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Students Knowledge based Advisor System for Colleges Admission With an Applied Case Study

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ABSTRACT*: This paper presents a knowledge based advisor system designed to aid preparatory year students to achieve their desire of colleges they wanted to be dwelled allocated. The system predicts the 2nd term GPA, and the final term GPA by knowing the 1st semester GPA, then advise students to suitable colleges. A student who is far from achieving his desire is advised to study some aided courses. The system uses historical data extracted from the university database. Then statistical prediction algorithms are developed, to evaluate and to match students' current desires with colleges' qualified criteria*.

Keywords- *Academic Advising, Enrollment Systems, knowledge discovery, Statistical Analysis, Prediction algorithms.*

I. INTRODUCTION

Student advising is an important and time-consuming effort in academic universities. Advising students of what colleges they should enroll is a complicated problem than it first appears. At the highest level, the purpose is to guide a student both to reach personal academic goals and also to satisfy the college requirements for graduation.

This paper attempts for developing a web-based online advisor that helps students make better selections for the colleges that suits their desires. The academic advisor proposed is based on knowledge discovery rules.

The idea for using academic advising are discussed in several articles [1-10], however most of these works concerned on how a student can be enrolled into a suitable learning program, or course, as discussed in section (2). In this paper, the system proposed uses the students GPA record histories as the basis for students enrollment advising. It makes reasonable suggestions with a limited amount of domain knowledge. Thus, making an intelligent recommendation is a balancing act. It is necessary to have an understanding of the student's interests and strengths in order to choose from a list of potential colleges those that will be the most worthwhile. Equally important is to have an understanding of the rules for graduation in order to keep the students focused on the relevant colleges that satisfy their desires.

In King Abdulaziz University (KAU), as an example, students are enrolled into colleges according to their cumulative GPA at the end of the second term of the first preparatory year, and the desire of each prior college , according to the criteria and college placement accepted. The drawback of this method is that university admission authorities cannot identify students who wish to be enrolled in a certain college except after the appearance of the final results at the end of the second term. Also, a student cannot know which college he can be enrolled except after he finishes his 2nd term exam. In this paper, a new method is proposed. It depends on the possibility of predicting the 2nd term GPA by knowing the 1st term GPA for students.

First, we use statistical methods to prove that there is a significant relation between students 1st term GPA with his predicted 2nd term GPA and also with his predicted final GPA. Hence, the 1st term GPA or the final predicted GPA can be used as an indicator for how near or how far a student can achieve his desire to be enrolled into suitable college before he finishes his study at the end of the 2nd term exam.

II. RELATED WORK

Academic advising is a knowledge-intensive process of assessing a student's interests and determining the best program progression that satisfies graduation requirements. An advisor may have to have; for example; detailed knowledge of curriculum and student aptitudes as well as course offerings and time constraints to automating academic advising based on a rule-based expert system [11]. A knowledge based decision technique to guide a student for admission in proper branch of engineering was explained. It was based on using AIEEE2007 database [12]. A student takes admission based on AIEEE rank and family pressure. In [13] classification models and artificial neural network function generated using Waikato Environment for Knowledge Analysis (WEKA) was explained. The aim was to identify relevant student background factors that can be incorporated to design a framework, that can serve as valuable tool in predicting student performance as well as recommend the necessary intervention strategies to adopt. The design of a knowledge-based academic advising framework was explained in [14], adding intelligence to e-learning tools, supporting the ability to understand and profit from learning history data. A mechanism of a system that uses data mining techniques was explained in [15]. It calculates student achievement level regarding the available majors. Based on the system recommendation, the student can take a decision of perfect major based on the achieving level.

Most of the above reviewed systems did not tackle the problems related to students advising to help them how to be enrolled into suitable colleges that achieves their desires and satisfies college requirements. So that in this paper a developed system for automatically helping students' in colleges' enrollment processes are proposed.

The following sections describe the high-level architecture of the system and discuss its reasoning components. Afterward, results of the system are discussed, and closing with the conclusion.

III. FINDING OUT GPAS INTERRELATIONSHIP MODEL

In this part of the paper, a relational model that can represent the relationship between the 1st term GPA, 2nd term GPA, and final GPA will be predicted, with confidence accepted range.

