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Design and implementation of the multi-agent system in education

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Abstract

Nowadays, AI is a real springboard for finding solutions to optimize and improve learning and teaching processes. This issue has been a focus of humanity for millennia, and very significant advances have been made in this quest. This article aims to address the issue of optimizing and improving learning and teaching processes through AI (Artificial Intelligence), considering crossroads of research fields AIED (Artificial Intelligence in Education), EDM (Educational Data Mining) and LA (Learning Analytic). The research made use of secondary data collected from previous research on the topic and primary data was collected using a case study. A comparative analysis was conducted and based on this opportunity, we propose a multi-agent system based on AI techniques, which is capable of performing broader analyses of learning and teaching processes. The research also implemented a prototype of EMAS. Through this system, teachers and learners will be able to access a wide range of relevant and reliable information about learning and teaching processes.

Key words: AIED, EDM, EMAS, LA, recommendation system, education dropping out, emotion detection.

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1. Introduction

Nowadays, AI is a real springboard for finding solutions to optimize and improve learning and teaching processes. Based on this opportunity, we propose an Emotional multi-agent system (EMAS) based on AI techniques, which are capable of performing broader analyses of learning and teaching processes. This system consists of several intelligent agents, problem including university dropping out, the detection of emotional states through the analysis of the way or facial expressions, and the automatic recommendation of educational resources. Here, several aspects of learning or teaching are directly concerned among others pedagogy, didactics, cognitive sciences, adaptive and collaborative learning. The architecture of EMAS is easily extensible and interoperable. This research also implemented a prototype of EMAS. Through this system, teachers and learners will be able to access a wide range of relevant and reliable information about learning and teaching processes.

This research proposes a multi-agents system and exposes the different intelligent agents that compose it. For the implementation and exploitation of intelligent agents, we define the environment of the multi-agents system and the organization of hierarchical agents and their interactions. Also, we present the various technologies mobilized for the implementation of our system.

In this article, we will present classifier intelligent agents, each of which deals with a specific problem in the context of teaching or learning. Given that they all take place in the process of educational data for the understanding and improvement of learning. It would be interesting to group these agents in an organized way within the same system in order to converge each of which is dealing with a specific their contributions. By doing this, it will allow advanced and precise analysis of the learning; therefore, we could have a deeper understanding of it.

1.1. Purpose of study

Our research aims to develop effective strategies and tools based on AI techniques for the collection and analysis of educational data. On the one hand, these strategies must cover several dimensions of learning and teaching, especially the pedagogical, didactic, cognitive, metacognitive, emotional, collaborative dimension, etc. Thanks to this plurality of dimensions, we could have more in-depth and accurate learning and teaching processes. On the other hand, our goal is also to develop a system integrating these strategies in order to provide teachers and learners with support for optimizing efforts. Through predictive analyses and recommendations of appropriate educational resources, the system will make it easier for teachers and learners to make the best decision at each stage of the learning or teaching process. To achieve this goal, we define the main concepts on which we were based to develop our EMAS system. Subsequently we will expose the architecture of our system then we will consider case studies based on real data in order to examine the relevance of our system.

2. Methods and Materials

2.1. Data collection and analysis

This research sought to make a comparative analysis of Educational Recommendation System Proposals. The research collected secondary data from previous literature and this enabled the researchers to make substantial comparison. Primary data was also collected with the help of case study.

2.2. Research procedure

The research first collected data and made subsatantial analysis from the collected data. After this, the research went further to propose a system that could be used to solve the problem of the research, that is the EMAS (EMOTIONAL MULTI-AGENT SYSTEM).

3. Findings

3.1. Recommendation systems

The ability of computers to make recommendations has been recognized early in the history of computing. Grundy, a computerized librarian, gave the first step toward automatic RS. It was rather primitive, but it represented an important early entry into the field of recommendation systems (Rich, 1979). The RS study is relatively new compared to research on other conventional information system tools and techniques. They became an independent field of research in mid 1990 (Balabanovic and Shoham, 1997; Goldberg et al., 1992; Resnick et al, 1994; Grace, 2020).

In the early 1990s, collaborative filtering began to appear as a solution in online information spaces. Tapestry (Goldberg et al., 1992) was a manual collaborative filtering system: it was possible to search for items in an information domain, an email message, messages or actions (for example, give me all the messages sent by John). This would require the users' efforts, but it would allow them to exploit feedback from previous readers of correspondence to determine its relevance.

Automated collaborative filtering systems quickly followed so as to automatically locate advisories and aggregates to provide recommendations. GroupLens has used this technique to identify articles that may be of interest to a particular user. Users must only provide assessments or other observable actions. The System Combinals with Ratings are the users who have never been informed of them and do not need to know what other elements are used in the system. During the period of its work, the systems of recommendation and the filtering focuses on a question of interest, well-structured interviewer interactor man-machine, in machine learning and in search of information. This interest has resulted in a number of referral systems for different areas such as Ringofor music(Grace, 2020), BellCore for movies and Jester for jokes (Danaf et al., 2020).

