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Developing a Course Recommender by Combining Clustering and Fuzzy Association Rules

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Abstract

Each semester, students go through the process of selecting appropriate courses. It is difficult to find information about each course and ultimately make decisions. The objective of this work is to design a course recommender model that takes the students' characteristics into account to recommend appropriate courses. The model uses clustering to identify the students with similar interests and skills. Once similar students are found, dependencies between student course selections are examined using fuzzy association rule mining. The application of clustering and fuzzy association rules results in appropriate recommendations and a predicted score. In this work, a collection of data on undergraduate students at the Management and Accounting Faculty of College of Farabi in the University of Tehran is used. The records are from 2004 to 2015. The students are divided into two clusters according to the educational background and demographics. Finally, the recommended courses and predicted scores are given to the students. The mined rules facilitate decision-making regarding course selection.

Keywords: *Course Recommender Model, Course Selection, Clustering, K-means, Fuzzy Association Rules.*

1. Introduction

With the advent of E-learning systems and the rapid development of information technologies, vast amounts of data are being accumulated. This has led to complex decision-making processes as well as storage, management, and analysis challenges [1]. Converting raw data into useful information helps students and academics improve teaching and learning methods, while facilitating the decision-making processes [2].

Many systems force students to follow a pre-defined curriculum designed by the professors and universities. Although easy to execute, such systems offer a limited efficacy. Various methods have been proposed to enhance the effectiveness of educational systems, one of which is customized education [3].

Students are required to enroll in several courses, fitting their interests and skills in each semester. Gathering information pertaining to each course is a time-consuming process. Furthermore, students may not possess the necessary information about course selection as well as the time and effort necessary for succeeding in each course, which makes it more difficult to make decisions [4].

Recommender systems can guide users on a specific path. They may be used to choose suitable alternatives in a large space of options, thus reducing information overload [5]. A course recommender system is a type of recommender system able to suggest the best combination of courses to students and help them plan their educational schedules. Moreover, the system supports students in choosing appropriate courses and provides them with a basic knowledge of past student experiences [6].

In the remainder of this paper, first, a survey of the literature and previous works is presented. Section 2 details the proposed model of the study. Finally, Sections 3 and 4 present and analyze the results, respectively.

1.1. Literature

Initially, recommender systems emerged as tools for receiving recommendations from users as input, aggregating them, and providing the results to other appropriate users. This represents a type of recommender system technology known as collaborative filtering, which is a valuable starting point for research works on such systems and methods [7, 8].

From a technical perspective, recommender systems constitute the techniques and software tools that suggest items to the users based on their preferences; this ultimately helps the user in the decision-making process [7]. The user preferences can be obtained either implicitly or explicitly. Recommender systems work with three types of data: (1) social, (2) individual, and (3) content [8]. In order to take advantage of the available information, recommenders employ a number of filtering methods including collaborative, demographic, content-based, and hybrid [9].

In demographic filtering, a number of demographic variables such as age, gender, and other individual features are employed [10]. Content-based filtering takes advantage of the previously collected information regarding the user behavior and preferences in the system [11]. Finally, in collaborative filtering, the information and opinions provided by other users are used to make recommendations to the new users [12]. Simultaneous application of these filtering methods is known as hybrid filtering [13]. Collaborative filtering is among the most important methods of information filtering in recommender systems, which is often used in combination with other methods [14, 15]. However, there are several potential problems with recommender systems and collaborative filtering including the addition of new items or cold start and the sparsity problems [16], which may lead to a reduced performance [17, 18]. In order to tackle these issues and improve performance, quite often, hybrid filtering is used [19]. In this method, the cold start problem can be addressed through clustering, which is a common data mining technique [9].

Currently, collaborative filtering, content-based filtering, and data mining techniques are considered as popular and fundamental methods for constructing recommender systems. Typically, predictive methods in recommender systems utilize classification, whereas descriptive methods rely on the clustering and association rules more than the other methods [7].

Recommender systems are widely used in business; however, the first application of these systems in the field of education dates back to the early 2000s, when they were used in adaptive educational systems. During this time, recommender systems soared in popularity due to the increased interest in traditional E-learning systems. These systems aimed to assist students in selecting courses, subjects, and educational content. Since then, research works on recommender systems in the field of education have attracted a significant attention [20] with potential applications in designing learning paths [21], helping universities manage and control student learning [22], recommending learning resources [23], academic advising [24], and recommending appropriate courses [25]. The developments in this area are accompanied by the research works on designing recommender educational systems [26], application of technology [27] and digital learning resources [28], and use of social networks [29].

1.2. Related work

In the previous sub-section, a brief overview of common algorithms and methods in recommender systems was given. In what follows, in order to demonstrate how these algorithms can be used in educational recommender systems, a survey of the previous works in this area is presented.

