Group Formation in eLearning-enabled Online Social Networks

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***Abstract*—eLearning systems have been in use for a decade to manage content and collaboration. Still the major online source for coursework are open media like Wikipedia, while students' collaborative online activities are focused on online social networks (OSNs) and remain unrelated to learning. In this paper, we report on work-in-progress for socializing online learning. Our work is motivated by exploring the realm of group-centered online collaboration with task-based learning in the net. We address the problem of finding the proper people in an OSN, and present an automated approach for learning-oriented group forming. This serves as a primary building block for online social eLearning networks.**

***Index Terms*—Online social networks; teambuilding; adaptive educational hypermedia; computer-supported collaborative learning**

I. Introduction

Online Social Networks (OSN) stimulate their users to socialize with friends and communicate to each other. Discussions in groups are user-triggered and do not need a moderator or facilitator. OSNs enjoy an overwhelming popularity among students.

eLearning Content Management Systems (LCMS) allow physically distributed users to access structured content and to collaborate via inter-group communication on learning topics. Modern LCM-systems organize content in eLearning objects that interrelate to form an instructional or semantic network [1]. Usually they are bound to an instructor who creates groups, analyzes course results, and tracks learning progress. The use of LCMSs is commonly limited to dedicated courses or schools.

Our work tries to open the learning process and the building of learning groups to become part of social Internet eco system. We concentrate on integrating an OSN with an LCMS, thereby removing its dependency on an instructor. Such an eLearning-enabled OSN allows users to self-pace learning in topics of personal interest and teams of personal choice. The removal of an instructor in eLearning scenarios leads to the following challenges in designing the OSN [2]:

1) How to simulate a team building process that is effective for learners?
2) How to provide access to the relevant content for a learning group?
3) How to facilitate a consistent learning progress, include feedback and corrective actions?

This paper addresses the first question. Learning in groups creates motivation for a user through the ability to compare to each other, provided the group is well formed. There are many possible factors that can influence the quality of a learning group. Often criteria like knowledge and learning style are taken into account, but via an OSN it is also possible to account for social relationships between the users when building groups. In this context, possible metrics are the weights of the edges between two users for indicating former collaboration [3], or creating a representation of trust between users [4]. In our approach, we concentrate on user's availability, knowledge, learning style and the group density in the social network when forming a group for collaborative learning.

To access the problem of group formation more easily , our approach is divided in two parts. First we browse the social network and try to find a minimal number of suitable candidates for the formation of a group, which an initiator shaped on a chosen topic. Based on the candidates, the second part tries to optimize candidate constellation for a successful group learning experience. Both steps are grounded on metrics that are calculated from user configuration and statistics in the underlying online social network.

The remainder of the paper is organized as follows. The following Section II introduces related work. In Section III, we give a short overview of the approach to our eLearning-enabled OSN. Based on the Idea of our eLearning environment, we discuss our group formation approach including the used user model, the candidate selection process and the group formation phase in Section IV. The following evaluation in Section V is based on a synthetic test network and aims at quantifying the efficiency of our approach. Finally, the paper ends with a conclusion and an outlook on our future research.

II. Related Work

Group formation in the context of eLearning is a well studied field. Most approaches concentrate on forming groups for a classical learning model of a classroom, including a small set of students, and an instructor. In this context, the approach of Ounas et al. [5], [6] gained popularity. Authors stress the group formation problem as an constraint-satisfying task that is solved by anthologies and given rules, which define the desired group constellation.

As we focus on OSNs, we are interested in the social aspects of online learning. Vassileva [4] researches future trends of eLearning. She concentrates on the needs of digital natives, and derives two implications for the design of social learning environments. First, social learning environments attain a learner-centric nature, and should hide system decisions and adoptions to the user to maintain the impression of self-control. The requirements described in this context correspond to our problems of automation after removing instructors from the eLearning environment. Vassileva stresses the problem of how to find the right content for a user and how to find people, the user can collaborate with. The second implication that was derived for the design of social learning software is that learning should be more gratifying. This point will be considered in our future work.

