A Grid Based Adversarial Clustering Algorithm

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Abstract: Nowadays more and more data are gathered for detecting and preventing cyber attacks. In cyber security applications, data analytics techniques have to deal with active adversaries that try to deceive the data analytics models and avoid being detected. The existence of such adversarial behavior motivates the development of robust and resilient adversarial learning techniques for various tasks. Most of the previous work focused on adversarial classification techniques, which assumed the existence of a reasonably large amount of carefully labeled data instances. However, in practice, labeling the data instances often requires costly and time-consuming human expertise and becomes a significant bottleneck. Meanwhile, a large number of unlabeled instances can also be used to understand the adversaries’ behavior. To address the above mentioned challenges, in this paper, we develop a novel grid based adversarial clustering algorithm. Our adversarial clustering algorithm is able to identify the core normal regions, and to draw defensive walls around the centers of the normal objects utilizing game theoretic ideas. Our algorithm also identifies sub-clusters of attack objects, the overlapping areas within clusters, and outliers which may be potential anomalies.

Keyword: Adversarial Clustering, Adversarial Machine Learning, Cyber Security, Big Data, Game Theory

1 Introduction

Increasingly data analytics techniques are being applied to large volumes of system monitoring data to detect cyber security incidents. The ultimate goal is to provide cyber security analysts with robust and effective insights derived from big data. Unlike most other application domains, cyber security applications often face adversaries who actively modify their strategies to launch new and unexpected attacks. The existence of such adversaries results in cyber security data that have unique properties. Firstly, the attack instances are frequently being modified to avoid detection. Hence a future dataset no longer shares the same properties as the current training dataset. Secondly, when a previously unknown attack happens, security analysts need to respond to the new attack quickly without the help of readily labeled instances in their database to assist their work. Thirdly, adversaries can be well funded and make big investments to camouflage the attack instances. Therefore despite significant effort invested by the domain experts, a vast majority of the instances in their database may remain unlabeled. For example, a new malware can incorporate large amounts of legitimate code to masquerade as legitimate software and obfuscate its binary. In other cases, it may become laborious and expensive to label an instance.
Thus data analytics techniques for cyber security must also have unique capabilities. They need to be resilient against the adaptive behavior of the adversaries, and are able to quickly detect previously unknown and unlabeled new attack instances. Hence, recently, various adversarial machine learning techniques have been developed to counter adversarial adaptive behaviors. However, those previous adversarial machine learning work is mostly under the main assumption of the availability of large amounts of labeled instances (i.e., normal versus malicious objects). Although large amounts of data are generated by the cyber security applications, we often have few properly labeled instances to construct an effective classifier.

Given a large amount of unlabeled data, defender needs to capture the adversarial behavior, identify suspicious instances as anomalies for a more detailed investigation, and quickly respond to new attacks. However clusters identified by traditional clustering algorithms are likely mixed, since with a few attack objects, adversaries can bridge the gap between two previously well separated clusters. Sometimes a handful of labeled attack and normal instances are available. There are too few of them to build a classifier, yet they offer valuable information about the adversaries. In this paper, we develop a novel adversarial clustering algorithm so that we need only a few labeled instances to build robust defensive algorithm against the attack objects. Our algorithm can identify the centers of normal objects, sub-clusters of attack objects, and the overlapping areas where adversaries have successfully placed the attack objects. We then draw defensive walls around the centers of the normal objects utilizing game theoretic ideas. Our algorithm also identifies outliers as potential anomalies and outlying unknown clusters for further investigation.

Semi-supervised learning techniques also utilize information from both labeled and unlabeled instances. Adversarial clustering and semi-supervised learning operate under very different assumptions. In adversarial settings, attackers purposely modify the attack objects to make them similar to normal objects, though suffering a cost for doing so. Hence the assumptions commonly used for semi supervised learning do not hold for adversarial clustering. Instead we observe that objects similar to each other belong to different classes, while objects in different clusters belong to the same class. In adversarial settings, within each cluster, objects from two classes can overlap significantly. Consequently, adversarial clustering and semi-supervised learning techniques have very different goals too. Semi-supervised learning aims to assign labels to all the unlabeled objects with the best accuracy. Our adversarial clustering algorithm aims to identify the overlapping regions, and the core areas of the normal objects, within each cluster. The overlapping regions and outliers are not labeled by our algorithm. We draw defensive walls around the centers of the normal objects. The shape and the size of the defensive walls are determined through a game theoretic study. Inside the defensive walls, we have nearly pure normal objects, despite an increased error of blocking out the normal objects mixed with the attack objects outside of the walls. Adversarial clustering draws an analogy to airport security. A small number of passengers use the fast pre-check lane at the security checkpoint, analogous to the normal objects inside the defensive walls. All other passengers must go through more time consuming security check, analogous to the objects outside the walls. The goal is not to let a single terrorist enter an airport, at a cost of blocking out many normal objects. Meanwhile the ability to identify the overlapping regions leads to a more focused security check procedure, where attack and normal objects are similar to each other. We compare our algorithm with semi-supervised learning algorithms in Section 3.