In [30], a course recommender system is developed according to the professional and personal interests of students, which aims to recommend appropriate courses. The system is based upon a Bayesian network and includes information from 400 students. In order to recommend courses, [4] uses the C4.5 algorithm and takes advantage of the educational information and demographics obtained during the course selection process. The proposed system supports students in selecting the right number of appropriate courses. Using learning styles, a recommender system is devised in [31] for an educational system planning known as Protus. In this system, first, clustering is carried out according to the learning styles; then the student preferences and habits are analyzed using the AprioriALL algorithm. In [32], the authors use data on 230 graduate students of computer science to design a recommender system based on the association rules. In order to benefit from the past experiences in addition to the present opinions of students, both the collaborative and content-based filtering methods are employed to recommend the appropriate courses.

Combining different algorithms such as clustering and association rules for implementing recommender systems leads to improved outcomes. In [33], it is demonstrated that by combining machine learning algorithms such as K-means and Apriori, more desirable results and superior recommendations can be obtained. Different association rule algorithms used in educational recommender systems are compared in [34]. Focusing on Apriori, PredectiveApriori, Tertius, and Filtered Associator, the authors showed that the Apriori algorithm outperforms the other association rule algorithms in predicting the courses selected by the students. In another attempt, [35] presented a combination of clustering, classification, and association rules. In this method, the data is first clustered using K-means; next, ADTree is used for classification purposes; finally, the Apriori algorithm determines the optimal combination of courses. The results obtained demonstrate that the combined method outperforms each single method.

Table 1 summarizes the recent research efforts in this area. A glance at this table shows that the clustering and association rules are more commonly used for identifying groups of students and mining course selection patterns, respectively.

Table 1. An overview of recent papers on educational recommender systems.

References	Year	Content filtering	Collaborative filtering	Demographic filtering	Method
[36]	2010		✓	✓	Pearson correlation algorithm
[30]	2011			✓	Bayesian network
[31]	2011	✓	✓		AprioriALL & clustering
[37]	2012	✓			Classification & association rule (Apriori algorithm)
[38]	2012	✓	✓		Clustering
[39]	2012	✓	✓		Classification & association rule (Apriori algorithm) & clustering (K-means)
[33]	2013		✓		Clustering (K-means) & association rule (Apriori algorithm)
[40]	2014		✓	✓	Clustering (K-means) & association rule (Apriori algorithm)
[41]	2014			✓	Genetic algorithm
[42]	2014		✓	✓	Swarm intelligence algorithms
[43]	2015		✓		Logistic regression classification
[44]	2015		✓	✓	Association rule (Apriori algorithm)
[45]	2016		✓		Classification & association rule
[46]	2016		✓		K-nearest neighbors (K-NN), Sequential pattern mining (SPM)
[47]	2017		✓		Correlation thresholding and the nearest neighbors approach
[48]	2017	✓		✓	Apriori algorithm

Dividing the students into homogenous clusters according to their abilities is desired by the professors, and it is a necessity for understanding the characteristics of student groups [49]. Furthermore, clustering allows groups of students with similar performance to be identified [50], creating behavioral profiles of students [51], modeling student behaviors and predicting new learning styles [52].

The K-means algorithm is the most popular clustering method, whose success can be attributed to a number of reasons including the ease of implementation, ease of use, and high efficiency [53, 54]. In this paper, a large number of features including demographics and educational background are used for clustering. Aiming to improve the quality of the clusters, Principal Component Analysis (PCA) is utilized to reduce the number of data dimensions without data loss [55-57].

The previous studies utilized the Apriori algorithm for mining frequent patterns of course selections by the students. However, the algorithm acts in a binary manner without the ability to work with continuous data [58]. This constraint prevents us from incorporating the highly significant variable of score in the recommendations. The first solution to this problem is partitioning the continuous variable into intervals with sharp boundaries, effectively converting it into a binary variable. However, in this method, values near the boundaries may be ignored or used twice [59]. Instead of sharp boundaries, [60] proposes the application of fuzzy sets that represent intervals without sharp boundaries. The extracted rules are called fuzzy association rules [61].

2. Fuzzy association rule mining model

Figure 1 illustrates the proposed model used for mining fuzzy association rules in this paper. As shown, the model starts by defining the problem of the study and continues with data selection, analysis, and preparation. Once different groups of students are identified through clustering, fuzzy frequent patterns are extracted from each cluster. In this step, using membership functions, continuous data is converted into fuzzy variables, and the frequent patterns as well as fuzzy rules are mined. In what follow, the details of each step are discussed in a greater detail.

2.1. Problem definition

This work considers the problem of mining fuzzy association rules regarding student course selections. In the first stage, the mining domain is required to be limited so that rules can be extracted from similar groups of students. In order to identify groups with similar interests and behaviors, the clustering approach in data mining is used. The second stage involves identifying patterns in course selections. In this stage, rules are mined from similar groups of students using the fuzzy association rules.

