Hybrid Recommender System for Educational Resources to the Smart University Campus Domain

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Abstract: The development of new cutting-edge technologies in recent years and the ease of access to the internet, the amount of data circulating on the network have been severely increasing, making it difficult to access quality information and causing many users to waste their time looking for and filtering through data. Thus, recommendation systems appears. They are responsible for searching relevant information to the user through mechanisms capable of recognizing the user's possible interests and, with the use of recommendation algorithms, bringing the user resources that meet their interests. Actually, recommender systems are applied in many domains, including news, healthcare, and finance. Recently, recommender systems have been applied in smart campus domain, which defines systems and techonologies to be applied in university campus. From this scenario, the objective of this study is to develop a hybrid recommender system, attached to a software architecture, to provide general educational resources to users. The prototype of the architecture was evaluated using real item data and shown a significant accuracy in the recommendation process.

1 INTRODUCTION

With the exponential growth of the media in recent years, the increase in the amount of data circulating on internet has become a problem for many areas such as digital commerce, social networks, entertainment sites and many platforms in many domains. An example of domain which the ammount of data is not integrated between different systems is in academy or universities. The access of information that is really of user interest is frequently difficult in academic environment. In this context, recommender systems appear as an alternative to reduce this amount of data and make the task of searching for a particular item simpler and faster (Chun-Mei et al., 2021).

Along with this, in recent years, the frequently changing on the student's profile has led to a demand for new teaching and learning methods to better meet the student's needs. Thus, classic classrooms are not the only spaces learning process (Jordán et al., 2021) in the students' life. Online platforms are not limited by space or time, in addition, having a multitude of resources, they have become important and attractive in recent years (Zhong et al., 2020).

However, as much as these online platforms are convenient and have improved teaching and learning management and innovated education in general, there still issues of getting students to receive personalized recommendations and making their learning process more efficient. Because these platforms have a large amount of information, the time spent by students in the searching of quality resources is still a slow and painfully task, because, even though there is a system that already filters data, more and more information are constantly added. On the other hand, in very new platforms, the small amount of data limits the students' learning scope (Meng and Cheng, 2021).

With the development of new technologies such as IoT (Internet of Things), another area of research

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that has become popular is smart campuses, or smart university campuses. In order to adapt to students' demands through the use of new teaching technologies, many universities realized that it was possible to make changes within their environments using big data analysis and, consequently, raise the quality of the services offered, reduce their costs and improve efficiency of the local management of people, data and general resources (Xu et al., 2018).

Considering the presented context, the main objective of this study is to model and prototype a software architecture that integrate recommenders of different types and make the recommendation of educational resources: Courses, mini-courses, video classes, scientific articles, lectures, events, theses, teaching materials, e-books, among others.

The presentation of the paper is structured as follows: In Section 2 the concepts of recommender systems and intelligent campuses are presented, it also present related research focused on these areas. In Section 3 the proposed architecture and operation of the recommender systems are presented. The recommendation process is divided into two main filtering techniques: collaborative filtering (CF) and content-based filtering (CBF). In Section 4 the results obtained throughout the development of the research are presented. And, finally, in Section 5 the conclusions of this work are presented, which summarizes the information from the entire research, as well as information related to the future directions of the project.

2 BACKGROUND

This section presents the main concepts related to the proposed software architecture and presents a set of related work, with the main differences regarding this proposal.

2.1 Recommender Systems

With the popularization of the internet in the early 90s, the number of active users became extremely high, while the information circulating through it also grew exponentially every day, causing an overcrowding of data in websites, social networks and browsers, making it difficult for users to access relevant information (Meng and Cheng, 2021). Likewise, there was also great potential on the part of companies to use the internet as a means of selling products and publicizing their work, which would attract even more new users (Cho et al., 2007).

The problem of the massive amount of data on the internet makes the search for specific information an extremely slow and time-consuming task, in addition, linguistic variability and the use of different types of languages as well as expressions, slang and words with more meanings in documents and websites makes it even more difficult for the user to search for what he/she is really interested in (Benfares et al., 2017).

An example of this can be the comparison between social networks and scientific articles, where even though the informal language used in a conversation between two users addresses the same topic of an article, it will not have the information transmitted in the same way or its quality probably it will be much inferior to the language of the study, impairing its understanding. From this scenario, alternatives arise to get around the problem of large amounts of data on the network, which may be the use of artificial intelligence, automated learning systems or, also, recommendation systems (Benfares et al., 2017).