GPAs Significant Relations Proving

To prove an existence of interrelationship between the 1st term GPA (GPA1), 2nd term GPA (GPA2) and the final GPA (GPAF) for the preparatory year students, their correlation coefficients are investigated using IBM-SPSS Ver. 22. The results obtained are shown in Table-1. It show that all the correlation coefficients between GPA1, GPA2 and GPAF are positive and highly significant with p-value<0.001 for all cases. The highest correlation value is that the correlation between GPA2 and GPAF, with the value of 0.855, and a good result obtained between GPA1 and GPAF, with the value of 0.733, which is high enough for proving the confidence to predict the student GPAF, based on GPA1.

Table-1 Correlation Coefficients

	GPA1	GPA2	GPAF
GPA1	1	.537**	.733**
GPA2	.537**	1	.855**
GPAF	.733**	.855**	1

** P-value < 0.001

Students GPA Mean Values Function of Previous Years Results

The mean values for students GPA1, GPA2, and GPAF, for the previous five years are statistically investigated. The estimated results are tabulated as shown Table-2, and graphically as shown in Fig.1, where N is the number of students. These results will be helpful to find out the best models that can fit GPA2 based on GPA1, as explained in the next sections.

Table-2 Students means of GPA1, GPA2, and GPAF, for previous five years.

Year	2009			2010			2011			2012			2013		
GPA	GPA1	GPA2	GPAF	GPA1	GPA2	GPAF	GPA1	GPA2	GPAF	GPA1	GPA2	GPAF	GPA1	GPA2	GPAF
N	5201	5181	5223	5908	5716	5942	5471	5343	5513	6242	5916	6320	6069	6184	6202
Mean	3.5367	3.7358	3.6669	3.5870	3.8245	3.7536	3.7571	3.7864	3.8418	3.7400	3.8028	3.8194	3.7937	3.7429	3.8231

Fig.1 Averages of Students GPA during the previous 5 years.

GPA2 Fitting Models and Confidence Intervals

When building a model to estimate the 2nd term GPA values based on the 1st term GPA, Several models are investigated, among which are: Linear, Logarithmic, Inverse, Quadratic, Cubic, Compound, Power, S, Growth, Exponential, and Logistic models. Results show that all these models were not significant, except three models only, namely: Linear, Quadratic and Cubic models. Table-3 shows results summary for these significant models.

Table-3 Model Summary and Parameter Estimates

Dependent Variable: 2nd term GPA

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.289	11366.021	1	28010	.000	2.031	.473		
Quadratic	.419	10110.581	2	28009	.000	3.653	-.725	.192	
Cubic	.420	6759.741	3	28008	.000	3.592	-.536	.104	.011

The independent variable is 1st term GPA.

Results in Table-3 show that the cubic model; which can be presented by equation (1); has the highest value for the coefficient of determination R^2, hence it is considered the best model to predict 2nd term GPA based on the 1st term GPA. If Y_2 denotes the predicted value for the 2nd term GPA and x denotes the actual value for the 1st term GPA, then the regression equation are given as shown in (2).

$$Y = a_0 + a_1 x + a_2 x^2 + a_3 x^3 \quad (1)$$

$$Y_2 = 3.592 - 0.536\,x + 0.104\,x^2 + 0.011\,x^3;\ \ p\text{-value} < 0.001,\ R^2 = 0.420 \quad (2)$$

For instant, if the GPA of a student at the 1st term equals 3, then his 2nd term GPA can be predicted to be 3.217 approximately, as shown in Fig.2.

