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$RS_{RFA}CG$ – A Framework for Recommendation System to Suggest the Course Grade using Filtering Technique and Association Rule Algorithm in Education Sector

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***Abstract*: Recommendation system acts as a information filtering system that provide the suggestions to users based on many different factors. In the current study, a framework for recommendation system called CGRSFA is developed for recommending the grade of course in Education Sector. For this framework, semester-wise, year-wise and overall grade information of students' courses is stored in ten datasets. This framework uses real data gathered from university site related to Four Year Bachelor of Technology - Computer Science and Engineering Programme, counting on 8400 entries of 200 students and 42 courses. Relevant rules which indicates courses dependencies and courses prerequites for other courses are found using this framework for each dataset e.g. the meaning of the rule "Advanced_C_Concepts=A+ → Data_Structure=A+" is that if student receives 'A+' grade in Advanced C Concepts course then that student will received 'A+' grade in Data Structure course also as System Programming course is the prerequisite to the course Compiler Construction. Rules which are not relevant are irrelevant rules and such rules are discarded. Filtered Associator algorithm is used to find the correlation among the courses. In Filtered Associator algorithm, first the grade dataset is filtered using the filtering method - Reservoir sampling Algorithm to remove the data items from dataset that do not meet certain and then Apriori association rule algorithm is applied on the filtered dataset.**

This recommendation system is useful for instructor as well as students for improving academic performance. This system can also be used in MOOCs for recommending the course grade.

***Keywords*— Recommendation system, Filtering Algorithm, Apriori Algorithm, Support.**

***ICTIEE* Track*:* Technology Enhanced Learning**
ICTIEE Sub-Track: Transforming Education Through Technology: Best Practices and Case Studies

I. INTRODUCTION

A Recommendation System (RS) offers recommendations to users based on a variety of criteria, functioning as an information filtering system. RS is also used in education sector for predicting students' academic performance in the form of recommendations given to students related to the course grade based course dependencies and prerequisite for other courses. Teachers and students can both benefit from this recommendation system in terms of raising academic achievement.

A recommendation system framework titled as $RS_{RFA}CG$ (**R**ecommendation **S**ystem using ReservoirSample **F**ilter **A**priori Association Rule for **C**ourse **G**rade) is developed in the current study to suggest a course grade in the education sector. Nine datasets are used in this framework to record semester-wise and year-wise course grade information for students. This framework makes use of actual data that was collected from the university's website for Four Year Bachelor of Engineering Computer Science and Engineering program.

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The data counted on 8400 entries, representing 200 students and 42 courses. This framework is used for each dataset to find valid rules that indicate course dependencies and prerequite for other courses. For example, the rule "Advanced C Concepts = A → Data Structure = A+" means that if a student receives an A in Advanced C Concepts, they will also receive an A+ in Data Structure since Advanced C Concepts is a prerequisite for Data Structure. Rules that don't apply to a situation are invalid and should be dropped.

In this framework $RS_{RFA}CG$, three association rule algorithms such as Apriori Association Rule, Predictive Apriori Association Rule and Tertius Association Rule are applied on any of nine dataset and based on valid and invalid rules; the best association rule algorithm is decided. The best association rule algorithm found is Apriori association rule algorithm. This Apriori association rule algorithm is applied on dataset filtered using six filtering techniques such as RemoveDuplicate, RemoveFolds, RemoveFrequentValues, RemoveMisClassified, ReSample, and ReservoirSample to check the performance of best association algorithm on this filtered dataset. It is found that application of Apriori association rule algorithm on dataset filtered using ReservoirSample gives the useful course grade recommendation based on valid and invalid rules. This framework can help educators, instructors, and learners. It helps students to do better academically. This framework can also be used to suggest the course grade in MOOCs (Massive Open Online Courses) or LMS (Learning Management System). This recommendation system will help to predict students' performance in various courses, recommend the course grade, and improve teaching-learning process. This system can be implemented to suggest new topic based on the topic completed by the students of the particular programming language, Pass/ Fail status, whether students are interested in learning particular course, etc.

Rests of sections are covered as follows – Section 2 describes the state of art while Section 3 explains the framework for RSRFACG. Section 4 gives the algorithm for RSRFACG and Section 5 discusses the results of application of the algorithm as given in Section 4 on nine dataset. Conclusion and future direction is considered in Section 6 followed by references used while preparing this chapter.

II. Literature Survey

The main purpose of Recommendation System (RS) is to suggest the item or meaningful recommendations to the user based on data. It can be used as plug-in for MOODLE (De Medio, 2020). In this section, subsections such as literature survey related to the recommendation system, challenges and limitations of implementing recommendation system, research gap, motivation, problem statement and research objectives are considered.

RS play an important role in many sector such as education (Garg, 2016; Obeidat, 2019; Dhar, 2020; Ezz, 2020; Mondal, 2020; Rani, 2020; Yanes, 2020; Zhou, 2020; Urdaneta-Ponte, 2021; Anupama, 2022), e-commerce application (Singh, 2020; Santoso, 2021; Islek, 2022), medical (Bhansali, 2021; Tsai, 2022), agriculture (Desai, 2023; Priyanka, 2023; Thorat, 2023), pharmaceutical sector (Abbas, 2020; Aslam, 2023), etc. In education sector, RS is used for course recommendation system (Rani, 2020; Urdaneta-Ponte, 2021), best educational program for the best suitable academic path to achieve career goals from students' point of view (Dhar, 2020), online course recommendation (Obeidat, 2019), MOOCs recommendation system (Garg, 2016), prediction of students' best academic program (Ezz, 2020), student placement analyzer (Thangavel, 2017), etc. Various machine learning algorithms such as classification algorithm (Anupama, 2022), clustering algorithm (Mondal, 2020; Urdaneta-Ponte, 2021), and association rule algorithm (Obeidat, 2019) are used for recommendation of courses in education sector. Even collaborative filtering methods (Obeidat, 2019; Mondal, 2020; Anupama, 2022) are also used for analyzing the similarity between the students and course for an effective recommendation. The Systematic Literature Review results on the issue of recommender systems (RS) are presented in the research work (Murad, 2018) as a first step toward a future study on developing an intelligent learning management system for online learning with the help of Natural Language Processing techniques.