In the late 1990s, commercial deployments of the recommendation technology began to emerge. The "Amazon.com" website is perhaps the most well-known application of recommendation system technologies. Research on recommendation algorithms received particular attention in 2006 when Netflix launched the Netflix Award to improve the status of the film recommendation. The objective of this competition was to build a recommendation algorithm that could beat their internal CineMatch algorithm by 10% during offline testing. This triggered a wave of activity both in academia and among amateurs. The $ 1 million award demonstrates the place of the value suppliers on specific recommendations. In addition, there has been an increasing interest in referral systems as shown by the following facts: - Referral systems play an important role in websites such as Amazon.com, YouTube, Netflix, Spotify, LinkedIn, Facebook, Tripadvisor, Last.fm and IMDb. Also, many media companies are developing and deploying RS as part of the services they provide to their subscribers (Koren et al., 2009).

3.2. The use of educational recommendation systems

E-learning is a revolutionary way to provide virtual education, which is benefiting more and more people every day. E-learning sometimes makes use of recommendation systems. A recommendation system is software that helps users identify interesting and relevant learning information from a variety of educational information. Referral systems aim to provide learners with relevant research results tailored to their needs by making predictions about their preferences and by providing educational content that may be closer than expected (Sharma, 2021). In addition, referral systems must use different sources of information such as pedagogical databases, learning object repositories (LORs), LOR federations, and so on (Danaf et al., 2020).

Educational Recommendation Systems (ERS) can be classified into several types (Walek, 2020): the first one is Content-based ERS, in which recommendations are made only using the student profile already created. The second one is Collaborative ERS in which recommendations are based on the degree of similarity among users by applying collaborative filtering algorithms. The third one is ERS based on knowledge, so it uses the browsing history of the user to provide the appropriate educational resources. The last one is Hybrid ERS systems that seek to integrate some of the recommendation techniques to bring together the most accurate and best-fit features of the user profile, providing better recommendations. It is important to emphasize that RBAs for NAs use the characteristics and needs of learners to support their learning / teaching processes (Li, 2010).

In the educational context, different recommendation systems have been proposed in the literature. A recommendation module of a tutorial programming system called Protus was developed (Milicevic et al., 2011). This module can be automatically adapted to the interests and levels of knowledge of learners (Hamal et al., 2021). Protus can recognize different models of learning style and learner habits by testing learning styles of learners. First, Protus treats clusters based on different learning styles. Then, Protus analyzes the habits and interests of learners by exploiting the frequent sequences of the AprioriAll algorithm. Finally, Protus completes the personalized recommendation of the learning content according to the scores attributed to these frequent sequences.

An educational collaborative filtering recommendation agent was developed, along with an integrated learning style search tool (Muangprathub et al., 2020). The agent produces two types of recommendations: suggestions and shortcuts for learning materials and learning tools, which both help the learner to better navigate educational resources. A book recommendation system called PBRecS was developed (Pera et al., 2011). PBRecS is based on social interactions and personal interests to suggest attractive books for users. PBRecS relies on friendships established on a social networking site (e.g. LibraryThing) to generate more personalized suggestions by including in the recommendations only books belonging to friends of a user sharing common interests with the user, along with applying word correlation factors to partially associate book tags to disclose books with similar content.

Hsu (2008), proposes a personalized online English learning recommendation system that can provide English learners with reading lessons that respond to their different interests and thus increase their motivation to learn English. The recommendation system, which uses content analysis, collaborative filtering and data mining techniques, analyses actual reading data of the learners and generates recommendation scores by allowing the selection of appropriate lessons for the respective learners. Since its performance has been monitored over a one-year period, this recommendation system has been very useful in enhancing reading through the motivation and interest of English learners.

A personalized system for recommending auxiliary materials was proposed depending on the degree of difficulty of the auxiliary documents, the individual learning styles and the specific course topics (Ali et al., 2020). The proposal is based on several studies in which the effects of using Facebook were studied in various aspects of education and a learning platform was used for the exchange of auxiliary materials. A new multi-agents learning system called ISABEL provides each learner who uses a specific device with an agent that can autonomously monitor the behavior of a learner when accessing online learning websites (Kaaniche, 2020). Each site is associated in turn with a teacher. When a learner visits an e-learning site, the teacher works with some tutors associated with the learner to provide useful recommendations. An automatic personalization approach aims at providing automatic online recommendations for active learners without requiring their explicit return (Koutheaïr et al., 2009). The recommended educational resources were calculated based on recent browsing history of the learner, as well as the exploitation of the similarities and differences between his/her preferences and educational content. The proposed framework for creating automatic recommendations in e-learning platforms consists of two modules: (1) an offline module that processes data upstream to create learner and content models, and (2) an online module that uses these models on the Internet.

A system allowing speakers to define their best teaching strategies for use in the context of a specific class is presented (Schmid et al., 2020). The context is defined by the specific characteristics of the subject matter, by the specific objectives to be achieved during the classroom session, by the profile of the learners enrolled in the course, by the dominant characteristics of the teacher and the classroom environment for each session, and so on.

