Juni Khyat (UGC Care Group I Listed Journal)

ISSN: 2278-4632 Vol-10 Issue-5 No. 20 May 2020

Design and Analysis of Autonomous Anomaly Detection Models

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Abstract

Recent data mining deviation to recognition data point the expected system to sufficient dataset or is incomparably many data exhibits that as dimensionality increases there exists hubs and anti hubs the points that frequently occur in k nearest neighbor (kNN) lists. Ant hubs are points that uncommonly model in kNN lists. This proposed system to developing and comparing to autonomous anomaly detection models. This proposed method to details about the development and analysis of outlier (anomaly) detection methods is Local Outlier Factor (LOF), and Local Distance Based Outlier Factor (LDOF). Outliers outperforms the results of the previous systems to reference to speed, complexity and efficiency. The classification algorithms are used to finding the corresponding features and classify the criteria in data mining methods. These techniques deteriorate to increasing difficulty, size and variety of data sets. The proposed incremental LOF algorithm takes equivalent finding performance as the iterated static LOF algorithm while requiring less computational time. In addition to this, the incremental LOF algorithm is dynamically change the data of data points. This is a very important application, change data profiles to change over time.

Index Terms: Clustering-based, Density-based and Model-based techniques, Nearest Neighbours, Outlier Detection, Discrimination, Outliers, data mining, Clustering, Neural Network.

1. Introduction

Outlier detection or anomaly detection means identifying the data patterns that do not comply or far from other observations.[5] Outliers can have many anomalous causes. To normal behavior Outliers occur due to changes in system behavior, fraudulent behavior, human error and instrument error or simply through natural deviations in populations. Outliers may contain demanding and actionable information in fraud detection, intrusion detection and medical diagnosis. Data Mining is a non-trivial method of identifying valid, novel, potentially useful and finally understandable patterns [1]. Now, data mining is becoming an important area to convert the data into information. It is basically used in fraud detection, marketing and scientific discovery. Data mining actually refers to extracting the hidden interesting patterns from the huge number of datasets and databases [2]. Mining is basically used to show the patterns of the data, but this can be carried out on the sample of data. The mining process will be completely useless if the samples are not the good representation of the large body of the data. Automated identification of suspicious behavior and objects [3] based on information extracted from video streams is currently an active research area. Other important applications include traffic control, surveillance of commercial and residential buildings. These tasks are characterized by the need for real time processing and by variable, non-stationary and usually noisy environment. Hence, there is necessity for incremental outlier detection that can adapt to

ISSN: 2278-4632

(UGC Care Group I Listed Journal)

Vol-10 Issue-5 No. 20 May 2020

novel behavior and provide timely identification of unusual events.[4] The errand of distinguishing anomalies can be classified as administered, semi-regulated, and autonomous, contingent upon the presence of marks for exceptions and/or general occurrences. Regulated anomaly discovery procedures have an unequivocal thought of the typical and exception conduct and thus accurate models can be assembled. The downside here is that precisely marked preparing. Among these categories, autonomous methods are more widely applied, because the other categories require precise and representative labels that are usually prohibitively expensive to obtain [5].



Fig. 1 Modes of operation of outlier detection techniques

Autonomous methods include distance-based methods that mainly depend on a measure of distance or similarity in order to detect anomalies. Formulation of outlier detection relies upon the various factors such as input data sample type and distribution, availability of data and resource conditions introduced by application domain. Detecting unexpected entries in databases which ultimately detect anomalies for data mining, frauds or valid but unexpected entries,[6] Due to so many applications accurate detection of anomalies becomes must. Many outlier detection methods were suggested till date. In this paper, we will categorize and review some of the existing methods in the following sections. The overview of the techniques which will be discussed is given in the figure below:

