ONLINE FEATURE RANKING FOR INTRUSION DETECTION SYSTEMS

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ABSTRACT

Many current approaches to the design of intrusion detection systems apply feature selection in a static, non-adaptive fashion. These methods often neglect the dynamic nature of network data which requires to use adaptive feature selection techniques. In this paper, we present a simple technique based on incremental learning of support vector machines in order to rank the features in real time within a streaming model for network data. Some illustrative numerical experiments with two popular benchmark datasets show that our approach allows to adapt to changing network behaviour and novel attack patterns.

Index Terms— network security, intrusion detection, online learning, support vector machine, stochastic gradient descent

1. INTRODUCTION

The design of efficient intrusion detection systems (IDS) has received considerable attention recently. An IDS aims at identifying and mitigating malicious activities. Most of the current IDSs can be divided into two main categories: signature-based and anomaly-based IDS [1].

A signature-based IDS tries to detect intrusions by comparing the incoming network traffic to already known attacks, which are stored in the database as signatures. This class of IDS performs well in identifying known attacks but often fail to detect novel (unseen) attacks [2].

The second category is referred to as anomaly-based IDS. Those IDS models the normal traffic by learning patterns in the training phase. They label deviations from these learned patterns as anomaly or intrusion [3]. The implementation of real-time anomaly-based IDS is challenging due to rapidly evolving network traffic behavior and limited amount of computational resources (computation time and memory) [4]. Another challenge is the risk of overfitting due to the high-dimensional feature space and the model complexity of IDSs [5, 6, 7, 8].

In this paper we will address some of the short comings of existing anomaly-based IDS and present an efficient online feature ranking method. Our approach is based on online (or incremental) training of a support vector machine (SVM) which allows to cope with limited computational resources.

The closest to our wok is [9, 10], which applies SVM for feature selection in a static setting. In contrast, our feature ranker finds approximate to the best feature subset in real-time and in the case of streaming network traffic with changing behaviour. Some illustrative numerical experiments indicate that real-time intrusion detection mechanisms using our feature ranker can be trained faster and achieves less error rate compared to offline (batch) feature selection methods.

This paper is organized as follows: The problem setup is formalized in Section 2. In Section 3, we detail the proposed online feature ranking method. The results of some illustrative numerical experiments are discussed in Section 4.

2. PROBLEM SETUP

We consider a communication network within which information is exchanged using atomic units of data which are referred to as “packets”. These packets consist of a header for control information and the actual payload (user data). We represent a packet by a feature vector \( x = (x_1, \ldots, x_d) \in \mathbb{R}^d \) with \( d \) individual features \( x_i \) listed in Table 1. The last feature \( x_d \) is a dummy feature being constant \( x_d = 1 \).

A machine learning based IDS aims at classifying network packets into the classes \( \mathcal{Y} = \{0, 1\} \). Each packet is associated with a binary label \( y \in \mathcal{Y} \) with \( y = 1 \) indicating a malicious packet (an “attack”) and \( y = 0 \) for a regular (normal) data packet. We view an IDS as a classifier \( h : \mathbb{R}^d \to \mathcal{Y} \) which maps a given packet with feature vector \( x \), to a predicted label \( \hat{y} = h(x) \in \mathcal{Y} \). Naturally, the predicted label \( \hat{y} \) should resemble the true class label \( y \) as accurate as possible. Thus, we construct the classifier \( h \) such that \( y \approx h(x) \) for any packet with feature vector \( x \) and true label \( y \).

In particular, we measure the classification error incurred when classifying a packet with feature \( x \) and true label \( y \) using the classifier \( h \) by some loss function \( \mathcal{L}((x, y), h) \). We will focus on a particular choice for the loss function as discussed in Section 3.1.

We learn the classifier \( h \) in a supervised fashion by relying on a set of \( N \) labeled packets \( \{x_i, y_i\}_{i=1}^N \) (the training set). In particular, we choose the classifier \( h \) by minimizing the empirical risk

\[
(1/N) \sum_{i=1}^N \mathcal{L}((x_i, y_i), h)
\]
 incurred by \( h \) on the training data set \( \{x_i, y_i\}_{i=1}^N \). We will restrict ourselves to linear classifiers \( h \), i.e., which have a linear decision boundary. The corresponding hypothesis space, constituted by all such linear classifiers, is

\[
\mathcal{H} = \{ h(\mathbf{w}) | (\mathbf{w}^T \mathbf{x} \geq 0) \text{ for some } \mathbf{w} \in \mathbb{R}^d \}. \tag{2}
\]

