

Effective Team Learning in the Cloud

Forming Teams for Motivating Productive, Creative or Learning Projects

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Abstract—Learning in the cloud can be a lonely activity for self-directing and self-organizing learners. Lack of sustained learner motivation can lead to less effective, less bond-creating learning experiences. By providing collaborative project-based learning opportunities these shortcomings can be overcome. A service design is introduced for the onset of collaborative project-based learning and team formation in the cloud, based on learning materials in the cloud, project definitions and characteristics, and learner ‘knowledge’, ‘personality’ and ‘preferences’. The article specifies how the data required by the design can be gathered. Team formations rules are deduced from existing team formation research. They steer the team formation process towards facilitating learning, creative problem solving or increased productivity outcomes. The rules are implemented in three team formation equations. Deployment of the equations on a set of test data demonstrates the effectiveness of the team formation service.

Keywords—Cloud learning; project-based learning; project team formation; self-directed learning; team formation rules

I. INTRODUCTION

Nowadays, everyone with a connection to the Internet can learn from the cloud of knowledge it provides. The individual learners freely using the resources available are considered to be self-directing and self-organising. But individual learners can find it difficult to remain motivated [1]. The introduction of collaborative project-based learning can help overcome the drawbacks of individual learning. Project-based learning is considered to be motivating, bond-creating and effective [2] [3]. However, how are such teams of cloud learners formed in the absence of human agents such as teachers? To address this need, we present a design for a service that can support these learners to set up project-based activities and form teams.

Prior research indicates that for project-based learning to deliver optimal results, experts should form the teams [19] [20] [21], using their knowledge about the learners. As these experts are not readily available in the cloud, our design aims to mimic expert behaviour, but also takes into account learner self-direction and self-organisation. The concept of *Fit* [16] [22] is used to indicate whether a team of learners (in its unique combination of knowledge, personality and preferences) is suitable to perform a specific project.

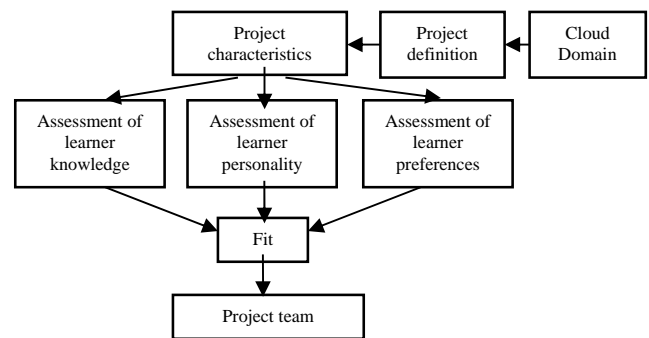


Figure 1. The team formation model

Following the team formation model depicted in Fig. 1 [4], our service is designed to work based on a knowledge representation of learning materials in some knowledge domain in the cloud. Such a representation can be created with language technologies such as Latent Semantic Analysis (LSA) [18]. In [23] the authors demonstrated that an LSA-based software tool is capable of fitting job descriptions to people's knowledge and learning materials.

The project-based learning and team formation process can be started by a learner or other project initiator by submitting a *project definition* (which details the project's aims), and the *project characteristics* (such as the preferred team size, duration, etc.) to the service.

The following is an example from the perspective of a prospective team member of how we envision the service can work: “May 2013: Emma recently started her new job at the microelectronics department. For the first two months her main task was to strengthen her knowledge in this domain. She decided to follow a highly recommended MOOC course. On top of the regular lectures and other materials, the MOOC also offered a project wall with the possibility to apply for a project assignment. The assignments varied from assisting peer students to participating in small and large projects proposed by peer students, companies and research institutes. The larger projects followed an automated, open procedure to select the best applicants. Emma selected a project on bio-chip design. The project was an interdisciplinary project to be performed

by at least 4 persons. She could apply by sending in a brief summary of around 100 words on her knowledge and skills with regard to a pre-defined list of topics, filling out her preferences (on language, availability, etc.) and taking a personality test. Emma decided to give it a try and sent in the required information and did the personality test. A few days later she received an invitation to participate in the project and contacted her fellow project members to make arrangements.”

The team formation model defines that in order to assess whether prospective team members are suitable for a project, data is needed in three categories: i) *knowledge*, ii) *personality*, and iii) *preferences*. However, as the main focus of this paper is on how teams can be formed, we assume that the required data has already been gathered. Therefore, in Section II, we only briefly introduce how the assessments are designed to work. For the remainder of this article, the data are then assumed to be available.

As project-based activities can have different purposes, in Section III we define three general team formation rules, which enable the team formation service to form teams that are aimed at *increased productivity*, *creative problems solving* or *facilitating learning* as outcomes. The rules are based on prior research findings about team formation. Here, we translated them into three team formation equations. In Section IV, we report on the results of the application of the equations to a set of test data. Finally, in Section V, the results are discussed, conclusions are drawn and future work is indicated.

