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Application of Blooms Taxonomy in day-to-day Examinations

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Abstract—Bloom's Taxonomy describes the classification of learning into various domains. The "Cognitive domain" tries to separate learning process into different levels based on the ability of a person to think. This is very helpful to detect whether a given question is memory based or application based. The primary aim of this paper is to demonstrate the utilization of Bloom's Taxonomy to grade a given paragraph and the utilization of prediction models over that grading. This paper describes the technique to utilize the past marks of a student and the question paper contents to classify the question paper to a particular level using the taxonomic principles of the Cognitive domain and the application of linear regression to foretell the total marks that the student mark

Index Terms— Bloom's Taxonomy, Classification Algorithms, Data Analysis, Predictive models.

I. INTRODUCTION

Bloom's taxonomy was a 1 ttempt to classify the various different questions present in the education system [1]. It was named after Benjamin Bloom who was the chair of the committee that was assigned to come up with this taxonomy. The original Bloom's Taxonomy published in 1956 had only the Cognitive domain. Two additional domains, the affective domain and the psychomotor domain, were added to the Taxonomy almost a year later [2].

The Cognitive domain focuses mainly on the thinking abilities of a person. Bloom initially divided it into six sub parts depending on what ability, a person must have, to grasp. These were listed in the increasing levels of complexity. The six domains are knowledge, comprehension, application, analysis, synthesis and evaluation [1].

Knowledge level focuses entirely on the memorization ability of the person. It is the least complex of the six domains. Sample keywords include what, name and label. The comprehension level is one level above the knowledge level. It involves those questions which a person can comprehend and explain what the person has memorized (hence the added complexity). A few keywords from this domain are generalize, interpret and report. The application level adds another layer of complexity by defining questions that relates to a person being able to apply the knowledge that has been acquired. The next

level is the analysis level where the person is able to recognize the different parts of what the person has learned by identifying certain parameters. The words like analyze, categorize and characterize belong to this level. The synthesis level explains the ability for a particular person to combine many coherent ideas into one. This level is very complex and contains keywords like design, hypothesize, and Develop. The last level is the evaluation level which tests highly skilled abilities. It describes the ability to critically interpret and also to pass comments on a given topic. Hence the keywords belonging to this domain are of the type judge, recommend and justify.

The taxonomy of a question into these domains provides us with satisfactory classified output data which can be further analyzed. After the classification, the data can be clearly analyzed to predict the future outcomes of the students who have taken a given test. Application of Linear Regression on this classified data will help predict the future values by utilizing previous stored and trained values.

The ultimate aim of this work is to enable teachers set better question papers which cover all the skills required by a student effectively. The teacher can also effectively monitor the skill of the individual students. The prediction system can effectively be used by the teacher to look into the future to check as to which areas the student may score less and thus those regions which need more mentoring. Thus this idea will not only help the teachers increase the student's knowledge about the course but also help the students fare better in their examinations.

The other objectives of this work include helping students find accurate electives according to their skill set. Many students face a dilemma when they are given a choice to choose between subjects. Utilizing the previous question papers of a particular subject, the subject can be given a particular skill set requirement. The students would also be given a skill set index. Hence the students can choose the elective most suited for them. This can even be used to encourage those students whose predicted grades are low to prepare better for the next examination.

Finally a far fetched application would be to grade those students who could not take up an examination for genuine reasons by predicting the marks that they would have scored based on their other performances. This could be made possible only if there is a very large training dataset.

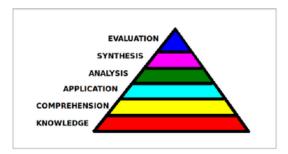


Fig. 1. The representation of the various levels of the Cognitive Domain as a triangle, commonly called as Bloom's Pyramid.

II. RELATED WORK

The application of Bloom's Taxonomy to classify data and implement prediction models is yet to be widely used. However the classification of data using the cognitive domain is well documented.

