An Association Rule Modeling For a Programme and Activity Recommendation System Supporting Student Counseling Management for Universities in Thailand

Kanokwan Watkins, Nutsana Napayap, and Chun C. Fung

***Abstract*—**Many technological innovations have supported the advances and management of academic operations and processes in order to enhance the number of completions. One of the initiatives designed to assist students and staff is the Student Counselling System, which aims to assist the academic development and achievement by the students. The purpose of this paper is to report the development of an association rule model in an Intelligent Recommendation System with an aim to forecast the programme recommendation for prospective students, and activity recommendation for current students. Association Rules based on GRI and K-means clustering were used in the experiment. The study is based on a sample of 9,001 student records and the results demonstrated that the accuracy of the recommendation model obtained higher performance than the benchmark model. This system will help the counselors in recommending the appropriate courses and activities for students thereby increasing their chances of success.

***Index Terms*—**Association Rules, K-Means Clustering, Intelligent Recommendation System, Data Mining.

I. Introduction

Higher education (HE) is essential to the development of a country's long-term economic performance and productivity [1]. As it requires substantial investments and resources, one of the key objectives of higher education institutes (HEIs) is to focus on improving student completion rates in respective programmes. In Thailand, records reveal that there is room for improvement in this area, one cause can be attributed to the high number of student dropouts. This has led to wasted resources and a reduced number of graduates to meet the demands of industry and the community. There are many reasons why a student may choose to drop out, such as finding that the programme is unsuitable. This problem usually originates at enrolment when the student selects or is recommended an unsuitable programme of study.

Previous studies have investigated the issues that can lead to student dropouts at university. One of these issues is depression. This can occur when the student is unable to cope with study, which is a common problem among tertiary students. This affects the student's behaviour, motivation level, concentration, feeling of self-worth and mood and can eventually lead to the student electing to drop out [2]. From a university perspective, causes for dropouts are related to the allocation of resources and inability to recruit students of appropriate calibre with a high probability of completion. Inappropriate management decisions can lead to unoccupied student placements and loss of potential tuition fees when students dropout. The problem of student retention in HE can also be attributed to low student satisfaction and student transfer [3]. In addition to these causes, previous studies have found that the quality and convenience of support services influence Thai students to change educational institutes in HE [4]. Therefore, it is necessary to meet student needs and to match their capabilities with suitable programmes of study in HE recruitment and enrolment processes. Understanding student needs will enhance their learning experience, increase their chances of success and reduce resource wastage that is due to dropouts and change of programs.

With a limited supply of resources and increasing competition for students in Thailand's HE sector, universities and institutes are focusing their efforts on increasing the rate of student retention and completion. In addition, reputation is being used increasingly to measure the university's quality and performance [5]. One aspect of such measurement is based on factors that affect student satisfaction. Gatfield [6] stated that it is vital that HEIs concentrate on quality through accreditation processes and various aspects of quality services from a student perspective.

Archer and Cooper [7] confirmed that the provision of counselling services is an important factor contributing to students' academic success. Urata and Takano [8] stated that the essence of student counselling should include advice on career guidance, identification of learning strategies, handling of interpersonal relationships, along with self-understanding of the mind and body. A key aspect of student services is to provide counselling on programme guidance because this will assist the students in their enrolment decisions and future university experience. Although many students choose particular programmes of study because of job opportunities, issues may arise if a student is not interested in the career or if the programme is not suitably matched with the student's capabilities [9]. Therefore, to assist with student retention, HEIs need to determine how they can attract or recruit students and how they can match students to appropriate programmes of study to achieve a high completion rate.

In order to assist university students, this research study aimed to investigate and develop intelligent recommendation models to provide academic recommendations for new students based on historical records of students who have successfully completed their programmes. Moreover, this project focused on techniques that enabled the recommendation system to improve student services, which,

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in turn, supported student-counseling system by assisting students to choose the most appropriate programme and activities for their study at university. This focus ensured that the objective was met, which was to improve completion rates in HEIs.

