XEL Group Learning – A Socio-technical Framework for Self-regulated Learning

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Abstract: We describe XEL-Group Learning, a socio-technical framework for socially oriented e-learning. The aim of the presented framework is to address the lack of holistic pedagogical solutions that take into account motivational theories, socio–technical factors, and cultural elements in social learning networks. The presented framework provides initiatives for collaboration by providing a dynamic psycho-pedagogical recommendation mechanism with validation properties. In this paper, we begin by highlighting the socio-technical concept associated with socially-oriented e-learning. Next, we describe XEL-GL's main mechanisms such as group formation and the semantic matching framework. Moreover, through semantic similarity measurements, we show how cultural elements, such as the learning subject, can enhance the quality of recommendations by allowing for more accurate predictions of friends networks.

1 INTRODUCTION

For many decades, standard formal education has applied strict pedagogical regulations to pressure students to pursue their studies. Such bureaucracy in formal settings limits the development of a growth mindset, i.e. students' belief that they can develop their intellectual abilities through performing challenging tasks (Dobronyi et al., 2019).On the contrary, recent studies have shown that students who maintain confidence that they are up to the challenge of developing their intellectual abilities are those who adopt more successful learning strategies (Dobronyi et al., 2019). In other words, there is a positive correlation between performance and adopting the growth mindset required to pursue effective self-regulated learning (SRL) strategies. Students' lifestyles outside the classroom are now characterized by dynamic social interactions, sharing, creativity, and freedom (McLoughlin and Lee, 2008; Dabbagh and Kitsantas, 2012). Social networks and media now offer a more attractive environment for Collaborative Learning (CL) among students (McLoughlin and Lee, 2008; Dabbagh and Kitsantas, 2012). Therefore, the use of social media among students has significantly increased lately, particularly for coursework and group-related tasks (Dabbagh and Kitsantas, 2012).

In general, students are affected by their daily social habits which include extensive engagement in social media networks. Therefore, designing new models for learning which meet the expectations of digital age student generations, which employ autonomy and methods to facilitate collective learning is paramount (McLoughlin and Lee, 2008).At the borderline between directed and self-directed learning lies the balance between applying democracy in education and validating the quality of the learning process. Since the beginning of this century, there has been a growing consensus that 'student-led' CL, supported by teachers, is the dominant trend (Wheeleret al., 2008).The real challenge, as suggested by McLoughlin and Lee (2008), is to trigger self-direction and learner control, while also offering a valid structure and appropriate support from a network of students, teachers, and experts. Addressing the latter challenge forms the primary motivation of this study. Nevertheless, our problem of interest is considering socially oriented e-learning as a socio-technical system in which the social and technical components evolve in parallel with emergent property of interaction between subsystems (Bednar et al., 2019). This problem has been in rise lately due to the lack of holistic approaches that address both social and technological factors, which also take into

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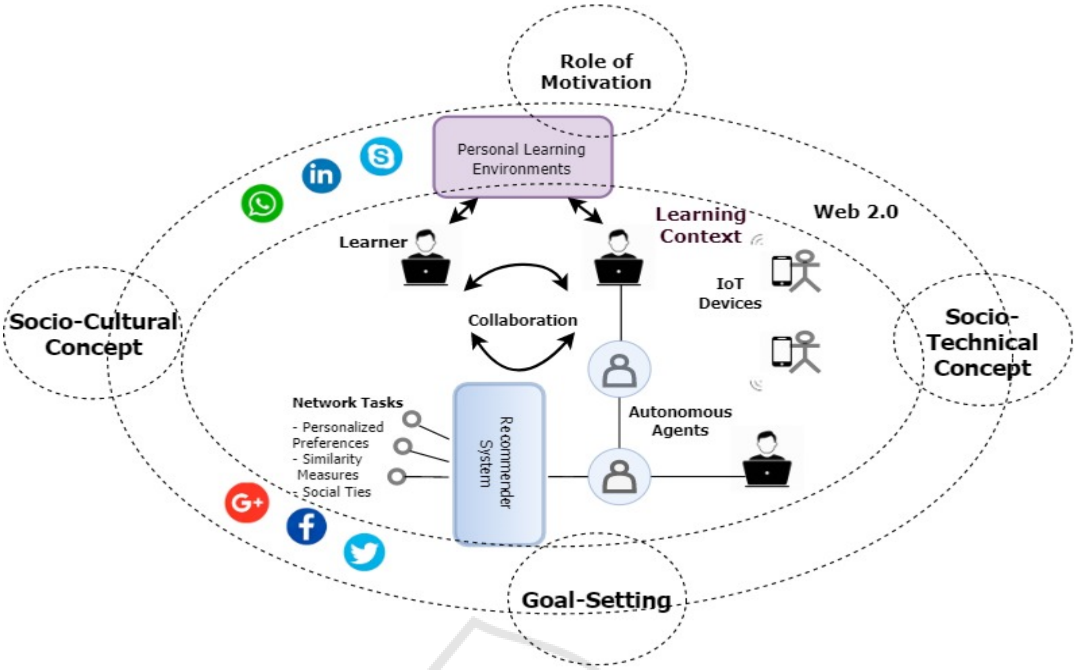

