Detecting Outliers in High Dimensional Data Sets Using Z-Score Methodology

PeruriVenkataAnusha, Ch.Anuradha, Patnala S.R. Chandra Murty, Ch. Surya Kiran

Abstract*: Outlier detection is an interesting research area in machine learning. With the recently emergent tools and varied applications, the attention of outlier recognition is growing significantly. Recently, a significant number of outlier detection approaches have been observed and effectively applied in a wide range of fields, comprising medical health, credit card fraud and intrusion detection. They can be utilized for conservative data analysis. However, Outlier recognition aims to discover sequence in data that do not conform to estimated performance. In this paper, we presented a statistical approach called Z-score method for outlier recognition in high-dimensional data. Z-scores is a novel method for deciding distant data based on data positions on charts. The projected method is computationally fast and robust to outliers' recognition. A comparative Analysis with extant methods is implemented with high dimensional datasets. Exploratory outcomes determines an enhanced accomplishment, efficiency and effectiveness of our projected methods.

Keywords: Outliers, Ionosphere, Z-score Method, Clusters, High Dimensional Data.

I. INTRODUCTION

An outlier is designated as a data point that is very different from the respite of the data based on certain estimation. Such an attribute frequently hold beneficial information on anomalous functioning of the structure defined by the data. Anomaly detection is a significant analysis in data mining that derives the items that are extensively different, incomparable and unpredictable with respect to the large data in an input databank. In current years, we have observed an incredible study concern sparked by the eruption of data composed and transmitted in the form of streams. This constitute new prospects as well as difficult tasks for research exertions in outlier recognition.

Outlier detection shows an extreme part in many areas, such as, pattern classification grouping, and decision-making, due to the fact that it can disclose rare but essential circumstance, and find interesting /unpredicted data items. At present, anomaly recognition one of the essential challenge in data mining, and has variety of practical application areas like Intrusion Detection, Medical and Public Health, Mobile phone Fraud Recognition, Fraud Detection, Credit Card fraud Recognition, Insurance, Trading, Structural Defect Detection, Fault Detection in Mechanical Units, Industrial Damage Detection, Text data detection, Image Processing etc. In this paper, we presented a statistical approach called Z-score method for outlier detection in high-dimensional data using. Z-scores is a novel method for estimating distant data based on data positions on charts. The projected method is computationally fast and robust to outliers' recognition.

The organization of this article is as follows: Segment 2 covers earlier research in outlier recognition. In Segment 3, we present our outlier detection methodology. Segment 4 covers our experimental results, followed by our summary in Segment 5.

II. RELATED WORK

Various techniques have been projected in current centuries for anomaly, but in order to handle anomalies in high dimensional data, they are not particularly considered as novel approaches. There are numerous works that are stated from the literature survey. All those works are broadly considered as: Clustering and Density-based, Statistical/Model-based, Distance-based methodologies and other methodologies for mixed-type attribute and categorical data. The subsequent segment gives a concise interpretation on outlier detection.

Angiulli et al. [8] estimate k-NN samples using a Hilbert Space Filling Curve, Moreover this technique needs correctly p+1 (where p is the dataset length) scans out of 39 datasets, also this procedure is restriction for high-dimensional and distributed dataset. This method is applied effectively to density-based approaches with some restrictions. The dataset utilized in approach contains mixed attribute that cover anomalies, Distance-based techniques fail to estimate anomalies based on global anomaly criterion. In Knorr et al. [10] work, projected a k-NN method, within the specified length, p nearest neighbors are considered as not an anomaly points. In the next article, if the data point is considered as anomaly if it is p% far from the specified length. Projected approaches increases the complexity exploration and practically it is difficult to applying for large datasets.

J. Branch et al. [6] projected an anomaly recognition technique using the concept of Entropy estimate. The entropy cut-off for each entity is estimated based on the disruption of rest of data entities. The author utilized k-scans dataset to estimate k-anomalies. Projected procedure is secure contrast to Local Search Algorithm (LSA). Automatic detection of optimal no of anomalies is not possible with this approach. Branch interested this article to originate BAD score procedure. Koufakou et al. [9] projected Attribute Value Frequency (AVF). AVF cut-off for every record is estimated through

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single scan of entire dataset and it is easiest task also. The accurateness and complexity exploration is good in contrast with other systems and also it generates many problems. This article is base for many investigation works. Latecki et al. [3] projected and estimated strong local density circumstance using nonparametric anomaly recognition method with movable kernel. Projected article is a shade improved contrast to the procedures LOF and LOCI that are derived based on local anomaly circumstance. This approach is better contrast to existing approaches but is not be virtuous for large datasets of more no of archives and elements.