This study is separated into various sections. Next section presents the objectives of the study and Section 3 presents the input and output variables selection with a description of the dataset. The experimental design is explained in Section 4 and a discussion on the instructional techniques that are employed is provided in Section 5. Section 6 presents the experimental results, which is followed by the discussion and future work. The final section acknowledge the organizations and people who encourage the author to finish the study.

II. Objectives of the Study

This study aims to find the ranked programme and activity recommendation based on past records from the student database. This is intended to assist supervisors and counsellors in advising prospective students and enrolled students at university, investigate and develop the ranked programme and activity prediction model in the proposed intelligent recommendation system. ARs are employed to identify the relationship between the data. Moreover, it aims to improve the performance of the recommendation model using clustering techniques and proposes the integrated techniques as well as improves the accuracy of the recommendation model in the proposed intelligent recommendation system.

III. Input and Output Variables Selection

In this experiment, the sample data were chosen from the university's database of 11,400 student records. After the data cleaning process, 9,001 student records were used in this study. The distribution of the students, with respect to programmes, is illustrated in Figure 1.

In Figure 1, the tertiary student data were obtained from seven academic years of records (2001–2007), excluding summer semesters. Student data included records from first year to graduation. The data comprised of 30.62 per cent of students from business computing, 19.02 per cent from accounting, 22.18 percent from management, 14.75 percent from marketing, 5.2 percent from human resource management, 4.84 percent from business English and 3.38 percent from law. The data in this study did not indicate any personal information because of privacy issues, and no student was identified in the research. The university randomised the data and all private information was removed in this experiment.

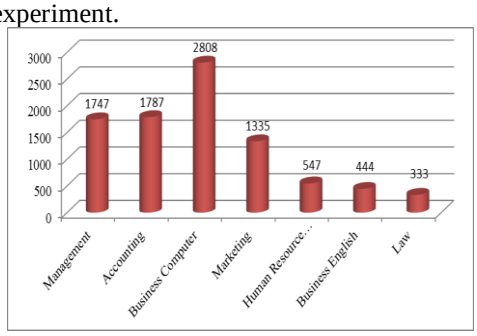

Fig. 1. Number of undergraduate students by programme of study (2001–2007).

TABLE I
Variables Used In The Ranked Programme

Module 1 Ranked Programme Recommendation	
Variable name	Type
University Major	Target
Previous school GPA	Input
Gender	Input
Talents and interests	Input

TABLE II:
Variables Used In The Ranked Activity Modules

Module 2: Ranked Activity Recommendation	
Variable name	Type
Activity type	Target
Previous school GPA	Input
University major	Input
Talents and interests	Input

To choose variables to support the programme and activity selection for GRI algorithms, the study of Geiser and Santelices [10] found that previous school GPA was the best predictor not only for new students but also for student outcomes in four years. Another study found that gender and interests also related to the success of study of tertiary students [11]. Therefore, the variables chosen in Module 1 (previous school GPA, gender and talents and interests) are input variables with the target of major or programme of study. In addition, with the purpose of choosing activities to improve the student's performance in their study and future career, a study by Hoover and Dunigan [12] found that the majority of students who joined collegiate organisations also improved their performance during their study and future career. In the framework, 'university major' is a significant input to discover the types of activities that should be supported by extracting the successful cases from the student database. This ranked activity recommendation module provides information on recommended activities to the students after they have determined their programme of study at university and before obtaining their GPA results in the first semester. Most students are expected to use the ranked programme activity at the beginning of the first semester. In the same module, the three variables (previous school GPA, university major and talents and interests) are input with the target output from the module to be ranked activities. Details of the methodology used in this experiment are described in the next section.