2. Related Work

The classification and recognition of individual characteristics and behaviors create a preliminary step and is an important aspect in the behavioral sciences. Current statistical approaches do not always give satisfactory results [3]. To improve performance in this area, we present a methodology based on one of the principles of artificial neural networks, the back-propagation gradient. In classification tasks, data set that comply to a certain representation or a classification model was considered. If one were to confuse a few data samples by making small changes to some of their attribute values, the original classification model which represents the data set was modified. Also, if one were to delete those data instances, the original model could change significantly [7], The magnitude of modifications to the original model provided clues to the criticality of such data instances that are comparatively noncritical. The hub marvel has been as of late seen in a few application territories including sound and picture Data quickly say hubness

(UGC Care Group I Listed Journal)

ISSN: 2278-4632

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in the setting of chart development for semi-directed learning. Also, there have been endeavors to dodge the impact of center points in 1-NN time-arrangement order, obviously without clear knowledge about the presence of the wonder (Islam et al.) and to represent conceivable imbalance of the circulation of N1 in converse [8] nearest neighbor look where Nk(x) indicates the quantity of times point x happens among the k closest neighbors of every other point in the Data set. None of the said papers, be that as it may, effectively break down the reasons for hub or sum it up to different applications. Initially proposed outlier detection methodologies determine outliers once all the data records (samples) are present in the dataset. We refer to these algorithms as static outlier detection algorithms. In contrast, incremental outlier detection techniques identify outliers as soon as new data record appears in the dataset. Incremental outlier detection was also used within more generic framework of activity monitoring [18]. In addition, [19] proposed broad requirements that incremental algorithms need to satisfy, [21] used online discounting distributional learning of Gaussian mixture model and scoring based on the estimated probability density function. In [8] propose a outlier ranking depending upon the objects anomaly in a set of relevant subspace projections. It do not include irrelevant projections showing no clear difference between outliers and the relevant objects and find objects which deviates in multiple relevant subspaces. The study in [9] distinguishes three problems occurred by the "curse of dimensionality" in the context of data mining, searching and indexing applications like poor inequity of distances caused by concentration, presence of irrelevant and duplicate attributes, all of which make difficult the usability of traditional similarity and distance measures. Parameter free outlier detection algorithm [10] to compute Ordered Distance Difference Outlier Factor Formulate a new outlier score for each instance by considering the difference of ordered distances. Then use this value to calculate an outlier score.

3. Density Based Approaches

Distance-based approaches are very known to face the local density problems created by the various degrees of cluster density that exist in a dataset. In order to solve the problem, density-based approaches have been proposed. The basic idea of density-based methodology is that the density around an outlier remarkably varies from that around its neighbors [14]. The density of an object's neighborhood is correlated with that of its neighbor's neighborhood. If there is a significant anomaly between the densities, the object can be considered as an outlier. To implement this idea [11], several outlier detection methodologies have been developed in recent past. The detection methods estimate the density around an object in different ways [15], implemented the local outlier factor (LOF), which is amongst the most commonly a used method in outlier detection methodology. LOF is influenced by different variations like local correlation integral (LOCI) [16]. Local distance-based outlier factor (LDOF) [17], and local outlier probabilities (LOP) [18]. Now we will look into some density-based outlier detection methodologies. Many outlier methods are proposed till date, these existing methodologies can be broadly classified as: distribution (statistical) based, clustering based, density based and model-based methodologies [13]. Statistical methodologies [12] assume that the data follows some standard or predetermined distributions, and this type of approach aims to find the outliers which doesn't follow such distributions. The methods in this class always assume the typical example follow a particular data distribution. Nevertheless, we

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ISSN: 2278-4632

Vol-10 Issue-5 No. 20 May 2020 cannot always have this kind of priority data distribution information in practice, mainly for high volumes of multidimensional real data sets [13].



Fig. 2 Classification of Outlier Detection

4. Neural Network Methods

Neural Network methodologies are usually non parametric and model based and suits well to the hidden patterns and are capable of learning complex class boundaries. The entire data set has to be traversed multiple times to allow the network to settle and model the data correctly .Neural Networks are comparatively less vulnerable to the jinx of dimensionality as compared to the statistical methods, the neural networks are further classified into two types - Supervised Neural Methods and Unsupervised Neural Methods[16]. Supervised Neural Networks uses the classification of the data to drive the learning process. If this classification of the data is not available, then it is known as unsupervised neural network.