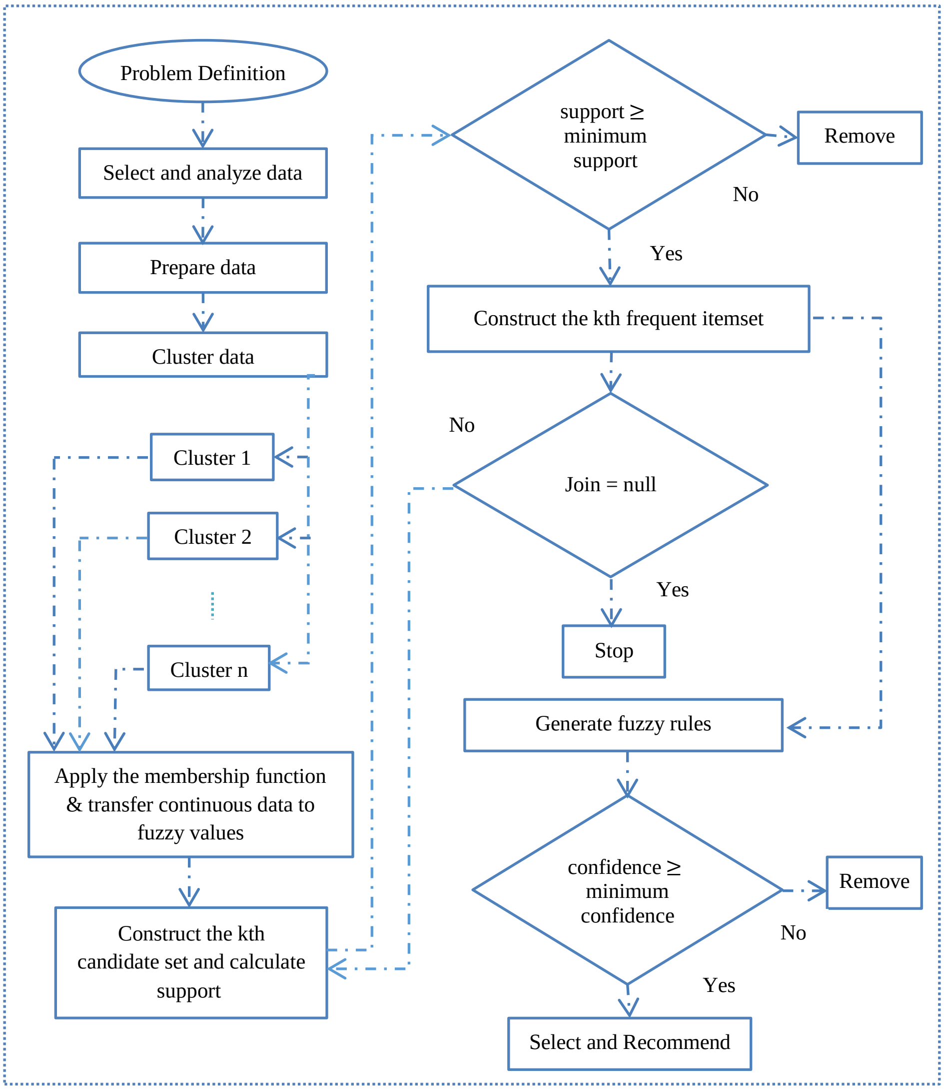

Figure 1. Fuzzy association rule mining model.

2.2. Data selection and analysis

This paper uses the course selection records from 798 undergraduate students of business administration, financial management, public administration, and accounting from the Management and Accounting Faculty of College of Farabi in the University of Tehran between 2004 and 2015.

In this paper, two types of data are used for two different purposes. First, the students with similar preferences and behaviors are identified using demographics such as age and gender in addition to indicators of educational background including high school Grade Point Average (GPA), and scores in literature, theology, Arabic, English, mathematics, and physics on the university entrance exam. These records are given as input to the clustering algorithm. The second type of data, i.e. records on elective courses together with student scores in each semester, can be used for mining fuzzy association rules.

In the data selection step, due to the application of demographics and educational information, a demographic filter is used. Furthermore, in order to mine association rules, course selection records from the previous students are utilized, thus making collaborative filtering an appropriate choice.

2.3. Data preparation

Data preparation is a critical and often time-consuming step in data mining projects, which involves selecting, cleaning, integrating, reducing, and transforming data.

In order to deal with outliers, the statistical concept of dispersion was used. Outliers are defined as values that do not conform to the overall distribution of the data. The standard deviation can be used to detect outliers when the distribution is normal; on the other hand, in non-normally distributed data having skewness, interquartile ranges can prove effective [62]. Once the outliers are eliminated, the problem of missing values is addressed. Missing data can be assigned with the average of the corresponding feature, which is a constant value.

Since the number of features used for clustering is very large, the dimension reduction techniques are used to increase the quality of clusters. Specifically, PCA, which is a pre-processing technique, is employed [55]. The K-means algorithm only works with numeric variables [56]. Therefore, the nominal variable of gender is converted to a binary variable of 0 and 1.

2.4. Clustering

Aiming to identify the students with similar preferences and behaviors, in this step, students are clustered using the K-means algorithm. Clustering refers to the task of classifying a set of objects into a set of homogeneous groups such that the objects within the same group (i.e. cluster) are most similar while having the greatest dissimilarity to objects in other groups [68].

