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ANALYSIS OF INFORMATION SYSTEMS IN THE DEVELOPMENT OF EDUCATIONAL PROGRAMS FOR ELECTIVE COURSES

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Abstract

In these days, with the rapid development of information technologies and the education system of higher educational institutions, huge amounts of data are accumulating, and a large number of available courses are being developed. Consequently, students face difficulties in finding suitable courses that match their interests. As a solution, several course recommendation systems have been developed over the course of a decade, and many data mining methods for cluster data have been applied. The recommendation system allows students to notice their preferences and returns results that are useful to them, based on the assessments of other users and the assumptions of the system itself. With the help of recommendation systems, the student's learning process will be planned more productively and efficiently. The purpose of this study is to determine the general criteria of the recommendation system to meet the interests and objectives of students. In order to gain a deep theoretical understanding, a thorough review of the literature on works published over a 5-year period (2015-2020) was conducted. The paper analyzes the technologies that are used to create recommendation systems. The results obtained show common approaches, algorithms, and evaluation measurements of the recommendation system.

Keywords: recommendation system, course selection, Collaborative Filtering (CF), Content-Based Filtering (CBF), algorithms.

Аңдатпа

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БІЛІМ БЕРУ БАҒДАРЛАМАЛАРЫН ӘЗІРЛЕУ КЕЗІНДЕ ЭЛЕКТИВТІ КУРСТАР ҰСЫНАТЫН АҚПАРАТТЫҚ ЖҮЙЕЛЕРГЕ ТАЛДАУ

Қазіргі таңда, ақпараттық технологиялар мен жоғары оқу орындарында білім беру жүйесінің қарқынды дамуыда және де көптеген элективті курстар әзірленуде. Десекте, деректердің үлкен көлемі студенттердің өздерінің қызығушылықтарына сәйкес келетін курстарды табуда қиындықтарға әкелуде. Атап өтілген мәселелінің шешімі ретінде, соңғы он жыл ішінде шешім ретінде бірнеше элективті курстарды ұсыныстын ақпараттық жүйелерлер әзірленуде, сонымен қатар кластерлік мәліметтер үшін көптеген деректерді іздеу әдістері қолданылды. Элективті курстарды ұсынатын ақпараттық жүйелер студенттерге басқа пайдаланушылардың бағалары мен курс туралы ойларын білу арқылы, ең тиімді деген курстарды таңдауға мүмкіндік береді. Ұсыныс жүйелерінің көмегімен студенттің оқу процесі нәтижелі және тиімді жоспарланады. Осы зерттеудің мақсаты ұсынымдық жүйенің жалпы өлшемдерін анықтау болып табылады. Бұл зерттеудің мақсаты студенттердің мүдделері мен міндеттерін қанағаттандыру үшін құрылып қатқан ақпараттық ұсыныс жүйелерінің жалпы критерийлерін анықтау болып табылады. Терең теориялық түсінік алу үшін 5-жылдық кезеңде (2015-2020 жылдар) жарияланған жұмыстар бойынша әдебиеттерге мұқият шолу жасалды. Алынған нәтижелер ұсыныс жүйесінің жалпы тәсілдерін, алгоритмдерін және бағалау өлшемдерін көрсетеді.

Түйін сөздер: ақпараттық ұсыныстар жүйесі, курсты таңдау, коллаборативті фильтрлеу, контенттік фильтрлеу, алгоритмдер.

Аннотация

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АНАЛИЗ ИНФОРМАЦИОННЫХ СИСТЕМ ПРИ РАЗРАБОТКЕ ОБРАЗОВАТЕЛЬНЫХ ПРОГРАММ ПО ЭЛЕКТИВНЫМ КУРСАМ

