LA-UR-02-1148

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Title: ANOMALY DETECTION ENHANCED CLASSIFICATION IN COMPUTER INTRUSION DETECTION

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Submitted to: INTERNATIONAL CONFERENCE ON PATTERN RECOGNITION, AUGUST 2002
MONTREAL CANADA

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Anomaly Detection Enhanced Classification in Computer Intrusion Detection

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1 Introduction

This report describes work with the goal of enhancing capabilities in computer intrusion detection. The work builds upon a study of classification performance, that compared various methods of classifying information derived from computer network packets into attack versus normal categories, based on a labeled training dataset[1]. This previous work validates our classification methods, and clears the ground for studying whether and how anomaly detection can be used to enhance this performance. The DARPA project that initiated the dataset used here concluded that anomaly detection should be examined to boost the performance of machine learning in the computer intrusion detection task[2]. This report investigates the data set for aspects that will be valuable for anomaly detection application, and supports these results with models constructed from the data.

In this report, the term *anomaly detection* means learning a model from unlabeled data, and using this to make some inference about future data. Our data is a feature vector derived from network packets: an "example" or "sample". On the other hand, *classification* means building a model from labeled data, and using that model to classify unlabeled (future) examples. [1]

There is some precedent in the literature for combining these methods. One approach is to stage the two techniques, using anomaly detection to segment data into two sets for classification. An interpretation of this is a method to combat nonstationarity in the data. In our previous work, we demonstrated that the data has substantial temporal nonstationarity[1]. With classification methods that can be thought of as learning a decision surface between two statistical distributions, performance is expected to degrade significantly when classifying examples that are from regions not well represented in the training set. Anomaly detection can be seen as a problem of learning the *density* (landscape) or the *support* (boundary) of a statistical distribution so that this characterization can be compared to data points. Nonstationarity can then be thought of as data that departs from the support of the distribution.

[1] Classification and anomaly detection are also referred to as *supervised* vs. *unsupervised* training respectively in the data mining and machine learning literature

Since we can judge that these "anomalous" examples will be classified poorly, we can treat them differently (or not at all).

A second approach uses anomaly detection with an assumption that any examples that are different are suspicious, which is an assumption that may or may not be true in an application. We will call this the *Outlier Assumption.* With this assumption there are simply the performance gains to be had from combining models that have uncorrelated errors into an *ensemble* with better performance than any of the individual models. This family of techniques has many names, including model averaging, multiple regression, and the very popular boosting approaches. In this approach the two methods are "peer" results, which are then combined to generate a final result.

Staged anomaly detection with the outlier assumption can also be used to create data sub-categories into which the classification method is specifically tuned, or *vice-versa.* This is an avenue for further work in this application area, and will not be demonstrated in this study.

As in our previous work, this report does not attempt to address issues in dataset generation or feature selection. The details of the network and data collection process as well as the way in which this "raw data" is transformed into well-defined feature vectors is a very important problem. However that exploration is beyond the scope of this effort.

