A LEARNING COMMUNITY SIMULATION

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ABSTRACT

In this paper we discuss the simulation of a learning network using NetLogo. The aim of the simulation is to study how different collaboration behaviours can influence the growth of collaboration in a learning network. We will use the simulation to test several hypotheses in order that we can design a 'social search engine' for the learning network. The search engine should be designed in such a way that it brings together users who profit most from collaborating.

KEYWORDS

Learning community, simulation, prisoners' dilemma, NetLogo

1. INTRODUCTION

Generally, learning communities are defined as groups of students and teachers who use computers in learning (Goodyear, 2001). More specifically, they "use computer mediated communication to support the delivery of courses in which anytime, anywhere access to interactions among the students and between the instructor/facilitator and the students are key elements" (Hiltz, Alavi et al. 2004). In our view, learning communities should be self-organizing; that is, learners are not assigned a group or tutors towards whom they could turn for help. To emphasize this emergent character we prefer to talk about 'learning networks'. They themselves have to find peers for collaboration or exchange. This is only possible if the learners have the means to search and locate peers of interest (Hummel 2005).

People use communication tools because they can talk with interesting peers. Someone goes to a forum because he or she knows that interesting people are there, someone sends an instant message to a peer because he knows that this peer will give an interesting response. Thus simply providing a community with communications tools or services such as forums, chats, instant messaging will not be sufficient, online learners need incentives to use such communication services. That is why we want to provide an online learning community with tools to find *interesting* and *available* peers.

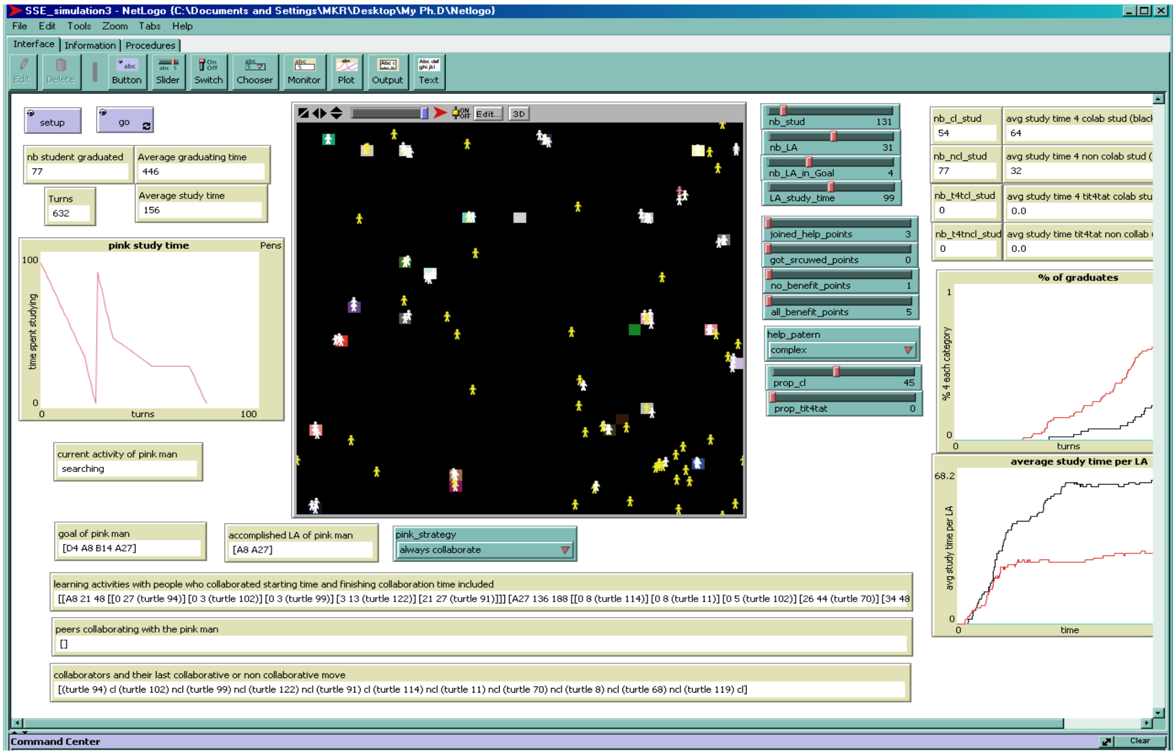
We call such a tool a social search engine because it uses the social network to find people. The first step towards building a social search engine is to investigate the dynamic behaviour of learning communities. Unfortunately, for practical reason it is impossible to do this trough field experiments only. Too many users are involved and too much time would be needed to survey a significant amount of users. That's why we decided to build as a first step a simulation of an online learning community. The simulation will help us understand the mechanisms by which online learning communities function. For example, Preece (Preece, Nonneke et al. 2004) finds the heterogeneity of a community an important factor contributing to the quality of the knowledge transferred. With a simulation we can determine for example if the size of the community influences the knowledge transferred. Also, a simulation could tell us how to populate a leaning community with the right proportion of veterans and newbies (Brown 2001).

