

UIVLP: An Improved User Interface and Visualization Technique to Visualize Learners' Performances

Mukesh Kumar Rohil^a and Trishna Paul^b

Department of Computer Science and Information Systems, Birla Institute of Technology and Science, Pilani, India

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Abstract: In most of the educational setups, the grading of students' performance is based on their relative standing in the class. In this work, we develop and present a user interface to visualize students' performance, expressed in terms of marks, out of same maximum marks for each subject, scored by the students in various evaluation components for a subject. First, we statistically select three most informative subjects for the whole class and then find the individual student's average score in all components along with the overall average of whole class for an evaluation component. We assume that the three courses' performance for which the 3D visualization is required, is either specified by the evaluator or selected by the system basis principal component analysis. The visualization procedures have been developed for both, the individual student and the entire class. The interactive 3D visualization and the bar-graphs can be compared side-by-side and we visually observe that the scatter-plot of clusters provides better insights as compared to the conventional bar-graphs. We also observe that the proposed visualization is better than the bar-graphs basis no-reference BRISQUE image quality assessment. However, there may be certain situations when both types of graphs might be needed.

1 INTRODUCTION

YA data collection can consist of scalar numbers, vectors, higher-order tensors, or any mix of these data types. Data sets can exhibit either two-dimensional or multi-dimensional characteristics. Color coding is a singular method for representing a collection of data visually. Other methods encompass contour plots, graphs, charts, surface renderings, and depiction of volume interiors. Furthermore, the integration of image processing techniques with computer graphics is employed to provide a multitude of data visualizations (Hearn & Baker, 2015; Johnson & Wichern, 2007).


The objectives of scientific visualization include:


- 1) Investigating and utilizing data and information,
- 2) Improving comprehension of concepts and processes,
- 3) Acquiring novel (unanticipated, profound) insights,
- 4) Presenting essential characteristics effectively by rendering the unseen visible.
- 5) Ensuring the accuracy and reliability of simulations and measurements,
- 6) Enhancing scientific output

and efficiency, and 7) Facilitating communication and collaboration among researchers (Hearn & Baker, 2015; Johnson & Wichern, 2007).

In the present work we propose a technique to visualize students' performance in a course by clustering the display around the average (mean) of the marks obtained by student in various evaluation components assuming that each evaluation component has been evaluated out of same maximum marks. In many universities the relative grading for a course is done based on the total marks obtained by the student. For this purpose the evaluator uses histogram of the marks (i.e. count of students scoring a particular marks is arranged in increasing or decreasing order of marks). The histogram is plotted as bar graph. We suggest to draw the marks of students in three subjects or topics and three areas are selected as the top three principal components.

After this short introduction, subsequently the paper has been structured as follows. The Section 2, Related Work provides a review of the related literature, The Section 3, summarizes the Theory

^a  <https://orcid.org/0000-0002-2597-5096>

^b  <https://orcid.org/0000-0003-2823-0812>

related to the purpose of clustering in the context, The Section 4 describes the problem, methodology, implementation and experimentation. The Section 5 describes the results and finally the Section 6, concludes the findings and lists scope for future research.

2 RELATED WORK

The progress in human-computer interaction has led to the development of novel approaches for examining graphical data in a dynamic manner, allowing users to have adaptable control. Although the majority of this research focuses on the presentation of statistical data, there has also been significant collaboration with advancements in information visualization as a whole. This is especially true for the representation of extensive networks, hierarchies, databases, and text, where the difficulties of handling massive amounts of data persistently arise (Hearn & Baker, 2015; Al-Barrak & Al-Razgan, 2016).

The field of statistical graphics encompasses the creation of various contemporary methods for visualizing data, including bar and pie charts, histograms, line graphs, time-series plots, contour plots, and other techniques. Thematic cartography evolved from individual maps to extensive atlases, which portrayed data on diverse subjects such as economics, society, ethics, medicine, and physical features. This advancement also offered innovative methods of representing information through various symbols (Hearn & Baker, 2015; Johnson & Wichern, 2007).

Most of the work related to the visualization of the students' performance are focusing on the user interface for the students to visualize their performance rather than helping the evaluator to visualize the insights in the dataset of the marks. These simply displays the marks in 3D or 2D without performing principal component analysis. Some works related to visualization of data mining and predictions of the students' performance (Al-Barrak & Al-Razgan, 2016; Misailidis et al., 2018) are helping the both the students and the evaluators. The work done by Humphries et al. (2006) helps the students to visualize their grade as their performance and the work by Deng et al. (2019) is course specific and does not combine more number of related or selected courses.

