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A Simulation for Content-based and Utility-based Recommendation of Candidate Coalitions in Virtual Creativity Teams

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Abstract

Psychological literature shows that people do not always make rational choices with respect to whom to collaborate with. Providing the value of candidate connections may help them choosing the right people to connect with in a network. This paper presents a model about coalitions in creativity that will be used to generate content-based and knowledge-based recommendations of candidate coalitions.

Keywords: Utility-based recommender system; coalition formation; open innovation; simulation; virtual teams

1. Introduction

The transformation of the Internet over the past decade into a social web (Web 2.0), and the adoption of social networking websites has paved the way for engineers to model the preferences of users in online systems and generate recommendations. In networked innovation, which has been identified as a very promising new form of innovation [1-4], people and firms use their social networks to advance knowledge. In other words, they create a network of learners [5], or a community of practice [6], to build and share knowledge. The network perspective to learning and innovation is a promising way of dealing with knowledge, but two major problems arise. Firstly, in large networks, people will be faced with an information overload [7]. Secondly, while people engage in knowledge sharing activities in their network, they need to be aware of which people are most valuable to them [8]. These problems arise when firms try to openly innovate by searching for new employees, people or firms to co-operate with, or joint ventures. An abundance of choices are available (information overload) and no metric is present to express the value of candidate alliances (value awareness).

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In this research, we plan to generate recommendations about users to connect with. These recommendations are based on two types of information: user similarity (content-based), and information about the strength of a group in which members mutually support each other (utility-based).

We start with a brief discussion of the theoretical background and our envisaged seven-phase development approach (Section 2). We present our simulation model (Section 3) and its implementation (Section 4). The simulation results are presented in Section 5. Section 6 will include a discussion of our results and our concluding thoughts. Section 7 discusses future work.

2. Theoretical Background

Akin to recommendation systems (RS) for the selection of movies [9], products in e-commerce [10], and Usenet news [11], we aim to aid people in decision making, in particular people that participate in networked innovation. Roughly three types of RS exist: collaborative filtering, content-based, and knowledge-based RS. Herlocker et al. [12] define a set of user tasks or requirements that have to be met by all RS, for example *annotation in context*, *find good items*, *express self* and *help others*. These user tasks should not be ignored in the designing of a RS. Earlier research on user modelling for recommendation includes the work by Harper et al. [13] (economic modelling of MovieLens users), Zhang and Koren [14] (model learning), Beham et al. [7] (user modelling) and Manouselis and CostoPoulou [15] (Multi-Criteria Decision Making). Knowing your own and other people's value within a network may help in receiving a fair reward for your collaboration. Therefore we emphasise the characteristics of the connections people make in networked innovation, named *coalitions*. Coalitions are temporary alliances between distinct parties (people or firms). Coalition members share a common intention, for instance sharing knowledge or skills. This common intention is initiated by an individual goal, such as advancing in knowledge or making profit. Members of a coalition should therefore receive a fair share of the coalition's payoff, the so-called side payment. Methods to distribute a coalition's payoff include the Shapley value [16, 17] and the nucleolus [18, 19].

2.1. A Recommender System for Networked Innovation

In order to recommend candidate connections in a network of innovators, a number of challenges have to be tackled. First, we need to know what causes a coalition to be formed. This includes knowledge about the characteristics of the members that form a coalition. Second, we need to know how this coalition influences the overall outcome. If we know the influence of a coalition on the overall outcome, we may compute the coalition's payoff with the Shapley value and the nucleolus. If we know the coalition's payoff and we know the individual coalition members' contributions to it, we can compute the payoff for the members of a coalition. This will lead to the knowledge or utility-based recommendation of candidate connections in an innovation network.

Before attempting any empirical work, we decided to model coalition formation in a simulation environment, in order to 1) understand the dynamics of coalition formation, and 2) understand the influence of antecedents on formation of coalitions. To implement such a model, we adopted a seven-phase development approach (see Figure 1). We started with the development of two models: a literature-based model (1a), and an expert-generated model (1b). These models will be integrated (2) and implemented (3 and 4). A simulation is run (3 and 4) and its results will be validated by experts (5), leading to adaptation of the model. A new round of implementation (6a), simulation (6b) and validation (7) will result in a final model of coalition formation in virtual creativity teams. The simulation and its results will be discussed hereafter.

3. Model Development

The simulation model was designed by adapting a literature-based model that we presented in one of our earlier papers [20]. To be sure we did not fail to see anything important and to gather a diversity of opinions, we invited eleven experts with a variety of expertise (education, technology enhanced learning, social web, language, etc.), to create an expert model. The experts were divided into two groups and each group was asked to generate a model that comprises factors that influence the formation of coalitions in networked innovation. No inducement was offered to the experts. Their models revealed that we should include the (perceived) value of an idea, and that some of the factors could be subsumed under social identity and power. Figure 1 summarises our thoughts on factors that influence coalition formation. Next, we elaborate on the factors that are comprised in our model.

