AN ANOMALY DETECTION FRAMEWORK FOR HETEROGENEOUS AND STREAMING DATA

A Thesis

by

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ABSTRACT

Anomaly detection has become one of the most important research areas due to its wide range of use such as abnormal behavior detection in network traffic, disease detection in MRI images, and fraud detection in credit card transactions. In many real-world anomaly detection problems, we face heterogeneous data comprising different types of attributes including categorical and continuous attributes. The heterogeneity of data makes it really difficult to compare data instances. Furthermore, the behaviors of data may change over time in streaming environments. Finally, it is hard to get the labels of data since we get too many data per day to manually classify them. To tackle these challenges, in the paper, we propose an anomaly detection framework for heterogeneous and streaming data. By introducing our own distance metric for categorical features and using an ensemble of two outlier detection methods, we effectively deal with both heterogeneous and streaming data. Furthermore, the ensemble model keeps updating its backend information during classification tasks so as to adapt to changing data behaviors. The framework, also, provides the interpretation of detected outliers in order to reduce the effort of human experts to get labeled data. Finally, we train a supervised machine learning algorithm using the feedback from human experts for anomaly detection tasks. Our experiment results show the efficacy of the proposed framework.

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NOMENCLATURE

CE	Clustering Estimation
kNNa	k-Nearest Neighbor Approximation
$iForest$	Isolation Forest
$HSTrees$	Hafl-Space Trees
LOF	Local Outlier Factor
RNN	Replicator Neural Network
ROC	Receiver Operating Characteristics
AUC	Area Under the (ROC) Curve

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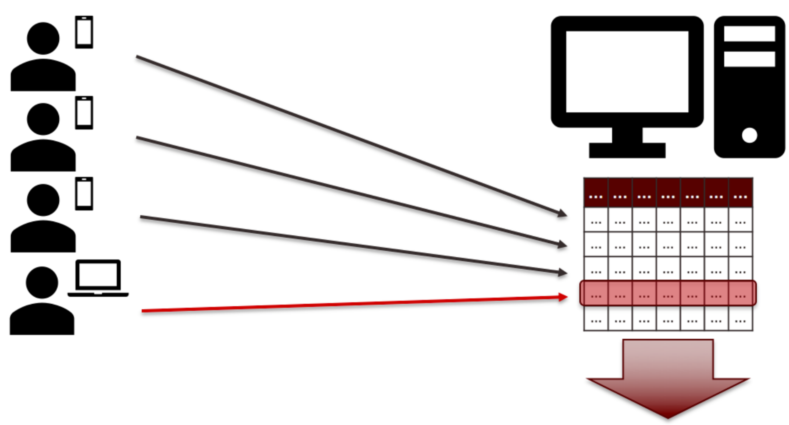
1. INTRODUCTION

Discovering unexpected patterns or behaviors (aka anomalies, outliers, novelties, and exceptions) [1] in data has been essential because it has a wide range of use. For example, our credit cards sometimes get frozen when we travel somewhere or spend too much money since credit card companies think that these behaviors do not match the previous records of our transactions. In the area of computer networks, we also can find anomalous packets, which can be either an attack or some kind of failure. This problem is getting important since these anomalous behaviors or patters are often associated with a huge financial loss. Due to the importance of anomaly detection, there have been a lot of studies on it [1, 2], but this is still an open problem.

When we closer look at real-world datasets, they generally consist of different types of attributes including continuous, categorical, and binary attributes. This is where one of the major difficulties of anomaly detection comes from: *heterogeneous data.* Figure 1.1 shows an example of heterogeneous data in computer networks.



time	user_id	src_ip	…	protocol	src_byte	logged_in
11:15:31	4976188	211.194.x.x	…	UDP	6,882	1
09:00:01	8182376	171.68.x.x	…	TCP	1,477	0

Figure 1.1: Input data example in the area of computer networks

In the example data, the features are of different types. For example, *time, user_id, src_ip, and protocol* are categorical features, *src_byte* is a continuous feature, and *logged_in* is a binary feature. Since each categorical feature can have different number of categorical values and all of the features are heterogeneous, it is really hard to measure the distance or similarity between two data instances. For example, what is the distance between the TCP and UDP protocols? Also, in streaming environments like computer network or credit card transaction example, the behaviors or distributions of data may change over time. What if a person living in Texas got a job in a different city of state and moved there? The pattern of credit card transactions of that person is going to totally change and credit card companies will get a lot of false alarms. In computer networks, attackers keep changing their behaviors so that they can prevent their anomalous behaviors from being detected by anomaly detection algorithms. This problem is also called *concept drift* and outlier detection algorithms for streaming data should be able to deal with this problem. Finally, it costs a lot of time and money to get the ground truth (labels) of data since we get very large amount of data everyday. Thus, we should assume that the ground truth of data is not available for anomaly detection tasks.

To tackle the aforementioned challenges, we propose an anomaly detection framework for heterogeneous and streaming data. Our strategies to deal with the challenges are motivated by previous work on anomaly detection. First of all, ensemble analysis has been overlooked for a long time because of the unsupervised nature of anomaly detection problems. By using an ensemble, we expect to achieve the diversity of detected outliers since each outlier detection algorithm reacts to categorical features differently. Also, we propose a distance metric for categorical features in order to make sure the ensemble model handles categorical features well. Second, outlier interpretation is very helpful for human experts to check whether detected outliers are really anomalous or not. Thus, we provide the interpretation of detected outliers to reduce the effort of human experts to get labels of data. Next, we enhance existing outlier detection methods so that they update their backend information regularly and can deal with concept drift issue. Finally, anomalies are not necessarily bad or malicious. Let me give you the credit card transaction example, again. In that example, the credit card user just moved to other place, which is not a malicious activity, but just a less frequent activity. We do not want this kind of activities to be detected by our methods since these outliers increase false positives, which would cause the distrust on our framework. To address this problem, we use a supervised anomaly detection model along with the ensemble of unsupervised outlier detection methods.