Figure 1: Socio-technical e-learning model based on the industry 5.0 smart working concept.

account motivational theories and cultural elements. The precise research question we address is:

RQ: How could we validate the quality of e-learning given a socio-technical perspective that fosters social, technological, cultural, and motivational elements?

The contribution we put forward is an exercise-based socio-technical framework for group learning called XEL-Group Learning (XEL-GL).We show in the rest of the paper that XEL-GL exhibits the following properties:

1. Collaborative goal-setting with validation and correctness property.
2. A multi-dimensional similarity metrics based on social ties and semantic similarity scores between learning subjects.
3. A dynamic SRL strategy recommender which uses social ties between network users, in addition to semantic similarity between learning topics.
4. An adaptive property by taking into consideration time-related decay factors.

In the following section, we explain the background and rationale behind our design and we review related work. Section 3 describes the main components of XEL-GL framework. Sections 4 and 5 describe the semantic matching process and present analysis results of semantic relatedness between learning topics. Section 5 highlights our future work. Finally, section 6 concludes the paper.

2 BACKGROUND AND RELATED WORK

Validating the quality of the learning process in a socially oriented e-learning environment depends on many factors that include social, cultural, and technological elements. The socio-technical and socio-cultural problems in e-learning have been addressed in much work recently. For example, the values of encouragement and providing support to others are cultural elements which positively influence social interactions and make group activity more constructive (Määttä et al.,2012).On the contrary, online learning in the presence of many digital cultures (such as shopping websites and online games) could have negative effect on student concentration, therefore, educational interventions are used to increase student social engagement with their peers in a CL environment (Tsai,2013). Therefore, the socio-cultural concept combines both social and cultural aspects and analyse the effect cultural elements have on social interactions. On the other hand, socio-technical studies analyse complex logical processes of interaction between social actors and technology and how these processes affect learning activities, such as SRL practices, and learning outcomes. An example of a socio-technical problem is how software tools affect handling cognitive load in CL (Winne et al., 2010).

In general, the approach towards new generation smart systems, known as industry 5.0, is that social and technological systems interrelate in an orchestrated manner to bring about technological sustainability, i.e. continuous innovation, and human development (Bednar and Welch, 2019). In other words, the system of interest, as stated by Bednar and Welch (2019), is one with an emergent property of interaction between subsystems. But this also enforces complexities when designing smart socio-technical systems that are highly autonomous, which also comprise a socio-cultural perspective. Drawing on the 'smart working' concept (Bednar and Welch, 2019), figure 1 above illustrates our model of interest; a socio-technical e-learning model in which subsystems ideally span technological, cultural, social, and motivational elements.

