Neural Network Modeling for an Intelligent Recommendation System Supporting SRM for Universities in Thailand

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Abstract: - In order to support the academic management processes, many universities in Thailand have developed innovative information systems and services with an aim to enhance efficiency and student relationship. Some of these initiatives are in the form of a Student Recommendation System (SRM). However, the success or appropriateness of such system depends on the expertise and knowledge of the counselor. This paper describes the development of a proposed Intelligent Recommendation System (IRS) framework and experimental results. The proposed system is based on an investigation of the possible correlations between the students' historic records and final results. Neural Network techniques have been used with an aim to find the structures and relationships within the data, and the final Grade Point Averages of freshmen in a number of courses are the subjects of interest. This information will help the counselors in recommending the appropriate courses for students thereby increasing their chances of success.

Key-Words: - Data Mining, Neural Network, Student Relationship Management, Intelligent Recommendation System

1 Introduction

The growing complexity of technology in educational institutions creates opportunities for substantial improvements for management and information systems. Many designs and techniques have allowed for better results in analysis and predictions. With this in mind, universities in Thailand are working hard to improve the quality of education and many institutes are focusing on how to increase the student retention rates and the number of completions. In addition, a university's performance is also increasingly being used to measure its ranking and reputation [1]. One form of service which is normally provided by all universities is Student Counseling. Archer and Cooper [2] stated that the provision of counseling services is an important factor contributing to students' academic success. In addition, Urata and Takano [3] stated that the essence of student counseling should include advices on career guidance, identification of learning strategies, handling of inter-personal relation, along with self-understanding of the mind and body. It can be said that a key aspect of student services is to provide course guidance as this will assist the students in their course selection and future university experience.

On the other hand, many students have chosen particular courses of study just because of perceived job opportunities, peer pressure and parental advice. Issues may arise if a student is not interested in the course, or if the course or career is not suitably matched with the student's capability[4]. In Thailand's tertiary education sector, teaching staff may have insufficient time to counsel the students due to high workload and there are inadequate tools to support them. Hence, it is desirable that some forms of intelligent recommendation tools could be developed to assist staff and students in the enrolment process. This forms the motivation of this research.

One of the initiatives designed to help students and staff is the Student Recommendation System (SRM). Such system could be used to provide course advice and counseling for freshmen in order to achieve a better match between the student's ability and success in course completion. In the case of Thai universities, this service is normally provided by counselors or advisors who have many years of experience within the organisation. However, with increasing number of students and expanded number of choices, the workload on the advisors is becoming too much to handle. It becomes apparent that some forms of intelligent system will be useful in assisting the advisors.

In this paper, a proposed intelligent recommendation system is reported. This paper is structured as follows. Section 2 describes literature reviews of Student Relationship Management (SRM) in universities and issues faced by Thai university students. Section 3 describes Neural Network techniques which are used in the reported Intelligent Recommendation System, and Section 4 focuses on the proposed framework, which presents the main idea and the research methodology. Section 5 describes the experiments and the results. This paper then concludes with discussions on the work to be undertaken and future development.

2 Literature Review

2.1 Student Relationship Management in Universities

According to literature, the problem of low student retention in higher education could be attributed to low student satisfaction, student transfers and drop-outs [5]. This issue leads to a reduction in the number of enrolments and revenue, and increasing cost of replacement. On the other hand, it was found that the quality and convenience of support services are other factors that influence students to change educational institutes [6]. Consequently, the concept of SRM has been implemented in various universities so as to assist the improvement of the quality of learning processes and student activities.

Definitions of SRM have been adopted from the established practices of Customer Relationship Management (CRM) which focuses on customers and are aimed to establish effective competition and new strategies in order to improve the performance of a firm [7]. In the case of SRM, the context is within the education sector. Although there have been many research focused on CRM, few research studies have concentrated on SRM. In addition, the technological supports are inadequate to sustain SRM in universities. For instance, a SRM system's architecture has been proposed so as to support the SRM concepts and techniques that assist the university's Business Intelligent System [8]. This project provided a tool to aid the tertiary students in their decision-making process. The SRM strategy also provided the institution with SRM practices, including the planned activities to be developed for the students, as well other relevant participants. However, the study verified that the technological support to the SRM concepts and practices were insufficient at the time of writing [8].