На сегодняшний день, с быстрым развитием информационных технологий и системы образования высших учебных заведений накапливаются огромные объемы данных, разрабатывается большое количество доступных курсов. Следовательно, студенты сталкиваются с трудностями в поиске подходящих курсов, которые соответствуют их интересам. В качестве решения в течение десятилетия было разработано несколько систем рекомендаций по курсам, а также применено множество методов интеллектуального анализа данных для кластерных данных. Рекомендательная система позволяет студентам замечать свои предпочтения и возвращает результаты, которые полезны для него, основываясь на оценках других пользователей и предположениях самой системы. С помощью рекомендательных систем учебный процесс студента будет спланирован более продуктивно и эффективно. Целью данного исследования является определение общих критериев рекомендательной системы для удовлетворения интересов и задач студентов. Для получения глубокого теоретического понимания был проведен тщательный обзор литературы по работам, опубликованным за 5-летний период (2015-2020 годы). В работе анализируются технологии, которые используются для создания рекомендационных систем. Полученные результаты показывают общие подходы, алгоритмы и оценочные измерения рекомендательной системы.

Ключевые слова: рекомендательная система, выбор курса, коллаборативная фильтрация, контентная фильтрация, алгоритмы.

Introduction

Recently, many aspects of receiving a high education have been changed. The volume of course-related information available to students is rapidly increasing. As a consequence, students pursuing higher education degrees are faced with many challenges: a myriad of courses from which to choose and a lack of awareness about which courses to follow and in what order. To make decisions students at the elective courses' specific content, easy courses to obtain higher scores and sometimes they look at professors. In most cases, their decisions are influenced by students' feedback [1], consultation with their advisors [2], and so on. Hence, there is a need for a recommender system to aid students to make relevant course choices as elective courses are integral components variable system of the educational process at the levels of basic general and secondary (complete) general education, ensuring successful profile and professional self-determination of students. The recommender systems could aid students in suggesting suitable courses as well as shortening the time to explore courses to follow [3]. A recommender system (RS) is an information filtering tool that attempts to recommend information items (courses, movies, etc) that are likely to meet users' references [4]. Bhaskar Mondal et al. defined RS as an intelligent system that recommends a personalized set of information extracted from a dynamically generated huge volume of data [5].

Recommender systems are programs and services that assess users' preferences and attempt to forecast what will be most interesting to them at any given time. Such systems display a user's choice for content depending on data given by the user expressly or based on his interaction with the system. The following characteristics should be present in recommender systems: the system should be tailored to a specific user, as preferences vary greatly from person to person; the system should take into account the user's current preferences, adapting to him over time; the system must constantly seek out new areas of information to offer to the user. This study's main concern is that students are being assigned to courses in which they have little interest, that they are having problems acquiring knowledge, and that they are being overloaded with information during their application for admission to higher learning institutions. Students find it challenging to make educated judgments when they have a large number of options from which to choose and research in order to develop a list of courses in which they are interested. Because of the abundance of universities offering a wide range of courses from which a student can choose, students often miss out on placement in the courses they desire owing to a lack of proper guidance while making course selections during the application period. Hence, there is a need to provide a solution that recommends a filtered list of courses based on their interests and performance

The main goal of RSs is to deliver customized information to a great variety of users according to their preferences [6]. Considering the various aspects of the course section and technological process, it is necessary to generate a recommendation system that meets students' needs and navigates through the learning process. The success of the recommendation system can be generated through the analytical capabilities and completeness of its features. This study is aimed to identify the general criteria of the course recommendation system. To archive this goal it needs to be supported by a theoretical basis and approaches. Furthermore, in this study, there are the main themes that become the research question. First, «what are the approaches to building a recommendation system?». Second, «what algorithms are used to process the interaction between the learner and system?». This study was conducted through a literature review relating to course selection recommendation systems published papers over a five-year period between 2015 and 2020.

Methods

The process of the literature review conducted in this study consists of several steps. First, the source of research articles (IEEE, Google Scholar, Science Direct, and Web of Science) and search keywords ("elective course" AND "recommendation system" OR "recommender system") were established. Found papers were inputted the "Studies found". Second, papers' titles and abstracts were scanned to find research questions – matching papers. Eventually, after reading thoroughly the introduction and the contents of the whole paper according to research questions, the papers were saved as "Selected studies". The complete list of selected papers is shown in table 1.