The system presented is the Pedagogical Models Recommendation System (PMRS). A hybrid recommendation system for learning materials based on their attributes is used to improve the accuracy and quality of recommendations (Rhanoui, 2020).The system has two main modules:

1) an explicit attribute-based recommender and 2) an attribute-based implicit recommender. In the first module, the implicit or latent attribute weights of materials for the learner are considered as chromosomes in a genetic algorithm, which optimizes weights based on historical notation. The recommendation is then generated by the Nearest Neighborhood Algorithm (NNA) using the implicit attributes of optimized weighted vectors that represent the opinions of learners. In the second module, a matrix of preferences is presented. It can model the interests of a learner based on explicit attributes of learning materials in a multidimensional information model. Then, a new measure of similarity between the MPs is introduced, and the recommendations are generated by NNA. DELPHOS is a framework utilized for assisting users in finding learning objects in repositories and showing an example of application in engineering (Gordillo et al., 2020). LORs can be used in engineering not only to learn and train learners, instructors and professionals, but also to share knowledge about engineering problems and projects. The proposed approach is based on a weighted hybrid recommender that uses different filtering or recommendation criteria. The values of these weights can be assigned by the user him/herself or can be calculated automatically by DELPHOS adaptively and dynamically.

A work in progress is presented in order to develop a recommendation system for the personalization of activities in e-learning 2.0 environments (Holenko and Hoic-Bozic, 2014), The main components of the proposed system are the activity, the learner and group models and the recommendation module. The activity model will be used for the representation of the learning design and will include elements that can be recommended to learners: e-learning activities, potential collaborators, tools and tips. To provide recommendations tailored to the characteristics of the learner and the group, an important model of the system will include learner and group models. The recommendation module, as the third component of the system, will include original pedagogical rules, as well as algorithms that adapt known recommendation techniques to the educational context.

Finally, the recommendation for online educational resources uses the resources and learners attribute and the sequential models of the learner's accessed resource in the recommendation process (Hu, 2020). Learner Tree (LT) is introduced to consider the explicit multi-attribute of resources, the learner's time-varying multi-preference and the learner's rating matrix simultaneously. Implicit attributes are introduced and discovered using matrix factorization. The BIDE algorithm is also used to discover sequential models of access to resources to improve the quality of recommendations. In order to further analyse the work described above, Table 1 presents a comparative analysis summarizing the relevant contributions of this related work. These initiatives have several drawbacks: (a) Some works are based on the use of learning objects as elements to recommend; (b) multi-domain works use a single algorithm for all domains; (c) this work is based solely on user evaluation to generate the recommendations. These gaps can be improved by (a) a recommendation system that implements a specified metric for each type of data through using the user and item information, and by (b) a system that automatically generates this type of recommendation system in a simple manner through providing a set of user-friendly user interfaces. Table 1 illustrates a Comparative Analysis of Educational Recommendation System Proposals

Table 1. Comparative Analysis of Educational Recommendation System Proposals

Research work	Entity type	Objective	Algorithm	RS Type
A personalized English learning recommender system (Ali et al., 2020)	Unknown	Provide ESL students with reading lessons that suit their different interests and therefore increase the motivation to learn	Clustering Association rules Algorithm	hybrid
PROTUS (Milicevic et al., 2011)	Learning Objects	Estimate automatic recommendations to an active learner based on learning style and learning sequence.	Apriori All Collaborative Filtering	Collaborative Filtering
Personalized recommendation of learning material	Learning Objects	Propose a new material recommender system framework and relevant recommendation algorithms for e-learning environments.	Sequential pattern mining Apriori and PrefixSpan, Nearest neighborhood.	Hybrid
Hybrid attribute based recommender system for learning material (Rhanoui, 2020)	Resource	Propose a hybrid recommender system for learning materials based on their attributes to improve the accuracy and quality of recommendation.	Nearest neighborhood, Preference Matrix, Genetic Algorithm	Hybrid
DELPHOS (Gordillo et al.,2020)	Learning Objects	Assist users in the search for learning objects in repositories and which shows an example of application in engineering.	Unknown	Hybrid
A hybrid system of pedagogical pattern recommendations (Schmid et al., 2020)	Unknown	Present a system that allows lecturers to define their best teaching strategies for use in the context of a specific class.	Singular value decomposition, Nearest neighborhood	Hybrid
Application of implicit and explicit attribute for learning resource recommendation (Hu, 2020)	Resource	Propose a new resource recommender system framework for e-learning based on implicit and explicit collaborative filtering and sequential.	K-means Bi-Directional Extension based frequent closed sequence mining	Collaborative Filtering
U-Learn (Muangprathub et al., 2020)	Learning Objects	Help learners to accomplish their goals, offers suggestions of educational bibliographic materials and tools through a recommender agent based on learning style	Unknown	Collaborative Filtering

3.3. Artificiel Intelligence

3.3.1. Notions on Artificial Intelligence

In attempts to elucidate the term of AI, several definitions have been proposed. According to the Webster Dictionary, the main definition of intelligence is the ability to learn and solve problems. However, this definition is independent of human intelligence or machine intelligence. For Wikipedia, AI is the intelligence presented by machines or software. (McCarthy, 1963), who is one of the pioneers of artificial intelligence and the inventor of this term, defines it as the science and engineering of making intelligent machines. Finally, the definition we adopt in this chapter derived from Russell and Norvig, authors of the famous book "Artificial Intelligence" (Russell and Norvig, 2010). For these authors, AI refers to the study and design of intelligent agents where an intelligent agent is a system that perceives its environment and consequently takes actions that maximize its chances of achieving its objectives.

