Association Rule Mining and Collaborative Filtering-Based Recommendation for Improving University Graduate Attributes

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Summary
Outcome-based education (OBE) is a tried-and-true teaching technique based on a set of predetermined goals. Program Educational Objectives (PEOs), Program Outcomes (POs), and Course Outcomes (COs) are the components of OBE. At the end of each year, the Program Outcomes are evaluated, and faculty members can submit many recommended measures which dependent on the relationship between the program outcomes and its courses outcomes to improve the quality of program and hence the overall educational program. When a vast number of courses are considered, bad actions may be proposed, resulting in unwanted and incorrect decisions. In this paper, a recommender system, using collaborative filtering and association rules algorithms, is proposed for predicting the best relationship between the program outcomes and its courses in order to improve the attributes of the graduates. First, a parallel algorithm is used for Collaborative Filtering on Data Model, which is designed to increase the efficiency of processing big data. Then, a parallel similar learning outcomes discovery method based on matrix correlation is proposed by mining association rules. As a case study, the proposed recommender system is applied to the Computer Information Systems program, College of Computer Sciences and Information Technology, Al-Baha University, Saudi Arabia for helping Program Quality Administration improving the quality of program outcomes. The obtained results revealed that the suggested recommender system provides more actions for boosting Graduate Attributes quality.

Keywords:
Outcome-based education; Education Data Mining; Collaborative Filtering; Association Rule Mining.

1. Introduction

Recently, the key of higher education is to improve educational standards and quality of education, and students' performance is an important basis to assess the quality of teaching, and it is important to analyze the data of students' performance [1]. Student accomplishment is an important criterion for assessing the quality of education and a key indicator of whether students have mastered the knowledge they have learned. At the same time, effort to improve the students' academic achievement is the goal of every university. OBE is a helpful method of teaching that is based on a predetermined set of expected outcomes [2]. Many publications in the literature, like [3- 6], state that outcome-based education involves explicitly emphasizing and organizing everything in the educational system that is vital for all students to be able to accomplish successfully at the end of the course/program/graduation. In [7, 8], state that Learning outcomes (LOs) describe what learners are supposed to know, understand, or are able to do at the end of the Program or course. LOs are depending on the learner's requirements, the needs of society and what the learner should know about a particular subject in order to perform successfully (career and personal lifestyle). Therefore, LOs are statements of what the student will know and to be able to perform or demonstrate as a result of their learning and are part of a student-centered approach and must be measurable or observable. Student Learning Outcomes Framework as illustrated in Fig. 1, consists of Student Needs, Institutional Mission, Program Outcomes, Course Outcomes, Teacher Objectives, Assessment Methods, Teaching Strategy. Furthermore, the benefits of Learning Outcomes as the following: (i) Learning outcomes measure & characterize the values that an institution, program, or course have articulated for student development & performance; (ii) A set of student learning outcomes define what students will know and capable to do when they have completed any degree, regardless of his/her major; (iii) Student learning outcomes will help guide faculty across the university to develop curricula, plan courses, determine financial needs, build syllabi, create learning activities, and measure student learning; (iv) LOs give a framework for learners and advisers to discuss the curriculum's aims as well as individual students' particular career ambitions.

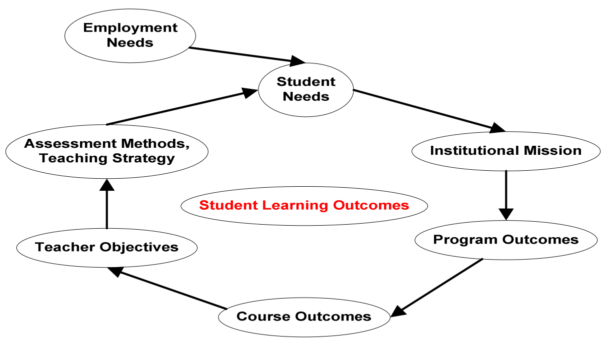

Fig. 1. Learning Outcomes Framework.