IV. Experiment Methodology and Design

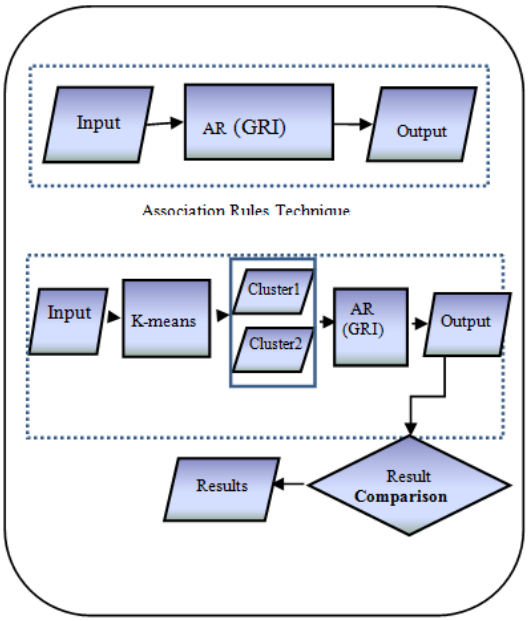

Fig. 2. Process to compare performance of GRI for Ranked Programme and Activity Recommendations.

This section describes the methodology and the ranked programme and activity recommendation model. Normalisation of the data was first carried out as an essential step in pre-processing. To prepare the dataset for the GRI algorithm in the data analysis process, quantitative data was required. For the training, validation and testing of the model, the dataset was randomised and divided into three sets: 60 per cent, 20 per cent and 20 per cent of data, respectively. The proposed model is illustrated in Figure 2

The GRI algorithm was used in the first stage. To improve the prediction accuracy, the K-means clustering technique was incorporated with the GRI algorithms, as shown in Figure 2. In this study, 9,000 random records with the aforementioned parameters for ranked programme and activities were used. Based on the recommendations from supervisors and lecturers, the number of clusters used was two. The model execution flowchart is provided in Figure 3.

Figure 3 shows that, after determining the ARs using GRI algorithms to find the correlations between student records in the dataset, the confidence levels of the rules from the results in the first stage are sorted according to the ranked programme majors and activities. The extracted rules are filtered and categorised according to the confidence levels 80–100 per cent, 60–79 per cent and 40–59 per cent as the top, second and third ranked programme majors and activities, respectively.

After the three rule levels have been set, the next step is matching the rules with the student profiles. Examples of the displayed results are shown in Table 3 and 4.

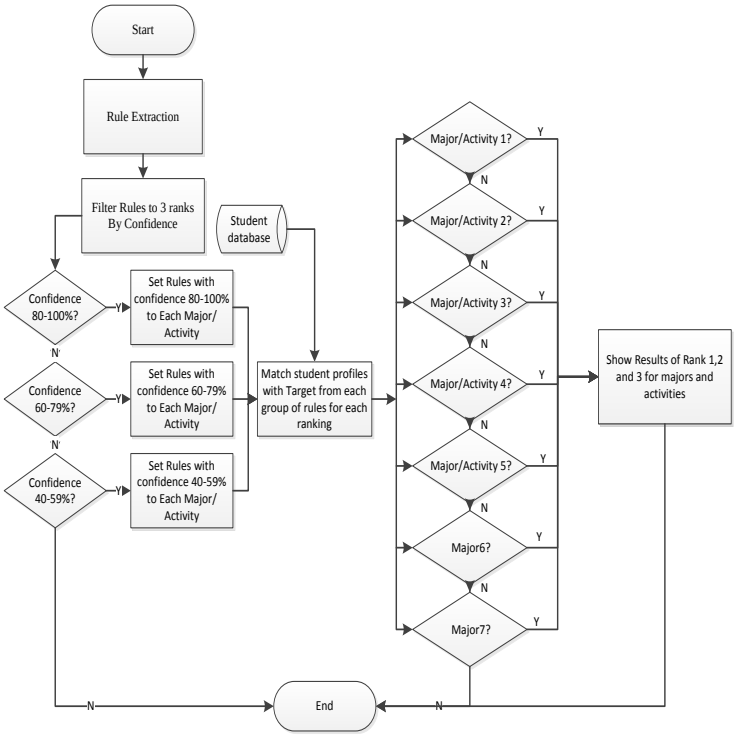

Fig. 3. Flowchart to derive recommendation for three ranked programme majors and activities.