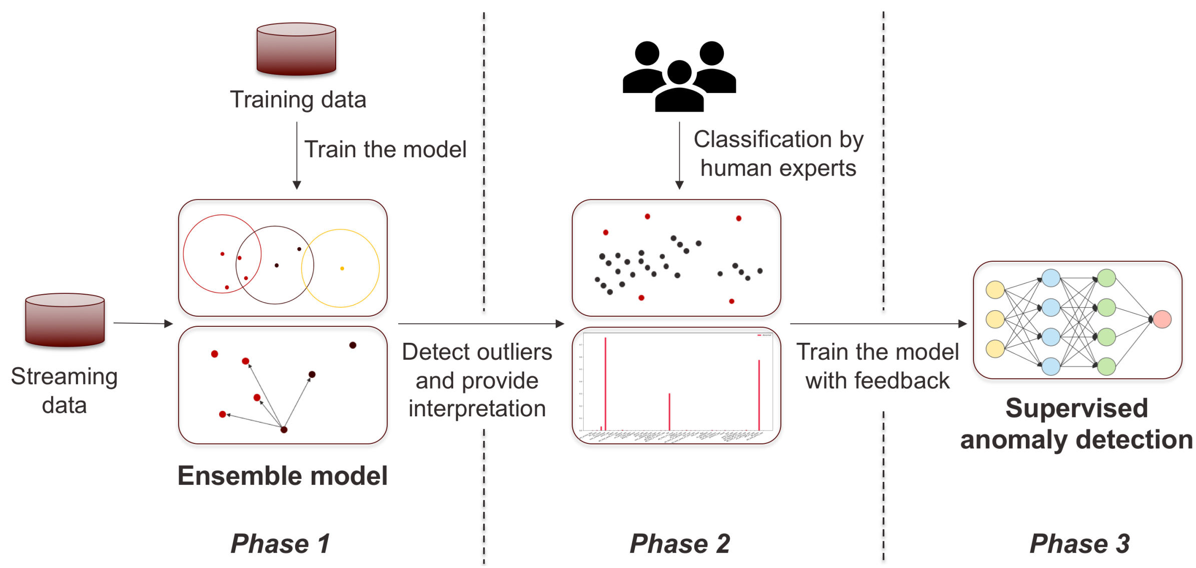


Figure 1.2: The architecture of the proposed framework

The architecture of the proposed anomaly detection framework is illustrated in Figure 1.2. With these motivations, we build our framework having three phases. In the first phase, we detect suspicious records (outliers[1]) in streaming data by using an ensemble of two outlier detection methods. These methods are enhanced to update their backend information and deal with concept drift issue. We also introduce our own distance metric for categorical features so we can reasonably compute the distance between two heterogeneous data instances. In the second phase, the framework provides the interpretation of detected outliers in order to help human experts check whether the outliers are really anomalous or not and create the ground truth for the next phase. Finally, we

[1]In this paper, the terms outliers and anomalies are interchangeable.

use a supervised anomaly detection model, which is a feed-forward neural network, and train this model using the ground truth from the previous phase to reduce false positives. Our feed-forward neural network has an embedding layer for categorical features in data to better deal with heterogeneous data unlike other conventional supervised machine learning algorithms. This supervised model is simply used for binary classification tasks. Our framework has the following advantages over conventional anomaly detection methods:

- The framework can handle heterogeneous data by using an ensemble of outlier detection algorithms and our own distance metric for categorical attributes.
- The framework reduces the effort of human experts to classify anomalies by providing the outlier interpretation based on clusters and nearest neighbors.
- The framework can adapt to changing data behaviors in streaming data by updating its back-end information in real time.
- The framework reduces false positives as much as possible by using a supervised model and the feedback from human experts.

2. RELATED WORK

2.1 Anomaly Detection

A large number of studies on anomaly detection have been conducted, resulting in various techniques to address the problem. Scholkopf *et al.* [3] proposed Support Vector Machines with one-class setting for outlier detection. Some works try to detect outliers using density-based approach [4, 5] and clustering-based method [6, 7, 8, 9]. Traditional nearest neighbor-based techniques have also been applied for outlier detection by [7, 10, 11]. Because of the characteristics of anomaly detection, some methods have been developed for specific purpose such as detecting outliers in attributed networks [12, 13].

With the recent success of neural networks, they have been used to capture anomalies in a unsupervised fashion. Hawkins *et al.* proposed Replicator Neural Networks (RNNs) for one-class anomaly detection and they are conceptually the same as autoencoders [14]. The RNNs try to learn input patterns and to reproduce them. The reconstruction error computed by subtracting the reconstructed output from an input instance is used as an anomaly score. Some recent works take advantage of deep architectures [15, 16, 17], showing that deep architectures can be used for unsupervised anomaly detection.

2.2 Heterogeneous Data

Not much of work on heterogeneous data exist since most of traditional outlier detection methods focus on numerical attributes [1]. Otey *et al.* [18] proposed a distributed outlier detection method for heterogeneous and streaming data. This method captures dependencies among features of data so that they effectively compute the distance between two data points. The problem of this model is that it shows bad performance when data has only numerical attributes [18].

When it comes to categorical attributes, many existing models are probability based due to its discrete nature of data [19, 20]. One of interesting studies on categorial features is COMPREX proposed by Akoglu *et al.* [21]. Anomalies are detected by this model if they have high compression cost when compressing them. Chen *et al.* recently introduced a model addressing the problem of heterogeneous categorical data by finding pairwise interactions between categorical attributes using embeddings of them [22]. These models, however, can deal with only categorical attributes.

2.3 Streaming Data

Most studies on anomaly detection in streaming environments have been conducted in signal processing [23, 24, 25], which means they use only numerical data. The model introduced by Otey *et al.* [18] can deal with streaming data, but as we discussed above its performance deteriorates when using datasets with only numerical attributes. Tan *et al.* proposed Streaming Half-Space Trees in order to address the problem of concept drift and memory requirement [26], but the study solely focuses on numerical data like other traditional methods.

2.4 Ensemble Methods

Ensemble analysis has received considerable attention for supervised machine learning methods due to its ability to boost a collection of algorithms. Following the trend, ensemble methods for outlier detection also have been studied but in a limited way because of the unsupervised nature of the problem [27, 2].

One of the well-known ensemble methods for outlier detection is Local Outlier Factor (LOF) [4]. The LOF method computes LOF values within a range of values of k, referring to the number of neighbors of a data instance. By taking the maximum of all the LOF values, they get an anomaly score for each instance. Isolation Forest proposed by [28] is an ensemble of isolation trees, which try to isolate each data instance from the rest of data instances. If a data point has a shorter path in a forest of such trees, then the point is highly likely to be anomalous. Recently, Chen *et al.* [29] introduced RandNet, employing autoencoder ensembles, to detect outliers. They could achieve the improved diversity and reduced training time by making autoencoders in RandNet have different structures and connection densities.

2.5 Interpretable Methods

The interpretation of outliers is important considering what we can benefit from it: interpretation (1) can help non-experts in a certain area look into results effectively and (2) reduce the effort of human experts and engineers analyzing results. Some works provide the interpretation of outliers by selecting features with which outlier detection methods find outliers most effectively [30, 31, 32]. There exist a general framework to explain classification results provided by any machine learning classifiers [33] and framework built for outlier interpretation [34].

2.6 Similarity Measures for Categorical Features

For measuring the distance or similarity between categorical attributes, the measure called the *overlap* measure [35] is the simplest and most widely used. In this measure, we just assign a value of 1 if two categorical values are same and assign a value of 0 if not. Although it does not depend on the ordering of categorical data, this measure is still too simplistic since it does not take into account other information which we can extract from categorical attributes such as the frequency information for each category.

By making use of these kinds of information, a lot of similarity or distance measure for categorical data have been proposed. Eskin *et al.* introduced a data-dependent normalization kernel along with their anomaly detection algorithms in [7]. In this kernel, the distance between two categorical data is $\sum \frac{2}{|f_i|^2}$ if two values of f_i are different, where f_i is i-th feature in data. This kernel gives more weight to attributes that take small values when computing distances. The inverse occurrence frequency derived from the inverse document frequency in information retrieval can also be used for a distance measure for categorical features. Each categorical value has a value of $\log(\frac{N}{freq(f_i)})$, where N is the number of instances in data, $freq(f)$ is the number of occurrences of the feature f in data, and f_i is i-th feature in data. Other than these methods, probability-based measures [36, 37, 38] and measures based on information theory [39, 40] have been proposed due to its discrete nature.

There exists a very helpful survey conducted by Boriah *et al.* explaining 14 similarity measures for categorical data [41]. They revisited traditional techniques of the similarity measures for categorical data, proposed 6 variants of the existing methods, and perform experiments in the context of outlier detection. Their experiment results show that the performance of the similarity measures highly depends on datasets since different datasets have different characteristics of categorical attributes.