Most of the learning analytics tools and discussed in (Darcy, 2022; Paolucci et al., 2024; Mukred et al., 2024; Atif et al., 2013) displays bar graphs, pie-charts etc.

depicting the distribution of learners' performance including performance improvement (or degradation) over time, but these tools do not display 3D scalar and vector plots for most discriminating courses of study.

3 PURPOSE OF CLUSTER ANALYSIS

Cluster analysis aims to condense a vast dataset into significant subgroups of individuals or things. The division is achieved by categorizing the objects based on their similarity across a predetermined set of parameters. Anomalies pose a challenge to this methodology, frequently arising from an excessive number of extraneous factors. It is essential for the sample to accurately reflect the population, and it is preferable for the components to be independent of each other. There are three primary clustering techniques: hierarchical, which follows a tree-like procedure suitable for smaller data sets; non-hierarchical, which necessitates specifying the number of clusters in advance; and a hybrid approach that combines both methods. The development of clusters is guided by four primary principles: distinctiveness, accessibility, measurability, and profitability (sufficiently significant to have an impact).

In the present work for 3D visualization we cluster the marks about the point in 3D representing the mean of scores in three subjects. These three subjects are selected by Principal Component Analysis (Johnson & Wichern, 2007).

4 PROBLEM, METHODOLOGY, AND IMPLEMENTATION

The problem dealt in this paper is a multivariate problem so that students' performance can be graded using this. Cluster analysis technique is employed to solve this problem.

A. Problem Description

The problem is to graphically represent marks obtained by different students. We take a case of four students. Each student registers in three different subjects. Each student attempts fixed number of tests, given by the instructor, in each of the three subjects. So input for the problem is four text files, one for each student namely student1.txt, student2.txt, student3.txt, student4.txt. In other words all the data related to marks obtained by a particular student is

stored in a single text file. Thus there are four different files for four students. In each text file numerical data is provided in a matrix form. Row1 represents test1 (i.e. evaluation component 1) marks, Row2 represents test2 (i.e. evaluation component 2) marks, and so forth. Similarly, column1 represents subject1, column2 represents subject2 and so forth (please refer tables I to IV).

B. Input

Input data for the problem is presented in the form of tables below. Each text file corresponding to particular student is presented as a table i.e. Each table corresponds to a particular student.

Table 1: Marks of Student 1.

	Subject 1	Subject 2	Subject 3
Test 1	250	150	70
Test 2	250	250	250
Test 3	270	250	90
Test 4	310	150	50
Test 5	280	170	50

Above table shows the marks of student1 in three different subjects i.e. subject1, subject2 and subject3.

Table 2: Marks of Student 2.

	Subject 1	Subject 2	Subject 3
Test 1	0	100	20
Test 2	0	200	0
Test 3	20	200	40
Test 4	60	100	0
Test 5	90	130	0

Above table (i.e. Table 2) shows the marks of student2 in three subjects i.e. subject1, subject2 and subject3.

Table 3: Marks of Student 3.

	Subject 1	Subject 2	Subject 3
Test 1	0	0	100
Test 2	0	100	0
Test 3	100	0	0
Test 4	100	100	0
Test 5	0	100	100

Marks of student3 in different subjects are presented in the Table 3.

Table 4: Marks of Student 4.

	Subject 1	Subject 2	Subject 3
Test 1	150	50	70
Test 2	0	100	0
Test 3	100	0	0
Test 4	100	100	0
Test 5	0	100	100

Marks of student4 in three subjects are presented in the above table.

C. Methodology, Implementation, and Experimentation

Now all the numerical data from one text file has to be represented as one cluster i.e. marks obtained by a particular student in different subjects for different tests has to be represented as one cluster. Therefore four different clusters should be obtained for four different students i.e. each cluster represents marks obtained by a particular student.

For showing these clusters in three dimensional space three axes X-axis, Y-axis and Z-axis are drawn on a frame developed in Java Language. Each axis represents a subject. Hence the values in first column of the text file mapped along the X-Coordinates of a three dimensional point. Similarly values of second column are mapped to the Y Coordinates and values of third column are mapped to the Z-Coordinates. So marks obtained by a student in three subjects in a particular test are represented by a point in three dimensional space.

