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Markov Model Simulation and Analysis for Future Expectation of Awarded Grades for IB Secondary Schools

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Abstract Markov Chains can be a valuable tool for analyzing expected awarded grades in the International Baccalaureate (IB) program for secondary schools. A core principle of the IB program is the emphasis on student progress throughout the two-year Diploma Programme (DP). Markov Chains excel at modeling transitions between states, which in this case, could represent different grade levels (e.g., predicted grade of 4 transitioning to a final awarded grade of 5).

One of the complicated parts in the teaching system is how to conduct the evaluation process. The absence of an ideal evaluation standard is a problem in the teaching system at all [4, 5]. In this study, it is aimed to implement Markov mathematics in analyzing and modeling the IB Diploma Statistical Bulletin of May examination sessions, which is interesting and the most common to any IB student. Markov model will be realized using students' grades which were contained the awarded grades for each of the six EE groups. The data are examination results from 427452 students in 2211 schools for nine years of the IB Diploma statistical bulletin of May examination sessions 2006 – 2014 [6].

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Keywords: *Markov Model, Wavelet Transform, Multiwavelet Transform Neural Network*

1. INTRODUCTION

The mathematic of Markov statistics was introduced by a Russian mathematician called A.A. Markov (1856–1922) through which he proposed the basic concepts of transition probabilities [1]. This statistic is used in estimating the distant future, for example in weather forecasting, and developed further by scientists around the world and regarded as one of the most powerful theories for analyzing modeling and simulation of various world phenomena.[3 ،2]

By analyzing historical data on student performance and transitions between predicted and awarded grades, you can build a Markov Chain model. This model can then be used to predict the likelihood of students achieving a particular final grade based on their initial predicted grade.

Markov Chains are relatively easy to understand and implement compared to more complex statistical models. This makes them accessible to educators who may not have a strong background in statistics.

By using a data-driven approach, schools can move beyond subjective judgments and make more informed decisions about student progress and resource allocation. Some additional points to consider can be taken into account for such analysis and expectation of results. The accuracy of the predictions will depend on the quality and quantity of historical data you have available. Next, the Markov Chains assume that the probability of transitioning to a particular grade only depends on the previous grade, not on any other factors. In reality, other factors such as student effort, teacher effectiveness, and external circumstances can also play a role. Finally, the choice of grade levels used as states in the model can impact the results. It's important to select states that are relevant and informative for your analysis. Overall, Markov Chains can be a valuable tool for analyzing expected awarded grades in the IB program. However, it's important to be aware of the limitations and to use the model in conjunction with other sources of information.

Assuming that it is possible to access to data on student performance throughout the program (e.g., scores on practice exams or assignments), then wavelet transform and mixed transforms could potentially be used to analyze these time series and identify patterns in student progress {8-16]. This information could then be used to inform predictions about awarded grades, but the wavelet transform wouldn't directly predict grades itself. In conclusion, while Wavelet and Mixed

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Transforms are powerful tools for signal analysis, they are not the most suitable choice for analyzing expected awarded grades in the IB program. Markov Chains, Logistic Regression, and Decision Trees offer more appropriate statistical methods for this task [17-26.[

This paper can be helpful for:

- **Targeted Support:** Identifying students who are at risk of falling short of their predicted grades and providing them with additional support.
- **Resource Allocation:** Optimizing resource allocation by focusing on students who are most likely to benefit from additional support.
- **Benchmarking:** Comparing your school's performance to historical data or to other schools to identify areas for improvement.

2. MARKOV MODEL

Consider a process that proceeds in a finite number of states (time, sequence… etc.) and it is currently in state i, and then it will occupy state j in the next period. There are combinations of probabilities and matrix operations that can model such process [2, 3]. These transitional probabilities *P* (i, j) are determined by the current state and remain fixed over time. Under these conditions, this process is a Markov chain process, and the sequence of states generated over time is a Markov model. The model can be in one of the possible states of the process $S = [s_1, s_2, ..., s_n]$. The parameters of the model process can thus be summarized by a transition matrix written as [2, 3]:

$$P = \begin{bmatrix} P(1,1) & P(1,2) & \dots & P(1,n) \\ P(2,1) & P(2,2) & \dots & P(2,n) \\ \dots & \dots & \dots & \dots \\ P(n,1) & P(n,2) & \dots & P(n,n) \end{bmatrix} \dots (1)$$

Further, the sum of the probabilities of each row of *P* must be equal to 1. It is possible to find the probability of being in any given state many steps into the process.

As an example, to demonstrate these computations, an artificial data was generated for students finished their gymnasium study from three cities (*X*, *Y* and *Z*) and their distribution on universities in the same cities as follows:

- From the 1600 Students graduated from gymnasiums in city *X*,1200 of them are accepted in the universities in the city *X* and 200 students are accepted in the universities in each of the cities *Y* and *Z*.
- From the 1400 Students graduated from gymnasiums in city *Y*, 350 of them are accepted in the universities in the city *X*, 875 of them are accepted in the universities in the city *Y* and 175 students are accepted in the universities in city *Z*.
- From the 1000 Students graduated from gymnasiums in city *Z*, 250 students are accepted in the universities in each of the cities *X* and *Y* and 750 students are accepted in the universities in city *Z*. Table (1) summarize the distribution of these numbers.