3. ANOMALY DETECTION FRAMEWORK

In this section, we propose an anomaly detection framework for heterogeneous and streaming data in order to tackle the challenges we discussed earlier: (1) heterogeneous data (2) concept drift issue in streaming data (3) no labeled data (4) not malicious anomalies. The framework has three phases to detect anomalies in streaming data and we explain each phase in detail as follows. The notations used in this paper are listed in Table 3.1.

Notation	Definition
D	training dataset
x_i	a data instance
x_{ij}	an attribute value of x_i
w	the width of a cluster
k	the number of nearest neighbors
C	a set of clusters
c	a cluster $\in C$
$d(x_i, x_j)$	the distance between x_i and x_j
$d_f(x_i, x_j)$	the feature distance for the feature f
K_{x_i}	a set of k-nearest neighbors of x_i
$s(x_i)$	the outlier score of x_i

Table 3.1: Notations used in the paper

3.1 Outlier Detection Methods

We selected two existing outlier detection algorithms from different outlier detection categories based on [1, 2]. The two selected methods are the Clustering Estimation (CE) and the k-Nearest Neighbor Approximation (kNNa) introduced by Eskin *et al.* [7]. The rationale behind selecting these two algorithms is, first of all, they are very simple and intuitive so we are able to provide the interpretation of results very easily. Second, they use the same backend information, which is the cluster information, so only one training is required for both methods. Furthermore, when updating our backend information to deal with concept drift problem, we do not need to consider two different backend information for each method because we only have one backend information. Finally, they are computationally efficient so they are suitable for streaming data. We explain how each algorithm works and how we enhance them below.

3.1.1 Clustering Estimation

This method is also called fixed-width clustering [7]. It clusters data based on the fixed-width w of a cluster, which is a hyperparameter. The procedure of this algorithm is as follows. The method iterates all point in training data and it tries to find the closest cluster to each point. After finding the closest cluster to a point, the method checks if the point is within the closest cluster based on the fixed-width w. If the point is within the closest cluster, then the point is added to the cluster. If not, the point will be the center of a new cluster. Formally we describe the procedure as: for each instance x_i, x_i is added to the closest cluster $c \in C$ to x_i if $d(x_i, c) \leq w$. If $d(x_i, c) > w$, then x_i becomes the center of a new cluster. Algorithm 1 illustrates the pseudocode for the CE.

Algorithm 1: Clustering Estimation algorithm

Let C be an empty set;
for *each record in training data* **do**
    Find the closest cluster c to the current record x_i;
    if *d(x_i, c) $\leq w$* **then**
        $c := c \cup \{x_i\}$;
    else
        makeNewCluster(C, x_i);
    end
end
return C

The time complexity of this method for clustering (training) is $O(n|C|)$, where n is the number of instances in a given training dataset D. Since the number of clusters is typically much less than the number of instances in training data, we can cluster training data very efficiently. The outlier score $s(x_i)$ for a new instance x_i is the inverse of the size of the closest cluster to x_i if x_i is within the cluster c and is formally defined as:

$$s(x_i) = \begin{cases} \frac{1}{|c|}, & \text{if } d(x_i, c) \leq w \\ 1, & \text{otherwise} \end{cases} \tag{3.1}$$

where w is the predefined cluster width, c is the closest cluster to x_i and $c \in C$, which is a set of clusters. For outlier detection, we train the model with training data, which means that we get clusters C based on the training dataset. After training, we evaluate a new instance x_i in streaming data by finding the closest cluster c to x_i and computing the outlier score of x_i. Computing the outlier score of an instance takes $O(|C|)$ time since we find the closest cluster to the instance. The higher score an instance has, the more outlying it is.

3.1.2 k-Nearest Neighbor Approximation

As the name of the method suggests, it finds k-nearest neighbors of an instance to detect anomalies. We modified the original algorithm in [7] to make it more simple and efficient. Here is how it works. First of all, we apply the Clustering Estimation algorithm to get our backend cluster information C. We find the closest cluster c to a new instance x_i from streaming data, which means that we compute $\text{argmin}_{c \in C}\ d(x_i, c)$, and then add all instances in c to a set K_{x_i} if $|c| \leq k$ - $|K_{x_i}|$. After that, we find the second closest cluster and do the same process. If the condition is not met, then randomly pick k - $|K_{x_i}|$ number of instances in c and add them to K_{x_i}. Algorithm 2 shows the pseudocode for the kNNa.

The time complexity of this method for training is the same as that of the CE since the training process is the same and it only takes $O(|C|)$ when finding k-nearest neighbors for a single instance. The outlier score $s(x_i)$ for a new instance x_i is the sum of the distances between x_i and each instance in K_{x_i} and is formally defined as:

$$s(x_i) = \sum_{y \in K_{x_i}} d(x_i,\ y) \tag{3.2}$$

Algorithm 2: k-Nearest Neighbor Approximation algorithm

Let C be the result of the CE algorithm;
Let $C_{checked}$ be an empty set;
Let x_i be a new instance from streaming data;
Let K_{x_i} be an empty set;
while $|K_{x_i}| < k$ **do**
  Find the closest cluster $c \in C$ - $C_{checked}$ to x_i;
  if $|K_{x_i}|$ + $|c| \leq k$ **then**
    $K_{x_i} := K_{x_i} \cup \{$ all points $\in c$ $\}$;
  else
    P := k - $|K_{x_i}|$ points picked from c at random;
    $K_{x_i} := K_{x_i} \cup$ P;
  end
  $C_{checked}$:= $C_{checked} \cup \{c\}$
end
return K_{x_i}

For outlier detection, we train the model with training data by using the CE to get clusters C. After that, we find k-nearest neighbors of a new instance x_i in streaming data using this method and compute the outlier score of x_i. The higher score an instance has, the more outlying it is.

3.2 Update Backend Information

To deal with concept drift, we update our backend cluster information by adopting the idea used for the Streaming HS trees [26]. The Steaming HS trees maintain two separate backend information. At first, one called *reference* window is created using training data and the other called *latest* window is created using streaming data (latest data). The *reference* window is used for classification task when they get a new data instance and they save this instance to the *latest* window for future use. After getting enough information about streaming data, they replace the *reference* window with the *latest* window. By doing so, they can adapt to changing data behaviors in streaming environments.

Thanks to the characteristic of the clustering algorithm that we use, we can adopt this idea. As a new data instance arrives, we can apply the CE method to cluster streaming data. This process takes only $O(|C|)$ time, where $|C|$ is the number of clusters, so we can efficiently do this in streaming environments. At the same time, we do the classification task for the new data instance by using our original backend information based on training data. The classification task also takes $O(|C|)$ time as we discussed in the earlier sections. Thus, we are able to not only classify a new data instance but also use it for clustering in streaming environments. Figure 3.1 and 3.2 illustrate how this process works.