Apriori association rule algorithm is considered for suggesting courses based on grades (Mondal, 2020), sales strategy (Santoso, 2021), MOOC courses (Fauzan, 2020), the longtime products in e-commerce (Lourenco, 2020), user profile creation (Singh, 2021), etc.

Filter methods are very important for feature selection as they can be used with any machine learning model and significantly shorten the time it takes for machine learning algorithms to run (Bommert, 2020). Filter method are also used for optimum bias reduction (Le Bras, 2020), providing relatively high classification accuracy (Chen, 2020), reducing computational complexity (Ghosh, 2020), evaluating and ranking the features (Xue, 2023), providing a better representation as solution for high dimensionality problem (Cekik, 2020), etc.

A. Challenges of implementing the recommendation system

Main challenge in any recommendation system from research article reviewed was related to the data collection and size of that dataset (Mondal, 2020; Urdaneta-Ponte, 2021). The model built on particular dataset works for that dataset only and generalization of model on other educational dataset needs to check (Ezz, 2020). Even data scalability, data sparsity, etc. are also challenges in building the recommendation system. Use of few attributes in dataset is another challenge in the recommendation system.

B. Limitations of implementing the recommendation system

There is various limitation of existing recommendation system. As stated in research article (Dhar, 2020), more datasets which are based on academic related problems are required and at the same time, verification of generated

predictions should be done. Even different test datasets are also the requirement of this research study (Dhar, 2020). Requirement of more features and more dataset was the limitation in case of research article (Haruna, 2020). Other limitations such as generalization of model building on other educational dataset (Ezz, 2020), dataset needs to be increased (Mondal, 2020,), etc. are also observed from research articles reviewed.

C. Research Gap

Following points related to the research gap are found from the literature survey:

- Only Apriori association rule algorithm (Fauzan, 2020; Lourenco, 2020; Mondal, 2020; Santoso, 2021; Singh, 2021; Xiao, 2022) is used in any recommendation system.
- Only collaborative filtering methods (Obeidat, 2019; Li, 2020; Mondal, 2020; Murad, 2020; Anupama, 2022; Jin, 2023; Muzdybayeva, 2023; Wang, 2023) are used for recommendation purpose.
- Recommendation system is developed and tested using only one dataset (Haruna, 2020; Mondal, 2020; Rani, 2020; Urdaneta-Ponte, 2021). RS should be tested on more than one datasets to evaluate the effective performance of the model.
- Small dataset size is considered (Mondal, 2020; Urdaneta-Ponte, 2021). Enough information may not be provided by the small dataset which results in inaccurate recommendations to be suggested to students.
- Classification algorithm is considered for the recommendations system (Bommert, 2020; Cekik, 2020; Chen, 2020; Ezz, 2020; Haruna, 2020; Anupama, 2022).

D. Motivation

Providing recommendations to students related to the academic performance is very helpful in education sector to improve teaching-learning process. Several techniques such as collaborative filtering, association rule algorithms, etc. are available for the RS related to the predictions of student's performance. But limited approaches using both filter techniques and association rule mining are explored in the educational domain. In addition to this, the dataset size also matter for researcher for building the recommendation system. So there should be an improvement in the existing recommendation system. In this work, recommendation system is implemented with the help of filter techniques and association rule mining using the real time datasets prepared.

E. Problem Statement

The problem statement for this chapter is to create a novel framework that can recommend the course grade to students with the help of filter techniques and association rule algorithm on real time data in Educational System.

In this research, the dataset prepared using data collected from result analysis of students is filtered using six filter techniques such as RemoveDuplicate, RemoveFolds, RemoveFrequentValues, RemoveMisClassified, ReSample, and ReservoirSample. Apriori association rule is applied on the dataset filtered using these six techniques for selecting the best result and providing the recommendations related to the course grade in education sector.

F. Research Objectives

Research objectives for this chapter are given below:

- Study of various state of art related to recommendation system in education sector.
- Collection and preprocessing of the dataset for suggesting course recommendation rules to students.
- Design of a framework for Course Grade Recommendation System based on Filter techniques and association rule algorithms.
- To compare results obtained using various filter techniques using performance parameters as well as relevant and irrelevant rules.
- Suggesting the course grade recommendations to students

III. FRAMEWORK FOR $RS_{RFA}CG$

The framework for $RS_{RFA}CG$ is shown in Figure 1. The framework for this $RS_{RFA}CG$ consists of following phases

- Data Collection
- Data Preparation
- Data processing using Microsoft Excel
- Course Grade Dataset for $RS_{RFA}CG$
- Selection of Association Rule Algorithm
- Selection of Filtered Associator Algorithm
- Suggestion of Recommendation Rules to Students

These phases are explained in the following subsections.

A. Data Collection

Data collection is the important step in any research in which collected data is gathered and analyzed from relevant resources. For this framework $RS_{RFA}CG$, data is collected from university site related to Four Year Bachelor of Engineering – Computer Science and Engineering stream for Academic Year 2014-15 and 2015-16 in the form of result analysis ledgers. These ledgers downloaded from the site http://www.sus.ac.in/examination/Online-Result-(Ledger) are available in PDF form

B. Data Preparation

The result analysis ledgers downloaded from university site were available in PDF form and the PDF ledger contain the student-wise result of particular semester such as Semester-I, II, III, IV, V, VI, VII, and VIII. So data is prepared semester and year-wise.

C. Data Processing using Microsoft Excel

To process the data and prepare the dataset for $RS_{RFA}CG$, various Microsoft Excel features were used such as

- **Text to Column – Delimited is use**: It is used to separate the marks of each course using delimiter.
- **Text to Column - Fixed width**: It is used to separate the part of particular string

- **Filter:** The 'Filter' function in Excel is used to filter marks course-wise.
- **Conditional Formatting – Highlight Cells Rules – Text that contains:** Conditional formatting is used to indicate different color for status of students such as Pass/ ATKT/ Fail.
- **Formulae used** are SUM, IF, COUNTIF, MOD, Percentage

Data processing and preparation of dataset for $RS_{RFA}CG$ is given in Figure 2.