3.3.2. Machine Learning: An Important Sub-domain of AI

Machine learning deals with the theoretical, algorithmic, and applicative aspects of learning from previous examples. In short, learning from examples means that we try to build a machine (i.e., a computer program), which can learn to perform a task by observing examples. Machine learning methods can be divided into three categories: supervised (Buro, 2002), unsupervised and reinforcement learning (Hu and Wellman, 1998). In our study we focus the most uses popular algorithm witches **J48** decision tree algorithm.

3.3.3. The J48 decision tree algorithm

The J48 classifier is an extension of C4.5 developed by Quinlan (1986) as part of supervised learning. It generates a binary tree, the decision tree that is built to model the classification process. For a given instance, a tree is constructed to model the classification process in decision tree the internal node of the tree denotes a test on an attribute, branch represent the outcome of the test, leaf node holds a class label and the topmost node is the root node. (Margaret and Sridhar, 2006).

J48 does not take into the consideration the lost values while building a tree and allows classification through decision trees or the rules produced by them. We can predict the value for that item by using what is known about the attribute values in the other records (Shafiq et al., 2020).

Decision trees have been used as classifiers for many fields, e.g. medicine. For some areas, the trees produced by C4.5 are small and accurate, resulting in fast and reliable classifiers. These properties make decision trees a valuable and popular tool for classification.

```
Algorithm J48:
INPUT:
D                  //Training data
OUTPUT
T                  //Decision tree
DTBUILD (*D)
{
T=ϕ;
T= Create root node and label with splitting attribute;
T= Add arc to root node for each split predicate and label;
For each arc do
D= Database created by applying splitting predicate to D;
If stopping point reached for this path, then
T'= create leaf node and label with appropriate class;
Else
T'= DTBUILD(D);
T= add T' to arc;
}
```

3.4. Multi-agents systems

3.4.1. Definitions and characteristics of multi-agents systems

Conventional artificial intelligence models the behavior of a single intelligent agent; however, distributed artificial intelligence focuses on so-called collective intelligent behaviors.

Multi-agents systems (MAS), which are derived from distributed artificial intelligence, are computer models composed of basic entities and agents. The latter are autonomous and allow activities to be solved through their interaction and cooperation in an environment where they are organized in society (Ferber, 1997).

Thus, MAS is defined with the following equation (Demazeau, 1995):

MAS = Agents + Environment + Interactions + Organizations (AEIO)

However, according to (Chaib-Draa et al., 2001), MAS is generally EMIacterized by:

1. Each agent has limited information or problem-solving capabilities, so each agent has a partial point of view;

2. There is no global control of the multi agent system;

3. The data is decentralized;

4. The calculation is asynchronous.

MASs are ideal systems for representing problems with multiple resolution methods, multiple perspectives, and/or multiple resolvers. These systems have the traditional advantages of distributed and concurrent resolution of problems such as modularity, speed (with parallelism), and reliability (due to redundancy). They also inherit the potential benefits of Artificial Intelligence such as symbolic processing (at the level of knowledge), ease of maintenance, reuse and portability; but most importantly, they have the advantage of involving sophisticated interaction patterns.

3.4.2. Interactions between agents

Ferber defines an interaction as the dynamic linking of two or more agents through a set of reciprocal actions. Therefore, this interaction can be determined by a trace left by an agent in the environment (for example, displacement of an object) and the perception of this trace by another agent, as it can also be EMIacterized by a message that is exchanged between two agents or by a speech that is performed by them (Ferber, 1997) .

Interactions can be in the form of the overall work that agents do to achieve a common goal; that is, agents are said to cooperate to contribute to the success of the group by exchanging information about the environment or their intentions. Agents can also organize problem resolution by avoiding harmful interactions and exploiting beneficial interactions, and this is called coordination. This negotiation between agents tries to reach an agreement acceptable to all the concerned parties (Chaib-Draa et al., 2001).

- **Cooperation**: It is said that there is cooperation between the agents {A, B, C ...} in the environment E if (1) the agents only interact, and (2) if they have goals (Legras, 2006).
- **Coordination**: Coordination is defined in a set of agents if (1) these agents interact and (2) at least some of these interactions take the form of information transmission by articulated language or other codes (Legras, 2006).

- **Negotiation**: Negotiation not only resolves conflict, but it also prevents disagreements between individuals from becoming an open struggle and the system that does not degrade its performance (Ferber, 1997).

Durfee and his colleague (Durfee and Lesser, 1989) defined negotiation as the process of improving agreements on common viewpoints or action plans through the structured exchange of relevant information.