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Nowadays, Education Data Mining (EDM) is a new and fast-growing interdisciplinary research field which assisting academic staff in improving the teaching and learning quality. The huge amount of information accumulated in educational institutions that creates a useful knowledge can be discovered. As presented in [10], they can be drawn as main areas related to Educational Data Mining and Learning Analytics as the integration of three main areas, i.e.: computer science; education; and statistics (See Fig. 2).

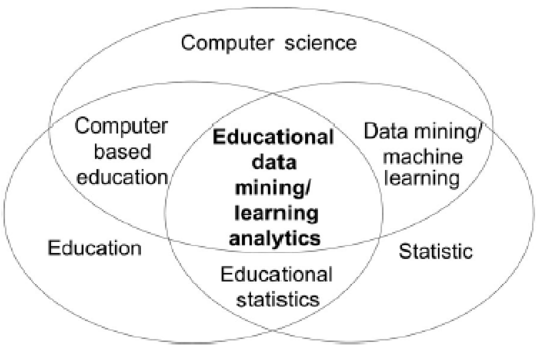


Fig. 2. Main areas of Educational Data Mining

Association rule mining is a common technique in data mining used to identify rule relationship patterns in large-scale transactions. This idea can be transferred to collaborative recommendation. In other words, the goal will be to recognize rules like "If userX loved both item1 and item2, then X will most likely enjoy item5" automatically. By determining which of the discovered rules to recommend to the active user, recommendations can be created. For example, based on facts about the co-occurrence of products in sales transactions, generating a prioritized list of proposed things based on whether the user likes item1 and item2. The goal of rule-mining algorithms such as Apriori algorithm is to automatically detect such rules and calculate a measure of quality for those rules [15, 16, 17]. Indeed, various techniques and applications in area of EDM have been studied and described the most popular their methods [9- 10]. However, these proposed categorized are not inclusive; they do not cover all the possible tasks. There are many more specific objectives depending on the viewpoint of the end user. The rest of the paper is laid out as follows. The works that are connected are presented in Section 2. The proposed methodology is discussed in Section 3. The experimental setup and results are presented in Section 4. The proposed recommender system is analyzed and discussed in Section 5. Finally, Section 6 reaches the conclusion and suggestions future research.

2. Related Works

The generated data by educational environments play a significant role to improve the quality of education and improvement of the graduate attributes process, which is suitable for the modern labor market. There are many models or techniques have been used to deal with those generated data in order to develop further the educational data management and recommender systems. This section presents some of the techniques and works most directly related to the proposed work. Researchers in [11] have presented architecture for recommendation of courses in E-learning system based on student's profile using k-means algorithm. They have considered data mining and warehousing in order to learn the students' learning behavior/pattern which helps them to recommend them most appropriate courses. In [12], the authors have presented a machine learning-based recommender system for improving students learning experiences to enhance the quality of courses they teach and therefore the overall educational program. In this proposed work, five machine learning algorithms are used for predicting suitable actions. Four methods are classified as problem transformation methods while and the fifth method is the adaptive. In another work, Ougiaroglou and Paschalis [13] discussed association rules mining from the educational data of Web-Based application and using the Knowledge Discovery in Databases (KDD) approach to perform association rules mining on the database, which contains educational data. A Critical Relative Support (CRS) was proposed by Abdullah and et al. [14] as mining significant association rules from educational data to discover the significant and critical least association rules. The experimental results show that CRS can easily discover the significant and least association rules and reduce the number of unwanted rules up to 98% as compared to the traditional minimum support threshold. There are also a number of particular studies on the use of recommender systems and association rule mining in e-learning systems. [15] developed a portfolio analysis method based on associative material clusters and the sequences observed inside, Educators might use this information to investigate dynamic browsing structures and identify intriguing or unexpected learning patterns. Moreover [16] presented a recommender system that uses interactive iterative association rule mining and collaborative filtering in order to help the teachers in maintaining and continuously improving e-learning courses. We propose a recommender system using an extended algorithm based on collaborative filtering and association rule mining, for predicting suitable actions to enhance the Graduate Attributes. The experiment was performed based on the results of Computer Information Systems program, Computer Science and Information Technology College, Al-Baha University, Saudi Arabia by analyzing the progress of the students achieving the program learning outcomes which, related courses learning outcomes. The proposed work aims to discover interesting transactions, which could contribute to predicting the courses and Program Learning Outcomes (PLOs), based on the rules that should be generated depend on the support and the confidence as provided by the algorithm used.

