

ANALYSIS OF THE BENEFITS OF COLLECTIVE LEARNING THROUGH QUESTION ANSWERING

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Abstract: Online collaborative learning between peers seems a viable complementary method to traditional learning, even as the input no longer comes from only one man – the tutor – but from a number of people with different levels of competence. Furthermore, nowadays an increasing number of people turn to social networks when they need to find answers, for reasons like trust, response time and effort. Thus social networks behave at times similarly to online collaborative learning networks. This paper presents a model of Questions & Answers (Q&A) learning where students are the ones that ask and also answer questions, as a method to increase and reinforce knowledge.

1 INTRODUCTION

Recent surveys, notably Chi (2009), show that people turn to social networks when they need information or seek answers to subjective or open questions. The main enablers are trust (Q&A sites provide answers from strangers, while social networks provide answers from people you know), response time (social networks are faster than Q&A sites), effort, personalization, and social awareness (Morris et al., 2010). People often resort to social networks as they find it easier to formulate a full question, rather than to recurrently try to find the right key words, and moreover when answers come from friends, which have a certain degree of trust and expertise, known by the questioner.

We claim that Questions & Answers (Q&A) is a proper model for collaborative learning (CL). Glasser (1986) argued that students remember more information when they are actively engaged in learning as a social act: we learn more by collaborating, communicating within a group. Glasser's trial data reveal that we remember 10% of what we read, 20% of what we hear, 30% of what we see, 50% of what we hear and see, 70% of what we talk with others, 80% of what we experiment and **95% of what we teach others.**

An interesting new approach, the Self Organized

Learning Environments (SOLE) (Mitra et al., 2010) can be empowered by online social networks, mobile applications, and social currencies. It leans on Social Constructivism for computer supported collaborative learning (CSCL). The former Mitra's hole-in-the-wall experiments (2003) showed that groups of children, given shared digital resources, seem not to require adult supervision for learning. Students learn best when they actively construct their own understanding through social interaction with peers. The responsibility of the instructor is to facilitate the students' learning process around a particular content. This method of learning from peers is also known as Reciprocal Peer Tutoring (RPT) (Allen et al., 1978) or adaptive collaborative learning support (ACLS) (Walker et al., 2009).

2 SIMULATIONS OF COLLABORATIVE LEARNING

The Walker model (2009) basically encourages solving own problems, by offering hints, but also provides the alternative of asking questions to a peer tutor. This was the general context which allowed us to propose a *peer* Q&A simulation of CSCL and compare it to a traditional *tutor* Q&A system. In peer Q&A systems students answer each other's

questions, a process supervised and facilitated by tutors. For the initial model we drew inspiration from Moreno et al. (2009) - completing Frequently Asked Questions (FAQ) as a sort of a Wikipedian approach of collaborative learning on a subject.

Each student initially has all its classmates in the contact list. Further on, he can add whomever he chooses to, from parents to friends outside school. The model is similar to *Facebook* (or any social network) in the sense that a user can post a question on his wall or send email to a list/group of friends (by means of the extinct *Quora*). Such a question would be visible to his network friends who could answer it in the eventuality they had the knowledge and the availability to do so. We chose these approaches to avoid spamming everybody in the network list. In the eventuality a friend does not know the answer, but he is willing to help, he can share the question on his own wall, so that his friends can see it. The difference from Facebook resides in the fact that, in the eventuality that a friend of a friend responds to the question, both the initial asker, and the helping friend would receive the answer. This is a method that would help to also increase the knowledge of the mediator, the friend.

Every student entering the system has a LCV (Learner Competences Vector) which includes various domains of user knowledge (we will refer them further on as *subjects*) and also a level of competence for each of these matters. In order to rate the competences of the answerer in each subject, we drew inspiration from Bloom's taxonomy of educational goals (1956): competences range between 1 and 6, being: 1 - knowledge, 2 - comprehension, 3 - application, 4 - analysis, 5 - synthesis, and 6 - evaluation. We introduced the 0 value to declare the *forgetting factor* (the user *knew* something about that domain, but no longer *does*).

LCV initially contains no competences (\emptyset). The competence value is built upon the user's answers. For example, after few answers about the following subjects: *a, f* and *h*, the LCV could be $L = \{a4, f2, h3\}$ that means competence of *analysis* in subject *a*, of *comprehension* in subject *f* and *application* on subject *h*. After a period of time in which a user does not answer any question in the *a* subject, *a* competence would decrease by a factor. In our simulations, initial values for LCV (subjects and competences) were randomly generated.

