Smart Collaborative Learning:
A Recommended Building Team Approach

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ABSTRACT

Technologically enhanced learning has shifted from digital resources to smart components to afford more content, support tools, and provide learning guidance that meets a learner's needs and interests by delivering smart university services. Smart interaction is essential in smart university, it is a concept that offers new opportunities and new channels of communication between learners. This communication is reinforced by the concept of collaboration, an important factor for knowledge sharing. The current study concerns team building based on the recommendation of the most appropriate collaborator in order to make groups of learners promoting universal participation of all members of the team. The complexity of this problem requires collaborative filtering algorithms to find the potential collaborators for each learner, taking into account problem-solving as a parameter representing items of the recommendation matrix.

KEYWORDS

Collaborative Filtering, Collaborative Learning, Memory-Based Collaborative Filtering, Problem-Solving, Recommendation System, Service Oriented Architecture, Smart City, Smart University

INTRODUCTION

The appearance of innovative technology-based learning and teaching strategies has involved the educational government. Additionally, technology-based learning allows moderns learning approaches, that encourages students to be more interactive and engaged within a team of workers. Smart collaborative pedagogy (SCP) guides educators and students to use technology for collaboration and navigation of the potentially conflicting role of autonomous collaborative learning. Furthermore, SCP highlights the importance of students contributing personal meanings and using appropriate communication strategies as they work together using interactive technologies in innovative ways.

This approach supports the use of collaboration in an academic environment and more specifically in a smart university (SU), which offers opportunities for smart interactions. Smart interactions are mechanisms of transmission and technological means through which the learner interacts with their environment, promoting his participation, collaboration, and optimization of their capabilities. In fact, the modernization of learning techniques has emerged a new way of interacting between different

stakeholders of an SU. This new generation of interaction requires recent data processing techniques, in order to offer smart services adapted to a learner profile, in terms of accessibilities and capabilities. Among these techniques, recommendation system remains an essential concept in the implementation of these approaches, through which the student benefits from ample services tailored according to their needs, performances, and competences. In addition, this creates a collaborative workspace that allows the sharing and acquisition of knowledge in an optimal, efficient, and intelligent way.

In an academic environment, team building plays a key role in the acquisition of knowledge and skills through courses and practical work. Through team building, the learner composition has a specificity compared to what can be found in a professional environment in terms of objectives, participants, and means. In fact, the university's collaboration aims at the universal integration of all learners into working groups and the ability to share information in a fair way. This complexity has led the authors to think of a method for building learning teams by promoting universal and participatory integration that is mainly based on a collaborative filtering algorithm.

In this study, the authors investigate the introduction of a recommendation system in the SU in order to create work teams characterized by their complementarity and efficiency through the selection of the most appropriate collaborator in a work team, and the assignment of tasks to the learner by taking into account its accessibility and capabilities. To do this, the authors have used a memory-based collaborative filtering recommendation system, which better responds to this challenge, basing on three steps: 1) Neighborhood identification; 2) Predicting calculation; and 3) Active collaborator selection. This allows the student to benefit from many services adapted to their profile and ensures interaction between the different stakeholders of an SU.

The remaining parts of the paper are mainly structured in sections that include a review of the literature focused on background information on the analysis of the present situation, as explained in Section 2. Section 3 consists of explanations regarding the proposed methods of collaborative learning (CL), followed by the system architecture, functional algorithms, and effective parameters. Section7 explains the validation process and Section 8 discusses the conclusion.

RELATED WORK

The Recommendation of the most appropriate collaborator within a team of learners has especially obtained increasing pedagogical interest in recent years. The Context-aware Collaborator Recommendation (CACR) aims to recommend high potential new collaborators for people's academic context-restricted requests. To this end, the authors elaborate a novel recommendation framework, which consists of two fundamental components: the Collaborative Entity Embedding network (CEE) and the Hierarchical Factorization Model (HFM) (Liu, Xie, & Chen, 2018). Also (Chaiwanarom & Lursinsap, 2015) took into account the context that proposes a new hybrid algorithm based on dynamic collaboration over time for recommending an appropriate collaborator. This algorithm considers three basic factors concerning social proximity, friendship, and complementarity skill. Additionally, (Zhang, Mao, & Li, 2019) recommends collaborators by directly mining the publication context. By taking into account the temporal- and academic-influence-based publication information and the spatial related personal information, this method facilitates more efficient collaboration recommendation results. This STSL (Spatial-Temporal restricted Supervised Learning) model preserves the scaled local geometric information in both data-level and class-level scales.