Halimi et al [7] introduce solearn, a social learning network. Based on social relations and activities, it provides intelligent recommendations for the best collaborators, tutors or learning tool but no group formation approach is introduced.

Arndt and Guercio [8] introduce a group formation process, which creates groups from of a social network of classroom members. The goal of this approach is to assign each member to a group. The minimum group size is defined by an instructor. In the group formation process, the position of a classroom member is regarded. In the first phase of the algorithm, all cliques in the graph with higher membership than the minimum group size are selected as groups. Thereafter the k-connected components are selected. Remaining vertices in the graph are assigned to one group. The overall goal of the approach is to achieve a personalized and shared ubiquitous eLearning experience.

Another relevant group formation approach is introduced with the goal of building expert teams in a professional context. Dorn et al. [3] try to build expert teams based on the skill of the users, and their relation within the social network. The edges, which indicate former interaction, take an important in role in this scheme. Authors also introduce a recommendation mechanism which serves the purpose of routing to another expert, if the desired one is not available. This paper proofs that multi-objective team composition is NP-complete. Thus Dorn et al. introduce heuristic optimizations to solve the problem of finding the best team configuration. The group formation approach in total is divided into three main parts: network establishment, candidate selection and heuristic optimization. We adopt this strategy to our model.

Looking at the group formation problem in social networks at large, the field of searching social networks becomes relevant. Zhang and Ackermann [9] compare several algorithms for social network search in the context of finding an expert with a vector of required skills. To evaluate the algorithms, they generate a test network from an e-mail data set, where the vertices are generated based on keywords spotted in the mails, and edges represent email exchange between vertices. Besides the computational costs of this algorithms, authors also measured the social impact. They found that social network search algorithms, which take the degree of a vertex into account, perform better by finding one expert in the social network.

III. eLEARNING-ENABLED OSN

In this section we want to introduce a first approach of our eLearning-enabled Online Social Network. An early concept is presented in Roreger and Schmidt [2], which covers a component-driven view. Here we want to present the data model in use. To concentrate on eLearning-related problems, a commercial OSN will be extended incrementally by the eLearning features we need. This can be achieved by using available APIs. All communication-related features like chat or group discussions will be handled by the commercial OSN.

Social Networks are formalized by graphs, where edges can be directed or undirected indicating asymmetric or symmetric relations between vertices that represent individuals. Our eLearning-enabled OSN is modelled by an undirected graph with different types of vertices. Because of the user-centric nature of our OSN, the key vertex type is the user object. It extends the given profile of the commercial OSN by including an availability flag of a user, and by encoding the knowledge and learning style. The motivation of a user to start or join to work on a collaborative task is modelled by the availability flag, which is true, when the user is motivated, or false if busy. This flag can be set manually, or the system can automatically detect availability based on other topics a user works on or other metrics based on user activity. Besides a motivation to join a group, the user's learning style is also present. We use the Felder and Silverman Theory as its representation [10], which is broadly accepted for representing learning style in engineering education. A key feature of this theory is that it does not try to force a user into one specific category of leaning, but only assigns a preference of a learner in four defined dimensions:

- Active or Reflective (Processing)
- Visual or Verbal (Input)
- Sensing or Intuitive (Perception)
- Sequential or Global (Understanding)

In each of these dimensions, the user can have three different strengths, i.e., fairly well balanced, moderate preference and a very strong preference. The goal is to determine the learning style of a user automatically. Different approaches are discussed in Roreger and Schmidt[2]. To represent the knowledge of a user, we use tags. Each tag, which is assigned to a user, is augmented by an activity index. This index, evaluated as normalized exponential averages, indicates the relevance of a learner in the field of the tag. To match a topic with possible group members, each topic has a tag vector with weights that encode the relative relevance.