Fig. 3 Structure of a Neural Network

Unsupervised neural networks contain nodes which compete to represent parts of the data set. As with Perceptron based neural networks, decision trees or k-means, they require a training dataset to allow the network to learn. They individually cluster the input vectors through node placement to allow the underlying data distribution to be modeled and the normal/abnormal classes differentiated [18]. They assume that related vectors have common feature values and depend upon identifying these features and their values to topologically model the data distribution. The neural network uses the class to adjust the weights and thresholds to make sure the network that can correctly classify the overall

ISSN: 2278-4632

(UGC Care Group I Listed Journal) Vol-10 Issue-5 No. 20 May 2020 network. These methods are also used to detect the noise and novel data [19]. Neural Network is a very crucial methodology that plays a crucial role in the outlier detection.

5. Outlier Detection Algorithms

Clustering and outlier identification is one of the important tasks in high dimensional data. Clustering methodologies are supported by outlier detections for new optimistic methodologies. The thrust of the new optimistic approach applies nearest neighbor-based clustering method and detect outliers in high dimensional data.

A. Local outlier factor (LOF)

In LOF, compare the local density of a instances with the densities of its neighborhood instances and then assign anomaly score to given data instance. For any data instance to be normal not as an outlier, LOF score equal to ratio of average local density of k nearest neighbor of instance and local density of data instance itself.

Incremental LOF insertion (Dataset S) •Given: Set $S\{\overline{p_1}, \dots, p_n\}$ $p_i \in \mathbb{R}^0$, where **D** corresponds to the dimensionality of data records. •For each data point p. in data set S insert(p_)
Compute kNN(p_) • $(\forall p_i \in kNN(p_c))$ compute reach-dist, (p, p) using Eq. (1); //Update_neighbors of p. S_{update k distance} = kRNN (p_c); • $(\forall p_j \in S_{update \ k \ distance})$ $update \ k \ distance(p_j)$ using Eq.(5);
$$\begin{split} & s_{\text{update} ird} = s_{\text{update} k \text{ distance}}; \\ & (\forall p_j \in s_{\text{update} k \text{ distance}}), \ (\forall p_i \in \text{KNN}(p_j) \setminus \{p_i\}) \\ & reach-dist_k(p_i, p_j) = \text{k-distance}(p_j); \end{split}$$
if $p_i \in kNN(p_i)$ $S_{update_{ird}} = S_{update_{ird}} \cup \{p_i\};$ $(\forall p_n \in S_{update_{ird}})$ $update_{ird}$ using Eq. (2); $S_{update_LOF} = S_{update_LOF} \cup kRNN(p_n);$ • $(\forall p_i \in S_{update LOP})$ update LOF(p_i) using Eq.(3); • compute lrd(p) using Eq.(2); • compute LOF(p) using Eq.(3); End //for

To find local density for data instance, find radius of small hyper sphere centered at the data instance. The local density for instances is computed by dividing volume of k, i.e. k nearest neighbor and volume of hyper sphere. In this assign a degree to each object to be an outlier known as local outlier factor. Depends on the degree it determines how the object is isolated with respect to surrounding neighborhood [20]. The instances lying in substantial region are normal instances, if their local density is similar to their neighbors, the instances are outlier if their local density lower than its nearest neighbor. LOF is steadier with top-n manner. Hence it is called as top-n LOF means instances with highest LOF values considered as outliers.