The term and concept of recommender systems was first introduced in the 1990s by Jussi Karlgren (Karlgren, 1990). Recommender systems are responsible for making predictions about the preferences of a given user over a massive amount of data by calculating the similarity between items, users and the applicant's interests. These systems look for affinities between information in order to identify possible data to be recommended (Mrhar and Abik, 2019). These systems have a wide variety of applications and can appear on sales sites, news, food (Wang et al., 2021), music (Zhao et al., 2019), social networks, movies and series (Benfares et al., 2017), services, jobs (Zhou et al., 2019), tourism (Hu et al., 2017) and also platforms aimed at the academic field ((Samin and Azim, 2019), (Uddin et al., 2021)).

It also happens that with the advancement of the internet and its increasingly wide use in new technologies, recommendation systems evolve together and constantly with it due to the fact that new fronts and study trends emerge with the objective of optimizing the use of these systems or creating new applications for them (Dennouni et al., 2018). Initially, for example, recommendation systems were focused on services and products (e-commerce), later on social networks and user contextual information (geographical location, social relationships, tastes, etc.) and, finally, the union with technologies such as IoT (Internet of Things) and LBS (Location Based Systems) in mobile applications (Dennouni et al., 2018).

Each recommender uses a recommendation technique to make the best options for items for each user based on their interactions with other items, purchases, watched movies, games, profiles of other users, accessed courses, etc. types of food, places visited, among other parameters. There are several filtering techniques used to reach a small number of resources with a very high probability of being relevant to the user, these techniques include algorithms and programming libraries that together make up the recommendation system. Among the most famous are collaborative, content-based and hybrid filtering.

Collaborative filtering takes into account information from users with similar interests to filter items (Jordán et al., 2021). For example in a sales website, when a purchase is about to be made, a tab with the "other users also bought:" message and then the related products are displayed, that is, the system recommends to the user other items that would possibly be of his interest taking into account what he is buying and what other users, who have also interacted with the same product, are interested in.

Content-based filtering aims to recommend resources taking into account the description and parameters of the items themselves and similar to the user's interests (Mrhar and Abik, 2019). In a video platform, for example, when the user accesses a certain video, it is also offered to him a series of other contents with themes similar to the one being reproduced. When accessing a video about cake recipes, a possible item to be recommended would be a *pudding* recipe, as both fit into the categories *recipe*, *cooking*, *sweets*, for example.

Finally, hybrid filtering is the union of two or more filtering techniques (Jordán et al., 2021), so that the advantages and applications of one are able to cover the disadvantages of the other, causing a variation in the type of item that is being presented to the user and not always maintaining the same pattern.

2.2 Smart Campus

The word *smart*, over the last few years, has accompanied the development of new technologies and is used in multiple terms of applications such as smart systems, smartphones, smart homes, smart energy, smart manufacturing, smart buildings, smart cities, among others (Zhang et al., 2022).

In addition, there are several definitions for "intelligent", which can be the ability to make adaptations in response to changing circumstances; ability to demonstrate intelligence; ability of a system to convert input data into an action (Imbar et al., 2020). Smart can also be understood as an acronym with the following meanings: Self-directed (schools with cloud-based infrastructure), Motivated (strengthening teachers' skills), Adaptive (encouraging online classes), Resource (development and use of digital teaching materials) and Technology (global reach of information) (Imbar et al., 2020).

This means that the tools used in education must be smart for both students and teachers, that their interests in class are shared equally and that teaching resources are made available through technologies that use cloud services, developing and enriching knowledge. provided by these systems (Imbar et al., 2020).