In the context of educational institutes, the students may be considered having a role as "customers", and the objective of Student Relationship Management is to increase their satisfaction and loyalty for the benefits of the institute. SRM may be defined under a similar view as CRM and aims at developing and maintaining a close relationship between the institute and the students by supporting the management processes and monitoring the students' academic activities and behaviors. Piedade and Santos (2008) explained that SRM involves the identification of performance indicators and behavioral patterns that characterize the students and the different situations under which the students are supervised. In addition, the concept of SRM is "*understood as a process based on the student acquired knowledge, whose main purpose is to keep a close and effective students institution relationship through the closely monitoring of their academic activities along their academic path*" [9]. Hence, it can be said that SRM can be utilised as an important means to support and enhance a student's satisfaction. Since understanding the needs of the students is essential for their satisfaction, it is necessary to prepare strategies in both teaching and related services to support Student Relationship Management. This paper therefore proposes an innovative information system to assist students in universities in order to support the SRM concept.

2.2 Issues Faced By Thai University Students

Prior studies have studied issues faced by Thai students during their time in the universities. For example, Sarawut [10] studied the causes of dropouts and program incompletion among undergraduate students from the Faculty of Engineering, King Mongkut's University of Technology North Bangkok, that the general reason for underachievement is a teaching and learning issue. Furthermore, the study shows that three unaccomplished group have different reasons. The main reason of the first group is a student's attitude towards the field of study. This group has perception that their field of study is too hard. The main reasons of the second and third group are related to teaching and learning. Hence, this indicates the need to match the course requirements and academic capabilities of the students.

Another study at Dhurakij Pundit University, Thailand looked at the relationship between learning behaviour and low academic achievement (below 2.0 GPA) of the first year students in the regular four-year undergraduate degree programs. The results indicated that students who had low academic achievement had a moderate score in every aspect of learning behaviour. On average, the students scored highest in class attendance, followed by the attempt to spend more time on study after obtaining low examination grades. Some of the problems and difficulties that mostly affected students' low academic achievement were the students' lack of understanding of the subject and lack of motivation and enthusiasm to learn [11].

Moreover, some other studies had focused on issues relating to students' backgrounds prior to their enrolment, which may have effects on the progress of the students' studies. For example, a research group from the Department of Education[12], Thailand studied the backgrounds of 289,007 Grade 12 students which may have affected their academic achievements. The study showed that the factors which could have effects on the academic achievement of the students may be attributed to personal information such as gender and interests, parental factors such as their jobs and qualifications, and information on the schools such as their sizes, types and ranking.

Therefore, in the recruitment and enrolment of students in higher education, it is necessary to meet the student's needs and to match their capability with the course of their choice. The students' backgrounds may also have a part to play in the matching process. Understanding the student's needs will implicitly enhance the student's learning experience and increase their chances of success, and thereby reduce the wastage of resources due to dropouts, and change of programs. These factors are therefore taken into consideration in the proposed recommendation system in this study.

3 Neural Network Based Intelligent Recommendation System to Support SRM

In term of education systems, Ackerman and Schibrowsky [13] have applied the concept of business relationships and proposed the business relationship marketing framework. The framework provided a different view on retention strategies and an economic justification on the need for implementing retention programs. The prominent result is the improvement of graduation rates by 65% by simply retaining one additional student out of every ten. The researcher added that this framework is appropriate both on the issues of places on quality of services. Although some problems could not be solved directly, it is recognized that Information and Communication Technologies (ICT) can be used and contributes towards maintaining a stronger relationship with students in the educational systems [8].

In this study, a new intelligent Recommendation System is proposed to support universities students in Thailand. This System is a hybrid system which is based by Neural Network and Data Mining techniques; however, this paper only focuses on the aspect of Neural Network (NN) techniques.

With respect to the Neural Network algorithm that was used in this study, the back propagation learning algorithm (BP) was used to perform the supervised learning process [14]. The implementation of back propagation learning updates the network weights and biases in the direction in which the system performance increases most rapidly. An iteration of this algorithm can be written as

$$B_{m+1}=B_m - \infty_m A_m \qquad (1)$$

Where B_m is a vector of the current weights and biases, A_m is the current gradient, and ∞_m is the learning rate. This study used a feed-forward network architecture and the Mean Square Error (MSE) to define the accuracy of the models.

4 The Proposed Framework

Several solutions have been proposed to support SRM in the universities; however, not many systems in Thailand have focused on recommendation systems using historic records from graduated students. A recommendation system could apply statistical, artificial intelligence and data mining techniques by making appropriate recommendation for the students. Figure 1 illustrates the proposed recommendation system architecture. This proposal aims to analyse student background such as the high school where the student studied previously, school results and student performance in terms of GPA's from the university's database. The result can then be used to match the profiles of the new students. In this way, the recommendation system is designed to provide suggestions on the most appropriate courses and subjects for the students, based on historical records from the university's database.