The steps are-

- Collection CSE Result Analysis Ledgers: As the framework $RS_{RFA}CG$ is designed for Computer Science and Engineering students, so the data of Second, Third and Final students is considered to provide the recommendations to students.
- Data Preparation – Course, Semester and Year-wise: As the result analysis ledgers contains the semester-wise result of students, so it is required to prepare the Course-wise, Semester-wise (Semester- III, IV, V, VI, VII and VIII) and Year-wise (Second Year, Third Year and Final Year) result of each student.
- Mapping of Permanent Registration Number (PRN) of all Result Analysis : Once the Course-wise, Semester-wise and Year-wise result of each student is prepared, all semester-wise result may not contain the PRN (Permanent Registration Number) in order, so it is required to map PRN of all semesters
- All semester Result Analysis as per PRN mapping: After mapping of semester-wise result as per PRN, all semester-wise result is arranged as per PRN so that one row contains the result of Second Year, Third Year and Final Year of one student.
- Combining Result Analysis Yearwise: The semester-wise results are combined into year-wise results.

Detailed explanation and procedure used for processing the data using Microsoft Excel is given in the research article (Dol, S. M., et.al., 2024)

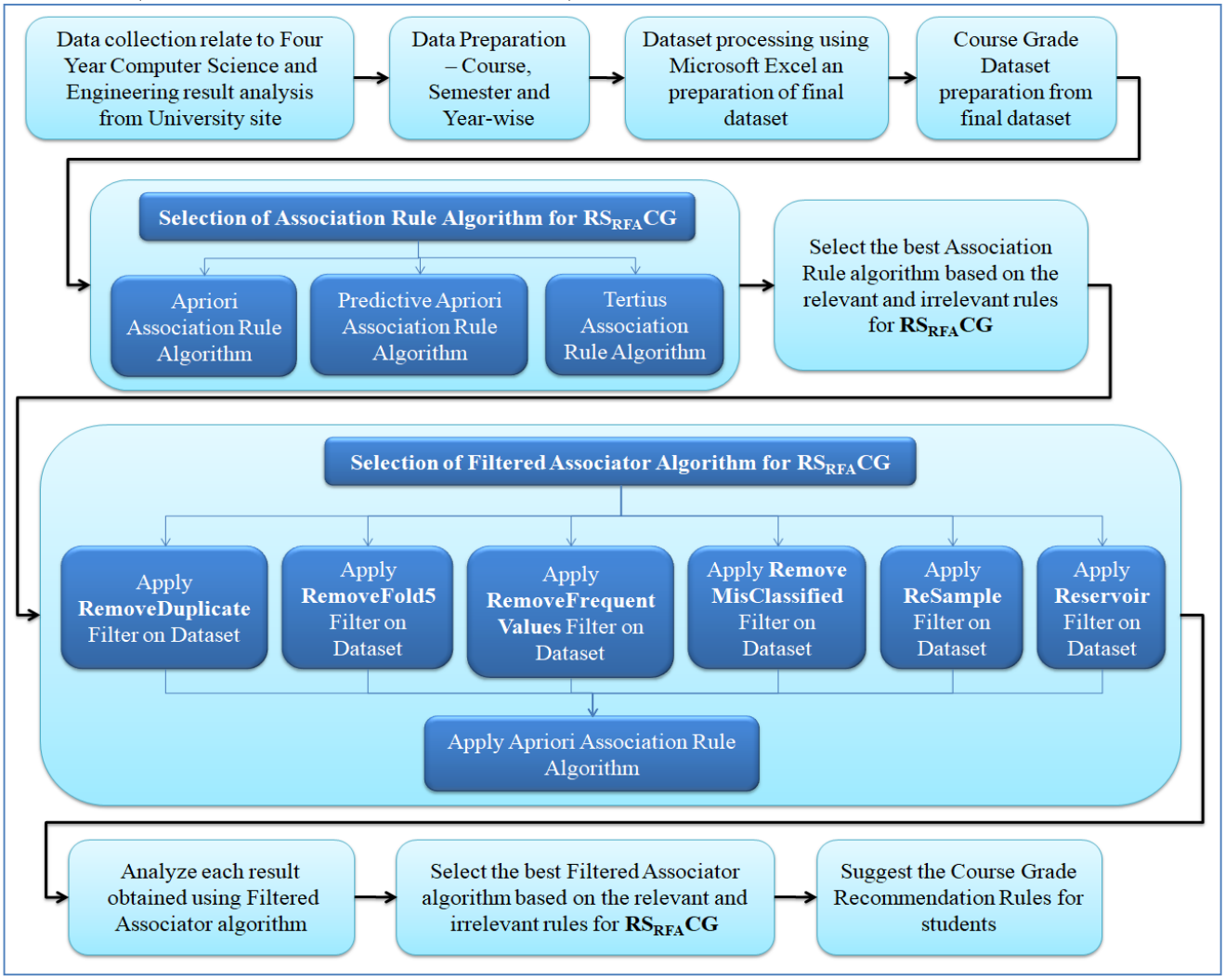

Fig. 1. Framework for Recommendation System $RS_{RFA}CG$

Extraction of Grade data for semester-wise and year-wise courses from Final Dataset of Student for $RS_{RFA}CG$: After preparing the overall result analysis dataset, the grade data for semester-wise and year-wise courses is extracted from final dataset to prepare the dataset for the framework $RS_{RFA}CG$.

Following abbreviations are used for various courses:

Applied Mathematics-I (AM-I), Discrete Mathematical Structures (DMS), Advanced C Concepts (ACC), Digital Techniques (DT), Computer Graphics (CG), Lab-Visual Basic (VB), Applied Mathematics-II (AM-II), Theory of Computation (TOC), MP (MP), Data Communication (DC), Data Structures (DS), Lab-Object Oriented Design & Programming Through C++ (OODP), Operating System Concepts (OSC), Computer Networks (CN), System Programming (SP), Design and Analysis of Algorithm (DAA), Computer Organization (CO), Lab-Java Programming (JP), Self Learning-I (SL-I), Database Engineering (DBE), Compiler Construction (CC), Unix Operating System (UOS), Mobile Computing (MC), Software Engineering (SE), Lab-Programming in C#.net (C#), Mini Project (Mproj), Self Learning -II (SL-II).