The paper is organized as follows. Section 1.1 discusses the related work. In Section 2, we present our adversarial clustering algorithm. In Section ??, we conduct a game theoretic study to examine the sizes and the shapes of different defensive walls used in our adversarial clustering
algorithm. In Section 3, we evaluate our algorithm with simulated and a network intrusion data sets. Section 4 concludes the paper.

1.1 Related Work

Robust learning techniques have been proposed in the past, for example, to defeat poisoning attacks [35], purposely generated malicious errors [24], and missing or corrupted features [15]. Classification in adversarial settings has also received considerable attention in the literature, e.g., [14, 20, 28, 29, 47]. In [9, 21], Stackelberg game is used to model the sequential actions between a defender/classifier and active adversaries. Adversarial classification techniques were developed for the Facebook social network to defeat the fake and spam accounts [40]. However even with the information obtained from a large training sample of labeled normal and attack objects, building a robust classifier to block out the attack objects, which are constantly being modified by adversaries to avoid detection, is not an easy task.

Compared with adversarial classification, there is fewer work on adversarial clustering, which is a much harder learning problem. [4] considered the problem of evaluating the security of clustering algorithms in an adversarial setting. [4] then evaluated the security of single linkage hierarchical clustering algorithm under poisoning attacks and obfuscation attacks. [5] further studied the effects of poisoning attacks on complete linkage hierarchical clustering algorithm. [16] showed that a few well-constructed attack objects could lead to a larger mixed cluster, and hence significantly reduce the effectiveness of a clustering algorithm. [41] showed that subspace clustering has a certain tolerance for noisy or corrupted data.

Semi-supervised learning techniques utilizes information from both labeled and unlabeled instances. It has an extensive literature. In general there are two types of semi-supervised learning techniques, semi-supervised classification and semi-supervised clustering. There are many different approaches for semi-supervised classification, such as transductive support vector machine (TSVM), generative mixture models, self-training and co-training. TSVM extends SVM to the semi-supervised learning scenario. Labels are assigned to the unlabeled instances such that the classification boundary has the maximum margin on the original labels and newly assigned labels (e.g., [10, 45, 38]). TSVM avoids the high density regions, which may not be the optimal solution when two classes are heavily overlapped. Under mixture model assumption, EM algorithm is used for semi-supervised classification (e.g., [32, 18]). This approach allows the classification boundary to go through the densest region of the data points. However users need to pay attention to model identifiability issue and whether the model assumption fits the data or not (e.g., [31, 33, 12]). Self-training approach iteratively assigns labels to new data points, and then includes both the existing labels and newly assigned labels to train another classifier (e.g., [34, 13, 19]). Co-training splits the available features into two sets and build two classifiers, each using only one set of features. In an iterative process, each classifier learns from the other one with the most confident predicted labels (e.g., [3, 11, 46]).

Often semi-supervised clustering algorithms use pairwise must-link and cannot-link constraints. Must-links ensure the objects with identical labels are grouped in the same cluster, while cannot-links ensure the objects with different labels are in different clusters (e.g., [2, 6, 22]). Meanwhile many work extends K-means algorithm to semi-supervised clustering settings (e.g., [42, 7, 43]). [8] developed a hierarchical density based semi-supervised clustering algorithm. However if the density varies significantly among clusters, the algorithm has difficulty to extract the natural cluster
structure. [26] extends DBSCAN to semi-supervised settings. Instead of having one set of values for the parameters as in DBSCAN, [26] finds multiple sets of parameter values to better handle the situation when densities vary significantly among clusters.