Table (1).*Graduated Students from Gymnasiums Distributed on the Universities.*

Gymnasiums of the city	Universities of the city			Total: graduated from the gymnasiums in the city
	X	*Y*	*Z*	
X	1200	200	200	1600
Y	350	875	175	1400
Z	250	250	500	1000
Total: accepted in the universities in the city	1800	1325	875	4000

What is the probability that a new student graduated from a gymnasium in the city *Y* will be accepted in a university in the city *Z* next year? To build the Markov chain we have to find first the transitional probability matrix *P*. The values of first row of *P* i.e. *P*(1,1), *P*(1,2) and *P*(1,3), can be found through the division of the individual numbers in this row over their sum. Hence:

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$$P(1,1) = \frac{1200}{1600} = 0.75,\ P(1,2) = \frac{200}{1600} = 0.125 \text{ and } P(1,3) = \frac{200}{1600} = 0.125 \ldots\ldots\ldots\ldots (2)$$

Similarly, we can find values of other rows of *P* and all these values are given in Table 2 (it is clear that the probabilities, corresponding to *X*, *Y* and *Z*, in every row of Table 2 sum up to one).

Table (2) The Transition Probabilities P (st+1 = j | st= i)

Graduated from City Gymnasiums	Accepted in City Universities			The Initial state probability *(S)*
	X	*Y*	*Z*	
X	0.75	0.125	0.125	0.4
Y	0.25	0.625	0.125	0.35
Z	0.25	0.25	0.5	0.25
The Final State Probability *(U)*	0.45	0.33125	0.21875	1

We can use the data of the last column of Table (1) to compute the initial state probabilities (sxsy and sz) by the direct division of the sum of each row over the total sum of this column, hence

$$s_x = \frac{1600}{4000} = 0.4,\ s_y = \frac{1400}{4000} = 0.35, \text{ and } s_z = \frac{800}{4000} = 0.25 \ \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Thus the initial vector *S* = [0.4 0.35 0.25]. These probabilities can be represented by the state diagram given in Fig. (1). Also there is another representation of these probabilities by a tree diagram, as shown in Fig. (2).

Now it is possible to answer the question raised about the probability that a new student graduated from a gymnasium in the city *Y* will be accepted in a university in the city *Z* next year. The answer will be the direct multiplication of probabilities from the state labeled 1 to the state labeled *XZ* in Fig. (2), which is equal to 0. 04375.We can use these probabilities to compute a final state vector $\underline{U}^{(m)}$ = [uX uY uZ] (where m gives the step number) and $U^{(1)}$ can be determined as follows [1,2]:

$$U^{(1)} = S \times P \ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

$$U^{(1)} = [0.4\ 0.35\ 0.25]\begin{bmatrix} 0.75 & 0.125 & 0.125 \\ 0.25 & 0.625 & 0.125 \\ 0.25 & 0.25 & 0.5 \end{bmatrix} = [0.45 \quad 0.33125 \quad 0.21875]$$

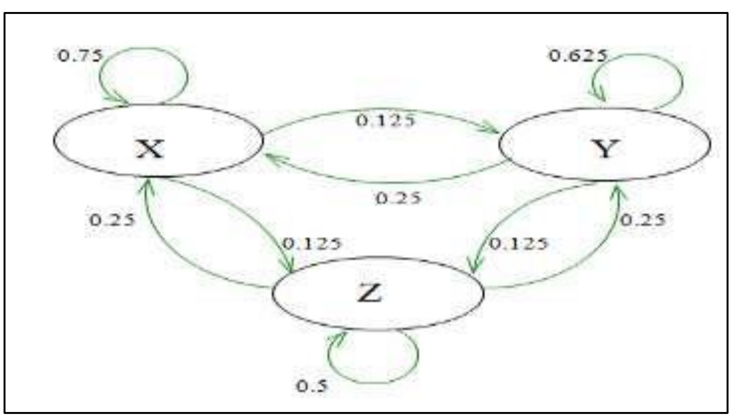

Fig. (1). *State Diagram of Transitional and State Probabilities Given in Table (2).*

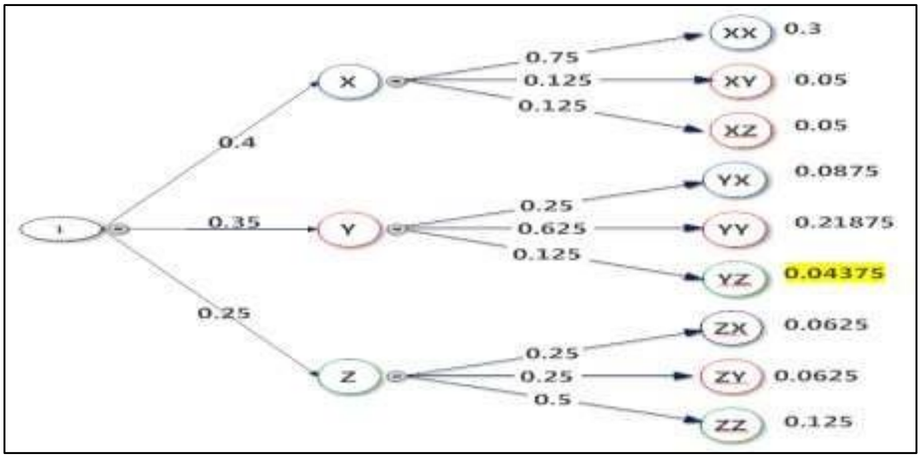

Fig. (2). *The Tree Diagram Representation of probabilities given in Table (2).*

Assuming all of these policies holds this year, and then the chance of a student graduated from gymnasiums of the three cities next year being accepted at the universities in the cities *X*, *Y* and *Z* will be 45%, 33.125% and 21.875% respectively.

