Anomaly detection for the Big Data

Xin Han

Xichen Tang

Shaowei Pan

# Introduction

Nowadays, data has increased in a large scale in various fields such as Internet, business, and biosciences. Big data is referred to describe the large and distributed nature of the data sets, this area has become a focus of scholarship. Doug Laney [24] defined challenges and brought about big data with a 3Vs model, i.e., Volume, Velocity, and Variety. Volume means the size of the data that becomes increasingly big; Velocity means data collection and analysis must be rapidly and timely conducted; Variety indicates the many types of data, which include structured, semi-structured, and unstructured such as video and text.

Later, the core challenges of big data have been extended to 4Vs which contained Volume, Variety, Velocity, and Value [14]. The Value highlights the meaning and necessity of big data, i.e., discovering the huge hidden values from datasets. In academia and industry, discovering abnormal patterns from the datasets is referred as anomaly detection or outlier detection is received widespread attention. It has widely used to detect many abnormal events such as intrusion detection [15], fault detection [19], fraud detection [5], event detection in social networks [32].

An anomalier defined by Hawkins [17] as “an observation which deviates so much from the other observations as to arouse suspicions that it was generated by a different mechanism.” Based on the definiton of Hawkins, many data-driven methods are proposed to detect the behavior that is out of the normal from data. Most of them work by identifying anomaliers by creating a model of the normal patterns in the data, and then compute an outlier score of a given data point on the basis of the deviations from these patterns [8]. The main advantage of data-driven anomaly detection is that it does not require prior knowledge of an intrusion and thus can detect new anomaly behavior.

Because there is no rigid definition of which observation exactly is an anomalier, every method relying on certain assumptions of what qualifies as an anomalier. Some popular models are based on the distribution of objects [8, 22, 35], the distance [20] between objects, or on the density of the neighborhood of an object [1, 7, 28], or based on the ensemble method [40]. These methods represent different attempts to make the rather vague intuition about what anomalier are more concrete, typically in an implicit, procedural way.

However, many challenges brought by the different “V” of big data make the traditional anomaly detection method ineffective. This paper aims to discuss the specially challenges of anomaly detection in age of Big Data and show existing methods to overcome them.

The rest of the chapter is organized as follows. We first introduce the existing methods of classic anomaly detection. Then, we introduce challenges of anomaly detection in big data. Then the popular evaluation methods in anomaly detection are introduced. Finally, we introduce the published tools of methods of anomaly detection, followed by the conclusions in the last section.

# Traditional Method of Anomaly Detection

Many anomaly detection methods have been proposed in data mining literature. The general methods can be divided into four categories as follows: statistical, distance, clustering and Ensemble [9].

## Statistical Based Methods

The statistical based detection assumed that if the difference between the data and the statistical distribution or the specified model is greater than a specific range [8], the data object is considered as anomalier. It includes two special method: distribution-based approach and depth-based approach [37].

As for the distribution-based method, after given a distribution, a method of consistency checking is used to find anomalier. However, the actual distribution of the data set is always unknown, and it is difficult to estimate the data distribution in high-dimensional. To solve those problem, self-organizing map (SOM) [35], Support Vector Regression [22] (SVR) and other machine learning based methods are introduced to improve those shortcomings.

The depth-based approach considers that each object is a point with a specified depth in n-dimensional space, and that a data object may be anomalier with a lower depth. Although some dimension reduction methods such as Primary Component Analysis (PCA) [10], and Independent Component Analysis (ICA) are commonly used in this category, it still has a high computational complexity and has a low efficiency in the big data with high-dimensional and large data sets.