Our adversarial clustering algorithm has a very different goal. Compared with semi-supervised learning, we do not label all the previously unlabeled objects and attempt to achieve the maximum accuracy. Instead we identify the centers of normal objects using defensive walls. We focus on having nearly pure normal objects inside the walls, often at the expense of blocking out many normal objects mixed with abnormal objects. Hence the overall accuracy of our algorithm may decrease but we identify the center normal regions where the percentage of normal objects is much higher, and can be considered as relatively safe regions. We do not label the objects in the regions where normal and abnormal objects are mixed. Instead we mark out the whole mixed areas, where attacks take place and objects must be examined carefully. We also leave unknown clusters and outliers unlabeled, since they should be investigated carefully as being potential anomalies or a new attack.

2 Adversarial Clustering

In cyber security applications, adversaries actively manipulate the objects under their control to break through a defensive algorithm. Hence the properties of the data under attack are drastically different from the data without an attack. Even though the normal population remains unchanged, the adversaries can inject a small amount of attack objects to fill in the gap between abnormal clusters and normal clusters, and make previously relatively pure normal clusters mixed, as pointed out in [4, 5, 16]. Traditional clustering algorithms are able to produce clusters and a few outliers. Without any labeled instances, that is the only result we can expect, not knowing whether a cluster is mixed, or nearly purely normal or abnormal. On the other hand, if a large number of labeled instances are available, we can build a classifier with a well defined classification boundary that separates the normal and abnormal objects within one cluster, and separate the relative pure normal clusters from the abnormal objects.

In this paper, we consider a scenario where there are a large number of unlabeled instances and only a handful of labeled instances (i.e., the number labeled being far less than the number of unlabeled ones). A classifier created using very few labeled objects is very inaccurate when being applied to the large number of unlabeled ones. On the other hand clusters, produced by traditional clustering algorithms, may become mixed clusters under attack, where extra efforts are needed to identify normal and abnormal regions inside these mixed clusters. Therefore we develop a grid based adversarial clustering algorithm, which is able to utilize the handful of labeled objects, identify relatively pure normal and abnormal regions within one cluster and their overlapping area, and further identify outliers and outlying clusters which need more effort to investigate their properties.

A classifier with a well defined classification boundary is analogous to a point estimate. When the sample size is too small (i.e., too few labeled instances), a point estimate is way too inaccurate. Hence our clustering algorithm identify overlapping areas between the normal regions and the abnormal regions, analogous to confidence regions. When a large number of labeled instances are available, a classification boundary is a defensive wall against the adversaries, since it blocks out the attack objects. When facing active adversaries, a classifier needs to be more conservative, i.e., a classification boundary is pulled back toward the center of the normal population, as shown...
in [47]. With a large number of unlabeled instances, our adversarial clustering algorithm offers more valuable information to capture both normal and abnormal regions. Our adversarial clustering algorithm then plays a conservative strategy. We draw defensive walls inside the normal regions to protect the relatively pure normal centers. All objects outside of the walls need to be examined carefully, while many normal objects can be blocked out. How conservative the defensive walls need to be is determined through a game theoretic study in Section 2. If the defensive walls are too close to the center of the normal regions, we miss a large portion of the relatively pure normal areas. If the defensive walls are too relaxed, we have too many attack objects in the walls. Hence we utilize the equilibrium information to determine the sizes of the conservative defensive walls for our algorithm.

2.1 A Grid Based Defensive Clustering Algorithm

Since cyber security applications often produce big data sets, we need a computationally efficient algorithm, which needs to be easy to tune as well. Inspired by a traditional grid based clustering algorithm [44], we develop a grid based adversarial clustering algorithm (ADClust). Our algorithm applies a Gaussian kernel classifier to compute the probability scores for every unlabeled data points. Then using a pre-specified weight, we obtain re-weighted density of the data points. In the first pass, our algorithm groups the data points into normal sub-clusters, abnormal sub-clusters, unlabeled sub-clusters and unlabeled outliers. Notice that the choice of the weight affects the size of the overlapping areas and the normal and abnormal regions. Then in a second pass, we do not use label information, and simply group the data points into large unlabeled clusters and identify unlabeled outliers. The next step is to match the normal, abnormal, unlabeled smaller clusters from the first pass with the unlabeled larger clusters from the second pass. This way we are able to identify normal and abnormal regions within one cluster along with the unlabeled overlapping regions. The last step is to play a conservative strategy, drawing defensive walls inside normal regions to ensure that we identify relatively pure normal core positions. Figures 2, 3, and 4 in Section 3 show how our algorithm work on three simulated datasets.