Terry Scott in his paper entitled "Bloom's taxonomy applied to testing in computer science classes." [3] clearly describes the utilization of Bloom's Taxonomy to classify questions into various levels. He mentions that traditionally asked questions normally fall into the lower level of the Bloom's Pyramid and do not exploit the inherent skill present in the student. Finally he remarks that a good exam paper must contain questions from all the domains. This work utilizes the grading mechanism from Terry Scott's work [3]. The different levels are given a particular grade and the overall cumulative sum will be used classify a question to a particular value.

III. ALGORITHM AND IMPLEMENTATION

A. Collection of Data

The preliminary step is to collect sufficient input to work upon. Two types of data has to be collected. One set of data is the total marks scored by a student for two subjects (minimum). The marks for one subject is utilized as the training dataset for the model whereas the predictive approach is applied on the other set of marks (testing dataset). The other set of data required is the marks scored by a student per question in a particular question paper. This is needed to find out if higher levels of intricacy leads to better results from the model. Along with these two datasets the question papers for which these marks were obtained also needs to be collected. The dataset is then truncated by removing the top and bottom 5%. This was done to eradicate the edge cases which would reduce the accuracy of prediction.

Apart from these data, the catalog of keywords also needs to be collected. A list of keywords pertaining to the Cognitive domain of Bloom's Taxonomy was initially published by GM Almerico and R Baker [4]. This list has been enhanced by many others and has been made available at the public domain. The keywords list also has a few ambiguous keywords with respect to the particular level that the word should fit in. An example can be the word "explain". This particular word can

either be in the comprehension level (the answerer must be able to comprehend the idea before explaining) as well as to the synthesis domain (The answerer must be able to integrate the final explanation from many sources). In this work, these kinds of words have been taken into account, and have been assigned to both the levels.

B. Classification Of Collected Data



The questions collected has to be first classified into one of the six levels of the Cognitive domain by utilizing specific keywords. Also each of the levels is assigned a numerical value in increasing order starting from 1 for the "knowledge" level and 6 for "evaluation" level.

The classification is done by removing the punctuation symbol from the given question and splitting the stripped question on the space character. The individual words were then scrutinized to identify if they belonged to any of the levels in the domain. If they did belong to a particular level then the word is marked with a color specific to that level and called as a hit word. The colors are the same as represented in Figure 1. These hit words are assigned a particular number corresponding to the particular level.

Another level of sophistication is brought into the system by adding a synonym check which checked for all the available synonyms for a non hit word. If any of the synonyms of a particular word is present in any of the predefined list of keywords then that word is also marked as a hit word. Additionally the new word which was earlier not present in the keyword list is now added to the list.

The above procedure needs to be followed for every question in input data. The final output available after the classification is a list of hit words along with their domain levels and the associated numbers for each of the question in the paper.

C. Calculation of the Bloom's Level

The output obtained after the classification is pipelined to the Bloom's level calculator. The Bloom's calculator calculates the cumulative sum of all the level numbers associated with the hit words and divides it over the total number of words found. The final value obtained from Equation 1 is called as the Bloom's level.

$$\sum_{i=0}^{n} a_i \tag{1}$$

where n is the total number of hit words and a_i starting from i=1,2 and so on are the number associated with the particular hit words.

The Bloom's level for each of the questions has to be calculated. Similarly the total Bloom's level for the complete question paper is also calculated.

An interactive online version of this Bloom's calculator was also created and has been hosted at http://future-blooming.github.io. This calculator accepts questions as an input and returns the Bloom's level of that question at that instant.

TABLE I. SAMPLE DATA FOR DEMONSTRATING PREDICTION

Levels	Exam 1	Exam 2	Exam 3
Knowledge	25/30	10/15	22/25
Comprehension	10/20	22/25	12/15
Analysis	12/15	15/20	10/15
Application	14/15	12/15	16/20
Synthesis	08/10	13/15	07/10
Evaluation	04/10	06/10	08/15
Total	73/100	78/100	75/100

D. Prediction Of Results

For the prediction of the future based on the classified delinear regression is used. Linear regression in simple words is a statistical method for finding out the relationship between a dependent variable and an independent variable [5]. For example, consider the marks scored by a student as shown in Table 1. The marks are represented in three different evaluations with the score the student has obtained in each level against the maximum marks for that level.