## Distance Based Methods

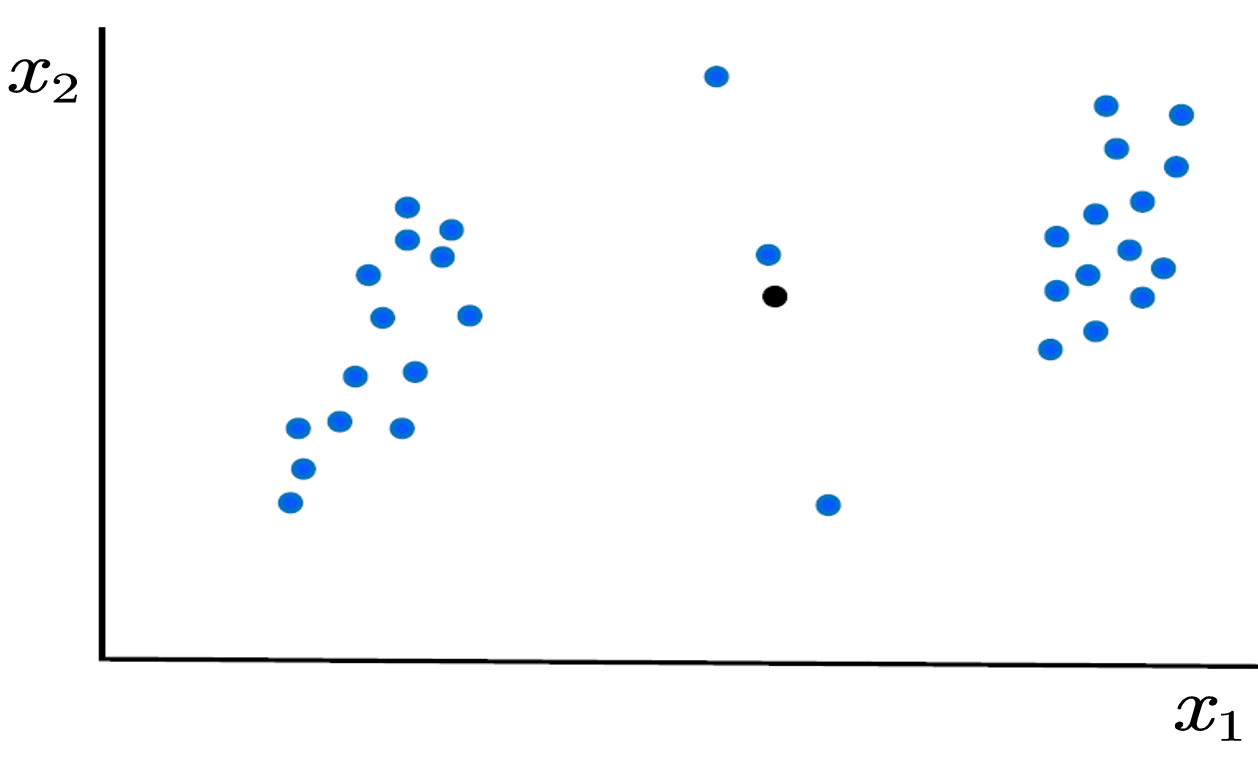


Figure 1: Distance Based Anomaly Detection Methods

The distance-based anomaly detection assumes that anomaliers are far away from other points. It calculates the distance between data points in data space after setting a distance function. As shown in Figure 1, a data object is regarded as anomalier when the distance between itself and others is large. The firstly anomaly detection method based on distance is proposed in [20]. Then it is extended to using K-neighbor distance to build the anomaly detector [23, 30]. The K-neighbor distance of each object is calculated and sorted from small to big, the objects which have largest distance are considered as anomaliers.

The distance-based anomaly detection method is easier to realize and is widely studied. But the complexity of the algorithm is relatively high, such as the computation complexity of KNN is , where the is the number of data points. and it cannot consider the size of data sets and the scalability of data dimension. Thus, the practical application of distance-based methods is limited.