Here, we used the indicator function \( \mathcal{I}(\text{"statement"}) \in \{0, 1\} \) which is equal to one of the argument is a true statement and equal to zero otherwise. Using the parameterization \( \mathbf{w} \), learning the optimal classifier for an IDS amounts to finding the optimal weight vector \( \mathbf{w} \in \mathbb{R}^d \):

\[
\min_{\mathbf{w} \in \mathbb{R}^d} \left( \frac{1}{N} \sum_{i=1}^N \mathcal{L}( (x_i, y_i), h(\mathbf{w}))) \right). \tag{3}
\]

It turns out that most of the relevant information for classifying network packets is often contained in a relatively small number of features due to redundant or irrelevant features \( \mathbf{w} \). Thus, it is beneficial to perform some form of feature selection in order to avoid overfitting and improve the resulting classification performance. Moreover, for an online or real-time IDS, feature selection is instrumental in order to cope with a limited budget of computational resources.

Most existing feature selection methods are based on statistical measures for dependency, such as Fisher score or (conditional) mutual information, and therefore independent of any particular classification method \( \mathbf{w} \). In contrast, feature ranking methods use the entries \( w_j \) of the weight vector \( \mathbf{w} = (w_1, \ldots, w_d) \) of a particular classifier, e.g., obtained via solving \( \mathbf{w} \), as a measure for the relevance of an individual feature \( w_j \). We will apply feature ranking based on the weight vector obtained as the solution of \( \mathbf{w} \) for the particular loss function which is underlying the support vector machine (SVM).

3. GENERAL ARCHITECTURE OF THE FEATURE RANKER

![Fig. 1. General architecture of the proposed mechanism](image)

Figure 1 shows the architecture of our system with an ability to rank features of the streaming data in real time based on the weights of the support vector machines (SVM) classifier. For the simplicity of our experiments, we used the same SVM also for the IDS part, but it might be any other intrusion detection mechanism using machine learning techniques.

Before training the feature ranker and the IDS, the first \( N \) packets are collected as a historical data. These packets are used for pretraining the feature ranker and the IDS. In our feature ranker, features critical to detect attacks have negative values, while features contributing for the normal traffic have positive values. After waiting another \( N \) packets and predicting the label of each packet as normal or attack, the mean squared error

\[
\frac{1}{N} \sum_{i=1}^N (y_i - \tilde{y}_i)^2
\]

is measured between the actual labels \( y_i \) and the predicted labels \( \tilde{y}_i \). If this error is quite high, then the feature ranker and the learning model is retrained by feeding the actual labels to the mechanism. Thus, feature weights are adapted to changes in normal network behaviour or new attack strategies.

3.1. Support Vector Machines (SVM)

Our design of an IDS is based on \( \mathbf{w} \) using the particular loss function

\[
\mathcal{L}( (\mathbf{x}, y), h) = \left[ 1 - y (\mathbf{w}^T \mathbf{x}) \right]_+ + (\lambda/2) ||\mathbf{w}||^2, \tag{5}
\]

with the shorthand \( [z]_+ = \max\{0, z\} \). The loss function \( \mathbf{w} \) consists of two components: The first component in \( \mathbf{w} \) is known as the hinge loss and underlying the SVM classifier. The second component in \( \mathbf{w} \) amounts to regularize the resulting classifier in order to avoid overfitting to the training data. and a regularization parameter \( \lambda > 0 \) which allows to avoid overfitting. Inserting \( \mathbf{w} \) into \( \mathbf{w} \) yields the weight of the SVM classifier

\[
\hat{\mathbf{w}} = \arg\min_{\mathbf{w} \in \mathbb{R}^d} \sum_{i=1}^N \left[ 1 - y_i (\mathbf{w}^T \mathbf{x}_i) \right]_+ + (\lambda/2) ||\mathbf{w}||^2. \tag{6}
\]

Note that \( \mathbf{w} \) is a non-smooth convex optimization problem which precludes the application of basic gradient based optimization methods \( \mathbf{w} \). Instead, as detailed in Section 3.2, we apply the stochastic sub-gradient method to solve \( \mathbf{w} \) in an online fashion.

