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A Review on Detection of Outliers Over High Dimensional Streaming Data Using Cluster Based Hybrid Approach

Abhishek B. Mankar[1], Namrata Ghuse[2]

[1]ME (CSE) Scholar, Department of CSE, P.R. Pote (Patil) College of Engg. & Management, Amravati-444605, India

[2]Assistant Professor, Department of CSE, P.R. Pote (Patil) College of Engg. & Management, Amravati-444605, India

Abstract: ***Finding Outlier detection in data streams has gained broad importance presently due to the increasing cases of fraud in various applications of data streams, data cleaning, network monitoring, invasive species monitoring, stock market analysis, detecting outlying cases inmedical data etc. Finding outliers in a collection of patterns is a very well-known problem in the data mining field. An outlier is a pattern which is dissimilar with respect to the rest of the patterns in the dataset. Proposed Method for outlier detection uses hybrid approach. Purpose of approach is first to apply clustering algorithm that is k-means which partition the dataset into number of clusters and then find outliers from the each resulting clusters using distance based method. The principle of outliers finding depend on the threshold. Threshold is set by user. The main objective of the second stage is a finding out the objects, which are far away from their cluster centroids. In proposed approach, two techniques are combining to efficiently find the outlier from the data set. The experimental results using real dataset demonstrate that proposed method takes less computational cost and performs better than the distance based method. Proposed algorithm efficiently prunes of the safe cells (inliers) and save huge number of extra calculations.***

Keywords: Outlier, Inliers, Cluster-based, Distance-based

1. Introduction

Data mining is a process of extracting hidden and useful information from the data and the knowledge discovered by data mining is previously unknown, potentially useful, and valid and of high quality. Data mining, in general, deals with the discovery of non-trivial, hidden and interesting knowledge from different types of data with the development of information technologies. Finding outliers is an important task in data mining. Outlier detection as a branch of data mining has many important applications and deserves more attention from data mining community. In recent years, conventional database querying methods are inadequate to extract useful information, and hence researches nowadays are focused to develop new techniques to meet the raised requirements. It is to be noted that the increase in dimensionality of data gives rise to a number of new computational challenges not only due to the increase in number of data objects but also due to the increase in number of attributes.

Outlier detection is an important research problem that aims to find objects that are considerably dissimilar, exceptional and inconsistent in the database. Medical application is a high dimensional domain hence determining outliers is found to be very tedious due to the Curse of dimensionality. There are various origins of outliers. With the growth of the medical dataset day by day, the process of determining outliers becomes more complex and tedious. Efficient detection of outliers reduces the risk of making poor decisions based on erroneous data, and aids in identifying, preventing, and repairing the effects of malicious or faulty behavior. Additionally, many data mining and machine learning algorithms and techniques for statistical analysis may not work well in the presence of outliers. Outliers may introduce skew or complexity into models of the data, making it difficult, if not impossible, to fit an accurate model to the data in a computationally feasible manner. For example, statistical

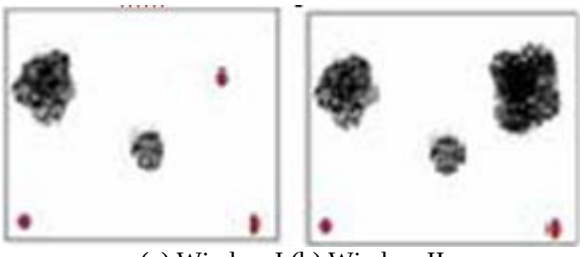
Measures of the data may be skewed because of erroneous values, or the noise of the outliers may obscure the truly valuable information residing in the data set. Accurate and efficient removal of outliers may greatly enhance the performance of statistical and data mining algorithms and techniques [1]. Detecting and eliminating such outliers as a pre-processing step for other techniques is known as data cleaning. As can be seen, different domains have different reasons for discovering outliers: They may be noise that we want to remove.