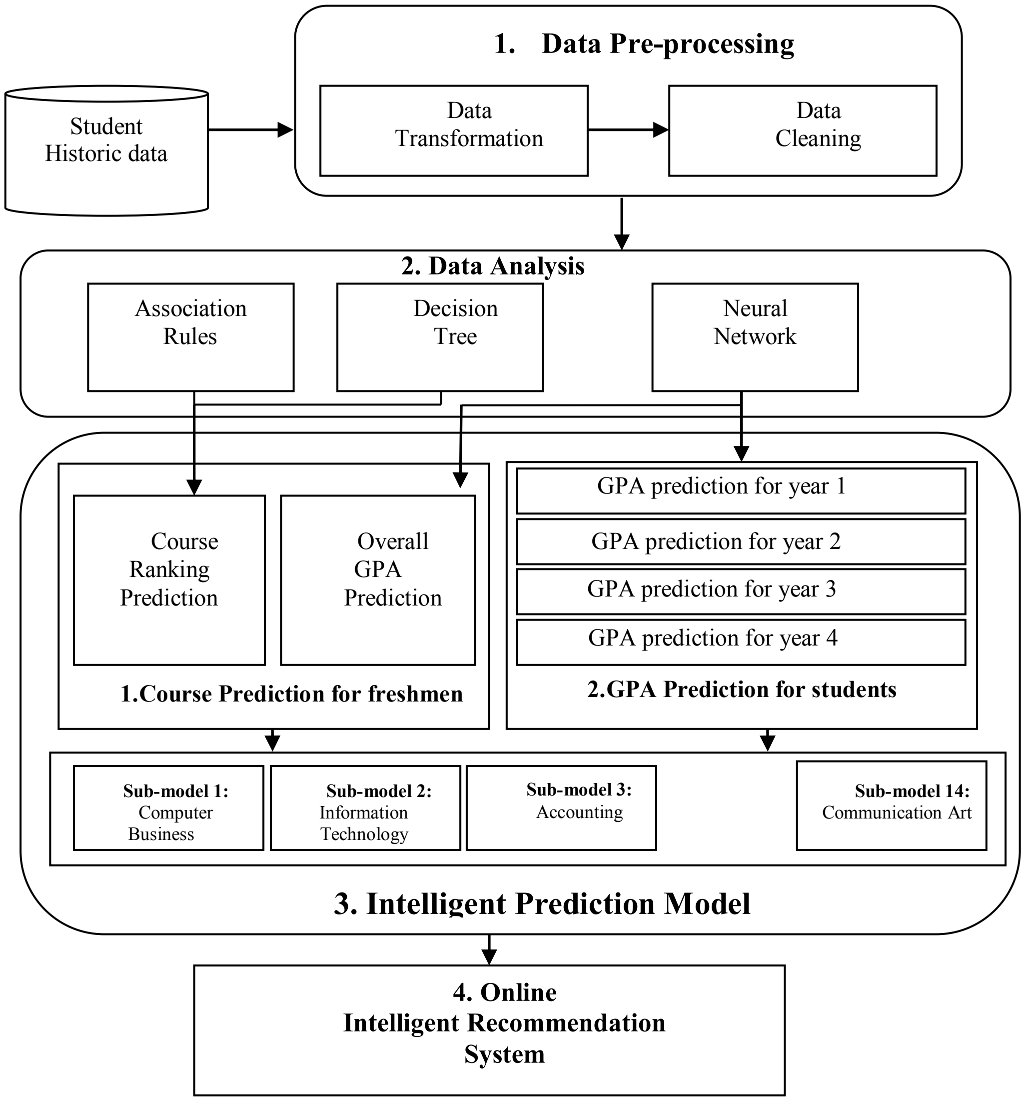

Fig.1 Proposed Hybrid Recommendation System Framework to Support Student

Relationship Management (SRM)

4.1 Data-Preprocessing

Initially, data on the student records are collected from the university enterprise database. The data is then re-formatted in the stage of data transformation in order to prepare for processing by subsequent algorithms. In the data cleaning process, the parameters used in the data analysis are identified and the missing data are either eliminated or filled with null values [15]. Preparation of analytical variables is done in the data transformation step or being completed in a separate process. Integrity of the data is checked by validating the data against the legitimate range of values and data types. Finally, the data is separated randomly into training, validation and testing data for processing by the Neural Network.