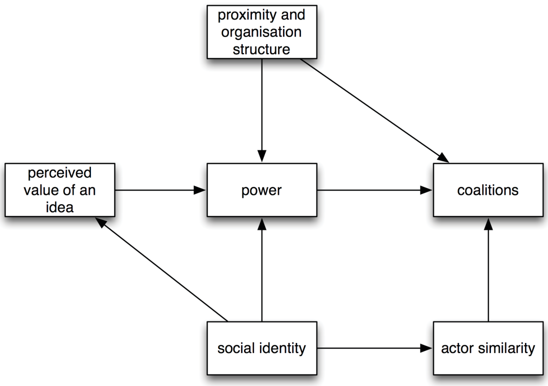

Fig. 1. A model of antecedents of coalition formation on the personal level during collaborative creativity.

3.1.1 Proximity and Organisation Structure

The organisation structure is modelled using three degrees of rank within the organisation. Ranging from high to low, these are: 1) the President rank, 2) the Manager rank, and 3) the Associate rank, respectively. Proximity is defined as the relational distance between ranks. Ranks have equal distance and distance is transitive, that is, the distance between Associates and Managers is 1, the distance between Managers and Presidents is 1, and the distance between Associates and Presidents is 2.

3.1.2 Social Identity

Keltner et al. [21] showed that identity criteria influence social status, or power. Identity of an agent consists of an agent's personality, it being a lead user, age, and gender. Identity influences the power of an individual agent and the actor similarity between agents. Identity is modelled using either one of the Belbin Team Roles [22], which include individuals who are creative (Plants) and individuals who try to maintain trust and coherence within a group (Coordinators).

3.1.3 Perceived Value of an Idea

Kratzer and Lettl [23] found that being a 'lead user' (the degree to which a user represents the needs of others and how beneficial the user's position within a network is, to profit from new solutions to these needs) positively correlates with the creativity of an individual. Besides, they found that age and betweenness centrality (the degree to which one is in-between other users in a network) of an in

dividual have a positive influence on creativity. Perceived value of an idea is modelled by the 'lead userness' of an agent.

3.1.4 Power

There are three factors that influence the power of an agent. First, there is organisation structure. Changes in the organisational distance of two agents affect their power relationship. The agent that is higher in the organisational hierarchy increases its power. Second, social identity influences power. For instance, if agent A is older than agent B, agent A will increase in power with respect to agent B. Third, power can be influenced by the perceived value of an idea that is generated by an agent. If an agent's idea is perceived as good, then the power of that agent increases.

3.1.5 Actor Similarity

Actor similarity has been defined as a function of age, gender, and personality. For example, if agent A has an age of 20, agent B has an age of 30 and agent C has an age of 35, then agents B and C show the highest similarity, *ceteris paribus*.

4. Simulation

In the simulation, an agent expresses its interest to form a coalition with another agent by sending a *proposal*. Interest may be achieved in three ways: 1) high actor similarity, 2) high rank proximity (having a similar rank), and 3) high power of one of the agents. Note that a coalition can only be formed with an agent that generated an idea. Whenever an agent is interested in another agent, a new proposal object is created, with a sender and receiver property. When an agent receives a proposal, it first checks which agent sent the proposal. Next, it checks whether it is interested in the other agent. If so, the agent accepts the proposal. Otherwise, the proposal is not accepted. A *coalition object* is created and the coalition 'picks up' the two agents that would like to form a coalition.

4.1 Parameter settings

For the simulation, we used a set of parameters for each of the factors that influence formation of coalitions between users modelled. Table 1 shows the settings that were used in the present simulation.

Table 1. Settings of parameters required for simulation.

Parameter / Agent	Adam	Bob	Carol	David	Eddie
Age	25	40	40	40	35
Gender	male	male	female	male	male
Position	Associate	Associate	President	Associate	Manager
Personality	Plant	Plant	Coordinator	Completer	Monitor
Lead userness	0.8	0.8	0.2	0.2	0.2
Power	0.2	0.2	0.2	0.2	0.2

Note that every individual starts with equal power. Power will be updated: 1) when an idea is valuable, 2) when another user is perceived to be higher in rank, and 3) when another user is older.

4.2 The Brahms Simulation Environment

The Brahms simulation environment [24] is an environment that aids the structuring of a simulation. The environment is JAVA-based and allows for an interface between agents (i.e. that represent users), objects and their locations. The Brahms language is spatio-temporal, meaning that it keeps track of both the time and place of agents and their actions. Several actions are distinguished, such as communication (based on the FIPA ACL Message Structure Specification [25]), perception of changes in the environment (so-called *detectables*), movement along locations, and interactions with the environment (e.g. picking up, moving and dropping items).