Another vertex type is the topic object. It describes a task or a field of work. Edited and managed by a user, it also includes a definition of the desired knowledge and a number of required collaborators. To simplify the search of relevant

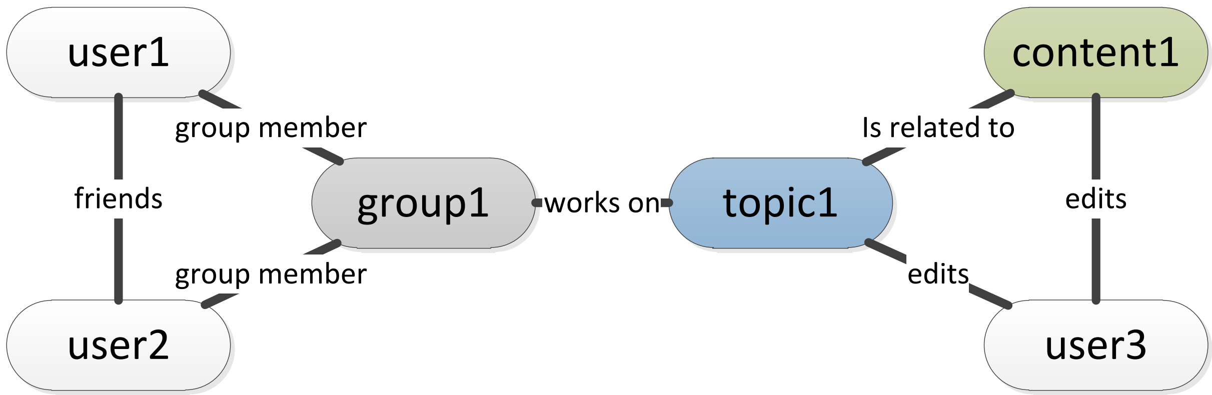

Fig. 1. Examplenetwork

content for a topic, the topic vertex can be connected with a content object. These objects can represent any kind of content that is managed by the same user. To associate users with a topic they are working on, a group object is needed. If a group is created, all members subscribed to the chosen topic connect to the group objects. Figure 1 shows an example network.

This unified approach, cf. [11], adds many implicit relations to the network. In a classical social network, where only one type of vertices can be connected, it is only possible to traverse the network by the direct relations between users. In the presented approach, users may be connected via relations with other object types like topics or content. So it is possible to find users who have many common objects they are related to, but no personal interconnect.

IV. Group Formation

Grounded on our model of an eLearning-enabled Online Social Network, we present our group formation approach in this section. To start group formation, a user decides to initiate collaborative work on a topic. Initially, topics are user-defined, but can be selected later. The system starts searching for candidates and suggest different group constellations. Now the initiator selects a preferred group invites all group members. If all members agree to work in this group, they can immediately begin collaboration on the topic. After the task is finished, the group is closed.

A. User Model

The central entity in our group formation approach is the user object. The user model introduced in the last section is now detailed out with measures for determining the distance between two nodes or a node and a given topic.

To formalize the availability of a user, we use the function $A(a)$ which return $true$, if user a is available, or $false$ if not. The learning style is represented as a vector $L(a)$ with an entry for each dimension of the Felder and Silverman Theory. Possible values are 1, 0 and -1 indicating a positive or negative or neutral characteristic in each category. The learning style distance D_L between two users is evaluated by summing up the pairwise differences of its components. The distance is normalized by the maximum possible distance. In the case of a maximal distance of 2 in one dimension $(1-(-1))$ the total maximum distance of all four dimensions is 8.

$$D_L(a,b) = \frac{\sum_{i=0}^{4} |L_i(a) - L_i(b)|}{8} \tag{1}$$

Our knowledge model is build on tags, which are assigned to a chosen topic and each user. A topic holds a list of tags and a vector which represents the weights of each tag for the topic. The weights are normalized to form a probability distribution.