3.4.3. Communication between agents

The interest of a common universal language allowing the various agents to communicate was necessary with the advent of applications based on the MAS. ACL stands for (Agent Communication Language) is a standard language proposed for agent communication. There are two popular ACL approaches:

- Knowledge Query Manipulation Language (KQML) (Finin et al., 1994)

- FIPA - ACL (Foundation for Intelligent Physical Agents - Agent Communication Language).

Both approaches are based on the theory of speech act developed by Searle (1969), in which a set of performance is defined even though its content is not standardized; that is, it varies from one system to another.

So as to communicate, agents must have a common ontology in addition to the common language. This is a part of the agent knowledge based on describing the type of issues that the agent can deal with.

In order to support students, we have designed a multi-agents system capable of collecting and analyzing data EMIacterizing various aspects of learning or teaching, to extract pedagogically relevant information. To do this, we conducted research work leading to the proposal of several intelligent agents, each of which is dealing with a specific problem that concerns particular aspects of learning or teaching:

- Agent DO: Identification of learners at risk of dropping out.
- Agent EM: Detection of the emotional states of the learner.
- Agent Recommender: Recommendation of Educational Resources and Learning Activities.

3.5. *Design of the multi-agents system (EMAS)*

EMAS is a multi-agent system, each agent can deal with a specific problem:

- Agent DO: Identification of learners at risk of dropping out.
- Agent EM: Detection of the emotional states of the learner.
- Agent Recommender: Recommendation of Educational Resources and Learning Activities.

In this study we systematically present our proposal. First, we present the communication of agents in our system as well as their integration into the database and then we present the recommendation agent.

3.6. Modeling of intelligent agents

Agents work in a distributed environment, which means that we need to create a number of evaluation agents and a handle message exchange. This multi-agent has two types of agents: Manager and Classifier. All agents proposed previously are types of classifiers such as Agent DO, Agent EM, Agent FA, Agent VO, Agent CB, Agent CF1, and Agent CF2.

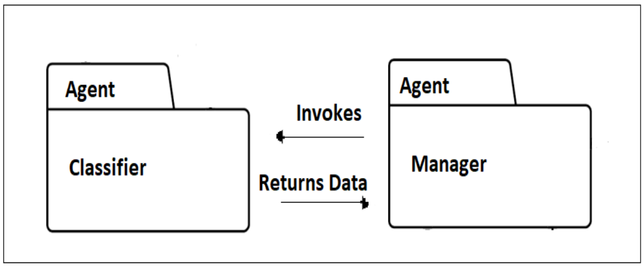


Figure1. Component Diagram: general scheme of operation

- Agent manager: it deals with loading the data, updating or creating the classifying agents according to the configuration performed by the user. It then receives their answers and then transmits them to the user.
- Classifying agent: A classifier applies a specific recommendation or prediction technique to the data sent by the manager. Thus, the managing agent chooses the classifier according to need.

3.7. The main bridge of integration: the database of the e-learning platform

Here, we consider an e-learning platform according to a representation in three layers: the front-end, the back-end, and the data layer.

- The front-end constitutes all the elements of the platform mobilized for the realization of the user interfaces.
- The back-end contains the elements that implement the features of the platform.
- The data layer includes the storage of data in a structured manner and the policy of access thereto.

The integration of EMAS into an e-learning platform is mainly based on the data layer. Either it is a direct access to the database of the e-learning platform or access via an API.

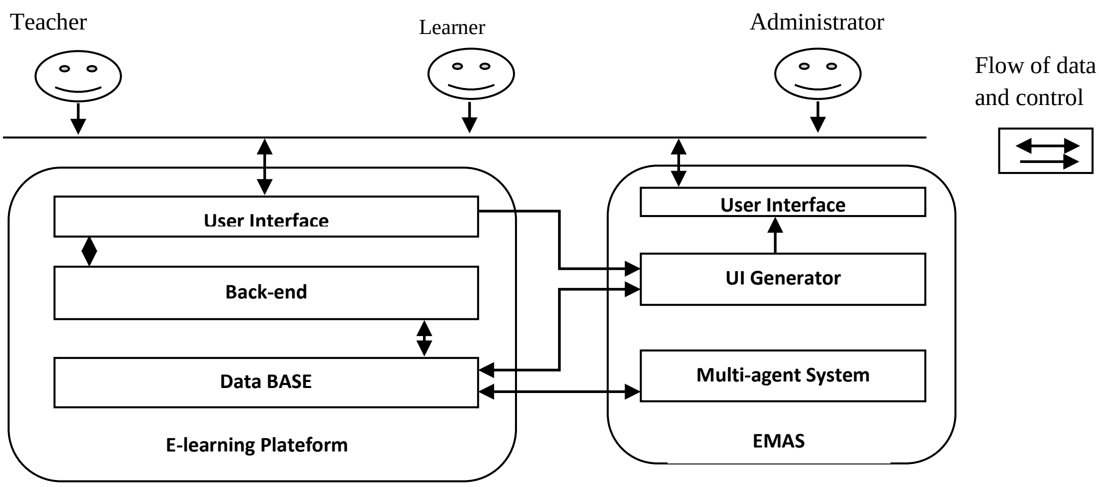


Figure 2. Architecture of EMAS integration

Note: In this article we limit our study to the recommeder one.