B. Local distance-based outlier factor (LDOF)

Local distance-based outlier factor Measure the objects outlierness in distributed datasets. In this uses the relevant location of an object to its neighbors to obtain the object deviation degree from its neighborhood instances. In this distributed neighborhood is considered. Higher deviation [21] in degree data instance has, more likely data instance as

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an outlier. In this algorithm evaluate the local distance-based anomaly factor for each object and then sort and ranks the n objects having highest LDOF value. The first n objects with highest LDOF values are consider as an outlier



Fig. 4 Proposed System Architecture

6. Novel Boundary Based Classification Approach (NBBC)

The proposed Novel Boundary based categorization including the imputation methods and ordinal classification methods are explained in this section. The detailed description of WDBC dataset as follows. WDBC dataset: The Wisconsin Diagnostic Breast Cancer (WDBC) contains various attributes namely, diagnosis, ID number and real valued features. There are ten real valued features namely, radius, area, perimeter, smoothness, texture, compactness, concave points, concavity, symmetry and fractal dimension computed from digitized image of breast mass.[8] For each class, an added classification representation is built or trained by first deriving data set, which is a separation of the innovative training data set. The new data set was derived by relating a subset of the original data records into two new classes

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Training Procedure:

Step1: Compute Triangular Area // using eqn(3)

Step1: 2For I = 1,2.... z do

Step1: 3 TA \leftarrow \square TA_l^c

Step1: 4End For

Step1: 5 Compute |\tilde{h}||_{\overline{r}} \leftarrow \frac{1}{z} \sum_{i=1}^{z} \overline{T_i^c}

Step1: 6 Compute Covariance Matrix Cov^c // using eqn(8)

Step1: 7 For I = 1,2,... z do

Step1: 8 Compute MD^{c,l} \leftarrow MD^{c,l}(TA_l^c, \tilde{h}||_{\overline{r}})

