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What's in it for me? Recommendation of peers in networked innovation

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Abstract

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What's in it for me? Recommendation of Peers in Networked Innovation

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Abstract: Several studies have shown that connecting to people in other networks foster creativity and innovation. However, it is often difficult to tell what the prospective value of such alliances is. Cooperative game theory offers an a priori estimation of the value of future collaborations. We present an agent-based social simulation approach to recommending valuable peers in networked innovation. Results indicate that power as such does not lead to a winning coalition in networked innovation. The recommendation proved to be successful for low-strength agents, which connected to high-strength agents in their network. Future work includes tests in real-life and other recommendation strategies.

Keywords: open innovation, artificial intelligence, recommender systems, coalition formation
Categories: K.4.3, H.1.1, H.1.2, I.6.5, I.6.6

1 Introduction

Several studies argue that groups are more innovative than individuals [Paulus and Yang, 2000; Paulus, 2003]. Individuals by themselves do not possess all the knowledge that is needed for innovation, for innovation to be successful it requires networked interactions [Downes, 2010]. That is, knowledge has become diffused, as Henry Chesbrough [Chesbrough, 2000] emphasises. He argues that, to keep up with today's dynamically changing environment, firms need to adopt open innovation. It occurs as a result of opening up, or freely distributing knowledge. Thereby, a firm profits from 1) the advancements others make with that knowledge and 2) complementary knowledge that lies beyond the borders of the firm. This is consistent with earlier work by Barnard [Barnard, 1968] and Simon [Simon, 1991] that firms cannot rely on their own internal knowledge to flourish. Viewed from a collaborative learning perspective, Yazici [Yazici, 2005] found that a collaborative learning style influences team performance positively. Cassiman and Veugelers [Cassiman and Veugelers, 2006] proved that complementary knowledge present in an R&D's social network may significantly boost new product development. This network perspective on creativity and innovation is highlighted by a number of studies: Kratzer and Lettl [Kratzer and Lettl, 2008] concluded that people that are on the edge of two social networks, so-called 'lead users', tend to be more creative than others in their network, as they are more informed. Ronald Burt [Burt, 2004] uses the term 'brokerage' to denote the same phenomenon. Perry-Smith [Perry-Smith, 2006] stresses the importance of a central network position and weak ties beyond the borders of the firm in order to be more creative.

Even though the network perspective to creativity and innovation is a promising way of dealing with knowledge, it is not without problems. While people engage in knowledge sharing activities in their network, they need to be aware of which people are most valuable to them. Psychological research points out various decision-making problems, such as bounded rationality [Simon, 1982]: Due to cognitive limitations and incomplete knowledge, people are not capable of computing probability in a reliable way, being 'boundedly rational'. In networked innovation, bounded rationality is encountered in a similar way. While searching for valuable peers, one is faced with an abundance of peers to connect to (information overload / incomplete knowledge) and our minds lack a proper metric for assessing the value of peers (cognitive limitations).

The human mind is complex and it is thus challenging to model its cognitive abilities. Cooperative game theory addresses this complexity by assuming human beings – players – to behave rationally. Cooperative game theory describes decision making about cooperation in a game. It enables one to make an a priori estimate of the value of cooperation. Such an estimate strengthens one's cognition of the network, which is found to positively correlate to power as perceived by others [Krackhardt, 1990]. Agent simulations are an often used approach to model players in a network, using game theoretic considerations. Previous studies that simulated creativity and innovation include the use of computer simulation [Phelan, 2002], system dynamics [Wu et al., 2010], agent-based simulation [Schwarz and Ernst, 2009; Albino et al., 2006; Ma and Nakamori, 2005] and swarm-based simulation [Battacharrya and Ohlsson, 2010].

In this paper, we model observations from literature to simulate behaviour in networked innovation. Recommendations are generated to inform agents about the value of peer agents. In Section 2, we provide the underlying theory necessary for understanding the proposed simulation method, which is described in Section 3. Section 4 comprises the results of our simulation, which we will discuss in Section 5. Future work is discussed in Section 6.

