

Educational Data Mining: A Blend of Heuristic and K-Means Algorithm to Cluster Students to Predict Placement Chance

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ABSTRACT

Educational data mining emphasizes on developing algorithms and new tools for identifying distinctive sorts of data that come from educational settings, to better understand students. The objective of this paper is to cluster efficient students among the students of the educational institution to predict placement chance. Data mining approach used is clustering. Ablend of heuristic and K-means algorithm is employed to cluster students based on KSA (knowledge, Communication skill and attitude). To assess the performance of the program, a student data set from an institution in Bangalore were collected for the study as a synthetic knowledge. A model is proposed to obtain the result. The accuracy of the results obtained from the proposed algorithm was found to be promising when compared to other clustering algorithms.

Keyword: Educational data mining, clustering, efficient student, heuristic, K-means, KSA concept

1. INTRODUCTION

Educational data mining (EDM) is the presentation of Data Mining (DM) techniques to educational data, and so, its objective is to examine these sorts of data in order to resolve educational research issues.

An institution consists of many students. For the students to get placed, he/she ought to have smart score in KSA. KSA is knowledge, communication skills and attitude. This is often one of the vital criteria used for choosing student for placement. It's also a proven fact that better placements end up in good admissions. All the students will not have high KSA score. Therefore, it's necessary to find those students who possess smart KSA and who don't. Therefore, there's a requirement for clustering to

eliminate students who don't seem to be competent to be placed.

2. PROBLEM STATEMENT

Normally many students are there in institutions. It is a tedious task and time consuming to predict placement chance for all students and it's not necessary additionally to predict placement chance for those students who are incompetent academically. Therefore, there's a necessity for clustering the efficient students having smart KSA score whose placement chance may be predicted.

3. RELATED WORKS

Performance appraisal system is basically an interaction between an employee and also the supervisor or management and is periodically conducted to identify the areas of strength and weakness of the employee. The objective is to be consistent regarding the strengths and work on the weak areas to boost performance of the individual and therefore accomplish optimum quality of the process. [8]. (Chein and Chen, 2006 [9] Pal and Pal, 2013[10]. Khan, 2005 [11], Baradwaj and Pal, 2011 [12], Bray [13], 2007, S. K. Yadav et al., 2011[14]. K-means is one amongst the best and accurate clustering algorithms. This has been applied to varied issues. Kmeans approach cut samples apart into K primitive clusters. This approach or technique is particularly appropriate once the quantity of observations is huge or the file is gigantic. Wu, 2000 [1]. K-means method is wide utilized in segmenting markets. (Kim et al., 2006[2]; Shin & amp; Sohn, 2004 [3]; Jang et al., 2002[4]; Hruschka & amp; natter, 1999[5]; K-means cluster may be a variation of k-means cluster that refines cluster assignments by repeatedly making an attempt to subdivide, and keeping the simplest

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ensuing splits, till some criterion is reached. Dan pelleg, andrewMore, K-means: Extended K-means which is an effective Estimation of the quantity of Clusters [6], Thomas aloe, Remi Servien, The K-Alter algorithm: a parameter-free method to perform unsupervised clustering [7].

4. METHODOLOGY

5. DATA DESCRIPTION





Concept and research framework

The methodology along with its computational processes for determining the efficient student, is outlined below:

Step 1: Data collection.

The goal is to identify proficient students within the college under consideration viz., KK for the year 2017-18. The students hail from numerous courses. The courses are MBA, MCA, BCA, B.Com, and BBA.

Step 2: Data pre-processing using normalization

In our study, the attribute 'percent' is measured in (%) and 'skill' using numbers starting from [1 to 10].

In our study percentage (%) prevails on skills. Therefore, there's a necessity for standardization or normalization.

Step 3: Proposed Clustering technique

This step clusters efficient students among all the students of the institution using proposed clustering algorithm.