Numerical data from each file is read and the values are plotted in three dimensional space using graphics functions in Java Programming Language. Mean values for the X-Coordinates, Y-Coordinates and Z-Coordinates in text file are calculated. The mean value of X-Coordinates of a particular text file represents the average value of the marks obtained by the student in all tests of subject1. This becomes the X-Coordinate for the data point corresponding to the mean value of marks obtained by a student in all tests of three different subjects. In the same way mean values of Y-Coordinates and Z-Coordinates represents average marks obtained by a student in all tests of subject2 and subject3 respectively. These values become Y-Coordinate and Z-Coordinates for the mean value data point. It implies that we have a mean value data point for each student i.e. for each cluster representing marks of student there is a corresponding mean value data point. Then a line is drawn from each data point (representing marks in three subjects) of a cluster to its corresponding mean value data point.

The lines drawn from each point of a cluster to its corresponding mean value data give clear picture of

deviation of the average marks of all tests from the marks obtained in each test or looking in a different perspective we can say that these lines give an idea about the closeness of the average marks in all tests from the marks obtained in each test.

Conventionally, in a university setup, for the relative grading of students' performance the visualizations of the frequency-histogram represented as bar-graph but we propose to use 3D-Visualization of clusters also to arrive at cutoff for grading because as we explore later 3D-Visualizations of cluster provides more insights like depth-queuing and relative standing of a student's performance with respect to three subjects (or three topics) as compared to the total marks as depicted in the bar-graphs. To show it we use Blind/Reference less Image Spatial Quality Evaluator (BRISQUE), no-reference image quality scores, calculated as per the algorithm given by (Mittal et al., 2012), and its interpretation is as follows, smaller the score better the image quality and better the visualization considering the image quality.

5 RESULTS

For comparison, in Figs. 1 to 5, we plot bar-graphs and cluster plots side-by-side and provides specific details in the figure caption. The following screen shots presents the output of the Java program developed as a solution to this problem.

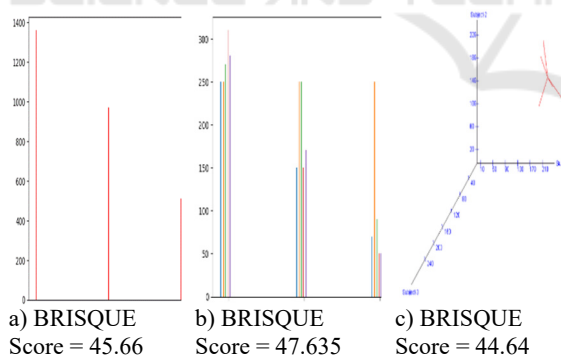


Figure 1: Visualization of marks of student 1, a) Subject wise totals; subject1 marks are denoted by left-most bar, subject2 marks are to the right of it, and so on, b) Evaluation component marks subject-wise; list of bars in the left-most portions represents marks obtained by the student in Test1 to Test5 in subject1; to the right of this, subject2 marks for five tests taken by the student are displayed and subject3 marks for five tests are displayed right-most, c) 3D display of marks for five tests clustered about mean-score of three subjects evaluation-wise for the corresponding student.

In the screen capture (Figure 1) one can clearly see the graphical visualization in three dimensional space. Distribution of marks obtained by student 1 is represented as a cluster. Cluster representing the marks of student 1 can be clearly seen. Lines are drawn from each data point to the data point corresponding to the mean value of the marks of student 1. Deviation of the average of marks from all tests from marks obtained in each test in the case of student 1 can be estimated using these lines.

We observe that because of no slanting lines in Figure 1 (a) and (b) (i.e. display is mostly generated by horizontal and vertical lines which are usually smooth), visually the Figure 1 (a) and (b) may seem good compared to Figure 1 (c) but image quality analysis in the terms of BRISQUE score evaluates to best for the Figure 1 (c).

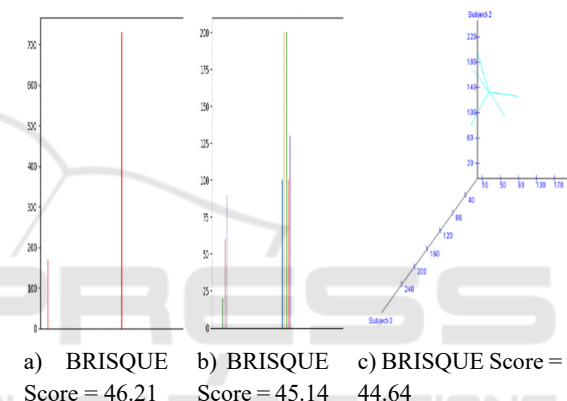


Figure 2: Visualization of marks of student 2, a) Subject-wise totals; subject1 marks are denoted by left-most bar, subject2 marks are to the right of it, and so on, b) Evaluation component marks subject-wise; list of bars in the left-most portions represents marks obtained by the student in Test1 to Test5 in subject1; to right of this, subject2 marks for five tests taken by the student are displayed and subject3 marks for five tests are displayed right-most, c) 3D display of marks for five tests clustered about mean-score of three subjects evaluation-wise for the corresponding student.