## Density Based Methods

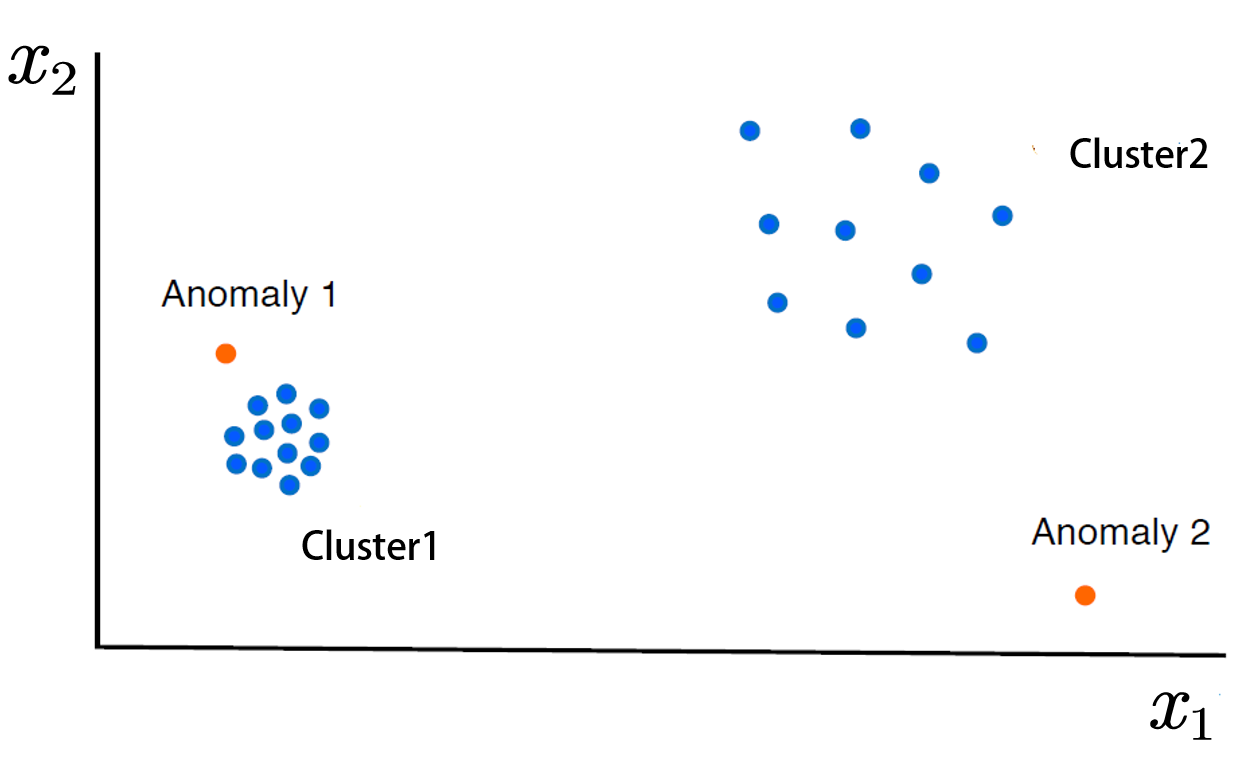


Figure 2: Density Based Anomaly Detection Methods

Anomaliers are usually detected from an individual’s point of view, i.e. the anomaliers are far from their neighboring clusters as shown in Figure 2. Therefore, it is not appropriate to use the overall distance as statistical based and distance-based methods do. The density-based anomaly detection algorithms are proposed to solve this problem. The Local Outlier Factor (LOF) [7] is proposed to detect anomaliers by comparing the local density of an object to the local density of its neighbors. If the density of the data object is much lower than that of its neighbors, this data object is considered as anomalier. Local parsimony factor (LCF) is proposed to reduce the complexity of the computation by considering the maximum distance between the nearest objects as distances [1].

The density-based idea is closer to Hawkins’ definition of exception than the distance-based idea [17]. Therefore, it can detect local anomaliers, and have high detection accuracy. However, the time complexity is still very high, and the result of detection is sensitive to the selection of parameters such as the threshold of the outlier, which is difficult to determine.

## Ensembles Based Methods

Because each model is specifically designed for different characteristics of perception. It is only applicable to certain aspects of the “whole truth.” So it is best to integrate different third-party observational results to reach consensus. The main idea of this method (called “ensemble”) is that if these judgments do not contain all the same errors. It is useful to combine individual judgments or the results of marginalized observations [40]. One would think that this is a majority vote of the jury: one or another judgment on the statement may be wrong, but the majority judgment is still correct as long as the judgment is generally reliable. Isolation Forest [25] can be treated as typical ensemble method, it builds an ensemble of “Isolation Trees” (iTrees) for the data set, and anomaliers are the points that have shorter average path lengths on the iTrees. It has a low linear time complexity and a small memory requirement and is able to deal with high dimensional data with irrelevant attributes [8]. FuseAD [27] takes advantage of both statistical approach ARIMA and deep-learning-based approach CNN to propose a novel network: it shows great improvement on Yahoo Webscope benchmark.