Continuing to multiply *U* by the transition matrix again gives the estimation of these percentages after two years: $U^{(2)}$=[0.475 0.31796875 0.20703125] … [5]

Continuing the multiplication of produced $U^{(m)}$ vector by *P* matrix will reach a steady state condition and this occurs here after 22 repetitions and usually $U^{(22)}$ will be denoted by $U^{(\infty)}$:

$$U^{(\infty)} = U^{(22)} = [0.5 \quad 0.3 \quad 0.2\ ] \ldots (6)$$

Multiplying $U^{(\infty)}$ by *P*, the transition matrix has no effect. It just returns $U^{(\infty)}$, Students will continue to move between universities year – to - year, but the numbers going from one to other will be compensated by their counter transitions. Therefore the proportions in each state will remain the same and the steady state distribution reached.

3. Markov Modeling of Extended Essay (EE) Results

The major purpose of this section is to implement the application of concept of Markov chain process and to indicate its potential usefulness in analyzing problems such as EE examination results. As a particular vehicle for the implementation, a data base concerning the distribution of a sample of IB Diploma statistical Bulletin of May examination sessions for nine years (2006 – 2014) will be analyzed. Several assumptions need to be made in order for the Markov properties are plausible, we set the following:

1) The samples must be proportional to the overall student numbers of the different years.
2) Each student must be registered in the final year of his study in order to enter the data.
3) The new year students must have been continuously enrolled as their previous years.Thus the IB policies hold for all years of the data.
4) Only the last state influences the next state.

The interpretation of these assumptions is that the outcome of a given year results of EE depends on the outcome of the immediately preceding years results and that these dependencies the same at all states. Hence it is possible to define a Markov chain model for such case by determining number of states, specifying the meaning of the n^{th} state and describing the initial state probabilities.

The grades are distributed, in the statistical Bulletin, between the given five levels A and E for EE results. However, we added another grade level F corresponding to the remaining registered candidates that have none of the five grades. We split the nine years data into two sets, namely, the analysis set from 2006 to 2011 and the test set from 2012 to 2014. This is necessary in order to convince the state number of the grade levels and to use one part of the data for analysis (2006-2011) and the other for the prediction test (2012-2014).

We started the analysis with the first group (G1) of EE results where the data set represents EE results for 39207 candidates. The process can be in one of the six states that represent the grade from A to F and the six years from 2006 to 2011to form a matrix of 6 x 6 elements as given in Table (4). Number of

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candidates awarded a particular grade in each year is the variable selected for current measurement. Table (4) can be regarded as stationary Markov chain process with finite states and initial start states and will be used as a basis for the empirical analysis to follow. Each row is corresponding to a year of data from 2006 to 2011, and each column corresponds to a specific grade level from A to F. The last column represents number of candidates registered per a given year and the last row represent the total awarded for each of the six particular grades.

Table (4) *Extended Essay (EE) Results of Group 1 from May 2006 to May 2011.*

Yearly Awarded for Group 1 EE Subject	Number of Candidates Awarded a Particular Grade in EE Subject						Total of All Registered Candidates
	A	B	C	D	E	F	
2006	1,005	1,053	1,674	736	121	50	4,639
2007	1131	1,218	1,890	818	140	140	5,337
2008	1,187	1,373	2,194	1,017	177	43	5,991
2009	1539	2,054	2,302	1,079	77	55	7,106
2010	1615	2222	2589	1215	80	52	7,773
2011	1746	2,339	2,876	1262	72	66	8,361
Total of All Awarded a Particular Grade	8,223	10,259	13,525	6,127	667	406	39,207

We now proceed to employ the ideas of Markov chain analysis in the study of this sample of candidate's results. It would then be possible to construct the transition probabilities matrix *P* and the state probabilities *U* for the current group (G1) through the following steps:

1) Note that, we have only one variable which is the number of candidates awarded a particular grade. By considering Table (4) it is clear that it can be represented by six states and hence 6 x 6 transitional probabilities. The transition probabilities remain invariant throughout the relevant six years period. While this is obviously a strong restriction, however, this specification is analogous to that used in many of the analyses involving steady state comparative statistics [2, 3].
2) The evolution of a grade changes through these states can be regarded as a Markov process with probabilities of transition constant in year time and the probability of moving from one estate to another a function only of the six states involved.
3) The elements of *P* matrix will be determined by direct division of the number of students awarded a specified grade on the sum of the row which represents the total number of registered candidates for the year under consideration. For example the first row of the matrix *P* (Results of group 1, for the year 2006) can be obtained as follows:

$$P(1,1) = \frac{1005}{4639} = 0.216642,\ P(1,2) = \frac{1053}{4639} = 0.226989,\ \ldots,\ P(1,6) = \frac{50}{4639} = 0.010778 \ldots\ldots\ldots\ldots (7)$$

The complete values of P matrix are given in Table (5).