Timothy de Vries et al. [2] projected an innovative methodology called Projection Indexed Nearest Neighbors (PINN) and calculating the extended nearest neighbor sets to get precise value in KNN distances. They enhanced the Local Outlier Factor (LOF). Though this method is derivative for discovering local anomalies in image database, it can also be utilized for our categorical dataset. This method is applied huge datasets with less no of dimensional. Acuna et al [4] equated the distinct anomaly methods with data mining approaches statistical based method, and clustering techniques. Due to removing of anomalies in some circumstances that leads to a mislaying of data. Particularly in data classification scenario, elimination of necessary data leads to major anomalies problems.

III. Z-SCORE METHODOLOGY FOR OUTLIER DETECTION

The Z-score method is a system of representing abnormal behavior items in terms of its association with the standard deviation and mean of a collection of arguments. Estimating the Z-score is just plotting the items into a scattering diagram, standard deviation and mean is indicating as 0 and 1. The objective of estimating Z-scores is to eliminate the properties of the position and scale of the data points, permitting dissimilar datasets to be associated exactly. The principle used by Z-score technique for anomaly recognition is that, after plotting the data items in the scattering diagram, the items those are far from the value zero is considered as anomaly. The process of detecting anomalies can be stated in the subsequent code:

```
def outliers_Z_value (xs):
      cut-off value = 3
      mean_x = np.mean (xs)
      sdev_x = np.std (xs)
     z_score = [(x-mean_x) / sdev_x for x in xs
 return mv.where (mv.xys (z_value)>cut-off value
```

The following step by step procedure shows detection of outliers in high dimensional datasets using z-score method:

Step 1: Null Hypothesis: There is no significance discrepancy between the standard deviation and mean of data items.

$$H_0: \mu_1 = \mu_2$$

Step 2: Alternative Hypothesis: There is significance discrepancy between the standard deviation and mean of data items.

$$H_1: \mu_1 \neq \mu_2$$

Step 3: Level of significance: The level of significance is denoted with

$$\alpha = 0.001 \text{ (or) } \alpha = 0.005$$

Step 4: Test Statistics: The test statistics for outlier detection is given by

$$Z = \frac{x-\mu}{\sigma\sqrt{(\frac{1}{n})}}$$

Step 5: Critical Region: At position, we are determining whether data points are outliers are or nor as revealed in figure1:

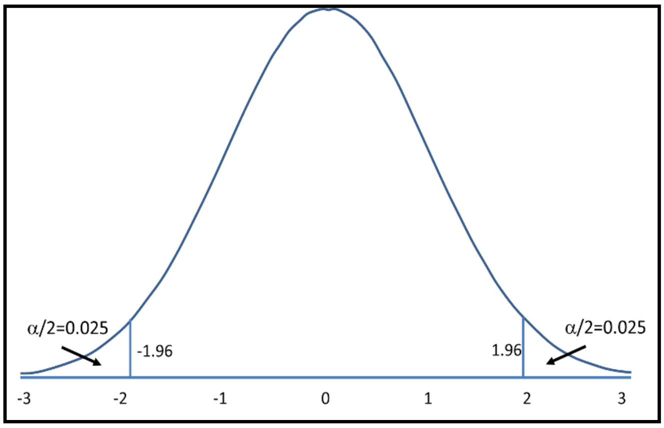

Figure 1: Critical Region

In this process we compute the z-score for each reflection (fix this). If the estimated z-score is > 3 or < -3 is considered an anomaly. From practical rule, all of the data i.e 99.7% should be within 3σs from the mean. By computing the z-score, observations are arranged in proper order, now the value of standard deviation is one. Thus from the practical rule we expect 99.7% of the estimated z-scores within -3 and 3. Table 1 shows calculation and covering problem of the Z-Score technique using sample dataset.