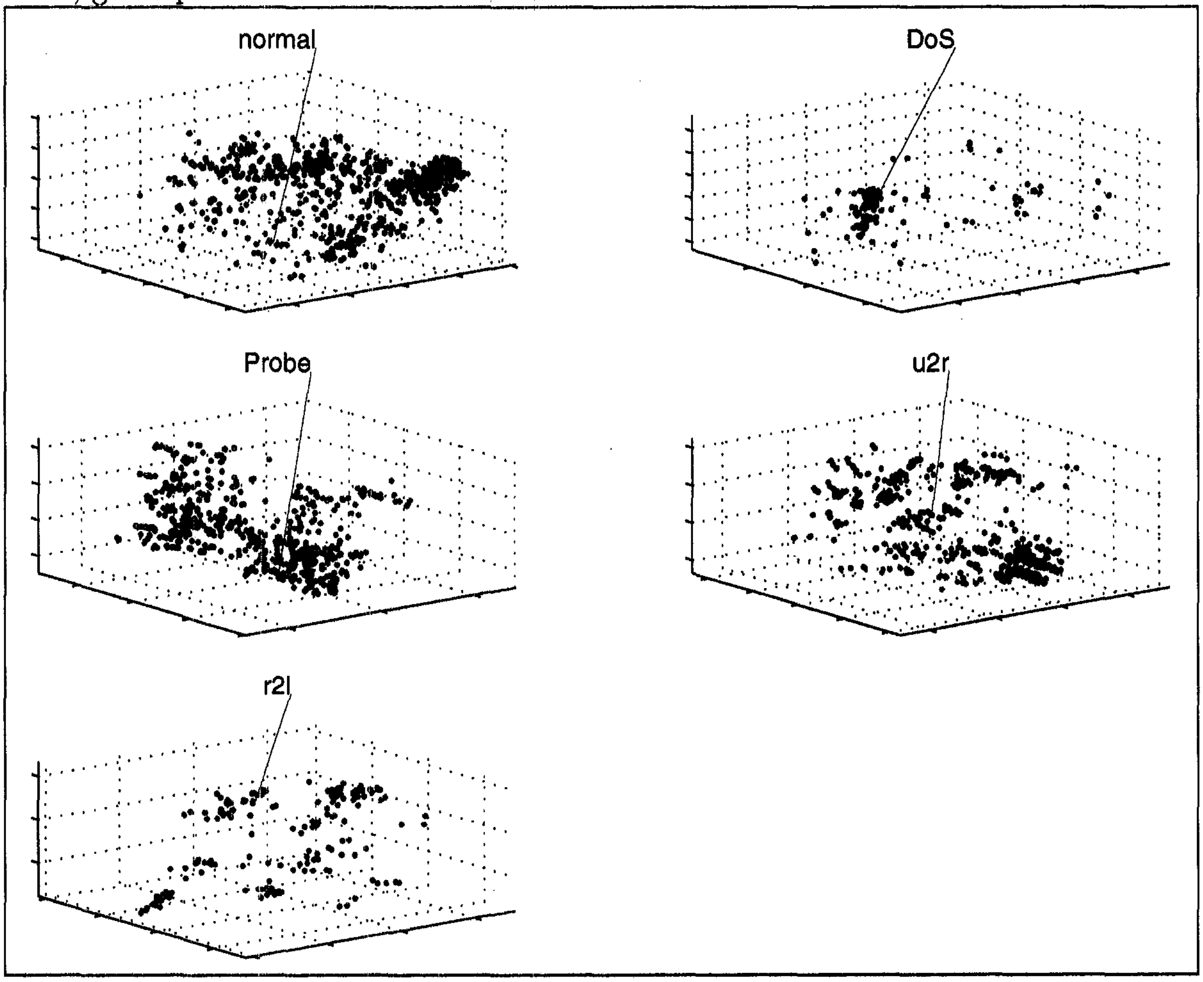
2 Dataset Description

The data is described in more detail in [1]. Briefly, we are using data derived from a DARPA project which set up a real network and logged normal and attack network traffic. This experiment yielded a *training set*, and a *test set.* The test set was recorded after the training set, and is known to reflect somewhat different activity. The data from this experiment were transformed into a "clean" dataset for the 1999 KDD-Cup, a competition associated with the Knowledge Discovery and Datamining conference. This dataset has 41 features for every example, with a training and test set size of approximately 500,000 and 300,000 examples, respectively. The data are labeled as attack or normal, and furthermore are labeled with an attack type that, although too fine-grained to allow experimentation, can be grouped into four broad categories of attacks: denial of service (DoS), probe, user to root (u2r), and remote to local (r2l). This is of particular interest since performance was shown previously to be very different for these categories, plausibly because they exhibit distinct nonstationarity.

We have found it useful to further segment the dataset. The training set from KDD was broken into three parts to investigate modeling on a stationary dataset: 10% was sampled for model training, 5% for model tuning (adjusting modeling parameters), and the remainder is used for validation (assessment of performance on the stationary data). The test set remains intact as a method of exploring the impact of nonstationarity. Although this makes the model training set a small part of the available data, our explorations indicate the performance is stable with this data size. It is also more convenient for model training.

These methods assume ordered numeric data. Therefore, a method of ANOVA trans-

Figure 1: Plots of the four attack types. In each plot Black points are the training set attacks, green points are the test set attacks.



formation is applied to all variables, both categorical (by individual values) and real (by segmenting into intervals). Each discrete subset (value or interval) is modeled by the observed probability of attack in the training data, for each variable independently. This results in a transformed dataset of the same size but with a consistently scaled metric basis. This dataspace mapping will have a significant effect on the results of the automated learning.