In a heterogeneous network, Zhou Ding, Li, and Wan (2017) introduces an algorithm named Random Walk with Restart-based Collaborator Recommendation (RWR-CR) to solve the collaborator recommendation problem. This method includes three steps: 1) heterogeneous bibliographic network construction; 2) edge weighting; and 3) random walk with the restart. Using a social network, Liao et al (2019) has proposed an algorithm that recommends a suitable core reviewer for Pull Request (PR), which combines the topic model with a social network. The Social Network and Topic Model-

based Core-Reviewer Recommendation Algorithm (NTCRA) use the text information in PR to build a relationship between collaborators and topics.

Meanwhile, the authors use the review relation of collaborators to construct a collaborator–PR heterogeneous network. On his part, Wang, Liu, Yang, Kong, and Xia (2019) proposes sustainable collaborations for scholars by taking advantage of the conference closure. Wang, Liu, Yang, Kong and Xia (2019) used the conference closure to bias the random walk in scientific collaboration networks to recommend diverse potential collaborators. This was done through extensive experiments on data sets extracted from DBLP with attendees of 10 academic conferences. All these recommendation approaches have satisfied academics environment needs by using recommendation-based context or social networks, including heterogeneous relationships. In this regard, this paper will address the perspectives of these works, in order to improve the efficiency and the optimal recommendation of collaborators.

COLLABORATION IN SMART UNIVERSITY

Introduction

SU requires a collaborative vision to create innovative solutions that help to increase educational success. Universities and educational institutes can collaborate to offer a wide range of interdisciplinary expertise (Verstegen, Dailey-Hebert, Fonteijn, Clarebout, & Spruijt, 2018). Through a process of interaction between academics and organizational structures, the collaborative learning promotes modern methods of collaboration between teams of learners and leads to a sustainable interface between universities and companies that remains crucial in developing the skills and competence of learners. Collaboration can potentially enhance professional skills through which the trainee acquires co-ordination and co-management techniques by working as a member of a team in various contexts and with other members who have different expertise (interprofessional collaboration). Also, collaboration is a way to develop collective intelligence to achieve common goals.

In this paper, the authors present an intelligent system that meets the requirements of today's university: a modern university that values the participation and collaboration of intelligent learners as a pedagogical strategy for creating an academic environment for sharing and mutualizing knowledge and material resources. This is completed by following a learning process (project, course, and tutoring, professional experience) that is mainly based on collaboration as a collective tool to achieve educational goals in an optimal way.

The objective of the collaboration is to improve the learning quality and the student performance during their educational processes. The collaboration focuses on contextual, personalized, and transparent learning to encourage the emergence of learners' intelligence, based on heterogeneous knowledge and driven by a team-learning setting. Thus, collaboration as a pedagogical model remains essential for the establishment of an intelligent university that allows sharing through the following three aspects: resources, interdisciplinarity and trust.

Resources

Experts in collaborative learning have developed and evaluated technology-enhanced learning resources in higher education and they maximize educational resource mutualization. In fact, scholars can exchange different ideas and share experiences, expertise, and resources with each other (Kong et al., 2018). Another benefit of collaborative learning environment consists of a dynamic mix of many different types of resources and facilities, which teachers should be aware of, and adapt to, the learner in his/her current context to better coordinate and optimally use the educational resources (Fang & Sing, 2009).

Interdisciplinarity

The interdisciplinary and collaborative projects were rewarding experiences (based on informal student feedback on both campuses) that focused on enhancing interdisciplinary research, collaboration, and shared leadership skills, along with improving critical thinking oral and written communication skills (Basu Ray & Maitra, 2017).

Trust

Trust is a factor that mitigates the barriers to collaboration and reduces both orientation-related and transaction-related barriers (Bruneel, D'Este, & Salter, 2010). This may be because trust relies on strong bonds of mutual understanding and adjustment. Therefore, trust helps firms to manage their differing expectations of research and to lower the considerable transaction costs of working with university partners (Bruneel, D'Este, & Salter, 2010).

COLLABORATIVE LEARNING

CL is an educational approach to teaching and learning that involves groups of students working together to solve a problem, complete a task, or create a product (Fang & Sing, 2009), (Ray & Maitra, 2017). The main CL features include: (a) active use of online tools and to instruct students:(b) student collaboration (interaction, communication) with those teachers and other students: and (c) team-working approach to problem-solving while maintaining individual accountability. Based on published reports, CL (a) develops social interaction skills: and (b) stimulates critical thinking and helps students clarify ideas through discussion and debate (Ramírez-Donoso, Pérez-Sanagustín, & Neyem, 2018). The main aim of the collaborative learning module was to integrate interdisciplinary learning while engaging our students and helps them to develop knowledge and problem-solving skills. Thus, building a team of learners is crucial to group learner in an optimal way.