The increasing applications of data streams in the fields of fraud detection, network flow monitoring and data communications, has led to an increasing demand for data stream mining. Anomaly detection deals with the detection of data elements that are different from all the other elements in the data set. Traditional methods for anomaly detection dealt with data sets that were static and the data could be accessed a number of times so these methods cannot give efficient results for the analysis of data streams. Detecting outliers has important applications in data cleaning as well as in the mining of abnormal points for fraud detection, stock market analysis, intrusion detection, marketing, network sensors. Finding anomalous points among the data points is the basic idea to find out an outlier. Distance based techniques use the distance function for relating each pair of objects of the data set. Distance based definition (these definitions are computationally efficient) [1, 2] represent a useful tool for data analysis [3]. Outlier detection deals with detecting data elements from a data set which is different from all the other data elements in a set. Anomalies can arise due to different reasons such as mechanical faults, other

changes in the system, fraudulent behaviour, instrument error, human error or natural deviation. Usually anomalous observations are more interesting and need excess examination. It is not easy to define exactly what is an anomaly or an outlier. Traditional methods for outlier detection can produce good results on stored static dataset. Traditional data mining methods cannot be applied to streaming data efficiently as these methods are suitable for the environment where the entire dataset is already available and algorithm can operate in more than one pass. A general framework for mining data streams need small constant time per record along with the minimum memory requirement, using at most one scan of data. As the nature of data stream is unbounded the problem of mining outlier in data streams is often performed based on certain times intervals, usually called windows. In brief, to avoid pair wise distance calculations, to detect better outlier even if the evolution of data stream change, to let user free to provide sensitive parameters, and to mine high dimensional data stream even in limited memory resources.

2. Literature Survey

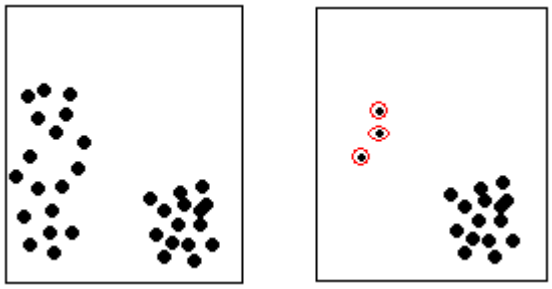
Anomaly detection deals with detecting data elements from a data set which is different from all the other data elements in a set. Anomalies can arise due to different reasons such as mechanical faults, other changes in the system, fraudulent behavior, instrument error, human error or natural deviation. Traditional methods for outlier detection can produce good results on stored static dataset. Traditional data mining methods cannot be applied to streaming data efficiently as these methods are suitable for the environment where the entire dataset is already available and algorithm can operate in more than one pass. The evolution of data streams led to the change in the characteristics of the data streams like dimensionality, object features so a point which is an outlier in one phase may become an inlier in the next phase. The evolution of data streams led to the change in the characteristics of the data streams like dimensionality, object features so a point which is an outlier in one phase may become an inlier in the next phase.



(a) Window I (b) Window II
Figure 1: Evolution of data stream from (a) to (b)

Fig.1. shows two windows. three points appearing as temporal outliers in WINDOW I are left with only two outliers in WINDOW II, due to dynamics of the data streams. One of the outliers in Window I, has a dense region around it in Window II making it an inlier.

Object properties can change over time hence, evaluating an object for outlierness when it arrives, although meaningful, often can lead us to a wrong decision, because of dynamic nature of the data stream. With the help of following example we will point out the problem in most of existing methods for data stream. Two diagrams shown in Figure 2 which shows the evolution of data stream.



(b) 2nd Window (a) 1st Window
Figure 2: Outliler Detection Over Data Stream

We will refer to these two diagrams as 1st window and 2nd window. During the processing of 1st window three points are outliers. Most of the existing methods detect these points as outlier just by considering the current window at the time. But as in data stream the data distribution may change as the stream evolves. Points which are declared as outliers at the time of 1st window, may belongs to a dense region with the evolution of 2nd window. So here we can see that three outliers detected in 1st window actually belong to a dense region with the evolution of 2nd window.