Step 4: Evaluate the result

| | Tuble T. Dutubuse Description | |
|----------------------|---|------------------------|
| VariablesDescription | | Possible Values |
| Stu id | Id of the student | {Int} |
| Name | Name of the Student arch and | {TEKT} |
| Sub | Subject Name evelopment | {TEKT} |
| M1, M2, M3, M4 | Marks scored in each subject | {1, 2, 3, 4, 5100} |
| T in % | Total marksSSN: 2456-6470 🛛 💕 类 | { 1% - 100% } |
| Skill | (Communication skills+Attitude) score out of 10 | {1, 2, 3, 4, 510} |
| Min | Minimum Marks for passing a subject | 32 |
| Max | Maximum Marks for passing a subject | 100 |

Table 1: Database Description

Stu_Id:- ID of the student. It can take any integer values.

Name: - Name of the student.

Sub: – represents the name of the topic. It will take solely the values starting from A-Z.

M1, M2, M3..:-various subject marks scored by a student. It will take solely the numeric values from 0 to 100.

T: – total marks scored by every student depicted within the form percentage i.e., 1% to 100%.

Skill: - Communication and attitude score out of ten

Min: - Minimum marks for passing a subject

Max: - maximum marks for passing a subject

6. EXPERIMENTAL EVALUATION

Step 1: Data collection

| rable 2. input rable | | | | | | | | |
|----------------------|-----|--------|-----------|------|-------|--------|------|--|
| Stu id | | | 1 | 2 | 3 | 4 | •••• | |
| Name | | | Vikas | Guru | Sayed | Deepak | ••• | |
| Sub | Min | MaK | M1 | M2 | M3 | M4 | M5 | |
| Ca | 32 | 100 | 20 | 98 | 45 | 92 | ••• | |
| Bi | 32 | 100 | 23 | 98 | 69 | 83 | | |
| Java | 32 | 100 | 24 | 97 | 67 | 74 | | |
| Se | 32 | 100 | 25 | 96 | 89 | 92 | ••• | |
| Cf | 32 | 100 | 26 | 95 | 88 | 88 | | |
| Db | 32 | 100 | 28 | 90 | 56 | 81 | •••• | |
| ••• | ••• | ••• | ••• | ••• | ••• | | | |
| T in % | | | 25 | 90 | 65 | 80 | | |
| Skill | | \sim | 7 | 9 | 7 | 8 | | |

Table 2: Input Table

Fields or variables listed higher than Marks scored in selected subjects for the year 2017-18 is considered and collected from an institution in city.

Step 2: Data Pre-processing: Pre-processing is done using Normalization.

| | | D | - X | | | |
|--------|--------|-------|-------|--------|-------|--------------------------------|
| Tabl | e 3: P | re-pr | ocess | ed tab | ole | |
| Stu id | 1 | 2 | 3 | 4 | ••• | |
| Sub | M1 | M2 | M3 | M4 | M5 | mational Journa <mark>r</mark> |
| Ca | 20 | 98 | 45 | 92 | ς.Τ | rend in Scientifie |
| Bi | 23 | 98 | 69 | 83 | | rena in ocientino |
| Java | 24 | 97 | 67 | 74 | | Research and |
| Se | 25 | 96 | 89 | 92 | | Development |
| Cf | 26 | 95 | 88 | 88 | | pevelopment |
| Db | 28 | 90 | 56 | 81 | | |
| ••• | | Ś | S. | | | ISN: 2456-6470 🛛 📲 |
| T in | 25 | 00 | 65 | 80 | • | |
| % | 23 | 90 | 05 | - 00 | | |
| Skill | 7 | 9 | 7 | 8 | 11.20 | 3 |

Steps of the proposed algorithm are explained below:

Step 1: Clustering using proposed algorithm.

- Step 1.1: Pre-processed table are going to be the input.
- Step 1.2: Cluster efficient students and determine the precise number of clusters. K-value is calculated using heuristic method by incrementing the K-value in each step by one and the results are shown below.