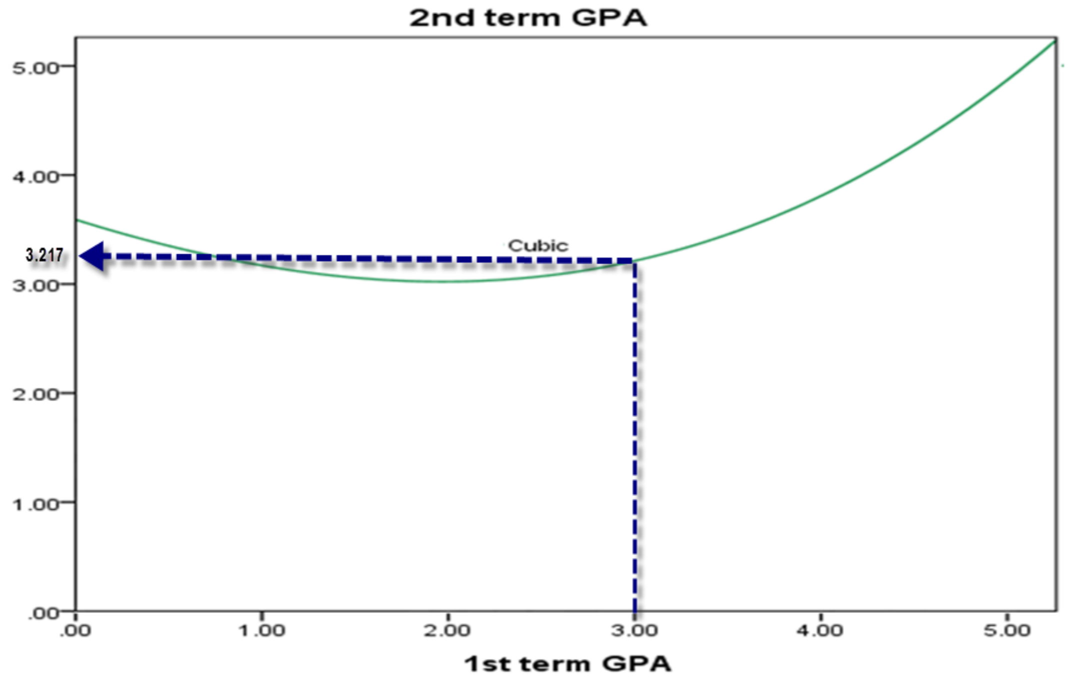

Fig.2 Predicted model of 2nd term GPA based on the 1st term GPA.

The confidence intervals (CI) and the standard errors (SE) of cubic model are also investigated. Table-4 shows results for the SE and the 95% CI, including both the lower and upper bounds for the cubic model coefficients.

Table-4 Parameter Estimates

Parameter	Estimate	SE	95% CI Lower Bound	95% CI Upper Bound
a_0	3.591	.028	3.537	3.645
a_1	-.536	.036	-.606	-.466
a_2	.104	.015	.074	.134
a_3	.011	.002	.007	.015

GPAF Fitting Models and Confidence Intervals

In addition, to estimate the best model to fit the GPAF based on the 1st term GPA, the same models explained in the previous sections were investigated. Results obtained show that all models were not significant, except three models only, namely: Linear, Quadratic and Cubic models. Table-5 shows a summary for these results.

Table-5 Model Summary and Parameter Estimates

Dependent Variable: GPAF

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.537	33504.406	1	28879	.000	1.725	.559		
Quadratic	.781	51643.278	2	28878	.000	3.610	-.846	.227	
Cubic	.792	36614.122	3	28877	.000	3.806	-1.467	.518	-.036

The independent variable is 1st term GPA.

As the cubic model has the highest value for the coefficient of determination R^2. Hence, the best model to predict GPAF based on the 1st term GPA is the Cubic model. If Y_f denotes the predicted value for the GPAF and x denotes the actual value for the 1st term GPA, then the regression equation (2), will be as follows:

$$Y_f=3.806 - 1.467\,x + 0.518\,x^2 - 0.036\,x^3\text{; p-value} < 0.001,\ R^2 = 0.792 \qquad (3)$$