There is a lot of literature on the outlier detection problem which describes a variety of approaches like, Distance-Based outlier Detection is proposed by Knorr and Ng [5]. Given parameters k and R, an object is a distance-based outlier if less than k objects in the input data set lie within distance R from it. Further extended by Ramaswamy et al in [6] having idea, in order to rank the outliers, introduced the following definition: given k and n, an object o is an outlier if no more than n-1 other objects in the dataset have higher value for Dk than o, where Dk(o) denotes the distance of the *kth*nearest neighbour of o. This concept is future extended in [7]-[8]-[9] where each data point is ranked by the sum of distances from its k nearest neighbours. Distance based outliers are not suitable if the clusters have different densities so to overcome the shortcoming of distance based outliers Breunig et al proposed a concept of LOF [10] which are the objects outlying relative to their local neighborhoods, with respect to densities of the neighbor-hood. This concept is useful but to compute the LOF value large number of k-nearest neighbor searches makes it computationally expensive. On the bases of observing density distribution from the data, Aggarwal and YU proposed a technique for outlier detection. The basic idea in their definition is, a point is an outlier, if in some lower dimensional projection it is present in a local region of abnormally low density. This method is also an efficient method for high dimensional data set. Some Clustering-Based outlier detection techniques are proposed [12]-[13]. This technique work in two basic steps, fixed width clustering with w(radius) and after the first phase the next step is sorting of clusters produced in the first step. Points in the smaller clusters are declared as outliers. Clustering-Based techniques are further extended by proposing the concept of cluster based local outlier, in which a measure for identifying the outlierness of each data object is defined. A deviation based technique for outlier detection where a point is considered an outlier if its features deviates

from the features of other data points. For finding outliers in high dimensional data Deviation-based techniques identify outliers by inspecting the characteristics of objects and consider an object that deviates these features, declared as an outlier [14].

The replicator neutral network (RNN) based technique is introduced to detect outliers by Harkins, et al. [15]. Although there is lot of research on outlier detection, but there is little research in the direction of outlier detection in dynamic data streams. This area still needs lot of attention because the existing methods are not appropriate in the stream environment. There is an abundant literature addressing Data Streams, but their main focus is to solve the problem of clustering [13]-[10], query processing [14], frequent pattern mining [15]-[16] but they also didn't address the problem of anomaly detection in Data Streams. Clustering techniques are categorized into several different methods: partitioning, hierarchical [17], a pair of initial clusters are successively merged until the predefined number of clusters is left. The density-based DBSCAN [18] and CLIQUE [19] regards a cluster as a region in a data space with the proper density of data elements. Clustering on a data stream is categorized by k means/k-median and grid based methods. In order to identify the clusters of objects occurring in a data stream, a k-median algorithm is proposed. It regards a data stream as a sequence of stream chunks. In the grid-based method, the data space of the feature is partitioned into a set of mutually exclusive equal-size initial cells. As a new user activity is performed continuously, each initial cell monitors the distribution statistics of its corresponding feature values within its range. Eventually, a dense region of each initial cell is recursively partitioned until it becomes the smallest cell called a unit cell.

3. Outlier Detection Approaches

3.1 Outlier Detection

Outlier detection is a primary step in many data-mining applications. It refers to the problem of finding patterns in data that do not conform to expected normal behaviour or anomalous behaviour. These anomalous patterns are often referred to as outliers, anomalies, discordant observations, exceptions, faults, defects, aberrations, noise, errors, damage, surprise, novelty, peculiarities or contaminants in different application domains.

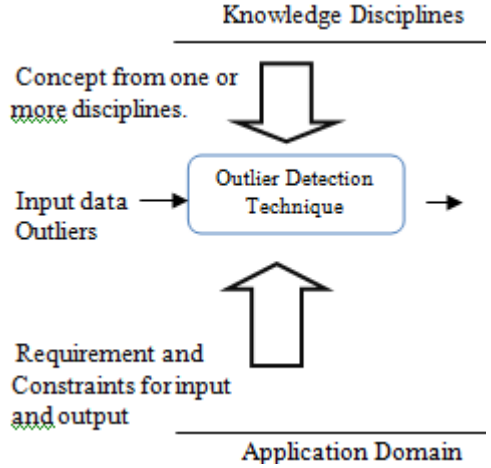


Figure 3: A general design of an outlier detection technique

As illustrated in Figure 1, any outlier detection technique has following 0major ingredients;

1) Nature of data, nature of outliers, and other constraints and assumptions that collectively constitute the problem formulation.
2) Application domain in which the technique is applied. Some of the techniques are developed in a more generic fashion others directly target a particular application domain.
3) The concept and ideas used from one or more knowledge disciplines.

Outlier detection has been a widely researched problem and finds immense use in a wide variety of application such as web logs, fraud detection, web click streams, network intrusion detection. Depending on the approaches used in outlier detection, the methodologies can be broadly classified into following major categories.

3.2 Classical Outlier Detection Approaches

Classic outlier approach detects outlier based on numeric or symbolic dataset, where dataset is collection of data elements with parametric value. Data elements present within dataset are having additional items describe dataset entity or context of the entity. Detecting Outlier over such dataset is simple relatively with other dataset.