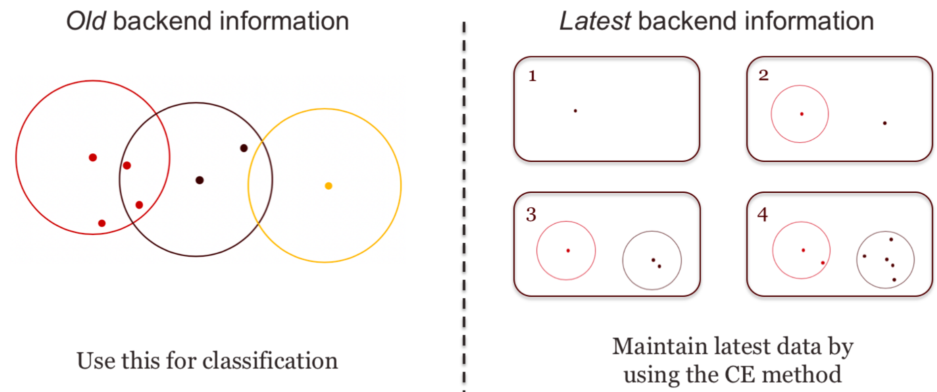


Figure 3.1: Two separate backend information; we use the *old* backend information for classification tasks and apply the CE method to save latest data information.

We have two separate backend cluster information as the Streaming HS trees do: one that we call *old* backend information based on training data and the other that we call *latest* backend information based on streaming data. When we get a new data instance, the outlier score of the new instance is computed using the *old* backend information based on training data. With the new data instance, we also apply the CE method to the *latest* backend information for clustering task. We keep doing this process until the number of instances in the *latest* backend reaches a predefined threshold. After that point, we replace the *old* backend information with the *latest* backend information. By doing so, we expect to deal with concept drift issue.

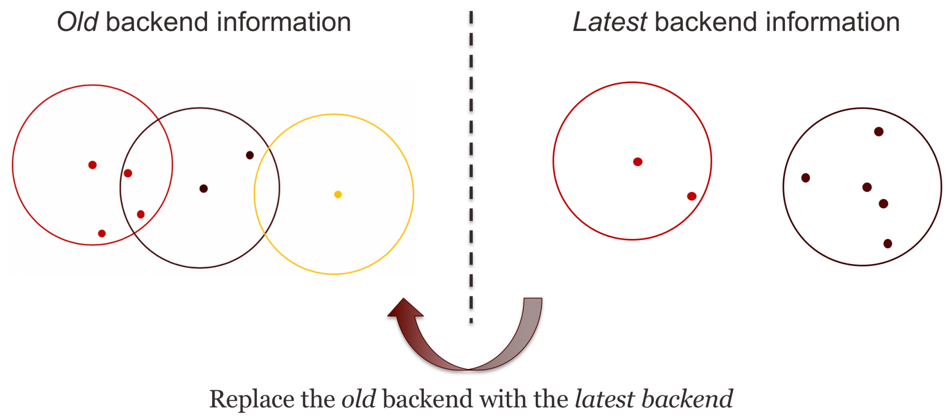


Figure 3.2: Replacement of the backend information; when the number of instances in the *latest* backend exceeds a predefined threshold, we replace the *old* backend with the *latest* one.

3.3 Distance Metric for Categorical Attributes

It is hard to compute the distance between two categorical instances since categorical data cannot be ordered in most cases. For example, we cannot say that *udp* is greater that *tcp* or *http* is less than *smtp*. Due to this issue, we usually apply one-hot encoding where each category is translated to an one-hot vector corresponding its categorical value or use Hamming distance, which is the number of categories which have different categorical values between two instances. However, these techniques do not take into account the data distribution so it is unlikely that these are helpful for anomaly detection tasks. Table 3.2 shows an example of categorical values and their frequencies of $protocol\_type$ and $service$ categories.

According to a survey on similarity measure for categorical data, introduced by Boriah *et al.* [41], we cannot choose a single measure as the best one for categorical data since the performance of similarity and distance measure depends on datasets. However, some of them show consistently better performance on the benchmark datasets that they used and they are in common in terms of the use of the frequency information for each category. They give higher weight on infrequent values if two values are different. We intend to adopt this concept along with the data-dependent normalization kernel proposed in [7] to introduce a new distance metric for our

protocol_type		*service*	
Value	**Frequency**	**Value**	**Frequency**
tcp	20,526	http	8,003
		private	4,351
udp	3,011	smtp	1,449
		ftp_data	1,396
icmp	1,655	telnet	483
		other	1,944

Table 3.2: Categorical values and their frequencies of $protocol\_type$ and $service$ categories

framework.

The first thing we need to consider is the number of possible categorical values for each category, which is called $arity$. The reason is that the importance of the value difference between a category having 3 possible values and a category having 6 possible values should be differentiated. Let me take an example of Table 3.2. The value difference of $protocol\_type$ should be more weighted than that of $service$ because the value difference of attributes that take many values is more like a marginal difference than that of attributes that take small number of values.

Second, we also need to consider the frequency of each categorical value since in outlier detection tasks the less frequent value is considered anomalous. In Table 3.2, for example, the distance between "http" and "smtp" should be greater than that between "smtp" and "ftp_data" considering the frequency gap. With these in mind, we define the distance $d(x_i, x_j)$ and the feature distance $d_f(x_i, x_j)$ between x_i and x_j as follows:

$$d_{f_{cat}}(x_i, x_j) = \begin{cases} \frac{\log(1+|freq(f_{x_i}) - freq(f_{x_j})|)}{arity(f)}, & \text{if } f_{x_i} \neq f_{x_j} \\ 0, & \text{otherwise} \end{cases} \tag{3.3}$$

$$d_{f_{num}}(x_i, x_j) = (f_{x_i} - f_{x_j})^2 \tag{3.4}$$

$$d_f(x_i, x_j) = \begin{cases} d_{f_{cat}}(x_i, x_j), & \text{if } f \in F_{cat} \\ d_{f_{num}}(x_i, x_j), & \text{if } f \in F_{num} \end{cases} \tag{3.5}$$

$$d(x_i, x_j) = \sqrt{\sum_{f \in F} d_f(x_i, x_j)} \tag{3.6}$$

where F is a set of attributes of data, F_{cat} is a set of categorical features $\in F$, F_{num} is a set of numerical features $\in F$, f is an attribute $\in F$, f_{x_i} is an attribute value of x_i for the attribute f, $freq(f_{x_i})$ is the number of occurrences of f_{x_i} in training data, and $artiy(f)$ is the number of possible attribute values of the feature f. By using these distance metrics, we can compute the distance between <tcp, http> and <udp, private> as $\log(1 + |20,526 - 3,011|)/3 + \log(1 + |8,003 - 4,351|)/6$ equal to 4.6242, which ls greater than the distance between <tcp, smtp> and <udp, ftp_data> equal to 3.9218.

3.4 Outlier Ensembles

Ensemble methods in outlier detection areas have not been studied very well due to the fact that the ground truth of data is not available [27, 2]. Because of this constraint, we are not able to adopt ensemble techniques used in supervised settings such as boosting. In order to achieve the diversity of detected outliers and higher performance of our framework, we intend to combine the aforementioned outlier detection methods altogether. Since all of these algorithms are unsupervised and different types of models, it is hard to combine outlier scores provided by them. We have two major issues for the ensemble process according to [27, 2], normalization and combination issues.

The normalization issues arise from the fact that outlier scores from different methods cannot be directly compared since different algorithms use different scales of outlier scores. For example an outlier score from the CE method is computed based on a cluster size, but an outlier score from the kNNa is computed based on the nearest neighbors of a detected outlier. Outlier scores from CE ranges from 0 to 1, but those from the kNNa ranges from 0 to some number that we do not know. Normalizing these scores could solve this issue, but streaming data make this worse since it is difficult to normalize outlier scores in streaming data environments.