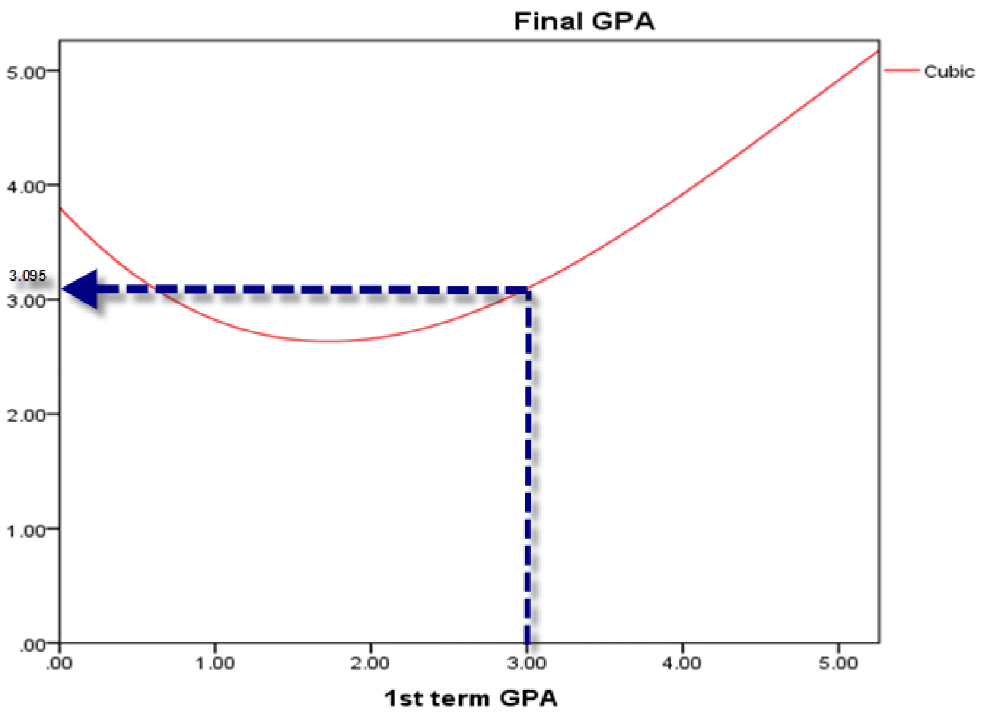

Fig.3 Predicted Students Final GPA from the 1st term GPA.

For instant, if the GPA of a student at the 1st term equals 3, hence, his Final term GPA can be predicted to be 3.095 approximately, as shows in Fig.3. Table-6 also gives the SE and the 95% CI for the cubic equation coefficients.

Table-6 Parameter Estimates

Parameter	Estimate	SE	95% CI	
			Lower Bound	Upper Bound
a_0	3.806	.014	3.779	3.833
a_1	-1.467	.018	-1.503	-1.432
a_2	.518	.008	.503	.534
a_3	-.036	.001	-.038	-.034

Comparing the Real GPAF with the Predicted GPAF

Students sample data for the results are extracted from the ODUS+ DB from KAU web site, for previous five years. Then, results of the real final GPA are compared with the predicted final GPA generated from the cubic equation model explained the above in section. Fig.4 shows students highly demanded university colleges, namely: Medical, Engineering, Computer, Science, and some others for applied medical. The results are almost identical between the real GPA and the predicted GPA with highly confidence 95%.