Team Formation and Composition

Teamwork is an effective way to improve learning outcome. It is a means of learning used in most general or professional programs. Building an efficient and harmonious team is a major challenge for collaborative learning. Therefore, the success of this environment is often the result of a close collaboration between the different teammates, allowing a convergence of the knowledge of each of these members. The cohesion of teamwork is based on the quality of the relationships between its different members in order to achieve optimal objectives. To achieve that, there are three models of team composition.

Composition Based Learner

The smart learner plays a vital role in building a smart university by participating in successful learning processes and problem-solving. This is why collaborative strategies consider smart learner as an important part of team building that is focused on the profile and abilities of learner. In order to group it under knowledge, skills, attitudes, and values (Liao et al., 2019). The participation of each learner takes into account accessibility and capabilities and requires a deep understanding of profile member in order to create a complementary participation between each member of team. Its main challenge is to integrate and stimulate participation of a learner in order to: 1) share knowledge; 2) integrate each student in the learning process; and 3) develop communications and collaborations skills within a team of learners.

The composition of a team in an intelligent university has certain specificities because its main objective is to share and transmit knowledge between all learners in an optimal and personalized manner, as opposed to the collaboration in a professional field that aims to realize a project. More precisely, collaboration is a pedagogical means of developing team spirit

among learners by pooling the material resources used in a course or an educational project, as well as for exchanging ideas. Unfortunately, in a university system, the tutor is responsible for building the work team using data that remains restricted in accounting the abilities of each member. This method fails to encourage effective sharing of knowledge and achievement of collaborative work goals.

In this regard, the recommendation of the most appropriate collaborator is a solution that allows building an agile training team thanks to the self-organization team, which relies mainly on the following recommendation-based parameters:

- User profile
- Regrouping students by performance
- Homogenous similar collaborator
- Heterogeneous difference collaborator
- Randomly groups

Composition-Based Problem-Solving

Problem-solving learning is a great opportunity to improve student collaboration, and these strategies can help to ensure true collaboration in the learning process. Problem-solving learning refers to grouping smart learners around a project according to their interests, which are presented as a description of the project. These aspects motivate students to work together toward a common goal, generating positive interdependence within the team and creating individual responsibilities for each student to benefit the group's progress (Ramírez-Donoso, Pérez-Sanagustín, & Neyem, 2018). The assignment of a learner to a project is based on its interest or deduced from its histories, such as learner evaluations, feedbacks, and performed interventions. Also, task assignment is based on the predefined role of the project that is part of its description. Participation in this project is a voluntary activity that motivates students to improve their academic performance. The team composition based problem-solving relies mainly on the following aspects:

- Educational relationships
- Learners management
- Organizational role
- Project description

The authors approached several techniques to deduce and calculate the best collaborators participating in a problem-solving team, namely: classification, binary trees, and fuzzy logic. This constitution of teams and communities remains limited compared to the stake of the collaboration, which consists of sharing, discussing and evaluating ideas. Indeed, the power of the collaboration helps with:

- Communicatio
- Time management
- Resource allocation
- Openness

All of these factors required the recommendation as a technique to promote participation and contribution in a team. Also, the recommendation maintained the environment of collaborative work through a permanent suggestion for the benefit of learners to perform together as a group.

THE APPROACH OVERVIEWS

The concept of a "Smart University" is an emerging and fast evolving area that represents the creative integration of innovative concepts (Uskov, Bakken, Howlett, & Jain, 2017). However, one of the major challenges within the smart university is managing the mass of data collected from various sources between learners every second of the day. Additionally, these data sets are not only large but also in various forms, such as images, text, and audio (Mohanty, Bhuyan, & Chenthati, 2015). In addition, it becomes very difficult to collect and analyze the communication between learners and their contexts in order to optimize learning in a smart environment. In other words, thoroughly analyzing the types of data to be collected for each collaborator is a daunting task because they have different, heterogeneous characteristics, in this respect, artificial intelligence and machine learning methods, plays a crucial role in responding to these problems. In this context, we propose in this present paper an intelligent architecture "smart service architecture for collaborative learning" as part of smart university, with the aim of creating similar collaborators to facilitate access to services in a consistent and relevant way that better matches their needs, and to increase data sharing appropriately. This will improve the level of intelligence within the university. For this reason, the authors have adopted the recommendation system algorithms that better respond to the problem, that they precisely based on the Collaborative Filtering method.

