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Innovative Inter Quartile Range-based Outlier Detection and Removal Technique for Teaching Staff Performance Feedback Analysis

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Abstract : The teaching-learning process plays an important role in education. To improve this process valuable and timely feedback is taken from the students. That feedback can be used for two main purposes: one is to improve the process according to student expectations and another is to evaluate the teaching faculty's performance for the sake of appraisal. However, some students can give unfair and biased feedback. Such feedback may produce an adverse effect on appraisal. To remove these anomalies generated due to favoritism and biasness in the feedback innovative interquartile range (IQR) based outlier detection and removal technique is implemented in this article. The proposed technique removes the outliers based on IQR and precisely selects the central tendency (mean or median) from the feedback data distribution based on skewness. Then the identified central tendency will be considered to compute the appraisal indicator. To conduct the experiments feedback data is collected from the students via questionnaire. The questionnaire is prepared by expert academicians. The questionnaire contains twenty-one questions which are divided into five categories. By confirming experimental results, the proposed IQR-based outlier detection and removal technique removes the outliers from the data set and improves the performance analysis which intern helpful for teaching faculty performance appraisal.

Keywords : Interquartile Range (IQR), data distribution, Skewness, Outlier, Performance Appraisal, Feedback Analysis.

1. Introduction

Today is the era of competition. Education is the key factor to imbibe a competitive culture among students [15]. Nowadays, due to several technological advancements, most of the information is available with a single click [4]. It is a primary need to uplift the quality of education. The standard of education depends upon several factors such as the background knowledge of the student, educational facilities provided by the educational institute, and the quality of the teacher, just to mention a few. Out of all, the teacher's involvement is always at the core. That is, though education (i.e. teaching-learning process) is a student-centric activity, teachers play a crucial role [9]. In today's technological world, teachers are not just content providers, however, teachers act as facilitators [23]. Being a facilitator, it is the responsibility of every teacher to support every individual student to think critically and be ready for future competition [26].

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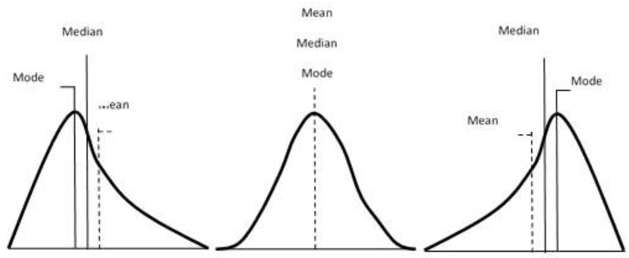
Maintaining the quality of education is a challenging task. To provide benchmark quality, teachers need to work hard and deliver quality content with class participation and student engagement. Teachers must be ready with various activities, assessment methods, and evaluation parameters to check student growth. To improve and analyze the student understanding and performance of an instructor, generally timely feedback is collected from the students [6]. The feedback collected from the students is very valuable [13]. However, feedback given by the student should be fair and unbiased. There are various ways to collect feedback from the students such as interviews, questionnaires, record reviews, and observations, just to mention a few [19]. Amongst all, the questionnaire feedback collection mechanism is used mostly because it is possible to collect a huge number of responses at once. By observing data, it is found that generally, few students give extraordinary feedback for the favorable faculties whereas give negative feedback for unfavorable ones.

This scenario leads to the existence of outliers in the sample. Such outliers should be detected and removed before further processing. That is, for a fair and unbiased evaluation of the teaching faculty performance for the appraisal, it is necessary to clean the data received in terms of student feedback [30]. To achieve this interquartile range (IQR) based on outlier detection and removal technique is proposed. In addition to this, the proposed technique precisely selects central tendency (mean or median) from the feedback data distribution based on skewness. Then the identified central tendency will be considered to compute the appraisal indicator. To detect the outliers, the proposed IQR-based technique initially identifies the quartiles and then determines the desired range of the data. This means that the values of lower and upper limits are identified. The data points fall below the lower limit and above the upper limit are treated as outliers. Such identified data points are removed from the dataset before further processing.