The K-means algorithm works by randomly selecting k points as the initial centroids of clusters. A measure of distance (e.g. Euclidean distance) is then calculated for each one of the other points, and each one is assigned to the cluster having the closest centroid. Subsequently, a new centroid is computed for each one of the clusters. This iterative process of assigning points to clusters and updating the centroids continues until the sum of squared errors is minimized [54].

When using the K-means algorithm, the appropriate choice of k is often difficult to determine [63]; thus, in this paper, the algorithm is run for two, three, four, and five clusters. Moreover, PCA is conducted with three, four, and five components for the purpose of dimension reduction. The silhouette coefficient is then employed to assess the clustering quality based on different numbers of clusters and components. In this fashion, intra-cluster cohesion and inter-cluster separation are determined; larger values indicate a higher quality clustering [64]. Finally, by comparing the silhouettes for different numbers of clusters and components, a decision is made regarding the number of clusters. This clustering allows us to identify the groups of students with similar preferences and behaviors, to whom elective courses can then be recommended.

2.5. Transforming numerical variables into fuzzy variables

The data in this step comprises records of course selections along with student scores in each cluster. Since the score is a continuous numerical variable, it is transformed into a fuzzy one. An illustrative example of ten students and five elective courses is presented later on. The membership function for mapping scores to the [0, 1] interval is depicted in figure 2. The scores can also be labeled as “low”, “middle” or “high” using this function.

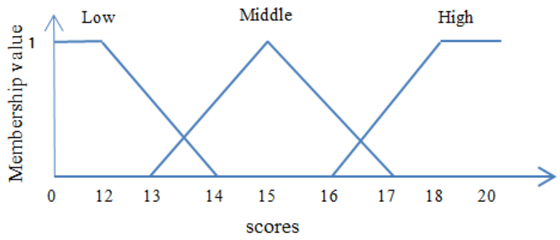

Figure 2. Membership function.

Equations (1-3) represent the membership functions for the low, middle, and high regions in figure 2. Table 2 presents the scores of ten students for five elective courses, where dashes indicate a course not being selected by a student. In table 3, a shorthand representation of course names is used. Student scores are converted using the three membership functions and shown in columns L, M, and H corresponding to the low, middle, and high membership functions, respectively.

$$f_{low}(x)=\begin{cases}1 & if \quad x<12\\ \dfrac{14-x}{14-12} & if \quad 12\leq x\leq 14\\ 0 & if \quad x>14\end{cases} \quad (1)$$

$$f_{middle}(x)=\begin{cases}0 & if \quad x<13 \text{ and } x>17\\ \dfrac{x-13}{15-13} & if \quad 13\leq x\leq 15\\ \dfrac{17-x}{17-15} & if \quad 15< x\leq 17\end{cases} \quad (2)$$

$$f_{high}(x)=\begin{cases}0 & if \quad x<16\\ \dfrac{x-16}{18-16} & if \quad 16\leq x\leq 18\\ 1 & if \quad x>18\end{cases} \quad (3)$$

2.6. Mining fuzzy frequent patterns

Following the fuzzification of the data, fuzzy frequent patterns can be mined. The Apriori algorithm uses k-itemsets to mine (k+1)-itemsets. Initially, 1-itemsets are identified by counting the items in the database. The sets that meet or exceed the minimum support threshold are selected. The result of this iteration is denoted by L1. Next, L1 is used to identify the pairs of items having minimum support, i.e. L2, which is used to find L3. The procedure continues until no frequent k-itemsets can be found. Support for set X is calculated using (4) [71].

Table 2. Sample student scores.

No	Marketing and Market Management (M&MM)	Work Relationships in Organizations (WRO)	Financial Management (FM)	Auditing and Financial Control (A&FC)	Production and Plant Management (P&PM)
1	18.50	18.50	15.50	20	17
2	18	17.75	19.50	15.50	16.30
3	15	-	13	10	-
4	18.50	18	16	-	16
5	20	20	20	14	19
6	13.50	17.75	-	16	19.50
7	17	18	10.50	17	-
8	19.50	16.50	19.50	9.50	20
9	20	16	17.50	9	20
10	18	17.75	19.50	15.50	16.30

Table 3. Converted fuzzy scores from Table 2.