Table1. Source of Publication

	Title	*Reference*	*Year*	*Type*
1	*Helping university students to choose elective courses by using a hybrid multi-criteria recommendation system with genetic optimization*	*[1]*	*2019*	*J*
2	*An Automated Recommender System for Course Selection*	*[2]*	*2016*	*J*
3	*Recommender Systems for University Elective Course recommendation*	*[3]*	*2017*	*C*
4	*A K-Nearest Neighbour Algorithm-Based Recommender System for the Dynamic Selection of Elective Undergraduate Courses*	*[4]*	*2019*	*J*
5	*A course recommendation system based on grades*	*[5]*	*2020*	*C*
6	*Skill Based Course Recommendation System*	*[6]*	*2020*	*C*
7	*Module Advisor: Guiding Students with Recommendations*	*[7]*	*2018*	*J*
8	*Elective course recommendation model for higher education program*	*[3]*	*2018*	*J*
9	*An Intelligent Student Advising System Using Collaborative Filtering*	*[9]*	*2015*	*J*
10	*PRCS: Personalized course recommender system based on hybrid approach*	*[10]*	*2017*	*C*
11	*A Hybrid Course Recommendation System by Integrating Collaborative Filtering and Artificial Immune Systems*	*[11]*	*2016*	*J*
12	*Next level: a course recommender system based on next level: a course recommender system based on career interests*	*[12]*	*2019*	*Masters' thesis*
13	*A Recommendation System for Prediction of Elective Subjects*	*[13]*	*2017*	*C*
14	*Developing a Course Recommender by Combining Clustering and Fuzzy Association Rules.*	*[14]*	*2019*	*C*

Results and discussion

The aim of a literature review in this study was to identify the general criteria of the recommendation system. They are recommendation system approaches, algorithms and recommender system evaluation measures. One of the challenges that universities tend to achieve is students' course enrolment recommendation. It not only assists students in deciding what to study, but it also maximizes their performance if they are able to study what they enjoy or are interested in. Based on our review, three main approaches of recommendation systems identified. While collaborative filtering was a widely implemented technique, rule mining was found only in a couple of papers. Hybrid filtering and content-based filtering were also used to generate RSs. The present study examined the recommender systems and among existing methods, the introduce algorithms were compared focusing on collaborating filtering based on association rules mining, as illustrated in Figure 1.

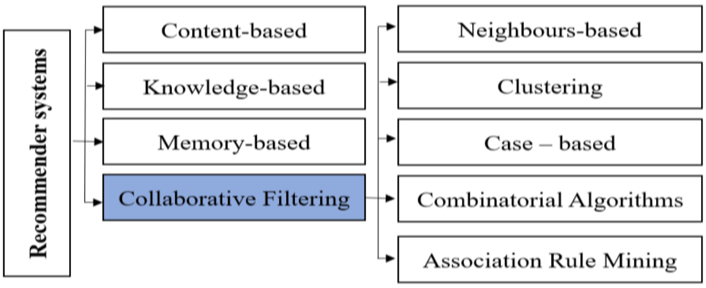

Figure 1. Distribution of approaches employed in recommendation systems

Collaborative Filtering (CF)

Collaborative filtering (sometimes called top-N) recommends an item to a user by investigating the user's similarity with the user's information in a system, and predict the item that the user would be interested in. This approach is attractive due to its data storage mechanism, as it does not store the personal information of each user and merely keeps item-related items. The similarity employed in similarity majors like Pearson Cosine has a significant impact on the performance of CF-systems. A similarity major is chosen depending on the date available in the repository. Similarity, Correlation Coefficient, and Euclidean distance are often used to evaluate similarity between users. Collaborative filtering has the advantage of being both simple and accurate to apply. They do, however, have a cold start problem, in which they fail first-time users whose information is not stored in the system. Memory-based and model-based CF algorithms are two major classes existing today. Memory-based collaborative filtering algorithms use the entire database to generate a recommendation, while model-based systems extract a subset of information about users and items. Memory-based collaborative filtering algorithms further divided into item-based and user-based collaborative filtering. Memory-based CF algorithms anticipate using the entire user-item database. These algorithms employ statistical approaches to identify a group of users known as neighbours who have exhibited similar behaviour in the past to the target user. Following the collection of neighbourhood data, these strategies employ various algorithms to aggregate neighbourhood preferences in order to generate a forecast or top-N recommendation for the active user. Hence, such methods are also known as user-based collaborative filtering or nearest-neighbour filtering.