After identifying and removing the outliers the cleaned feedback data is considered for appraisal, to determine the exact central tendency of the data to compute performance indicator skewness technique is used. That is, skewness in the data distribution is used to determine whether to consider mean or median to compute performance evaluation indicators. If the distribution of data is symmetric then the values of the mean, median, and mode are the same



(a) Positive skew (b) symmetrical distribution (c) negative skew
Fig. 1 : Interpretation of Skewness

(Fig. 1 (b)) and that value is added to the performance indicator. If the skewness exists in the data, then the value of the median is added to the performance indicator. Fig. I (a) and (c) show the positively skewed and negatively skewed distribution of the data respectively [12, 27, 30].

This paper is structured as follows. The existing anomaly detection methods developed to detect and remove the outliers are discussed in Section II. In addition to this, it also reviews the latest techniques developed to compute teaching faculty performance based on student feedback. Section III provides detailed information about the proposed methodology. This initially speaks about the data collection process. Then it includes complete information about outlier detection techniques and computation of faculty feedback. Section IV describes the proposed algorithms of outlier detection technique and computation of faculty feedback. The comparative results of the proposed method are presented in Section V. Conclusive remarks and directions for future work are discussed in Section VI.

2. Literature Review

Outliers are surprising veridical data [27] or noise points situated outside a predefined cluster [1]. Another way outliers may be defined as points different from norms [3]. Outliers are generated because of mechanical faults, fraudulent behavior, natural deviation in population, behavioral changes in the system, and human errors, just to mention a few [29]. The presence of such outliers may mislead the prediction. It is better to detect and remove such noisy points through further processing.

The technique of outlier detection is very useful in several application areas such as machine learning, and data mining [2]. Pattern recognition, and Security applications like credit fraud detection [20], medical analysis [25, 32], and network fault identification [17, 11]. Detecting as well as removing the outliers in student feedback is also no exception to this analogy.

In students, feedback outliers may be present due to unbiased behavior and favoritism. To identify outliers from student feedback, a weighted density-based outlier recognition method is discussed by [9]. [22] proposed the radial basis function-based outlier detection method to remove the misclassified instances from given data. Further, the cleaned data is used to anticipate the Academic Performance of the pupils.

In addition to a few research attempts some predefined tools and packages are available to detect and remove the outliers such as an environment for developing knowledgeN discovery in database applications supported by Index Structure (ELKI) in Data mining, RapidMiner tool in Java, and outlier package in R is available. ELKI is a data mining software developed using the Java programming language [5]. This is open-source technology preferably used in research for clustering and detecting outlier anomalies. RapidMiner is the most popular and comprehensive data science platform with full automation and visual workflow design. The outlier package in R performs a chi-squared test to detect an outlier in the vector.

Feedback received from the student is very useful in the process of evaluating faculty performance. To evaluate feedback with precision each criterion needs to be considered separately and need to assign different weights for each criterion. The traditional evaluation methods merely lack in assigning specific weights to individual criteria. In such situations, a fuzzy logic-based faculty performance analysis system is a suitable [18]. The fuzzy logic-based method can be used effectively to deal with uncertainty and ambiguity in given data. [10] used a fuzzy approach to measure faculty proficiency and competency. The proposed system is developed in MATLAB using a MATLAB fuzzy controller.

[14] proposed a data mining and machine learning-based system to predict faculty performance based on student feedback. The Cross Industry Standard Process for Data Mining (CRISP-DM) is used to perform predictive analysis. Decision tree-based iterative dichotomiser (ID) 3, and naïve Bayes algorithm are adapted to perform the classification. [16] proposed a hybrid method to evaluate teacher performance. The proposed method is implemented by combining CRISP-DM, decision tree, and fuzzy Logic to evaluate faculty performance. In the proposed work in addition to the fuzzy logic controller, the J48-generated IF-THEN rules are utilized to predict individual or institutional faculty performance [21] using predictive analytics software (PASW) Statistics 17.0 to organize the data, K means algorithm to categorize the data in different groups and a regression tree is generated to evaluate the faculty performance. The proposed regression tree-based method is used to perform recursive partitioning to divide training data into clusters with similar labels.

