Supporting Learners' Group Formation with Reciprocal Recommender Technology

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Abstract: Learning in groups has many pedagogical and social benefits. However, effective group formation for collaborative learning is challenging and requires instructors to make a number of non-trivial decisions. There are several issues to address. (i) Scalability: when facing a handful of students in a classroom scenario, instructors can use their experience and knowledge of the students to group them optimally. However, as numbers grow in, for instance, a MOOC scenario, this manual process simply does not scale up. (ii) Which features help maximise learning and collaboration: while CSCL theories provide an excellent basis for identifying these features, which are best for a given task and a given set of students? For instance, should groups be formed heterogeneously or homogeneously? Should they be reformed after some time? (iii) Supporting instructors in effectively and easily using these features to scaffold learning and guide collaboration: for instance, should they do the grouping on their own or can students (or a system) support the grouping? Reciprocal Recommender algorithms, which aim at recommending to a user a set of other users in a way that simultaneously satisfy the users' mutual needs and preferences, provide a promising approach to tackle these issues. We discuss how we envision this approach can work and the challenges that lie ahead.

1 Introduction

Learning in groups has many pedagogical and social benefits. Group work helps students develop a range of generic skills, such as turn taking and supporting claims, and, when they are designed in a way that promotes teamwork and deep collaboration, has been shown to contribute positively to student learning.

However, simply assigning students to groups is not sufficient for these benefits to occur. Indeed, as many teachers and instructors can attest, successful implementation of small group work can be very challenging. In particular, effective group formation for collaborative learning is difficult to implement as teachers need to make non-trivial decisions when forming their student groups: Which criteria are the most critical (e.g., prior knowledge, ability, gender, friendships, personality)? Should groups be

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re-formed iteratively (and, if so, based on what criteria)? Who should determine the grouping; the teacher (or the system), the students, or both?

These issues quickly become intractable as the pool of students increase in size. For instance, online learning environments, such as massively online open courses (MOOCS), are rapidly emerging as a common learning platform, yet do not provide an effective means for supporting learners in small group collaboration. This is because there is no support to help instructors and students form groups in an effective and semi-automated way.

In this paper, we describe our approach to address the issue of student group formation and re-formation through the use of *reciprocal recommender* software, which has been successfully used for matching users with one another (Pizzato et al 2013). We intend to apply our approach to MOOCS, where thousands of students may be participating in a given class and small group formation within the class is an important issue.

2 Group formation

Research on productive group formation has looked at group characteristics, including homogeneous vs. heterogeneous ability grouping (Sampson & Clark, 2011; Webb, 1992). Results have been mixed, with some support for socially homogeneous grouping to foster group cohesion (Gijlers, van Dijk, & Weinberger, 2011; Sampson & Clark, 2011), and some support for cognitively heterogeneous grouping to foster socio-cognitive conflict (Webb & Palincsar, 1996; West, 2002). Overall, the results suggest that homogenous groups may be more motivating to students, while heterogeneous groups may provide better learning opportunities.

Besides initial and static group formation, *dynamic group formation*, regrouping of learners at different stages of group work (Dillenbourg, 2002), has been investigated. While dynamic group formation may disrupt established social patterns, learners may benefit from being exposed to multiple perspectives (Goltz, 1998). Some attempts to automatically and dynamically form groups include e.g., Graf & Bekele, 2006; Paredes, Ortigoza, & Rodriguez, 2010; Zurita, Nussbaum & Salinas, 2005.

Another issue is *group formation agency*: Who has control in grouping and regrouping the students? The instructor, the students, or an informed assignment done by software? Who is grouping the students may influence what characteristics are taken into account, as well as learners' acceptance and motivation for learning collaboratively. Typically, group formation is externally regulated, (i.e. the instructors or a system groups students rather than students grouping themselves) and non-dynamic (i.e. the group is formed at the beginning of a session and does not change).

We propose to use reciprocal recommender software to help with grouping and regrouping of students as they work together on their task. In a remote student learning scenario – such as a MOOC, the kind of learning scenario we ultimately target in our work – we envision the system supporting group formation co-agency by allowing students and teachers to build groups, using the system's analysis of a large pool of learners, and also supporting dynamic regrouping. In the following section we explain what reciprocal recommender software is and how we propose to bring it to bear in supporting group learning.

3 Reciprocal Recommenders and Application to Education

Online recommender systems are becoming ubiquitous. Many online commercial vendors, such as Amazon and Barnes & Noble, use these systems, which rely on machine learning techniques, to recommend products, services and other items to people. Recommendation in online learning is much more complex than in online shopping due to the richness of pedagogical theories and learner's needs (Manouselis et. al., 2010). Whereas commercial recommender systems make suggestions based on predicted or estimated taste, educational recommender systems aim to suggest resources that are helpful for learning (Buder & Schwind, 2011). Despite these differences, recommendation algorithms based on, for instance, collaborative filtering methods have often been used in education (Drachsler et.al. 2008). Avancini and Straccia (2005) have proposed recommendation of resources, users and communities from a digital library based on collaborative filtering. Manouselis et. al. (2010) compared different collaborative filtering algorithms to recommend learning resources, considering teacher evaluations. More automated approaches for learning which use user feedback to recommend learning resources have also been proposed (Cummins, Yacef & Koprinska 2009).