Kiratijuta Bhumichitr et al. developed a collaborative-based recommendation system using Pearson Correlation Coefficient and Altering Least Square (ALS). In the paper of Adewale Opeoluwa Ogunde, a system was developed for undergraduate students considering the previous performances of other students in the course. Kathiravelu Ganeshan and Xiaosong Li proposed a web-based intelligent student advising system applying collaborative filtering. In order to understand what drives students to choose a particular course, their GPA, Age, Ethnicity, and gender were analyzed. The K-means experiment results found that between 24 and 27 aged male students from European, Maori, and Asian backgrounds preferred the software major.Pei- Chann Chang et al. proposed a two-stage user-based collaborative filtering process with an artificial immune system to predict the students' grades and a filter for professors' ratings.

Content-based Filtering (CBF)

Content-based filtering recommends an item to a user by considering the description of the item and clustering the item and the user into groups to gain similarity between them. The main advantage of the CDF approach is that system is tailored to users' unique interests, which allows avoiding the cold-start problem for new and unpopular items. CBF based on criteria related to course information, competence, professors, theoretical and practical content, and knowledge area. Shehba Shahab in her thesis presented a recommender system that uses CBF along with K-means clustering and TF-IDF to recommend suitable skills and courses based on students' career interests [12]. Creating a content-based recommender system entails recommending things that are comparable to those that the user has previously preferred. These systems are scalable, perform well regardless of the number of users in the system, and do not have cold start concerns because they take into account a user's prior preferences and an item's characteristic. However, these systems require sufficient information about the object to be provided in order to accurately discriminate items; otherwise, accuracy suffers.

Hybrid Recommender

Hybrid recommender systems combine different types of recommender systems to ensure that they complement one other by compensating for one type's deficiencies with the strengths of the other. In order to solve the ramp-up problem, collaborative filtering is frequently supplemented with other techniques. The main goal of a hybrid system is to improve recommendation accuracy as well as to avoid certain drawbacks (e.g., new items and, new user problems) of traditional recommender approaches. Nina Hagemann et al. proposed a hybrid recommender system consisting of two components. First, a traditional content–based recommender to find candidates that have the same conten as in the student's profile; Meanwhile a hierarchical taxonomy is developed to prioritize candidates from outside the student's program area. Zameer Gulzar et al. developed a hybrid RS that can be integrated to reinforce the efficiency of an E- Learning system, and focused on N-gram query classification for retrieving expansion-based information along with ontology support.

Association Rule Mining

The Rule Mining approach focuses on recommending a series of items to a user by discovering the interrelation between each item such as selling amount, as a rule, As regards course selection, the recommendation could be a series of courses that students prefer taking those courses. Sh.Asadi et al. built a course recommender model to assist in course section decision-making. Clustering was used to begin the process since it was necessary to obtain a better understanding of the students and their characteristics. Students with similar interests, skills, and behaviors were identified using the given technique. Then, in each cluster, fuzzy association rules were mined with the goal of evaluating patterns in student course parts as well as the associations between them.

Algorithms

There are a number of algorithms employed to extract and cluster complex and huge masses of data. In our work, the following algorithms were found: s-means fussy algorithms, SVD-based algorithm, genetic algorithm, Pearson Correlation Coefficient, ALS algorithm, fuzzy association rules mining algorithm, N-gram query classification, TF-IDF. One of the algorithms which were found in many proposed recommendation systems is K-nearest- neighboring algorithm owing to its ease to use and high efficiency [4, 2, 9]. K-nearest Neighbour is a simple algorithm that keeps all accessible cases that classify new base based on a similarity measure (e.g., distance functions). In the proposed advising system [9], the high performance, merit performance, and low-performance students groups were identified by the K-means algorithm. Unlike the recommended algorithms above, Viddhelsh et al. utilized the c-means fuzzy algorithm to arrive at a better solution to predict an elective course for students.