In the literature, handful of methods are available to detect the outliers [8, 31]. However, specifically to detect outliers in students' feedback to predict teaching faculty performance evaluation very few research attempts are made. Faculty performance analysis for an appraisal is an unexplored area. Only a few research attempts are made to evaluate faculty performance based on student feedback. Most of the attempts are based on a fuzzy logic-based system. To use machine learning-based models' an ample amount of data is a must [24]. No such student feedback data is available. To work on this niche area genuine attempt is made in this work.

3. Methodology

A detailed data-gathering process, a general idea of outlier detection, and a detailed explanation of how it is applied to remove outliers generated due to biased feedback in teaching staff performance are described in this section. In addition to this, the effective use of skewness to understand data distribution and selection of better central tendency to evaluate the performance of teaching faculty for the sake of appraisal is also explained in this section.

A. Data Collection:

Several techniques are available to gather the primary data. Some of them are interviews, questionnaires, surveys, observation, record reviews, and case studies [7].

In this proposed work, the questionnaire is used to collect feedback data from the students. The primary reason behind the consideration of a questionnaire as a data-gathering tool is it is possible to collect data in a huge amount at once. Geographic location also does not matter. The questionnaire is prepared by experts in the educational sector. The questionnaire contains twenty-one questions which are further categorized into five segments. These segments are the excellence of coaching, factors in learning, accountability, timekeeping, valuation of learning, mentoring, and counseling.

Table 1 :Category With Its Weights

Sr. No.	Category	Weight
1	Excellence of Coaching	350
2	Impact of teaching	50
3	Accountability and Timekeeping	250
4	Assessment criteria	150
5	Guidance and support	200
	Total	1000

Table I lists the above-mentioned categories of questions.

The questionnaire is of one thousand points. These points are further distributed per question as per the importance of each question. Point distribution per question is also done by consulting experts.

The detailed questionnaire is listed in Table II. Outstanding (1), appreciable (2), superior (3), normal (4), and not satisfied (5) are considered evaluation parameters. These weights are blind for the students during the data collection procedure.

To conduct the experiment, feedback was collected from seven different educational institutes belonging to Solapur and Satara District in Maharashtra. Table III enlists the institutes who have helped in the data collection process.

Table 2 : Weight Assignment to Each Subsection For Student Feedback Appraisal

	CHARACTERISTICS	Evaluation Parameter				
		1	**2**	**3**	**4**	**5**
1	**The excellence of Coaching**			**350**		
1.1	Time of explanation, demonstration	50	40	30	20	10
1.2	Relevance of demonstration & illustration	50	40	30	20	10
1.3	Inspiration to class participation	30	24	18	12	6
1.4	Teaching board usage	40	32	24	16	8
1.5	Usage of animation	40	32	24	16	8
1.6	Classroom engagement and activities	40	32	24	16	8
1.7	Generate curiosity in topic	50	40	30	20	10
1.8	Speech clarity	50	40	30	20	10
2	**Impact of teaching**				**50**	
2.1	Contribution in concept understanding	25	20	15	10	5
2.2	Topic clarity and definite outcome per session	25	20	15	10	5
3	**Accountability and Timekeeping**		**250**			
3.1	Time punctuality	50	40	30	20	10
3.2	Evaluation methods	60	48	36	24	12
3.3	Promoting Learners for extracurricular activities	70	56	42	28	14
3.4	Dedication and devotion	30	24	18	12	6
3.5	Organization of debate, seminar, exhibition	40	32	24	16	8
4	**Assessment criteria**			**150**		
4.1	Feedback on the assignment was useful	50	40	30	20	10
4.2	Problem sets assisted me in acquiring knowledge	50	40	30	20	10
4.3	Fairness in Evaluation	50	40	30	20	10
5	**Guidance and support**			**200**		
5.1	The outside approach of the faculty	50	40	30	20	10
5.2	Sympathetic nature of the faculty	70	56	42	28	14
5.3	Personal problem support & motivation	80	64	48	32	16
5.2	Sympathetic nature of the faculty	70	56	42	28	14
5.3	Personal problem support & motivation	80	64	48	32	16