The sample of the dataset prepared using Microsoft Excel features is shown in Table 1. As from Table 1, it is found that OSC Total and Grade is calculated based on OSC End Semester Examination (ESE), OSC In-Semester Examination (ISE), OSC Internal Contineous Assessment (ICA), and OSC Practical Oral Examination (POE). Grade of any course is decided based on the following range –

- O grade for the mark range 100-80,
- A+ grade for the mark range 70-79.99,
- A grade for the mark range 60-69.99,
- B+ grade for the mark range 55-59.99,
- B grade for the mark range 50-54.99,
- C+ grade for the mark range 45-49.99,
- C grade for the mark range 40-44.99, and
- F grade for the mark range 0-39.99.

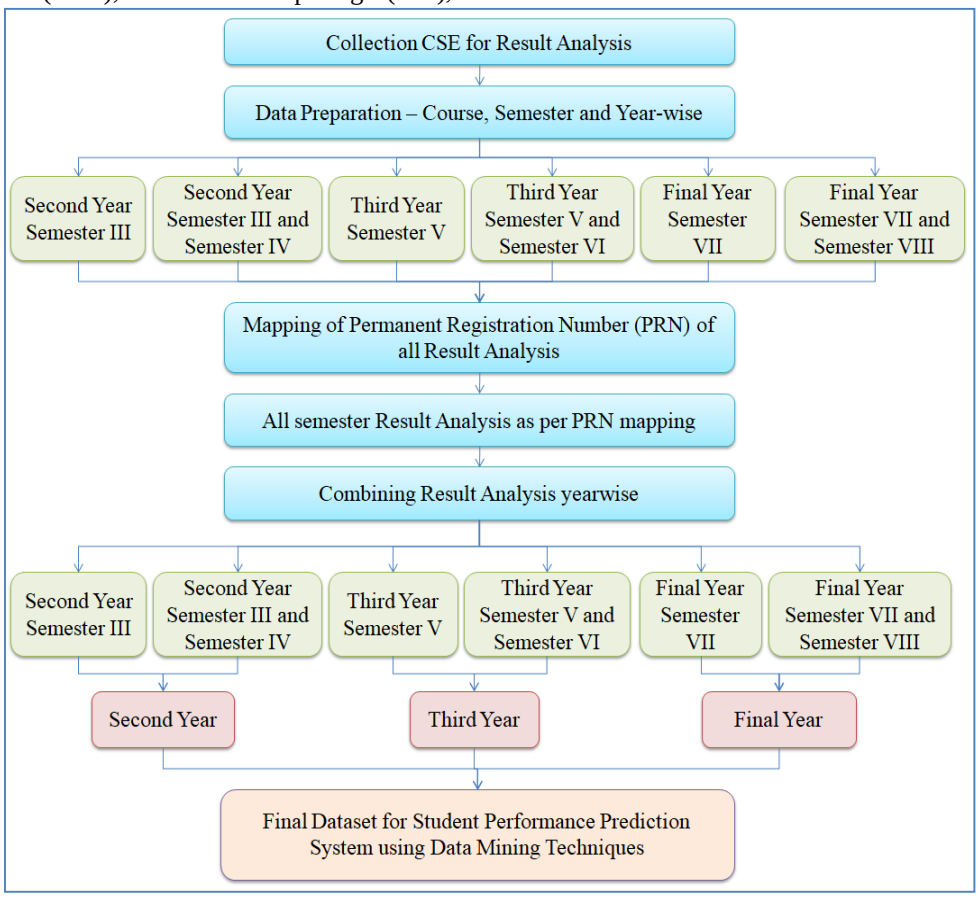

Fig. 2. Data Processing using Microsoft Excel for Recommendation System

TABLE I
SAMPLE OF THE DATASET PREPARED USING MICROSOFT EXCEL FEATURES

OSC(70443101) ESE (70)	OSC(70443101) ISE (30)	OSC(70443101) Theory Status	OSC(70443101) Theory Condon Grace	OSC(70443101) ICA (25)	OSC(70443101) POE (50)	OSC(70443101) Practical Status	OSC(70443101) Practical Condol	OSC(70443101) Total (175)	OSC(70443101)Grade	..
38	15	P	0	22	21	P	0	96	B	.
31	18	P	0	15	40	P	0	104	B+	.
.	.	.	.	.	.	.	.	.	.	
61	26	P	0	23	42	P	0	152	O	.

In the same way, the data is prepared for other courses of semester also. Table 2 shows the sample of the dataset for the Recommendation System. This dataset consist of grades O, A+, A, B+, B, C+, C and F obtained by students in the courses of particular semester/ year.

TABLE II
SAMPLE OF THE DATASET FOR THE RECOMMENDATION SYSTEM

OSC(70443101) Grade	CN(70443102) Grade	SP(70443103) Grade	DAA(70443104) Grade	CO(70443105) Grade	JP(70443106) Grade	SL-I Grade
B	B+	B	B	C+	O	A
B+	C+	A	A	B+	A+	C+
..	..	..	..	..	..	..
O	O	A+	O	A+	O	A

D. Course Grade Dataset for RS$_{RFA}$CG

The course grade dataset used for the framework RS$_{RFA}$CG is given in Table 3. This table contains the Dataset Description, Dataset Abbreviations and Number of Categorical Attributes considered for each dataset. So there are nine dataset related to Second Year Semester III; Second Year Semester IV; Second Year Semester III and Semester IV; Third Year Semester V; Third Year Semester VI; Third Year Semester V and Semester VI; Final Year Semester VII; Final Year Semester VIII; and Final Year Semester VII and Semester VIII. Yearwise dataset contains the number of attributes that depends on the number of attributes of two semester covering that year. So Second Year Semester III and Semester IV; Third Year Semester V and Semester VI; and Final Year Semester VII and Semester VIII; contain 12, 15 and 15 categorical attributes respectively.