3. Methodology

The four main phases involved in the proposed method are the Association Rule Mining and Collaborative Filtering architecture as illustrated in Fig. 3.

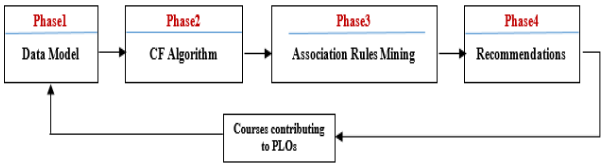


Fig. 3. Main phases of the Association Rule Mining and Collaborative Filtering architecture

Phase1: Create a data model of an assessment of graduate attributes that involving the learning outcomes for courses and programs, evaluation methods used to demonstrate the achievement of each outcome and relate all together. Phase2: Apply an algorithm based on collaborative filtering to create PLOs-Courses Ratings Matrix as the students complete 4 years academic. Phase3: Association rules mining. This phase aims to find association rules on the generated dataset. Once the data has been pre-processed, it is used as input of the Predictive Apriori algorithm. Furthermore, the Programs Quality Administrations (PQAs) could select specific data and attributes in order to restrict the search domain and predicting suitable actions to enhance the Graduate Attributes. Phase4: Recommendations. The expected rules found by the Phase 2 joined to the more intuitive tuples format mentioned in Phase 3, are then used in this last phase to show them to PQAs, PQAs in most cases are not expert in data mining, possible solutions to some problems detected in the course. The teacher analyzes the recommendation and determines if it is relevant or not.

3.1. Data Model

A class diagram is an illustration building block in object-oriented modeling and be used by the Unified Modeling Language (UML). They are implemented to show different objects in a system, their attributes, their operations and the relationships among them. The class diagram of the proposed data model is shown in Fig. 4.

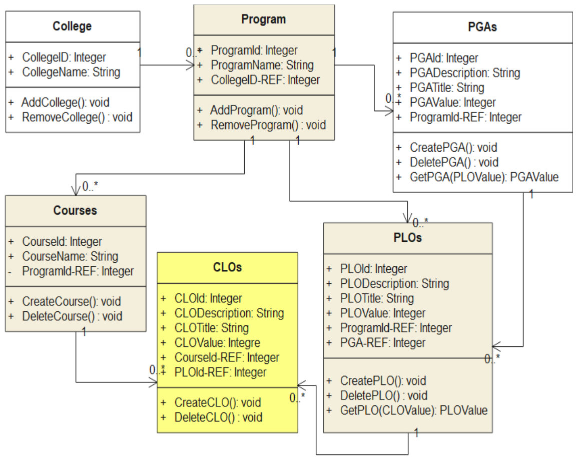


Fig. 4. Data Model

The dataset of the proposed recommender system is extracted based on the student course learning outcomes, program learning outcomes and then graduate attributes where the students in each semester study several courses in different scientific domains until the study plan ends in the program during four academic years. The proposed plan for evaluating the program using learning outcomes is based on the academic program cycle, meaning we will divide the number of PLOs by the number of program academic years (For example, if it is 12 PLOs and the duration of the program is 4 years, the number of measured PLOs is 3 outputs for each year). For the experiment purpose, the dataset was collected from the 45 courses taught in the four academic years 2018, 2019, 2020 and 2021 from Computer Information Systems program, College of Computer Sciences and Information Technology. There are some steps in dataset collection to ease and retrieve it at any time from data model, based on programs quality administration as the following.