Per institute randomly two teaching faculties were selected to collect the feedback. Table IV provides detailed information about the batch size and response received. The feedback is collected for fourteen faculties. In total six hundred forty-seven feedback was received from the students. This feedback is converted along with its associated weight as per Table II. The fifty-six samples of converted feedback data faculty 1 are tabulated in Table V. The column heading is sub-section numbers, and the row heading represents the unique number assigned to student participants. To carry out further research the dataset will be freely available upon request.

B. Outlier detection

The concept of outlier detection can be treated as anomaly detection. Generally, anomaly detection refers to the identification of infrequent items, observations, or facts present in the population. Such anomalies must be identified precisely and need to be removed to improve the accuracy of the result.

Outlier detection algorithms also exactly do the same and are extremely appreciated in several fields such as big data processing, fraud detection, fault diagnosis, detection of intrusion in network security,

Table 3 : Institute Information

Inst.No.	Institute name	Program
1	School of Computer Science, PAH Solapur University, Solapur	MSc CS
2	Dahiwadi Science College, Dahiwadi	BCA
3	Shriram Institute of Information Technology, Paniv	BSc CS
4	Sangola College, Sangola	BSc CS
5	Vidnyan Mahavidhyalaya, Sangola	BSc CS
6	Greenfingure college of Computer technology, Akluj	MCA
7	Karmveer Bhaurav Patil College, Pandharpur	BSc CS

Table 4 : Data Collection Statistics

Teacher No.	Received feedback	Batch Size	Sample collection (%)
1	56	60	93.33
2	52	60	86.67
3	44	60	73.33
4	49	60	81.67
5	45	60	75.00
6	52	60	86.67
7	48	60	80.00
8	44	60	73.33
9	28	30	93.33
10	30	30	100.00
11	51	60	85.00
12	36	40	90.00
13	57	60	95.00
14	55	60	91.67
Sample Collected	**647**	**760**	**85.13**

and pathological detection in medical science just to mention a few. Teaching staff performance analysis and appraisal computation is also no exception to this analogy.

To detect the outliers first total feedback marks is calculated. The total weight of feedback out of 1000 is enlisted in this list [917, 226, 961, 966, 927, 225, 967, 787, 875, 756, 653, 440, 823, 913, 968, 968, 668, 763, 931, 899, 819, 921, 480, 906, 731, 823, 919, 407, 543, 575, 727, 872, 887, 742, 528, 694, 935, 344, 952. 953, 876, 982, 968, 238, 258, 893, 808, 730, 807, 435, 774, 835, 957, 967, 960, and 228]. The total is collected from the last column of Table V (feedback of fifty-six students of MSc CS for Faculty I). For better understanding, the weights are visualized in Fig II. By confirming the scatter plot it is observed that the series contains three outlier samples 225, 226, 228, and 238.

These expected outliers need to verify using the scientific approach. To achieve this IQR-based outlier recognition and removal method is presented in this work. The developed method is well described in Algorithm I.