TABLE III
DATASET DESCRIPTION FOR RS$_{RFA}$CG

Sr. No.	Dataset Description	Dataset Abbreviations	No. of Categorical Attributes
1	Second Year Sem-III	D_N1	6
2	Second Year Sem-IV	D_N2	6
3	Second Year Sem-III and IV	D_N3	12
4	Third Year Sem-V	D_N4	7
5	Third Year Sem-VI	D_N5	8
6	Third Year Sem-V and VI	D_N6	15
7	Final Year Sem-VII	D_N7	8
8	Final Year Sem-VIII	D_N8	7
9	Final Year Sem-VII and VIII	D_N9	15

E. Selection of Association Rule Algorithm

In this section, 3 association rule algorithms such as Apriori, Predictive, and Tertius Association Rule are compared to select the best association rule algorithm based on valid and invalid rules. Valid and invalid rules are defined as below –

- **Valid Rules** – Valid rules are those in which one course is dependent on other course or one course is prerequite to another course.
  e.g. 1) In case of two courses Advanced C Concepts and Data Structure, the course Advanced C Concepts is the prerequisite to the course Data Structure so the rule like Advanced_C_Concepts_Grade = A+ → Data_Structure_Grade = A+ or Data_Structure_Grade = A+ → Advanced_C_Concepts_Grade = A+ is valid rule.

  2) In case of two courses C Programming and Data Structure, all assignments related Data Structure can be implemented in C Programming language hence these two courses are dependent on each other and the rule Data_Structure_Grade = A → C_Programming_Grade = A or C_Programming_Grade = A → Data_Structure_Grade = A is valid rule.

- **Invalid Rules** - Valid rules are those in which one course is neither dependent nor prerequite to other course. E.g. In case two courses such as Microprocessor and Software Engineering, the course Microprocessor is neither prerequisite nor dependent on Software Engineering course. Hence the rule Microprocessors_Grade = A → Software_Engineering_Grade = A or Software_Engineering _Grade = A → Microprocessors_Grade = A is invalid.

1) Apriori association Rule Algorithm

Apriori association rule algorithm is often used in many applications such as in education sector (Fauzan, 2020; Mondal, 2020), sales strategy (Santoso, 2021), e-commerce (Lourenco, 2020), user profile creation (Singh, 2021), etc. Apriori is a data mining technique that finds and establishes association rules for frequently occurring item groups in a

dataset. This algorithm is based on the idea that every subset of a frequent itemsets must likewise be frequent.

Apriori association rule algorithm works as follows:

1. Frequent itemsets is identified in the given dataset
2. Each itemset is divided into two or more subsets which are not empty.
3. The performance parameters such as support and confidence are calculated for each rule.
4. Rules with a minimum confidence threshold are considered.

The parameter such as support is used or the performance of association rule algorithm. Support is used to decide how often data items or course appears in the given dataset.

Table 4 shows the result of Apriori algorithm on sample dataset D_N = 6. From this Table, it is observed that all rules obtained using Apriori association rule algorithm are valid rules e.g. in the rule JP=O C#=O → MProj=O, this rule is valid as for the project work, programming languages are required. Even the rule DBE=A+ → MProj=O is valid rule as if students are planning the application which involved the backend then he/ she should know the concepts of the Database Engineering.

For the value of support 0.3, ten association rules are generated but if the value of support is increased, then one valid rule is received for maximum support 0.5.

TABLE IV
RESULT OF APRIORI ASSOCIATION RULE ALGORITHM

Min. Support	Best rules found	No. of Rules
0.3	1. DBE=A+ C#=O → MProj=O	10
	2. SE=A+ C#=O → MProj=O	
	3. C#=O → MProj=O	
	4. JP=O C#=O → MProj=O	
	5. SE=A+ → MProj=O	
	6. OSC=A+ JP=O → MProj=O	
	7. DBE=A+ → MProj=O	
	8. OSC=A+ → MProj=O	
	9. SP=A → MProj=O	
	10. JP=O → MProj=O	
0.35	1. C#=O → MProj=O	8
	2. JP=O C#=O → MProj=O	
	3. SE=A+ → MProj=O	
	4. DBE=A+ → MProj=O	
	5. OSC=A+ → MProj=O	
	6. SP=A → MProj=O	
	7. JP=O → MProj=O	
	8. CC=A → MProj=O	
0.4	1. C#=O → MProj=O	3
	2. JP=O C#=O → MProj=O	
	3. JP=O → MProj=O	
0.45	1. C#=O → MProj=O	2
	2. JP=O → MProj=O	
0.5	1. JP=O → MProj=O	1

2) Predictive Apriori association Rule Algorithm

Accuracy, a single parameter in the predictive Apriori association rule algorithm, is the combination of support and confidence. This prediction accuracy is used to build the Apriori association rule in this Predictive-Apriori association rule method. Table 5 explains the result of Predictive-Apriori algorithm on dataset D_N = 6.

From Table 5, it is noted that the rule "Computer_Network_Grade=O Self_Learning-I_Grade = Advnced_C_Concepts_Grade = A+ → Programming_in_C#_Grade = O" is invalid. For this rule, the course Self Learning-I is neither prerequisite nor dependent on remaining courses Computer Networks, Compiler Construction and Programming in C#. Hence this association rule algorithm cannot be considered for the framework $RS_{RFA}CG$.

TABLE V
RESULT OF PREDICTIVE APRIORI ASSOCIATION RULE ALGORITHM

	Best rules found	No. of Rules
1.	CN=O DBE=O → MProj=O	10
2.	OSC=O MC=A+ C#=O → MProj=O	
3.	CN=O MC=A+ → MProj=O	
4.	SP=A+ DBE=O → MProj=O	
5.	CN=O SL-I=A CC=A+ → C#=O	
6.	OSC=A+ CC=A C#=O → MProj=O	
7.	CC=O → MProj=O	
8.	OSC=O SP=A+ → MProj=O	
9.	OSC=O MC=A+ → MProj=O	
10.	CN=O DAA=O → JP=O	

3) Tertius association Rule Algorithm

The Tertius algorithm is a combination of decision trees and association rule mining. For classification tasks, it finds frequently occurring itemsets and extracts decision rules that are helpful. Table 6 discusses about the result of Tertius algorithm on the dataset D_N = 6. As in Table 6, the rule System_Programming_Grade = A+ → Computer_Network_Grade = O is invalid as System Programming and Computer Networks are not related courses or dependent on each other. Hence this algorithm also cannot be considered for this recommendation system framework.