During the initialization stage of our algorithm we create the cells, compute the distance threshold RT and the density threshold DT. We choose a pre-determined positive weight $k$ to assign re-weighted density to every unlabeled point. The value of $k$ affects the size of the overlapping regions. Section 3 examine different $k$ values and recommend $k$ around 30. $\text{coef}_{RT}$ and $\text{coef}_{DT}$ are also tuning parameters. In Section 3 we set $\text{coef}_{RT} = 20$ and $\text{coef}_{DT} = 0.95$, which achieve good results. There are three initialization steps.

**Initialization Step 1.** Creating cells: For every variable $X_i$, divide its range $[\min(X_i), \max(X_i)]$ into $m_i$ equal sized sections, $i = 1, ..., q$. We choose the number $m_i$ to ensure each section has roughly 5% to 10% of the data points. For different variables, the number of sections $m_i$ can be different. Hence in the $q$-dimensional space, the sections along each dimension together form small $q$-dimensional cells. Given a particular cell, we call the cells in its hypercube neighborhood with radius 1 as its neighbor cells.

**Initialization Step 2.** Thresholding: Compute the distance threshold RT and the density threshold DT as follows.
• Distance Threshold RT: For a data point \( p \) in cell \( c \), we compute the pairwise distances \( d(p, o) \) between \( p \) and all the points in cell \( c \)’s neighbor cells. For point \( p \), let \( a(p) = \text{mean}(d(p, o)) \) be the average of all the pairwise distances. Let \( d(c) = \text{mean}_{p \in c}(a(p)) \) be the average over all the points in cell \( c \). The distance threshold

\[
RT = \frac{\text{mean}(d(c))}{q \times \text{coef}_{RT}}.
\]

• Density Threshold DT: For a data point \( p \) in cell \( c \), its density \( n(p) \) is the number of points within the distance threshold \( RT \) from the data point \( p \). A cell \( c \)’s density is \( n(c) = \text{mean}_{p \in c}(n(p)) \), the average of the densities of the points in cell \( c \). The density threshold

\[
DT = \frac{\text{mean}(n(c))}{\ln(N)} \times \text{coef}_{DT},
\]

where \( N \) is the total number of data points.

Initialization Step 3. Weighting: We build a Gaussian kernel classifier with the handful labeled data points. Normal objects are labeled as 1s and abnormal as 0s. We then apply the Gaussian kernel classifier to the unlabeled objects. Each unlabeled points \( p \) is assigned a probability score \( b_p \in [0,1] \). A pre-determined positive weight \( k \) is used to map the scores \( b_p \) from \([0,1]\) to \([-k,k]\).

Our adversarial clustering algorithm has five steps. Algorithm 1 shows the function Merge. Algorithm 2 is the main algorithm, with the initialization steps and the following five steps.

Merge 1: Creating labeled normal and abnormal sub-clusters: Use each point’s re-weighted density \( n(p) \times b_p \). First take the points whose re-weighted densities are greater than density threshold \( DT \) as cluster centroids. Merge the remaining points with the cluster centroids if their distances to a cluster centroid is less than distance threshold \( RT \). If a point’s distance to multiple cluster centroids are less than \( RT \), then those small clusters are merge into one big cluster. Continue to merge. The data points not assigned to any cluster remain unlabeled.

Merge 2: Clustering the remaining unlabeled data points: Remove all the normal and abnormal sub-clusters. For the remaining data points, use their original density \( n(p) \). Merge the remaining unlabeled data points.

Merge 3: Using the same \( RT, DT \), and \( k \) parameter values, and every data point’s original density \( n(p) \), we merge all the data points without considering the labels. We obtain unlabeled clusters, and unlabeled outliers.

Match: Match the above unlabeled clusters with the normal and abnormal sub-clusters, and the clusters of the remaining unlabeled data points from the first pass. Now we are able to identify clusters which contain normal and abnormal regions and their overlapping areas. The points in the overlapping areas are not labeled. If there are remaining unlabeled clusters, they are outlying
unknown clusters. The rest are outliers, i.e., potential anomalies.