Once we have learnt the optimal weight vector \( \hat{\mathbf{w}} = (\hat{w}_1, \ldots, \hat{w}_d)^T \) by solving \( \mathbf{w} \), we can classify newly arriving packet with feature \( \mathbf{x} \). Therefore, for any testing sample \( \mathbf{x}_i \), the SVM classifier \( h(\cdot) \) can be written as

\[
h(\mathbf{x}) = \mathcal{I}(\hat{\mathbf{w}}^T \mathbf{x} > 0). \tag{7}
\]

Thus, the classification result depends on the features \( \mathbf{x}_i \) via the weights \( \hat{w}_i \). A weight \( \hat{w}_i \) having large absolute value implies that the feature \( x_i \) has a strong influence no the classification result \( \mathbf{w} \). It is therefore reasonable to keep only those
features $x_i$ whose weights $w_i$ are largest and discard the remaining features in order to save computational resources and avoid overfitting.

### 3.2. Stochastic Gradient Descent (SGD)

A naive implementation of SVM does not scale well due to excessive computational time and memory requirements [13]. In order to cope with the requirements of real-time IDS one typically needs to use online implementations of SVM. A simple modification of the linear SVM method can be done by incorporating gradient methods and adapting optimum weight vector as new data arrives.

Since SVM is trying to solve a convex cost function, we can find a solution by using iterative optimization algorithms. Stochastic gradient descent is one of the optimization algorithm that minimizes the cost function by performing the gradient descent on a single or few examples. In SGD, each $k$-th iteration updates the weights of the learning algorithms including SVM, perceptor or linear regression, with respect to the gradient of the loss function $L$

$$w^{k+1} = w^k - \alpha \nabla_w L_n(h(x), y),$$

where $\alpha$ denotes constant learning rate and $n$ is a set of indices randomly sampled from the training set $\{x_i, y_i\}_{i=1}^N$. In our setup, we approximate the gradient by drawing $M$ points uniformly over the training data and perform mini batch iterations of SGD over SVM. Therefore the updates of weight vector $w$ will become

$$w^{k+1} = w^k - \alpha \frac{1}{M} \sum_{j=0}^M \nabla_w L(g(x)_j, y_j)$$

Although the hinge loss is not differentiable, we can still calculate the subgradient with respect to the weight vector $w$. The derivative of the hinge loss can be written as:

$$\frac{\partial [1 - y_i(w^T x_i)]_+}{\partial w_k} = \begin{cases} -y_i x_i & y_i (w^T x_i + b) < 1 \\ 0 & \text{otherwise}. \end{cases}$$

Therefore, the gradient update for Equation 9 at $k$-th iteration is calculated as:

$$w^{k+1} = w^k - \alpha \lambda w_k - \frac{1}{M} \sum_{j=0}^M I[(w_j^T x_j + b_j) < 1] y_j x_j,$$

where $I[(w_k^T x_j + b_j) < 1]$ is an indicator function which results in one when its argument is true, and zero otherwise.

In large scale learning problems, SGD decreases the time complexity, since it does not need all the data points to calculate the loss. Although, it only samples few data point to reach the optimum point, it provides a reasonable solution to the optimization problem in the case of big data [19].

In our proposed feature ranker mechanism, the weight vector of a SVM classifier is optimized in an online fashion using SGD with mini batch size $N$. After predicting the labels of packets in the next mini-batch, the predicted labels are compared to the true classes of packets, which are decided by experts. If the predicted labels highly deviate from the true labels based on the MSE, then the weights are updated according to this $N$ packets. This also enables an online correction of the feature weights, since the weight vector is updated based on the incoming $N$ packets with a possible different connections, applications or attacks.

### 4. EXPERIMENTAL RESULTS

We verified the performance of the proposed IDS by means of numerical experiments run on a 64-bit Ubuntu 16.04 PC with 8 GiB of RAM and CPU of 2.70GHz. Two different datasets, the ISCX IDS 2012 dataset and CIC Android Adware-General Malware, were used for our experiments to test both batch and online algorithms. The ISCX-IDS 2012 dataset [20] was generated by the Canadian Institute for Cybersecurity and mostly used for anomaly based intrusion detection systems. This dataset includes seven days of traffic and produces the complete capture of the all network traces with HTTP, SMTP, SSH, IMAP, POP3, and FTP protocols. It contains multi-stage intrusions such as SQL injection, HTTP DoS, DDoS and SSH attacks. The CIC Android Adware-General Malware dataset [21] is also produced by the same research group. This dataset consists of malwares, including viruses, worms, trojans and bots, on over 1900 Android applications.
Both datasets are provided as pcap files including both malicious network packets and normal packets. We selected different malware types (InfoStl, Dishigy, Zbot, Gamarue) for testing batch (offline) feature ranking. We used the ISCX-IDS 2012 dataset for the online feature ranking, since it has the complete capture of one week network traffic data without any interruption to the overall connection. From each dataset, we transferred raw packets to a file with 43 features using “tshark” network analyzer. Table 1 lists all the features measured with tshark and used in the experiments.