# Challenges of Anomaly detection in big data

In the age of big data, the design of anomaly detection methods has become increasingly complex. The features of big data that have the greatest effect on the anomaly detection and each feature has its individual challenges. The Volume requires that the proposed method could effective detect anomaliers in large data set. The Velocity brings challenges when data are increasing and arriving at speed as data streams. These features make the anomaly detection method become highly complex and ineffective. Here, we describe challenges of anomaly detection brought by each feature of big data and show the existing method to overcome them.

## Challenges in the Volume of big data

When the potential probability distribution is not known and the size of the data set is huge, the computational requirements increase. The Volume feature of big data emphasizes storage, memory, and computing power of the system to cope with ever-increasing data size [13]. When the data size is large, the traditional anomaly detection methods may become invalid, because of the limited computational power and associated factors. To overcome this issue, several parallel and distributed computing methods are proposed.

Managing computational power and disk input/output (I/O) communication can improve the efficiency of the method. D-cube [33] is a disk-based detection method to find fraudulent lockstep behavior in large scale data and runs in a distributed manner across multiple machines. It is proved that could successfully detect network attacks and synchronized behavior in rating data with highest accuracy. Nested loop (NL) [21] is a straightforward method to detect anomaliers in a database. Hung and Cheung [18] introduced an efficient and parallel version of the NL algorithm that reduces both computation and disk I/O costs.

Ramaswamy et al. [30] proposed a distance-based anomaly detection method to detect anomalier in huge data sets. It segregates input data into separate subsets and prunes partitions that do not contain anomaliers, resulting in considerable savings in computation. DOLPHIN [3] is also a distance-based anomaly detection method that works on disk-resident data sets in huge datasets.

Arning et al. [4] proposed a linear algorithm using a dissimilarity function to capture the similarity rate of a data point. Erfani et al. [12] introduced an unsupervised method for large-scale dataset to detect anomaliers that are a combination of a deep belief network (DBN) and one-class support vector machines (SVM). One-class SVMs (1SVMs) are used for detecting anomaliers through unsupervised learning and aim to model the underlying distribution of data while not considering irrelevant attributes or anomaliers in the training records. Conversely, a DBN is a multiclass semi-supervised approach and dimensionality reduction tool. It uses multilayer generative models (non-linear manifold) that learn one layer of features at a time from unlabeled data.

## Challenges in the Velocity of big data

Most traditional anomaly detection methods assume that the data set is generated by an unknown but stationary probability distribution, the volume of data is finite, and the entire dataset could be stored for analysis [34]. However, in the big data age, the data set would be an infinite set of data instances in which each instance is a set of values with an explicit or implicit time stamp and it is referred as data stream [31]. The data stream are unbounded sequences and the entry rate is continuously high, as the respective variations repeatedly change over time. The anomaly detection on data stream, as show in Figure [3](#fig:streamAnomaly), is a highly challenge tasks because of the unbounded volume of data, the high rate of data generation, and data be stored will run out of memory space [31].