An Introduction to the Recommender System

The basic idea of the recommendation system is to use different data sources to deduce "users" interests". In addition, recommendation systems offer an effective solution to the problems of information overload. Their main role is to select and filter the information in a mass of information to the user in a transparent manner (Asanov, 2011). and make suggestions of topics of interest with which the system will provide the user with a list of resources according to their preferences to meet their needs (Benfares, El Bouzekri El Idrissi, & Abouabdellah, 2017). Individualized content minimizes the information load for users and provides the refined content they want, in order to make relevant decisions and understand user needs. These systems work by using the characteristics of the users, their preferences, and their profiles or their past interactions to provide suggestions of relevant content. There are large numbers of recommendation techniques; the authors present the three basic approaches to recommendation systems (Figure 1): content-based filtering, collaborative filtering, and hybrid technology (Aggarwal, 2016).

Basic Models of Recommender System

There are two methods for the construction profile of users: collection explicit data or collection implicit data.
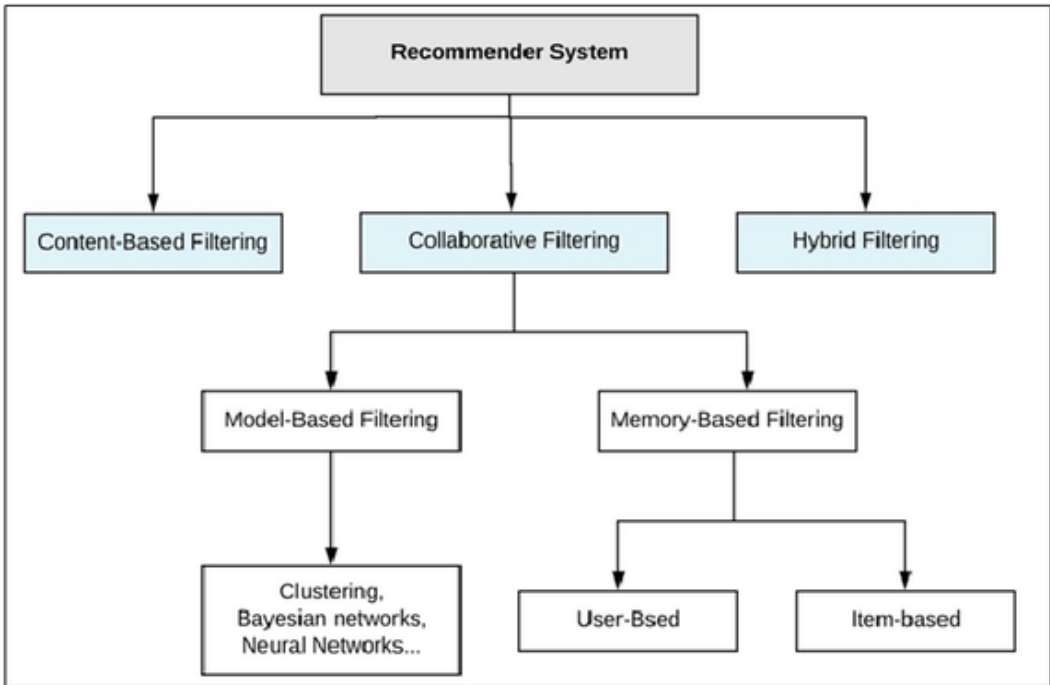
Collaborative Filtering

Collaborative filtering models use the collaborative power of the ratings provided by multiple users to make recommendations (Benfares, Idrissi, & Hamid, 2019). Furthermore, the technique used in collaborative filtering is calculation of the similarity between the preferences of the current user and those of other users, and it is based on a used matrix. This approach has been used in many applications in different fields such as e-commerce, e-learning, online services, etc. (Sarwar, Karypis, Konstan, & Riedl, 2001).

There are two types of methods that are commonly used in collaborative filtering, which are referred to as memory-based methods and model-based.

Memory-Based

Researchers also refer to memory-based methods as neighborhood-based collaborative filtering algorithms. There are two types to memory-based methods (Aggarwal, 2016): collaborative

Figure 1. Recommendation techniques

filtering based on the user and item-based collaborative filtering. The memory-based approach deals with user assessments of items as a matrix, in order to produce future predictions. First, the memory-based method mainly applies statistical techniques in order to identify neighboring users, i.e., users who have similar appreciations to the active user. In order to calculate the similarities of the assessments between the users (Mohanty, Bhuyan, & Chenthati, 2015), several measures have been exploited. Among these measures, the authors can mention the correlation coefficient of Pearson, the measurement based on the cosine, and the correlation of Spearman (Sarwar, Karypis, Konstan, & Riedl, 2001). After identifying neighboring users, the memory-based method uses different algorithms to combine neighbors' ratings and generate recommendations to the active user. The method used most frequently for calculating these predictions is the "weighted sum."