2 Theoretical Background

2.1 Game Theory

A 'game' in the sense of game theory is a situation in which one or more players use strategies to optimise their reward. Rules of play identify the character of the game and players have to comply with these rules. Games such as Chess are played for fun, but more serious and realistic games are played as well. In daily life, games (in the game-theoretic sense) are played every day and everywhere. Though, many of us are not aware that they are playing a game. On eBay, buyers that bid for a product play a game against each other and the seller of that product. In labour negotiation, a game is played between future employee and future employer. Each game has one or more players. Players comply with a set of rules that define the game. Players strive to win (or optimise their outcome), and this may result in competing (non-cooperative) play against others, or cooperative play with others. To optimise the outcome of a game, a player follows certain strategies, or heuristics to win a game. Such strategies often include an estimate of a game's prospective reward, which is called the expected utility. A player can win everything, like a product in the auctioning game in the eBay example, but this means the other players lose. A player can negotiate an outcome, like in contract negotiation. When a game of Chess is played, a player may win (+1), draw (+0) or lose (-1). Chess is a zero-sum game. A game is said to be zero-sum if the sum of wins (+1) and losses (-1) of all players equals zero. Akin to zero-sum games, a constant-sum game is a game in which the sum of all wins and losses equals a constant. The bidding game on eBay is a constant-sum game, as one player wins and pays for a product and the other players lose and pay nothing. The constant sum in this game equals the price of the product. The reward that you receive after playing a game is called the payoff. Players try to rationalise what other players are about to do, to maximise their payoff.

2.1.1 Coalitions

For clarifying purposes, we have to distinguish between cooperation, collaboration and coordination. When people decide to work together, based on their individual goals, we speak of cooperation [Axelrod and Hamilton, 1981]. When people work together, based on common goals, we speak of collaboration. When people agree to perform the same actions (interactional synchrony), we speak of coordination [Arrow et al., 2000]. When people cooperate temporarily and coordinate their actions, a coalition is formed. In other words, a coalition is a temporary alliance in which players share a common intention. It is, however, based on individual interest, or goals [Cyert and March, 2005]. A labour contract can be seen as a coalition. Employee and employer agree to a common intention, that is, work for the company, but they have individual goals: the employer wants to make profit, and the employee wants to earn a living. Coalitions are often formed in games in which the payoff can be divided among members of a coalition. If a payoff can be divided, or transferred without costs, we may speak of transferrable utility. What characterises a cooperative game with transferrable utility, is that it is often more profitable to form a coalition and share the payoff, than to go it alone and most likely receive less or nothing.

Shapley Value

The Shapley value [Shapley, 1953; Hart, 1987] was designed by Lloyd Shapley in 1953 to evenly distribute the payoff in a game with transferrable utility among members of a coalition. The Shapley value is calculated by measuring the strength of a coalition, minus the strength of its subcoalitions. Subcoalitions may consist of multiple persons, but one-person and zero-person coalitions may also be identified.

2.2 Agent-based Social Simulation

Agent-based social simulation is a way to understand certain social phenomena through simulations of agent societies. According to Davidsson [Davidsson, 2002], this field can be best characterised by the intersection of social science, computer simulation, and agent-based computing. Social science is the study of social phenomena done in a variety of research areas, such as social psychology, biology and economics. Computer simulation is a field in computer science that is used to study social events. The aim is to predict future behaviour of such a social event. Agent-based computing is also a field in computer science and it includes intelligent agents and multi-agent systems. Agents are computer programs, that are supposed to act autonomously, pro-actively, reactively, and socially able [Wooldridge, 1998]. In multi-agent systems, agents interact with each other, often to solve a (divisible) problem or to observe the agents' behaviour.

3 Simulation method

3.1 Simulation Model

Below, we provide the model used for simulation of coalitions in networked innovation. This model may be regarded as the internal reasoning structure of an agent.