While traditional item/product recommenders have thus far dominated recommender research, *reciprocal recommenders* have recently started to emerge, matching people with one another (Pizzato, Rej, Akehurst, Koprinska, Yacef & Kay, 2012). These systems make recommendations to people about other suitable people, focusing on satisfying the preferences and/or needs of *both* parties simultaneously. Examples of domains where such recommenders are used include finding friends, professional contacts, and partners on social networks and searching for jobs on employment websites. Reciprocity is a core requirement for systems designed to facilitate mutual connection between people. The precise definition of reciprocity, and of recommendation success, depends on the context in which it is used: will the people like each other, work/learn well with each other, or help each other? In contrast, standard recommender systems recommend items to people such as books, movies, etc., considering only one-sided preference: satisfying only the need or interest of the person for whom the recommendation is.

Pizzato et al. (2012) conducted an extensive analysis of the distinctive aspects of reciprocal recommenders, uncovering clear evidence that reciprocity is key to generating good people-to-people recommendations. Indeed, a number of case studies demonstrated that reciprocal recommenders outperformed their equivalent non-reciprocal versions, such as for recommending people on a social networking website (Cai et al., 2010) and matching partners on dating websites (Diaz, Metzler & Amer-Yahia, 2010; Pizzato et al., 2011; Akehurst et al., 2011). Other reciprocal recommender systems have, for instance, matched people and jobs, combining the results of two recommenders (Malinowski et al, 2006) or suggested helpers to people, i.e., i-Help (Bull et al., 2001). The successor to i-Help, PHelpS (Greer et al., 1998), accounts for characteristics of both helpers and helpees.

4 Assisting Group Formation with a Reciprocal Recommender

4.1 Aim of the group formation recommender

Recommending students to fellow students can be a reciprocal recommender task, because students are looking for mutual benefits and the recommendations must aim to satisfy these benefits on both sides. The goal can be, for instance, maximizing argumentation levels between students, maximizing final performance, increasing motivation and engagement, maximizing shared and individual learning outcomes, or a weighted combination of all of these aspects. The recommender may produce a set of recommendations (i.e. for a specific student S, a ranked list of potential partners S1, S2, ... Sn), which optimizes the match between student S and the proposed candidates, exploiting student data such as:

- cognitive features (i.e. knowledge, skills, learning strategies)
- problem-solving strategy used in students' previous work
- general and social information, such as gender, personality, personal preferences, geographic location
- past history of the students' interactions with the system.

It can also obey specific constraints such as:

- a desired combination of theory-driven features (such as homogeneous or heterogeneous ability grouping, diversity of knowledge, skills and/or learning strategies)
- external constraint characteristics, fixed by the teacher (e.g. maximizing balanced gender representation, geographical distance or socio-economic distance, which can be important in fostering collaborations across different communities and so on).

Through the different weights given to these features, a recommender engine can guide the way groups are formed. For instance, a recommender may suggest the formation of cognitively heterogeneous groups by matching students based on the diversity of their problem solving approaches, learning strategies, and/or knowledge and skills. It can also foster cross-gender and cross-cultural collaborations by promoting the recommendations of students with different gender and geographical locations.

In the case of subtle external regulation and system-student co-agency, student S can make a choice of who he or she wants to team up with, after being presented with a list of recommendations from the system. In the case of teacher-system-student co-agency, the recommender can provide meta-recommendations to teachers about the potential student groupings and let them select the arrangement across students, or make further suggestions to the students.

4.3 Design of the Recommender Engine

The reciprocal recommender we envision will generate, for a particular student X, a list of optimal matching students who that student would work well with *and* who would also work well with X. The characteristics will be primarily cognitive but will also include, e.g., the students' preferences. The recommendations will be ordered in decreasing order of preference for X.

We plan to investigate the use of two reciprocal recommender engines: (i) RECON, a purely content-based algorithm (Pizzato et al 2011) which considers reciprocal preferences to recommend users to each other; (ii) and CCR, a hybrid content-collaborative algorithm (Akehurst et al. 2011) which in essence is a collaborative filtering algorithm addressing the cold start user problem by finding users with similar profiles and providing recommendations based on the successful groupings of these users. This approach reduces the reliance on the user's explicitly stated preferences.

An additional challenge is that students might require groupings all at once, ensuring that students are all allocated to a group. For example in a large (500 students) University course, typical or even small for a MOOC, all students need to be paired up for their assignment. The group formation problem then needs to be addressed at a course level: a grouping that groups optimally 20% of students but leaves 20% of students ill-matched is problematic. It might be better to have a slightly less optimal grouping where no student is left out. To address this, we plan to create a *meta-reciprocal recommender* that will, for a set of students (say a large classroom), suggest the most optimal grouping of *all* the students, as provided by one of the two recommenders above. It will do so by using a constraint satisfaction and optimization algorithm that can handle preferences (Rossi et al. 2008). It will treat the recommendation lists of each student as preferences. A recommendation by the meta-reciprocal recommender will be a list of possible groupings of all the students, with the top recommendation being the one which most satisfies the students' top recommendations, and where each set of recommendations comes with satisfaction measures for each features: for example one set of recommendations may achieve a higher matching of cognitive features on average, but a lower average gender balance than another one.

5 Summary

Reciprocal recommender technology appears to provide a solution that addresses some challenges of effective group formation: Firstly, by varying grouping recommendations based on students' cognitive and social features, teachers and instructional designers can study and then choose which maximize learning and deep collaboration for the given group task. Secondly, these features, as well as external constraints, can be computed automatically, which means they can be used not only by teachers in large classrooms but also by MOOCs and other online environments. Lastly, the efficiency of the reciprocal recommender algorithms means they can be used on the fly, hence making regrouping easy if necessary.

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