**Draw defensive walls:** We draw $\alpha$-level defensive walls inside the normal regions to ensure that we protect the relatively pure normal positions.

\begin{algorithm}
\textbf{Data:} $d(p), n(p), DT, RT$
\textbf{for point $p_j$ in the space do}
\hspace{1cm} \textbf{if} $n(p_j) \geq DT$ \textbf{then}
\hspace{2cm} Assign $p_j$ a new label;
\hspace{1cm} \textbf{end}
\textbf{end}
\textbf{while} No more clusters can merge \textbf{do}
\hspace{1cm} \textbf{for every cluster $cl_i$ do}
\hspace{2cm} \textbf{for every cluster $cl_j$ do}
\hspace{3cm} \textbf{if} exist a point $p_1$ in $cl_i$ and a point $p_2$ in $cl_j$, distance($p_1, p_2$) $\leq RT$ \textbf{then}
\hspace{4cm} Merge($cl_i, cl_j$);
\hspace{3cm} \textbf{end}
\hspace{2cm} \textbf{end}
\hspace{1cm} \textbf{end}
\end{algorithm}

**Algorithm 1:** Function Merge

3 Experiments

3.1 Simulated Experiment

We conduct three simulations to compare our ADClust with two semi-supervised learning algorithms, EM least square [25] and S4VM [27]. In all three simulations, we generate data points from several bivariate normal distributions. The bivariate normal distributions have the same variance-
**Data:** Unlabeled points, labeled points, confidence \( \alpha \) initialization;

\( q \leftarrow \text{dim(space)}; \)

\( N \leftarrow \text{count(points)}; \)

\( k \leftarrow \text{function(\( \alpha \))}; \)

**for every cell** \( c_i \) **in the space do**

**for every point** \( p_{ij} \) **in the cell** \( c_i \) **do**

**for every point** \( q_{ijk} \) **in** \( c_i \)'s neighborhood **do**

\( d(p_{ij}, p_{ijk}) \leftarrow \text{distance}(p_{ij}, p_{ijk}); \)

end

\( d(p_{ij}) \leftarrow \text{mean}(d(p_{ij}, p_{ijk})) \) **for every** \( k; \)

end

\( d(c_i) \leftarrow \text{mean}(p_{ij}) \) **for every** \( j; \)

end

\( \text{RT} \leftarrow \frac{\text{Mean}(d)}{q \times \text{coefRT}}; \)

**for every cell** \( c_i \) **in the space do**

**for every point** \( p_{ij} \) **in the cell** \( c_i \) **do**

\( n(p_{ij}) \leftarrow \text{count(distance}(p_{ij}, p_{ijk}) \leq \text{RT}) \) where \( p_{ijk} \) **are the points in** \( c_i \)'s neighborhood;

end

\( n(c_i) \leftarrow \text{mean}(p_{ij}) \) **for every** \( i; \)

end

\( \text{DT} \leftarrow \frac{\text{mean}(n(c_i))}{\lg(N)} \times \text{coefDT}; \)

**for every point** \( p_j \) **in the space do**

\( w(p_j) \leftarrow k \times \text{GaussianKernelClassifier}(p_j, \text{points, known labels}); \)

end

Assign(abnormal or normal) \( \leftarrow \text{Merge}(d(p) \times w(p), n(p), \text{DT, RT}); \)

Assign(no-label to remaining points) \( \leftarrow \text{Merge}(d(p \text{ neither abnormal nor normal}), n(p \text{ neither abnormal nor normal}), \text{DT, RT}); \)

Assign(no-label to all points) \( \leftarrow \text{Merge}(d(p), n(p), \text{DT, RT}); \)

Match Assign(abnormal or normal) and Assign(no-label to remaining points) with Assign(no-label to all points);

Draw \( \alpha \)-level defensive walls inside normal sub-clusters;

**Algorithm 2:** Main Clustering Algorithm
Figure 2: Simulation 1 comparison with $\alpha = 0.6$. Left to right: 1) ADClust with $k = 10$; 2) ADClust with $k = 20$; 3) EM least square; 4) S4VM

Figure 3: Simulation 2 comparison with $\alpha = 0.6$. Left to right: 1) ADClust with $k = 10$; 2) ADClust with $k = 20$; 3) EM least square; 4) S4VM

Figure 4: Simulation 3 comparison with $\alpha = 0.6$. Left to right: 1) ADClust with $k = 10$; 2) ADClust with $k = 20$; 3) EM least square; 4) S4VM

covariance matrix 

$$\Sigma = \begin{bmatrix} 0.4 & 0 \\ 0 & 0.4 \end{bmatrix}. $$

Figure 1 shows the true labels of the points for the three simulations. Solid triangles and solid circles are the 2% labeled points. Figures 2-4 show the comparison results. We set $\alpha = 0.6$. Blue dots are used for normal points, either true or labeled. Orange dots are used for abnormal points, either true or labeled. Purple dots are for unlabeled points in mixed regions. Yellow dots are for unknown unlabeled clusters. Black dots are for unlabeled outliers. Different regions are marked using different colors.