In our approach, each user has a list of tags t, which he / she acquires by working on topics. Tags are arranged in a weighted vector w, which assigns each tag an activity index. These indexes represent the relevance of a user per tag and is accumulated during the history in the system as a normalized exponential average. To calculate the knowledge rank D_K between a topic and a user, the first step is to match the tags, if they fit, the knowledge rank is 0. If the tags match, the scalar product of the weighted vector of the topic t and the activity vector of a user w is calculated. This value indicates, how a user correlates to the required knowledge of a certain topic.

The total distance D between an initiating node a and a chosen topic t with a possible candidate b is calculated as the weighted sum of these two parts.

$$D(a,b,t,w) = (1 - D_K(b,t,w)) * w_K + D_L(a,b) * w_L \tag{2}$$

w_K and w_L make it possible to adjust the weight of the knowledge rank or learning style.

B. Candidate Selection

The first step of our group formation approach is the candidate selection. Its task is to extract possible group members from the underlying social network. To reduce the complexity of group formation, it is necessary to select a small set of well suiting user-nodes. Starting at the initiator user, the network is searched for nodes with a common learning style and knowledge base as the initiator node. Graph traversal techniques as breath or depth first search are not satisfactory in performance in real sized OSNs as Facebook [1] or Google+ [2] with hundreds of million users.

The choice of the search algorithm is essential for the group forming process. Because several algorithms optimized to social networks try to find special nodes, the group distance in the social network is here relevant.

To reduce the complexity of the candidates selection, it can be parametrized with the maximal number of candidates and a threshold, which determines whether a node is added to the candidate set. These parameters determine the quality of the result. If the threshold is high, the candidates are near to the initiator, but have a high distance in the sense of learning style and knowledge. When the threshold is low, the search algorithm will select nodes that have a higher distance in the social network, but are closer in the sense of learning style and knowledge. By choosing a low threshold the performance needs consideration.

The position of a user-node is not used in the candidate selection, because in this phase of the algorithm, the candidates are a loose set and no statements can be made who is a group member. So it remains unclear how the group density will be. Although the initiator cannot be the center of the group, this means, that he could be the least connected part of the group.

To select the best-suiting search algorithm it is necessary to take the overall requirements into account. By considering the density of group members in the social network, a team with experts in their topic at an equal learning style, but with a low density in the network does not satisfy the requirements. Also this team configuration would have high computational cost. Three different search algorithms are selected based on the evaluation of Zhang and Ackerman [9] and assumptions concerning the distance of the searched nodes in the social network.

a) Breath First Search: Breath First Search (BFS) is a classic way to traverse a graph. Starting from the initiator node, BFS would probably find the nearest candidates, because it traverses the social network with an increasing distance.

b) Random Walk: Random Walks (RW), introduced by Adamic and Adar[12], traverse the social network by random paths. Contrary to BFS Random Walk's distance to the initiator node increases very fast. This could lead to candidates who have a high distance to the initiator node. This phenomenon can be reduced by restarts.

[1] www.facebook.com

[2] plus.google.com

c) Best Connected Search: Best Connected Search (BCS) performs well at networks with a power-law distribution of nodal degrees. The strategy is to select nodes by the number of neighbors [13].

C. Group Formation

When a set of candidates is selected, the next step is to find a group constellation, which is recommendable to the initiator. We define a well-suiting learning group as a set of members that provide

- a common learning style
- a high score in the knowledge ranking
- a low distance in the social network

To achieve these goals, we generate a set of tuples x with all combinations of group members. Using these set, we can use the function G_{DL} to measure the average distance of all group members in learning style.

$$G_{DL}(x,t) = \frac{1}{n}\sum_{i=1}^{n} D_L(x_i(1), x_i(2), t) \qquad (3)$$

The task of the group formation process is to find a group with a small value for G_{DL}.