Table III
Example Results Of Ranked Programme Recommendation

Rank	Recommended programme	Programme name
1	Programme = 0.2	Accounting
2	Programme = 0.1	Business Computing
3	Programme = 0.5	Human Resource Management

Table IV
Example Results Of Ranked Activity Recommendation

Rank	Recommended activity	Activity name
1	Activity = 0.1	Academic activity, such as academic competition related with student major
2	Activity = 0.3	Acting activity, such as theatre club
3	Activity = 0.4	Social development activity, such as rural development volunteering club

The results in ranked format are provided to counsellors and supervisors to assist them with their recommendations for the students.

V. Intelligent Techniques Used

Data-mining techniques were used in various recommendation systems to determine the relationship between data records [13]. Classification is one important technique in data mining that can be used to classify data and discover knowledge from large databases [14]. In this study, to solve the multiclass-classification problem, the AR tool, proposed by Agrawal et al. [15], was an important tool in data mining that aimed to extract a model to find the relevant relationships between the attribute set and class labels [16]. There have been many research reports on the use of AR for classification purposes [15-27].

A concept to construct a concise and accurate classifier using an AR was proposed by Xu et al. [14]. They presented a novel classification algorithm classification based on atomic ARs (CAAR). Compared with the DT algorithm, they

claimed that their proposed CAAR classification rule set achieved the highest average accuracy and was faster than classification based on ARs.

Another study by Paireekreng et al. [28] proposed an integrated method by using classification and association rule techniques to extract knowledge from mobile content in a user profile. This proposed method simplified the association from outcomes of the classification and clustering processes for the non-interactive recommendation system. Another study by Soliman and Adly [29] also proposed an algorithm using an AR to find the best subset of rules for all possible ARs to build an efficient classifier. Therefore, many research reports have shown that ARs are an accomplished technique for the classification [24-29]. In this study, ARs based on GRI were used to extract the rules for the multiclass-classification problem. Many research reports have shown that the results of ARs based on GRI were of high quality.

To improve the performance of ARs, K-means clustering, Plasse et al. [30] found that the clustered data, which were extracted by ARs, gained more accuracy than normal data. Therefore, in this proposed GPA recommendation model, K-means clustering was used to enhance the performance of the model.

VI. Experimental Results

This section compares the results from the GRI algorithms with the results from the combination of K-means clustering and GRI algorithms. In the example results illustrated in the tables, 'consequent' represents the target programme or activity, 'antecedent' represents the extracted rules, 'support' shows how often the rule appears in the student dataset and 'confidence' represents the percentage of number of transactions, including all target programmes or activities in the consequent, as well as the antecedent, to the number of transactions that include all items in the antecedent.

A. Example results of ranked programme and activity recommendations based on GRI algorithm

The results in Table V illustrate output from extraction of the programme recommendation. The details include 'programme', which refers to one of the seven programmes of study (major), 'G' refers to gender, 'PGPA' refers to one of the five ranges of previous GPA and 'TI' refers to one of the seven choices of talents and interests.

Similarly, example results from rule extraction of the activity recommendation are shown in Table VI . 'Activity' provides recommendations based on one of the five activities, 'programme' refers to one of the seven programmes of study (major), 'PGPA' refers to one of the five ranges of previous GPA and 'TI' refers to talents and interests

TABLE VI
Example Results Of Rules Extraction By GRI For Ranked Programme Recommendations

Consequent	Antecedent	Support (%)	Conf. (%)
P = 0.2	PGPA = 0.1 and TI = 0.4 and G = 0.1	25.02	100
P = 0.5	PGPA = 0.3 and TI = 0.6 and G = 0.1	12.02	100
P = 0.3	PGPA = 0.2 and TI = 0.6 and G = 0.2	11.04	100
P = 0.3	PGPA = 0.1 and G = 0.1	15.23	80.95
P = 0.1	PGPA = 0.4 and TI = 0.7 and G = 0.1	25.08	71.43
P = 0.7	PGPA = 0.2 and TI = 0.7	15.18	68.75
P = 0.6	PGPA = 0.2 and TI = 0.7	25.03	66.67
P = 0.3	PGPA = 0.1 and TI = 0.1	15.09	62.5
P = 0.2	PGPA = 0.3 and TI = 0.4 and G = 0.2	17.96	61.65
P = 0.3	TI = 0.4 and G = 0.1	27.18	58.67
P = 0.5	PGPA = 0.5 and TI = 0.6 and G = 0.2	15.08	57.14
P = 0.2	PGPA = 0.3 and TI = 0.4	18.46	53.7
P = 0.4	PGPA = 0.1 and TI = 0.2 and G = 0.2	8.61	52.73
P = 0.3	PGPA = 0.3 and TI = 0.3 and G = 0.1	15.52	48.94
P = 0.7	PGPA = 0.4 and TI = 0.2 and G = 0.1	17.56	46.52
P = 0.4	PGPA = 0.1 and TI = 0.2	15.72	44.62
P = 0.4	PGPA = 0.5 and TI = 0.1	15.16	42.86
P = 0.2	PGPA = 0.1 and TI = 0.1 and G = 0.2	29.00	40.98
P = 0.3	PGPA = 0.2 and TI = 0.6	15.06	40