In these three simulations, we show the data points after attacks have taken place. In Simulation 1 previously separated normal and abnormal clusters now have overlapped areas and are merged into one big cluster. In Simulation 2, an attack takes place between two normal regions, and attack objects manage to mix three clusters into one big cluster. Simulation 3 suffers the strongest
Figure 5: Quantitative measures as the weight $k$ increases from 1 to 100. Left Column: Top panel is percent of abnormal points in mixed region and bottom panel is percent of abnormal points among outliers; Right Column: Top panel is the number of points in mixed region and bottom panel is the number of points as outliers.

Figure 6: Left Panel: The boxplots of percent of normal objects within Manhattan defensive walls with different $\alpha$ levels and weight $k$. The corresponding $\eta(\alpha)$ values are 5.89, 7.25, 8.97, 11.51, 13.72; Right Panel: The boxplots of percent of normal objects within Euclidean defensive walls with different $\alpha$ levels and weight scalars.
attack, where normal and abnormal clusters are heavily mixed. There is also a previously unknown cluster in simulation 3, which cannot be identified as either normal or abnormal at the training time, potentially a new attack.

Defensive walls, studied under a game theoretic framework, are a crucial factor in our algorithm. With wall size $\alpha = 0.6$, as in the recommended range from the game theoretic study considering defender being a follower, the defensive walls mark out the center areas of the normal regions with nearly pure normal objects in Simulation 1 and 2, where attacks have not yet reached the centers of the normal. In Simulation 2, the defensive walls in our ADClust algorithm successfully mark out the two centers of the two normal regions. On the other hand the semi-supervised learning algorithms still make a hard separation of normal vs. abnormal. One normal cluster is completely wrongly labeled by the two semi-supervised learning algorithms. In Simulation 3, our algorithm leaves an previously unknown cluster unlabeled. It needs to be examined carefully later since it can potentially be a new attack. The two semi-supervised learning algorithms label the unknown cluster as normal, making a high risk decision.

Simulation 1: There are two sets of random samples generated from two bivariate normal distributions, centered at $(0, -1)$ (normal class), and $(1, -1)$ (abnormal class) respectively. Each has 300 data points. We random select $2\%$ of the points and save their labels. EM least square and S4VM make a hard separation, and try their best to label all the points in the mixed region. Hence they make noticeable mistakes in the mixed region. Our ADClust does not assign class labeled to the points in the mixed region. We instead mark out the whole region. The comparison between our marked mixed region and a classification boundary is similar to a confidence band vs a point estimate. We also identify and leave outliers unlabeled, as shown in Figure 2.

Simulation 2: There are three sets of random samples generated from three bivariate normal distributions, centered at $(-1, -1)$ (abnormal class), $(0, 0)$ (normal class), and $(1, 1)$ (abnormal class) respectively. Each has 300 data points. We random select $2\%$ of the points and save their labels. EM least square and S4VM divide the big cluster into two areas. They fail to distinguish three overlapping clusters. Our ADClust is able to identify the three clusters and mark out the two mixed regions, without assigning class labels there, as shown in Figure 3.

Simulation 3: There are four sets of random samples generated from four bivariate normal distributions, centered at $(0.5, -1)$ (normal class), $(1, -1)$ (abnormal class), $(1, 1)$ (normal class), and $(3, 3)$ (unknown class). They have 300, 300, 300, 100 data points respectively. We random select $2\%$ of the points from only normal and abnormal classes and save their labels. The unknown class has no labeled point. EM least square and S4VM label the unknown cluster as normal, where there is no reliable information. Furthermore, their assigned labels are highly inaccurate in the mixed regions. Our ADClust leave out the unknown cluster as unlabeled, and identify the mixed region without assigning labels there, as shown in Figure 4.