CLOs assessment matrix: Presently, most of the undergraduate programs at Al-Baha University consider 60% and above as minimum threshold to be successful in each PLOs. The percentage of students who achieved the minimum threshold (i.e. 60%) in the respective learning outcomes of courses targeting each one of the Program learning outcomes. Summative assessment is most often being used to measure learning outcomes both at the program level and course level (e.g., written and practical exams, case studies, oral presentations and etc.). It includes the evaluation of results of the graduates at the end of each of the levels of learning process. Student achievement of the CLOs for each course in the academic program is measured and included in the course report (See Fig. 5).

Learning Outcomes		CLO1				CLO2		...	CLO$_N$	
#	Student Name	Assessment tools				Assessment tools			Assessment tools	
		Quiz	Oral presentation	Mid	Final	Mid	Final	...	Class Participation	Oral/Written communication skills
		Total marks allotted for this domain multiplied by the total number of students that appeared				~		...	~	
1								...		
2								...		
...								...		
The total mark of each item										
The total marks for each LO		*(Total marks received by students divided by total marks assigned to this domain) X 100*				~			~	

Fig. 5. CLOs assessment results (per each student)

PLOs assessment matrix: Student achievements are aggregated in relation to those courses that contribute to all program learning outcomes as illustrated in Fig. 6. The following formula explains the relationship between the CLOs, the PLOs and Program Graduate Attributes (PGAs):

$$\forall CLO_i \subset CLO_n \; where \; CLO_n \in PLO \; and \; PLO \; \in PGA \quad (1)$$

PLOs	PLO-contributing courses	total the points earned by students on each CLO	Percentage of marks scored by the students related to each course to get total grade for this PLO
PLO1	DBA001	CLO1 + CLO2 + CLO5 (Example)	Aggregation of total marks obtained by the students with regard to all the courses to obtain a value for this PLO
	PBM002	CLO1 + CLO2 + CLO5	
	ENG002	CLO3 + CLO4	
PLO2	DSS001	CLO7 + CLO8	~
	GIS001	CLO1 + CLO3 + CLO4 + CLO5	
	STF001	CLO6	
....	....	....	....
PLOn	DBA001	CLO1 + CLO2	~
	GIS001	CLO4 + CLO6	
	STF002	CLO5	

Fig. 6. Aggregate students' achievement with regard to those courses contributing to each PLO

The consistency of PGAs to PLOs matrix: Furthermore, we have extracted the alignment of Program Learning Outcomes (PLOs) with Program Graduate Attributes (PGAs) as in the Program Specification from data model as shown in Fig. 7.

Program Graduate Attributes (PGAs)	PGA-contributing PLOs	Percentage of marks scored by the students related to each PLO to get total grade for this PGA
PGA1	PLO1	Aggregation of total marks obtained by the students with regard to all the PLO to obtain a value for this PGA
PGA2	PLO2	~
PGA3	PLO3	~
	PLO4	
PGA4	PLO5	~
.....	.....	.....
PGAN	PLON	~

Fig. 7. Matrix of PGAs to PLOs.

Hence, we can create the ratings matrix on which collaborative filtering depends on. First, Fig. 8 shows the PLOs versus courses relation according to PQAs. Second, instead of using a five-point scale, we'll utilize a binary "Achieved/Not Achieved" scale. The relevant rating matrix is shown in Fig. 9, with zeros indicating "Not Achieved or No Relation with PLO" and one indicating "Achieved".