Table 1: Calculation and covering problem of the Z-Score method

Sequence	Case 1 μ =4.46, σ =2.95		Case 2 μ =3.79, σ = 1.92	
	x_i	Z-score	x_i	Z-score
A.	3.1	-0.47	2.9	-0.46
B.	3.3	-0.42	3.2	-0.41
C.	3.6	-0.39	3.8	-0.37
D.	3.6	-0.38	3.4	-0.33
E.	3.7	-0.39	3.5	-0.31
F.	3.8	-0.35	3.7	-0.27
G.	3	-0.36	3	-0.16
H.	3	-0.34	3	-0.17
I.	3.9	-0.31	3.7	-0.20
J.	4.0	-0.34	3.9	-0.15
K.	4.5	-0.19	4.2	-0.03
L.	4.7	-0.15	4.3	0.01
M.	13	**2.96**	13	**2.90**
N.	14	**2.31**	---	-----

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For case 1, with all of the sample data comprised, it seems that the values 13 and 14 are outliers, yet no observation outstrips the unconditional data of 3. For case 2, with the most risky data, 14, among example data omitted, 13 is measured an outlier. This is because multiple risky values have preciously overestimated standard deviations.

IV. EMPIRICAL RESULTS

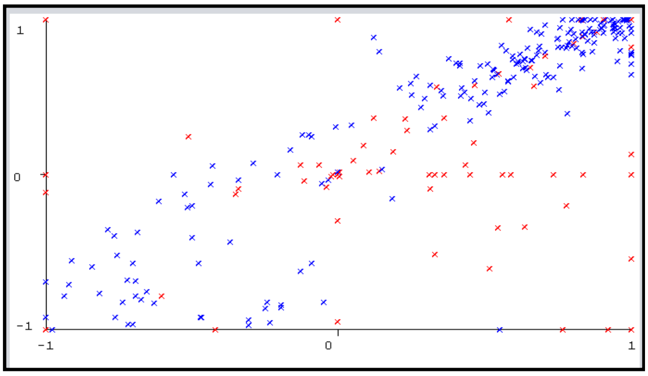
In the outlier detection experimentations, the Ionosphere data set is used to testify the enactment of projected method.

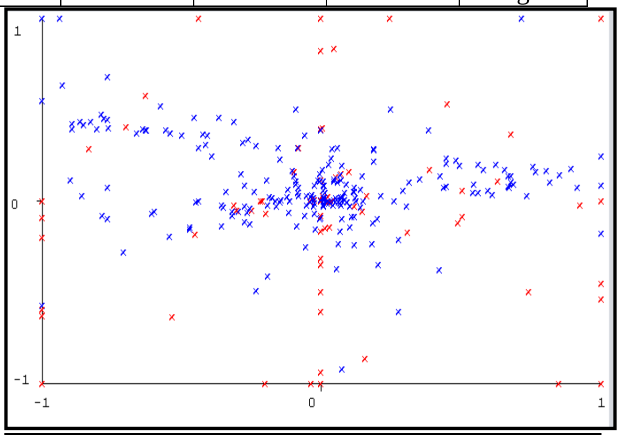
The dataset is accessible from 3 sources shown as follows: UCI Repository, ELKI Datasets and KEEL Datasets. It is a binary classifying databank with dimensionality 34. At particular point, having values all 0s, that is rejected. The total quantity of measurements are 33. The 'good' class is marked as' inliers and the 'bad' class as outliers. Sample Ionosphere dataset for Outlier Detection Using Z-score method is shown in table 2:

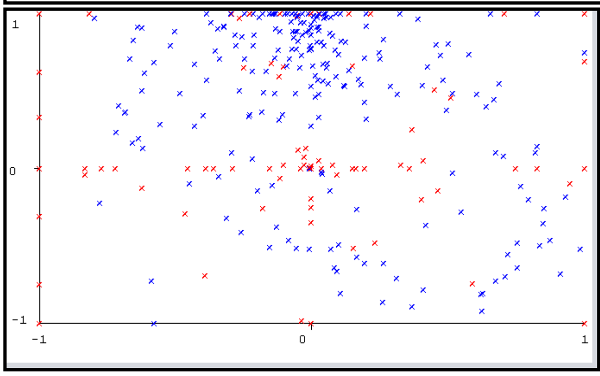
Table 2: Sample Ionosphere dataset for Outlier Detection Using Z-Score method