2.1 Related Work

Learners join Social Learning Networks (SLN) to perform a wide variety of collaborative activities, part of which is query-answering. Query-answering provides motivation for students to join SLN wherein students seek informal learning practices, and they may also follow strategic behaviours to build social ties in order to solve assignments and coursework questions. In the socio-technical part of CL, an emerging field of work is psycho-pedagogical recommendation mechanisms. Psycho-Pedagogical Recommenders (PPR) are known to be based on relevant theoretical models unlike collaborative filtering recommenders which need large communities to extract similarity measures (Lachmann and Kiefel, 2012; Möditscher et al., 2011). Moreover, PPR rely on personalized preferences such as personal profiles, individual skills, personal study habits, and preferences that relate to tutoring methods. Thus, PPR approaches are more flexible to matching a wider variety of learners' interests. An example of recent works in PPR models is the work of Freed et al. (2017) which presents a recommender system, called PERLS which provides content recommendation for SRL.PERLS classifies learning goals based on the topics of interest. In other words, goals vary from one topic to another. Recommendations are based on the personalized preferences that relate to learners'

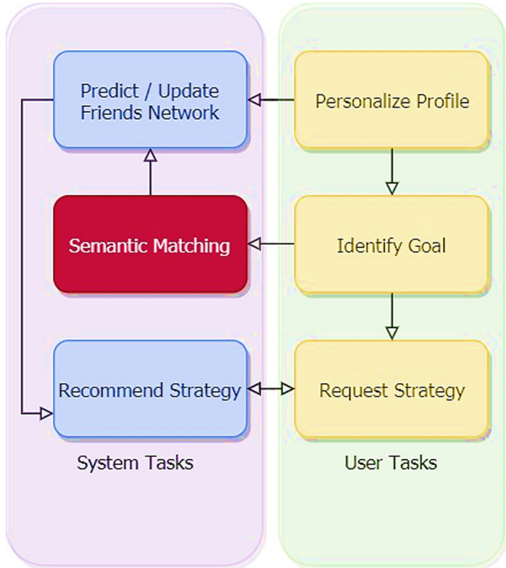

Figure 2: Main activities in XEL-GL Learning Framework.

direct and indirect interests. Evidence of direct interest comes directly form the learner and is demonstrated by the learner's self-efficacy to perform topic-related tasks. Moreover, topics are hierarchically structured and indirect interest is evidenced by the relation between current learning topics and their parent or child topics. Unfortunately, PERLS is not a CL framework but it only targets assisting individual learners.

Nussbaumer et al. (2012) present an ontology-based recommendation system which stores SRL entities in widgets. SRL entities represent different SRL activities such as goal-setting, note taking, etc., widgets are then used to recommend SRL activities that best match learners' preferences. A shortcoming of their approach is that most of the tasks need to be executed manually, for example, tutors need to create specific PLE (Personal Learning Environment's) templates and then learners use these templates to search for the specific widgets that match their preferences.

3 XEL – GROUP LEARNING FRAMEWORK

XEL – Group Learning is a query-answering socio-technical learning framework that offers a holistic approach to collaborative e-learning. As shown in figure 2, the XEL-GL system performs three main tasks, 1.predicting friends networks based on social ties.2.semantic matching of learning topics.3.Recommending SRL strategies in the form of answers to goal-based queries issued by learners.

In our context, goals are conceptually and syntactically specific, as shown in table 1 below. We take the SMART (Specific, Measurable, Achievable, Relevant, Timely) goal criteria as our reference for the goal-setting activity in the learning community. A goal consists of a target tag and a topic. Target tags are syntactically specific, i.e. limited to a single word, while the topic represents the concept to which the target is bound. Contrary to target tags, learners have the freedom to write their concept/topic in a free sentence form. Semantic relatedness between topics contributes to updating the learner's friend's network as we will describe later. Upon joining the network, learners identify their topics of interest, and they can issue their goals in the form of a query that encapsulates a topic and a target tag. The SRL recommender uses query tuples to provide the most relevant resource from those in the friends' network, particularly it gathers recommendations from users who have the strongest ties and with highly similar profiles. Queries/Goals are identified as in definition 1 below:

Definition 1: A Query is the tuple(G, T), where G is the finite set of pre-identified target tags, and T is the finite set of topics. A query q_i is identified by the pair (g, t), where g is the tag associated with topic t.