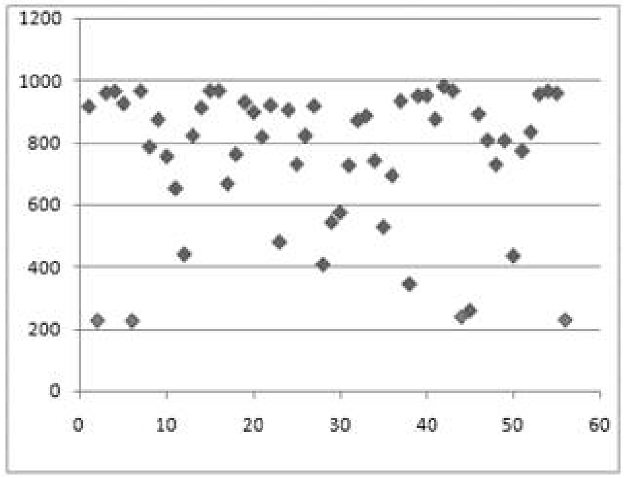


Fig 2 : Data representation using Scatter Graph

C. Computation of teacher performance indicator

To compute teaching faculty performance skewness-based method is developed. Skewness helps to predict the data distribution. Depending on the data distribution appropriate central tendency (mean or median) is added to compute the performance indicator of the teaching faculty. The skewness-based performance computation method is presented in Algorithm II.

4. Algorithm

This section facilitates a detailed explanation of a proposed algorithm to detect outliers and compute teacher performance appraisal.

The proposed algorithm OutlierDetection () (explained in Algorithm I) accepts student feedback data and initially arranges that data in a non-decreasing (ascending) order. Then the first of third quartile Q1 and Q3 are identified respectively, and the interquartile range is calculated by subtracting Q3 from Q1. Equation I and II are used to calculate the upper and lower limit respectively. At last, the sample points lesser than the identified lower limit and greater than the upper limit are identified and removed.

UpperBound:= Q3 + (1.5 * IQR) --------------------(I)

LowerBound:= Q1 - (1.5 * IQR) --------------------(II)

The algorithm PerformanceAppraisal () (explained in Algorithm II) computes the mean, median, mode, and skewness for each column. The skewness value is used to identify the data distribution and to compute the faculty performance indicator. If the skewness of a particular column is zero, then the value of the mean is added in the performance indicator else i.e. if skewness is non-zero then the median is added. At last overall performance of the faculty is calculated by equation III.

OverallPerformance:=(PerformanceIndicator/1000)* 100 --(III)

Algorithm I OutlierDetection()

Require: feedback dataset
Ensure: outlier points in the feedback dataset
1. Arrange the data in non-decreasing order.
2. Q1:= first quartile; Q3:= third quartile;
3. IQR:= Q3-Q1;
4. UpperBound (LB) := Q3 + (1.5 * IQR);
5. LowerBound (UB) := Q1 - (1.5 * IQR);
6. If (SampleValue < LB OR SampleValue >UB) then
   Outlier (sampleValue):=True;
else
   Outlier (sampleValue):=False;
7. Endif
8. Return modified dataset.

Algorithm I: Outlier detection algorithm

5. Results and Discussion

Algorithm outlierDetection () (explained in Algorithm I) is applied to student feedback data. The proposed algorithm returns the Boolean value. That is if the data point is within range, it returns true else returns false. The sample points with false values are treated as an outlier and removed before further processing.

Algorithm II performanceAppraisal ()

Require: feedback dataset
Ensure: PerformanceIndicator
1. Foreach column in dataset do
2. Calculate mean, median, mode skewness
3. If (skewness = 0) then
4. PerformanceIndicator:= PerformanceIndicator + mean;
Else
5. PerformanceIndicator:= PerformanceIndicator+ median;
6. Endif
7. End Foreach
8. OverallPerformance:= (PerformanceIndicator /Total Weight) *100
9. Return Performance;

Algorithm II: To compute performance appraisal

Table 6 :Boolean Result of Detecting An Outlier Variable

SN	Data	outlier	SN	Data	outlier	SN	Data	outlier	SN	Data	outlier
1	917	F	15	968	F	29	543	F	43	968	F
2	226	T	16	968	F	30	575	F	44	238	T
3	961	F	17	668	F	31	727	F	45	258	F
4	966	F	18	763	F	32	872	F	46	893	F
5	927	F	19	931	F	33	887	F	47	808	F
6	225	T	20	899	F	34	742	F	48	730	F
7	967	F	21	819	F	35	528	F	49	807	F
8	787	F	22	921	F	36	694	F	50	435	F
9	875	F	23	480	F	37	935	F	51	774	F
10	756	F	24	906	F	38	344	F	52	835	F
11	653	F	25	731	F	39	952	F	53	957	F
12	440	F	26	823	F	40	953	F	54	967	F
13	823	F	27	919	F	41	876	F	55	960	F
14	913	F	28	407	F	42	982	F	56	228	T