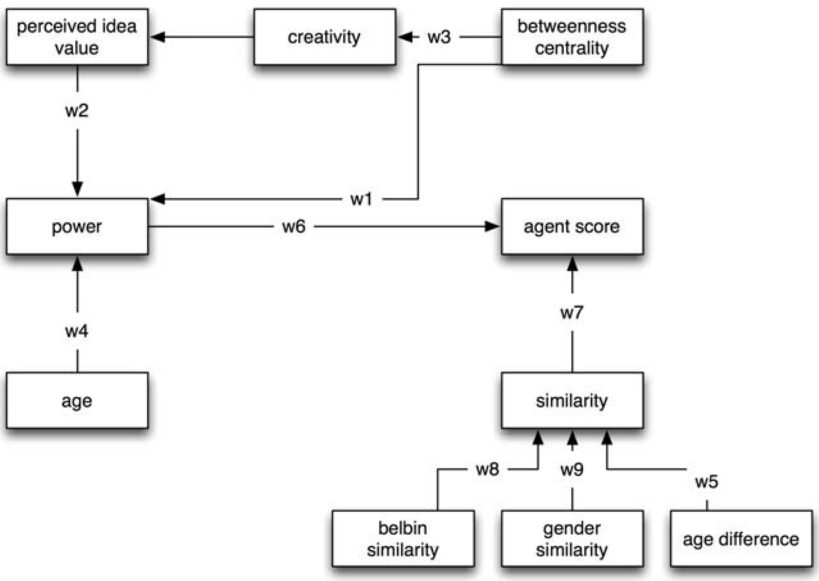


Figure 1: The simulation model; for a detailed description, see text

Two factors are highly influential for the formation of coalitions: 1) power and 2) similarity between people (homophily). These two directly contribute to an agent's score for each of the agents in our model. An agent's score determines the likelihood that an agent is interested in forming a coalition with another agent. There are seven factors that indirectly, through the two central factors, contribute to an agent's score.

From Social Network Analysis Theory [Wasserman and Faust, 1994], we choose to use the concept of betweenness centrality to express someone's position in the organisation. Betweenness centrality is a measure of how dependent others are one a target node in a network. It is computed by the number of shortest paths that pass through a node, as a proportion of all shortest paths possible. In our case, betweenness centrality measures how dependent people are on one another if they want to connect. People cannot form a coalition if there is no path that connects them. If an agent possesses high betweenness centrality, agents very likely have to pass him to reach any one person in the network. Betweenness centrality influences a number of factors. Firstly, Kratzer and Lettl [Kratzer and Lettl, 2008] found that 'lead users', people that are on the edge of two networks, are more likely to be creative than others. Tsai and Ghoshal [Tsai and Ghoshal, 1998] underscore this by reporting that social interaction (often viewed as degree centrality) and resource exchange were positively correlated to product innovations. Kraatz [Kraatz, 1998] extends this view by emphasising that interorganisational ties may advance social learning, thereby contributing to organisational growth. Secondly, various studies report that people that are more central are found to be more powerful [Perry-Smith, 2006; Krackhardt, 1990; Ibarra, 1993; Ibarra, 1984; Brass, 1984].

Power is also influenced by age and the perceived value of an idea. Age is reported to correlate positively with power [Burkhardt and Brass, 1990]. Klein and Sorra [Klein and Sorra, 1996] suggest that 'innovation-values fit', the extent to which an innovation (idea) fits the perceiver's values, influences . In our model this is represented by the perceived value of an idea.

Herminia Ibarra [Ibarra, 1984] reports that similar people (homophily) are more likely to form support and friendship relationships. This is emphasised by McPherson et al. [McPherson et al., 2001]. They distinguish between various types of homophily, such as age and gender. For our model, we use age, gender and personality to express similarity.

3.2 Agent Characteristics

Age is represented as a random value between 15 and 65, the so-called 'working age' of people. Gender is represented as a random value of 0 (female) or 1 (male). Personality is difficult to represent. Multi-attribute personality scores such as the Big Five personality traits have been considered, but for the time being, we choose to use the Belbin Team Roles [Belbin and Belbin, 1996]. The nine Belbin profiles express the role of a person within a team. Use of these predefined team roles eases the computation of similarity.