Recommendation of educational resources and learning activities: thanks to the implementation of the recommender agent, these agents allow the recommendation of educational resources, each of which are based on a technique and specific aspects of learning.

- Agent CB: Content-based Resource Recommendations

- Agent CF1: Resource Recommendations Based on Learner Preferences

- Agent CF2: Recommendations Based on Collaborative Filtering

We conducted a case study concerning the recommendation of books to the library of the EMI faculty of Fez, in order to offer students the most appropriate books for their needs.

3.8. Agent Recommander

- **Content-Based Resource Recommendations by the CB Agent**

The user of the search engines (Google, AltaVista, Yahoo, etc.) must systematically formulate their needs by using keywords.

- **Resource Recommendations Based on Learner Preferences by CF1 Agent**

Each student has a particular learning profile and specific preferences. The profile of the student plays a vital role

- **Recommendations based on collaborative filtering by the CF2 agent**

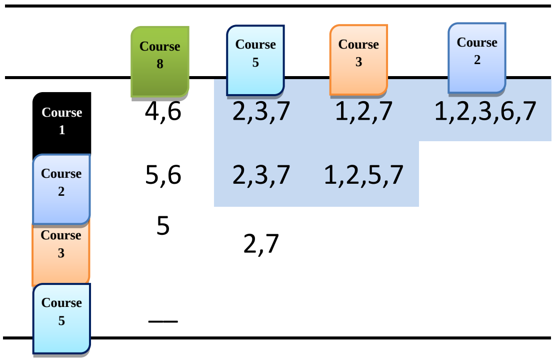
In the context of the provision of additional resources to students, we always specify that the students must choose which categories of resources their wishes to consult. So each student selects a group of resource categories. Thus, the data of all the students form lots of categories of resources. Starting from this dataset, we apply the association rule discovery technique. In other words, it is a question of identifying the similarities between the students' choices. To do this, we apply the association rule discovery technique to this dataset.

Table 2; *Frequent courses selected by different student*

Student	Courses
1	Course 1, Course 2, Course 3, Course 4
2	Course 4, Course 1, Course 2, Course 3, Course 5, Course 6
3	Course 1, Course 6, Course 2, Course 5, Course 7
4	Course 7, Course 1, Course 8, Course 9
5	Course 2, Course 8, Course 3, Course 10, Course 11
6	Course 2, Course 8, Course 1, Course 9
7	Course 3, Course 11, Course 1, Course 5, Course 2

We begin our search for similarities between two resource categories and then compare the students who choose the two. The table below illustrates more the similarities of the selected courses that the text cannot express:

Table 3: *The similarities of selected courses among different students*



Let us consider the association rule whose general form is X ⟹ Y where X is a set of elements and Y is an element. The implication of the rule is that if all elements of X are chosen by a student, then Y is likely to be chosen by that student. Let I be the set of all items and T= {t1, t2,…,tN} be the set of all transactions.

The support count: $\sigma(X) = |\{t_i \mid X \subseteq t_i, t_i \in T\}|$

The support: $s(X \Longrightarrow Y) = \sigma(X \cup Y)/T$

The confidence: $c(X \Longrightarrow Y) = \sigma(X \cup Y)/\sigma(X)$

In our example above, let us consider the association rule :{category 1, category 2}⟹{category 3}. The number of supports σ (category 1, category 2, category 3) = 3

- *Support:* s = σ (category 1, category 2, category 3) /T=3/7=0.42
- *Confidence*:

c = σ (category 1, category 2, category 3) / σ (category 1, category 2) = 3/5 = 0.6

Confidence of an association rule is an important measure as it gives us insight into the reliability of the conclusion of the association rule. For a given rule, the higher the confidence is , the more it is likely that price 3 here is present in the transactions containing prices 1 and 2.
Finding all the similarities or categories of resources is here interesting thanks to two main reasons:

- Highlight the relationship between different types of information on a topic. This is useful for the teacher. That is, by knowing this report, he/she is going to manage the structure of his/her course. This information could also be helpful to teachers in finding other teachers.
- Help students in the choice of different categories of information. In fact, a student may not know the subject, but he/she may start exploring it. With this approach, he/she will be assisted in this task, which could increase his/her motivation.

3.9. Case study: book recommendations to students

This work respectively presents all the phases of the realization of a practical case of application of the recommending agent. This is the recommendation of books based, in one hand, on the historical borrowing books to the library of the EMI; on the other hand, the system is also based on the demographic data of the students. Starting from this various information, therefore, the system recommends to each student the books most likely to interest him/her, according to his/her profile, the disciplines and the different sessions of the academic year.
In this study, we first collected and pretreated the available data. Then, we applied the j48 decision tree technique to the data.