II. THE KNOWLEDGE, PERSONALITY AND PREFERENCES ASSESSMENTS

As introduced above, the team formation for project-based learning starts with the definition of a project related to a knowledge domain in the cloud. The service then deduces to how many and which specific topics in the domain the proposed project primarily refers, by using the project description as a query into the domain knowledge representation.

Next, the fit of the prospective team members is assessed with respect to their knowledge, personality and preferences, related to other members and the knowledge requirements of the project. We will briefly describe these assessments:

The *knowledge assessment* determines how much knowledge, if any, learners have available on the topics the project refers to. For this assessment the learners submit knowledge evidences, which are used as queries into the domain knowledge representation.

The *personality assessment* uses data on learner personality, which are gathered through a personality test. The resulting learner personality profile is made up from a person's *conscientiousness* [5] [6]. This personality construct consists of the personality characteristics carefulness, thoroughness, sense of responsibility, level of organization, preparedness, inclination to work hard, orientation on achievement, and perseverance. ‘Conscientiousness’ is chosen specifically because it predicts a person's future performance in a team. The learner's conscientiousness score is established by using the Big Five personality test [7]. We

consider the inclusion of personality as a factor in the team formation process to be of particular importance as team formation literature shows a strong tendency to focus merely on knowledge as a general indicator for successful participation in a project, while other studies indicate that other factors better predict success [8].

The *preferences assessment* is performed on learner data entered on such variables as availability for the duration of the project, time zone, possible collaboration languages and preferred tools into a learner preferences profile. The assessment then determines the overlap between the project characteristics and the learners' project work related preferences. When preferences do not overlap, they constitute ‘condiciones sine qua non’ for inclusion in a team. (E.g., when one learner indicates to be available on Mondays, while another learner indicates to never be available on Mondays, their calendars are mutually exclusive and thus these two learners will never be matched in a team).

It is, however, important to notice that the data gathered from learners is *not of a static nature*, but can be refreshed every time a learner re-enters knowledge evidence for a project, retakes the personality test, or updates preferences.

As a first step in the team formation process, the preferences assessment can limit the number of learners to be considered for inclusion in a team. Learners might, however, negotiate preferences and re-enter them in their preferences profile. After this step is completed, the team formation process continues with the knowledge and personality data.

III. DEFINITION OF THE TEAM FORMATION RULES AND EQUATIONS FOR TARGETING SPECIFIC OUTCOMES

Assuming the data from the knowledge and personality assessments and the project characteristic “preferred team size” are available, the team formation service combines the two separate sets of data by following particular team formation rules. In the design of these rules we take into account prior research findings on team formation. We sort the findings into three possible teamwork outcomes (productive problems solving, coming up with creative solutions, and facilitating learning) and present the general rules we deduced for forming teams suited to achieve these outcomes. Based on these general rules, we present three team formation equations.

A. Teams fit for increased productivity

We considered the follow research outcomes for the creation of teams aimed at increased productivity:

a) Differences in conscientiousness scores impede task negotiations [9];

b) Members of productive teams should be capable and conscientious and must have domain knowledge [10].

The general team formation rule we deduce from these findings is: *Productivity is fostered when team members show high levels of conscientiousness and have supplementary high knowledge on the project topics.*

This rule is translated into the team formation equation for productive teams (1). When applied, it determines which teams have the highest average knowledge scores and the highest average conscientiousness scores.

$$FitP_i = W_K * \frac{Avg_K_i}{Max_K} + W_C * \frac{Avg_C_i}{Max_C} \quad (1)$$

Explanation of the terms used in (1): *FitP_i*: Fitness of a team *i* for productive outcomes; *Avg_K_i*: Average knowledge of all members of a team *i* on all topics; *Max_K*: Maximum possible score on knowledge on a topic; *Avg_C_i*: Average conscientiousness score of all members of a team *i*; *Max_K*: Maximum possible score on conscientiousness; *W_K*, *W_C*: Weights.

B. Teams fit for creative problem solving

For the formation of creative problem solving teams, we considered the follow research outcomes:

- a) Too much complementary fit in knowledge can lead to a loss of creativity and group thinking [11];
- b) People with high conscientiousness scores tend to be less creative [12] [13];
- c) Groups with members that possess different knowledge backgrounds will be more innovative because they contribute from different perspectives [14];
- d) Successful research teams are heterogeneous [15].