2.1 Dataset Nonstationarity

Some data summaries will indicate the nonstationarity present. Figure 1's 3D plots show the distinction between the training set and the test set by attack type. These are plots of the first three principle components of the data examples.

Another view of nonstationarity is presented in Table 1. We will use methods to draw a boundary around a dataset, and then check whether new data falls within that boundary. From the presentation in Fig. 1 we expect there to be a distinct difference in the test

Table 1: Test data performance comparison of the SVM-RBF and Mahalanobis outlier detection methods.

Attack type	% inlier by both	%outlier by SVM	%outlier by Mahal	%outlier by both
Normal	95.24	1.15	1.99	1.62
DoS	98.17	0.45	0.67	0.71
Probe	55.11	2.02	32.12	10.75
R2L	91.10	0.12	7.73	1.04
U2R	40.35	0.44	37.28	21.93

Table 2: Validation data performance comparison of the SVM-RBF and Mahalanobis outlier detection methods.

Attack type	% inlier by both	%outlier by SVM	%outlier by Mahal	%outlier by both
Normal	90.29	3.78	3.00	2.93
DoS	98.77	0.70	0.49	0.04
Probe	67.95	0.25	30.34	1.46
R2L	57.30	0.00	39.61	3.09
U2R	30.00	0.00	48.00	22.00

examples compared to the boundary generated on the training data. We used the training set, including both normals and attack examples, to derive such a boundary (within which lies 98% of the training set). Then, we examine the test set attack data, as to whether it lies within this boundary or not. We use two methods, Mahalanobis distance (MHD) and a Support Vector Machine with radial basis kernel (RBF), to construct the boundary. Table 1 shows the percent of each attack type in the test set that were called inliers[2] by both methods, that were called outliers by only one method, or that were called outliers by both methods. Table 2 is similar for the validation set.

We can make two broad observations from this table. First, some attack types have apparently changed significantly in the test set. Second, the methods do not perform identically, since in some cases there are significant portions of the attack that were classified as outlier by one method, and inliers by the other.

Table 3 shows that the proportion of normals is similar between the training and test sets, but the attacks are not. This is a constructed feature of the datasets, and they are not only nonstationary in frequency, but also in type. This is a representative performance of the method.

[2] we have adopted the term "inliers" to mean those points that are inside the boundary

Table 3: Distribution of categories in the train and test datasets.

Attack	Train(%)	Test (%)
Normal	19.69	19.48
DoS	79.24	73.90
PROBE	0.83	1.34
R2L	0.23	5.20
U2R	0.01	0.07

3 Description of Learning Methods

3.1 Anomaly Detection Methods

3.1.1 Mahalanobis Distance

Let y be a $p \times 1$ random vector in the Euclidean space R^p. Assume that the mean vector of y is μ and the covariance matrix is Σ. The (squared) Mahalanobis distance from y to μ is defined to be

$$D^2 = (y - \mu)'\Sigma^{-1}(y - \mu). \tag{1}$$

The Mahalanobis distance is often used to measure how far a random vector is from the center of its distribution, see [4] and [5]. Usually μ and Σ are unknown and must be estimated from data with the sample mean, $\bar{y}$ and the sample covariance matrix, $\hat{\Sigma}$, respectively.

One way to use the Mahalanobis distance for outlier detection is to draw a random sample from the population of interest, and then compute the Mahalanobis distance of each observation to the sample mean vector, $\bar{y}$. Next, determine the value of the largest Mahalanobis distance, say d_N. For future observed data compute the Mahalanobis distance of each observation to $\bar{y}$ and if any observation has a computed distance greater than d_N label that observation as an outlier. Any observation with a Mahalanobis distance less than d_N is considered to be "normal" or an inlier.

An obvious modification to the above procedure for identifying outliers is to use a threshold other than the observed maximum Mahalanobis distance, d_N. For example, the 99th percentile of the observed distances could be used as the threshold, say $d(99)$. If a future observation has a Mahalanobis distance greater than $d(99)$ then this new observation is considered an outlier, otherwise it is considered an inlier.

The equation

$$d_N = (y - \bar{y})'\hat{\Sigma}^{-1}(y - \bar{y}) \tag{2}$$

defines an ellipsoid in R^p. Geometrically, the above procedure for identifying outliers amounts to calling any point outside this ellipsoid an outlier and any point inside the ellipsoid is an inlier.