Partition of ECS is finished at first by taking K=2

After Applying proposed algorithm with K=2, we've got

Table- 4: Partial view of clusters of students,

| for | for K=2 | | | | | | | | |
|----------|----------|--|--|--|--|--|--|--|--|
| Cluster1 | Cluster2 | | | | | | | | |
| 1 | 2 | | | | | | | | |
| 10 | 3 | | | | | | | | |
| | 4 | | | | | | | | |
| 12 🔍 | 5 | | | | | | | | |
| 13 | 6 | | | | | | | | |
| 16 | 7 | | | | | | | | |
| 18 🖸 | 8 | | | | | | | | |
| 210 | 9 | | | | | | | | |
| 22 | 14 | | | | | | | | |
| 24 | 15 | | | | | | | | |
| 26 | 17 | | | | | | | | |
| 27 | 19 | | | | | | | | |
| 29 | 20 | | | | | | | | |
| 30 | 23 | | | | | | | | |
| 5 | 25 | | | | | | | | |
| | 28 | | | | | | | | |

The above table 4 shows the grouping of students into two groups.

Table - 5: Difference between clusters for K=2

| Cluster | Cluster1 | Cluster2 |
|----------|----------|----------|
| Custer 1 | 0 | 0.229 |
| Custer 2 | 0. 229 | 0 |

For K=2, group distances are tabulated. In this rounded value 0.23 is the minimum.

Applying K-means for k=3, we've the subsequent results.

Table- 6: Partial view of three clusters, for K=3 Cluster2

2

3

4

5

6 7

8

9

14

15

17

19

20

23 25

28

Cluster1

1 10

11

12

13

16 18

21

22

24

26

27

29

30

Table- 8: Partial view of four clusters, for K=4

| | Cluster 1 | Cluster 2 | Cluster 3 | Cluster 4 |
|--------------|-----------|-----------|-----------|-----------|
| | 1 | 9 | 3 | 2 |
| | | 10 | 4 | |
| | | 11 | 5 | |
| | | 12 | 6 | |
| | | 13 | 7 | |
| | | 16 | 8 | |
| | | 18 | 14 | |
| | | 21 | 15 | |
| | | 22 | 17 | |
| | | 24 | 19 | |
| | | 26 | 20 | |
| | | 27 | 23 | |
| - COM | 177 | 29 | 25 | _ |
| | J. | 30 | 28 | |
| \sim Color | al sa 🔊 🔊 | N I N | | |

Table- 9: Comparison of distance between the

| 'e, `` | clusters |
|--------|----------|
| | |

| Cluster 1 | Cluster 2 | Cluster 3 | | | Cluster | Cluster | Cluster | Cluster |
|-----------|-------------|-----------|-----------|----------------|-------------|---------------|-------------|--------------|
| 1 | 9 | 2 | ITCE | Cluster | 1 | 2 | 3 | 4 |
| 10 | 24 | 3 | IJ I OF | Custer | 0 | -0.104 | 0 1 9 7 | 0.242 |
| 11 | Х а, | • 4 | motione | 1 | | 0.104 | 0.187 | 0.342 |
| 12 | とれ | 5 | mationa | Custer | 0 104 | | 0.083 | 0.238 |
| 13 | ロヨー | 6 f T | rend in S | Sci2nti | 0.104 | | 0.005 | 0.230 |
| 16 | No | 7 | | Custer | 0.187 | 0.083 | 0 | 0.154 |
| 18 | 2う ' | 8 | Researc | n asiq | | | Ů | |
| 21 | 2 -2 | 14 | Develon | Custer | 0.342 | 0.238 | 0.154 | 0 |
| 22 | S N | 15 | | 4 | | <u>9</u> 4 | | |
| 26 | 5 | 17 | CNI 2454 | | table air | an about | diamlaria t | ha distance |
| 27 | N S S | 19 | JON. 2434 | omparative | e table giv | Table | alsplays t | ne distance |
| 29 | A Y | 20 | | lustors in to | rms of die | Table - | yoon thom | Cluster 3 |
| 30 | Ś | 23 | | histor $1 = 0$ | 187 giver | in row 1 | column | 4 Similarly |
| | | | | -0 | IUI GIVUI | 1 111 10 10 1 | conullin - | 1. Similarly |

The above table-6 indicates the partial view of 3 clusters.