Even if we can normalize these scores, all of the scores should be combined in some ways after the normalization process. How we combine these scores also affects the performance of the ensemble, which makes this problem difficult. To avoid these issues, we use the majority voting ensemble by setting a score threshold for each outlier detection method. In majority voting, each method classifies a new data instance and the majority opinion of the methods that we have would be our classification result. Since our framework has only two outlier detection methods, a new data instance is classified as an anomaly if both methods agree on that. The framework is a general framework where users can add their custom outlier detection methods to the ensemble. Thus, if users added their custom model to the ensemble, then a classification result would be made based on the result of the majority of the methods. Furthermore, the framework provides the confidence that represents the result of a majority voting. For example, if 4 methods out of 5 agree that a new instance is an anomaly, then the new instance would be classified as an anomaly with the confidence of 80%.

3.5 Classification By Human Experts With Outlier Interpretation

In Phase 2, human experts check whether detected outliers in the previous phase are really anomalous or not. In order to facilitate this work, we provide the interpretation of detected outliers based on clusters and nearest neighbors information. What we would like in this phase is to provide the interpretation of a new instance as soon as we classify it since the framework is working in streaming environments. Due to this constraint, we are not able to use the existing interpretation methods for the framework. Now, we introduce our interpretation method for streaming data.

3.5.1 Interpretation of Outliers

Our strategy is to find features that make detected outliers anomalous, which is a traditional approach for machine learning interpretation [30, 31, 32]. Since we have the cluster information of training data and nearest neighbors of detected outliers, we utilize this information to achieve the interpretation of detected outliers. We define the feature importance score of each feature for a detected outlier o based on our backend cluster information and k-nearest neighbors of o as follows.

$$s_f(o) = \sum_{c \in C} |c| d_f(o, c) + \sum_{y \in K_o} d_f(o, y) \tag{3.7}$$

where K_o is a set of nearest neighbors of a detected outlier o and y is an instance $\in K_o$. The first term is computed based on the cluster information and the nearest neighbors of o are used to compute the second term. The intuition behind these terms is that (1) the smaller clusters, the more anomalous and (2) the nearest neighbors of o are the most relevant information of it because o is classified as an outlier based on them. Thus, we give more weights to large clusters using the size of clusters so that points in large clusters (i.e., normal clusters) have more impact on computing the feature importance score. If some attribute value of o is different from that of points in large clusters, then the feature importance score of that attribute would be high. Also, the nearest neighbors of o are used to classify a detected outlier o so we already know the nearest neighbors of it. Because of this fact, we can save time to find the nearest neighbors of a detected outlier. With the nearest neighbors of o, we compute the feature importance score by summing up the feature distance between o and each instance of its nearest neighbors for each attribute. We can think of the first term in Equation 3.7 as the *global* interpretation because we basically use all of information in training data. On the other hand, we can think of the second term as the *local* interpretation since the nearest neighbors of o are the local information of detected outliers. By incorporating the local information (i.e., nearest neighbor information) with the global information (i.e., cluster information), we expect to provide reasonable interpretations of detected outliers.

With the help of outlier interpretation, human experts could identify "actual" anomalies in detected outliers more easily. After the classification tasks by human experts, they provide a feedback (i.e., ground truth) containing abnormal instances to the next phase. The rest of the data that are not classified as anomalies are considered normal.

3.6 Supervised Anomaly Detection

Outliers are obviously different from normal instances but they might not be bad or malicious. In order to distinguish not-malicious outliers from malicious outliers, we use a supervised anomaly detection approach in Phase 3. For this task, a feed-forward neural network is used. Figure 3.3 shows the architecture of the feed-forward neural network used in our framework.

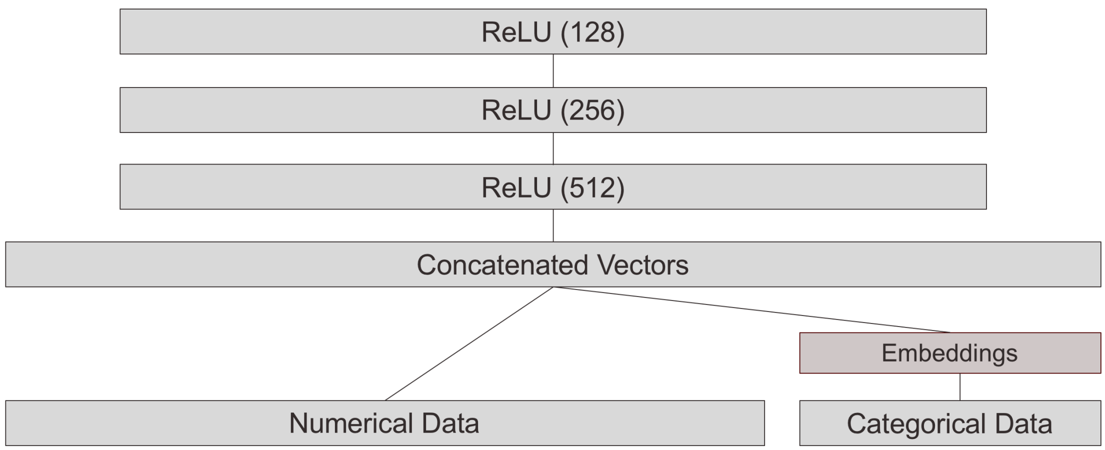


Figure 3.3: The architecture of a neural network used in Phase 3

The neural network has a embedding layer to better deal with categorical data, but numerical data are directly used. After the embedding layer, we concatenate numerical data and embeddings for categorical data. On top of concatenated vectors, we have three ReLU layers. As for the output layer, the sigmoid function is used as the activation function. The model can be replaced with traditional supervised machine learning algorithms, but they should be able to handle both heterogeneous and streaming data. For example, a logistic regression model may not be suitable for this task since the model cannot deal with heterogeneous data.

The procedure of this phase is as follows. First, we get the feedback from human experts in Phase 2. With the feedback, we train our supervised model. If the amount of data in the feedback is not enough, we wait for another feedback and accumulate the feedbacks so that we can train the model properly. Our ultimate goal is to skip the first and second phase and just to use the supervised model for anomaly detection tasks. Users of the framework may continue to use the first two phases when too many false positives occur due to concept drift or other reasons.

4. EXPERIMENTS

By performing experiments on real world datasets, we show the efficacy of our proposed framework. We would like to answer the following questions in this section: (1) Can the framework deal with heterogeneous data? (2) Can the framework handle concept drift? (3) Are interpretation results reliable? (4) Can the framework reduce false positives? To answer the first question, we evaluate our ensemble model by using two types of datasets: one with only numerical features and the other with all features. For the evaluation on streaming data, we follow the experiment setup in [26] to simulate changing data behaviors. We show some examples of the interpretation results of detected outliers for the evaluation on outlier interpretation. Finally, we simulate each phase in the framework to evaluate the whole framework.

4.1 Dataset

For our experiments, we use two network intrusion detection datasets: NSL-KDD [42] and UNSW-NB15 [43]. The NSL-KDD dataset is introduced to improve problems that the KDD-CUP99 dataset [44] originally has such as a lot of redundant instances. It has 24 types of attacks in the training set and additional 14 types of attacks in the test set, which are not available in the training set. The UNSW-NB15 contains 9 types of attacks in both the training and test sets. Both datasets have real normal activities along with synthetic attack behaviors and consist of different types of attributes. Table 4.1 illustrates the details of the datasets.