Model-Based

Model-based methods have been incorporated into recommendation systems to address the problems of memory-based methods. Model-based filtering is based on machine learning techniques, such as: clustering, decision trees, Bayesian networks, etc. (Benfares, El Bouzekri El Idrissi, & Abouabdellah, 2017). This approach potentially offers the benefits of both speed and scalability.

Content Based

Content-based recommendation systems are systems that recommend items similar to ones the user liked in the past (Benfares, El Bouzekri El Idrissi, & Abouabdellah, 2017). Indeed, the process consists of calculating the similarity between the attributes of a user profile with the attributes of the items in order to recommend new, interesting objects to the user.

Hybrid

Hybrid recommendation systems combine the strengths of different systems recommendation approaches (Figure 2) to create better techniques in a wide variety of contexts (Aggarwal, 2016).

THE SYSTEM ARCHITECTURE

The architecture of the authors' system includes different layers that contribute to the development of their approach; it is a multi-layer architecture that provides scalability in terms of data and processing to maintain the resiliency of the system. To ensure the success of the proposed approach, the authors present a service-oriented architecture for the system, which is composed of the layers represented in Figure 3.
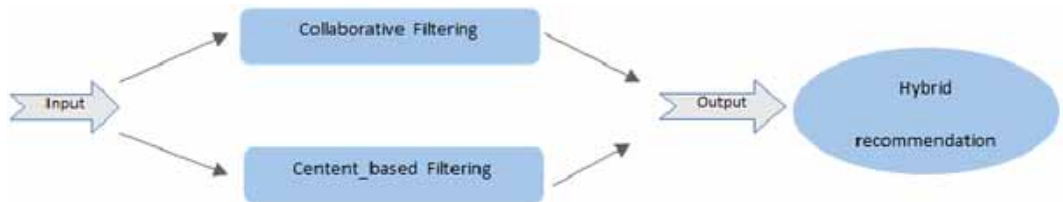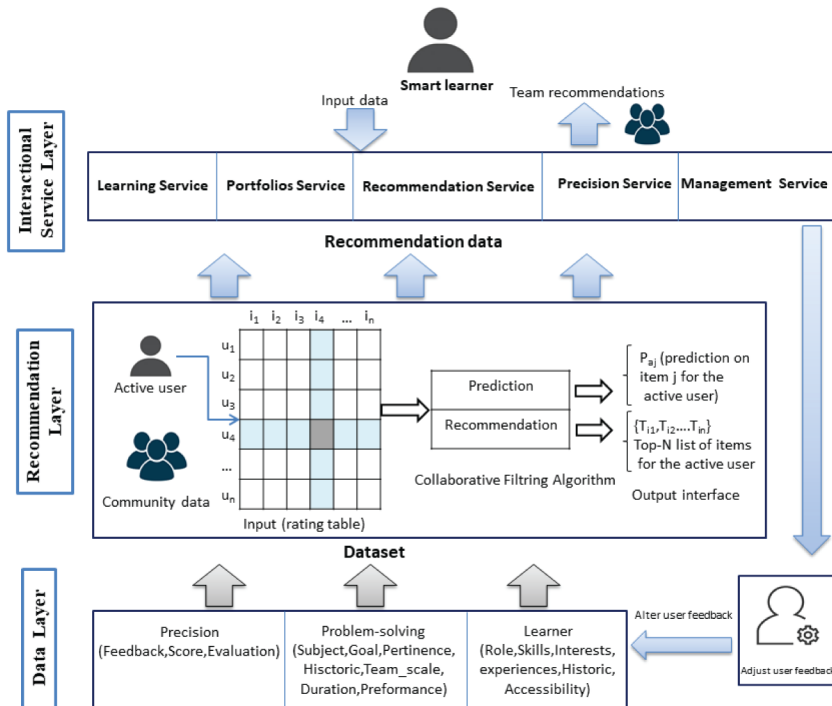
Figure 2. Hybrid approach

Figure 3. Smart collaborative learning architecture

Data Layer

Data layer contains the input data used in the recommendation processing categorized into qualitative and quantitative types. This data is represented in Tables 1 and 2.