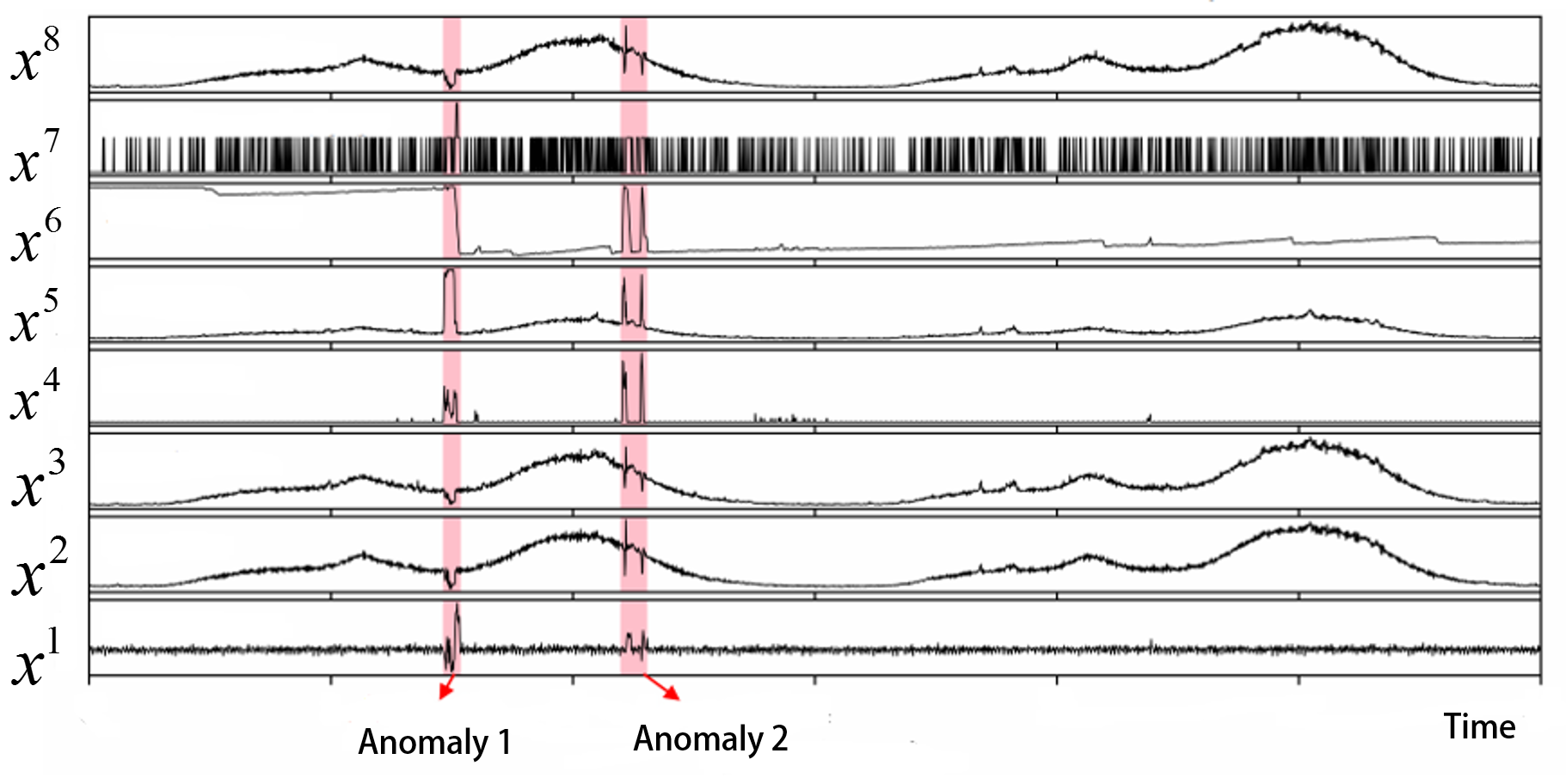


Figure 3: Anomaly detection on stream data

In data stream scenarios, more recent information can reflect the new trends or changes on the data distribution. Most method use the sliding-window model to capture this feature of data stream. In the sliding-window model. only the data which from the current time up to a certain period in the past are stored in a data structure where the window size can be variable or fixed. This data structure is usually a first in, first out (FIFO) structure i.e. first object added will be the first one to be removed, an example of the sliding-window model is presented in Figure [4](#fig:slidingWindow).