Step1: 9 End For

Step1: 1 Compute \mu

Step1: 1 Compute \sigma

Step1: 2Return
```

A. The Greedy Algorithm

Overview

Our greedy algorithm takes the number of desired outliers (supposed to be -k) as input and selects points as outliers in a greedy manner, Initially the set of outliers (denoted by OS) is specified to be null and all points are marked as non-outlier we need k scans over the dataset to select k points as outliers[3]. In each scan, for each point labeled as non-

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ISSN: 2278-4632

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outlier, it is temporally removed from the dataset as outlier and the entropy object is recalculated. A point that achieves maximal entropy impact the maximal decrease in entropy experienced by removing this point, is selected as outlier in current scan and added to OS. The algorithm terminates when the size of OS reaches k. In the initialization phase of the greedy Algorithm each record is labeled as non-outlier and hash tables for attributes are also constructed and updated (step 01- 04). In the greedy procedure, we need to scan over dataset, we read each record t that is labeled as nonoutlier, its label is changed to outlier and the changed entropy value is computed. A record that achieves maximal entropy impact is selected as outlier in current scan and added to the set of outliers (step 05-13). In this algorithm, the key step is computing the changed value of entropy. With the use of hashing technique, I o(1) expected time ,we can determine the frequency of an attribute value in corresponding hash table. Hence, we can determine the decreased entropy value in o(m) expected time since the changed values is only dependent on the attribute values of the record to be temporally removed [17].

One of the simplest methods for showing that a greedy algorithm is correct is to use a "greedy stays ahead" argument. This style of proof works by showing that, according to some measure, the greedy algorithm always is at least as far ahead as the optimal solution during each iteration of the algorithm. Once you have established this, you can then use this fact to show that the greedy algorithm must be optimal.



Fig. 5 Greedy Algorithm Example

Algorith	III
Input:	D // the categorical database
	k // the number of desired outliers
Output:	k identified outliers
/* Phase	1-initialization */
01 Be	gin
02	foreach record t in D
03	update hash tables using t
04	label t as a non-outlier with flag "0
/* Phase	2-Greedy Procedure */
counter	= 0
05	Repeat
05 06	Repeat counter++
05 06 07	Repeat counter++ while not end of the database do
05 06 07 08	Repeat counter++ while not end of the database do read next record t which is labeled "0 //non-outlier
05 06 07 08 09	Repeat counter++ while not end of the database do read next record t which is labeled "0 //non-outlier compute the decrease on entropy value by labeling t as outlier
05 06 07 08 09 10	Repeat counter++ while not end of the database do read next record t which is labeled "0 //non-outlier compute the decrease on entropy value by labeling t as outlier if maximal decrease on entropy is achieved by record b then
05 06 07 08 09 10 11	Repeat counter++ while not end of the database do read next record t which is labeled "0 //non-outlier compute the decrease on entropy value by labeling t as outlier if maximal decrease on entropy is achieved by record b then update hash tables using b
05 06 07 08 09 10 11 12	Repeat counter++ while not end of the database do read next record t which is labeled "0 //non-outlier compute the decrease on entropy value by labeling t as outlier if maximal decrease on entropy is achieved by record b then update hash tables using b label t as a outlier with flag "1
05 06 07 08 09 10 11 12 13	Repeat counter++ while not end of the database do read next record t which is labeled "0 //non-outlier compute the decrease on entropy value by labeling t as outlier if maximal decrease on entropy is achieved by record b then update hash tables using b label t as a outlier with flag "1 Until counter = k

ISSN: 2278-4632

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For the comparable fractional problem, however, the greedy strategy, which takes item 1 first, does yield an optimal solution. Taking item 1 doesn't work in the 0-1 problem because the thief is unable to fill his knapsack to capacity, and the empty space lowers the effective value per pound of his load. In the 0-1 problem, when we consider an item for inclusion in the knapsack, we must compare the solution to the sub problem in which the item is excluded before we can make the choice. The problem formulated in this way gives rise to many overlapping sub problems--a hallmark of dynamic programming, and indeed, dynamic programming.

7. Experimental Setup and Results

System Requirement Our algorithms have performed on high dimensional dataset that is Cover Type dataset from UCI machine learning Repository The experiment was performed on an Intel core i5 CPU at 2.53 GHz and RAM 4 GB, having a Windows 7 as its operating system. The algorithms were implemented in Java to process data instances in high dimensional data. Results The figure 6 shows the data insertion time required in five datasets and figure 7 shows the comparative study of outlier detection rate with existing and proposed algorithms for outlier detection.



Fig. 6 Data insertion time required

DB5

DB1 DB2 DB3 Db4



Fig. 7 Outlier detected