Courses (Items) / PLOs (Users)	I1 ENG001	I2 PRO001	I3 ALG001	I4 INT003	I5 STF001	I6 HCI001	I7 FIS001	I8 DBA002	I9 ENG002	I10 ASI001	I11 DSS002	I12 STF002	.....	I45 GIS002
PLO1	√	√	√	√									.....	
PLO2							√	√	√				.....	
PLO3					√	√				√			.....	
PLO4											√	√	.....	
.....	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....
PLO12			√			√							.....	√

Fig. 8. PLOs-Courses Database

Courses (Items) / PLOs (Users)	I1 ENG001	I2 PRO001	I3 ALG001	I4 INT003	I5 STF001	I6 HCI001	I7 FIS001	I8 DBA002	I9 ENG002	I10 ASI001	I11 DSS002	I12 STF002	.....	I45 GIS002
PLO1	1	0	0	1									.....	
PLO2							1	1	1				.....	
PLO3					0	1				1			.....	
PLO4											0	0	.....	
.....	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....
PLO12			1			0							.....	1

Fig. 9. PLOs-Courses Ratings Database

3.2. Association rules mining and Data Preprocessing

Most of the effort of applied data mining researches are preparing and formulating the data to be in suitable format for association rule mining algorithms that is necessary to convert the data to an appropriate form for solving each specific issues. This conversion involves choosing what data to collect, focusing on the questions to be answered, and making sure the data align with the questions. Generally, this process can reduce and transform all available attributes into a summary table for better analysis and should maintain and protect the students data' by anonymizing and deleting all personal information (not useful for mining) such as name, e-mail, telephone number, and so on. Before using the Apriori algorithm to discover patterns among courses, there are many pre-processing steps that have to be conducted on the data to prepare it for the mining process. These pre-processing steps convert the data to be suitable for mining. The pre-processing steps are as follows:

After entering the target Program Learning Outcome or PLO#, the system will find all the PLOs in that program. For example, if the PLO program is Computer Science, then the system should look for all PLOs whose program is Computer Science.

For each PLO, the system will create one transaction for each semester that the PLO had been registered in. The transaction consists of the courses taken by the specified program given that the course score is equal to or greater than value determined by the program for each learning outcome. For example, suppose that two PLO1 and PLO2 are the set of PLOs whom are in the same program of the target PLO and they take the courses represent in Table 1. Then the system will create the transactions as represent in Table 2.

Table 1. PLOs Data

PLOs	Academic Year	Semester First - S1/Second - S2	Course Code	Rate
PLO1	2018-2019	S1	ENG001	1.0
		S1	PRO001	0.55
		S1	INT003	1.0
		S2	ALG001	0.61
		S2	WEB001	0.91
		S2	DBA001	0.85
		S2	PBM002	1.0
PLO2	2018-2019	S1	ENG002	0.82
		S1	INT004	0.72
		S1	PRB001	0.35
		S1	FIS001	0.95
		S2	DBA002	1.0
		S2	DSS001	1.0
		S2	GIS001	1.0
PLO3	2019-2020	S1	STF001	0.68
		S1	HCI001	1.0
		S1	DBA003	0.53
		S2	ISP001	0.99
		S2	ASI001	0.89
PLO4	2019-2020	S1	ITI001	0.55
		S1	DSS002	0.49
		S2	ISP001	1.0
		S2	GIS002	0.96
		S2	STF002	0.44

Table 2. PLOs transactions

Transaction ID	Transactions
1	ENG001, INT003
2	WEB001, DBA001, PBM002
3	ENG002, INT004, FIS001
4	DBA002, DSS001, GIS001
5	HCI001
6	ISP001, ASI001
7	ITI001
8	ISP001, GIS002

Frequent Pattern Discovery generation is conducted as shown in the following pseudo-code:

Input: *Program Learning Outcome Data (PLOD), CODE of program learning outcome to be advised (CODE)*
Output: *Suggested Courses*
Step1: *Foreach PLO (CODE) in PLOD*
Foreach semester (CODE) have been registered in PLOD
Add a transaction consisting of the courses in this semester
whose scores (>= 0.65) to the transactional database (TDB)
Step2: *Apply Apriori algorithm on the (TDB).*
***Step3*:** *Foreach generated rule of the form X→Y, Z*
if the PLO has never registered X then
Delete the Rule X→Y, Z
else if the PLO has already registered Z then
Modify the rule X→Y, Z to be X→Y.
Step4: *Rank the resulting rules according to their confidence*
Step5: *Extract the right-hand side of all the rules, course ID.*
Put the extracted courses in an ordered list of Recommendation Courses (RCs)