Smart campus can be described in different ways depending on the author, but all concepts are valid and similar. A universal definition for "smart campus" (Chagnon-Lessard et al., 2021) was not found, however several authors present the following definitions for smart campuses, according to some of them:

- **(Du et al., 2016):** Smart Campus is the integration of all kinds of application service systems, creating a living environment with intelligent learning and teaching, which is suitable for: management, teaching, scientific research and health, and is also based on IoT;
- **(Zhang et al., 2022):** Smart Campus is the deployment of advanced information and communication technologies (ICT) to increase the effectiveness and efficiency of campus activities;
- **(Xu et al., 2018):** Smart Campus is the new direction of information education. Social networks, cloud computing, big data, mobile technology, IoT and other technologies serve as support for educational informatization, which provide new ideas for the study of education technologies. The development of information technologies reflects, mainly, in the development of the understanding of this information in universities;
- **(da Nóbrega et al., 2022):** Smart Campus is a higher education institute that creates an ecosystem through information and communication technologies (ICT) to achieve sustainability using an adaptive and collaborative learning model to promote a better user experience.

According to (Imbar et al., 2020), a university can only be called intelligent if it manages to use its knowledge for study, resolve conflicts of interest between users (students, professors, employees, employees), and use the intelligence and skills of the public to contribute to system development. Based on the definitions presented, it is possible to say that a smart campus is a university environment capable of providing its users with tools, services and resources that aim to resolve their conflicts of interest, through cutting-edge technologies such as IoT and smart objects. A list of key characteristics of an intelligent campus was definey by (Abualnaaj et al., 2020):

- **Smart Card or e-Card:** Access to classrooms, laboratories, dormitories, library; digital wallet payments; data storage control.
- **Smart Classrooms:** Virtual reality; interactive and collaborative platforms; remote teaching and learning; collaborative research.
- **Energy Management:** Sustainable and smart energy management systems; use of renewable energies; smart lighting; electric vehicle charging system.
- **Adaptative Learning:** Personalized teaching methods; specific supplementary courses and disciplines; computerized fitting tests; **educational resource recommender systems**.
- **Smart Transportation:** Smart parking; tracking of vehicles used on campus; smart navigation.
- **Security and Safety:** Intelligent security and protection systems.
- **Optimization and Analytics Data Center**;
- **Smart Facilities Services:** Sports centers, libraries, restaurants, shops; campus social media.

2.3 Related Work

This section brings an overview of similar works that fit into the areas of recommender systems and intelligent campuses, highlighting the types of recommended items and the filtering techniques used in each one.

(Ibrahim et al., 2019) proposed a framework aimed at the academic area that aims to recommend undergraduate and graduate courses (masters, doctorates, among others) for students in general. In his hybrid system, he chooses to use collaborative and content-based filtering along with ontology for extracting and integrating information from multiple sources.

(Kong et al., 2017) bring in study a model of collaborator recommendation system, that is, researchers with similar research interests so that other researchers can be active and help to develop other scientific works. The model is based on collaborative filtering, content-based filtering and another type known as social network-based, creating a hybrid model.

(Mrhar and Abik, 2019), in turn, proposes a recommendation system for online course platforms that can make personalized recommendations based on each user's profile. The author makes use of content-based filtering and deep learning to improve the accuracy of the algorithm.

(Xiao et al., 2018) finally, brings a personalized recommendation system based on the interests and history of each user to recommend them didactic materials and resources necessary for their learning. This system makes use of content-based and collaborative filtering.

Table 1: Studies and characteristics of your recommendation systems.

Studies	**Recommended item**	**Filtering**
(Ibrahim et al., 2019)	Undergraduate and postgraduate courses	Ontology based filtering, Content-based filtering, Collaborative filtering
(Kong et al., 2017)	Collaborating researchers	Collaborative filtering, Content-based filtering, Social network-based filtering
(Mrhar and Abik, 2019)	Online courses	Content-based filtering, Deep Learning
(Xiao et al., 2018)	Didactic materials for learning	Collaborative filtering, Content-based filtering
This research	Educational resources (courses, mini-courses, video lessons, teaching materials, e-books, lectures, events, scientific articles, theses, similar user profiles, other educational platforms)	Collaborative filtering, Content-based filtering

Based on these and other studies in these areas, this work aims to develop a platform that would not be limited to recommending just a few types of items, but a variety of them, covering both the items discussed above and many others. Table 1 presents the types of resources recommended in each study and the techniques used for data processing.

3 HYBRID RECOMMENDATIONS TO SMART CAMPUS DOMAIN

In this section we present the definition of the proposed software architecture and the definition of the recommendation strategies applied to it.

3.1 The SmartC Software Architecture

The SmartC platform is designed to be a software architecture, modeled in a set of services, to provide the main structures to use different recommender systems for different types of items. The services and layers of the architecture were defined specially for the smart campus domain (presented in Figure 1).