No	M&MM			WRO			FM			A&FC			P&PM		
	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H
1	0	0	1	0	0	1	0	0.75	0	0	0	1	0	0	0.5
2	0	0	1	0	0	0.87	0	0	1	0	0.75	0	0	0.35	0.15
3	0	1	0	0	0	0	0.5	0	0	1	0	0	0	0	0
4	0	0	1	0	0	1	0	0.5	0	0	0	0	0	0.5	0
5	0	0	1	0	0	1	0	0	1	0	0.5	0	0	0	1
6	0.25	0.25	0	0	0	0.87	0	0	0	0	0.5	0	0	0	1
7	0	0	0.5	0	0	1	1	0	0	0	0	0.5	0	0	0
8	0	0	1	0	0.25	0.25	0	0	1	1	0	0	0	0	1
9	0	0	1	0	0.5	0	0	0	0.75	1	0	0	0	0	1
10	0	0	1	0	0	0.87	0	0	1	0	0.75	0	0	0.35	0.15

$$Support(X)=\frac{count(X)}{number\ of\ records\ or\ tranzactions\ in\ data\ base} \quad (4)$$

In table 4, the support values are shown in the last row as the sum of the values in each column. Fuzzy frequent patterns are mined by setting minimum support equal to two. The gray cells in the table denote frequent 1-itemsets, whose support is greater than the threshold.

In order to generate frequent 2-itemsets, denoted by L_2, 1-itemsets are joined. It should be noted that joining a course with itself, e.g. M&MM.M∩ M&MM.H, does not result in a valid pattern of size two. Table 5 examines whether itemset (M&MM.H, WRO.H) is frequent.

L2={(M&MM.H, WRO.H), (M&MM.H, FM.H), (M&MM.H, A&FC.L), (M&MM.H, A&FC.M), (M&MM.H, P&PM.H), (WRO.H, FM.H), (WRO.H, A&FC.L), (WRO.H, A&FC.M), (WRO.H, P&PM.H), (FM.H, A&FC.L), (FM.H, A&FC.M), (FM.H, P&PM.H), (A&FC.L, P&PM.H), (A&FC.M, P&PM.H)}

The min operator is used as the intersect operator. Since the support of the set exceeds two, it is considered to be a frequent pattern. It is, consequently, used in the next step of the process.

2.7. Mining and evaluating fuzzy association rules

In this step, association rules are mined from the frequent itemsets. The rules in each frequent itemset, say U, have X and Y as their antecedent and consequent, respectively, where the former is a subset of U and the latter is the subset composed of other members not in X. In order to evaluate the strength of each rule, the measure of confidence is used, as shown in (5). Only the rules having a confidence greater than the minimum threshold are selected [64, 65].

$$Confidence\left(X \rightarrow Y\right) = \frac{count\left(X \cap Y\right)}{count\left(X\right)} \tag{5}$$

The mined frequent itemset from the previous step is now used for mining and evaluating fuzzy rules:

First rule: M&MM.High → WRO.High

Second rule: WRO.High → M&MM.High

Next, confidence can be used to evaluate the rules. Equations (6, 7) show the confidence of the two above-mentioned rules. In this example, minimum confidence equals 70%.

Table 4. Calculating fuzzy support values.

No.	M&MM			WRO			FM			A&FC			P&PM		
	L	M	H	L	M	H	L	M	H	L	M	H	L	M	H
1	0	0	1	0	0	1	0	0.75	0	0	0	1	0	0	0.5
2	0	0	1	0	0	0.87	0	0	1	0	0.75	0	0	0.35	0.15
3	0	1	0	0	0	0	0.5	0	0	1	0	0	0	0	0
4	0	0	1	0	0	1	0	0.5	0	0	0	0	0	0.5	0
5	0	0	1	0	0	1	0	0	1	0	0.5	0	0	0	1
6	0.25	0.25	0	0	0	0.87	0	0	0	0	0.5	0	0	0	1
7	0	0	0.5	0	0	1	1	0	0	0	0	0.5	0	0	0
8	0	0	1	0	0.25	0.25	0	0	1	1	0	0	0	0	1
9	0	0	1	0	0.5	0	0	0	0.75	1	0	0	0	0	1
10	0	0	1	0	0	0.87	0	0	1	0	0.75	0	0	0.35	0.15
Support	0.25	1.25	7.5	0	0.75	6.86	1.5	1.25	4.75	3	2.5	1.5	0	1.2	4.8

Table 5. Examining frequent itemsets of length 2.

No	M&MM.High	WRO.High	M&MM.High∩ WRO.High
1	1	1	1
2	1	0.87	0.87
3	0	0	0
4	1	1	1
5	1	1	1
6	0	0.87	0
7	0.5	1	0.5
8	1	0.25	0.25
9	1	0	0
10	1	0.87	0.87
Support	7.5	6.86	5.49 ≥ 2

$$confidence_1 = \frac{\sum_{i=1}^{10}\left(M\ \&\ MM.High \cap WRO.High\right)}{\sum_{i=1}^{10}\left(M\ \&\ MM.High\right)} = \frac{5.49}{7.5} = 0.73 > 0.70 \tag{6}$$

$$confidence_2 = \frac{\sum_{i=1}^{10}\left(M\ \&\ MM.High \cap WRO.High\right)}{\sum_{i=1}^{10}\left(WRO.High\right)} = \frac{5.49}{6.86} = 0.80 > 0.70 \tag{7}$$

Since both rules satisfy minimum confidence, they are deemed strong. According to the first rule, with 73% confidence, the students having high scores in the "Marketing and Market Management" course have selected "Work Relationships in Organizations" and passed the course with relatively high scores. Therefore, high performers in the former are recommended to select the latter in order to obtain a high score.