Learner Context

Problem-Solving

See Table 2.

Precision

The data which represent the precision are calculated in the first step from the score which is the result of the recommendation, then it improved thanks to the accuracy layer.

Accuracy Layer

Adding an accuracy layer to the system's architecture allows an output of new feedback from the user during collaborative work. Thus, the recommendation is always improved by users' participation, skills, and experience, compared to their participation in a work team already recommended by the system. The accuracy layer plays an important role in the precision of future collaborative suggestions and the prediction of effective team participation that improves the accuracy of the recommendation.

Recommendation Layer

Phases of Recommendation Process

The authors offer recommendation system architecture to strategically collaborate inter-learners in order to ensure learner interactions with his environment by encouraging his participation, collaboration, and the optimization of users' abilities using their profile, history, and preference. Indeed, this approach aims first to analyze the traces of use, which represent the interaction of an active

Table 1. Learner context attributes

	Smart Learner	Role	Accessibility	Experience Indicator	Preference	Interests	Skills Level	Rating Score	His_collaboration
Data type	qualitative	qualitative	qualitative	quantitative	qualitative	quantitative	quantitative	quantitative	qualitative

Details:
Smart learner (ID_ smart learner, personals information)
Role (ID_ role, role_type, aggregation)
Accessibility (ID_ accessibilty, disability_type, tools, context)
Experience (ID_ experience, experience_label, evaluation)
Preference (ID_preference, learning_style)
Interests (ID_ interest, learning_content)
Skills (ID_ skill,skill, level, certificate)
Rating (ID_rating, Score, Topic)
Performance (ID,ID_skill,ID_role, ID_preference, ID_interest, level)
His_collaboration(ID,ID_smart_learner, evaluation)

Table 2. Problem-solving attributes

	Smart Knowledge	Subject	Goal	Pertinence	Deadline	His_collaboration	Team Scale	Performance
Data type	qualitative	qualitative	qualitative	quantitative	quantitative	quantitative	quantitative	quantitative

learner with the system, for example (its appreciation and its history). In addition, the approach creates a collaborative workspace to share and acquire knowledge optimally, efficiently, and intelligently.

In this regard, the authors have used a memory-based collaborative filtering recommendation system, for the best technical fit for system requirements, contributing to create work teams characterized by their complementarity and effectiveness. Firstly, the system selects the most appropriate collaborator, then assigns tasks to the learner, taking into account their accessibility and abilities. This is done to give the student many services adapted to their profile and to ensure interaction between the different stakeholders of an SU.

Recommendation Phase and Experimentation

During the learning phase, the author used the memory-based collaborative filtering algorithm to filter and predict the information collected from each learner. To do this, the database contains two essential components: the learner profile and the project. Each record of the learner contains the following categories: role, accessibility, experience indicator, interests, skill level, work structure, IT level, language level, management level. And each project variable record is contained by the following variables: Intelligent Knowledge, Subject, Objective, Relevance, Problem_Survey, Team_School, Duration, Performance. Table 1 presents an example of a learner assessment matrix (user matrix) that will be processed to calculate recommendations based on the items.

In Collaborative Filtering, the data is represented as a "User x Item" matrix. The columns represent the learners U = {u1, ... un}, and the lines constitute the items I = {i1, ... ij}. Table 3 presents an example for calculating the recommendation.

The first step focuses on the learners who provide their assessments of the items as a score. For the Learner 3, who has not expressed an opinion on an Item 1, the system searches for a neighborhood value to predict the missing score. As a result, and in order to predict the learner's recommendation for a given project, the authors followed the following steps:

Step 1 - Neighborhood Identification: To calculate recommendations for an active learner, the authors look for other users with similar preferences and select the recommendations in their items. To find similar users, the authors need to compare users' interactions. A common method is to calculate the correlation coefficient between their interactions. The authors used the Pearson correlation coefficient because it remains the most efficient in terms of prediction. The similarity formula is defined by the following formula:

$$S_{person}(a,b) = \frac{\left(\Sigma_{(\{x \in E_a \cap F_b\})} \left(u(a,x) - \overline{u_a} \right) * \left(u(b,x) - \overline{u_b} \right) \right)}{\sqrt{\left(\Sigma_{(\{x \in E_a \cap F_b\})} \left(u(a,x) - \overline{u_a} \right)^2 \Sigma_{(\{x \in E_a \cap F_b\})} \left(u(b,x) - \overline{u_b} \right)^2 \right)}} \quad (1)$$