TABLE VI
RESULT OF TERTIUS ASSOCIATION RULE ALGORITHM

Best rules found	No. of Rules
1. C# = O → JP = O	10
2. JP = O → C# = O	
3. OSC = O → CN = O	
4. CN = O → OSC = O	
5. CN = O → C# = O	
6. C# = O → CN = O	
7. SP = A+ → CN = O	
8. CN = O → SP = A+	
9. CC = A+ → CN = O	
10. CN = O → CC = A+	

The association rule algorithm - Apriori is found to be the best association rule algorithm among these three algorithms such as Predictive-Apriori, Apriori, and Tertius Association Rule.

F. Selection of Filtered Associator Algorithm

In this subsection, six filtering techniques such as RemoveDuplicate, RemoveFolds, RemoveFrequentValues, RemoveMisClassified, ReSample, and ReservoirSample are compared after applying these filter techniques on dataset and checking the result of Apriori algorithm on

these filtered datasets based on valid rules, invalid rules and support values.

1) RemoveDuplicate Filter and Apriori Association Rule Algorithm

The filter RemoveDuplicate returns copies of other batches of data after eliminating all duplicate occurrences from the first batch it receives. In This case, first dataset D_N = 3 is filtered using RemoveDuplicate filter technique and then Apriori algorithm is applied on the filtered dataset. Table 7 shows the result of Apriori Algorithm on filtered dataset using RemoveDuplicate Filter on the dataset D_N = 3. From Table 7, it is found that there are invalid rules such as the rule "Microprocessor_Grade = O → Object_Oriented_Design&Programming_Through_C++_Grade = O" is invalid because the course Object Oriented Design & Programming is the C++ programming with object oriented programming concepts and for the MP, generally TASM editor is considered which is used to convert assembly language file to an object file containing the machine code that the processor will execute. Even support value is also 0.15 only for ten rules. Hence this filter technique cannot be used for this framework of recommendation system.

TABLE VII
RESULT OF APRIORI ALGORITHM ON FILTERED DATASET USING REMOVEDUPLICATE FILTER

Min. support		Best rules found	No. of Rules
0.15	1.	ACC=O OODP=O → VB=O	10
	2.	DT=O OODP=O → VB=O	
	3.	ACC=O → VB=O	
	4.	DS=O OODP=O → VB=O	
	5.	DT=O → VB=O	
	6.	DT=O VB=O → OODP=O	
	7.	VB=O MP=O → OODP=O	
	8.	DS=O → VB=O	
	9.	AM-II=A+ OODP=O → VB=O	
	10.	MP=O → OODP=O	

2) RemoveFolds Filter and Apriori Association Rule Algorithm

In this case, the filter RemoveFolds which takes a dataset and outputs a specified fold (here k-fold value = 5) for cross validation is applied on the dataset D_N = 3. After application of filter method on the dataset, the association rules are obtained by Apriori algorithm on filtered dataset. Table 8 discusses about the result of Apriori algorithm on filtered dataset using RemoveFolds Filter technique on the dataset D_N = 3. From Table 8, it is observed that rules obtained using this filter techniques are invalid such as the rule "Applied_Mathematics-II_Grade = A + Microprocessor_Grade = O → Visual_Basic_Grade = O" is invalid rule. Hence this filter technique also cannot be used for this recommendation system.

TABLE VIII
RESULT OF APRIORI ALGORITHM ON FILTERED DATASET USING REMOVEFOLDS FILTER

Min. support		Best rules found	No. of Rules
0.15	1.	DMS=O → VB=O	10
	2.	AM-II=A+ MP=O → VB=O	
	3.	AM-II=A+ → VB=O	
	4.	DMS=O OODP=O → VB=O	
	5.	ACC=O DS=O → VB=O	
	6.	ACC=A+ DT=A+ → VB=O	
	7.	ACC=O → VB=O	
	8.	ACC=A+ CG=A → VB=O	
	9.	ACC=O OODP=O → VB=O	
	10.	ACC=A+ DS=A+ → VB=O	

3) RemoveFrequentValues Filter and Apriori Association Rule Algorithm

9 describes the result of Apriori algorithm on filtered dataset using RemoveFrequentValues Filter technique. With this filter technique, the instances are filtered based on the values of a characteristic that are retained, either frequently or infrequently. Values that have the same frequency are preserved in the same format as they were in the original instance object. For example, if you had the values "10, 20, 30, 40" with the frequencies "100, 50, 50, 30" and the two most prevalent values must be retained then "10, 20" would be returned since, while having the same frequency, "20" arrives before "30".

From Table 9, it is noted that the result contains invalid rules like "Microprocessors_Grade = O → Object_Oriented_Design&Programming_Through_C++_Grade = O" which results in not considering this technique for recommending courses to students.

TABLE IX
RESULT OF APRIORI ALGORITHM ON FILTERED DATASET USING REMOVEFREQUENTVALUES FILTER

Min. support		Best rules found	No. of Rules
0.2	1.	ACC=O OODP=O → VB=O	10
	2.	ACC=O → VB=O	
	3.	VB=O MP=O → OODP=O	
	4.	MP=O → OODP=O	
	5.	DS=O OODP=O → VB(70442106)=O	
	6.	DS=O → VB=O	
	7.	DMS=O → VB=O	
	8.	DMS=O OODP=O → VB=O	
	9.	AM-II=A+ OODP=O → VB=O	
	10.	VB=O DS=O → OODP=O	

4) RemoveMisClassified Filter and Apriori Association Rule Algorithm

Erroneously classified cases are eliminated by this RemoveMisClassified filter. This filter works well for eliminating outliers. Table 10 which shows the result of Apriori algorithm on filtered dataset using RemoveMisClassified Filter, contains the invalid rules such as Digital_Technique_Grade = A+ → Object_Oriented_Design&Programming_Through_C++_Grade = O. Hence this filter technique is not useful for suggesting the course grade to students.

TABLE X
RESULT OF APRIORI ALGORITHM ON FILTERED DATASET USING REMOVEMISCLASSIFIED FILTER

Min. support	Best rules found	No. of Rules
0.35	1. VB=O → OODP=O	10
	2. ACC=A+ → OODP=O	
	3. DS=A+ → OODP=O	
	4. MP=A+ → OODP=O	
	5. CG=A+ → OODP=O	
	6. DT=A+ → OODP=O	
	7. TOC=A → OODP=O	
	8. ACC=A+ VB=O → OODP=O	
	9. DMS=A+ → OODP=O	
	10. DC=A → OODP=O	

5) ReSample Filter and Apriori Association Rule Algorithm

The Resample filter adds instances from a class with few instances multiple times to the result data set. The Resample filter can use sampling with or without replacement to generate a random subsample of a dataset. The dataset needs to contain a nominal class property and have a predetermined number of instances in the created dataset. This filter method still is not suitable for this course grade recommendation system as the result contains invalid rules like "Visual_Basic_Grade = O Microprocessor_Grade = O → Object_Oriented_Design&Programming_Through_C++_Grade = O" as shown in Table 11.