The first set of experiments does not include online incremental learning of SVM weights. It implements the linear SVM classifier with SGD update, as well as other widely used feature selection algorithms, selects 20 features with the highest weight out of 43, and uses them as an input to a single-layer feedforward neural network with 10 hidden neurons and sigmoid activation function. The experiments were performed on various pcap files from the CIC Android dataset having different sparsity, attacks and malwares in order to prove that feature ranking with linear SVM weights in batch (offline) learning provides good performance compared to the other feature selection methods. Table 2 shows the experimental results of these feature selection methods by measuring the time spent on extracting the best features from the training set and the accuracy of the classification. It can be seen that linear SVM weights trained with the SGD method is quite fast and generally gives a higher accuracy than the other methods. Therefore, we can suggest that incremental version of the linear SVM approach can be extended to the case of streaming network traffic.

Table 2. Feature selection comparison with different malwares

| Malware type | F-score | Decision Trees | Chi2 |
|--------------|---------|----------------|------|
| InfoStl      | 0.005   | 0.893          | 0.005 |
| Dishigy      | 0.002   | 0.651          | 0.002 |
| Zbot         | 0.002   | 0.970          | 0.002 |
| Gamarue      | 0.002   | 0.933          | 0.002 |

Mutual info. SVM weights

| Malware type | F-score | Decision Trees | Chi2 |
|--------------|---------|----------------|------|
| InfoStl      | 0.2503  | 0.991          | 0.005 |
| Dishigy      | 0.364   | 1.0            | 0.001 |
| Zbot         | 0.633   | 0.988          | 0.001 |
| Gamarue      | 0.240   | 0.946          | 0.964 |

Bold: best result achieved

The second experiment was implemented with both offline and online SVM with a linear kernel in the case of streaming network data. Both feature weighting and classification is done by linear SVM in either online or offline fashion. Experiments were performed with the ISCX-IDS 2012 dataset. Figure 2 shows the mean squared error between the true and predicted labels of the streaming data while the network behaviour changes and new type of attacks are fed to the input. Unlike the offline SVM, online SVM changes its weight vector in a sliding window with $N$ packets. The training was implemented in the first 100 * $N$ packets which spans one day of network activities including injection attacks. The second day comes with a more complex and harder to detect injection attack and the third day also starts with a DoS attack. As can be seen in the figure, our online feature ranker model is able to adapt itself to a change in the network statistics. However, batch learning with SVM performs poorly when the arriving packets shows a completely different behaviour. In conclusion, online models quickly adapt to changing behaviour in the network data and achieves a notable improvement on the performance of prediction over batch learning.

Table 2. Feature Weights for Different Network Behaviors

```
Malware type  Window number
InfoStl       0 100 200 300 400 500 600 700
Dishigy      0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
Zbot         0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
Gamarue      0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
```

Fig. 2. MSE of the streaming test data with a load change

The last experiment was also implemented with the ISCX-IDS 2012 dataset by choosing 3 days of network data with different attacks to prove that the importance of features are different for each attack. Figure 3 shows the resulting absolute weights of randomly selected 5 features. Figure 3 indicates that feature weights change even from positive to negative in each day having different connections and different attack types. These results prove that our feature ranker mechanism works as we desired and adjusts the feature weights with streaming network data.

Fig. 3. Feature Weights for Different Network Behaviors
5. CONCLUSION

In this paper, we proposed a simple method based on incremental learning of linear SVM models to rank or weight features in real time. Experimental results indicated that our method can adjust the importance of any feature based on not only the changing network behaviour but also for novel attacks. In future research, the online feature ranking with a variable chunk size will be incorporated to better fine-tuning of our proposed method. In addition, the weights of the features will be used as input layer weights of neural networks based IDSs, which can be used as real-time and self-trained intrusion detection mechanism.

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