Furthermore, the second rule suggests that with 80% confidence, students who have scored well on "Work Relationships in Organizations" have selected "Marketing and Market Management" the next semester, and passed the course with a high score. Therefore, the students with a high score in the former are recommended to select the latter, thus increasing the chances of obtaining a high score.

3. Results

In this section, the results of the previous steps, i.e. clustering and fuzzy association rule mining, are presented and discussed.

3.1. Clustering

The K-means algorithm is executed with different numbers of clusters using PCA. Clustering is initially carried out without PCA with two, three, four, and five clusters. In order to assess the quality of each cluster, the silhouette coefficients are calculated. Without PCA, the coefficients are equal to the low value of 0.2. Then the students are grouped into different numbers of clusters with varying components. Finally, two clusters having higher silhouette values are generated with 299 and 499 students. The cluster quality analysis results as well as the optimal choice of number of cluster can be seen in table 6.

In the next subsection, fuzzy association rules in each cluster are mined, yielding course selection rules mined from similar students.

Table 6. Cluster quality analysis and the optimal choice of the number of clusters.

	Number of components	Two clusters	Three clusters	Four clusters	Five clusters
Clustering without PCA	-	0.2	0.2	0.2	0.2
	3	0.4	0.4	0.4	0.4
Clustering with PCA	4	0.5	0.3	0.4	0.4
	5	0.5	0.3	0.3	0.3

3.2. Mining fuzzy association rules

In this step, association rules pertaining to course selections are mined, and scores are predicted. The utilized variables consist of elective courses in each semester together with the corresponding student scores. Overall, 13 courses are considered, some of which could be selected by students of more than one major. As a result, a number of courses appear in both clusters. Scores are given on a scale of 0 to 20. The elective courses, in this work, are "Marketing and Market Management", "Work Relationships in Organizations", "Application of Computers in Management", "Auditing and Financial Control", "Production and Plant Management", "Entrepreneurship", "Managing Cooperatives", "Development Management", "Specialized English", "Principals of Accounting", "Financial Management", "Managing Local Organizations and Municipalities", and "Project".

Figure 3 presents the number of fuzzy association rules mined from the two clusters having a minimum support of 13% and a minimum confidence of 60%. Parts a-d depict areas having three, four, five, and six fuzzy regions, respectively.

Fuzzy association rules are mined with three to six fuzzy numbers on each cluster. The last case results in fewer recommendation rules and increased prediction accuracy. Therefore, in this paper, the rules resulting from six fuzzy numbers are used as the recommended rules. Since the scores are mainly distributed between 8 and 20, the fuzzy numbers (8, 12, 16), (12, 16, 20), and (16, 20, 24) can adequately represent low, middle, and high values, respectively. The remaining fuzzy numbers in Part d are ignored because very few scores and no rules belong to those intervals.

Frequent 1-itemsets are recommended to all students in each cluster. For each student, the previous scores are examined and categorized as low, middle or high according to the membership function. A score belongs to the region having the highest membership value. For regions having an equal membership, both rules of the regions are recommended to the students. For instance, a student's score on "Work Relationships in Organizations" belongs to both middle and low regions with equal memberships. Therefore, two sets of rules are used to make recommendations to this particular student: those having a low or a middle score for the course as an antecedent. In order to serve those rare students whose scores are smaller than 8, their scores are labeled as low, and recommendations are given using rules with low scores as antecedents.

3.2.1. Results of first cluster

A number of fuzzy association rules from the first cluster are presented in table 7. In what follows, we consider two of them in a greater detail.

R1: "Marketing and Market Management" with low score → "Auditing and Financial Control" with middle score.