The architecture can be divided into three sections each responsible for a part of the SmartC system's operation: the access environment, the recommendation management environment, and the persistence layer (da Silva Lopes et al., 2022). In the access environment, it is the part accessible to users, it is where recommendations are presented, users can interact with resources, direct themselves to other university portals, inform their interests, for example, all through devices such as cell phones. or computer.

In the recommendation management environment or development environment, only developers have access to it, because here are all the codes and functions of the system and where new codes are added or edited and corrected. This environment is also where the entire process of personalized recommendation for each user takes place, where their information is collected and processed and then requests are sent to the database so that the data obtained can be worked on by the recommendation algorithms.

Finally, in the resistance layer we have the database, responsible for storing all system information in tables, that is, descriptions of resources, interests of each user, interacted items, history of recommendations, evaluations, for example, are all saved in this section and which, when requested, are sent to the development management environment to start the filtering and recommendation process.

The recommendation algorithm, in turn, developed on the platform, aims to recommend to users, in a personalized way, educational resources based on topics of interest that the user must inform when accessing the system. It is a hybrid system because it has two types of filtering: content-based filtering and collaborative filtering. Because these two types are available, it was decided to switch between the filters every time the user requests new recommendations, making new resources recommended each time the system is called and avoiding a certain limitation. what the user can access. As such, each filter and its use is explained in the following sections.

3.2 Content-Based Recommender

In algorithms that use content-based filtering (CBF), items will be recommended based on the user's interests (Thannimalai and Zhang, 2021). This type of filtering also searches for items that are similar to each other, that is, based on the description of a given resource, the system will look for other resources with similar characteristics to be recommended. In addition, because this type of filtering depends only on the user's interests and the characteristics of the items, it is already capable of making good recommendations right from the start without the need for a prior information base, and it is also very volatile because if the user's interests change, the recommendations will also change (Eliyas and Ranjana, 2022).

For example, on movies and series website, whose system uses the CBF, recommendations will be made based on the content that the user has most watched or watched recently. In terms of security and privacy, CBF does not require, for example, that the user share his interests or have to make them public, it is enough for him to access the contents of the system and his preference information is already processed and properly stored (Thannimalai and Zhang, 2021).

In this study, the developed algorithm makes use of CBF works as follows: initially, the interests informed to the system by the user are stored in tables that relate the user to each of these topics and, from this relationship, all the resources that contain any of these topics are listed; once listed, if they have not yet gone through this process, any and all text present in the parameters of each resource is transformed into a string and goes through a textual filtering technique known as bag-of-words, which removes from a text all possible keywords (relevant words) and counts each one, creating a list of words and their appearances in the text which, in turn, is added as a resource parameter; after that, this same process is applied to the list of resources already favorited by the user, so that a calculation of similarity between the textual content of each resource with the other is performed using cosine similarity; finally, the 25 resources that are most similar to the user's favorites list are recommended to the user.

3.3 Collaborative Recommender

Collaborative filtering (CF) is the most successful and used technology in the area of recommender systems, its recommendation techniques have a wide range of applications in the most diverse sectors such as digital commerce (e-commerce) and social networks (Chen et al., 2018). The main idea of a recommendation algorithm that uses CF is to recommend items that are possibly of interest to the user based on their relationships with other users and/or relationships between (Zheng et al., 2020) items. This type of system is