Outlier-Detection Methods and the hubness phenomenon, extending the previous examinations of (anti) hubness to large values of k, and exploring the relationship between hubness and data sparsity Based on the analysis, we formulated the IQR, Greedy, AntiHub method for semi-supervised and unsupervised outlier detection, discussed its properties and proposed a derived method which improves in terms of speed and accuracy, reducing the false positive and false negative rate and improve the efficiency of density based outlier detection.

8. Conclusions

Outlier detection is very important and has applications in wide variety of fields. So it becomes important to learn how to detect outliers. The main objective of this paper is to review various outlier detection techniques and to study how the techniques are categorized. So we can conclude that, methods used for outlier detection are application specific. The training algorithm and testing algorithm are used for training and testing the class. Reducing the search close to the class boundaries saves computation time in identifying such nuggets. Results from the evaluation on the real-time WDBC data sets revealed that the proposed approach achieves better performance than the existing classification algorithm. Proposed a derived method which improves in terms of speed and accuracy, reducing the false positive and false negative rate and improve the efficiency of density-based outlier detection. The future implementation is in machine learning techniques such as supervised and semi-supervised methods.

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Future work on deleting data records from database is needed. More specifically, it would be interesting to design an algorithm with exponential decay of weights, where the most recent data records will have the highest influence on the local density estimation. In addition, an extension of the proposed methodology to create incremental versions of other emerging outlier detection algorithms Connectivity Outlier Factor (COF) is also worth considering. Additional real-life data sets will be used to evaluate the proposed algorithm and ROC curves will be applied to quantify the algorithm performance.

References

- Jun Wang. A Knowledge Network Constructed by Integrating Classification, Thesaurus, and Metadata in Digital Library. Intl. Inform. & Libr. Rev. Vol35 Issue 3. 2003, pp383- 397.
- [2] K. Ord. Outliers in statistical data: V. barnett and t. lewis, 1994, 3rd edition, (john wiley & sons, chichester), 584 pp., [uk pound]55.00, isbn 0-471- 93094-6. International Journal of Forecasting, 12(1):175-176, 1996.
- [3] S. Chawla, D. Hand, and V. Dhar. Outlier detection special issue. Data Min. Knowl.Discov., 20(2):189-190, 2010
- [4] Nilam Upasania, Hari Omb, "Evolving fuzzy min-max neural network for outlier detection" in International Conference on Advanced Computing Technologies and Applications (ICACTA-2015) Elsevier
- [5] N., Zadrozny, B., and Langford, J. 2006. Outlier detection by active learning. In Proceedings of the 12th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. ACM Press, New York, NY, USA, 504–509.
- [6] V. Chandola, A. Banerjee, V. Kumar, Anomaly detection: a survey, ACM Comput.41 (2009)15.
- [7] Milos Radovanovic, Alexandros Nanopoulos and Mirjana Ivanovic, 2014. "Reverse Nearest Neighbors in Unsupervised Distance Based Outlier Detection" IEEE Transactions on Knowledge and Data Engineering,
- [8] Karanjit Singh and Dr.Shuchita Upadhyaya 2012. "Outlier Detection: Applications and Techniques" IJCSI International Journal of Computer Science Issues, Vol. 9, Issue 1, No 3, January
- [9] Dasgupta, D. and Majumdar, N. 2002 "Outlier detection in multidimensional data using negative selection algorithm" In Proceedings of the IEEE Conference on Evolutionary Computation. Hawaii, 1039 - 1044.
- [10] K.S.Beyer,J.Goldstein,R.Ramakrishnan and U. Shaft, 1999 "When is "nearest neighbor" meaningful?" in Proc 7th Int Conf on Database Theory (ICDT), pp. 217– 235.
- [11] V. Chandola, A. Banerjee, and V. Kumar, "Anomaly detection: A survey," ACM Comput Surv, vol. 41, no. 3, p. 15, 2009.
- [12] M. M. Breunig, H.-P. Kriegel, R. T. Ng, and J. Sander, "LOF: Identifying densitybased local outliers," SIGMOD Rec, vol. 29, no. 2, pp. 93–104, 2000.

- (UGC Care Group I Listed Journal)
 [13] K. Zhang, M. Hutter, and H. Jin, "A new local distance-based outlier detection approach for scattered real-world data," in Proc 13th Pacific-Asia Conf on Knowledge Discovery and Data Mining (PAKDD), pp. 813–822. 2009.
- [14] W. Jin, A. K. H. Tung, J. Han, and W. Wang, "Ranking outliers using symmetric neighborhood relationship," in Proc 10th Pacific-Asia Conf on Advances in Knowledge Discovery and Data Mining (PAKDD), pp. 577–593, 2006.
- [15] C. Lijun, L. Xiyin, Z. Tiejun, Z. Zhongping, and L. Aiyong, "A data stream outlier delection algorithm based on reverse k nearest neighborspp. 236–239, 2010
- [16] Shu-Ching Chen, Mei-Ling Shyu, Chengcui Zhang, Rangasami L. Kashyap: Video Scene Change Detection Method Using Unsupervised Segmentation And Object Tracking. Proc. ICME 2001
- [17] Y. Tao, D. Papadias, X. Lian, Reverse kNN search in arbitrary dimensionality, In Proceedings of the 30th International Conference on Very Large Data Bases, Toronto, Canada, September 2004.
- [18] Amit Singh, Hakan Ferhatosmanoglu, Ali Tosun, High Dimensional Reverse Nearest Neighbor Queries, In Proceedings of the ACM International Conference on Information and Knowledge Management (CIKM'03), New Orleans, LA, November 2003
- [19]. Barnett, V. and Lewis, T.: 1994, Outliers in Statistical Data. John Wiley & Sons.3rd edition.
- [20]. Huber, P. 1974. Robust Statistics. Wiley, New York.
- [21] Grubbs, F. E.: 1969, 'Procedures for detecting outlying observations in samples'Technometrics11,