5. Results

During the simulation, five agents were active. These agents had different parameter settings, as is shown in Table 1. Two of the agents (Adam and Carol) create an idea at the beginning of the simulation. Next, all agents start expressing their interest in forming a coalition with Adam and/or Carol. Since each agent is interested in either Adam or Carol, each agent starts creating a proposal to form a coalition. Agents Adam and Carol may both accept a proposal that is received. Figure 3a explains how Adam accepted a proposal.

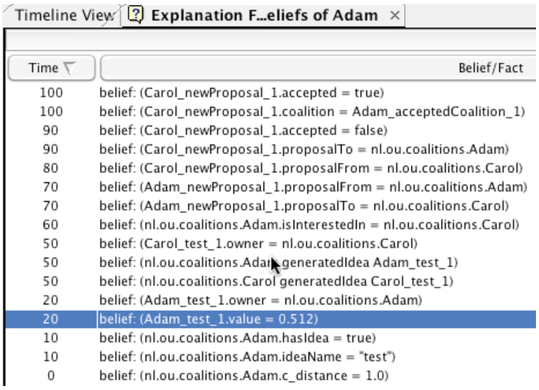

Fig. 2a. List of beliefs and facts per time unit for agent Adam.

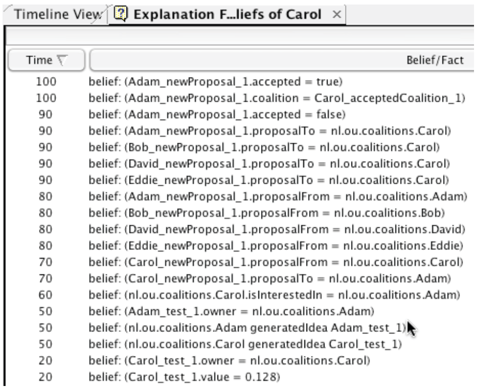

Fig. 2b. List of beliefs and facts per time unit for agent Carol.

From Figure 2a it follows that at time point 20, Adam has generated an idea with idea value 0.512. Based on this fact, Adam's power is raised with 0.4, which then passes the threshold of 0.5 to fire the interest workframe. Hence, agents Bob, Carol, David and Eddie start expressing their interest in Adam by sending a proposal to Adam. Figure 3a shows that Carol has sent a proposal to Adam (time point 80-90), which is accepted by Adam (time point 100), because he is interested in Carol (time point 60). A new coalition object is created for Adam and Carol.

From Figure 2b it follows that at time point 20, Carol generated an idea with value 0.128. Although this is not enough for soliciting interest from other agents, she is of a higher rank, which does trigger the interest and proposal-sending of other agents (time point 80-90). Carol accepts Adam's new proposal (time point 100), as Adam is interesting due to his idea value of 0.512.

6. Discussion and Conclusions

The simulation revealed that agents form coalitions based on their interest. The agents' interest was triggered by another agent's power and actor similarity. An agent's power was influenced by a number of things: 1) an agent's social identity, 2) an agent's higher organisational rank and 3) the value of an idea. Proposals for a coalition were only sent when the receiving agent had generated an idea, which corresponds to supporting someone in real-life that generated an idea. A remark, however, has to be made: Only one manual configuration was used for the parameters.

Besides, a relatively small group of agents has been used for the simulation. A larger group, or several groups may be preferred to represent real-life open networked innovation, that is, beyond the boundaries of the firm.

The experts that were asked to generate a model were scholars from a variety of fields of research. Open innovation takes place in an organisational context, though. To gain a better understanding, and to ensure quality, additional experts from business are needed to generate models about coalition formation in open innovation.

Last, but not least, we are well aware of the fact that no real data set was used. Currently, in the area of technology-enhanced learning, a challenge [26] has been identified to propose data sets for researchers to test their algorithms against. When available, we will use such data sets to test our approach.

7. Future Work

In terms of modelling and implementation, we envisage a number of things to be done. First, we plan to implement multiple-person coalitions. Multiple-person coalitions represent human coalition formation more realistically than two-person (dyadic) coalitions do.

Second, as coalitions influence the perceptions of power among agents, an agent's power needs to be updated when a coalition is formed. Power may positively influence the likelihood that an idea is accepted.

Third, multiple iterations of idea generation are envisaged. To represent the real situation in human collaborative idea generation, in which multiple ideas are generated, we need agents to generate new ideas and delete old ideas that are not important anymore.

Besides these improvements on the implementation side (phase 4 of our seven-phase development approach), we plan phases 5-7, which include expert feedback on our implementation results and adaptations of our model.

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