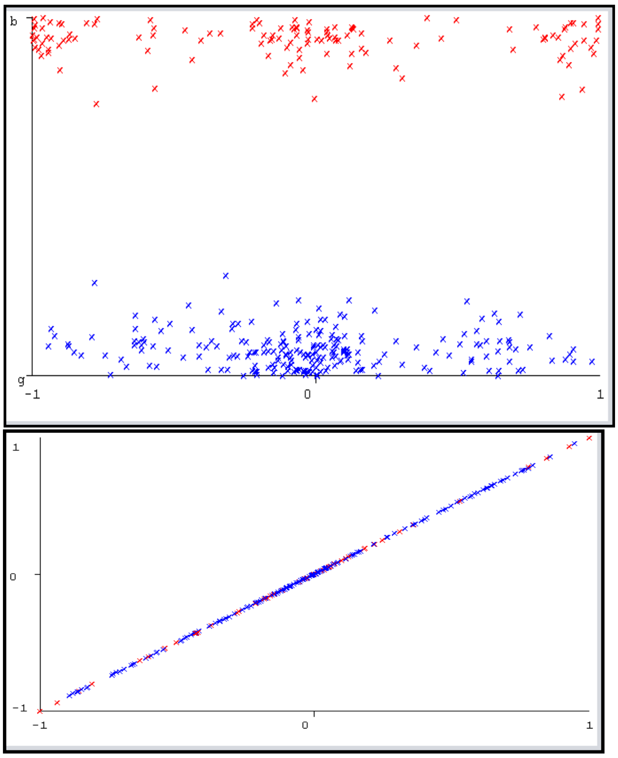
Pul1	Pul2	Pul3	Pul4	Pul5	Pul6	Pul7	Pul8	Pul9	class
1	0	0.99539	-0.05889	0.85243	0.02306	0.83398	-0.37708	1	g
1	0	1	-0.18829	0.93035	-0.36156	-0.10868	-0.93597	1	b
1	0	1	-0.03365	1	0.00485	1	-0.12062	0.88965	g
1	0	1	-0.45161	1	1	0.71216	-1	0	b
1	0	1	-0.02401	0.9414	0.06531	0.92106	-0.23255	0.77152	g
1	0	0.02337	-0.00592	-0.09924	-0.11949	-0.00763	-0.11824	0.14706	b
1	0	0.97588	-0.10602	0.94601	-0.208	0.92806	-0.2835	0.85996	g
0	0	0	0	0	0	1	-1	0	b
1	0	0.96355	-0.07198	1	-0.14333	1	-0.21313	1	g
1	0	-0.01864	-0.08459	0	0	0	0	0.1147	b
1	0	1	0.06655	1	-0.18388	1	-0.2732	1	g
1	0	1	-0.5421	1	-1	1	-1	1	b
1	0	1	-0.16316	1	-0.10169	0.99999	-0.15197	1	g
1	0	1	-0.86701	1	0.2228	0.85492	-0.39896	1	b
1	0	1	0.0738	1	0.0342	1	-0.05563	1	g

Moreover, we have made an experimentation on public datasets to estimate the standard outlier detection approaches. In this experimentations, we deliberated the data handling and distinct estimation procedures for outlier recognition process. Similarly, We equated the performance of distinct procedures on a large variation of datasets by considering the utmost frequently utilized dimension into interpretation, and providing a viewpoint analysis on the efficiency of these distinctive outlier recognition approaches. Finally, we deliberated the problems and forthcoming of outlier recognition approaches for the high-dimensional data. The Implementation of Z-score method using Ionosphere dataset is shown in the following figure 2 and Lost values totally substituted with mode / mean is shown in board 3.









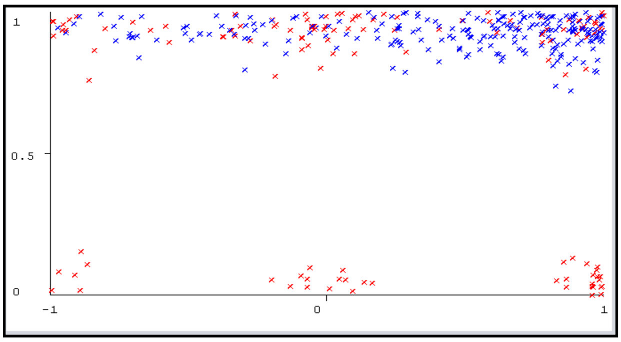


Figure 2: The experimental results on Ionosphere data set using Z-score Method.