In our example, the finite set of tags is G:{ MEMORIZE, ANALYZE, ANNOTATE, SOLVE, SUMMARIZE}.

The answer to any query is a SRL recommendation in the form of a strategic exercise. Nevertheless, as in learners' queries, a similar target tag is assigned to each exercise. Therefore, a tutor creates an exercise and assigns any tag $g \in G$ but in this case it refers to the exercise topic, i.e the topic in this case represents the title of the strategic exercise. Note that while it is most likely that the target assigned to any random answer will match a number of learners' queries, the semantic relatedness between a query's topic and an exercise title is the key to measuring the semantic similarity between a query and its answer. For instance, the first row in table 1 and the adjacent row in table 2 will score a high semantic relatedness score as we will show later, however, the target tags of both rows are different. In table 1, row 1, the learner's goal is 'MEMORIZE', and for the adjacent exercise in table 2, the target is 'SUMMARIZE'. Indeed, in our framework, the tutor's target is dominant and the learner's goal is corrected. In other words, the system exhibits a correctness property with respect to goals, and in the next iteration the recommender will automatically update the learner's target tag with respect to the associated topic. It should be noted that the recommendation (answer to learners query) does not necessarily come directly from tutors/experts, but rather they may come from other learners who are closest in the query issuer's friends network. This enriches the object relational-model in our framework and enhances the capability of providing more accurate predictions.

Table 1: Samples of queries issued by learners.

Goal	Learning Topic
MEMORIZE	Mexican-American War.
ANALYZE	Origin, composition and internal structure of the earth.
ANNOTATE	Use of Weapons in Ancient Civilizations.
SOLVE	Deductive reasoning.
REVISE	Psychology of Music

Table 2: Samples of answers issued by tutors.

Goal	Exercise Title
SUMMARIZE	American Mexican Conflict
ANALYZE	Origin, composition and internal structure of the earth.
ANNOTATE	Use of Weapons in Ancient Civilizations.
SOLVE	Deductive Reasoning.
MEMORIZE	Causes of Thirty Years War

3.1 Group Formation

YouTube and Flickr provide a successful model of user-generated content which eliminates the boundaries between users and creators of contents (Kazienko et al. 2011; Susarla and Tan, 2012). In such social network structure, communities of friends are formed based on shared interests. There are also ties with channels outside the friendship network (friends of friends) (Kazienko et al., 2011;

Susarla and Tan, 2012).YouTube relies on the social contagion phenomenon, which means that people's tastes about choices and actions are affected by others (Kazienko et al., 2011). The strength of ties is identified between different users based on semantics of multi-dimensional relations. There are three kinds of connections: 1.Direct Intentional Relation, 2.Object-based relation with similar roles, and 3.Object-based relation with different role.

In addition, there are many kinds of ties that can occur between users, for example, relations that are based on contact list, shared tags, opinions, etc. Each type of relation represents a relation level. In XEL-GL we use the strength of the relation between user i and user j to identify the basic logic of group formation. In this context, we build on the work of Kazienko et al. (2011). In particular, our interest is that the overall strength of the relation between user i and user j is identified as the quantitative measure of all activities performed by user i towards user j as a fraction of all user i's activities. Therefore, every relation level is indexed, assigned a priority factor to each relation, and an overall strength value of the tie between i and j is concluded as follows: (see Kazienko et al., 2011).

$$S_{ij}^{l} = \frac{\sum_k \alpha_k * S_{ij}^{k}}{\sum_k \alpha_k} \tag{1}$$

Where k is the index of the relation layer, α_k is the priority of layer k, S_{ij}^{k} is the strength of the k^{th}relation from i to j. Strength of linkage aggregates all strengths from all relation levels discovered in the system. Note that values of all strengths for both relations and ties are ∈ [0,1].

This mechanism represents the socio-technical component of XEL-GL and it relies on the fundamental logic of group formation used in social media networks. In the next section, we describe how the cultural element, which in our case is the learning subject, can enhance the accuracy of group formation in SLN.