4.2 Data Analysis

In Fig. 1, the Association rules, Decision Tree and Neural Network are used to analyse the input data; however, this paper focuses on Neural Network which uses the backpropagation algorithm to classify the data and to establish the approximate function. The backpropagation algorithm is a multilayer network with nonlinear differentiable transfer function and it uses log-sigmoid as the transfer function, logsig. In the training process, the backpropagation training functions in the feed-forward networks is used to predict the output based on the input data. The appropriate data series to be trained by Neural Network are significant.

4.3 Intelligent Prediction Model

The Integrated Prediction Model is composed of two parts: Course Prediction for freshmen, and GPA Prediction for students (years 1 to 4) respectively.

Part 1 focuses on the course prediction for freshmen and it is composed of two sections, which are the Course Ranking Prediction, and the Overall GPA prediction respectively. In Section 1, the Course Ranking Prediction is analysed by Association Rules and Decision Trees. The output of the prediction is an indication of the ranking of the appropriate courses. In the section 2 (Overall GPA Prediction) is analysed by the Neural Network technique. The output of this prediction is in terms of an expected overall GPA. The results of both parts can be used as suggestions to the freshmen during the enrolment process. Some example results from Section 2 are shown in this paper, and the input data of these 2 sections in the model are shown in Table 1.

Another part of the framework focuses on GPA prediction for students in each year. They are the GPA Prediction for students from year 1, year 2, year 3 and year 4 respectively. After the students selected the course to study and completed the enrolment process, the GPA prediction for year 1 results can be used to monitor the performance of this group of students. The input data of this process is the same as the one shown in Table 1, with the addition of the GPA scores from the previous yea. These are used as the extended features in the input to the neural network model. The result of the prediction is the GPA score of the year. In the same way, the system may be used to perform a GPA prediction for Year 2 based on results from the first year. The inputs for this module are shown in Table 1. Similar approach can be adopted for the prediction of Year 3 and 4 results. Some example results this part are shown in this paper.

To address the issue of imbalanced number of students in each course, the prediction model shown in Fig. 1 can be duplicated for different departments. The models' computation is entirely data-driven and not based on subjective opinion, hence, the prediction models are unbiased and they will be used as an integral part of an online intelligent recommendation system.

4.4 Online-Intelligent Recommendation System

It is planned that the new intelligent Recommendation Models will form an integral part of an online system for a private university in Thailand. The developed system will be evaluated by the university management and feedback from experienced counselors will be sought. The proposed system will be available for use by new students who will access the online-application in their course selection during the enrolment process. As for the prediction of the Year 2 and subsequent years' results, this could be used by the counselors, staff and university management to provide supports for students who are likely to need help with their studies. This information will enable the university to better focus on the utilisation of their resources. In particular, this could be used to improve the retention rate by providing additional supports to the group of students who may be at risk.

5 Experiment Design

The data preparation and selection process involves a dataset of 3,550 student records from five academic years. All the student data have included records from the first year to graduation. Due to privacy issue, the data in this study do not indicate any personal information, and no student is identified in the research. The university has randomised the data, and all private information has been removed. Example data from the dataset is shown below.

Table 1 Examples of training sample dataset

Uni ID	Input data: previous school data								target
	GPA	Type of school	Number of Awards	Talent & Interest	Channels	Admission Round	Guardian Occupation	Gender	Uni GPA
4800	2.35	C	0.2	1	Poster	1	Police	F	3.75
4801	3.55	B	0.3	4	Brochure	2	Governor	M	3.05
5001	2.55	A	0.9	3	Friend	5	Teacher	F	2.09
5002	2.75	G	0.4	5	Family	4	Nurse	F	2.58
5003	3.00	F	0.2	7	Newspaper	3	Teacher	M	2.77
5101	2.00	E	0.1	2	others	1	Farmer	F	2.11

Table 1 shows the randomized student ID, GPA from previous study, the type of school, awards received, talent and interest, channels to know the university, admission round, Guardian Occupation, Gender and Overall GPA from university. Table 2 provides the definitions for the variables used in the above table.