3.2.1 Statistical Outlier Detection

The statistical outlier detection techniques are essentially *model-based* techniques and these techniques are generally suited to quantitative real-valued data sets or quantitative ordinal data distributions. A data instance is declared as an outlier if the probability of the data instance to be generated by this model is very low. The statistical-based approaches are categorized into parametric and non-parametric based on how the probability distribution model is built. Statistical parametric methods either assume a known underlying distribution of the observations at least; they are based on statistical estimates of unknown distribution parameters [23]-[24].

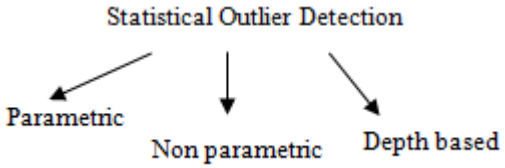


Figure 4: Classification of statistical outlier detection techniques.

The second category for outlier mining in statistics is depth-based. In the definition of depth, data objects are organized in convex hull layers in the data space according to peeling depth, and outliers are expected to be detected from data objects with shallow depth values. As the dimensionality increases, the data points are spread through a larger volume and become less dense. This makes the convex hull harder to discern and is known as the "*Curse of Dimensionality*".

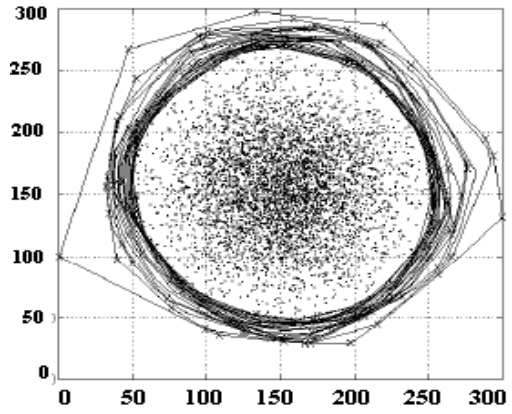


Figure 4: data objects in convex hull layer. [25]

3.2.2 Distance-Based Outlier Detection

Currently, so-called distance-based methods or outlier detection, as typical *non-parametric* methods identify outliers based on the measure of full dimensional distance between a point and its nearest neighbour in the data set.

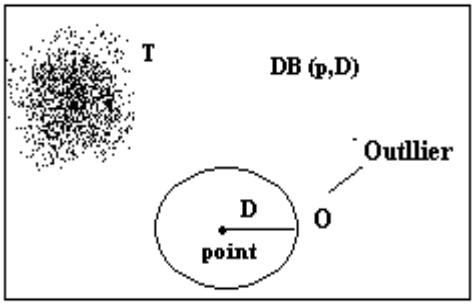


Figure 5: Basic model of distance based method.

The distance-based outlier method was presented in [4], where the definition of outlier becomes: "An object O in a dataset T is a DB (p,D)-outlier if at least fraction p of the objects in T lies at a distance greater than D from O". The parameter *p* is the minimum fraction of objects that must lie outside an outlier's D neighbourhood. Thus the algorithm is further extended based on the distance of a point from its k the nearest neighbour [3]. After ranking points by the distance to its k the nearest neighbour, the top k points are identified as outliers. Alternatively, in the algorithm proposed by Angiulli and Pizzuti [26], the outlier factor of each data point is computed as the sum of distances from its k nearest neighbours. A method for discovering outliers in near linear time has been presented in that randomize the data set for efficient pruning of the search space. Some recent work proposed by Branch et al uses a non-parametric, unsupervised method to detect outliers [27].

3.2.3Deviation Based Outlier Detection

Deviation based approach is used where dataset is having sparsely metric representation. Deviants are outliers defined based on a representation of sparsely metric. The sequential problem approach to deviation-based outlier detection was introduced in Arning et al [5]. These techniques identify outliers by inspecting the characteristics of objects and consider an object as an outlier if the object deviates from these features. Jagadish et al [28] gave the histogram based methods to deal with deviants in time series databases but this method does not fit into data stream scenario. Mining deviants in data stream but the problem of finding an optimal algorithm for deviants in multivariate case was still left open.

3.2.4 Density based Outlier Detection.

Density based outlier detection estimate density distribution of a data point within data set and compares the density around a point with the density around its local neighbour. The relative density of a point compared to its neighbours is computed as an outlier score and points which are having a low density is considered as an outlier.