TABLE VII
Example Results Of Rules Extraction By GRI For Ranked-Activity Recommendation

Consequent	Antecedent	Support (%)	Conf. (%)
Act= 0.4	TI = 0.5	29.78	100
Act = 0.1	TI = 0.3	28.23	100
Act = 0.3	Programme = 0.4 and TI = 0.2	24.18	100
Act = 0.5	Programme = 0.7 and TI = 0.1	14.11	90.28
Act = 0.4	PGPA = 0.2 and TI = 0.5	12.46	89.27
Act = 0.2	Programme = 0.2 and PGPA = 0.5 and TI = 0.6	15.02	89.2
Act = 0.3	Programme = 0.1 and PGPA = 0.2 and TI = 0.2	16.07	69.4
Act = 0.4	Programme = 0.5 and PGPA = 0.5 and TI = 0.5	19.03	68.6
Act = 0.5	Programme = 0.3 and PGPA = 0.1 and TI = 0.7	20.01	55
Act = 0.5	Programme = 0.1 and PGPA = 0.5 and TI = 0.1	13.00	54.2
Act = 0.1	PGPA = 0.5	36.63	50.7
Act = 0.1	Programme = 0.7 and PGPA = 0.5	18.78	50.4
Act = 0.4	Programme = 0.7 and PGPA = 0.1	13.44	42.5
Act = 0.1	Programme = 0.3	15.31	40.03

Please note that Act is 'Activity'

After the rule extraction process was executed, 201 rules were generated for the programme recommendation and 238 rules for the activity recommendation. The rules were then divided into three rankings according to the confidence

levels 80–100 per cent, 60–79 per cent and 40–59 per cent, respectively. The distribution of the rules in each ranking is displayed in Figure 4.

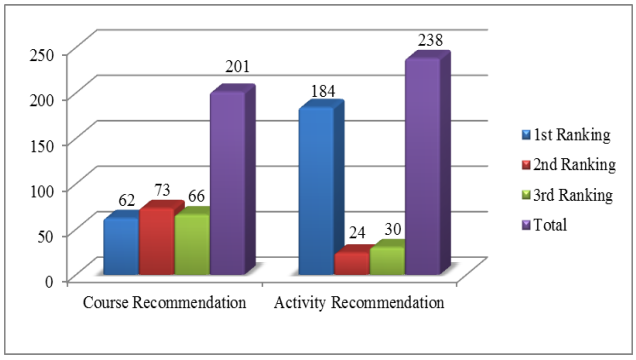

Fig. 4. Distribution of the rules in each ranking.

This figure shows that the number of rules in each ranking is not equal. Particularly, the number of rules for the activity recommendation in each ranking is quite different, which may affect the accuracy of the prediction results.

To evaluate the results, 20 per cent of the student data was used to test the accuracy of the rules. The results from the test, in terms of ranked programmes and activities, are presented in Table 7 and in Figures 5 and 6.