Table 3. User-item rating matrix

	Item 1	Item 2	Item 3	Item 4	Item 5
Learner 1	1	2	1	2	4
Learner 2	3	1	2	1	2
Learner 3	?	3	2	1	3
Learner 4	5	1	3	4	1
Learner 5	1	5	4	3	1

Step 2 - Calculating the prediction: Once the authors have calculated the similarity between the users, then they calculate the prediction generated according to the weighting sum. This is defined by the following formula:

$$u\left(p,c_1\right) = \overline{u_{c1}} + \frac{\left(\Sigma_{\left(\{c_2 \in Cp \in E_{c2}\}\right)} S\left(c_1, c_2\right) * \left(u\left(p, c_2\right) - \overline{u_{c2}}\right)\right)}{\left(\Sigma_{\left(\{c_2 \in Cp \in E_{c2}\}\right)} S\left(c_1, c_2\right)\right)} \qquad (2)$$

Step 3: After the prediction phase, the system selects the nearest neighbors that are correlated with the active user from a similarity threshold. The authors chose the threshold value of similarity (greater than 0.1).

Step 4: Finally, the system displays the Top-N elements to the target user.

Results

In this experiment, the authors used the Apache Mahout framework, an Apache Foundation project, to create a distributed machine learning algorithm implementations and eclipse software. The authors used the data presented in Table 4. They adopted the collaborative filtering algorithm based on memory, (more precisely the User-Based algorithm see Figures 4 and 5).

To predict the value of Learner_3 using the prediction equation, the authors take Learner 1 as a neighbor because they are well correlated. Table 3 presents the notes of all items from Learner 3. Therefore, the system recommends to Learner3 the following items in Table 5: Item 5 and Item 2.

Table 4. The values of the similarity between Learner 3 all other users

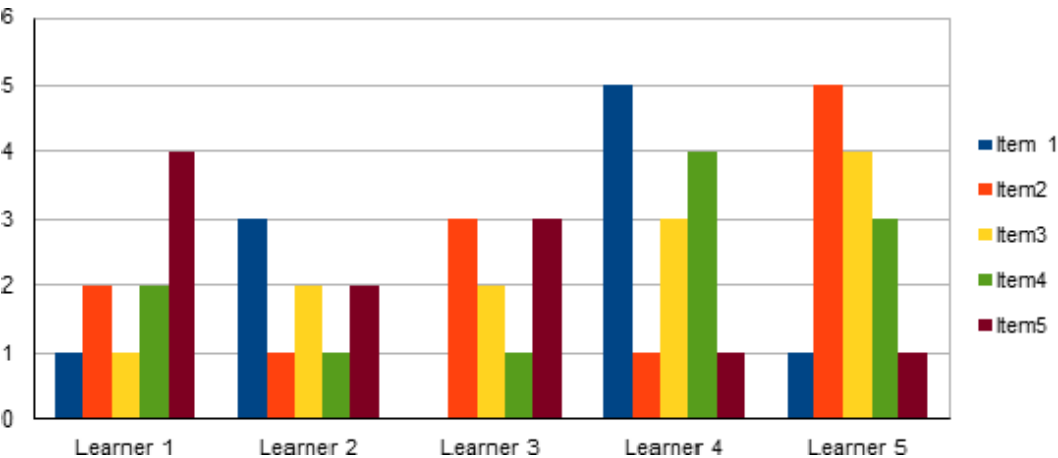| Learner$_3$ - Learner$_1$	Learner$_3$ - Learner$_2$	Learner$_3$ - Learner$_4$	Learner$_3$ - Learner$_5$
0,484200125 > 0,1	0,301511345 > 0,1	-0,98644005	-0,050964719