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| Table- 7 | 7: | Differences | between | clusters |
|----------|----|-------------|---------|----------|
|----------|----|-------------|---------|----------|

| Cluster | Cluster1 | Cluster2 | Cluster3 |
|----------|----------|----------|----------|
| Custer 1 | 0 | 0.116 | 0.165 |
| Custer 2 | 0.116 | 0 | 0.154 |
| Custer 3 | 0.165 | 0.154 | 0 |

For K=3, the distance between the groups are tabulated. In this0.12 (rounded) is the minimum value

For K=4; we have the following results.

Table-10: Cluster distance table

the other values are calculated. This table is the

resultant of application of Proposed Algorithm,

incrementing value of K in every step by 1.

| Number of clusters | The short Cluster distance |
|--------------------|----------------------------|
| Cluster 2 | 0.2293 |
| Cluster 3 | 0.1658 |
| Cluster 4 | 0.3428 |
| Cluster 5 | 0.3133 |

The first value 0.2293 within the shorter cluster distance field represents the distance between the cluster 1 and 2, similarly the second value viz., 0.1658 represents the gap between 1 and 3. The opposite values within the table are often interpreted similarly.

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From the above table 10 it is determined that, values within the 'shorter cluster distance' attribute starts increasing by great extent i.e., from 0.1658 to 0.3428, after cluster 2.Hence conclusion can be drawn that utmost number clusters which will be formed is 3.

Step 2: Choosing the cluster

We selectK=3 and 3rd cluster as a result. This is because the centroid of the third cluster is nearest to maximum marks of the subjects i,e., 2000(20 subjects).

Step 3: Identifying the elements of the cluster



The table 11 above represents the elements of the best cluster identified.

7. Results

Cluster 3 is found to be the best cluster having the number of efficient students given below:



Calculation of Precision and Recall for Proposed Algorithm and Other clustering algorithms

To analyse the accuracy of proposed algorithm in comparison with other clustering algorithms like Kmeans fast and K-Medoids it is necessary to identify the number of elements placed correctly and incorrectly into the clusters. Following formulae are used to calculate accuracy, precision and recall. Accuracy = (TA + TB) / (TA + TB + FA + FB), Precision = TA / (TA + FA) & Recall = TA / (TA + FB). TA and TB represent the elements that are placed correctly in class A and B, whereas FA and FB represent elements that are placed incorrectly in class A and B.

Table- 13: Comparison of precision, recall and accuracy for various algorithms

| Algorithm | Precision | Recall | Accuracy |
|-----------------------|-----------|--------|----------|
| Proposed Algorithm | 0.90 | 0.88 | 91.41 |
| k-medoids | 0.87 | 0.70 | 77.46 |
| k-means fast | 0.85 | 0.81 | 84.40 |

By the data available in table-13, it can be observed that the Accuracy, precision and recall values are comparatively better for proposed algorithm.



Algorithms Chart -1: Precision, Recall and Accuracy for different algorithms are represented in the above graph

8. CONCLUSION

The main objective was to identify efficient students by clustering i.e, a blend of heuristic and K-means algorithm based on KSA concept using data mining approach. An algorithm was proposed to accomplish the same. It was found that cluster 3 having efficient students emerged among the students of the institution as the best cluster. Proposed algorithm was compared with other clustering algorithms and it is observed that Proposed algorithm outperformed other algorithms with an accuracy of 91.41%. Thus, the solution for the above problem was found with success.

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