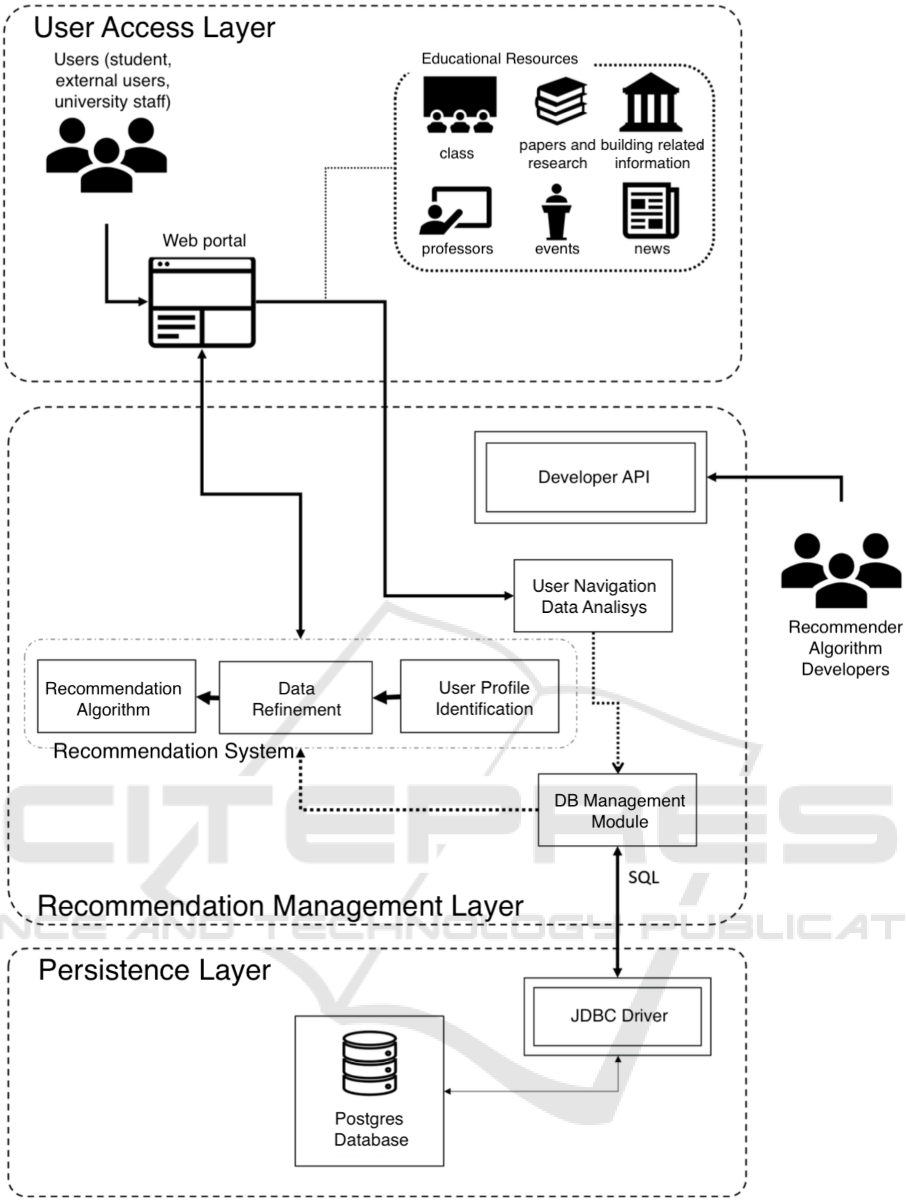

Figure 1: SmartC software architecture definition.

based on evaluation matrices where each user informs how relevant a given resource is for him or her, how much he or she liked or disliked a certain recommendation and the methods used act directly by processing and computing the information from these matrices to generate new recommendations (Valdiviezo-Diaz et al., 2019).

However, systems with FC may have impasses due to problems such as big data, information sparsity and cold-start, which severely affect the quality and accuracy of recommendations (Chen et al., 2018). Therefore, it is customary to make integrated use of other technologies and filtering techniques such as, for example, clustering, Singular Value Decomposition (SVD), Probability Matrix Factorization (PMF), recommendation with social trust ensemble (RSTE), Social rating Matrix Factorization (SocialMF), to work around these problems (Chen et al., 2018).

CF can be divided into two types of approaches: model-based and memory-based (Valdiviezo-Diaz et al., 2019). In a model-based approach, a model is created from data and then recommendations are made such that user ratings for certain items are modeled with a set of factors that represent characteristics of those users and items.

The most popular type of implementation of this approach is Matrix Factorization (MF), in addition, this method has achieved better results in terms of performance and accuracy. On the other hand, in the memory-based approach, the information to be recommended is obtained directly from the (Valdiviezo-Diaz et al., 2019) evaluation matrices. And algorithms that use this approach can be further divided into two types: user-based collaborative filtering (user-based CF) and item-based collaborative filtering (item-based CF) (Thannimalai and Zhang, 2021).

- User-based CF: makes comparisons between users with similar preferences based on ratings made on the same items.