Figure 4. User-item rating

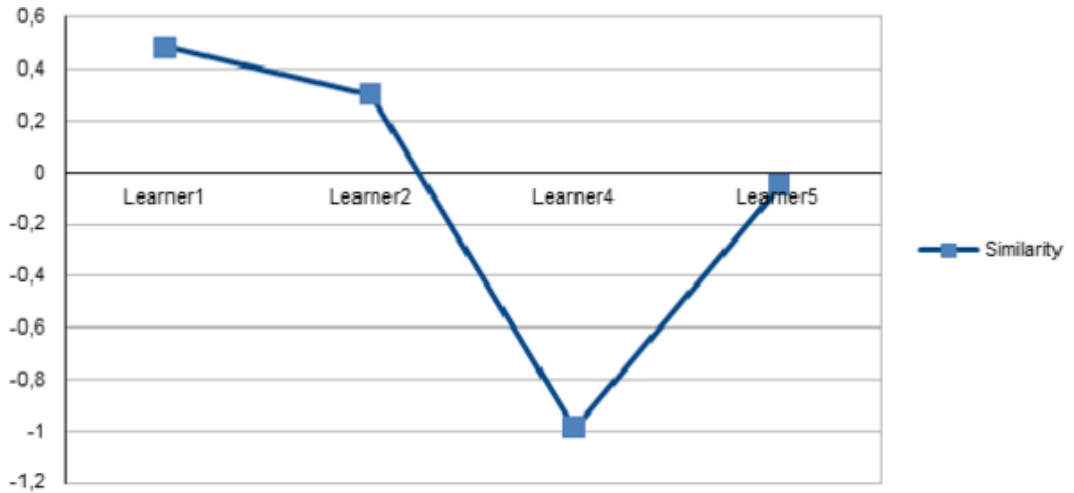**Figure 5. Degree of similarity between Learner3 and all other users**

Table 5. Learner_3 ratings after the prediction

Learner$_3$	Item$_1$ Pred (Learner, Item) $\approx$ 1	Item$_2$ 3	Item$_3$ 2	Item$_4$ 1	Item$_5$ 3

Interpretation

In this present work, the authors experimentally evaluated the algorithm of recommendation systems, specifically Collaborative Filtering, according to the results obtained, we find that they are efficient systems, in addition have definitely opens new options to search and filtering information, in order to recommend personalized services to learners. Especially in the intelligent university environment, recommendation systems are robust, and respond best to unsupervised data problems.

Interactional Service Layer

This layer represents the interactional means between the user and their collaborative environment; through dedicated services that meet the requirements of interoperability and collaboration between the different components of the SU. This layer provides additional services to meet learners' needs, tailored by their context and capabilities. This is accomplished to perform suitably in this environment based on their features. The main services that the authors quote include: service-learning, which allows collecting additional information that concerns the smart learner: portfolios service, which is a service of profiling and authentication: recommendation service, which suggests participation in teamwork: and finally, precision service, which loads user feedback to feed the accuracy layer. This layer will probably be boosted by new services that respond to the system's evolutions thanks to the modularity of services.

DISCUSSION

The SU is always looking for innovative solutions to improve access and knowledge-sharing between different stakeholders. Among these solutions, collaboration is a powerful concept that creates opportunities for sharing ideas in a virtual space with many collaborators. Collaboration is defined by objectives, tools, and duration. Indeed, trust is important to support these components and allows

flexible sharing of resources. To achieve these goals, it is essential to create smart teams to bring together effective communities for sharing and producing knowledge.CL is an educational approach that ensures collaboration between a team of learners. To instantiate this approach, researchers need to resolve the complexity of building a team of learners by recommending the most appropriate collaborator using collaborative filtering based-memory according to the user-based algorithm. The results may seem effective in achieving these goals, which has been supported by the authors' diagrams. In addition, the accuracy layer plays an important role in the precision of future collaborative suggestions and the prediction of effective team participation in order to improve the accuracy of the recommendation.

The interaction of the collaborators is done through a service layer that offers flexibility in terms of processing and customization of the services offered by the system. The authors consider the proposed approach to be an effective solution that can be integrated into an SU system to solve collaboration problems and building team workers more precisely. Also, is considered to be a starting point for the implementation of the main activity of a system in order to achieve an efficient and optimal collaboration.

CONCLUSION

The authors proposed a new approach for recommending the most appropriate collaborator within a collaborative learning environment. The key contributions of this study are summarized as follows:

- Identifying the user's profile on the basis of relevant data concerning their context, abilities, and skills. In fact, it is important in the definition of the collaborator to integrate them into a suitable team;
- Identifying the problem-solving information that will be represented as items in the recommendation matrix;
- Using feedback information as a set of accuracy data is a method for evaluating collaborator recommendations;
- Collecting data allowed the authors to create a dataset based on academic information that will be the input of our recommendation processing.

In this respect, the authors have designed a "Smart Collaborative Learning Architecture" that can meet collection and processing requirements and recommend the potential collaborator in a flexible, permanent, and optimal way. This architecture includes the data layer that stores information, the recommendation processing layer, the services layer, and the accuracy layer (Figure 2). Focusing on the recommendation processing layer, the architecture includes a recommendation engine that uses a collaborative filtering memory-based precisely on the user-based algorithm to output building team-based recommendation. Overall, this approach shows that the recommendation through this architecture can give satisfactory results that can be improved thanks to the service orientation of this architecture by the addition of collaborative services.

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