4) The elements of the initial starting state vector (S) are obtained by the division of the total number of students for each year over the total number of students for the six years period of time under consideration. Thus:

$$s_1 = \frac{4639}{39207} = 0.118321,\quad s_2 = \frac{5337}{39207} = 0.136124,\ \ldots,\quad s_6 = \frac{8361}{39207} = 0.213253 \ldots\ldots (8)$$

The descriptive statistics relating to of total grades awarded by candidates in EE within group 1, for each of six years under consideration are presented in Table (5). The elements corresponding to six years 2006-2011 and the six grades A-F represent the 36 components of the transitional matrix P. The last column entries represent the six components of the initial state vector S. The last row entries of the table represent the final state vector U(1), which can be computed either by using Equation (4), or by the direct division of each component of the row over their total sum

Table (5) *Markov Model of Extended Essay (EE) Results of Group 1 from May 2006 to May 2011.*

Transitional Probability *P*(i, j) Row for Group 1 EE Subject	**Transitional Probability *P*(i, j) Colum for Group 1 EE Subject**						**Initial State Vector *S***
	A (j=1)	**B (j=2)**	**C (j=3)**	**D (j=4)**	**E (j=5)**	**F (j=6)**	
2006 (i=1)	0.216642	0.226989	0.360854	0.158655	0.026083	0.010778	**0.118321**
2007 (i=2)	0.211917	0.228218	0.354132	0.15327	0.026232	0.026232	**0.136124**
2008 (i=3)	0.198131	0.229177	0.366216	0.169755	0.029544	0.007177	**0.152804**
2009 (i=4)	0.216578	0.289052	0.323952	0.151844	0.010836	0.00774	**0.181243**
2010 (i=5)	0.20777	0.285861	0.333076	0.15631	0.010292	0.00669	**0.198255**
2011 (i=6)	0.208827	0.279751	0.343978	0.150939	0.008611	0.007894	**0.213253**
Final State Vector $U^{(1)}$	**0.209733**	**0.261662**	**0.344964**	**0.156273**	**0.017012**	**0.010355**	**1**

5) We may now find it interesting to analyze the structure that the sample of awarded grades would eventually reach if the trend persisted through time. The period of time necessary to reach steady state does, of course, depend on the starting values. When the initial state vector and the transition matrix P are used, the steady state vector U(∞)can be reached in seven steps (U(∞) = S □ P(7)) for the current example as shown in Table (6), where the final values of U(∞) are:

$$U^{(\infty)} = [0.2086240.240087 \quad 0.354346 \quad 0.160051 \;\; 0.024301 \quad 0.012591] \ldots\ldots (9)$$

6) The concept of steady state is dynamic in nature for the individual grade levels. In other words, steady state in this example does not imply that there is no movement between the six grade levels. On the contrary, the dynamic conception of steady state explicitly requires that grades move in and out of each class. But on the average forces acting to increase the number of candidates in a given grade level are exactly counterbalanced by those tending to decrease it.

Table (6) *Next State probability $U^{(m)}$ computation for Probabilities Given in Table (5).*

Yearly Awarded for Group 1 EE Subject	**Percentage a certain grade level expected (Group 1)**					
	A	**B**	**C**	**D**	**E**	**F**
U(1)	0.209733	0.261662	0.344964	0.156273	0.017012	0.010355
U(2)	0.208778	0.239312	0.35453	0.159891	0.024484	0.013006
U(3)	0.208619	0.24011	0.354346	0.160054	0.024294	0.012576
U(4)	0.208624	0.240087	0.354346	0.160051	0.024302	0.012591
U(5)	0.208624	0.240088	0.354346	0.160051	0.024301	0.012591
U(6)	0.208624	0.240087	0.354346	0.160051	0.024301	0.012591
U(7)	0.208624	0.240087	0.354346	0.160051	0.024301	0.012591
Steady State Vector $U^{(\infty)}$	0.208624	0.240087	0.354346	0.160051	0.024301	0.012591

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7) Hence in steady state, for EE group 1 examination results, about20% of the student will awarded grade A, 24% will awarded Grade B, 35% will awarded grade C, 16% will awarded grade D, 2.4% will awarded grade E and 1.3% will awarded grade F. Although these results are not as extreme as some current predictions in regard to increases in the size of data, they are consistent in direction with what is currently being predicted and in steady state. It is clear that in steady state, 80 percent of the students were awarded grade levels A, B, and C. In contrast, only 20 percent of the students were awarded grade levels D, E and F for the period of time under consideration.