The c-means fuzzy algorithm optimizes $\sum_{j=1}^{k} \sum_{\mathrm{i} \in \mathrm{C_j}} \mathrm{u}_{\mathrm{ij}}^{\mathrm{m}} (x_i - \mu_j)^2$

where u_{ij} is membership value of point x_i to cluster c_j, μ_j is center of cluster j and m is the level of fuzziness.

The membership value u_{ij} is given as $u_{ij}^{m} = \frac{1}{\sum_{l=1} k \frac{(|x_i - c_j|)^{\frac{2}{m-1}}}{|x_i - c_k|}}$.

This approach implies that even if a student belongs to a cluster with a low degree of belonging, there is a high possibility that it has an output that is comparable to the cluster that is currently being looked after.

Table 2. Use of Algorithms for recommendation systems.

1	*S-means fussy algorithm*	*[6]*
2	*SVD – based algorithm*	*[8]*
3	*Genetic algorithm*	*[1]*
4	*Pearson Correlation Coefficient*	*[3]*
5	*ALS algorithm*	*[3]*
6	*Fuzzy association rules mining algorithm*	*[2,14]*
7	*K-means algorithm*	*[2,4,5,9,12,14]*
8	*N-gram query classification*	*[10]*
9	*TF-IDF*	*[12,7]*
10	*Multi-Layer Perception Algorithm*	*[13]*

Proposed prototypes

The growing interest in recommendation system has generated a lot of research and works devoted to the analysis and interpretation of huge volumes of academic data. Figure 2 shows a summary of the main characteristics of each proposal. It is considered both student and course specific criteria, as well as, the similarity measures utilised that a key element in the PS s for the students and courses more similar. It is relevant to highlight that most proposals use one or two criteria and one or two similarity measures.