Table 4: The reference SVM radial basis function classifier performance.

	Overall			DoS	Probe	R2L	U2R
	error%	det%	fp%	det%	det%	det%	det%
% attacks, test data				91.8	1.7	6.5	0.09
Validation	0.07	99.94	0.11	99.99	99.06	90.02	20.00
Test	6.86	91.83	1.43	97.30	79.26	18.29	25.88

3.1.2 One-class Support Vector Machines

Schölkopf et al.[6] proposed using the support vector machine to estimate the support of a distribution. Briefly, their idea is to specify a fraction, ν, of the observed data to be outliers and then to find a "small", region, say S, in feature space that contains at least $(1-\nu)\%$ of the observed data. Any point outside of S is considered an outlier. In general S need not be an ellipsoid. Schölkopf et al. estimate a function f that is 1 on S and -1 otherwise. In this way a future observation can be labeled as having come from S or not.

Assuming that the training data is a random sample from an unknown distribution P, Schölkopf et al. provide a bound on the probability that a new observation drawn from P will be outside of S; the bound holds with a user specified confidence. The larger the confidence the user specifies, the larger the region S. Technical details that we do not address can be found in [6].

Note, no claim is made that S is the "smallest" (by any metric) region that contains at least $(1-\nu)\%$ of the data.

A considerable amount of effort was spent exploring the relative performance of different SVM kernel and parameter settings. Our explorations led us to a choice of the RBF kernel, considering also linear and polynomial kernels of degrees up to seven.

3.2 Method of Categorization

Since we previously explored alternative methods for classification, in this study we have chosen a single method in order to limit the number of options. It is possible that other methods could result in better performance in this context, but since our strategy is exploration of different approaches through comparative performance, this aids in the clarity of the results.

The method chosen is Support Vector Machines using the radial basis function kernel[3]. An examination of the performance of this classifier is shown in Table 4. Note that this one performance point does not represent the entire spectrum of performance of the method across different detection rates. This provides indicative performance, and more detail is available in the report of our previous study[1].

Table 5: Predicted outliers by known class for the validation and test sets. The %O column shows the percentage of outliers represented by each category.

	RBF						MHD					
	validation			test			validation			test		
	in	out	%O	in	out	%O	in	out	%O	in	out	%O
Norm	79596	5726	68.4	58916	1677	32.7	80257	5065	59.5	58408	2185	25.1
DoS	341002	2543	30.4	227172	2681	52.3	341708	1837	21.6	226680	3173	36.5
Probe	3567	62	0.7	3634	532	10.4	2475	1154	13.6	2380	1786	20.5
R2L	942	30	0.4	16000	189	3.7	557	415	4.9	14768	1421	16.3
U2R	39	11	0.1	177	51	0.9	15	35	0.4	93	135	1.6
Total	425146	8372		305899	5130		425012	8506		302329	8700	

3.3 Anomaly Detection to Preprocess for Classification

The approach examined here is to combine the anomaly detection and classification in a serial fashion. As described above, anomaly detection will be used as a method to assess whether the example is similar to those in the training set. If so, the classification method is applied. If not, then the system cannot treat that example reliably.

Performance in the stationary data subset is expected to be better than overall performance, and therefore also better than the examples classified as nonstationary. However, how to treat the performance of the anomalous examples is an open issue. Should they be considered as "normals", lowering the detection rate, or as "attacks", raising the false positive rate, should they not be considered at all, or should they be classified using a different methodology or at least a different model? The performance results documented allow the impact of various system assumptions to be assessed. This will be taken up again below.

4 Results

In Table 5 we show the results from defining a region of feature space that contains 98% of the training data. Two methods were used to define a region: support vector machines with a radial basis kernel (SVM-RBF) and Mahalanobis distance (MHD). The MHD is a standard tool that will be used as a basis for evaluation of the SVM-RBF. From initial exploration the RBF kernel was found to be the most appropriate for this data. For each type of attack we present the number of observations that are considered inliers and outliers. In addition we also show the distribution of attacks conditional on being an outlier; these are the entries in the column labeled %O. Tables 1 and 2 highlight the degree of (dis)agreement between the two methods.