The second constraint of a high knowledge score is evaluated by G_{DK}.

$$G_{DK}(x,t,w) = \frac{1}{n}\sum_{x} D_K(x,t,w) \qquad (4)$$

To evaluate the group density the function $spl(x, y)$ is needed, which returns the length of the shortest path between the node x and y. With this function the group density is calculated like the group distance.

$$G_{DE} = \frac{1}{n}\sum_{i=1}^{n} \frac{spl(x_i(1), x_i(2))}{diameter} \qquad (5)$$

Using the defined functions, it is possible to evaluate a rank of a possible group constellation.

$$G_{Fit} = G_{DK} + (1 - G_{DL}) + (1 - G_{DE}) \qquad (6)$$

Focusing on computational cost, ranking all possible group constellation with G_{Fit} works fine for a small number of candidates. If the number increases, many constellation have to been ranked. To handle this scalability problem, we use Genetic Algorithms. Here a set of team configurations is represented as a population of chromosomes. Each chromosome is a group with users represented as genes. In each generation crossover and mutation operations are performed on the population. A crossover population splits two chromosomes and exchanges the parts. A mutation exchanges only one gene in the chromosome with another. Applying it to our approach a other user is selected from the candidate set. When the operation are finished, the fitness of all chromosomes is evaluated and the best are selected for the next generation.

After sufficient generations have been run, the best group constellations are recommended to the user, who can now send invitations for joining the group to the selected candidates.

V. Evaluation

As a pre-study to final implementation of our OSN, we have performed an evaluation of our group formation approach on synthetic data. This implies the problem of proper test data. There are several models for the generation of social networks with real world features. But there is a leak of data how our user specific data is distributed over the user profiles. The section begins with an introduction to the creation of our test data and continues with the impact of difference search algorithms. At the end the group formation as hole is evaluated.

A. Generating a social network

We build the base structure of the social network by using the Forest Fire Model [14] as proposed by Leskovec et al. This model reflects the characteristic features of a network and is popular in the literature, because it creates networks, which are similar to real measurements [15]. Besides the social network characteristics like heavy-tailed in and out degree and communities, the forest fire model also covers temporal dynamics like densification power law and shrinking diameter. For our evaluation, we generate a graph with 1000 vertices and 31522 edges. In this test network, only user vertices are created, which eases the evaluation of the group formation process, but does not show the effects of the unified approach of our eLearning-enabled OSN.

The next step for generating a test network is the assignment of user data. The easiest way of achieving this would be a randomly distribution of values to each node. But this could lead to a test network, which has no realistic characteristics. This is indicated by findings of Derntl1 and Graf [16]. They start from a blog as a learning diary to a course and try to find correlations between the blogging behaviour and the learning style of the students. By comparing the blogging behaviour and the active reflective dimension, they found a correlation to the number of blog posts. Active learners tend to write more blog posts than reflective. On the other hand, reflective learners read more posts than active. In addition active learners tend to follow the chart of rated blog posts because of their social orientation. These findings indicate a probability of a correlation between the degree of a user in the social network and the value in the active resp. reflective dimension of the learning style. Due to lack of empirical data, we will focus on this challenge in future research.

Another problem in assigning learning styles is to choose the distribution of dimension values. Felder and Spurlin [17] summarize the result of different studies and an average distribution can be used to assign the dimension values. Figure 2 shows the distribution of learning style assign to the vertices in our evaluation network.

We rely on knowledge tags. An assignment of this novel feature cannot be grounded on empirical data like the learning style distribution. For our test network, we randomly assign to each user one to ten out of 20 tags with an activity index between zero and one. As it was observed that tags generally follow a power law [18], we configure the probability of assigning tags respectively.