Table 2 Definitions of Variables

No.	Variables	Definition
1.	Uni ID	Randomized Student ID which is not included in the clustering process. They are only used as an identification of different students
2.	GPA	Overall GPA results from previous study prior to admission to university
3.	Type of school	The school types are separated as follows A: High School B:Technical College C: Commercial College D: Open School E: Sports, Thai Dancing, Religion or Handcraft Training Schools F: Other Universities (change universities or courses) G: Vocation Training Schools
4.	Number of Awards	Awards that students have received from previous study (normalized between 0.0 to 4.0, 0.0 – received no award, 4.0 – received max no. of awards in the dataset)
5.	Talent and Interest (in Group number)	Talent and the interest(1= sports, 2=music and entertainment, 3= presentation, 4=academic, 5=others, 6= involved with 2 to 3 items of talents and interests, 7= involved with more than 3 talents and interests)
6	Channels	The channels to know the university such as television, family
7	Admission Round	Admission round of each university which can be round 1 to 5
8	Guardian Occupation	The occupation of Guardian such as teacher, governor
9.	Gender	Gender: Female or Male
10.	Uni GPA	Overall GPA in university which the range is from 0 to 4

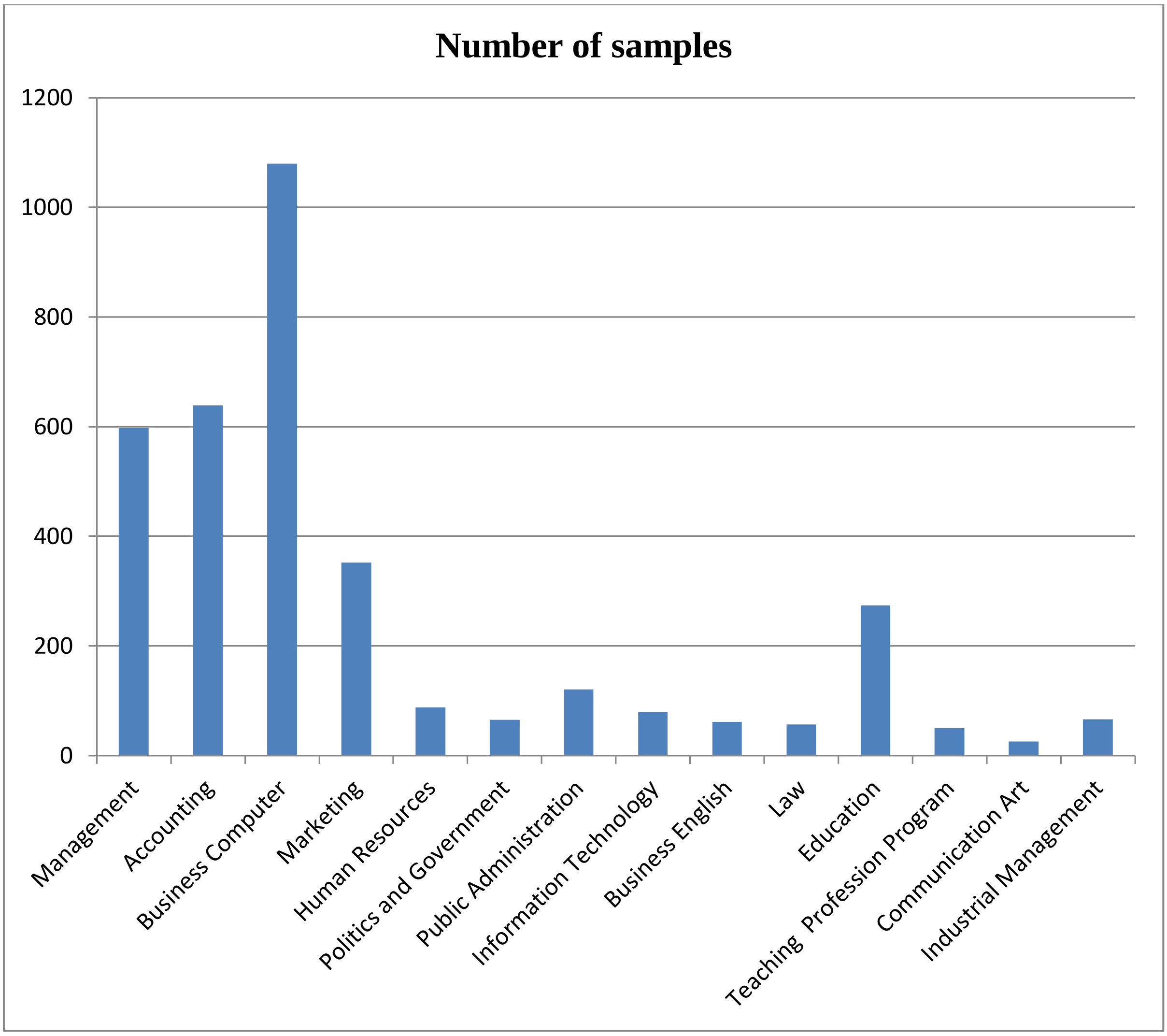

Fig.2 Number of samples in each department