Datasets	# Instances	Attributes			Anomaly class
		Numerical	Categorical	Binary	
NSL-KDD	125,973+22,544	32	3	6	attacks (24+14 types)
UNSW-NB15	175,341+82,332	37	3	2	attacks (9 types)

Table 4.1: Datasets used for the experiments

We do not use the cross-validation technique, but only use the given training and test sets. This is because the datasets are very sensitive to the number of attacks and types of attacks in training and test sets. The datasets are designed considering these issues and we would not be able to measure the performances of our framework and a baseline method If we use the cross-validation technique.

4.2 Experiment Setup

We randomly removed most of abnormal instances in the training data so that they contain about 1% of anomalies and 99% of normal instances, which is a more realistic setting than the original datasets. Even though the ground truth labels of the datasets are available, they are not used during training the ensemble model in Phase 1, but used solely for evaluation. As our baseline, we use Isolation Forest [28], which is one of the state of the art outlier detection methods. The Isolation Forest consists of isolation trees, which try to isolate each data instance from the rest of the data. Since outliers are different and a few, it is easier to isolate outliers than normal instances. Therefore, if an instance has shorter path length in isolation trees, then it is likely to be an outlier. Since the Isolation Forest is not designed for streaming data, we expect that the model shows bad performance in our simulated streaming environment.

As for the preprocessing of data, we standardize numerical attributes in our training data. Based on the mean and standard deviation of the training data, an incoming instance in streaming data is standardized. Categorical attributes are handled with our distance metric that we introduced in this paper. The mean and standard deviation information are updated when the backend information of the framework is updated.

4.3 Evaluation on Heterogeneous Data

In this experiment, we evaluate the ability of our framework to deal with heterogeneous data. Two types of datasets are used to see if the framework and the baseline can handle heterogeneous data well: one with only numerical features and the other with all features. We expect that if one can deal with heterogeneous data well, then the performance would increase. Table 4.2 shows the experiment results and AUC (Area Under Curve) values are reported as the evaluation metric.

AUC	NSL-KDD	UNSW-NB15
Isolation Forest (numerical only)	**0.9033**	0.7877
Ensemble (numerical only)	0.8871	**0.7913**
Isolation Forest (numerical+categorical)	**0.8975**	0.7824
Ensemble (numerical+categorical)	0.8938	**0.8023**

Table 4.2: Experiment results on static heterogeneous datasets

The ensemble model could show comparable performance with the baseline on NSL-KDD dataset in both cases where the dataset has only numerical attributes and all features. However, the performance of the Isolation Forest deteriorates when categorical attributes are added to the dataset, but the performance of the ensemble model increases as we expected. On the UNSW-NB15 dataset, the ensemble model constantly outperforms the baseline method and the performance of the ensemble increases when categorical features are used along with numerical features. However, the baseline on the dataset with only numerical features shows slightly worse performance than on the dataset with all features. The experiment results are consistent with our expectation that it can deal with heterogeneous data as the ensemble model shows better performance on the datasets with all features.

4.4 Evaluation on Streaming Data

In order to evaluate the ability of our framework to handle the concept drift issue, we simulate changing data behaviors by following the experiment setup in [26]; we train our ensemble model using data only with $smtp$ protocol, and then test the ensemble model using data with $smtp$ protocol followed by $http$ protocol. As the network protocol changes in the dataset, we expect the concept drift would occur. Table 4.3 shows the experiment results and AUC values are reported as the evaluation metric.

Surprisingly, both the Isolation Forest and the ensemble without updating performs quite well

AUC	smtp+http	
	NSL-KDD	UNSW-NB15
Isolation Forest	0.9284	0.5308
Ensemble (no update)	0.9148	0.4940
Ensemble (update)	**0.9403**	**0.8840**

Table 4.3: Experiment results on streaming datasets

on the NSL-KDD dataset. We speculate that the protocol change was not able to change data distributions using the NSL-KDD dataset. However, the ensemble with updating shows the best performance over the other models. On the UNSW-NB15 dataset, the ensemble model with updating performs really well, but the others show very bad performance as we expected. It shows that the ensemble with updating could adapt to changing data distributions and the other models are not able to deal with the concept drift since they are originally designed to detect anomalies in static datasets.

4.5 Evaluation on Outlier Interpretation

To verify that our interpretation of detected outliers are reliable, we show the interpretation results for both normal and abnormal instances in Figure 4.1, 4.2,and 4.3. In the bar graphs showing the feature importance scores, y-axis represents the feature importance score for each attribute and x-axis represents attributes in data.

As you see the bar graphs in Figure 4.1, the feature importance scores are almost uniformly distributed over features compared to the bar graphs of abnormal instances in Figure 4.2 and 4.3 since normal instances do not have specific anomalous attributes. Most of the feature importance scores of abnormal instances are very low and a few of them stand out. We could find the first and second most anomalous attributes based on the scores at the top in Figure 4.2 and 4.3 and further analyze the results by using scatter plots. In each scatter plot, there is a red point marked with a red circle and it represents a detected outlier used in each example. In Figure 4.2 example, the two anomalous attributes are *srv_count* and *srv_rerror_rate* and data instances are shown using these two attributes at the bottom of the figure. As you see the scatter plot, we are, indeed, able to distinguish most of abnormal instances from normal instances by using only these two attributes. In Figure 4.3 example, the two anomalous attributes are *dst_bytes* and *num_compromised* and data instances are shown using these two attributes at the bottom of the figure as we did above. Unlike the previous example, we are able to distinguish all of abnormal instances from normal instances by using only these two attributes as you see the scatter plot.

4.6 Framework Evaluation

The purpose of this experiment is to evaluate the whole framework. For this experiment, we divide the test dataset into 5 batches. After that, we detect outliers in a single batch and a feedback is created based on the ground truth to simulate the classification by human experts. Our supervised model is trained with the feedback and tested with the last batch (fifth batch), which is only used for evaluating the supervised model. We keep doing this process until the 4th batch. In summary, we detect suspicious records (i.e., outliers) in the first 4 batches in turn, and then we train the supervised model with the feedback from each batch. In this experiment, we report the values of precision, recall, and F_1 score shown in Table 4.4.

Batch		NSL-KDD			UNSW-NB15		
		Precision	Recall	F_1	Precision	Recall	F_1
1st Batch	Ensemble	0.89	0.73	0.80	0.76	0.70	0.73
	Supervised	0.89	0.75	0.82	0.98	0.65	0.78
2nd Batch	Ensemble	0.90	0.73	0.81	0.77	0.69	0.73
	Supervised	0.91	0.78	0.84	0.97	0.67	0.79
3rd Batch	Ensemble	0.89	0.72	0.80	0.78	0.71	0.74
	Supervised	0.92	0.79	0.85	0.96	0.71	0.82
4th Batch	Ensemble	0.90	0.74	0.81	0.77	0.70	0.73
	Supervised	0.94	0.79	0.85	0.97	0.73	0.83

Table 4.4: Experiment results for the supervised model in Phase 3

In Table 4.4, the results of the ensemble model are based on each batch. For example, the first batch is used to provide the result of the ensemble on the first batch. However, the result of the supervised model is provided based on the last batch (the fifth batch). As you see the table, the results of the ensemble are consistent over the batches, so we could tell the ensemble is stable to detect outliers. As for the supervised model, the performance gets better as we accumulate the feedbacks. We would like to remind you that the reason why we use the supervised model in the last phase is to reduce false positives, especially from outliers that are different from normal instances but not malicious. The precision values increase without the decrease of the recall values on the NSL-KDD dataset. Even though the precision values decrease by 0.01 to 0.02 as we get more feedbacks, the F_1 values increase on the UNSW-NB15 dataset. You may notice that the precision values on the UNSW-NB15 dataset are higher than those on the NSL-KDD dataset. We speculate that this may arise from the fact that the UNSW-NB15 dataset has less number of attack types so there is a chance that the supervised model is overfitted to some attack patterns. Overall, these results are consistent with our expectation that the supervised model could take advantage of accumulated feedbacks.