The general team formation rule we deduce from these findings is: *Team creativity is fostered when team members have low scores on conscientiousness, while showing highly differentiated scores on knowledge of the project topics.*

This rule is translated into the team formation equation for creative teams (2). It reaches a maximum when team members have a maximum difference in knowledge between their best score and their second-best score over their own topic scores, and when there is a maximum difference in knowledge between the best score and the second best score on a topic. It minimises the average conscientiousness score in the team.

$$FitC_i = W_K * \frac{\sum_j DifK_j}{TeamSize * Max_K} + W_E * \frac{\sum_t DifK_t}{NumTop * Max_K} + W_C * \frac{Max_C - Avg_C_i}{Max_C} \quad (3)$$

Explanation of the terms used in (3): *FitC_i*: Fitness of a team *i* for creative outcomes; *DifK_j*: difference between the highest and next highest topic knowledge score of member *j*; *TeamSize*: Number of team members; *DifK_t*: Difference between the highest and next highest knowledge score on topic *t*; *NumTop*: Number of topics; *W_K*, *W_E*, *W_C*: Weights

C. Teams fit for facilitating learning

For the formation of teams in which learning is facilitated, we considered that:

- a) Learning is fostered when team members provide a complementary fit in knowledge backgrounds and show a supplementary fit in personalities [16];
- b) Mutual teaching and learning are among the most important activities in defining and solving problems [14];

c) There is a maximum distance in knowledge (the zone of proximal development, or ‘zpd’) that can be bridged when learning with more capable peers [17].

From these findings we deduce as general team formation rule: *Learning in a team is fostered when knowledge on the project topics is distributed over the members (allowing each member to learn and teach), that differences in the levels of topic knowledge should not be too high, and that the members’ conscientiousness scores should all be high.*

This rule is translated into the team formation equation for learning teams (3). It reaches a maximum for teams whose members can teach and learn to and from each other inside each topic, while having a high score on Conscientiousness. It optimizes the match between possible teachers and learners in the team by using Vygotsky’s “zone of proximal development” (*zpd*) to calculate teaching and learning effectiveness.

$$FitL_i = W_K * \frac{\sum_t \sum_l \sum_j |score_{t,j} - score_{t,l}|}{d_{jt} \cdot zpd \cdot n \cdot k} + W_C * \frac{Avg_C_i}{Max_C} \quad (2)$$

Explanation of the terms used in (2): *FitL_i*: Fitness of a team *i* for learning outcomes; *score_{t,j}*: Score on topic *t* of member *j*; *score_{t,l}*: Score on topic *t* of member *l*; *d_{jt}*: Number of team members with a different score on topic *t* for student *j*; *zpd*: Zone of proximal development; *n*: Number of team members, *k*: number of topics; *W_K*, *W_C*: Weights.

These equations were deployed on a set of test data. The results of this experiment are presented in Section IV.

IV. RESULTS OF THE APPLICATION OF THE TEAM FORMATION EQUATIONS ON A SET OF TEST DATA

For the experiment, due to space limitations in this article, we used only a small set of test data (See Table 1). In the data set, the possible score for a learner on a topic (Topic 1 through Topic 3) ranges from 1 to 10. The knowledge scores are of the type ratio. The conscientiousness scores (Cons) range from 1 to 5. Following common practise, the conscientiousness scores are treated as type interval, even though they do relate back to the Likert scales with which the underlying personality characteristics were measured.

For each possible team, the team fitness values *FitP*, *FitC* and *FitL* are represented with a value between “0” and “1”, with “1” indicating the highest possible fitness for that outcome. This allows comparing teams with respect to fitness over their different target outcomes. If a learner or other project initiator wishes to do so, weights can be used to prioritise the importance of e.g., knowledge over conscientiousness in the team formation process. However, in the equations below all weights sum up to 1, with weights set to 1 / the number of weights used in the equation. Other weight distributions are currently not considered. For this experiment, the team size was set to 4 learners per team, and the number of topics in the project was set to 3.

TABLE I. THE TEST DATA SET.

Learner	Topic 1	Topic 2	Topic 3	Cons
L01	9	3	2	3
L02	4	8	3	2
L03	3	2	9	3
L04	6	10	8	4
L05	6	7	5	2
L06	9	8	6	4

When the equations above are applied to the test data set, all 15 unique combinations of 4 learners are calculated for their fit values. The number of unique combinations is calculated with $[n! / ((n - team_size)! * team_size!)]$, where n is the total number of learners in the data set and $team_size$ is the desired number of learners in a team.

The output in Table II lists all 15 possible teams and their scores on FitP, FitC and FitL. The scores in the three columns FitP, FitC and FitL are sorted from high to low. The results are truncated to three decimals.

TABLE II. TEAM FORMATION SUGGESTIONS FOR 15 TEAMS OF 4 LEARNERS, SORTED BY FitP, FitC OR FitL.