The PLOs' data are then transformed into transactional by generating a transaction for a PLO that includes the PLO-code and a list of courses in a particular semester. For example, if a PLO is registered in two semesters then two transactions are generated. These transactions are then mined using the Apriori algorithm to generate the association rules. The rules that have not-registered courses on the left hand side are filtered out or not achieved. The rest of the rules are then sorted by the confidence level.

4. Implementation and Experimental Results

After creating the PLOs transactions, the data become ready to be mined using the Apriori algorithm and can generate the rules that the target user can use to get recommendations about the courses and PLOs. The number of the rules that should be generated depend on the support and the confidence as provided by the program administer. Fig. 10 shows the generated transactions, while Fig. 11 depicts the generated rules after applying the Apriori algorithm on the transactions using Weka.

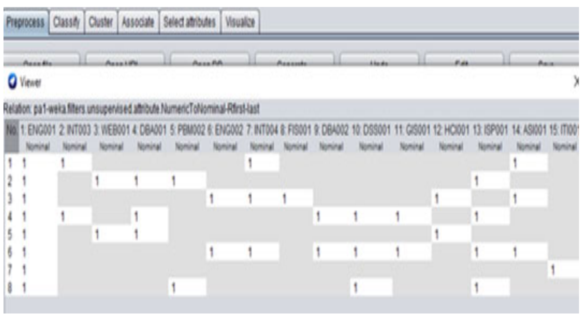
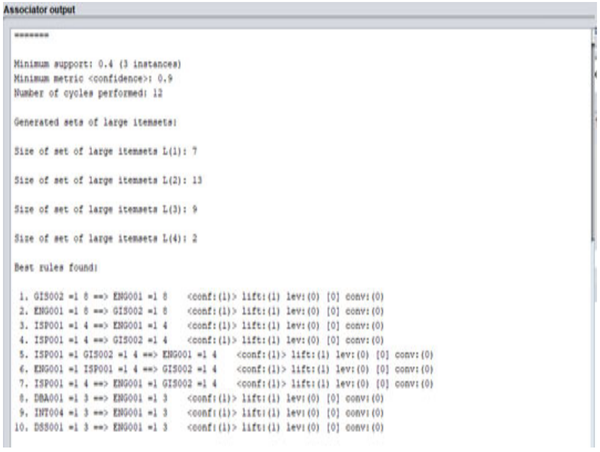


Fig. 10. Generated Transactions using Weka



```
Associator output
=======

Minimum support: 0.4 (3 instances)
Minimum metric <confidence>: 0.9
Number of cycles performed: 12

Generated sets of large itemsets:

Size of set of large itemsets L(1): 7

Size of set of large itemsets L(2): 13

Size of set of large itemsets L(3): 9

Size of set of large itemsets L(4): 2

Best rules found:

 1. GIS002 =1 8 ==> ENG001 =1 8    <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
 2. ENG001 =1 8 ==> GIS002 =1 8    <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
 3. ISP001 =1 4 ==> ENG001 =1 4    <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
 4. ISP001 =1 4 ==> GIS002 =1 4    <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
 5. ISP001 =1 GIS002 =1 4 ==> ENG001 =1 4    <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
 6. ENG001 =1 ISP001 =1 4 ==> GIS002 =1 4    <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
 7. ISP001 =1 4 ==> ENG001 =1 GIS002 =1 4    <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
 8. DBA001 =1 3 ==> ENG001 =1 3    <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
 9. INT004 =1 3 ==> ENG001 =1 3    <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
10. DSS001 =1 3 ==> ENG001 =1 3    <conf:(1)> lift:(1) lev:(0) [0] conv:(0)
```

Fig. 11. Generated Rules using Weka

Finally, the results of the analysis can be used as database and calculate a list of association rules and their corresponding confidence and support values to focus only on the relevant rules. Minimum threshold values for support and confidence are typically defined, through experimentation. Then will consider again the collaborative filtering rating matrix to show how recommendations can be made with a rule-mining approach. Fig. 12 shows the best of the PLOs versus courses relation based on results of recommendations.