4. Modeling Groups 2 to 6 of EE Examination Results

Within this framework, for the remaining five EE group results, we followed similarly the same assumptions used for modeling of EE examination results of group 1. Hence the number of candidates awarded a particular grade in EE group 2-6 is the variable whose movement over time is to be analyzed and the six year step intervals are used in defining the admissible states. Having defined the data and the ranges for each state, we traced the year-to-year history for a particular grade in terms of its movement among the various states and develop the transition matrix

through the six years under consideration. The steady state vectors $U_j^{(\infty)}$ were obtained for Groups j=2,…,6 i.e. G2, G3, G4, G5, and G6 of EE for 2006 to 2011 of May sessions examination results which are given in Table (7).

Table (7) *Steady state vectorsof Extended EssayResults for Groups1-6.*

Steady State Vector	Grade level of EE Subject Group					
	A	B	C	D	E	F
$U_1^{(\infty)}$ of Group 1, G1	0.208624	0.240087	0.354346	0.160051	0.024301	0.012591
$U_2^{(\infty)}$ of Group 2, G2	0.211947	0.221976	0.357535	0.176075	0.022883	0.009584
$U_3^{(\infty)}$ of Group 3, G3	0.098187	0.179547	0.383646	0.273432	0.056367	0.00882
$U_4^{(\infty)}$ of Group 4, G4	0.071775	0.162527	0.372573	0.310413	0.075798	0.006915
$U_5^{(\infty)}$ of Group 5, G5	0.071775	0.162528	0.372573	0.310412	0.075798	0.006915
$U_6^{(\infty)}$ of Group 6, G6	0.071775	0.162528	0.372573	0.310412	0.075798	0.006915

Still the natural question arises at the first paragraph of this study, in which group is better for a candidate to choose his EE subject next year?

Although $U_j^{(\infty)}(i)$ of an EE j^{th} group in the i^{th} state gives some indication of the best choice, if it is to be meaningful some basis of comparison is needed. For the comparison purpose we introduced an algorithm that involves the following procedure:

Step 1.In the first step the elements of each column of Table (7) will be rearranged in such a way to well meet the reflection of their elements ranks for a given grade level. To achieve this demand, the elements of each particular grade level (column) for all groups are arranged in descending order. For example, the application of this descending order on the third column of Table (7) (grade level C) the new sequence will be in the following order G3, G4, G5, G6, G2 and G1. The results of this reordering for all grade levels from A to F are given in Table (8).

Table (8) *Results of Reordering of columns of Table (7) in Descending Order*

Seq	A	Seq	B	Seq	C	Seq	D	Seq	E	Seq	F
G2	0.211947	G1	0.240087	G3	0.383646	G4	0.310413	G4	0.075798	G1	0.012591
G1	0.208624	G2	0.221976	G4	0.372573	G5	0.310412	G5	0.075798	G2	0.009584
G3	0.098187	G3	0.179547	G5	0.372573	G6	0.310412	G6	0.075798	G3	0.00882
G4	0.071775	G5	0.162528	G6	0.372573	G3	0.273432	G3	0.056367	G4	0.006915
G5	0.071775	G6	0.162528	G2	0.357535	G2	0.176075	G1	0.024301	G5	0.006915
G6	0.071775	G4	0.162527	G1	0.354346	G1	0.160051	G2	0.022883	G6	0.006915

Step 2. A set of numerical weights are provided in order to reflect the relative importance of the grade levels and evaluation categories. Their elements values should be selected to distinguish between the ranks of groups in a particular grade level. There is no "best" method for providing weights. Such criteria depend on the facts and axioms that a judgment wishes to follow, level of information desired for the weights, and the available resources for computing the weights. To achieve that, firstly, a two-dimensional weighting matrix *W* was constructed that allowing columns selection to record weighted scores. Secondly, a set of numerical vector weights *V* was provided in order to determine the relative importance of the six grade levels. These weights are serving as scaling factors to specify the relative importance of each rank within a particular grade level and they should be nonnegative numbers. The weight matrix *W* must fulfill these requirements, and must satisfy the steady state structure reached by the group results in our example. Hence the chosen weights for pass grade levels A, B, C& D are arranged in descending order. In addition to that, values of these columns are selected such that the smallest value in the proceeding column is higher than the maximum value in forthcoming column. On contrary, the values of weights for grade levels E & F are arranged in ascending order in order to reflect the nature of these fail grades. These values were selected by trail and errors process. The values of the weighted vector adapted from the weights of computing the average percentage grade for the graduated student from a six years medical college followed by many universities in Iraq.

$$W = \begin{bmatrix} 254 & 170 & 90 & 30 & 2 & 1 \\ 240 & 160 & 80 & 27 & 4 & 2 \\ 226 & 148 & 70 & 24 & 6 & 3 \\ 212 & 136 & 60 & 21 & 8 & 4 \\ 194 & 124 & 50 & 18 & 10 & 5 \\ 184 & 112 & 40 & 15 & 12 & 6 \end{bmatrix} \qquad (10)$$

$$V = [0.3 \quad 0.22 \quad 0.18 \quad 0.14 \quad 0.11 \quad 0.05] \qquad (11)$$

In the distribution values of *W* the columns interpreted as the grade level and the row as the rank in the corresponding grade level. For the vector *V* the weights are related to the grade levels A-F and summed to unity (or to 100%).