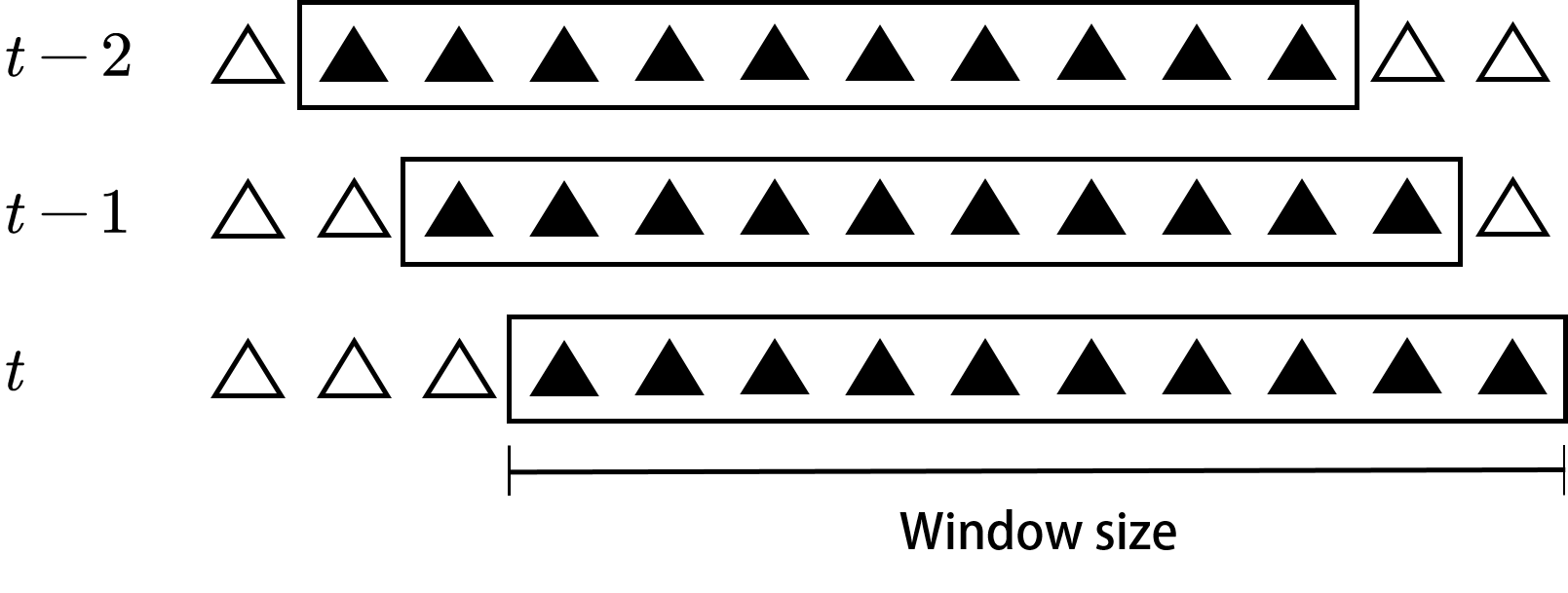


Figure 4: Sliding window model

Angiulli and Fasseti [2] proposed a method for developing distance-based anomaly detetion in data streams using a sliding window model in which anomaly queries are executed for the purpose of detecting anomaliers in the current window. Their method executes anomaly detection and return a score based on accurate estimations with a statistical guarantee. This method is based on a method known as stream outlier miner, or STORM, which is used to find anomaliers on distance based windowed data streams. A sliding window is used to continuously inspect the object until it expires.

CUSFgrowth (constrained uncertain data stream frequent item sets growth) [38], is a method based on the sliding window model for mining constrained frequent item sets on data streams. This method determines the order of items in transactions and analyzes the properties of constraints. In this method, a CUSF-tree is created according to the order of items which determined by the properties of constraints; after the frequent item sets are satisfied, the constraints are mined from the CUSF-tree.

In addition, enseble-based methods are also proposed to resolve the problem of detecting anomaliers in streaming data. iForestASD [11] uses sliding window to deal with streaming data. On the current complete window, iForestASD uses the standard iForest method to adapt streaming data anomaly detection.

# Evaluation of Anomaly Detection

Evaluation metrics are critical to building a successful anomaly detection system. Efforts have been made to determine the correct method for measuring the quality of abnormal detection. This section examines general evaluation metrics from two aspects: supervised detection and unsupervised detection which is distinguished by whether have labeled dataset.

## Supervised Evaluation

When the ground truth of dataset is valuable, the supervised evaluation method could be used. The most popular supervised evaluation methods are accuracy, recall, F1 score, ROC curve, and AUC.

### Confusion Matrix

The confusion matrix, as shown in Table [1](#tb:confusion), is a table two dimensions where each row of the matrix represents the instances in a predicted class while each column represents the instances in an actual class [29]. TP means true positives (i.e. items correctly labeled as belonging to the positive class), FP means false positives (i.e. items incorrectly labeled as belonging to the positive class), FN means false negatives (i.e. items which were not labeled as belonging to the positive class but should have been). TN means true negative (i.e. items correctly labeled as belonging to the negative class).