TABLE XI
RESULT OF APRIORI ALGORITHM ON FILTERED DATASET USING RESAMPLE FILTER

Min. support	Best rules found	No. of Rules
0.15		10
	1. DMS=O DS=O → VB=O	
	2. DT=O OODP=O → VB=O	
	3. ACC=O DS=O → VB=O	
	4. ACC=O OODP=O → VB=O	
	5. DT=O VB=O → OODP=O	
	6. DT=O → VB=O	
	7. DS=O OODP=O → VB=O	
	8. ACC=O → VB=O	
	9. VB=O MP=O → OODP=O	
	10. AM-II=A+ OODP=O → VB=O	

6) ReservoirSample Filter and Apriori Association Rule Algorithm

This filter ReservoirSample uses Vitter's reservoir sampling algorithm "R" to generate a random subsample from a dataset. While the reservoir must fit into main memory, the original data set does not. Table 12 shows the result of Apriori algorithm on filtered dataset using ReservoirSample Filter technique on the dataset D_N = 3. From Table 12, it is found that all rules are valid rules and support value is also 0.5 which is maximum support value among all other support value obtained using filter techniques like RemoveDuplicate, RemoveFolds, RemoveFrequentValues, RemoveMisClassified, ReSample and application of Association Rule Algorithm on filtered dataset. Hence this filter technique is considered for this framework $RS_{RFA}CG$ to recommend the course grade to the students.

TABLE XII
RESULT OF APRIORI ALGORITHM ON FILTERED DATASET USING RESERVOIRSAMPLE FILTER

Min. support	Best rules found	No. of Rules
0.5	1. ACC=O DS=O → VB=O	10
	2. ACC=O DS=O OODP=O → VB=O	
	3. ACC=A+ DS=O → VB=O	
	4. CG=A DS=O → VB(70442106)=O	
	5. ACC=A+ CG=A+ DS=A+ → VB=O	
	6. CG=A+ DS=O → OODP=O	
	7. CG=A DS=A+ OODP=O → VB=O	
	8. DS=O → VB=O	
	9. DS=O OODP=O → VB=O	
	10. ACC=O → VB=O	

G. Comparison of Filtered Associator Algorithm with Apriori Algorithm

Table 13 shows the application of Apriori Algorithm on dataset D_N6 filtered using ReservoirSample Filter. For support value 0.4, number of rules generated is ten. If the value of support is increased to 0.45, 7 rules are obtained. As the support value is increased, no. of rules obtained is less.

TABLE XIII
RESULT OF APRIORI ALGORITHM ON DATASET 6 FILTERED USING RESERVOIRSAMPLE FILTER

Min. support	Best rules found	No. of Rules
0.4	1. DBE=A+ C#=O → MProj=O	10
	2. SE=A+ C#=O → MProj=O	
	3. JP=O DBE=A+ → MProj=O	
	4. JP=O SE=A+ → MProj=O	
	5. C#=O → MProj=O	
	6. JP=O C#=O → MProj=O	
	7. DBE=A+ → MProj=O	
	8. SE=A+ → MProj=O	
	9. OSC=A+ → MProj=O	
	10. SP=A → MProj=O	
0.45	1. C#=O → MProj=O	7
	2. JP=O C#=O → MProj=O	
	3. DBE=A+ → MProj=O	
	4. SE=A+ → MProj=O	
	5. CC=A → MProj=O	
	6. Unix_Operating_System=A → MProj=O	
	7. JP=O → MProj=O	
0.5	1. C#=O → MProj=O	3
	2. JP=O C#=O → MProj=O	
	3. JP=O → MProj=O	
0.55	1. C#=O → MProj=O	2
	2. JP=O s→ MProj=O	
0.65	1. C#=O → MProj=O	1

Table 14 illustrates the comparison of support and number of rules after applying Apriori algorithm on original dataset D_N6 (as given in Table 2) with the application of Apriori algorithm on dataset D_N6 filtered using ReservoirSample Filter. From Table 14, is observed that for support value 0.4 using Apriori Association Rule Algorithm on Filtered Dataset using ReservoirSample Filter method, number of rules are 10 but using Apriori Association Rule Algorithm on original dataset, only three rules are obtained. For support value 0.45 using Apriori algorithm on Filtered

Dataset using ReservoirSample Filter method, seven rules are obtained but using Apriori Association Rule Algorithm on original dataset, number of rules are only two. Hence the application of Apriori algorithm on Filtered Dataset using ReservoirSample Filter is beneficial than simply applying Apriori algorithm on original dataset.

H. Suggestion of Recommendation Rules to Students

Last phase of $RS_{RFA}CG$ is the suggestion of recommendation rules using Apriori Association Rule Algorithm on Filtered Dataset using ReservoirSample Filter to students. This recommendation system will help students to improve their academic performance.