4 SEMANTIC MATCHING FRAMEWORK

Semantic modelling provides the capability of satisfying information needs of users / social actors by associating terms to concepts. This can be manually or autonomously executed by query-answering techniques. In XEL-GL, semantic matching is autonomously executed by the recommender system. The semantic matching process is the core component of the XEL-GL framework and its purpose is increasing the accuracy of group formation; hence, the accuracy of recommendations is also enhanced. The main task of the semantic matching component is updating the friends' network by adding a topic similarity dimension to the existing ties. In other words, not only those who have a higher probability of interacting are those in the learner's friends network but also participants who have highly similar profiles with respect to topics of interest.

Definition 2: A SLN similarity score is a tuple $\{U, A\}$where U is the set of finite non anonymous users, and a_{ij} ∈ A is the semantic similarity score between $(u_i, u_j) \in U$.

Consider the queries q_i and q_j issued by u_i and $u_j, m_{q_{ij}}$ is the semantic relatedness between q_i and q_j , and the similarity between (u_i, u_j) is :

$$a_{ij} = \sum_n \gamma_n * m_{q_{ij}} \tag{2}$$

Where γ_n is the n^{th} confidence score. Thus, from equations (1) and (2), the final similarity score between u_i and u_j is concluded as follows:

$$F_{u_{ij}} = \omega_{S_{ij}^{l}} * \frac{\sum_k \alpha_k * S_{ij}^{k}}{\sum_k \alpha_k} + \omega_{d_{ij}} * \sum_n \gamma_n * m_{q_{ij}} \tag{3}$$

Where $\omega_{S_{ij}^{l}}$ and $\omega_{a_{ij}}$ are weights assigned to the final value of the strength of tie and the final value of the semantic relatedness respectively, and both weights are ∈ [0,1].

Assuming the best recommendation for learner u_i comes from another learner, let's say u_j, after successfully completing a query-answering transaction between u_i and u_j , the system will have a record of an object-based relation with a similar role between two learners u_i and u_j, and an object-based relation with different roles between learner u_i and the tutor who issued the recommended exercise. In addition, we also have the popularity of the object, and the semantic relatedness that is based on the subject of the exercise topic. The semantic relatedness between two subjects represents the cultural element which enables measuring an estimate of the cultural closeness between u_i and u_j.

4.1 Distributed Net Similarity Metrics

The net similarity metric is based on the assumption that dependencies occur between the value of the strength of tie and the semantic similarity between u_i and u_j. In other words, a drop in the semantic similarity affects the value of the strength of tie between u_i and u_j and the vice versa.In a real-case scenario, a drop in the strength of tie between u_i and u_j could mean that u_j has not been engaging in learning activities , thus , recommendations from user u_j are less trustworthy than when highly engaged. Moreover, maintaining a strong tie with user u_j while the semantic similarity score is dropping could be an indication that u_j is regularly changing the topics of interest, or may even indicate a suspicious behaviour in the network. Therefore, we identify the net value of the semantic similarity between u_i and u_j as follows:

$$a_{ij}^{NET} = a_{ij} + \sum_{t=1}^{t} S_{ij}^{l} \quad (4)$$

Similarly, the net value of the strength of tie between u_i and u_j is:

$$S_{ij}^{NET} = S_{ij}^{l} + \sum_{t=1}^{t} a_{ij} \quad (5)$$

The previous definitions assume strong dependencies between the value of the strength of tie and the semantic similarity score. The net value of the strength of tie is the starting value (strength of tie) plus/minus the estimate of the total change in the position of the semantic similarity with respect to time. From another perspective, the DNSM ties one variable to the prediction of how the other variable could behave with respect to a certain time frame.