Team members	FitP	Team members	FitC	Team members	FitL
L02,L03,L04,L05	0.606	L01,L02,L03,L05	0.358	L02,L04,L05,L06	0.488
L02,L03,L04,L06	0.603	L01,L03,L05,L06	0.358	L02,L03,L04,L05	0.475
L01,L02,L03,L04	0.597	L01,L02,L03,L06	0.342	L03,L04,L05,L06	0.466
L02,L04,L05,L06	0.587	L01,L03,L04,L05	0.325	L01,L02,L04,L05	0.437
L01,L02,L04,L05	0.581	L02,L03,L05,L06	0.325	L02,L03,L04,L06	0.436
L01,L02,L04,L06	0.578	L01,L02,L03,L04	0.308	L01,L03,L04,L05	0.429
L03,L04,L05,L06	0.563	L01,L02,L04,L05	0.300	L01,L04,L05,L06	0.427
L01,L03,L04,L05	0.556	L01,L03,L04,L06	0.300	L01,L02,L03,L04	0.402
L01,L03,L04,L06	0.553	L01,L02,L05,L06	0.300	L01,L02,L04,L06	0.383
L01,L04,L05,L06	0.538	L03,L04,L05,L06	0.283	L01,L03,L04,L06	0.362
L02,L03,L05,L06	0.503	L01,L04,L05,L06	0.283	L02,L03,L05,L06	0.337
L01,L02,L03,L05	0.497	L01,L02,L04,L06	0.275	L01,L02,L03,L05	0.324
L01,L02,L03,L06	0.494	L02,L03,L04,L06	0.275	L01,L02,L05,L06	0.299
L01,L02,L05,L06	0.478	L02,L04,L05,L06	0.258	L01,L02,L03,L06	0.279
L01,L03,L05,L06	0.453	L02,L03,L04,L05	0.242	L01,L03,L05,L06	0.274

The highest scoring teams for FitP, FitC and FitL show fitness scores of 0.606, 0.358 and 0.488 respectively. This indicates that a team of 4 (consisting of learners L02, L04, L05, and L06), created from the set of learners best fits the outcome *increased productivity*, but still only with a value of 0.606. The best possible creative team from the set of learners would only receive a FitC value of 0.358, indicating a low probability of successfully achieving the outcome *creative problem solving* for that team. The best possible

combination of learners for *facilitating learning* outcomes (a team with learners L02, L04, L05, and L06) scores a FitL of 0.488, which indicates the members can only enjoy approximately half of the maximum learner and teaching effectiveness possible.

When the results are sorted on FitP, the highest scoring team on FitC is found on position 12. The highest scoring team on FitL is found on position 4. When sorted on FitC, the results show the highest scoring team on FitP is found on position 15, while the highest scoring team on FitL is found on position 14. Sorting on FitL reveals that the highest scoring team on FitC is to be found on position 12, while the highest scoring team on FitP is to be found on position 2.

The calculations' results show how the three equations, through their different handling of learner knowledge and conscientiousness, produce teams of different compositions. The results reveal the best team for a particular outcome, but also how well a particular team fits to any of the outcomes.

V. CONCLUSIONS AND FUTURE WORK

Our take on learning in the cloud is that cloud-based learners are not necessarily provided, nor can easily provide themselves, with effective, bond-creating and motivating learning settings. We argued that providing these learners with the possibility to start project-based activities affords motivating collaboration opportunities [2] [3]. We therefore suggested a design for setting up project-based learning and team formation services in the domain the learners are interested in, based on our team formation model [4]. The design puts learners in control over the process of defining and staffing projects, thus honouring these learner's self-directing and self-organising behaviour, while at the same time being firmly rooted in team formation theory. The design uses the data categories 'knowledge', 'personality', and 'preferences' from the team formation model and describes the ways in which the data can be gathered and processed to arrive at team formations suggestions. A benefit of the design is that it is also based on personality characteristics, which is rarely the case in existing tools, but which – according to literature [8] – are highly relevant in the team formation process.

In order to determine how learners should be teamed up based on knowledge and personality, we analysed existing research on team formation principles and team outcome criteria. From the team formation principles and outcomes we deduced three general team formation rules for forming productive, creative, or learning teams. These rules were formalised in team formation equations. The application of the equations to a set of test data demonstrated their ability to form teams and to suggest different teams based on the desired team work outcomes. It also showed the ability of the equations to determine for which of the three outcomes a team would be most suited.

We acknowledge that knowledge might also be contained in other forms of evidence currently not taken into account. There might also be personality aspects besides the ones underlying the personality construct 'Conscientiousness'

that are important predictors of a learner's success in project work or that facilitate learning and working collaboratively. The current equation for the formation of creative teams favours low conscientiousness scores for all learners, based on [12] [13]. We do, however, plan to compare the current choice with other distribution methods.

Our work for the immediate future focusses on a large scale experiment with the team formation service, using real data on knowledge from learner self-assessments and real data from learners on personality and preferences.

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