In the above screen capture (Figure 2) one can clearly see the graphical visualization in three-dimensional spaces. Distribution of marks obtained by student 2 is represented as a cluster. Cluster representing the marks of student 2 can be clearly seen. Lines are drawn from each data point to the data point corresponding to the mean value of the marks of student 2. Deviation of the average of marks from all tests from marks obtained in each test in the case of student 2 can be estimated using these lines. Image quality analysis in the terms of BRISQUE score evaluates to best for the Figure 2 (c).

Three dimensional space can be clearly in the above screen shot (Figure 3) too. Distribution of marks obtained by student 3 is represented as a cluster. Cluster representing the marks of student 3 can be clearly seen. Lines are drawn from each data point to the data point corresponding to the mean value of the marks of student 3. Deviation of the average of marks from all tests from marks obtained in each test in the case of student 3 can be estimated using these lines. Image quality analysis in the terms of BRISQUE score evaluates to best for the Figure 3 (c).

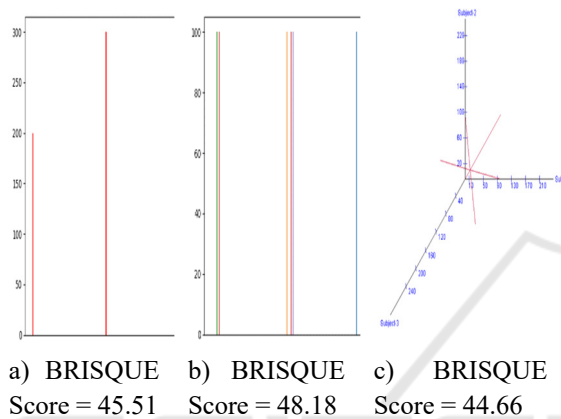


Figure 3: Visualization of marks of student 3, a) Subject-wise totals; subject1 marks are denoted by left-most bar, subject2 marks are to the right of it, and so on, b) Evaluation component marks subject-wise; list of bars in the left-most portions represents marks obtained by the student in Test1 to Test 5 in subject1; to the right of this, subject2 marks for five tests taken by the student are displayed and subject3 marks for five tests are displayed right-most, c) 3D display of marks for five tests clustered about mean-score of three subjects evaluation-wise for the corresponding student.

Figure 4 clearly presents the graphical visualization of three dimensional spaces. Distribution of marks obtained by student 4 is represented as a cluster. Cluster representing the marks of student 4 can be clearly seen. Lines are drawn from each data point to the data point corresponding to the mean value of the marks of student 4. Deviation of the average of marks from all tests from marks obtained in each test in the case of student 4 can be estimated using these lines. Image quality analysis in the terms of BRISQUE score evaluates to better for the Figure 4 (c).

From Figure 5 (a), we observe that the student1 performs the best, however student1's performance in subject3 is inferior as compared to the performance in subject1 and subject2. This is also evident from the Table I. The performance of the student3 is poor as we can see that the entire cluster is closer to the origin.

Similarly, insights about other students can be deduced and if required can be verified from the corresponding tables.

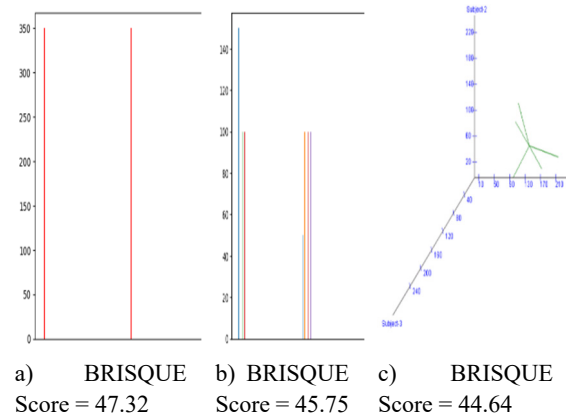


Figure 4: Visualization of marks of student 4, a) Subject-wise totals; subject1 marks are denoted by left-most bar, subject2 marks are to the right of it, and so on, b) Evaluation component marks subject-wise; list of bars in the left-most portions represents marks obtained by the student in Test1 to Test 5 in subject1; to the right of this, subject2 marks for five tests taken by the student are displayed, and subject3 marks for five tests are displayed right-most, c) 3D display of marks for five tests clustered about mean-score of three subjects evaluation-wise for the corresponding student.