The calculation of the predicted marks begins with the formulation of the least-squares fit line [6]. The least-squares fit is one of the approaches in linear regression. In this method a line called the least-squares line which is at an optimal distance from all the data points on the graph is calculated.

The formula for the calculation of the slope of the line is as shown in Equation 2.

$$m = \frac{\sum_{i=1}^{n} (x_i - \overline{X})(y_i - \overline{Y})}{\sum_{i=1}^{n} (x_i - \overline{X})^2}$$
(2)

where m is the slope of the least-squares line. The calculation of the Y-Intercept of the line is as mentioned in Equation 3.

$$c = \overline{Y} - m\overline{X} \tag{3}$$

The formula y = mx+c will give us the equation of the new least-squares fit line.

The least-squares fit line is formulated for all the six levels. For the prediction the test paper is split into the six levels. The maximum marks per level is substituted in the place of X in the respective six least-squares equations that are obtained. This gives the predicted marks for that particular level. After the summation of all the individual level predictions the total predicted marks is calculated. (In cases where only the marks of a single previous attempt is available simple cross multiplication is used instead of the regression technique to predict the marks).

The process can be graphically depicted by constructing a scatter plot for each of the levels. Here the maximum marks for the level is taken as *X* values and obtained marks is taken as *Y* values (after sorting the dataset based on *X* values). After plotting the *X* and *Y* values, The least-squares fit line is plotted. This helps to visualize the process in a better way. Figure 2 depicts a graph for the values mentioned in Table 1.

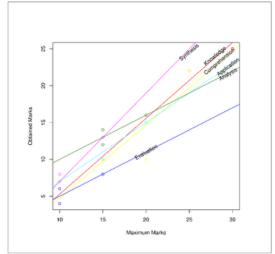


Fig. 2. Chart depicting the different least-square lines for the different data as provided in Table 1.

TABLE II. BLOOMS CLASSIFICATION FOR DIFFERENT PAPERS

Standard	Subject	Bloom's Level
6th Standard	Biology	2.73
10th ICSE Board	Physics	2.77
12th ISC Board	Physics	2.71
B.E. (C.S.E)	System Modeling	3.80

IV. RESULTS AND ANALYSIS

A. Comparing Different Papers based on Bloom's levels

Table 2 shows the Bloom's level of different question papers ranging from school to graduation. It can be clearly noted from the table that the levels of school based papers which are the 6th standard, the 10th board and the 12th board are all nearly 2.75. This implies that the question papers mostly tap the application and the comprehension skills of the student.

In graduate schools the bloom's level is well above 3. Also the number of question belonging to the evaluation domain is more. This clearly depicts the marked contrast between professional courses and teaching courses. (This cannot be a strong argument as only a single paper per standard has been considered, nevertheless, it does open up areas for more research).

B. Technique 1: Prediction using the paper as a whole

In this technique, the Bloom's level of the complete paper is utilized. Here the Bloom's levels of the training papers are fed into the prediction algorithm. The individual questions or Cognitive levels are not considered. The prediction again utilizes only the overall Bloom's level of the paper under consideration. The accuracy in this technique is 80% to 90% usually.

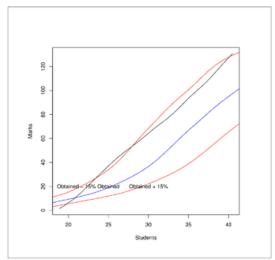


Fig. 3. Line Graphs showing the predicted marks using Technique 1. The thick black line is the predicted value.

TABLE III. THE DIFFERENT ACCURACY LEVELS OBTAINED USING TECHNIQUE 1

Bin	Accuracy Range in %	No of predicted values
1	95 - 100	15
2	90 - 95	22
3	85 - 90	32
4	80 - 85	31
5	75 - 80	8
6	0 - 75	22

The results of using this technique on a dataset of 130 students utilizing a single paper is shown in Figure 3. A single question paper of Bloom's level 3.19 was given as input. The result was calculated on another paper of Bloom's level 2.87. As seen in the chart the predicted marks are nearly 85% accurate. The average accuracy of this technique for the corpus of 130 students is 84.32%. Table 3 shows the different accuracy levels obtained for different ranges. It can be inferred from the table that the probability of getting a highly accurate prediction (above 75%) is nearly 85%.