2.1 Assumptions and Measures

Drawing inspiration from Pous et al. (1997), we consider that a set of pedagogical inputs can change

the state of the students, namely the LCV. Aside from the traditional input system, where the teacher provides the input that is supposed to change the pedagogical value of each student, our model introduces the student/peer input system, where:

$\mathbf{A} = \{A_i\}$ is the set of *students* in a class.

$\mathbf{K} = \{a, b, \dots, z\}$ is the set of subjects k_j ,

$\mathbf{c} = [0, 1, \dots, 6]$ are the *competence levels*

L_i is the LCV for each student A_i

\mathbf{C} is the *curricula*, pedagogical goals in terms of LCV for a class of students; for example $C = \{a6, b5, c6, d4\}$ means that subject '*a*' should be achieved at level '6', while content '*b*' at a lower level '5', etc.

q_i is the *increase/reinforcement factor*. It is calculated out of the Q&A of each student A_i that should increase his competence level c in a subject k_j

α is the *forgetting factor*. When a subject competence gets to 0, it means the student recognises it, he is aware he knew something about it, but now no longer remembers it. After every n weeks a pupil does not ask, nor answer any question about a subject, his competence decreases by a factor d_f

The goal is to make **average** L_i as close as possible to the curricula C (completeness), after a time frame of 12-15 weeks (a semester).

$$\lim_{t \rightarrow \infty} \text{average}_{vi}(L_i) = C \quad (1)$$

If the model behaves as Moreno et al. (2009) did, it would show that CL is faster to reach completeness (1), than the traditional tutor-based system. The premises are that learning can be *achieved* through receiving answers to questions and *reinforced* through question answering. Every time a student asks or answers a question, his competence level is increased by a factor q_i . Nonetheless, we consider that he will learn only when receiving answers from a peer with higher competence levels. As well, we assumed that having a considerable difference between the asker's and the answerer's competence is not that good for learning, as the answer could be too complex, eliminating thus the peer tutoring advantage.

The mechanism of the model seeks to avoid spamming network friends. This is achieved by posting the question on the wall (like in Facebook) or by sending email to a close group of friends. Communication by emails could be implemented with the Asknext protocol (Trias et al., 2010). The teacher stimulates the community of students by suggesting appropriate questions. He inspects the unanswered questions and decides if answering himself or inviting other students to answer. In the

future he will also have the possibility to correct answers; this implies an upgrade of the model so that it would allow the possibility to distinguish between good and wrong answers. Friends will also be able to rate the answers, which will lead to upgrading the social network.

2.2 Experiments

Let us consider a class of 8 students that do question answering, as well as the teacher does. The questions are related to one subject from the educational curriculum. The time frame is 12 weeks (one semester) to reach goals set up in the curriculum.

The student's *learning curve* is the amount of knowledge and the speed with which he achieves it. It depends on his native abilities and also on the effort he puts in. The *native abilities* will influence the stochastic model, while in our approach, a deterministic one, we only took into consideration the effort. *Effort* is considered to be the frequency with which a student answers and also asks questions. Asking questions is not viewed as a sign of laziness (not wanting to learn or solve problems by himself, thus asking questions), but as a sign of conscious and sustained, constant work. In this case each student has a questions' vector (consisting of questions asked in a period of 12 weeks), an answers' matrix (answers given every week) and an evolution vector (L_i). The *bandwidth* is seen as the number of questions one can answer. In this model the professor's bandwidth is considered to be infinite.

The social aspect (reorganizing the network's hierarchy according to *who do I trust most*, depending on received answers) is left for future improvements.

The students' evolution was simulated for a period of 12 weeks, where the following two aspects were rewarded with points:

- receiving answers to asked questions
- answering questions asked by different agents.

The answer factor, q_i of student A_i is:

$$q_i = f(I_c, t, \gamma) \tag{2}$$

Where:

- $I_c = C_c - a_c$, is the *competence index*. C_c is the curriculum target competence and a_c is the initial average competence of the class
- t , is the weeks allocated to reach C_c from a_c
- γ , is the number of questions a pupil has to answer each week (established by the tutor)

We calculated q_i with the following formula:

$$q_i = \frac{I_c / t}{\gamma} \tag{3}$$

Each pupil has to answer at least 4 questions/week; every time a pupil **gives** an answer to a question asked by a peer, he earns 0.1 points of competence; if he reaches answering the established target of 4 questions, he gains 0.4 points/week. If there was no answer in a week, his competence is decreased by the same value a week, entitled the *forgetting factor* ($d_f=0.4$). For each answer **received**, the student is considered to be achieving knowledge worth of 0.1 points.