Step 3. In this step, a weighted category score is calculated by multiplying the rank score of *W* by the category weight of *V*. Next the accumulated scoring will be computed which identify decision rank values for each given EE groups awarded results. The decision models address a numerical value assigned to each group indicating its final rank called score index (n). As shown in Table (10) various ranks are weighted differently according to its order in each grade level. The weighted numerical values are multiplied by the corresponding value of the weighted vector *V*. Next the individual results will be added in order to compute the overall score for each group. The group with the highest score is the best overall alternatives. Given an ordered steady state vector $U^{(\infty)}$ of an EE group awarded results, then the score index $R(n)$ can be computed.

Let the vector Q_n be the rank of grade level for the nth group. Hence, for the first group the elements of this vector are Q_1= [2 1 4 6 3 1] and the rest Q_n values are given in Table (9). We can express $H(\boldsymbol{k})$ as the specific weight of the nth group of the kth column of the weight matrix *W*.

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$$H(\boldsymbol{k}) = W(Q_n(\boldsymbol{k}), \boldsymbol{k}) \quad \text{for } \boldsymbol{k} = 1, \ldots 6. \quad \ldots \quad (12)$$

For group 1, H_1 = [240 170 60 15 6 1]. Thus, the score index (n) can be expressed as follows:

$$R(n) = \sum_{k=1}^{6} H_n(\boldsymbol{k}) \times V(\boldsymbol{k}) \quad \ldots\ldots\ldots\ldots\ldots\ldots (13)$$

Where (n) is the score of n[th] EE group and $H_n(\boldsymbol{k})$ is the value of the weighted matrix in its

$Q(k)$ row and its k^{th} column, and $V(k)$ is k^{th} value of the weighted vector. For example the score of first group (1) can be calculated as follows:

$$R(1) = W(2,1)\ V(1) + W(1,2)\ V(2) + W(4,3)\ V(3) + W(6,4)\ V(4) + W(3,5)\ V(5) + W(1,6)\ V(6)$$

$$R(1) = 240 \times 0.3 + 170 \times 0.22 + 60 \times 0.18 + 15 \times 0.14 + 6 \times 0.11 + 1 \times 0.05 = 123.01 \ \ldots\ldots\ (14)$$

Table (9) gives the computed values of the final scores for all EE groups. Reordering these groups according to their computed score indices in descending order give the rank of the EE groups, which is: [**G2 G1 G3 G4 G6 G5**]. Finally, the answer to the raised question regarding in which group is better to select the EE project by the candidates in future is achieved which is group 2 (language B).

Table (9) *shows how the weighted score distribution of the current data*

The Grade level	The group sequence and weight												The Weighted Vector V
	G1		G2		G3		G4		G5		G6		
	Q_1	H_1	Q_2	H_2	Q_3	H_3	Q_4	H_4	Q_5	H_5	Q_6	H_6	
A	2	240	1	254	3	226	4	212	4	212	4	212	0.30
B	1	170	2	160	3	148	5	124	4	124	4	136	0.22
C	4	60	3	70	1	90	2	80	2	80	2	80	0.18
D	6	15	5	18	4	21	1	30	2	27	3	24	0.14
E	3	6	4	8	2	4	1	2	1	2	1	2	0.11
F	1	1	2	2	3	3	4	4	4	4	4	4	0.05
R(n) Score	123.01		127.5		120.09		109.9		109.48		111.7		

5. Prediction of EE results using Markov Model:

We are interested in predicting 2012, 2013 and 2014 EE group results from the components of Markov chain obtained for the results of 2006 up to 2011. Thus we predict the EE results for each year (2012, 2013 and 2014) through the direct multiplication of their state distribution (S) vector by the transition probability P obtained for the period 2006-2011 using Equation (4). Results of these calculations are given for two groups (1 and 2) in Table (10).

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Table (10) *Steady state and actual vectors of EE group results*

Vector symbol		The components of the Predicted Vector					
Group 1	U^{2012}_{1}	**0.193812**	**0.290825**	**0.350129**	**0.146541**	**0.009669**	**0.009024**
	U^{2013}_{1}	**0.202573**	**0.29034**	**0.354043**	**0.136157**	**0.0091**	**0.007788**
	U^{2014}_{1}	**0.210928**	**0.290691**	**0.33901**	**0.141569**	**0.009633**	**0.008169**
Group 2	U^{2012}_{2}	**0.199775**	**0.199775**	**0.238557**	**0.252762**	**0.10124**	**0.007892**
	U^{2013}_{2}	**0.188769**	**0.188769**	**0.235066**	**0.267921**	**0.112903**	**0.006571**
	U^{2014}_{2}	**0.173757**	**0.173757**	**0.241158**	**0.295746**	**0.108406**	**0.007176**

Since we know the actual value for the years 2012-2014 it is interesting to calculate the difference between the actual and the predicted state vectors. We will employ in this study the following computation:

1) Find the square of the difference between the elements of the two vectors.
2) Find the sum of these squared values.
3) Find the average of the sum by dividing by 6.
4) Find the square root of the average.