C. Technique 2: Prediction using Higher details

As an improvisation of the previous technique, this approach, gives the individual questions a Bloom's level value. The total number of marks obtained per cognitive level is considered. For the prediction there are two cases which are considered.

In the first case individual questions in the question paper (considered for prediction) are assigned Bloom's level and marks are predicted for each of the questions. The total aggregated sum of all the scores is the predicted value. Here the accuracy is in the range of 90 to 95%.

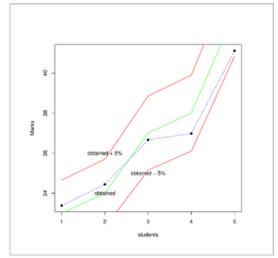


Fig. 4. Line Graphs showing the predicted marks using Technique 2 with outputs obtained using Case 2. The dotted line is the predicted value.

TABLE IV. RESULTS OBTAINED AFTER THE PREDICTION OF MARKS USING HIGHER DETAILS

Stude nt	Bloom's Level of Paper 1	Predicted Marks	Obtained Marks	Percent Difference	Accuracy
1	3.68	38.85	38	2.23	97.77
2	3.82	38.83	38	2.18	97.82
3	3.68	35.39	37	4.47	95.53
4	3.82	35.43	37	4.24	95.76
5	3.68	36.59	35	4.54	95.46
6	3.82	36.70	35	4.85	95.15

The second case the Bloom's level of the entire papers taken and the marks is predicted for the complete paper. In this technique the accuracy of prediction of the scores is more than 95%.

The results of testing this approach for 3 students using the first case is summarized in Table 4. The same paper is used for all the predictions, but two sets of papers are used as the training data set. The obtained values clearly show that the prediction for a given paper is almost same for a student no matter what previous paper is given as training data (along with the same accuracy). The higher accuracy of prediction (nearly 98%) for the first student's marks can be attributed to the fact that the student has answered more related to a particular domain. The other predictions are well within the 5% difference range. Thus it can be inferred that this algorithm can produce good results (even with a single paper as training data).

The results for using the approach for 5 different students using the second case is depicted as a line graph in Figure 4. It can be noted that the predicted marks again falls well within

the range of 5%. This when translated to marks implies that the predicted marks might differ 2 or 3 marks at the maximum.

V. FURTHER ENHANCEMENT

The future prospects of this project include the addition of nouns along with the present set of words. Also the detection of phrases like "with respect to" are not considered. The additional burden of this would be to scan the question paper multiple times, however, the accuracy of the results would be improved. Finally, we are working on creating a web based version of the complete system (at present only the calculator is live) and providing it to the world.

VI. CONCLUSION

In today's world of education the main focus of a tutor is to help the students attain the learning objectives of the course that is being taught. The tutor tries his best to understand the mind of the student and to induce the subject's concepts into the student's young brain. This work demonstrates a technique where in which a tutor can understand the abilities of a student and train him accordingly. Using this tool a teacher can successfully set a question paper which covers all the areas of learning effectively. We intend to bring out a user friendly version of this analysis tool and help make examinations easier for students.

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REFERENCES



- Committee of College and Unit rsity Examiners. Taxonomy of educational objectives. Vol. 1. New York: David McKay, 1956.
- [2] Krathwohl, D. R.; Bloom, B. S.; Masia, B. B. (1964). Taxonomy of educational objectives: The classification of educational goals. Handbook II: the affective domain. New York: David McKay Comp 3.
- [3] Scott, Terry. "Bloom's taxonomy applied to testing in computer science classes." Journal of Computing Sciences in Colleges 19.1 (2003): 267-274.
- [4] Almerico, Gina M., and R. Baker. "Bloom's Taxonomy illustrative verbs: Developing a comprehensive list for educator use." Journal of the Florida Association of Teacher Educators 5 (2005).
- [5] Freedman, David A. Statistical models: theory and practice. 8 hbridge university press, 2009.
- [6] Bretscher, Otto. Linear Algebra With Applications, 3rd ed. Prentice Hall, 1995.

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