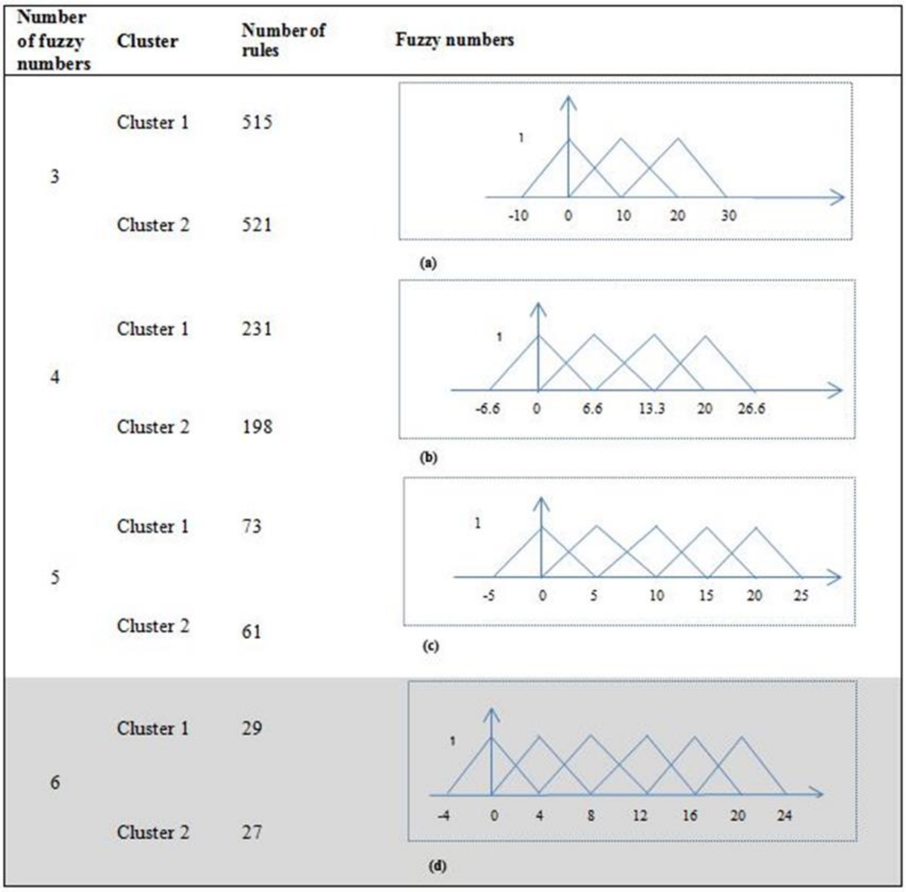

Figure 3. Number of extracted rules for each cluster with different fuzzy numbers. Part a: three fuzzy numbers. Part b: four fuzzy numbers. Part c: five fuzzy numbers. Part d: six fuzzy numbers.

Table 7. Fuzzy association rules from first cluster.

No.	Antecedent	Subsequent
1	"Marketing and Market Management" with low score	"Auditing and Financial Control" with middle score
2	"Work Relationships in Organizations" with high score	"Auditing and Financial Control" with middle score
3	"Application of Computers in Management" with high score	"Entrepreneurship" with high score
4	"Production and Plant Management" with middle score	"Entrepreneurship" with middle score
5	"Auditing and Financial Control" with middle score and "Entrepreneurship" with high score	"Managing Cooperatives" with middle score
6	"Marketing and Market Management" with middle score and "Auditing and Financial Control" with middle score	"Entrepreneurship" with middle score
7	"Work Relationships in Organizations" with middle score and "Auditing and Financial Control" with middle score	"Entrepreneurship" with middle score
8	"Auditing and Financial Control" with middle score and "Entrepreneurship" with middle score	"Work Relationships in Organizations" with middle score
9	"Application of Computers in Management" with middle score and "Auditing and Financial Control" with middle score	"Entrepreneurship" with middle score
10	"Entrepreneurship" with high score and "Managing Cooperatives" with middle score	"Auditing and Financial Control" with middle score

According to R1, the students with low scores in "Marketing and Market Management" are recommended to take "Auditing and Finical Control", which are predicted to pass with a middle score.

R2: "Work Relationships in Organizations" with high score → Auditing and Financial Control" with middle score.

According to this rule, the students who scored high in "Work Relationships in Organizations" with 60% confidence have selected "Auditing and Financial Control" in a later semester and achieved a middle score. Therefore, the students with high scores in the former course are recommended to select the latter, which are predicted to pass with a middle score.

Assume that a student has passed the following courses in the previous semesters:

- "Marketing and Market Management" with a low score.
- "Production and Plant Management" with a middle score.

The courses recommended to this student, along with the predicted scores, are as follow:

- "Auditing and Financial Control" with middle score.
- "Entrepreneurship" with middle score.

3.2.2. Results of second cluster

Table 8 presents a number of rules for the second cluster. In what follows, we consider an example:

R3: "Financial Management" with a high score → "Production and Plant Management" with a high score.

According to this rule, it is predicted that if the students with high scores in "Financial Management" select the "Production and Plant Management" course, they will have high scores.

Assume that a student has passed the following courses in the previous semesters:

- "Marketing and Market Management" with a middle score.
- "Financial Management" with a high score.

The courses recommended to this student, along with the predicted scores, are as follow:

- "Auditing and Financial Control" with a middle score.
- "Managing Local Organizations and Municipalities" with a high score.
- "Production and Plant Management" with a high score.

These courses are recommended to the student. If the student's objective is to increase his/her GPA, the last two courses are safer choices; however, the first course requires more effort.

Table 8. Fuzzy association rules from the second cluster.