The final value called the root mean square error (RMSE) for Markov prediction performance evaluation. Thus the RMSE between the predicted and the actual values of U vectors can be expressed by the following Equation [7]:

$$RMSE(k) = \sqrt{\frac{1}{6}\sum_{i=1}^{6}\left(U_j^n(i) - U_j^k(i)\right)^2} \quad \text{...(14)}$$

Where *RMSE(k)* is the root mean square error prediction of the k^{Th} year, between the n^{Th} predicted state vector of the j^{Th} group and the state vector of j^{Th} group for the k^{Th} year, (n=∞, for steady state, n=1, for 2012, n=2, for 2013 and n=3 for 2014), (j=1, …, 6) and (k=2012, 2013 and 2014). Table (13) gives the numerical values of these *RMSE*s for May EE group results.

RMSE is a general purpose average error metric for numerical predictions as well as it is a good indicator of average model performance. A smaller value indicates better model performance [7]. The maximum *RMSE* value given in Table (11) is 0.08059 which is a small value, and this indicates that modeling EE group results by Markov model succeeded as predictor.

Table (11) *RMSE values between the predicted and the actual vectors for three groups*

The Group			**The computed value of *RMSE* between U^n_j and the corresponding EE group vector**					
			G1	**G2**	**G3**	**G4**	**G5**	**G6**
The Year	**2012**	U^1 ***group***	0.008659	0.068336	0.01487	0.015544	0.021544	0.023304
		U^∞ ***group***	0.009679	0.066859	0.021866	0.026382	0.023821	0.068451
	2013	U^2 ***group***	0.009953	0.073849	0.026299	0.039713	0.024471	0.033044
		U^∞ ***group***	0.009745	0.074372	0.025789	0.038334	0.024236	0.068501
	2014	U^3 ***group***	0.013432	0.080581	0.026815	0.051109	0.025136	0.026097
		U^∞ ***group***	0.013437	0.08059	0.026828	0.051267	0.025153	0.061028

6.

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7. **When might transformations be useful?**

Markov Chains: They model transitions between states (predicted grades to awarded grades) based on historical data. Transform functions wouldn't be applied here. **Logistic Regression:** This method analyzes the relationship between independent variables (like predicted grade) and a dependent variable (awarded grade). Transformations might be used on the independent variables to improve the model's performance, such as log transformation for skewed data or standardization for variables measured on different scales. **Decision Trees:** These algorithms split the data based on decision rules involving the independent variables. Transformations might be applied to prepare the data for splitting, but they wouldn't be part of the core decision-making process within the tree. In some cases, transforming the data before applying Logistic Regression or Decision Trees can improve their performance. Here are some examples:

- **Normalization or Standardization:** If different variables are measured on different scales, transforming them to a common scale can ensure they have a similar impact on the model.
- **Log Transformation:** If a variable has a skewed distribution (e.g., many low values and few high values), a log transformation can make the distribution more symmetrical and improve the model's ability to learn linear relationships.
- **Box-Cox Transformation:** This is a more general transformation that can handle a wider range of data distributions.

Important to Note:

- Applying transformations blindly can sometimes have negative consequences. It's crucial to understand why a transformation is being used and how it affects the data interpretation.
- The choice of transformation often depends on the specific characteristics of your data and the statistical assumptions of the model being used.

Alternative Approaches:

Instead of relying solely on transformations, consider these approaches:

- **Feature Engineering:** This involves creating new features from existing ones that might be more informative for the model. For example, you could create a feature representing the difference between predicted and awarded grade in the previous year.
- **Model Selection:** Exploring different model types (e.g., Random Forests, Support Vector Machines) might lead to better performance without the need for extensive data transformations.

In conclusion, transform functions are not a core part of using Markov Chains, Logistic Regression, or Decision Trees for analyzing expected awarded grades. However, they can be used strategically to prepare data for these models and potentially improve their performance. Consider alternative approaches like feature engineering and model selection for a more comprehensive analysis

8. **Comparing Performance**

Here's a breakdown of how Markov Chains, Logistic Regression, and Decision Trees compare for analyzing and predicting expected awarded grades in IB secondary schools:

7.1 Markov Chains:

- **Strengths:**
  - Easy to understand and implement.
  - Captures the sequential nature of grade transitions (predicted to awarded).
  - Good for identifying students likely to fall short of predicted grades.
- **Weaknesses:**
  - Assumes transitions only depend on the previous grade, ignoring other factors.
  - Limited predictive power for students with large predicted-awarded grade discrepancies.
  - Not suitable for analyzing the impact of multiple variables.

7.2 Logistic Regression:

- **Strengths:**
  - Can handle multiple independent variables (predicted grade, past performance, demographics).
  - Provides probabilities of achieving different grades, offering a more nuanced prediction.
  - Relatively interpretable model, allowing you to understand which factors influence awarded grades.
- **Weaknesses:**
  - Requires larger datasets for accurate results.
  - Underlying assumptions about the data may not always hold true (e.g., linearity between variables).

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- May not capture complex interactions between variables.

7.3 Decision Trees:

- **Strengths:**
  - Flexible and can handle non-linear relationships between variables.
  - Easy to visualize, allowing for clear interpretation of how different factors influence awarded grades.
  - Can identify unexpected patterns or interactions in the data.
- **Weaknesses:**
  - Prone to overfitting if not carefully tuned (model becomes too specific to the training data).
  - Can be less interpretable for complex trees with many splits.
  - May not be as good at predicting for students outside the range of the training data.