In the three simulations, we use two weight values, $k = 10$ and $k = 20$. A smaller weight $k$ is a more conservative strategy, i.e., we get smaller labeled regions and a larger unlabeled mixed region. On the other hand, if we use a larger weight $k$, it is a more aggressive strategy. We expect larger labeled regions and smaller unlabeled mixed region. Drawing defensive walls following the game theoretic study correctly identify the normal centers, while semi-supervised learning algorithms completely fail to do so under certain scenarios.
3.2 KDD Cup 1999 Data

The KDD cup 1999 data was initially created by MIT Lincoln Labs [23]. The full dataset contains about 126k labeled objects for training purpose. Around 40 percent of the objects are network intrusion instances. There are 41 features for each object. [1] ranked the 41 features with respect to their effectiveness in separating normal instances from abnormal instances. We use the KDD Cup 99 data to demonstrate how our ADClust algorithm performs. We take 25192 instances from training set. We include top 7 continuous features according to [1] for each instance.

In the first experiment, in a single run, we randomly sample 150 instances and keep their labels. The rest are treated as unlabeled instances in the run. We perform 100 runs. An overwhelming majority (i.e., 99.4%) of the instances are unlabeled.

We gradually increase the weight $k$ from 1 to 100. Along with the increasing weight, we have less unlabeled points. As a result, it is a more aggressive strategy. Meanwhile, the normal region increases and it includes more points which are more likely to be mis-labeled abnormal objects. Therefore, we have a trade-off in choosing weight $k$. It is a trade-off between the size of the labeled regions within a cluster and the error rate of mis-labeled points. In Figure 5, the number of points in mixed regions and outliers decreases as we have a larger weight. The percentage of abnormal objects in the mixed areas and among outliers decreases from 76% to 73% as the weight $k$ increases, which means we have to exam the mixed areas very carefully.

In a second experiment, we draw two boxplots to show the percent of normal objects (i.e., the success rate) within the defensive walls as shown in Figure 6. We again have 100 runs. For each run, we randomly select 100 points to keep their labels. Based on the labels, we perform ADClust to cluster instances. Then we set different weights and examine different alpha levels for the defensive walls. We set $k$ to 1, 30 and 50 as low, medium and high weights. For each of the weight, we show the success rates for the two types of defensive walls.

We set $\alpha$ levels from 0.6 to 0.95. The median of the success rates varies from 0.85 to 0.87. We find that the weights $k = 30$ and $k = 50$ perform better than $k = 1$ in term of success rate. Furthermore, $\alpha = 0.8$ has the highest median success rate for Manhattan defensive walls and $\alpha = 0.7$ has the highest median success rate for Euclidean defensive walls. Both of the results are consistent with the recommended $\alpha$ range, 0.6 to 0.8, from the game theoretic studies.

Note semi-supervised learning techniques are designed to achieve the highest overall accuracy over all unlabeled normal and abnormal objects. On the other hand, our algorithm does keep many points unlabeled, hence we do not have an overall accuracy measure computed over all the unlabeled objects. Meanwhile one of our algorithm’s focus is to have objects as purely normal inside the defensive walls as possible, at the expense of decreased accuracy, since many normal objects are blocked out of the wall along with the abnormal ones. In this experiment, KDD data is a highly mixed data, yet we achieve on average nearly 90% pure normal rate inside the defensive walls, marked as the relatively safe regions. The unlabeled mixed regions, and unlabeled whole clusters if there is any, are another focus of our algorithm. Results from our algorithm can be used for tiered screenings of the objects, with the objects in the mixed region examined most carefully to separate normal from abnormal, and the unknown clusters examined for potential new attacks.
4 Conclusion

In this paper, we develop a novel adversarial clustering algorithm, a.k.a. ADClust, to separate the attack region and the normal region within mixed clusters caused by adversaries’ attack objects. With very few labeled instances, we cannot build an effective classifier, which has a clearly defined classification boundary to defend the normal population from the attack objects. However utilizing the few labeled objects, our clustering algorithm can identify the mixed area between the normal region and the attack region. Instead of a classifier boundary, analogous to a point estimate, an overlapping area is analogous to a confidence region, showing the strength of an attack. Furthermore defensive walls are drawn inside normal regions. This is a conservative strategy to defend the normal population against active adversaries. All objects outside the centers of the normal objects need to be examined carefully, especially in the mixed regions.

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