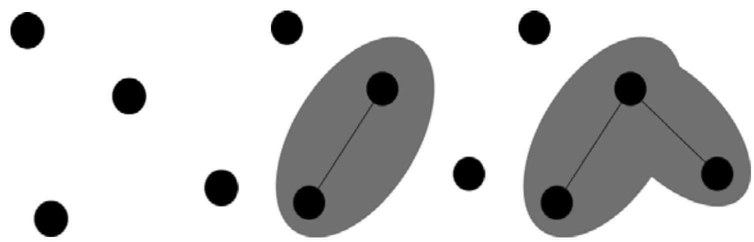
Agents have a power attribute, which corresponds to their power in the model. Agents' ultimate score is influenced by both their power and their similarity to other agents.

3.3 Network Characteristics

Akin to common networks, the network of innovators we model consists of nodes and links. Every node represents a person. Bilateral links between these nodes denote professional relationships between these persons. Combinations of links make paths through which people can be reached. A network is defined by its size (the number of agents/ people), its density (the number of links between people as a proportion of all possible links) and the path length. We use shortest paths between people to compute betweenness centrality.

3.4 Coalitions

If two agents decide to cooperate, they form a dyadic connection. Afterwards, all dyadic connections that overlap are gathered, thereby forming paths between multiple agents. These paths of accumulated dyad connections form a subnetwork within the whole network of agents. Such a subnetwork of cooperating agents we have called a coalition (see Figure 2).



2a 2b 2c

Figure 2: Evolution of a coalition. Only one-person coalitions (2a), two-person and one-person coalitions (2b) and three and one-person coalitions (2c).

3.5 Running the Simulation

We distinguish three elements that jointly make up a simulation scenario. During an iteration, agents perform several subsequent steps or actions. These steps or actions occur in the iteration's phases. Often, one iteration serves as input for the next iteration, to accomplish agent reinforcement learning. Several iterations make up a simulation run. Several simulation runs, often each with particular parameter settings, make up a simulation scenario. A simulation may, but need not, consist of several scenarios.

To run an iteration, it needs to be set up first. Every iteration starts with an initialisation phase, often followed by a number of phases in which agents interact. Every phase, a number of actions is performed by the agents and the agent environment. Klusch and Gerber [Klusch and Gerber, 2002] provide a four-phase approach to agent coalition formation during an iteration (note how, somewhat confusingly perhaps, the term 'simulation' here denotes a specific phase in an iteration):

1) Initialisation: variables are set to their initial values

2) Simulation: simulate possible coalitions and their prospective value
3) Negotiation: settle an agreement on the division of payoff
4) Evaluation: evaluate agents' ranking. Go back to step 2.

Our simulation scenario follows a similar procedure. Figure 3 shows the steps to be taken during each of the four phases Klusch and Gerber identified:

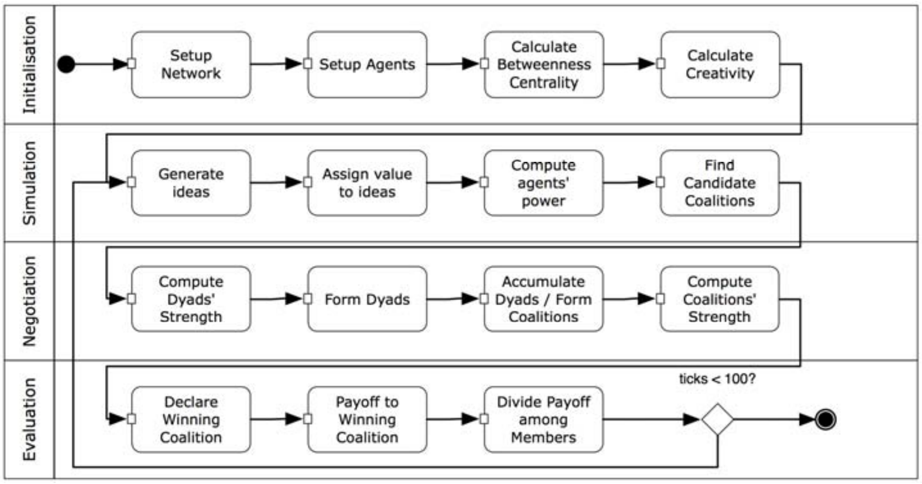


Figure 3: Steps to be taken during each of the phases in the simulation

During the initialisation phase, the network is set up. That is, a network type is chosen and relationships are drawn between agents according to this type of network. Next, agent characteristics (age, personality, etc.) are set to initial values and betweenness centrality and creativity are calculated for each of the agents. Betweenness centrality is calculated using an implementation of the pseudo-code provided by Ulrik Brandes [Brandes, 1994].

$$Cr_i = w3 * Cb_i \tag{1}$$

Where the creativity for agent i, Cr_i , is computed by multiplying the betweenness centrality Cb_i with a predefined weight, w3.

The simulation phase comprises several actions to be performed. First, agents generate new ideas. These ideas are given a value, based on the creativity of an agent. We use the following formula to do so:

$$v_{ij} = random(100) + Cr_i \tag{2}$$

Where the value v for idea j of agent i, v_{ij}, is computed by drawing at random a value between 0 and 100 for an idea, and adding the creativity for agent i, Cr_i, to it.

We choose to assign a random value to an idea, as we are convinced that anyone can generate a good idea. Other factors may influence the implementation of that idea, but this does not mean an individual cannot generate good ideas, whatever position their position in the organisation. An additional advantage of a random idea value is that it yields dynamics as a result of unpredictable behaviour in simulation of the model.

An agent's power is computed by combining an agent's betweenness centrality, perceived idea value and the actual power of the agent, multiplied by their respective weights. The formula is as follows:

$$P_i(t+1) = w1 * Cb_i + w2 * v_{ij} + w4 * age_i + P_i(t) \quad (3)$$

After updating the power of the agents, the values are normalised, such that every agent has a power value between 0 and 100. At the start of the simulation, t = 0, the agent's power is set to a random value between 0 and 100.

Next, each agent computes the scores that other agents have. Similarity to another agent, the power of that agent and the betweenness centrality determine the score of that agent. Similarity is calculated by the following formula:

$$Sim_{ik} = w9 * SimBel_{ik} + w10 * SimGen_{ik} + w5 * SimAge_{ik} \quad (4)$$

Where the similarity in personality between agents i and k, $SimBel_{ik}$, is determined by comparing their Belbin team role. If it is similar, $SimBel_{ik}$ is set to 100. The similarity in gender is computed by looking at the gender of both agents. If they are similar, $SimGen_{ik}$ is set to 100. As the maximum difference in age can be 50, we multiply the age difference between two agents ($SimAge_{ik}$) by 2, in order to have all three similarity measures carry equal weights.

The agent score is calculated by the following formula:

$$Score_j = w8 * Sim_{ik} + w6 * P_i \quad (5)$$

In this case, agent k computes the agent score for each of the other agents. Next, candidate coalitions are looked for, that is, agents that are 'known' through the connections that were set up during the initialisation phase. An agent knows another agent if they are directly connected to each other.

During the negotiation phase, the Shapley value provides a recommendation of candidate dyads. Dyads' Shapley value is computed by summing up the agent scores of the two agents that could form a dyad, minus the strength of the individual agents. The agent chooses to form a dyad with the candidate that is rated highest by the Shapley value. Subsequently, any two dyads sharing an agent are put into one coalition. As a consequence, all agents that are connected to each other through these dyad connections are put into one coalition. For instance, if agent A and B form a dyad, and agent B and C form a dyad, they together form a coalition that contains agent A, B and C. The coalition's strength is calculated by aggregating the scores of the members of the coalition.