The student records have been divided into 60% of training data, 20% of testing datasets and 20% of data validation randomly. The dataset includes both qualitative and quantitative information in Table 1 and 2. In terms of training, a maximum of 50,000 epochs is selected or until the network sum square error (SSE) falls beneath 0.1. The learning rate of 0.01 is set. This is to ensure that input vectors are being classified correctly. This study used a two layer feed forward network architecture with between a maximum of 20 neurons in the hidden layer (A half of input and output). Moreover, this study used the Mean Square Error (MSE) to define the accuracy of the models.

6 Results

6.1 Results of Course Prediction for freshmen: Overall GPA Prediction

Based on Mean System Error (MSE), the experimental results have shown that the Neural Network based models can be utilised to predict the GPA results of students with a good degree of accuracy.

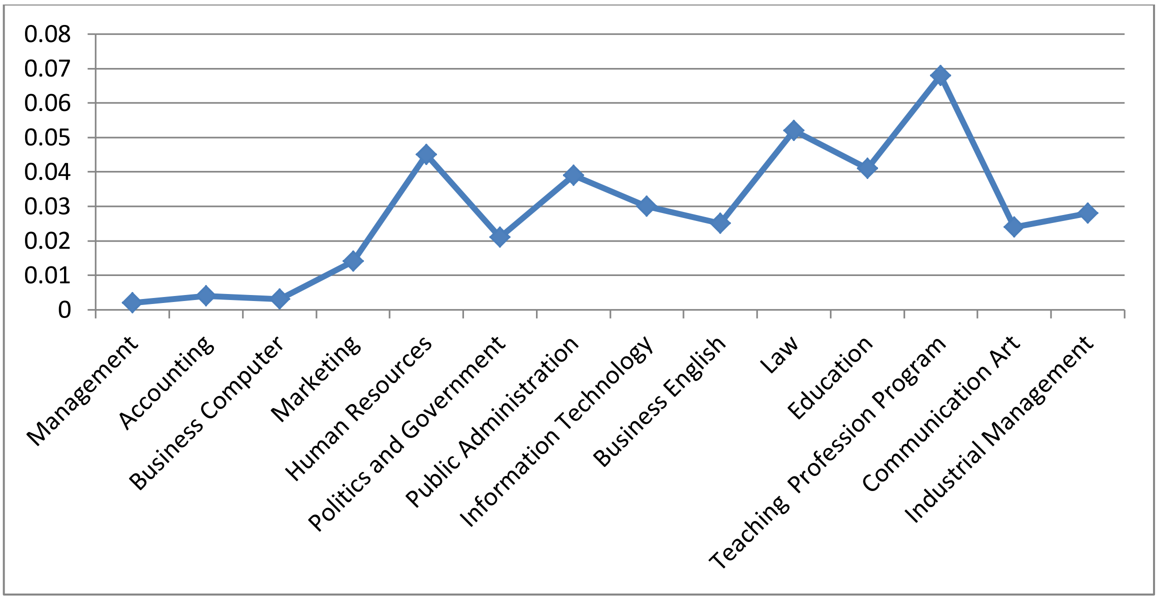

Fig.3 Comparison of Mean Square Error of each Department

In Fig. 3, it is shown that the highest value of MSE is 0.68 based on data from the Department of Teaching Profession. On the otherhand, the lowest value is 0.2 which was found in many schools such as the Department of Management. The average of Mean Square Error (MSE) of all models is 0.028. The overall results obtained indicated reasonable prediction results.

The following figure is an example of the results obtained from the model for the Business Computer course.