- Item-based CF: Creates a list of items similar to what the user has previously interacted with or rated.

In this study, the developed algorithm that makes use of the CF in the following way: in the same way as the CBF, the user informs the system of his interests; from that, the system will look for other users who have the same interests and will create a list for each one; then, a sum of the topics of both users is made and, for each common interest, 1 is added to the total; finally, the algorithm separates the resources that would be recommended to the most similar users in a list, shuffles it and returns it to the requesting user.

It is also important to point out that none of these filters, both CBF and CF, will fulfill its role if the user does not previously inform the system of his interests. More specifically, for CBF, if the user has not favorited any resource so far, the recommendations made to him will be based only on his interests.

The platform was prototyped using the following technologies: Angular framework for frontend application, Python, Flask, Scikit and Surprise! libraries for backend appplication and PostgreSQL database.

4 EVALUATION

This section presents the evaluation process of the prototyped architecture, the list of resources available in the system and the process of evaluating the accuracy of the recommender system based on collaborative and content-based filtering. Figure 2 presents an example of the UI that shows to user how a recommendation is presented and how the user can interact with this recommendation. The users can: (i) Visualize the item, (ii) Mark the item to be removed of the recommended set to the user, (iii) Mark the item as favorite and (iv) Evaluate the item in a Lickert scale (from one to five). All the interactions of the user with the items are recorded and analyzed by the recommenders of the software architecture.

4.1 Case-Based Scenario

From focus of the project, a survey of possible resources to be used in the recommendation system was carried out. A search was carried out for items within the scope of Federal University of Santa Maria[1], on items such as scientific articles, professors/supervisors, university courses, disciplines offered, mini-courses, technical courses and video lessons. The items were identified and crawlers were developed to import the metadata of the items to the recommender system.

Currently, the *dataset* is composed of 189 topics of interest and educational resources that cover, mainly, the study areas of the Cachoeira do Sul campus (Architecture and Urbanism, Electrical Engineering, Mechanical Engineering, Agricultural Engineering and Transport and Logistics Engineering). Table 2 shows the number of topics of interest and resources divided by category, which today make up the *dataset*.

Table 2: Educational resources used in the evaluation process.

Item Category	**Number of items**
Graduate program work	165
Professor	135
Minicourse	78
MsC. Dissertation	26
Research Project	14
Graduate Dissertation	9
Research paper	4
Extension Project	2
General Information Report	2
PhD. Thesis	1
Media publication	1
Total	437

4.2 Results and Discussion

To assess the accuracy of the recommendation algorithm, fictitious users and educational resources were created. Being the educational resources (total of 10 resources) related to a topic, as shown in Table 3.

A random number of users (between 20 and 100) was created for each topic of individual interest and a random number of users (also between 20 and 100) related to two topics of interest simultaneously. Table 4 shows the number of users interested in each topic or group of topics.

It can be seen in Table 4 that groups of users were purposely created with a common interest in Engineering and one of the four topics: Art, Science, Mathematics and Music.