TABLE XIV
COMPARISON OF SUPPORT AND NUMBER OF RULES AFTER APPLICATION OF APRIORI ASSOCIATION RULE ALGORITHM AND APPLICATION OF APRIORI ASSOCIATION RULE ALGORITHM ON FILTERED DATASET USING RESERVOIRSAMPLE FILTER

Apriori Algorithm on original dataset		**Apriori Algorithm on Filtered Dataset using ReservoirSample Filter**	
Support	**No. of Rules**	**Support**	**No. of Rules**
0.3	10	0.4	10
0.35	8	0.45	7
0.4	3	0.5	3
0.45	2	0.55	2
0.5	1	0.65	1

Algorithm : Course Grade Recommendation System $RS_{RFA}CG$
Input: Course Grade obtained by students in exam
Output: Recommendation Rule
Method:

1. Selecting the best Association Rule for $RS_{RFA}CG$
   a. Read dataset ARFF file containing course grade data (Consider D_N = 6)
      i. Apply association rule algorithm such as Apriori (AR=1), PredictiveApriori (AR=1) and Tertius (AR=3) on the dataset.
      ii. for j = 1 to 3
         A. If rules obtained are valid rules then
            The association rule algorithm is considered as the best association rule algorithm.
            Else /* rules obtained are the invalid rules */
            Discard the rules of the association rule algorithm.
         B. j = j + 1
   b. Return the best Association Rule algorithm

2. Selecting the best Filtered Associator Algorithm for $RS_{RFA}CG$.
   a. For D_N = 1 to 9
   b. Apply unsupervised filters for instances such as RemoveDuplicate (F_N = 1), RemoveFolds (F_N = 2), RemoveFrequentValues (F_N = 3), RemoveMisClassified (F_N = 4), ReSample (F_N = 5), and ReservoirSample (F_N = 6).
      i. For F_N = 1 to 6
         A. Apply the filter F_N algorithm on the D_N dataset and rename the dataset as FD_N.
         B. Apply Apriori Association Rule algorithm on the filtered dataset FD_N
            If rules obtained are valid rules the
            The association rule algorithm is considered the best association rule algorithm for $RS_{RFA}CG$
            else /* rules obtained are the invalid rules */
            Discard the rules of the association rule algorithm.
         C. F_N = F_N + 1;
      ii. D_N = D_N + 1;
   c. Return the valid recommendation rules obtained using Apriori association rule algorithm applied on filtered dataset.

3. Suggest recommendation rules to students using Apriori association rule algorithm applied on filtered dataset

IV. ALGORITHM FOR $RS_{RFA}CG$

In following algorithm, different variables use are -

- F_N: It indicates the Filter technique number as RemoveDuplicate (F_N = 1), RemoveFolds (F_N = 2), RemoveFrequentValues (F_N = 3), RemoveMisClassified (F_N = 4), ReSample (F_N = 5), and ReservoirSample (F_N = 6).
- ARFF: Attribute-Relation File Format used for dataset.
- AR: Association Rule algorithm - Apriori (AR=1), PredictiveApriori (AR=1) and Tertius (AR=3).
- D_N: It indicates dataset number D_N1 to D_N9.

This algorithm consists of mainly three steps –

1. Selecting the best Association Rule for $RS_{RFA}CG$
2. Selecting the best Filtered Associator Algorithm for $RS_{RFA}CG$.

3. Suggest recommendation rules to students using Apriori association rule algorithm applied on filtered dataset

V. Result and Discussion

Table 15 shows the result of Apriori algorithm on filtered dataset using ReservoirSample Filter in terms of support and number of rules on nine datasets D_N1 to D_N9. From this Table, it is found that for support value greater than or equal to 0.2 and less than or equal to 0.51, ten rules are obtained for all datasets while or support value greater than 0.35 and less than or equal to 0.7, number of rules are one or two rules. For dataset D_N1, ten rules are obtained while for support value 0.45, one rule is generated.

Similarly, in case of dataset D_N5, ten rules are generated for the support value 0.31, six rules for the support value 0.36, three rules for the support value0.44 and two rules for the support value. So in the same way, the result can be considered for all other dataset. As the minimum support value is increased, number of rules generated is less for maximum support value.

TABLE XV
RESULT OF APRIORI ASSOCIATION RULE ALGORITHM ON FILTERED DATASET USING RESERVOIRSAMPLE FILTER IN TERMS OF SUPPORT AND NO. OF RULES

Dataset	Apriori Association Rule Algorithm on Filtered Dataset using ReservoirSample Filter									
	Support	No. of Rules	Support	No. of Rules	Support	No. of Rules	Support	No. of Rules	Support	No. of Rules
D_N1	0.3	10	0.33	8	0.38	3	0.43	2	0.45	1
D_N2	0.2	10	0.25	7	0.31	4	0.35	3	0.38	1
D_N3	0.5	10	0.55	6	0.60	4	0.61	2	0.65	1
D_N4	0.25	10	0.28	7	0.35	4	0.4	3	0.45	1
D_N5	0.31	10	0.36	6	0.4	3	0.44	3	0.49	2
D_N6	0.4	10	0.45	7	0.5	3	0.55	2	0.65	1
D_N7	0.22	10	0.25	8	0.32	5	0.4	3	0.5	2
D_N8	0.35	10	0.4	6	0.45	4	0.48	2	0.55	1
D_N9	0.51	10	0.55	8	0.58	4	0.65	2	0.7	1

Conclusion and Future Work

In this current chapter, the framework $RS_{RFA}CG$ is developed for improving students' academic performance by suggesting the course grade recommendation rules. For deciding course grade recommendation rules, two rules such as valid and invalid rules are considered. If the one course is prerequisite or/ and dependent on other course then the rule formed using those two courses is valid rule otherwise it is invalid rule. The course grade recommendation rule such as C-Programming Grade = O

→ Java Programming Grade = O is valid rule as the course C-Programming is the prerequisite for Java Programming course as well as dependent course and the rule Microprocessor Grade = A → Database Engineering Grade = A is invalid as the course Microprocessor is neither prerequisite nor dependent on the course Database Engineering. For this framework, data related to four year Computer Science and Engineering stream for Academic Year 2014-15 and 2015-16 based on Credit System - Ten Point Scale is collected from university site and processed using Microsoft Excel. This framework $RS_{RFA}CG$ is applied in total nine datasets. Association rule algorithms such as Apriori Association Rule, Predictive Apriori Association Rule and Tertius Association Rule are compared based on valid rules, invalid rules, and support value to find the best association rule algorithm for this framework. Apriori association rule algorithm is found to be the best association rule algorithm for this recommendation system. Nine datasets are filtered using six filtering techniques. After preparing the filtered datasets, Apriori association rule algorithm are applied on these filtered dataset. It is found that the result of Apriori algorithm on dataset filtered using ReservoirSample filter technique suggest the valid recommendation rules.

In future, the combined approach of clustering algorithm followed by association algorithm on these dataset will be compared with the combination of clustering technique and association rule algorithm on dataset filtered using various filter techniques for course grade recommendation system. If more features such as demographics, learning behavior patterns, etc. are included then it could also strengthen the system's recommendations

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