The overwhelming number of examples for both the validation and test data correspond to DoS attacks: 79% for the validation data and 74% for the test data. There seems to be a bias on the part of both SVM-RBF and MHD to learn the region of feature space populated by DoS attacks. Evidence for this claim is seen by looking at the distribution of normals

Table 6: Predicted class by known category for the validation and test sets, using the support vector machine supervised classifier. The %A column shows the percentage of attacks represented by each category.

	validation				test			
	Normal	Attack	% Attack	%A	Normal	Attack	% Attack	%A
Norm	85222	100	0.12	0.03	60272	321	0.53	0.14
DoS	69	343476	99.98	98.70	6961	222892	96.97	98.43
Probe	50	3579	98.62	1.03	1043	3123	74.96	1.38
R2L	155	817	84.05	0.23	16143	46	0.28	0.02
U2R	50	0	0.00	0.00	172	56	24.56	0.02
Total	85546	347972		100.00	84591	226438		100.00

given the example is classified as an outlier. In the validation set, 68.4% of the outliers identified by RBF are normals and for MHD nearly 60% of the outliers are normals.

The SVM-RBF method is constructing the support in such a way that almost all of the probe, R2L, and U2R attacks are considered inliers. Together these three categories account for only 1.2% of the outliers. In contrast, nearly 19% of the outliers identified by MHD are probe, R2L, and U2R attacks.

The outlier selection rate of SVM-RBF on the test set is peculiar. Both SVM-RBF and MHD were trained so that approximately 2% of the observations would be beyond the support. In the test set, SVM-RBF identifies only 1.65% observations as outliers; MHD identifies 2.8% of the test data as outliers. Recall that the test data was constructed in such a way that it was in fact nonstationary (while the validation set is randomly partitioned from the same superset as the training set). Not only was the distribution of attacks different from the training data, but the types of attacks were also different.

Examining performance on the test set we find that for both SVM-RBF and MHD a lower percentage of the outliers are normals and and higher percentage are attacks. MHD is identifying a much higher percentage of probe, R2L, and U2R attacks as outliers than is SVM-RBF. In fact, these three categories is where the nonstationarity of the test data is concentrated.

In table 6 for both the validation and test data we show for each attack type the number classified as normal; the number classified as attack; the percent of each attack type classified as an attack; and the distribution of attack type within the predicted attack class. The classifier here is the supervised SVM discriminator described in Section 3.2.

In the validation set, nearly all the DoS attacks are being classified as attacks and within the observations classified as attack, DoS makes up nearly 99% data. As we move to the test data we see that while the distribution of attack types, within observations classified as attacks, is somewhat similar to the validation data, the percentage of each attack type being identified as an attack is quite different. For example, in the validation set, nearly 99% of the probe attacks are identified as attacks but in the test data only 75% are identified as attacks. Given an observation is classified as an attack, there is a 1.03% chance that observation is a

Table 7: Prediction: % classified as attack for outliers and inliers, by attack

	SVM-RBF				MHD			
	validation		test		validation		test	
	inlier	outlier	inlier	outlier	inlier	outlier	inlier	outlier
Normal	0.12	0.07	0.50	1.55	0.08	0.77	0.21	9.11
DoS	99.98	99.57	97.48	53.64	99.99	97.44	97.86	33.47
Probe	98.74	91.94	82.69	22.18	98.59	98.70	95.63	47.42
R2L	84.93	56.67	0.28	0.53	86.54	80.72	0.19	1.27
U2R	0.00	0.00	31.64	0.00	0.00	0.00	40.86	13.33

probe attack for the validation set and a 1.38% chance if we look at the test set.

The results presented in table 7 contrast how the prediction method performs for data considered as inliers versus data identified as outliers. We compare performance on the validation and test set using both SVM-RBF and MHD to identify inliers and outliers. It is important to keep in mind that the prediction method was trained on the entire training set and not on just the observations that would be considered inliers. We have more to say about this later.

First consider SVM-RBF on the validation set. This method is less likely to call an example from normal, DoS, probe, and R2L an attack if it is classified as an outlier than if it is classified as an inlier.

For normal examples in the validation data, the prediction model is less likely to call an example identified as an outlier by SVM-RBF an attack than it is if SVM-RBF calls that example an inlier. In contrast, if MHD identifies the example as an outlier the prediction model is more likely to classify that example as an attack than if it is considered an inlier. On the test set, the prediction model is more likely to call a normal example an attack if it is identified as a outlier than if it is identified as an inlier for both SVM-RBF and MHD. A normal example in the test set that is called an outlier by MHD is much more likely to be classified as an attack than a normal example called an outlier by SVM-RBF.