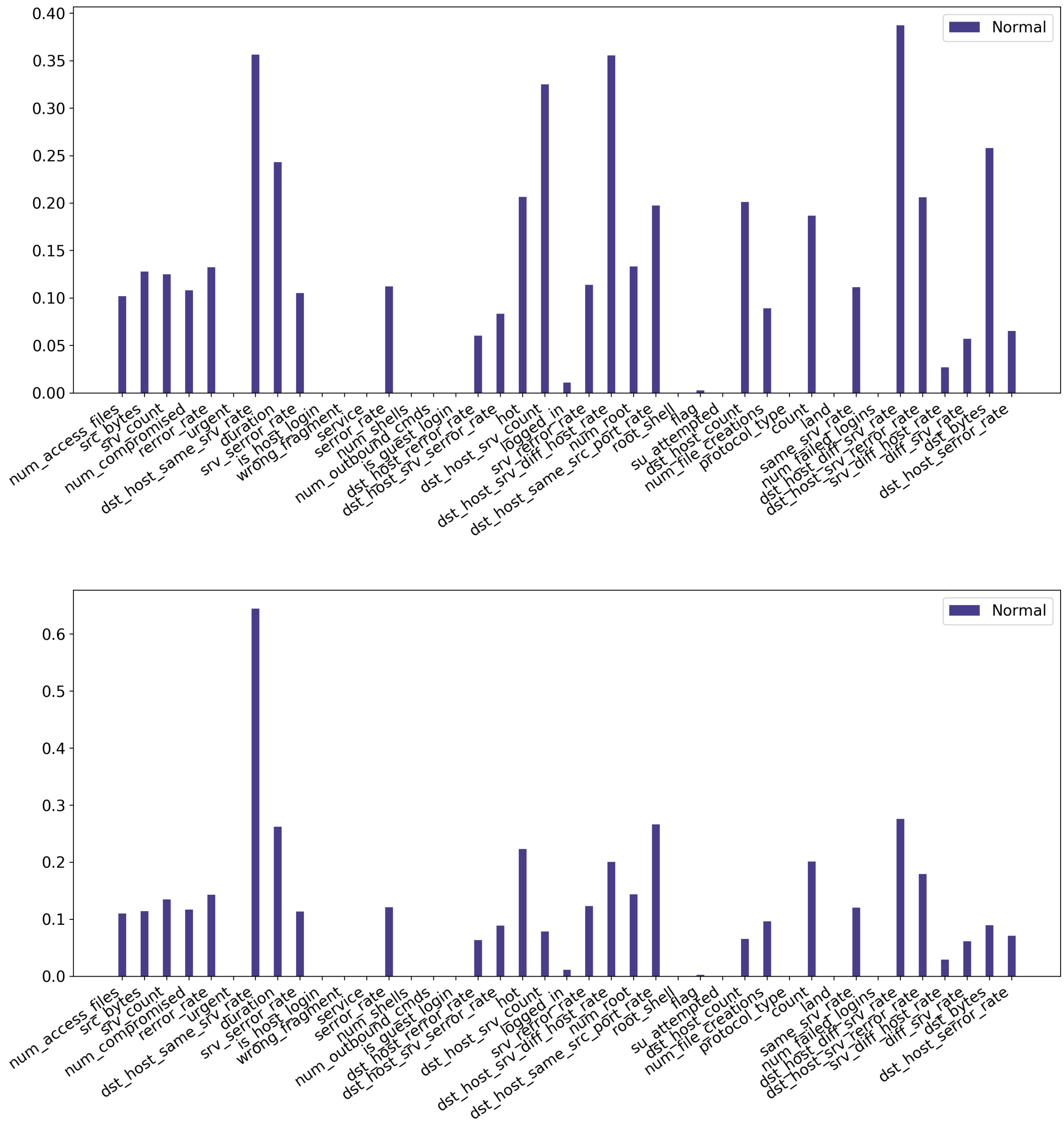


Figure 4.1: Examples of the interpretation results on the NSL-KDD dataset; the bar graphs show the feature importance scores for each attribute of normal instances. As you see the figures, the scores are well distributed over features. This is because normal instances do not have specific anomalous attributes.