In the next sections we will first describe the simulation, explain the algorithm, detail what assumptions we have made. Then we will briefly focus one our first hypothesis and present a test result before discussing possible extensions to the simulation.

2. SIMULATION DESCRIPTION

In this NetLogo simulation we assume that the time needed for someone to complete his goal (more on this later) represents his learning efficiency. This is a simplification, but avoids undue complications at this stage. Ultimately, we want to create groups of learners on the basis of their competences as well as their online behaviour. Therefore we simulate two types of behaviour, “collaborating” and “not collaborating”. For each behaviour type we measure the learners’ study time, which is the time spent by a learner studying. The study time is different from the graduation time, which is the time needed to graduate; the later includes both the time spent searching for a learning activity and the time studying. Below is a snapshot of the simulation interface. On the left side a pink graph is shown that represents the study load of a learner. One can distinguish two completed activities, marked by the curve hitting the X-axis.

Interface of the netLogo simulation



2.1 Hypothesis

To check whether our simulation algorithm (see below) performed as expected, we tested the following hypothesis: the average study time in a learning community populated with a majority of collaborative people should be lower that the average study time of a learning community populated with a majority of non collaborative people.

2.2 Algorithm

Each simulation consists of a fixed set of *learning activities* and *learners*.

A *learning activity* is defined by a particular competence; it is represented by a coloured square (Koper 2004). For each learning activity, we record who studied it, from when, and for how long. The absolute amount of work needed to complete a learning activity is an artefact of the simulation; however, we assume that all learning activities need the same amount of work to be completed.

A *learner* travels randomly from learning activity to learning activity in search of a learning activity that helps him to achieve his goal. We assume that all learners, except for a pink man used as reference, are similar and have the same characteristics.

The goal of a learner is to complete a specific set of learning activities. In this simulation all learners' goals contain the same number of activities. A learner has a current-activity which can be "searching for a learning activity", "studying a learning activity" or "having graduated". Figure 1 shows the major step of this multi-agent simulation.

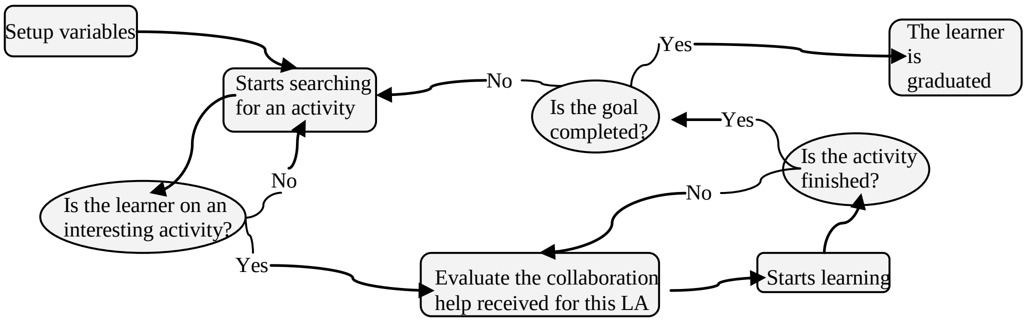


Figure 1. The simulation algorithm

2.1.1 Searching for a learning activity

The simulation consists of a sequence of turns. During a turn, a searching learner will move to a randomly chosen square and look if this square represents a learning activity element of his goal. If so, the learner's state will change to studying and a study timer will start running; if not, the learner will continue searching in the next turn.

2.1.2 Studying a learning activity

As indicated, when a learner finds a learning activity which is part of his goal, he starts studying it. Now he will also look for peers who study the same learning activity. We simulate the collaboration process in two different ways.