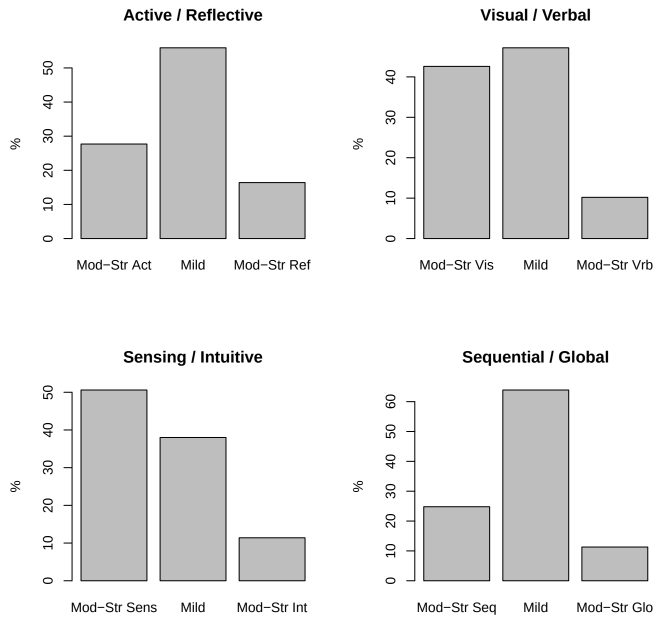

Fig. 2. Distribution of learning style in test network, based on average from [17]

B. User Model

To start the evaluation, we use the basic distance functions of the user model for measuring the density of the resulting values. In our test network, the density of distance in learning style is driven by the distribution of the dimension values. By assigning the learning style values corresponding to the referenced study, the learning style distance shown in Figure 2 approaches a normal distribution of mean ≈ 3.5. As a consequence of the initial learning style distribution, the average distance between two users is very low. Still there is a number of users with the same learning style.

To evaluate our knowledge rank, we generate 100 sample tag sets with weights and calculate the rank between the set and all vertices. The results are shown in Figure 4 and indicate that finding users with a high knowledge correlation may be very difficult.

C. Candidate Selection

Our candidate selection is evaluated by focusing on two aspects. First to identify which search algorithm selects the best candidates for each group function, and second to learn how much nodes are visited while selecting the given number of candidates.

Figure 5 shows the result of this evaluation. The group density function shows the largest differences between the search algorithms. Breadth First Search and Best Connected Search perform well in this case, as was expected from the discussion in Section IV-B. Random Walks admits only less

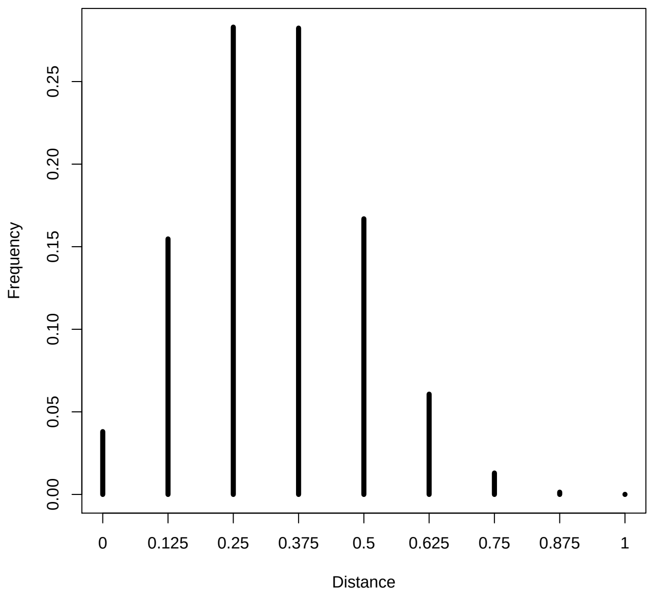

Fig. 3. Distance distribution in learning styles calculated over all vertex combinations