At run time, recommendations for user PLO1 can be efficiently computed based on the following scheme:
Determine the set of X ⇒ Y association rules that are relevant for PLO1– that is, where PLO1 has related all elements from X. Because PLO1 has related course1 (I1), the aforementioned rule is relevant for PLO.
Compute the union of courses appearing in the consequent Y of these association rules that have not been related by PLO1.
Sort the courses according to the confidence of the rule that predicted them. If multiple rules suggested one course, take the rule with the highest confidence.
Return the first N elements of this ordered list as a recommendation.

Courses (Items) / PLOs (Users)	I1 ENG001	I2 PRO001	I3 ALG001	I4 INT003	I5 STF001	I6 HCI001	I7 FIS001	I8 DBA002	I9 ENG002	I10 ASI001	I11 DSS002	I12 STF002	.....	I45 GIS002
PLO1	√			√									.....	
PLO2							√	√	√				.....	
PLO3						√				√			.....	
PLO4											√	√	.....	
.....	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....	.....
PLO12			√			√							.....	√

Fig. 12. Transformed ratings database after rule mining

Table 3 shows the comparative analysis of the best PLOs relationships against courses based on the results of the recommendations after rule mining, where a noticeable change has been made in the relationships of the learning outcomes of the program with some courses, as is the case from the beginning in Table 5, which will positively affect better results on the outcomes of the graduates of the program and thus the quality education.

Table 3. Comparative the relationship between PLOs and courses

	Collaborative Filtering				After Rule Mining			
PLO1	ENG 001	PRO 001	ALG 001	INT 003	ENG 001	PRO0 01	ALG 001	INT0 03
	√	√	√	√	√	x	x	√
PLO2	FIS0 01	DBA 002	ENG 002	-	FIS0 01	DBA 002	ENG 002	-
	√	√	√	-	√	√	√	-
PLO3	STF0 01	HCI0 01	ASI0 01	-	STF0 01	HCI0 01	ASI0 01	-
	√	√	√	-	x	√	√	-
PLO4	DSS0 02	STF0 02	-	-	DSS0 02	STF0 02	PRO0 01	ALG 001
	√	√	-	-	x	x	√	√
PLO12	ALG 001	HCI0 01	GIS0 02	-	ALG 001	HCI0 01	GIS0 02	-
	√	√	√	-	√	x	√	-

As shown Table 3 note the following:

- PLO1 was associated with courses (ENG001, PRO001, ALG001, INT003) and after implementing the link base mining algorithm, it is better to link to courses (ENG001, INT003).
- PLO3 was also associated with cycles (STF001, HCI001, ASI001) and after applying the algorithm, it was correlated with (HCI001, ASI001).
- Whereas PLO4 was cycle bound (SDSS002, STF002) and changed to (HPRO001, ALG001) based on the resulting recommendation. And so on for all PLOs.

5. Conclusion and future work

This paper proposed a recommender system for predicting the suitable actions that can be proposed by Program Quality Administration improving the quality of Graduate Attributes and therefore the overall educational program. The recommended actions will be based on course learning outcomes' assessments, program learning outcomes' assessments, and program graduate attributes' assessments. In this proposed work, parallel algorithm for Collaborative Filtering on Data Model and a parallel similar learning outcomes discovery method based on matrix correlation are used for predicting suitable actions. Further investigation is required and more work needs to be executed to enhance teaching strategies and maintaining academic integrity based on courses specifications and program specifications. In addition, the dataset of the recommender system needs to be increase to include peer results programs from diffident universities in Saudi Arabia.

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