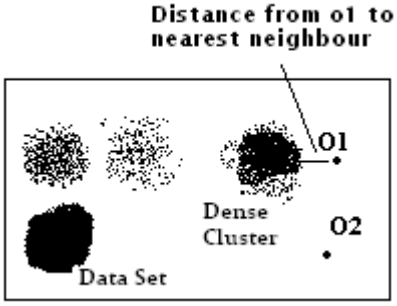


Figure 5: Data set and dense cluster with outliers.

Breunig et al. [29] originally introduce the notion of density-based local outliers based on the density in the local neighbourhood. Each data point is assigned a local outlier factor (LOF) value, which is calculated by the ratio of the local density of this point and the local density of its nearest neighbours. Points that have the largest LOF values are considered as outliers. The LOCI (Local Correlation Integral) method was proposed by Papadimitriouet al [30] which detects outliers based on the metric Multi Granularity Deviation Factor (MDEF) which is a measure of how the neighbourhood count of a particular data element compares with that of the values in its sampling neighbourhood.

3.2.5Clustering Based Outlier Detection.

Cluster analysis is popular unsupervised techniques to group similar data instances into clusters. The clustering based techniques involve a clustering step which partitions the data into groups which contain similar objects. The assumed behaviour of outliers is that they either do not belong to any cluster, or belong to very small clusters, or are forced to belong to a cluster where they are very different from other members. Concept of the cluster-based local outlier proposed by Z. He et al [31], in which a measure for identifying the outlierness of each data object is defined. Wei et al [32] introduced an outlier mining method based on a hyper-graph model to detect outliers in a categorical dataset. The earliest algorithms used or outlier detection are applicable only for single dimensional data sets. Outlier detection for high dimensional data is studied by Aggarwal and Yu [33]. Where data point which lies into low density pattern is called as outlier. Moreover, their algorithm has a high computational cost. The frequent pattern based outliers has been described. A major limitation of clustering-based approaches to outlier detection is that they require multiple passes to process the data set.

3.3 Spatial Outlier Detection Approach

Spatial outliers are spatially referenced objects whose non-spatial attribute values are significantly different from those

of other spatially referenced objects in their spatial neighbourhoods. Spatial outlier detection approaches are broadly categorized into set based and spatial set based.

a) set based outlier detection : Set based outlier detection approach considers statistical relationship among attributes while it ignores spatial relationship among objects. Such approaches are developed for different conditions, type of data distribution, expected outliers and there types.

b) Spatial set based outlier detection: This approach is further classified into space based approach and graph based approach

c) Space based approach*:* Space-based outliers use Euclidean distances to define spatial neighbourhoods. Kou et al. developed spatial weighted outlier detection algorithms which use properties such as canter distance and common border length as weight when comparing non-spatial attributes [34]. Adamet al. proposed an algorithm which considers both spatial relationship and semantic relationship among neighbours [35].

d) Graph based approach: Graph based Approach uses graph connectivity to define spatial neighbourhoods. Yufeng Kou et al. proposed a set of graph-based algorithms to identify spatial outliers, which first constructs a graph based on k-nearest neighbour relationship in spatial domain. The algorithms have two major advantages compared with the existing spatial outlier detection methods: accurate in detecting point outliers and capable of identifying region outliers [36].

e) Visualization based approaches: Visualization based approaches try to map the data in a coordinate space and detect the data instances which lie in sparse areas. One of the approaches proposed to detect telecommunications fraud in which abnormal activity appears different on the display and can be visually identified by a user.

4. Advances in Outlier Detection

Traditional Outlier Detection technique may not be applicable to large dataset or categorical data set. Some new techniques proposed for outlier detection are able to detect outliers within high dimensional data or multivariate data.

4.1 Information theory based Approach

Information Theory based techniques analyse the *information content* of a data set using different information theoretic measures such as *entropy, relative entropy etc.* The general idea behind these approaches is that outlying instances affect the information content of the data set because of their surprising nature. Lee and Xiang [37] list different information theoretic measures which can used to detect outliers in a sequence of operating system call. He et al. [38] find a *k*-sized subset from a given data set which when removed makes the entropy of the remaining data set minimal. They use an approximate algorithm called *Local Search Algorithm* (LSA) He et al. [39] to approximately determine this subset of outliers in a linear fashion.