For DoS attacks in the validation set, the prediction model works about the same on inliers and outliers for both SVM-RBF and MHD; slightly fewer DoS attacks identified as outliers by MHD are classified as attacks than are DoS attacks identified as inliers, (99.99% compared to 97.44%). On the test set there is a dramatic difference in performance between inliers and outliers. If SVM-RBF or MHD call a DoS attack an inlier the the prediction model classifies nearly 98% of these as attacks. However, if SVM-RBF calls a DoS an outlier, only 54% of these are classified as an attack; if MHD identifies the example as an outlier, only 34% these are predicted to be attacks.

Because SVM-RBF identifies so few probe, R2L, and U2R as outliers, as shown in Table 5 we should be cautious about any inferences we might want to make with respect to these attack types.

For probe attacks from the validation set, the prediction model is classifying approximately the same percent as attacks if MHD call the example an inlier or outlier; if SVM-RBF

Table 8: Performance on test set, with different selections of the data by anomaly detection

	MHD		SVM-RBF	
	det%	fp%	det%	fp%
Overall	90.3	0.5	90.3	0.5
Inliers Only	91.9	0.2	90.9	0.5
Outliers as Normals	89.5	0.2	89.7	0.5
Outliers as Attacks	92.1	3.8	91.0	3.3

calls the example an outlier then it is less likely to be classified as an attack than if called an inlier (92% compared to 99%). For probe attacks in the test set the prediction model is less likely to call an outlier an attack than it is an inlier, for both SVM-RBF and MHD. If MHD calls the example an outlier the model is more likely to classify it as an attack than if SVM-RBF calls the example an outlier (47% compared to 22%).

For R2L attacks in the validation set, approximately 85% of the examples called inliers by SVM-RBF are classified correctly and 86% of the examples called inliers by MHD are classified correctly. For examples identified as outliers by SVM-RBF, only 57% are classified correctly by the model. In contrast, of the outliers identified by MHD, the model correctly classifies about 81%. Recall that the SVM-RBF support estimation model only calls 30 examples in the validation set "outliers". The prediction model applied to the test data works poorly with respect to R2L attacks, regardless of whether or not the example is called an inlier or an outlier. Out of 16,189 R2L attacks, the prediction model classifies only 46 correctly. The MHD method identifies far more R2L attacks as outliers than does the SVM-RBF method (1421 compared to 189).

In the validation set the prediction model incorrectly classifies all (50) of the U2R attacks as normal. In the test set, SVM-RBF identifies 51 out of 228 examples as outliers and MHD identifies 135. The prediction model correctly classifies 32% of the SVM-RBF identified inliers and none of the SVM-RBF identified outliers. For MHD inliers the model correctly classifies 41% of the inliers and 13% of the outliers.

Table 8 summarizes the performance of the overall system including anomaly detection. In this evaluation, the simpler MHD method outperforms the SVM-RBF method. As expected the inliers have better performance in both cases. In a real situation, the outliers must be accounted for, and the results show what happens if we label by default all of the outliers as either attacks or normals. Labeling them as normals lowers the detection rate from the baseline (overall), with some improvement to the false positive rate (even though this is not significant for the SVM-RBF). Labeling outliers as attacks raises the detection rate, but also raises the false-positive rate significantly.

5 Discussion

The practical import of this analysis is not in terms of a finished algorithm product, since this study was on static and historical data. The primary contribution is the significance of considering network-based attack detection as distinct attack types, and the impact of anomaly detection on nonstationarity. The information presented shows clearly that different types of attacks have both very different signatures, as well as very different types of change. Also, simply the dominance in numbers of some categories will have a large effect on automated learners, as they try to minimize a criterion related to overall error minimization.

If these ideas were to be incorporated into a working system, the question of what to do with the outlier class arises. Choosing an arbitrary performance level on test set, the classifier along on all the data performance with a detection rate of 90.3% with a false-positive rate of 0.53%. On only the inliers the performance increases, but the outliers still need to be accounted for. Table 8 summarized these results. Further exploration of a staged approach where inliers and outliers have different detection thresholds, or even different models altogether will be a solution to improving overall performance.

