figure 9.

Connection between Adam and Brian set from 0.00 to 0.04
Connection between Anna and Brian set from 0.00 to 0.05
Connection between Bob and Brian set from 0.00 to 0.05
Brian: Emotional sensitivity set from 0.80 to 0.14
Brian: Extroversion set from 0.80 to 1.00
Brian: Negativity bias set from 0.80 to 0.50
Brian: General positivity set from 3.00 to 5.00
Connection between Brian and Adam set from 0.00 to 0.07
Connection between Brian and Albert set from 0.00 to 0.09
Connection between Brian and Cecilia set from 0.00 to 0.93
Connection between Brian and Barbara set from 0.00 to 0.88
Connection between Brian and Bob set from 0.00 to 0.98

Adding a new team member with constrained incoming connections

The results of the example shown in Figure 10.

Connection between Adam and Brian set from 0.00 to 0.07
Connection between Albert and Brian set from 0.00 to 0.02
Connection between Anna and Brian set from 0.00 to 0.03
Connection between Barbara and Brian set from 0.00 to 0.34
Connection between Bob and Brian set from 0.00 to 0.59
Brian: Emotional sensitivity set from 0.80 to 0.00
Brian: Extroversion set from 0.80 to 0.99
Brian: Negativity bias set from 0.80 to 0.50
Brian: General positivity set from 3.00 to 5.00
Connection between Brian and Adam set from 0.00 to 0.05
Connection between Brian and Albert set from 0.00 to 0.02
Connection between Brian and Cecilia set from 0.00 to 0.99
Connection between Brian and Anna set from 0.00 to 0.05
Connection between Brian and Barbara set from 0.00 to 0.99
Connection between Brian and Bob set from 0.00 to 0.95

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