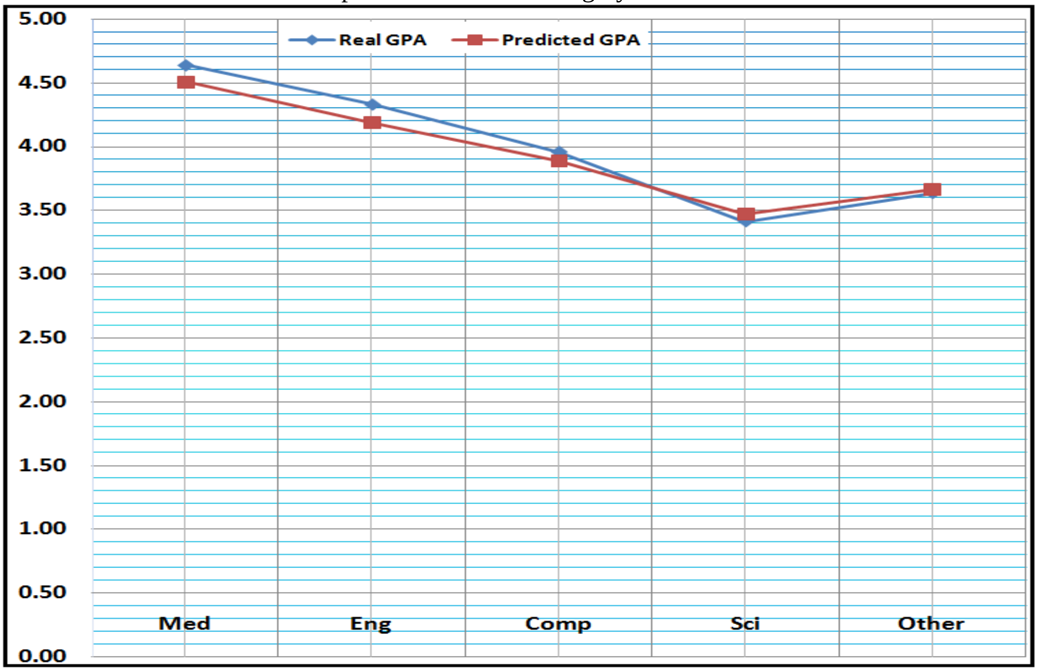

Fig.4 Comparison between the Real Final GPA and the Predicted Final GPA for the KAU top students demanded University Colleges.

Table-7 Knowledge discovery rules (KDR) applied to students' colleges' admission and enrollment, in KAU as an applied case study.

Rules (A)	*Preparatory Year Admission Criteria*	*Rules (B)*	*General Standards College's Allocation Criteria*
R1.1	Demographic student information.	R2.1	Passing all preparatory year courses.
R1.2	Weighted degree- Scientific Track.	R2.2	Relative rate for college allocation.
R1.3	Weighted degree- Literary Track.	R2.3	Capacity of each college.
R1.4	Weighted degree- Affiliated Track.		
R1.5	Colleges with No preparatory year.		
Rules ©	*Medical colleges: Medicine, Dentist, Pharmacy (Student should get B+ in the following courses)*	*Rules (D)*	*Faculty of Engineering (Student should get B in the following courses)*
R3.1	English	R4.1	English
R3.2	Biology	R4.2	Math
R3.3	Chemistry	R4.3	Physics
R3.4	Physics	R4.4	Statistics
R3.5	Interview		
Rules (E)	*Faculty of Computing and Information Technology (Student should get B in the following courses)*	*Rules (F)*	*Faculty of Applied Medical Sciences (Student should get B in the following courses)*
R5.1	English	R6.1	English
R5.2	Computer Skills	R6.2	Biology
		R6.3	Chemistry
		R6.4	Physics

These results are used for realizing the proposed advising system that automatically predict the college that a student may be enrolled to it. Since, it can predict the student final GPA, knowing his 1st term GPA. Then, it search for the student desire and according to the GPAF and prerequisite courses grades; shown in Table-7; a student is allocated to the most suitable college. If this college is not satisfied for student tendencies and his desire, he is advised to raise his grades of the prerequisite courses and his real GPA in the 2nd term, which in turn leads to raise the student real final GPA. These steps are illustrated in Fig.5.

The Knowledge based Advisor System Algorithm

Step-1:
Extract required parameters from student historical data (GPA, and courses marks for previous five years) and predicting the rates of students dwelling allocation for each college.

Step-2:
Apply KDR rules, given in Table-7, and obtain students enrollment qualified data according to each college criteria.

Step-3:
Compare student's information from step-1 with the student's information from step-2.

Step-4:
Apply obtained results from step-3 to indicate how fare or close a student from achieving his college desired, and guide the student to be enrolled into the suitable college.

Step-5:
For non-satisfied students, in step-4, (they did not achieve their desires) gives some recommendation; in the form of aided courses; to help students for reaching their goals, then go to step-2.

Fig.5 the algorithm developed to carry out the advisor system tasks.

IV. CONCLUSION

A This paper presented a knowledge based advisor system for recommending advises to students about colleges that they can be enrolled to it. The system uses knowledge-intensive data assessing of student interests and determining the best colleges that satisfies their graduation requirements. The system can be used to fill the gap between student desires achievement for college enrollment and college qualified requirements. It is capable to reuse the experience of past students data in order to infer appropriate colleges a student could enroll in the following semesters. This is done through a process of finding similar enrollment history sequences and extracting a relevant recommendation for the students. Evaluation of the advisor system showed that the system is promising, and it can enhance the automation processes for college enrollment in the university.

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