Table 7 : Comparative Analysis of Different Techniques

Teacherid	With Outlier				Without Outlier			
	Mean	Median	Mode	Skewness	Mean	Median	Mode	skewness
1	**75.19**	**78.30**	**94.20**	**78.30**	**78.17**	**78.80**	**94.20**	**78.8***
2	77.63	77.80	82.80	77.80	77.63	77.80	82.80	77.80
3	85.50	83.70	86.30	83.70	85.50	83.70	86.30	83.70
4	84.90	82.40	84.00	82.40	84.90	82.40	84.00	82.40
5	**83.94**	**81.30**	**84.60**	**81.30**	**86.00**	**86.10**	**86.10**	**86.1***
6	84.55	82.20	84.40	82.20	84.55	82.20	84.40	82.20
7	72.70	68.15	72.80	68.15	72.70	68.15	72.80	68.15
8	80.43	77.50	72.90	77.50	80.43	77.50	72.90	77.50
9	77.10	75.00	74.70	75.00	77.10	75.00	74.70	75.00
10	**80.86**	**88.20**	**94.20**	**88.20**	**90.09**	**94.20**	**94.20**	**94.2***
11	85.32	86.60	94.40	86.40	85.32	86.60	94.40	86.60
12	88.08	90.60	92.00	90.60	88.08	90.60	92.00	90.60
13	89.37	90.00	92.00	90.00	89.37	90.00	92.00	90.00
14	**79.82**	**85.40**	**93.00**	**85.40**	**82.76**	**87.80**	**93.00**	**87.8***

Table VI tabulates the results of the proposed algorithm on input data.

Cleaned data is passed to Algorithm II to understand data distribution via skewness and calculate the faculty performance indicator. Table VII tabulates the comparative analysis based on values of mean, median, mode, and skewness per faculty. By comparing results outliers adversely impact results. Rows 1, 5, 10, and 14 show a significant difference between values. There is an improvement in the values of mean, median, mode, and skewness after removing outliers.

Table VIII tabulates the faculty performance indicator with and without detecting outliers. It found outliers impact a lot of performance indicators and there is a significant improvement in the performance indicator after removing the outlier sample from the data.

Table 8 : Comparative Result With and Without Outlier Samples

Sr. No.	Attribute	Overall Performance			Weight Assigned to individual section
		mean	median	mode	
1	Excellence of Coaching	269	240	292	350
2	Factors in Learning	39.81	40	50	50
3	Accountability & Timekeeping	202.09	228	250	250
4	Valuation of Learning	118.87	120	150	150
5	Mentoring & Counseling	151.9	160	200	200
	Total	781.7	788	942	1000
	Without outlier sample (%)	78.17	78.8	94.2	
	With Outlier Sample (%)	75.19	78.3	94.2	

6. Conclusion

The feedback received from the student plays a dynamic role in the student development process, achievement of learning outcomes, and to evaluate the teaching faculty performance for appraisal. However, students may give biased feedback. This may lead to the existence of outliers in the data, which interns negatively affects faculty performance. To avoid this, an inter-quartile range-based outlier detection technique is implemented. The proposed technique identifies and removes outlier samples effectively. The further skewness-based method is used to understand underlying data distribution and to consider the appropriate central tendency to compute faculty performance indicators. By confirming the results outliers negatively affect the faculty performance and the proposed IQR-based outlier detection method works well. In the near future, we aim to implement fuzzy logic and machine learning-based methods to compute faculty performance. In addition to this, we aim to perform a comparative analysis, of the long-term impact of the assessment via the proposed method, bias detection and mitigation in anomaly detection, automation, and scalability, as well as the integration of multiple data sources to advance the field of teaching and learning process improvement in education.

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