5 ANALYSIS OF SEMANTIC MATCHING

For motivation, we analyse the semantic relations between various topics. Samples of the results are illustrated in figure 3 and figure 4. In this example, we compare semantic similarity between topics in two main subjects; History and Geology. We use the WS4J (WordNet Similarity for Java) API to measure semantic similarity/relatedness between topic sentences. WS4J provides a Java API for several published semantic similarity algorithms. WS4J has a number of schemes to calculate semantic relatedness in WordNet. Fundamentally, however, WS4J analyses semantic relations between single words. When comparing sentences, WS4J analyses the semantic relatedness between all two-word combinations in sentences S_1 and S_2, i.e all possible word pairs (W_1, W_2) where $W_1 \in S_1$ and $W_2 \in S_2$.The scheme we use in our semantic analysis is called RES scheme with a score range $\in [0, \infty]$, and 0 is the minimum score. The initial results are encouraging. Figure 3 shows the semantic similarity between the History topic '*Mexican American War*' and the Geology topic '*Origin Composition and Internal Structure of Earth*', while figure 4 illustrates the results of the semantic similarity scores of two history topics ; '*Mexican American War*' and '*Causes of Thirty Years War'*. The results show significant difference between both comparisons. The maximum semantic relatedness score achieved for word pairs in comparison 1 $(History, Geology)$ is 3.3826 between the pair $('war', 'composition')$. Indeed, the maximum semantic relatedness score for comparison 2 $(History, History)$ in figure 4 is for the pair $('war', 'war')$ which scored 11.0726,but more interestingly , the second best result in comparison 2 is for the pair $('war', 'causes')$ which achieved the semantic relatedness score: 8.3985.

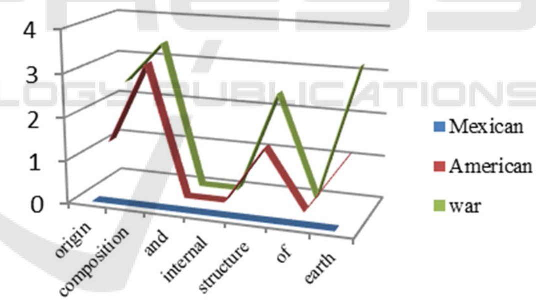

Figure 3: Semantic relatedness between a History and a Geology topic.

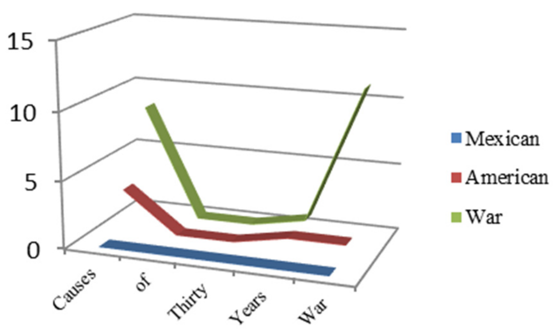

Figure 4: Semantic relatedness between two History topics.

6 DISCUSSION AND FUTURE WORK

Our next aim is to relax our assumption that strong dependencies occur between the strength of social ties and the semantic similarity of learning topics through conducting a number of pilot studies. This is an important socio-cultural perspective of e-learning to investigate the statistical dependencies between the learning subject and social ties in SLN. We have ignored the data distribution scheme and we rather focused on the socio-technical concept of our framework. However, some data distribution schemes can perform decentralized data aggregation with fast conversion rates. Moreover, they can foster reputation-based ranking mechanisms in P2P e-learning such as the one presented by Eid et al. (2019).Reputation-based ranking/voting can filter the most trusted learning resource objects (Eid et al.,2019) which can also enhance the quality of the recommender component of XEL-GL.

7 CONCLUSION

This paper has presented a socio-technical framework for group learning in social learning networks (SLN). The challenge we have addressed is providing learners with the freedom of identifying their learning goals and following their preferred strategies, but at the same time, maintaining the necessary level of tutoring and developing means of validation of the quality of SRL (self-regulated learning) practices. This challenge manifests as a more complex problem when considering the socio-technical perspective. Therefore, we have described XEL-Group Learning (XEL-GL) framework which provides a holistic approach to e-learning taking into account motivational, technological, and social factors. Nevertheless, we have clearly drawn the distinction between socio-technical and cultural elements. Our study supports this distinction, for example, we have shown how the learning subject, as a cultural element, can enhance the quality of building social ties in SLN.

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