No.	Antecedent	Subsequent
1	"Marketing and Market Management" with low score	"Auditing and Financial Control" with middle score
2	"Marketing and Market Management" with middle score	"Auditing and Financial Control" with middle score
3	"Financial Management" with high score	"Production and Plant Management" with high score
4	"Marketing and Market Management" with high score	"Managing Local Organizations and Municipalities" with high score
5	"Financial Management" with high score	"Managing Local Organizations and Municipalities" with high score
6	"Production and Plant Management" with middle score	"Managing Local Organizations and Municipalities" with middle score
7	"Marketing and Market Management" with middle score and "Work Relationships in Organizations" with middle score	"Auditing and Financial Control" with middle score
8	"Financial Management" with middle score and "Auditing and Financial Control" with middle score	"Marketing and Market Management" with middle score
9	"Marketing and Market Management" with middle score and "Auditing and Financial Control" with middle score	"Managing Local Organizations and Municipalities" with middle score
10	"Marketing and Market Management" with middle score and "Managing Local Organizations and Municipalities" with high score	"Auditing and Financial Control" with middle score

4. Discussion

In this work, the clustering technique was used to identify similar groups of students. This technique is capable of finding individuals having comparable preferences, skills, and behaviors. This allows appropriate rules for students to be identified.

Subsequent to clustering, the association rules between course selections were mined. In this step, using fuzzy association rule mining, the significant variable of score was incorporated into the procedure. As a result, in addition to course recommendations, it was possible to predict the student scores.

The extracted rules can be studied from three different perspectives: students, professors, and the university. Each entity can make different plans according to the consequent sections of the rules.

Appropriate courses together with the predicted scores are recommended to the students, enabling them to select courses based on their interests and predicted scores. The recommended courses match the student skills and interests. Furthermore, the predicted scores can be valuable

criteria for making decisions since students are more confident with courses in which they can perform well.
The proposed model also allows the professors to better understand the students. Based on the score predictions, the professors can devise additional measures such as extra classes or exercises.
Finally, the universities can make plans based on the recommended rules to create and organize the necessary resources.
Compared with the previous works, this paper combines the clustering and fuzzy association rules and incorporates the highly important variable of score into recommendations by predicting the score along with each recommendation.

5. Limitations and future works

In several instances, the missing data forced us to exclude some variables. Another imposing factor was the syllabus of each major, which forced the students to take certain courses in a particular sequence. Because the considered courses were elective and the students had not registered in all of them, a small value was set for minimum support. Finally, as in all recommender systems, there was the problem of new courses being introduced. As a result of their novelty, not many registration records are available for these courses; thus the courses have a small support and do not appear in any rules.
A portion of the extracted rules may be redundant. Therefore, it is recommended that an algorithm be used to eliminate such rules. The authors aim to employ optimization algorithms to configure fuzzy rules more accurately. Furthermore, it is suggested that different fuzzy numbers be used for different courses to consider each course separately and find more adequate fuzzy numbers.

6. Conclusions

In this paper, a course recommender model was presented to facilitate decision-making regarding the course selection process. Due to the need to gain an understanding of the students and their characteristics, the process began with clustering. Using this technique, the students with similar interests, skills, and behaviors were identified. This was followed by mining fuzzy association rules in each cluster, with the objective of analyzing patterns in course selections by students as well as the associations between them. In addition to providing recommendations pertaining to appropriate elective courses, the combination of clustering and fuzzy association rules made it possible to predict student scores. The mined rules facilitate decision-making regarding course selection. Moreover, through these rules, the professors and universities can benefit from a deeper understanding of the students, which can lead to an improved quality and a more effective education.

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نشریه هوش مصنوعی و داده کاوی

توسعه یک پیشنهاددهنده درس با ترکیب خوشه‌بندی و قواعد وابستگی فازی

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چکیده:

دانشجویان در هر نیمسال تحصیلی با فرایند انتخاب دروس مناسب مواجه می‌شوند. کسب اطلاعات در مورد دروس و در نهایت تصمیم‌گیری دشوار است. هدف از این مقاله طراحی یک مدل پیشنهاددهنده درسی با توجه به ویژگی‌های دانشجویان برای پیشنهاد دروس مناسب است. این مدل از خوشه‌بندی برای شناسایی افراد با علایق و مهارت‌های مشابه استفاده می‌نماید. پس از شناسایی دانشجویان مشابه، وابستگی بین دروس انتخابی دانشجویان با استفاده از کاوش قواعد وابستگی فازی بررسی می‌شود. استفاده از خوشه‌بندی و قواعد وابستگی فازی منجر به پیشنهاد دروس مناسب به همراه نمره‌ی پیش‌بینی شده می‌شود. در این پژوهش اطلاعات دانشجویان کارشناسی دانشکده مدیریت و حسابداری پردیس فارابی دانشگاه تهران مورد استفاده قرار گرفت. این سوابق مربوط به سال های۱۳۸۳ تا ۱۳۹۴ است. این دانشجویان با توجه به اطلاعات تحصیلی و جمعیت‌شناختی به دو خوشه تقسیم شدند. در نهایت دروس پیشنهادی به همراه نمره پیش‌بینی شده به سایر دانشجویان ارائه می‌شوند. قواعد کاوش شده تصمیم‌گیری در مورد انتخاب درس را تسهیل می‌نمایند.

کلمات کلیدی: مدل پیشنهاددهنده درسی، انتخاب درس، خوشه بندی، k-میانگین، قواعد وابستگی فازی.