Table 3: Missing values globally replaced with mean/mode

Attribute	Full Data	Cluster 0	Cluster1	Attribute	Full Data	Cluster 0	Cluster 1
Pul1	0.8917	0.9588	0.8089	**Pul18**	-0.0036	0.0008	-0.0091
Pul2	0	0	0	**Pul19**	0.3594	0.7517	-0.1254
Pul3	0.6413	0.8303	0.4079	**Pul20**	-0.024	-0.0005	-0.0531
Pul4	0.0444	-0.0266	0.132	**Pul21**	0.3367	0.7524	-0.177
Pul5	0.6011	0.8603	0.2807	**Pul22**	0.0083	0.0773	-0.077
Pul6	0.1159	0.0369	0.2135	**Pul23**	0.3625	0.7259	-0.0866
Pul7	0.5501	0.8348	0.1982	**Pul24**	-0.0574	-0.023	-0.0999
Pul8	0.1194	-0.0159	0.2865	**Pul25**	0.3961	0.695	0.0268
Pul9	0.5118	0.8118	0.1412	**Pul26**	-0.0712	-0.0133	-0.1427
Pulse 10	0.1813	0.0272	0.3718	**Pulse 27**	0.5416	0.7158	0.3265
Pulse 11	0.4762	0.8196	0.0518	**Pulse 28**	-0.0695	0.017	-0.1764
Pulse 12	0.155	0.0493	0.2857	**Pulse 29**	0.3784	0.6552	0.0365
Pulse 13	0.4008	0.8195	-0.1166	**Pulse 30**	-0.0279	0.0095	-0.0741
Pulse 14	0.0934	0.0229	0.1805	**Pulse 31**	0.3525	0.6419	-0.0051

Pulse 15	0.3442	0.8171	-0.2402		**Pulse 32**	-0.0038	0.0126	-0.024
Pulse 16	0.0711	0.0142	0.1414		**Pulse 33**	0.3494	0.6234	0.0108
Pulse 17	0.3819	0.7792	-0.1089		**Pulse 34**	0.0145	-0.0121	0.0473

A huge number of outlier recognition techniques providing in literature. The conventional outlier recognition methods can be usually clustered into subsequent classes: clustering-based approaches, distance-based approaches statistical based approaches, density-based approaches, Linear Regression techniques, High Dimensional approaches and Z-Score methods. The Implementations of these outlier recognition approaches are enumerated in Table 4.

Table 4: Comparative Study on Outlier Detection Techniques

Applications	Statistical Methods	Distance Methods	Density Methods	Clustering Methods	Linear Regression Methods	High Dim Methods	Z-Score method
Quality control	YES	YES	YES	YES	YES	YES	YES
Web log analytics		YES		YES	YES	YES	YES
Intrusion detection	YES	YES	YES	YES	YES	YES	YES
Text and social media	YES			YES			YES
Earth science		YES		YES		YES	YES
Medical Health	YES	YES	YES	YES	YES	YES	YES
Image Processing	YES	YES	YES	YES	YES	YES	YES
Financial System	YES		YES	YES		YES	YES
Fraud Detection	YES	YES	YES				YES
Sensor Networks		YES	YES		YES		YES

In the above Comparison table, the Z-score method is applied to a wide variation of real-world applications including, Medical and Public Health, Intrusion Detection, Credit Card fraud Recognition Fraud Detection, etc.

V. CONCLUSION

Outlier recognition is an interesting research area in machine learning. With the recently emergent tools and varied applications, the attention of outlier recognition is growing significantly. Currently, a significant no of outlier detection procedures have been observed and effectively applied in a wide range of arenas, comprising medical health, credit card fraud and intrusion detection. They can be utilized for conservative data analysis. However, Outlier recognition drives to find sequences in data that do not conform to estimate performance. In this paper, we presented a statistical approach called Z-score method for outlier recognition in high-dimensional data. Z-scores is a novel method for deciding distant data based on data positions on charts. The projected method is computationally fast and robust to outliers' recognition. A comparative analysis with extant procedures is implemented with high dimensional datasets. Exploratory outcomes determine an enhanced accomplishment, efficiency and effectiveness of our projected methods.

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