7.4 Choosing the Best Method for Specific Needs Depends on Several Factors:

- **Data Availability:** Logistic regression and decision trees typically require more data than Markov Chains.
- **Data Complexity:** If you want to analyze the impact of multiple variables, logistic regression or decision trees are better choices.
- **Interpretability:** If understanding how different factors influence awarded grades is important, logistic regression offers a good balance between interpretability and predictive power.
- **Prediction Focus:** If you primarily want to identify students at risk of falling short of predicted grades, Markov Chains can be a good starting point.

7.5 **possible remark:**

1. Start with a Markov Chain gave a quick initial assessment of student progress and identify potential risk groups.
2. Use Logistic Regression or Decision Tree suitable for a more nuanced analysis and prediction, consider using logistic regression or a decision tree, depending on your data complexity and interpretability needs.

It's also worth considering using a combination of these methods. For example, one could use a Markov Chain to identify at-risk students, and then use a logistic regression model to further refine the prediction for these students by considering additional factors.

- Regardless of the method chosen, data quality is crucial for accurate predictions.
- Regularly evaluating and updating your models with new data is important to maintain their effectiveness.

9. DISCUSSIONS

There isn't a single "best" statistical method for analyzing and predicting expected awarded grades in IB secondary schools. The best choice depends on several factors, including:

- **Data Availability:**
  - **Limited Data:** If you have a limited dataset, Markov Chains might be a good starting point due to their relative simplicity.
  - **Larger Datasets:** Logistic Regression and Decision Trees can handle more complex data and multiple variables, but require a larger amount of data to be effective.
- **Data Complexity:**
  - **Simple Analysis:** For a basic understanding of student progress, Markov Chains can be sufficient.
  - **Multiple Variables:** If you want to analyze the impact of factors like past performance, demographics, or study habits, Logistic Regression or Decision Trees are better choices.
- **Interpretability:**
  - **Clear Understanding:** If you need to understand how different factors influence awarded grades, Logistic Regression offers a good balance between interpretability and prediction accuracy.
  - **Focus on Prediction:** If the primary goal is to identify students at risk or predict awarded grades, Decision Trees can be effective, even if the inner workings of the model are less transparent.

Additional Tips:

- Regardless of the method chosen, data quality is crucial. Ensure you have accurate and complete historical data on student performance.
- Regularly evaluate and update your models with new data to maintain their effectiveness.
- Consider using a combination of methods for a more comprehensive analysis.

10. CONCLUSIONS

The Markov chain method has been suggested as a means of characterizing or summarizing EE by subject group over a period time of nine years taken from IB statistical bulletin. This analysis showed visible different results of the student's achievements between their EE group in numerical results and statistical evaluation. A weighted matrix and a weighted vector were proposed and implemented successfully through an expression that identifies a score index for a given group. It was an exciting adventure to get elements of the weighted matrix and the weighted vector to drill down to a real achieving of their constructions. The score Indies for the groups reflect the rank that would be possible to obtain. The results do seem to be reasonable and consistent with impressions in the system and are meaningful which decision-makers can rely on. For the EE the highest results are achieved in the group 2 and the lowest in the group 5. The *RMSE* computations indicate good performance and accuracy of Markov chain modeling in EE group results prediction. Fortunately, the aim of this study was reached through the selection of an EE group topic for the IB students depending on a score index introduced here. Based on the video that identifies the best group to be chosen in order to achieve the high grade [1] his conclusion was reasonable although based only on IB statistical bulletin of 2013 results. Through the implementation of research anyone can make mistakes and hence reach wrong results. We must take caution and check the results instead of just quote from others, what is built on falsehood is false and this leads to the spread of errors.

We can suggest some areas in which this method might be used as well as we hope that the work will suggest other alternative applications to the reader. The analysis could, of course, be extended to other categories of the IB Diploma Programme Statistical Bulletined like subject group results, or combinations of these categories. The distribution of additional points is another area in which this method might be effectively employed. For example, each state might be composed of given grades of both EE and TOK results. There is currently much interest in the potential future size distribution of number of school statistics. Adapting the scoring index introduced here would make it possible to rank the schools by these sub-classifications. In this way information could be shed on the past and future organizational pattern of the IB Diploma Programme.

This method might provide a means of measuring past and future changes in structure. The impact of certain disturbances on IB policies could be obtained by altering certain elements of the transition matrix. Problems relating to size and location of schools might be solved by this method. In such problems, size and/or location would be used to specify the states. Other programmes like GCES and AP are examples of systems that in the past 10 years have experienced changes in both size distribution and location. This method could be used to characterize these changes and to indicate the futures if past trends continue. This will lead to compare these systems from several points of view. In the area of number of candidates registering growth and diploma awarded, this method might be used to get a good idea of the structure of changes for a region or country and what the long-run consequences might be if the current structure was maintained.

Meta-heuristics algorithms are not typically used directly for analyzing and predicting expected awarded grades in IB secondary schools. These algorithms are more commonly employed for complex optimization problems where you're searching for the best possible solution within a large search space. While predicting awarded grades can involve some level of optimization, it's not the kind of problem typically addressed by meta-heuristics [27-39].

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