First, we assume that learners will study faster if peers ('collaborators') are studying the same activity. The reduction in the study time for a particular learning activity is proportional to the number of collaborators: the more collaborators, the speedier. So we assume that collaboration is 'good' and decreases the amount of time needed to complete a learning activity. Without any collaborators a learning activity has a standard (arbitrary) learning time. In that case, the amount of time needed to complete the activity is reduced by one unit on each turn. If there is collaboration, the study time is reduced by log(n +e), where n is the number of collaborators. We use the log function because we assume that adding collaborators will improve learning to an ever decreasing extent. Indeed, according to Weber (Weber 2004) at some point adding more people to a project will even slow down that project because adding one person also increases the possibility of misconceptions and errors by n (the number of communication channel between the people).

The second type of collaboration assumes that collaborators are faced with a prisoners' dilemma: users have the possibility to "collaborate" or "not collaborate". Table 1 shows the reduction in study time for a particular learning activity for each member of a duo, depending on whether they collaborate or not. Bear in mind that in the previous section, we assumed the study time to be decreased by one unit each turn. This corresponds to the cell in the lower right corner.

Table 1. Units of work done by two users depending on their behaviours

Learner A \ learner B	collaborative	non collaborative
collaborative	2 \ 2	0 \ 3
non collaborative	3 \ 0	1 \ 1

To start we tested the simulation with simple strategies. “always collaborate” or “never collaborate”. We used these two strategies to check expected behaviour. The results are shown in the next section. In addition to these two strategies we also have implemented the tit-for-tat strategies. “tit-for-tat collaborating first” and “tit-for-tat not collaborating first”. In a tit-for-tat strategy someone copies what his peer did the previous turn. We distinguish two tit-for-tats on the basis of what is done in the first move, either collaborating first or not collaborating first. In this strategy, the learners can remember the last behavioural move of their peer and adapt his own behaviour to it. For example, a user may first decide to collaborate. If the other learner is not collaborative then the user chooses not to collaborate the next time.

2.1.3 Graduation

A learner graduates once all learning activities contained in his goal are completed. When all learners have graduated, the simulation stops. It is possible to loop the simulation in order to sample several results. Using this so-called Monte Carlo’s method, we can study the variability in the results of the runs.

2.3 results

We ran two series of 10 runs each. The first series had a proportion of 100% of “non collaborative” people. The second series had a proportion of 100% of “collaborative” people. For each run we recorded the average time for the entire learning community to complete one learning activity. Figure 2 show the average of both series of 10 runs. The time needed to complete a learning activity was set to 125 units of time.

Figure 2. Influence of the behaviour on the learning efficiency

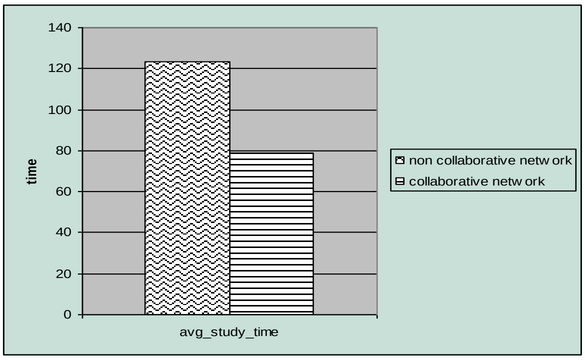


Figure 2 shows a significant difference between “non collaborative” and “collaborative” average time. The “non collaborative” users have the same average study time as would ‘lone’ learners. This is in line with the points attributed in the Table 1. There we can see that a non collaborative behaviour reduces the activity working load by one unit at each turn. This is the same as a lone learner.

On the other hand the collaborative people have an average time of 79 units which is about 2/3 of 125. One would have expected the average time of the collaborative people to be half the normal time because two collaborative people go twice as fast as the lone learners. This (deviating) result shows that collaboration did not occur at each turn. We can deduce the time spent working alone for collaborative people as: 1/6 of the global time. 2/3 of global study time - 1/2 global study time (the average study time if collaboration occurred at each turn) = 1/6 global study time.

3. CONCLUSION

We presented a simulation of an online learning community based on several assumptions. However, many of them are not realistic and should be relaxed in future runs of the simulation. For example, we assumed that the community had a fixed number of users, although, in most cases, this will not be the case. In big communities learners enter and leave the community on a daily bases. Also we assumed that each learning activity had the same learning time but in a real learning community one will find a variety of learning activity differing in size, in quality or prerequisites. In a future work we will investigate the effect both quantitatively and qualitatively on the simulation results.

Finally, even so we have included the tit-for-tat strategy, our strategy only take in account the last move. We should introduce in the model more elaborate behaviour taking in account for example the time of study, the learner's language or geographical position and, last but not least, we would like to give each learner a personal social network used to catalyse the help received from collaborators. Strategies followed with collaborators who are 'friends' should differ from strategies followed with strangers.

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