Finally, a winning coalition is declared during the evaluation phase. It is comprised of agents with the highest accumulated strength. Next, the payoff is rewarded to the winning coalition and equally divided among the coalition's members. The individual payoff is then used to update the agent's power. Each agent receives a share of the payoff equal to its share in the coalition's total strength. At this juncture, the current iteration ends. If less than 100 iterations have run, the run returns to the simulation phase; if 100 iterations have run, the simulation run ends.

In the simulation, dynamic behaviour is achieved in two ways. First, the agents generate ideas with a random value. This, in turn, affects the power of an agent. Second, agents that belong to a winning coalition receive a positive update of their power. One may call the result reputation.

3.6 Parameter settings

We used the following parameters for simulation:

parameter	setting
w1	0.45
w2	0.45
w3	0.67
w4	0.1
w5	1
w6	1
w7	1
w8	0.25
w9	0.25
# agents	30
network type	random
network density	0.04
payoff	100
# of runs	100

Table 1: Settings for the simulation parameters

The values for the weights w1 - w9 were found in the literature that we used for the development of our model.

4 Results

Figure 4 presents the results of the simulation. Note that the simulation is run in the middle window. Agents that are interconnected by the red lines form a coalition. Same colours for the agents denote that they are in the same coalition.

The histogram entitled 'turtle wins' shows the number of times turtles have won, as compared to their respective betweenness centrality and their average power.

Agents are represented on the x-axis 'turtles', starting from the left with agent 0. Red bars indicate the number of wins, black bars indicate the average power per agent, and the green bars indicate the betweenness centrality per agent.

The diagram entitled 'plot 1' shows a number of things. First, the black dots (that show up as a line) indicate the betweenness centrality as a function of the number of wins. The betweenness centrality is stable, as there are no new relationships formed over time. Second, the red dots indicate the power compared to the number of wins. Third, the green dots indicate the idea value compared to the number of wins.

The diagram entitled 'Totals' shows the number of coalitions formed while simulating. As one can see, the number of coalitions has an average of 15.

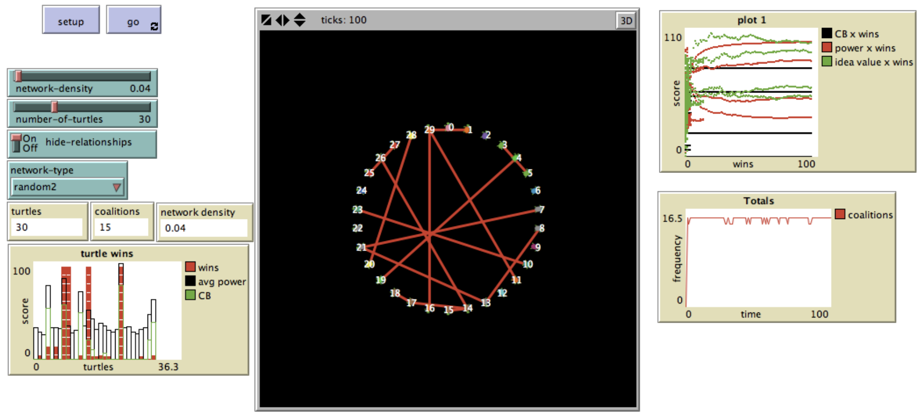


Figure 4: Results of the simulation

5 Discussion

The results may suggest that there is no direct indicator for a winning agent. Agents with a high score win often and agents with a low score win often. Though, something interesting occurs. If we take a close look at the red dots in plot 1, that is, the number of wins, we see that four agents win all iterations. If we compare this to the histogram 'turtle wins' we see these same four agents represented. The histogram is in the right order of agent number, so if we count from left to right, we see that agent 7, 8, 13 and 21 are winning agents. This is because they are in the same coalition, which is shown in the graphical representation in the middle. What does this mean? It means that their coalition was the strongest one. What made them form a coalition? The Shapley value that recommended valuable peers. This immediately explains why the low-power agents did win during the simulation. They connected to the right agents in their network.