4.2 Support Vector Machine-based Approach

This approach is followed in many areas because of high accuracy & able to handle high dimensional data. Based on the characteristics of the support vectors obtained from SVM-models of varying complexity was proposed. SVM-based methodologies are been widely used for outlier detection, because they do not require a-prior knowledge about any kind of statistical model, can be applied to data with high dimensionality and provide an optimum solution maximizing the margin of decision boundary [40].

4.3 Spectral Decomposition Based Approach.

This approach in general estimates the principal component vector for a given matrix. Using these vectors normal modes of behaviour in the data is detected. Principal component analysis (PCA) is a technique that is used to reduce dimensionality before outlier detection and finds a new subset of dimension which captures the behaviour of the data. PCA based outlier detection approach in wireless sensor network proposed by Chatzigiannakis et al. [41] used to solve to data integrity and accuracy problem. Dutta et al. [42] adopt this approach to detect outliers in astronomy catalogs. Sun et al. [43] propose an outlier detection technique using non-spectral matrix approximation. These techniques are more suitable where data has lot of anomalies and a mixed categorical data.

4.4 Fuzzy logic Based Approach.

This approach uses fuzzy logic for outlier detection. Fuzzy Logic (FL) is linked with the theory of fuzzy sets, a theory which relates to classes of objects with un-sharp boundaries in which object are having degree of membership. Fuzzy Rough Semi-Supervised Outlier Detection proposed by Xue et al. [44]. This approach combines the Semi-Supervised Outlier Detection method, which was proposed by Gao et al. [45], with a clustering method introduced by Huand Yu. [46]. Fuzzy based approach categorized as unsupervised method and supervised methods. Unsupervised based methods are having low performance. To improve performance of outlier detection recently semi supervised outlier detection methods proposed.

4.5 High Dimension-based Approach

High dimensional data contains sparse behaviour finding outlier within such data is difficult problem. According to sparse nature data element projection based ODHDP method is proposed. The basic idea of the approach is to find the outliers by clustering the projections of data set. Aggarwal et al. [47] proposed a new technique for high dimensional outlier detection that finds outliers by observing the density distributions of projections from the data. This new definition considers a point to be an outlier if in some lower-dimensional projection it is located in a local region of abnormally low density.

5. Discussions

Effective outlier detection requires the construction of a model that accurately represents the data. Over the years, a

large number of techniques have been developed for building such models for outlier and anomaly detection. To present effectiveness for outlier detection that require a handle following drawback of existing outlier detection techniques. We provide a review of existing outlier detection scheme with respective data mining and address some weakness that:

a) *Statistical based method*: This method depends upon the data distribution to fit the dataset. Basically statistical methods are applicable for single dimensional data elements. This method is having a curse of dimensionality as dimension increases.
b) Distance based Method: require a distance computation between two data points. If Data is large huge amount of computation required which increases computational cost.
c) *Density based method:* This method requires a prior assumption that the density around a normal data object is similar to the density around its neighbours. The density around an outlier is considerably different to the density around its neighbours. These methods are having a exponential runtime with respect to data dimensionality.
d) Clustering based Method: A major limitation of clustering-based approaches to outlier detection is that they require multiple passes to process the data set.

6. Conclusion

Review of outlier detection technique is proposed with the purpose how traditional methods and recent method work for outlier detection. We conclude from provided review of outlier detection methods is that most existing research focuses on the algorithm based on special background. Efficiency of an outlier detection method depends upon on type of data and data distribution that are processed. Different Outlier detections techniques depend upon different assumption for detecting outliers. For Instance Statistical outlier detection method requires model to fit data that is to be processed, which increase computational cost of outlier detection. Some techniques require a priori knowledge about data distribution in dataset such as distribution based methods. Assumption based method can work quite well if prior assumption made about data is correct.

If no prior information is available about data which is to be processed or property of data changes in unpredictable way with respective time. Over such situation the most efficient solution is to hybrid or combination of many outlier detection techniques having different principle. Such hybrid or combination of techniques will save high computational cost for detecting outliers.

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Author Profile

Mr. Abhishek B. Mankar received Bachelor's Degree in Computer Science Engineering from SGB Amravati University & Pursuing Master Degree in CSE from P. R. Pote (Patil) College of Engineering. Amravati-444602 Maharashtra, India

Prof. Namrata D.Ghuse, Received the Master Degree in Computer Science from SGB Amravati University. Working as a Assistant Professor In Department of Computer Science and Engineering at P. R. Pote (Patil) College of Engineering.Amravati-444602, Maharashtra, India.