If we align the 3D cluster plots of the students horizontally, vertically or along main diagonal then we can get more insights. For example, horizontal arrangement will depict easy understanding of variations in the performance of the students in subject2.

The screen-shot, Figure 6, gives complete output showing the clustering of the data of all the students. All the four clusters representing marks of all the students are represented here. This shows multivariate clustering of the numerical data from all the files. In a similar way this example can be extended to a large number of students and clustering can be visualized as above. Performance of each student can be assessed by observing this clusters and distribution of marks gives a clear picture of their relative performance. Image quality analysis in the terms of BRISQUE score evaluates to better for the Figure 6 (b) as compared to Figure 6 (a).

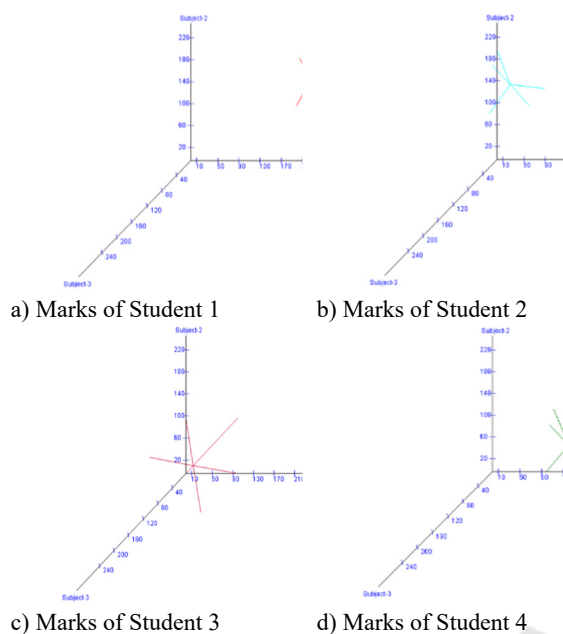


Figure 5: 3D display of marks for the four students in five tests clustered about mean-score of three subjects evaluation-wise.

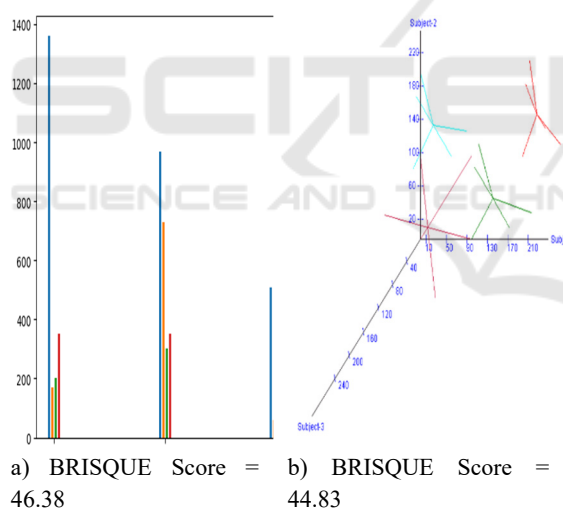


Figure 6: Visualization of marks of the four students, a) Evaluation component marks subject-wise, b) 3D display of marks clustered about mean-score evaluation-wise.

6 CONCLUSIONS

The problem of visualization of students' performance in terms of marks obtained in various subjects can be solved using the Cluster Analysis technique of multivariate analysis. Graphical visualization of clusters representing the marks of multiple students in different subjects is implemented

in Java. The distribution of marks of the students and deviation from average of marks from all tests from marks obtained in each test can be clearly observed from the graphical visualization provided. The 3D visualizations are compared with the bar-graph using no-reference image quality scores, BRISQUE, and it is observed that the BRISQUE scores are slightly better than the 2D bar-graph displays because lower the BRISQUE score better the image quality. In addition to this, it is observed that 3D cluster plots provide 3D clues and depth cues for further differentiating the students' performance for grading by considering marks in three subjects rather than just the total marks. As a future work, user interface (UI) can be developed for arranging the 3D plots along a selected axis so that UI can provide more insights. These insights can help in deciding the boundary cases for adjusting the cut-off for grading. In addition of this, future use of k-means clustering or Isodata algorithms can be made to visualize the students' performance along selected or most discriminating dimensions.

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