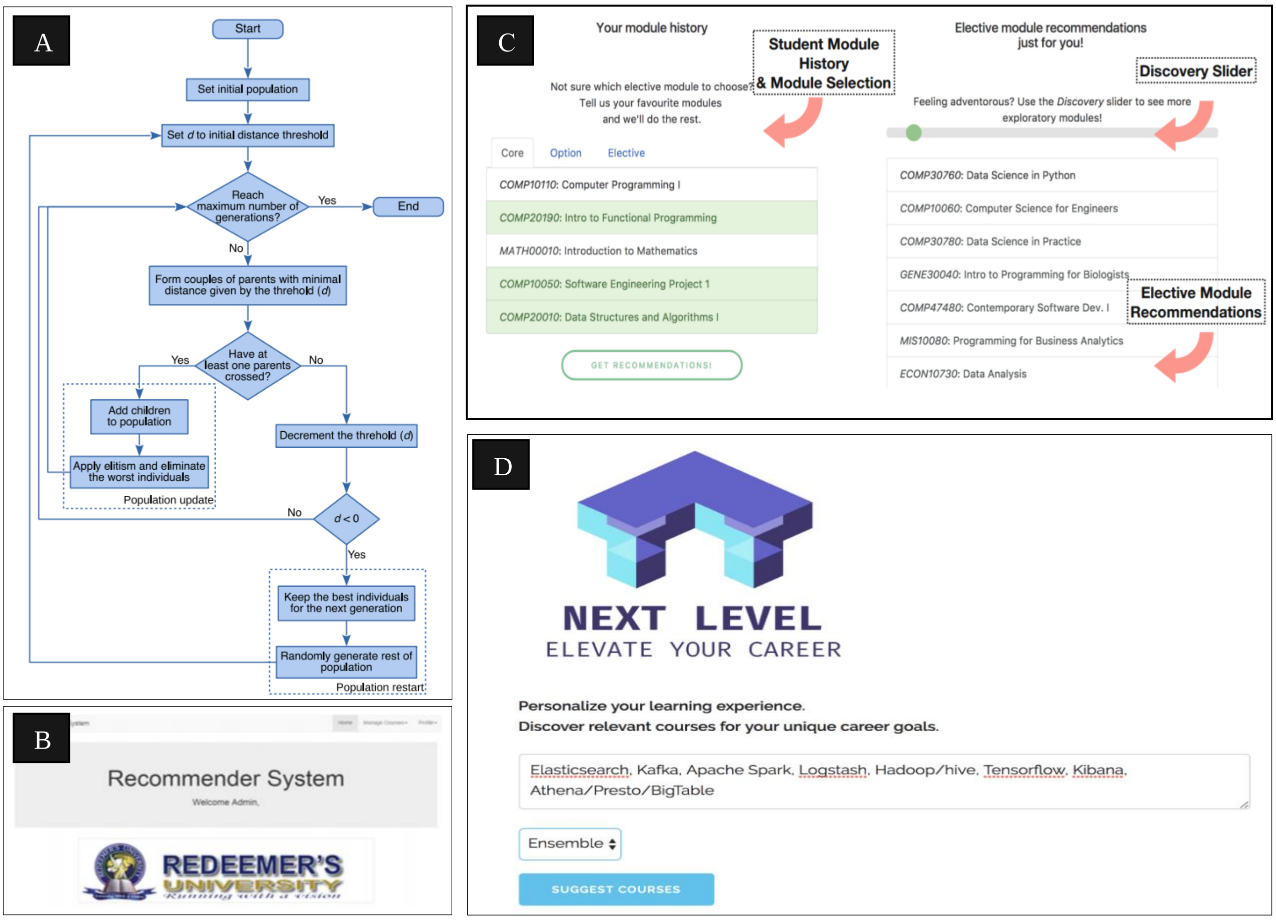

Figure 2. Interfaces of some analyzed prototypes (A) [1], (B) [4], (C) [7] and (D) [12].

A. Esteban an et al. proposed a model (Figure (A)) in a hybrid multi-criteria RS for university course recommendation. The suggested approach uses several tools such as CF based on neighborhood, CBF, and semantic analysis to mix inputs from the student and the course. An adapted Genetic Algorithm (GA) was utilized to create intelligible models in which they could manage the relevance of each criterion in the recommendations and acquire the best configuration of all RS parameters, such as similarity measures and number of neighbors.Genetic algorithm (GA) employed consists of several features as following:

- The GA is used as a pre-recommendation system stage (RS). As a result, GA optimizes the parameter setup of RS using training data. The RS is then configured according to these characteristics, and customized user recommendations can be made. The goal is that the GA does not increase the amount of time it takes to compute each recommendation.
- The GA examines the weight optimization for each criterion in both the CF and CBF systems. As a result, each factor will be relevant in determining the final recommendation.
- The GA takes into account the optimization of similarity measurements. Thus, each criterion can employ a variety of similarity measures, with the GA selecting the best appropriate for each.
- The GA takes into account the CF system's neighborhood size optimization. Thus, the size of the neighborhood will be optimized to the best value.
- The GA explores how to optimize the hybrid system's outputs. Thus, the GA will assign a weight to each system employed in hybrid RS to determine its importance.

Adewale Opeoluwa Ogunde et al used a collaborative filtering strategy based on the k-nearest Neighbour algorithm to uncover hidden linkages between previously passed relevant courses and currently available elective courses (Figure (B)). The recommendation model was built and tested using a dataset of real-life student results. The novel model was discovered to outperform previously published results. The established approach will not only assist students better their academic performance, but it will also help level advisers and school counsellors minimize their workload. In their research, the recommender system was created to include a knowledge base with collected experience as well as a set of rules for applying the knowledge base to each specific circumstance stated. The recommendation model and k-nearest Neighbour decision tree were created using WEKA, a popular data mining tool. This approach was used to predict rules and was implemented in a front-end web application.