The classical approach implies professors consistently answering to pupils' questions. The forgetting factor in the classical approach is not taken into account as students are supposed to learn based on the traditional input system – the tutor. Considering the ideal case that students would ask one question/week and that every answer would change their knowledge level, a simple simulation for 8 students, generated the evolution of the class's competences, as presented in Figure 1.

Let us see how students evolve with collaborative learning through question answering. Pupils gain knowledge by answering questions asked by peers. The rating mechanism is described by equation (3). There are a few more things that were taken into account when measuring the evolution of students' competences: answers were accepted only from agents of higher competence in the subject as well as the difference between competences was lower than 4 - an $a1$ student (who knows content a with competence level of 1) should receive answers from $a2, a3, a4$ students, but not from $a5$ and $a6$, as it would no longer be *peer tutoring*. Results obtained after multiple simulations are summarised in Figure 2.

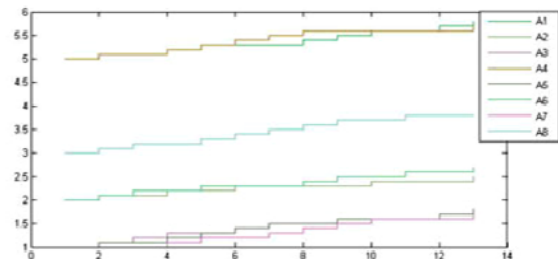


Figure 1: Classical model of learning, where students are asking, and tutors are answering.

For generating Figure 1 and 2 we used 8 agents with the same initial competences and questions' vector. In the first one (where only tutors' answers contribute to the students' competence increase), a

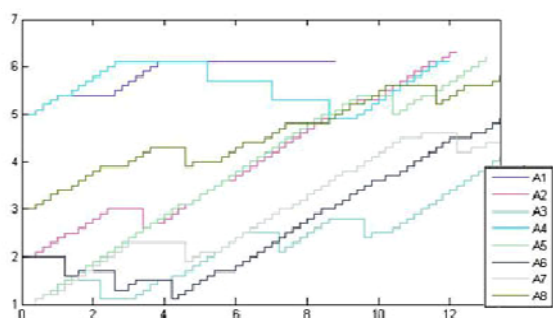


Figure 2: Q&A model of Collaborative Learning.

slight improvement can be observed in the established period of time, whilst in the second one, peer-to-peer interaction appears to be the best method to boost competence.

Even in the worst case scenario, a week without any activity, the overall results at the end of a 12 weeks semester were encouraging.

Table 1 presents an example of the increase in competences (points gained), during 12 weeks, for both of the above models, one subject, one set of simulations.

Table 1: Competences gained during 12 weeks in the classical (C), and in the collaborative learning (CL) model.

	A1	A2	A3	A4	A5	A6	A7	A8
C	0,8	0,5	1,6	0,7	0,8	0,7	0,7	0,8
CL	1,1	4,3	3,1	1,1	5,0	3,5	3,6	5,1

3 FINAL COMMENTS

In recent years studies have offered constant proof of the impact collaborative learning has on the way students accumulate knowledge. Peer-to-peer learning appears to succeed where classic tutor input fails or faces resistance. The Q&A model proposed in this paper seeks to increase knowledge by emphasizing the importance of questions and answers among peers in online social networks, a process sustained and enhanced by tutors. Simulations compared two models: the classic model, where students ask and teachers answer, and proposed one, where students ask and peers answer. Simulations showed the increase in knowledge was more significant in the latter case.

Expanding the network, allowing network friends from different classes, and even from outside school could only lead to an increasing Q&A activity, to more questions and faster answers, lowering thus the necessity for tutors to intervene, in order to stimulate the answering process.

Furthermore agents will be used to speed up the question answering, by automatically answering questions they have answers for in a special Q&A list (consisting of questions and answers approved or given by tutors) and by suggesting contacts (other agents) that could answer question from a certain field (using the Learner Competence Vector).

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