Table 1: Confusion Matrix. TP is True Positive; FP is False Positive; TN is True Negative; FN is False Negative.

|  |  |  |
| --- | --- | --- |
|  | Actual value | Actual value |
| Predicted value | TP | FP |
| Predicted value | FN | TN |

### Precision

The *Precision* measures the ratio of examples predicted as positive that are truly positive [36].

### Recall

The *Recall* measures the ratio of positive examples that are correctly labeled.

### F1 Score

The *F1 score* is a tradeoff between the *Precision* and *Recall*:

F1 metric weights recall and precision equally, and a good detection algorithm will maximize both precision and recall simultaneously. Moderately good performance on both will be favored over extremely good performance on one and poor performance on the other.

### AUC

*AUC* (area under curve) refers to the area under the *ROC curve*. The vertical and horizontal axis ranges are (0,1), so the total area is less than 1 [6]. The larger the *AUC*, the better the classification effect.

The *AUC* value can be thought as the probability that the two randomly selected objects (positive example (anomalier) and negative example (normalier)) are arranged correctly (i.e., anomalier is classified before the normalier value) [16]. The *ROC curve* and *AUC* analysis inherently address the problem of imbalance using relative frequencies, making them particularly popular in evaluating the detection of exclusion.

## Unsupervised Evaluation

If some tasks of anomaly detection have no ground truth, the unsupervised evaluation method such as comparative evaluation, generating pseudo tags, and similarity analysis can be used.

### Comparative Evaluation

For unsupervised learning, a common evaluation strategy is to rank the results according to the score of anomaliers, and then iteratively set the threshold from the first to the last. This will form n ancestor values (true positive rate and false positive rate), and a ROC curve can be obtained. The integral AUC of ROC can be used as a measure to test the performance.

### Generating Pseudo Tags

There are a lot of learning efforts to transform unsupervised learning into supervised learning, and there are now feasible methods. Then, we can use the evaluation methods of supervised learning, such as accuracy.

### Similarity Analysis

Unsupervised learning often depends on the similarity between data, which can be expressed as spatial density or distance measurement. In the evaluation of anomaly detection algorithm, it can be assumed that many normal data are closely adjacent (can form multiple clusters), and anomaliers are often quite different from these normal points.

# Anomaly detection software packages

 Many companies have built their own anomaly detection systems in order to meet their specific business needs. However, there are still many open source anomaly detection packages available. In this section, we review some of the popular software packages for practitioners to build their anomaly detection systems.

## Distributed Computing frameworks

Distributed computing is one of the most important techniques to handle big data. Many frameworks for distributed computing such as Apache Hadoop (<https://hadoop.apache.org/>), Apache Spark (<https://spark.apache.org/>), and Apache Flink (<https://flink.apache.org/>) were developed to address the challenges of big data. Most of these frameworks have many machine learning (ML) libraries to build the application of anomaly detection.

## PyOdds

PyODDS (<http://pyodds.com/>) is an end-to end Python system for anomaly detection. It provides several anomaly detection algorithms and support both static and time-series data type.

## PyOD

PyOD [39] (<https://pypi.org/project/pyod/>) is a comprehensive and scalable Python toolkit for detecting anomalier in multivariable data. It includes more than 20 detection algorithms, including new deep learning models and ensembles methods.

## ADTK

Anomaly Detection Toolkit (ADTK) (<https://adtk.readthedocs.io>) is a Python package for unsupervised / rule-based time series anomaly detection.

## Scikit-Multiflow

Scikit-Multiflow [26] is the main open source machine learning framework for multi-output, multi-label and data streaming. Implemented in Python language, it includes various algorithms and methods for streams mining.

# Conclusions

Anomaly detection has been extensively attended in recent years in the modern industry. However, many challenges brought by the Big Data make the method of traditional anomaly detection ineffective. This chapter aimed to discuss the anomaly detection in the age of Big Data. This has included traditional anomaly detection method based on distribution, distance, density, cluster and ensemble. We discuss the challenges brought by the feature of Volume and Velocity of Big Data and present the state-of-the-art anomaly detection method for overcoming them. In addition, we reviewed commonly used two categories including supervised and unsupervised to evaluate anomaly detection method. Finally, we provided a list of free and open source software packages for practitioners to create their own anomaly detection systems.

A wide range of studies have been carried out in the field of abnormal detection. As this chapter only covers this topic, we recommend reader to read more detail in the references of this chapter.

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