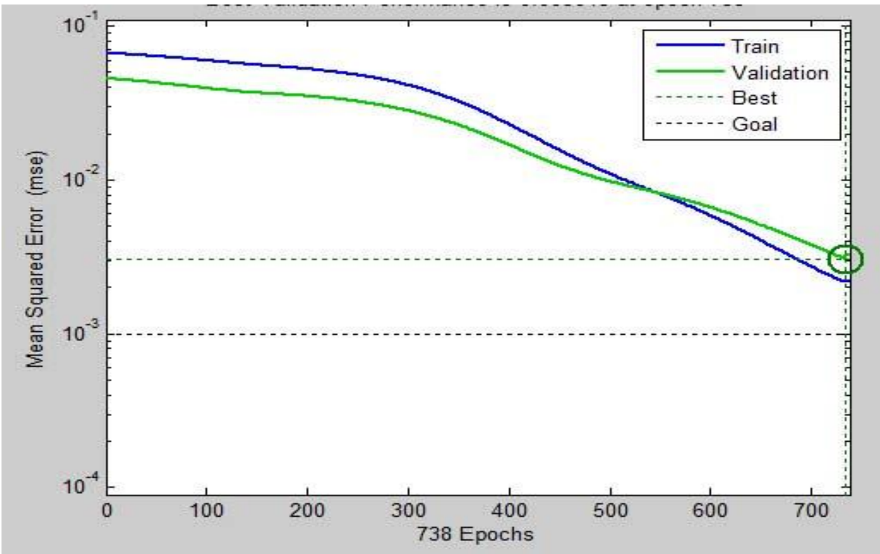

Fig.4 Example result from the model for the Business Computer Department

The chart shows that Mean Squared Error (MSE) goes down slightly from 0.1 to 0.001. The MSE starts at a large value and decreases to a small value. The training stopped when the validation error decreased after 738 Epochs. The plot shows two lines, one for the training and the other for the validation. However, testing was carried out in the final step of the experiment in each model, which used 20% of data. From the experiment, it was observed that no significant over-fitting occurred by iteration 738, where the best validation performance occurred.