TABLE VIII
A COMPARISON OF THE ACCURACY BETWEEN THE RANKED PROGRAMME AND ACTIVITY RECOMMENDATIONS

Rule	1st (%)	2nd (%)	3rd (%)	Average
GRI programme recommendation	67.642	70.056	70.950	69.549
GRI activity recommendation	76.648	64.413	65.307	68.790

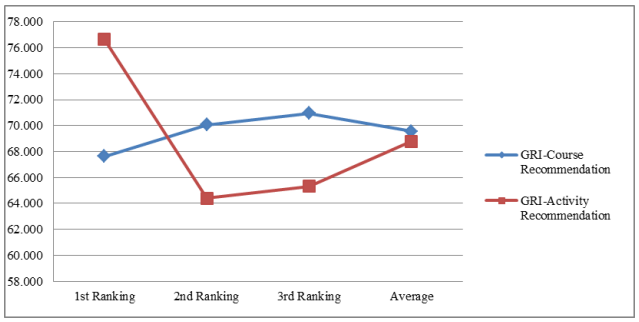

Fig. 5. Comparison of the accuracy between ranked programme and activity recommendations.

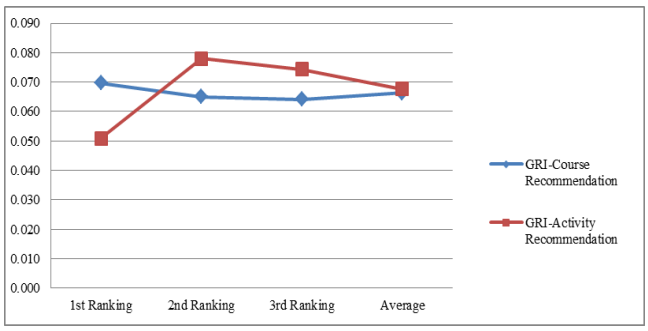

Fig. 6. Comparison of means absolute error between ranked programme and activity recommendations.

The comparison in Figure 5 and 6 shows that the ranked programme recommendation average slightly outperformed the activity recommendation average. The accuracy of the results from programme recommendation by GRI in each ranking is similar, whereas the accuracy of the first-ranked activity recommendation by GRI is significantly better than the other two. It can be observed that the number of rules for the first-ranked activity recommendation in Figure 5 is also higher; this correlates with the higher accuracy of the result and, subsequently, provides a better first-ranking result.

B. Example results of ranked programme and activity recommendations based on GRI and K-means clustering

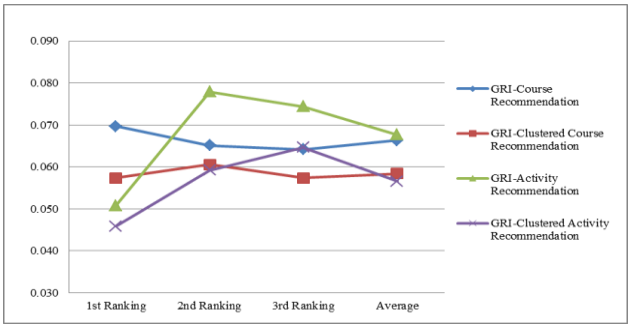

Fig 7. Comparison of mean absolute errors between ranked programme and activity recommendations

Figure 7 show that the proposed techniques using K-means clustering and GRI, in terms of the GRI-clustered programme recommendation, obtained more accuracy than using GRI alone, in terms of the GRI programme recommendation. In addition, the results of each ranking are similar in both accuracy and MAE. Considering the activity recommendation results, the GRI-clustered recommendation also obtained more accuracy than GRI techniques alone. However, the first-ranking results, in both accuracy and MAE, obtained higher performance than the second and third ranking.

VII. CONCLUSION AND FUTURE WORK

With the availability of historical student records, educational institutes could make use of such resources and data-mining techniques to support SRM. In this study, a model for the recommendation of ranked programmes is proposed to provide three ranked programmes, as well as three ranked activities, to the students and counsellors. The use of clustered data could assist to improve the accuracy of the results. In both modules (ranked programme recommendation and activity recommendation), it was found that ARs based on GRI with the incorporation of two sets of clustered data by K-means clustering outperformed the results from the ARs technique based on GRI with uncluttered data. In future work, programme and activity recommendation in different techniques could be tried out to enhance the performance of the recommendation. Also, other types of recommendation; for example, classroom management recommendation could be considered in order to guide cousellors and supervisor including instructors to manage classrooms efficiently.

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