We are well aware that the results obtained with our model and simulation do not necessarily fully apply to reality. First, it is said that the simple simulation models often outperform the more complex ones, as complex models often distort the representation of reality. There are a few things that need to be pointed out, however. Game theory presumes rational play, or rational behaviour among players of the game. Rational play means making optimal decisions, given the actions of other players. Such optimal decisions may maximise the individual or group outcome of playing a game. In reality, players often do not play rationally. Examples include the one-shot version of the Prisoner's Dilemma, in which players are very likely to defect, as they meet only once. Thus, to meet with such irrationalities, we need to adapt the utility mechanism that was used in this simulation. On the other hand, Colman et al. [Colman et al., 2009] states that people do perform team reasoning, as opposed to the irrational behaviour that people are often presumed to have.

Second, the Shapley value has some issues. It does not take into account expected contributions to the coalition. The nucleolus [Schmeidler, 1969; Kohlberg, 1971] does take this into account, and during payoff distribution, it tries to minimise the maximum dissatisfaction of participants in a coalition. We plan to implement this in a new model and compare its results to the current simulation. Also, the Shapley value does not take into account costs for coalition formation. From Lloyd Shapley's perspective, this is quite reasonable, as it is very difficult to capture such costs in a single formula that applies to all situations in which coalitions may occur. Therefore, development of a cost mechanism for coalition formation in networked innovation may be a suitable way to improve our model.

It should be added furthermore, that the Shapley value may be computed in two ways. First, the Shapley value may be computed for people that simultaneously make a move. That is, every person makes a decision whether to cooperate at the same time point. This is the approach we used in the current simulation. We think this method is best for evaluation purposes, in which people decide to cooperate, or vote for someone, after ideas have been generated. Second, the Shapley value may be computed for sequential moves. Coalitions gradually develop in size as more and more people join the coalition. At a certain point, it is not profitable anymore to have someone join the coalition. For instance, a coalition may already be a winning majority, implying that someone joining the coalition will result in dividing the payoff among more people than necessary. For networked innovation, this second way of computing the Shapley value may actually be more promising, but further research into it is required.

Third, for ease of computation, we used Belbin team roles to express someone's personality. Personality may be expressed in more detail using personality traits. In this way we gain a better understanding of which factors influence the perception of similarity among people. This brings us to another point of critique, which is the derivation of the model. Although we did study literature extensively, and used correlation scores from literature for the weights in our model, a tailored approach may be more suitable for our model. Therefore, we plan to test this model on a real dataset of networked innovation. Such a dataset ideally includes personal characteristics and alliances measured over time, and may lead to a more profound model of coalitions in networked innovation. As gaining access to an ideal dataset is likely to be very difficult, we have several options at our disposal. First, viewing co-authoring of academic papers as a kind of innovative collaboration, we plan to use an existing co-authorship network to generate recommendations based on the existing network structure. Second, we plan to develop an 'innovation game' that satisfies the model that we presented in this paper. Particularly, the game will ask participants to provide access to the network data in their LinkedIn accounts. Additional personal information may contribute to an adequate recommendation of valuable peers for innovation.

Finally, our simulation covered only one scenario with a fixed set of parameter values. Future research should look into the sensitivity of the model results with respect to changes in parameter values. This way the robustness of the results obtained can be assessed. Also, a run consisted of a number of sequential iterations, that is, iterations that adopt the values of a previous iteration as its input (until 100 iterations were run). This however does not show possible variations in the dynamic behaviour of the system. Such variations are to be expected as an agent's creativity is a stochastic variable (equation 2). To estimate the consistency of the dynamic behaviour in the face of this random element, parallel iterations with the same initial values, will also be run.

6 Conclusion

In this paper, we used the Shapley value to generate recommendations of valuable peers in a social network simulation. The algorithm proves to be successful for both low and high scoring agents. Low scoring agents form a coalition with higher scoring agents, thereby loafing on the higher scoring agent's power. By doing so, the higher scoring agents gain a necessary majority for winning the iteration. Thus, both low and high scoring agents profit from the recommendation of valuable peers. The Shapley value, though, presumes rational behaviour of players, which is not always the case. Further research with the present system and improvements of it are suggested.

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