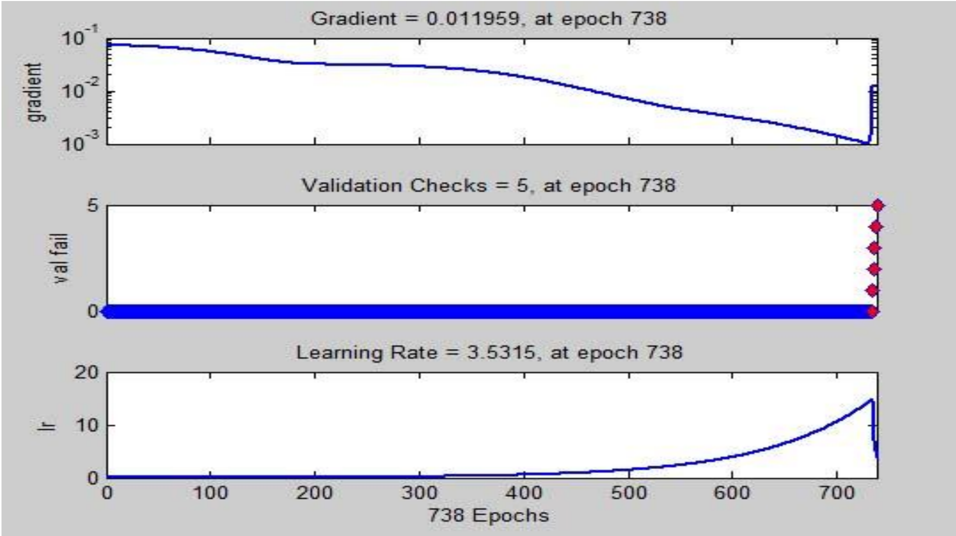

Fig.5 Example result of training state business computer department

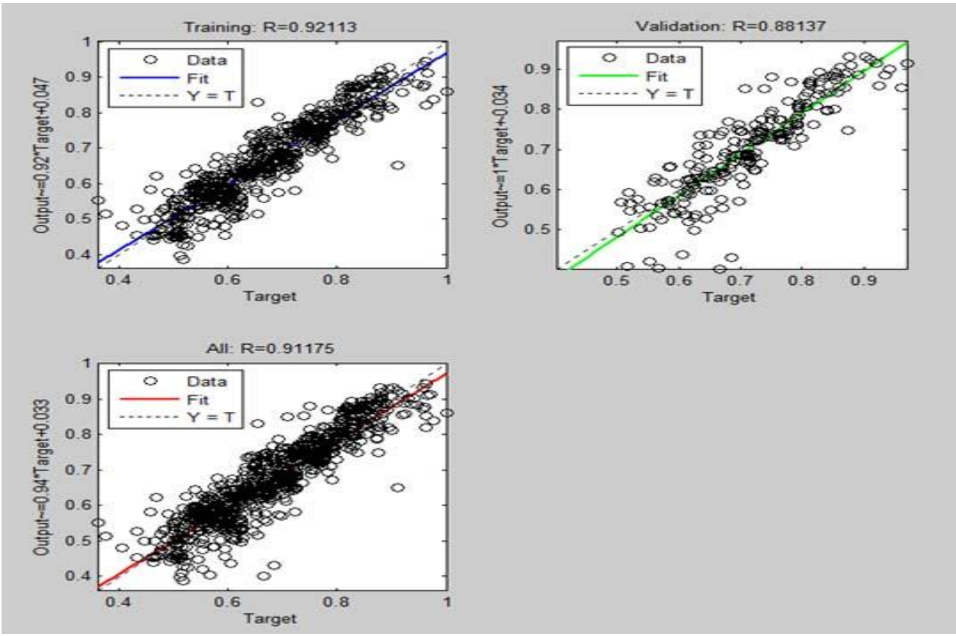

Fig.6 An illustration of Regressions between training, validation and testing data for the Business Computer Department

The chart shows the regression of training and validation results based on the test data. The R-value of training state and validation are 0.921 and 0.881 respectively. Finally, all R-values are over 0.90 and the outputs seem to track the targets reasonably well.

6.2 Results of GPA Prediction for students

The experimental results have shown that the Neural Network based models can also be utilised to predict the GPA results of students each year. The bars as shown in fig 4

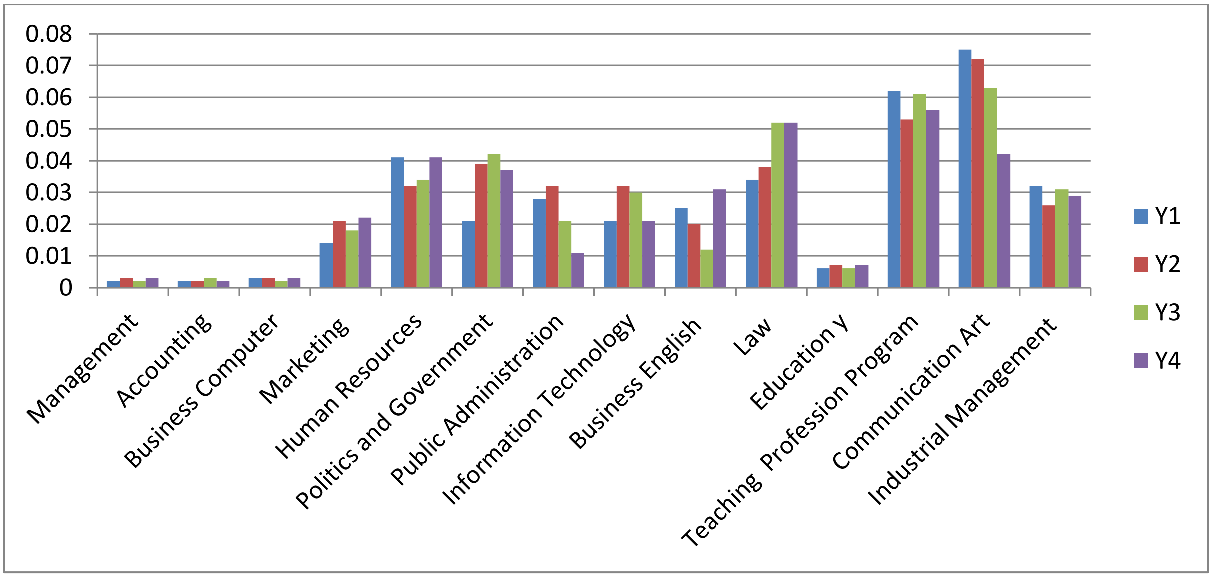

Fig.7 The Mean Square Error of the model of GPA Prediction for students

Fig 7 shows a comparison of the Mean Square Error (MSE) from each department in four years. The vertical columns are the Mean Square Errors of each department, and each bar shows MSE of year 1 to year 4 respectively. Comparatively, the highest value of MSE is 0.75 from the Department of Communication Arts in year 1, while the lowest value is 0.2 which was found in many departments. The lowest in this case is Year 1 result from the Department of Management and Accounting. Moreover, MSE of the models of Management, Accounting and Business computer department are smaller. It may be due the larger number of the samples. Overall, the Neural Network Models have indicated that they possess the capability to present reasonable prediction results.

7 Conclusions

This article describes a proposal on a recommendation system in support of SRM and to address issues related to the problem of course advice or counseling for university students in Thailand. The recent work is focusing on the development and implementation of each process in the framework. The experiments have been based on Neural Network models and the accuracy of the prediction model is improved. It is expected that the recommendation system will provide a useful service for the university management, course counselors, academic staff and students. The proposed system will also support Student Relationship Management strategies among the Thai private universities.

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