3.10. Data collection and pre-processing

3.10.1. EMIbook database:

EMIbook is the database made up of our three databases:

– The database which contains all the books available at the library of the faculty of EMI Fez.

- The EMI Faculty student database, which contains various information on 4660 students.
- Book loan sheets at the library of the Faculty of EMI, Fez. The information presented on these sheets relate to the categories of books borrowed along with their borrowing periods.

EMIbook data can be represented through several tables as follows

- *StudentBook* is the dataset taken from the borrowing sheets.

Table 4: *StudentBook data columns*

Student_id	**Each Student has a unique identifier**
Book_id	Each book has a unique identifier
Emprunt_date	The borrowing period of a book "Fall Session" or "Spring Session"

- *Students* is the set of student demographic information

Table 5: *Columns of Students data*

Student_id	**The student id is unique**
Birth_date	Student birth_date
Sexe	Can be male or female
Bac	The type of baccalaureate
PFE	Indicates whether the student has the end of study project or not
Option	The specialty studied by the student

- *Books* is the set of information for each book

Table 6: *columns of Books data*

Book_id	**each book with a single identifier**
Title	the title of the book
Type	type of book
Nb_emprunts	the number of times a book has been checked out

3.10.2. Pre-processing

After we performed a preprocessing on the EMIBok database, we obtain several sets of data: **StudentBookEmprunt**: We did a preprocessing on the StudentBook set and we got the StudentBookEmprunt set. We have therefore deduced other information very useful for the recommender.

-Student_id: we used demographic information (Content-Based), which allowed us to solve the problem of cold starts so according to the profile of a new student. In other words, recommending a book to a student, who has never borrowed a book from the EMI library in Fez, requires looking for demographic similarities among students who are already in database.

-Book_id: we use the book identifier so that we can get the Type.

-Nb_emprunts: it allows us to determine the period of borrowing book as an important step for making a reliable recommendation that best satisfies the student.

Table 7:*columns of studentBook Emprunt data*

Student_Id	Age : from the date of birth Bac : option of the baccalaureate Sexe : male / female

Book_Id	Type
	Nb_emprunts : the number of times a book has been borrowed
Session	Book borrowing date provides information on the session in question "autumn" or "spring"

AllStudents : this set is obtained after preprocessing on the Students set

Table 8:*AllStudents data table*

Student_Id	**Id student's identifier**
birth_date	Information about the age of the student 17 years - 25 years = "class A" Over 25 years = "class B"
Sex	Male / Female
Option	The specialty studied by the student
BAC	Bac : option of the baccalaureate

AllBooks : this set is obtained after preprocessing on the Books set

Table 9:*AllBooks data table*

Book_id	**Book ID**
Book_title	The book's title
Type	The type the book belongs to
Nb_emprunts	The number of times the book has been checked out

These different datasets constitute our new EMIbook database.

3.11. Books recommendation

Our recommendation system is based on three main methods:

- **Using a classifier**: before predicting whether a book given will be interested or not a student in a specific period, we need to take into consideration all the information about that student. In the case of a recommendation for a student who already borrowed certain books, we trained the classifier from all data StudentBookEmprunt.
- **From User-User similarity**: That is to recommend to a student the same books borrowed or likely to interest students whose profiles most closely resemble the given student. To do this, several methods exist; we have opted for choice from that of cosinus as one of the most used methods.
- **Based on the Item-Item similarity**: The aim is to recommend to a student the books closest to those from which he/she has already borrowed.

In the case that the ***classifier*** based method provides book recommendations to the student in question. It is a list of all kinds of books likely to interest the student, sorted in descending order. From this list, we make a selection of the most borrowed books.
Here, since the student has never borrowed books, he/she therefore has no history. Hence, the recommendation methods based on the similarities "***User-User***" and "***Item-Item***" do not provide any sufficient results.
Therefore, starting from this result can make a union to obtain the final list of recommendation of books, which is represented in the following diagram:

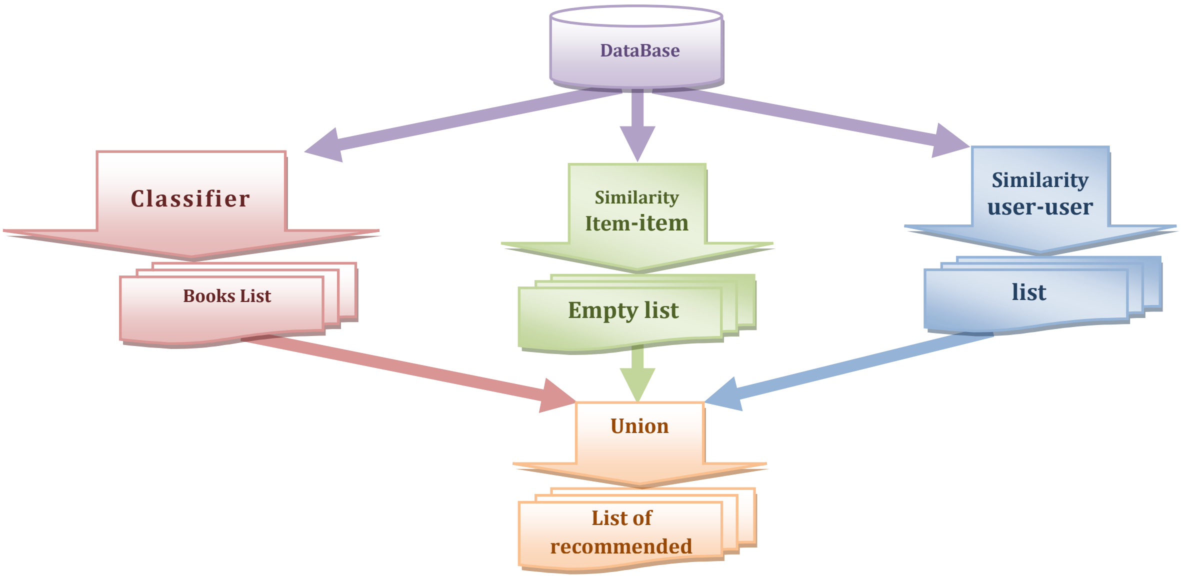
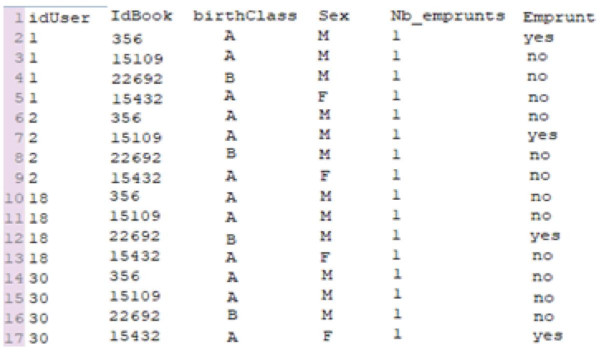


Figure 3. Recommendations of books to a student with no borrowing history

Using J48 classifier We have proposed a recommendation system based on decision trees J48 which allows us to know the user



	idUser	IdBook	birthClass	Sex	Nb_emprunts	Emprunt
1	idUser	IdBook	birthClass	Sex	Nb_emprunts	Emprunt
2	1	356	A	M	1	yes
3	1	15109	A	M	1	no
4	1	22692	B	M	1	no
5	1	15432	A	F	1	no
6	2	356	A	M	1	no
7	2	15109	A	M	1	yes
8	2	22692	B	M	1	no
9	2	15432	A	F	1	no
10	18	356	A	M	1	no
11	18	15109	A	M	1	no
12	18	22692	B	M	1	yes
13	18	15432	A	F	1	no
14	30	356	A	M	1	no
15	30	15109	A	M	1	no
16	30	22692	B	M	1	no
17	30	15432	A	F	1	yes

Figure 4. Learning file

For the evaluation of our system we calculated sensitivity, specificity and G

Table 10:*Evaluation of the system*

	Sensitivity	Specificity	G
J48	0,79	0,89	0,98

With this result we can start our online library application in order to collect a large amount of information for the proper start of the recommendation system.

Table 11:*Calculation of the similarity*

User- User Similarity	Item-Item Similarity

IdUser IdUserSimil 1 93 2 13 3 245 4 234 5 120 6 276 7 393 8 276 9 46 10 7	IdItem IdItemSimil 1 13 2 393 3 655 4 234 5 512 6 276 7 612 8 276 9 46 10 7
We calculate the similarity according to the history of users existing in our database and we obtained the result	It calculates the similarity between the books viewed by a given user. In this case we use the cosine distance

Through different case studies carried out for certain agents in particular, we pragmatically show the feasibility, and we highlight the relevance of these agents in the context of the EMI faculty. For the recommender agent, the start of applying this kind of agent online will help raise a significant amount of information for the proper operation of the recommendation system.

1. An evaluation phase, therefore, will first try to determine the performance of our system; in case that the error is large, we will try to propose new solutions for the system.
2. Adding the rating to a book will increase the performance of the system
3. The automatic book borrowing will make it possible to better serve to have the data necessary for the good prediction.

4. Conclusion

Thanks to its architecture, our multi-agents system enjoys a great capacity for extension. Indeed, we could add new classifiers to the system so as to give us the opportunity to address new challenges as needed. Whenever the system integrates a new classifier, this will further improve the relevance of the results. Thanks to EMAS, we could carry out an analysis of the learning by considering several aspects: notably the motivation of the learners, the metacognition, the pedagogical approach of the teacher, the didactic of the materials, etc. therefore, we could implement several learning modalities among others adaptive learning and collaborative learning.

This interoperability strategy relies mainly on the process of accessibility to the source data and the flexibility to structure it. Likewise, it relies on the UI Generator device, which allows the automatic generation of user interfaces. These interfaces present a user-friendly graphic design for displaying information according to their relevance. In addition to the scalability of EMAS, the simplicity of its interoperability strategy further enhances its genericity. These EMIacteristics are factors that strongly encourage the adoption of EMAS. This could lead to its massive use in the area of IAED, EDM and LA solutions.

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