The anomaly detection segmentation increases the classification performance of inliers, as was expected. The details of the performance, as discussed in Section 4, are sometimes puzzling and counterintuitive. For example, the percentage of outliers decreases from the validation to test sets for the SVM-RBF overall, and for some categories in the MHD, when natural expectation is that they would increase for a nonstationary dataset. Also, why the individual attack categories have their respective behavior with respect to nonstationarity in particular is not understood.

These algorithms are suitable for inclusion on a high speed network analysis tool, such as the programmable FPGA based *NIW Sensor* developed at Los Alamos[9]. This hardware package is capable of analyzing network traffic at gigabit speeds, and is the flip-side of this project in algorithm development.

Note that this analysis assumes packets are independent, when they are in reality not. In this dataset, we have no indicators of membership of a packet in a specific attack. However it is clear that a denial of service attack will contain more than a few packets. Perhaps a more appropriate performance evaluation would consider attack groups as the unit of assessment, and flagging *any* packet in the group would be sufficient. It would be expected that in this mode of evaluation perceived performance would increase significantly.

Finally, we will comment on our experience in using these methods. SVMs with nonlinear kernels are challenging to use as a stand-alone tool for exploratory data analysis. Our experience is that changes in parameters (e.g., kernel, regularization) can have significant changes in the performance of the algorithm, but yet these changes typically don't have clear causes. In an data analysis situation, it often isn't enough to simply tune for the best performance. One also wants to gain a better understanding of the data and problem. Kernel SVMs (and other nonlinear learners) are often deficient in this respect.

However, as these results show, in comparison to an intuitively understandable method such Mahalanobis distance, SVMs can be a valuable tool for gaining information regarding high-dimensional data, as well as good classification performance. If no comparative method is used, it would not be apparent whether the SVM is approximating Gaussian forms, or whether, as is the case here, the SVM is fitting a more wandering boundary. The analysis here clearly shows two things: the data is not approximately Gaussian (as is also suggested by the graphs), and the degree of flexibility in the model of the support has a significant effect on the results both overall and by category.

We explored and used both the currently popular *libSVM* and *SVMLight* software for this work[7][8]. Currently, neither tool yields continuous values for outlier status, which, although theoretically unsound, would be useful for exploration of performance around the margin, and would provide a rough method for rank-selecting outliers.

6 Conclusion

Computer network attack detection is potentially tractable using automated learners and classifiers. Challenges remain for this methodology. One challenge is to develop an understanding of whether core attack types have a long-term signature; if not, tedious filtering data by hand to generate labeled datasets at intervals is required. Anomaly detection methods have significant promise in this area, but they have not been demonstrated to have a performance with significant enough probability of detection at acceptable false-alarm rates.

Anomaly detection used as a method for filtering nonstationary example and ensure that classifiers operate in domains that were populated sufficiently in their training sets has been demonstrated to increase performance in this problem domain, as expected. The question remains of how to treat the outlier data robustly so that performance can be increased overall. One solution to this would be to relax the degree of discrimination of inliers, so that the training set will yield enough outliers to train an outlier-specific model. Another method could employ pure anomaly detection methods for the outliers. These are interesting directions for future work.

In this case, the SVM method did not lead to the boost in performance of the Mahalanobis distance method. There are several possible reasons for this. One is that there is perhaps not enough data to accurately assess the support of the distribution in all cases. The strong assumptions in the Mahalanobis distance measure, i.e. that the data can be represented by estimated mean and covariance, may provide a degree of regularization not available in the SVM. On the other hand, it is true that the SVM can be tuned to produce a more rigid classification surface, and can probably provide similar performance in this way. Another possible explanation is that the margin attention of the SVM emphasized different classes naturally, and so simply provides a very different performance method. Although the SVM method would not be selected on the basis of this study, they have provided insight into the data characteristics, and remain a tool for data exploration and classification.

Additional areas for research suggest themselves. On-line adaptive anomaly detection is an intuitively interesting area, but whether an adaptive method can be biased with sufficient accuracy to distinguish attacks from non-attacks is an open question. Classification models of each category, with corresponding methods for distinguishing what is an inlier vs. outlier for each category seems like a compelling direction for improving performance. Studying how these machine learning methods complement rule-based systems is important to assessing overall performance. This leads to the general topic of model ensembles: how good performing families of models can be constructed for this application, and how much performance increase can be gained.

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