[1]https://www.ufsm.br

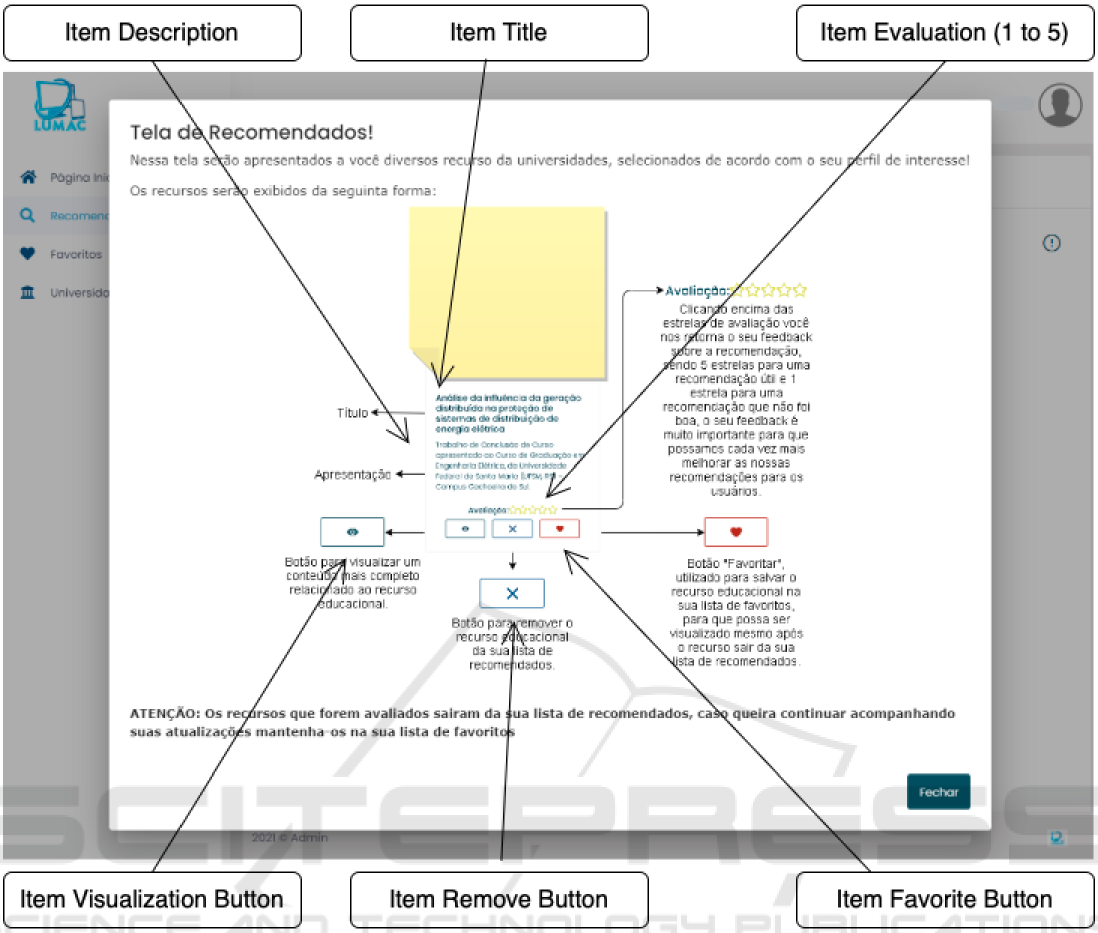

Figure 2: Example of the interface of a recommended item, with the explanation of the possible interactions (in portuguese).

Table 3: Educational Resources.

Id	Topic
0	Engineering
1	Math
2	Science
3	Art
4	Music
5	Sports
6	History
7	Geography
8	Literature
9	Philosophy

Through this, it is clear that there is a relationship between users who are interested in engineering and users who are interested in mathematics, science, art and music. Therefore, it is expected that the algorithm will be able to identify this relationship and recommend these educational resources to users with an interest in engineering only.

Table 5 presents the result of the recommendation system based on collaborative filtering, where the topic column represents the recommended resource in descending order for a user with an interest in engineering alone.

Table 4: Interest topics.

Interest Topics	Number of Users
Art	49
Art, Engineering	77
Science	76
Science, Engineering	55
Engineering	81
Engineering, Math	73
Engineering, Music	94
Sports	90
Philosophy	40
Geography	52
History	66
Literature	38
Math	56
Music	46

Table 5: Prediction of the evaluations.

user_id	topic
0	Engineering
0	Art
0	Music
0	Science
0	Math
0	Sports
0	Philosophy
0	History
0	Literature
0	Geography

It can be seen in Table 5 that the resource with the best prediction of interest for user 0 was art, followed by music, science and mathematics, that is, the algorithm proved to be capable of identifying the probable interests of a user with an interest in engineering alone.

5 CONCLUSIONS

The introduction of state-of-the-art technologies on university campuses in order to make intelligent campus an efficient way to develop and improve the services and resources offered by the university, making its users able to fully achieve their goals. The application presented in this study aims to serve as a tool for the development of an intelligent campus, by recommending educational resources to users based on their interests, making use of multiple filtering techniques and libraries in its algorithm. The results of the system evaluation demonstrate that the algorithm is able to make accurate predictions about possible interests of a user, even if he has informed few or even just one topic of interest.

As future objectives, it is intended to implement a resource evaluation system in the algorithm and make the generated recommendations also take this parameter into account. With this, it is expected that the accuracy of the SmartC system will be even greater and that the recommended resources will please even more the tastes of the users.

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