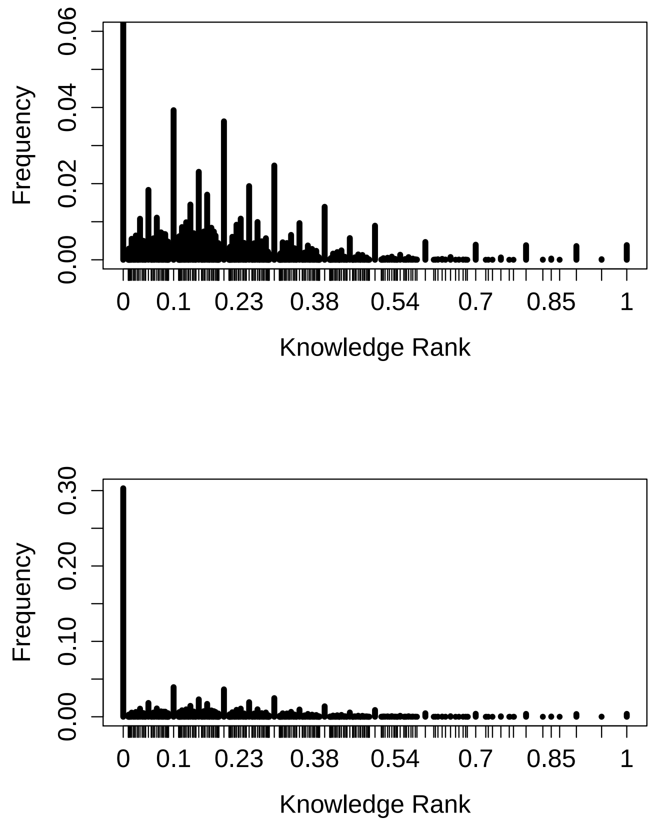

Fig. 4. Distribution of distances in knowledge - the upper graph displays a detail

than half of the group density in average. The comparison for the case of group learning style shows the same rank as for the group density.

The group knowledge function shows an nearly even result for all three search algorithms. Only BFS has a little lower performance. These high and nearly equal distances in knowledge are caused by the distribution of knowledge.

The second part of our evaluation of the candidate selection concentrates on measuring the visited nodes while finding candidates. Results are displayed in figure 6. Here Best Connected Search (BCS) and Breath First Search (BFS) converge at a threshold at 0.9, while Random Walk Search performs better at lower thresholds, it does not approach the performance of the other search strategies.

D. Group Formation

In the final evaluation of the group formation progress, we try to answer two questions: (i) How do optimal group selection functions differ from heuristics? (ii) How is the correlation between the number of potential candidates and actual group sizes. We analyse these questions with the help of the 'fitness' metric from the field of Genetic Algorithms. In our setting, a high fitness value indicates that the group formation process led to a well-formed group.

For this purpose, we chose a scenario with the goal to find a group of four users. For the candidate selection, we used Breath First Search with a threshold of 0.8 corresponding to the results of the previous section. As candidate count we chose a sequence from 8 to 40. Figure 7 visualizes the fitness of a group obtained from a genetic algorithm based on a candidate set. These results show an overall successful group

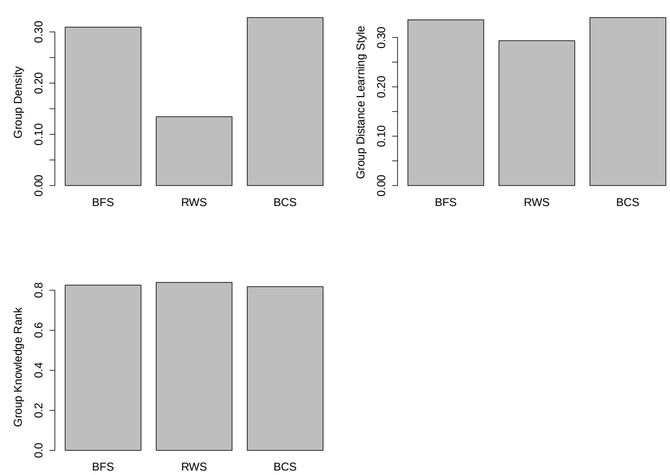

Fig. 5. Search algorithms compared by group functions

formation of satisfying quality. Still there is a flaw around 20 candidates, even though the difference between the values is small. However, there is a remarkable low dependence on the preselected candidate set, which indicates that the quality