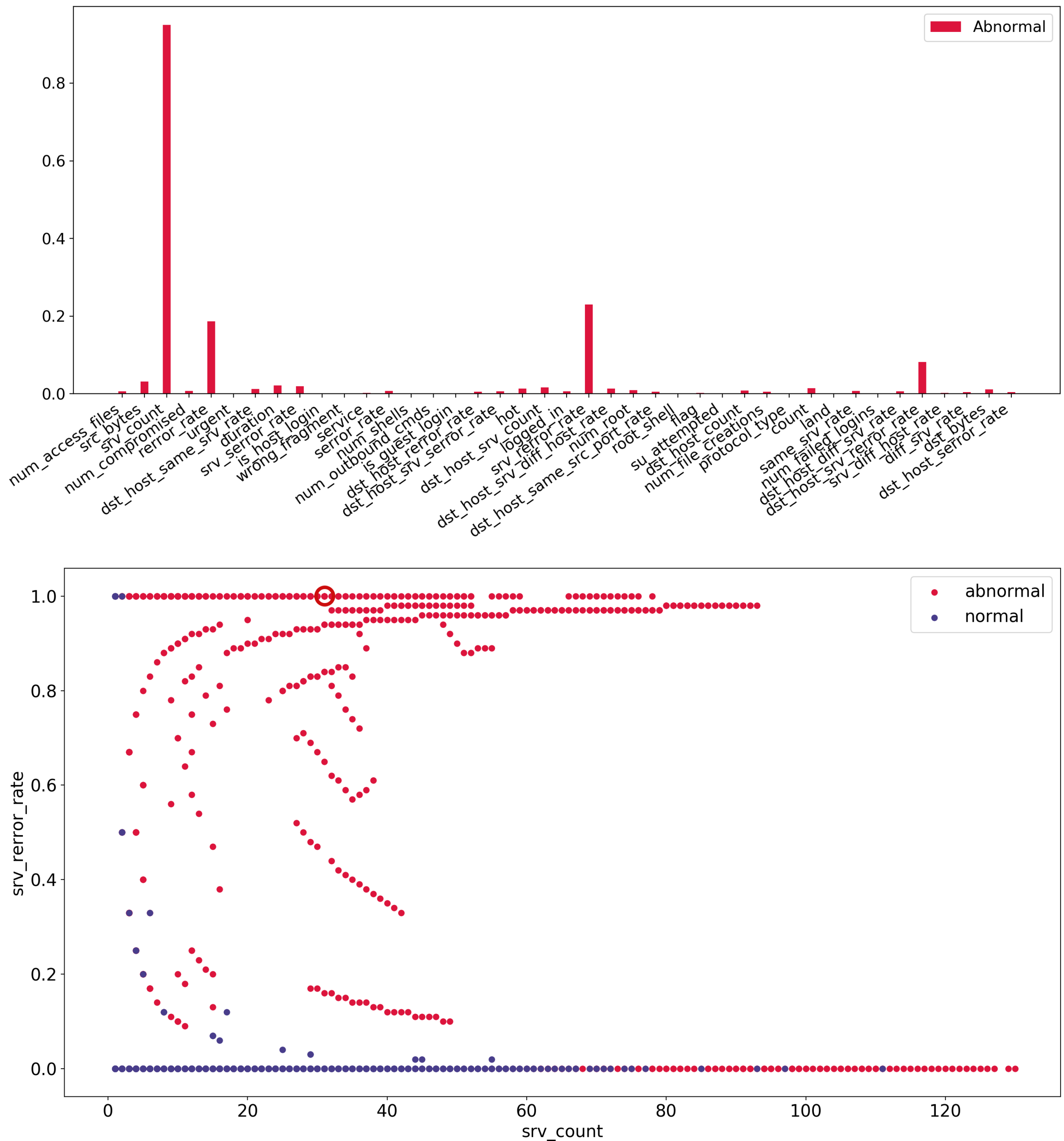


Figure 4.2: Examples of the interpretation results on the NSL-KDD dataset; the top figure shows the feature importance scores for each attribute of a detected outlier, and the bottom figure shows a scatter plot of the first and second most anomalous attributes, *srv_count* and *srv_rerror_rate* based on the feature importance scores. In the scatter plot, red points represent abnormal instances, and blue points represent normal instances. The red point marked with the red circle refers to the detected outlier.

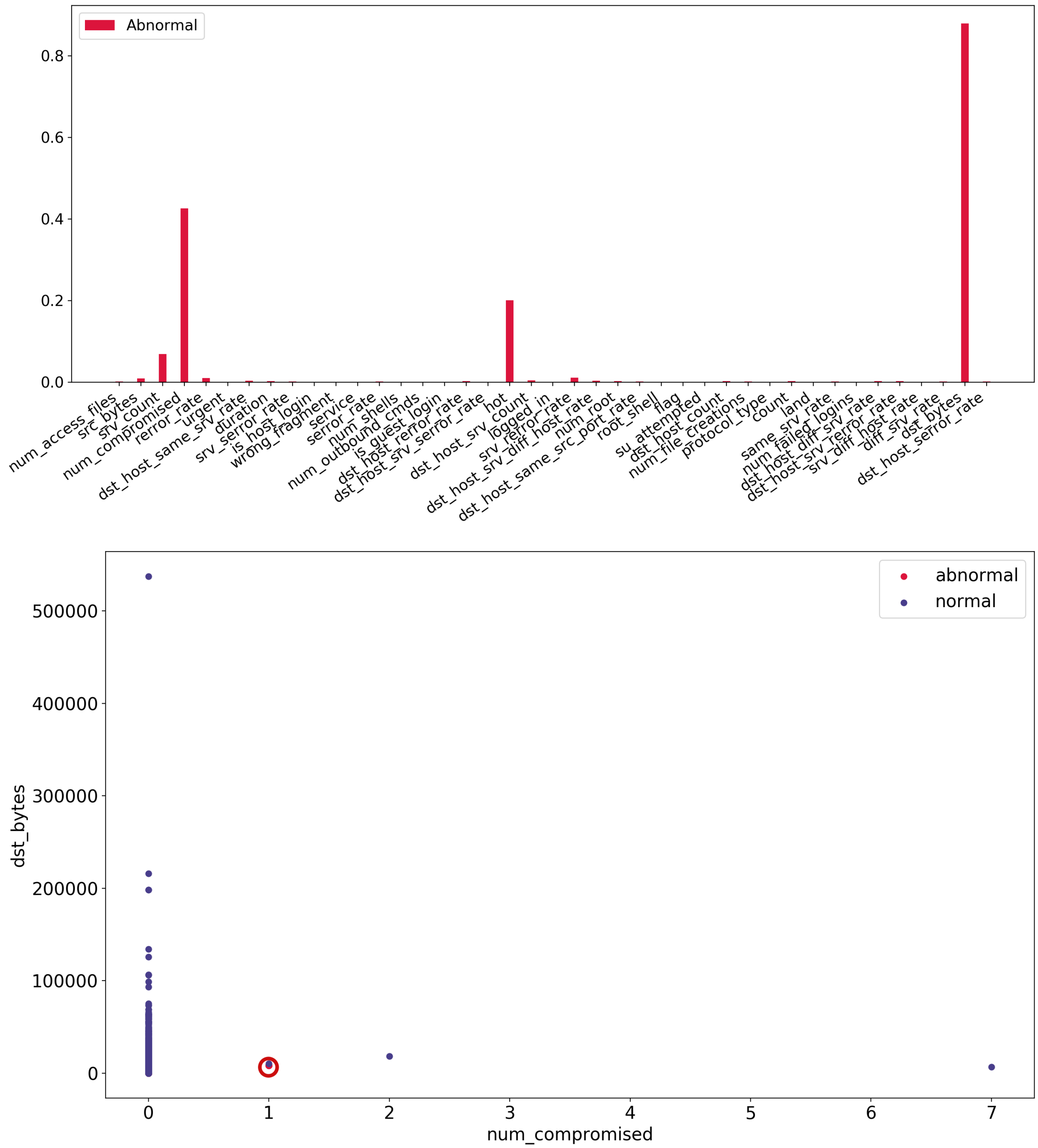


Figure 4.3: Examples of the interpretation results on the NSL-KDD dataset; the top figure shows the feature importance scores for each attribute of a detected outlier, and the bottom figure shows a scatter plot of the first and second most anomalous attributes, *dst_bytes* and *num_compromised* based on the feature importance scores. In the scatter plot, red points represent abnormal instances, and blue points represent normal instances. The red point marked with the red circle refers to the detected outlier.

5. CONCLUSION AND FUTURE WORK

In this paper, we propose an anomaly detection framework for heterogeneous and streaming data. The framework was able to handle heterogeneous data and achieve comparable performance with the state of the art baseline method on the network intrusion detection datasets using an ensemble of two outlier detection algorithms and our distance metric for categorical attributes. These methods are enhanced to update the backend cluster information so that they could adapt to changing data behaviors (*concept drift*). In the second phase of the framework, outlier interpretation is provided to help human experts to check whether detected outliers are really anomalous and we have shown that interpretation results are reasonable, giving the interpretation examples. Finally, the supervised machine learning algorithm was trained with the feedbacks from Phase 2 and successfully reduced false positives with accumulated anomaly information.

The work can be extended by trying parameter optimization techniques based on the predefined contamination ratio (outlier ratio) since we have a score threshold for each method to tune. Using different supervised models which can handle heterogeneous and streaming data such as Hoeffding Trees [45] and Wide & Deep Learning model [46] might help the framework. Finally, it would be very helpful to analyze detected outliers and the interpretation of them if we had the graphical interface of the framework.

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