Nina Hagemann et al. created a prototype web tool (Figure (C)), as illustrated in Figure B, to assist students in finding appropriate elective modules. This application contains a personalized recommender system that allows students to select modules from their module history and receive recommendations for elective courses depending on their selection. Students can adjust the degree of discovery in the recommendations made using a slider. Moving the slider adds diversity to the recommender system's algorithm and provides a natural justification for the modules that are recommended. As a result, students are able to gradually explore modules outside of their subject of study and increase their understanding of the various modules accessible. To generate recommendations, the suggested hybrid recommender has two components. The first component identifies applicants who are most likely to succeed. The first component prioritizes candidates with content comparable to those in the student's profile; a typical content-based (CB) recommender is utilized for this purpose. The second component prioritizes candidates who are not in the student's program area; in this scenario, a hierarchical taxonomy of the available programs of study and associated modules is constructed, and candidates who are the most distant from the student's profile are recommended.

Shehba Shahab developed a novel Next level approach in her paper " Next level: a course recommender system based on career interests " which has various advantages over previous course recommender systems(Figure (D)). They presented a course recommender system that uses content-based filtering and an ensemble learning method using k-means clustering and TF-IDF to suggest suitable skills and courses based on the career interests of students in her paper. The approach's fundamental premise is to portray both users and courses using skills as features. The vector space approach represents queries and courses as vectors in a high-dimensional space, with each vector corresponding to a phrase in the collection's vocabulary. Given a query vector and a set of courses vectors, choose the one that best fits your needs.
They rank the courses by computing the cosine similarity between them, given a query vector and a set of courses vectors, one for each course in the collection:

$$similarity(\vec{skill}, \vec{course}) \frac{\vec{skill}}{\left|\vec{skill}\right|} * \frac{\vec{course}}{\left|\vec{course}\right|}$$

Similarity measures

CF using criteria is mostly student-related information, as ratings, grades and branches, while CBF based on criteria related to course information, as professors, theoretical and practical contents, competencies, and knowledge area. In the paper of Asadi Sh et al. many features including demographics and educational background are used to cluster. Moreover, Bhumichitr K et al. proposed a recommendation system based on the similarity between the course templates of students as well as academic records based on user profiles were built. Bhaskar Mondal et al. proposed a machine learning approach to suggest relevant courses to students based on their learning history and past performance. A hybrid recommendation system was generated with professor and student information datasets. In their paper, Viddhelsh et al. propose a skill-based recommender system. The authors' method is based on finding similar students which will serve to shortlist courses that are suitable. A hybrid multi-criteria recommendation system was developed by A.Esteban et al, where they considered multiple criteria for course selection. The developed CF estimated similarity measures, including grades, ratings, and brand, while Content-based filtering similarity measures considered professors, competencies, knowledge area, contents of a course.

Recommender system evaluation

Recommendation system can be evaluated by standard information retrieval measures. The accuracy value is employed to measure the performance and effectiveness of the system using equation 2 [10]. In most papers, the system was tested on the basis of precision, recall and F-score.

Precision is the percentage of the number of recommended courses taken to the total number of recommended courses.

Precision = (# of recommended courses taken) /(total # of recommended courses)

Recall is the percentage of the number of recommended courses taken to the total number of courses taken by the students [2].

Recall = (# of recommended courses taken)/ (total # of courses taken by students)

F-score is the harmonic means of precision and recall. It can be calculated using the formula [12]:

F-score = (2*precision*recall) / (precision +recall)

Conclusion

The application of recommender systems to suggest elective courses are now in demand. This growth can be related to need to make right decisions in opting for beneficial courses both educational and future job landing. In this paper, 14 papers are reviewed to have a clear insight to direction of given tendency. Through this literature review, the recommender systems techniques and data extracting algorithms were identified. While collaborative filtering approaches will give accurate results in a traditional sense, it will not help the problem of discoverability of modules as it promotes primarily already popular modules. We have concluded that hybrid recommendation system comes with the following advantages:

1. Hybrid recommender systems combine different types of recommender systems to ensure that they complement one other by compensating for one type's deficiencies with the strengths of the other.
2. It can improve recommendation accuracy as well as to avoid certain drawbacks (e.g., new item and, new user problems) of traditional recommender approaches.

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