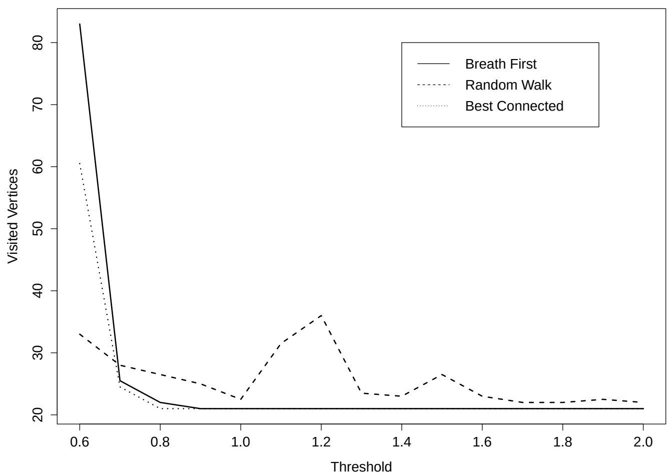

Fig. 6. Search Algorithms compared by on average visited vertices

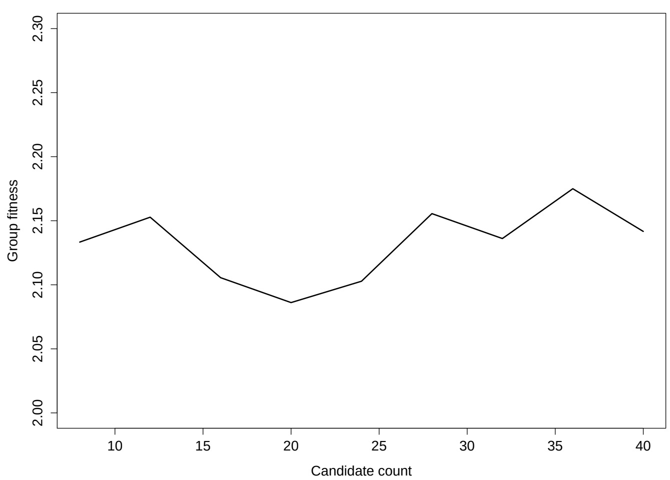

Fig. 7. Group fitness of best group by candidate count

of the group formation is fairly independent of this initial selection. Based on this evaluation it can be concluded that the candidate count may be chosen as a small value without significant influence on the group fitness.

VI. Conclusion and Outlook

This paper introduces a central building block on the path to eLearning-enhanced social networking. We discussed the central research questions in this field, and focused on the problem of group formation within a knowledge-aware social network.

We presented a multi-steo group formation approach for an eLearning-enabled Online Social Network. Based on a unified social network, which includes all functional objects like users, content, groups and topics, a roadmap to searching suitable candidates was derived. A user is selected as a candidate with respect to his learning style, knowledge, and social proximity. To represent the learning style of a user, we employed the theory of Felder & Silvermann. The knowledge and competence of a user was represented by tags with activity weights assigned. To compare the requested knowledge for a given topic with the knowledge provided by a user, we calculated a knowledge rank build on a importance vector of the topic and the activity index vector of a user.

The efficiency to search for suitable candidates in a real-world social network is of vital practical importance. We implement three search strategies, Breath First Search, Random Walk Search and Best Connected Search. Based on the resulting candidate sets, we applied genetic algorithms to find the best group constellations using a group fitness function that includes (i) the distance between the group members in learning style, (ii) the level of knowledge ranks, and (iii) the group density in the social network.

In the corresponding evaluation of automated candidate selections we could show that degree based search strategies perform well when the density of the search vertex is taken into account. Results from brute force best group vs. heuristics are still under way.

In our future work, we will focus on including tie strength [19] in the group formation progress and improve the evaluation by using real test data from online social networks. Also, we intend to improve our current network with empirical evaluations on degree correlations with learning style and tag distribution of users.

The main direction in our future research will address the two remaining research questions posed at the beginning, how to bring relevant content to the learning group, and how to facilitate a consistent learning process. In face of these ambitious goals, we will rely on our previous work on managing eLearning content resources, the hylOs approach [20], [21], [22]. Accompanying empirical studies should reveal the effectiveness and relevance of this still promising direction.

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