

# Detection of DDoS Attack on the Client Side Using Support Vector Machine

Donghoon Kim \* and Ki Young Lee\*\*

\*Department of Information and Telecommunication Engineering, Incheon National University, Incheon, 22012, Korea.

\*\* Department of Information and Telecommunication Engineering, Incheon National University, Incheon, 22012, Korea.

Corresponding author: Ki Young Lee, Professor.

## Abstract

Nowadays, cyber-attack attempts have been increasing and DDoS (Denial of Service) attacks are one of the major threat in computer networks. It attempts server's resources unavailable and generates massive traffic on the network. These attacks are evolving very quickly in scope and complexity. Also, it is not possible to prevent the network congestion even if these attacks are detected on the server side, unless client as act a zombie blocks their attack packets. To detect DDoS attack early and invalidate the attack itself, this paper proposes a method to detect DDoS attack on the client side using machine learning algorithm

**Keywords:** DDoS Attack, Attributes Selection, SVM, Cyber Security, Machine Learning

## INTRODUCTION

Nowadays, cyber-attack attempts have been increasing and DDoS (Denial of Service) attacks are one of the major threat in computer networks. In the past, DDoS attacks have forced server's resources to be used or making the network itself congested. However, recent scope of the attack has been extended to make zombie PC's hard drive unavailable for removing their cyber foot prints. And there are many side effects because of the attack. It generates huge traffic on the network, so many of the general users could suffer from low latency. Furthermore, the users who do not know that their PC is performed an attack may suffer financially by the billing. Therefore, not only servers need to detect the attack, but also clients should recognize whether the attack is performing by their own. It is possible to reduce network traffic and mitigate success of the attack to server.

Many research studies continue to figure out the solution for DDoS attack. The traditional method for detecting DDoS attacks has been used the pattern matching. However, the methods of DDoS attacks are getting complicated and variant to avoid the pattern matching algorithms. In recent years, various types of machine learning methods have been introduced into detection systems to detect such complex, disordered, and changing attacks. However, machine learning algorithm can flexibly adapt to various variants of attacks.

The remainder of this paper is organized as follows. In Section 2, we review publications in this research. In Section 3, we propose attributes for classification and propose a method for detecting DDoS attacks on the client side using SVM (support vector machine). Then we evaluate performance of our method and we make a conclusion and suggest future works.

## RELATED WORKS

Many of detection method for DDoS attack using machine learning such as Bayesian network, SVM and other algorithms. The machine learning algorithms use predefined attributes for classification and generate a model using a large amount of data set composed of this information. Then apply the new data to this model for classification. Most of studies on DDoS detection using machine learning have studied the improvement of performance by decreasing the false positive rate, increasing the detection rate and/or decreasing computational complexity using 41 attributes and data set defined in KDD99 [1, 2].

**Table 1.** Basic features of individual TCP connections.

| Attribute      | Description  |
|----------------|--|
| duration       | length (number of seconds) of the connection               |
| protocol_type  | type of the protocol.                                      |
| service        | network service on the destination                         |
| src_bytes      | number of data bytes from source to destination            |
| dst_bytes      | number of data bytes from destination to source            |
| flag           | normal or error status of the connection                   |
| land           | 1 if connection is from/to the same host/port; 0 otherwise |
| wrong_fragment | number of wrong fragments                                  |
| urgent         | number of urgent packets                                   |

**Table 2.** Content features within a connection suggested by domain knowledge.

| Attribute          | Description   |
|--------------------|---|
| hot                | number of hot indicators                            |
| num_failed_logins  | number of failed login attempts                     |
| logged_in          | 1 if successfully logged in; 0 otherwise            |
| num_compromised    | number of compromised conditions                    |
| root_shell         | 1 if root shell is obtained; 0 otherwise            |
| su_attempted       | 1 if su root command attempted; 0 otherwise         |
| num_root           | number of root accesses                             |
| num_file_creations | number of file creation operations                  |
| num_shells         | number of shell prompts                             |
| num_access_files   | number of operations on access control files        |
| num_outbound_cmds  | number of outbound commands in an ftp session       |
| is_hot_login       | 1 if the login belongs to the hot list; 0 otherwise |
| is_guest_login     | 1 if the login is a guest login; 0 otherwise        |

**Table 3.** Traffic features computed using a two-second time window.

| Attribute          | Description   |
|--------------------|---|
| count              | number of connections to the same host as the current connection in the past two seconds    |
| serror_rate        | % of connections that have SYN errors   |
| rerror_rate        | % of connections that have REJ errors   |
| same_srv_rate      | % of connections to the same service  |
| diff_srv_rate      | % of connections to different services  |
| srv_count          | number of connections to the same service as the current connection in the past two seconds |
| srv_serror_rate    | % of connections that have SYN errors   |
| srv_rerror_rate    | % of connections that have REJ errors   |
| srv_diff_host_rate | % of connections to different hosts   |

However, W. Wang et al. pointed out that some of the attributes may be redundant or even act like noise which decrease detection performance [3]. They ranked for 41 attributes through information gain and chi-square test. Then they showed that the best performance was obtained by using only 9 attributes through their experiment.

S. Umarani et al. used PCA (principle component analysis) to reduce dimension to remove redundant and noise form attributes [4].

However, many of the attributes defined in KDD99 are composed of information that can be obtained from the server side and it contains information about various cyber-attacks such as unauthorized access from a remote machine, port scanning or buffer overflow, as well as information about DDoS as shown in the table 1-3, so it is not appropriate to use on the client side for detecting DDoS attacks. Therefore, it is one of the main issue to select appropriate attributes for detecting attacks from huge massive traffic.

Other studies are focused on increasing performance with various machine learning algorithms used in detection of DDoS attacks including decision tree, Naïve Bayes, artificial neural networks and SVM [5-10]. Nowadays, SVM has become an extremely popular algorithm for classification and future estimate problems because Naïve Bayes and artificial neural networks depends on the number of data set and attributes. These algorithms require huge amount of data set to minimize empirical error. Therefore, in the absence of enough training set, a significant drop in performance may occurs. On the other hand, SVM requires relatively less data set than above techniques, so it performs very well without enough training set especially in binary classification. However, complex data transformations and resulting boundary plane are very difficult to interpret.

### PROPOSED ALGORITHM

In this section, we propose attributes and a method for detecting DDoS attack on the client side. Detection performance in machine learning is dependent on the number and definition of valid attributes, and the number of training sets for learning. Since each machine learning has advantages and disadvantages, it is important to select the appropriate technique depending on the application. For binary classification, we defined attributes given in Table 4 and choose SVM as machine learning algorithm

**Table 4.** Attributes for detecting DDoS attack on the client side.

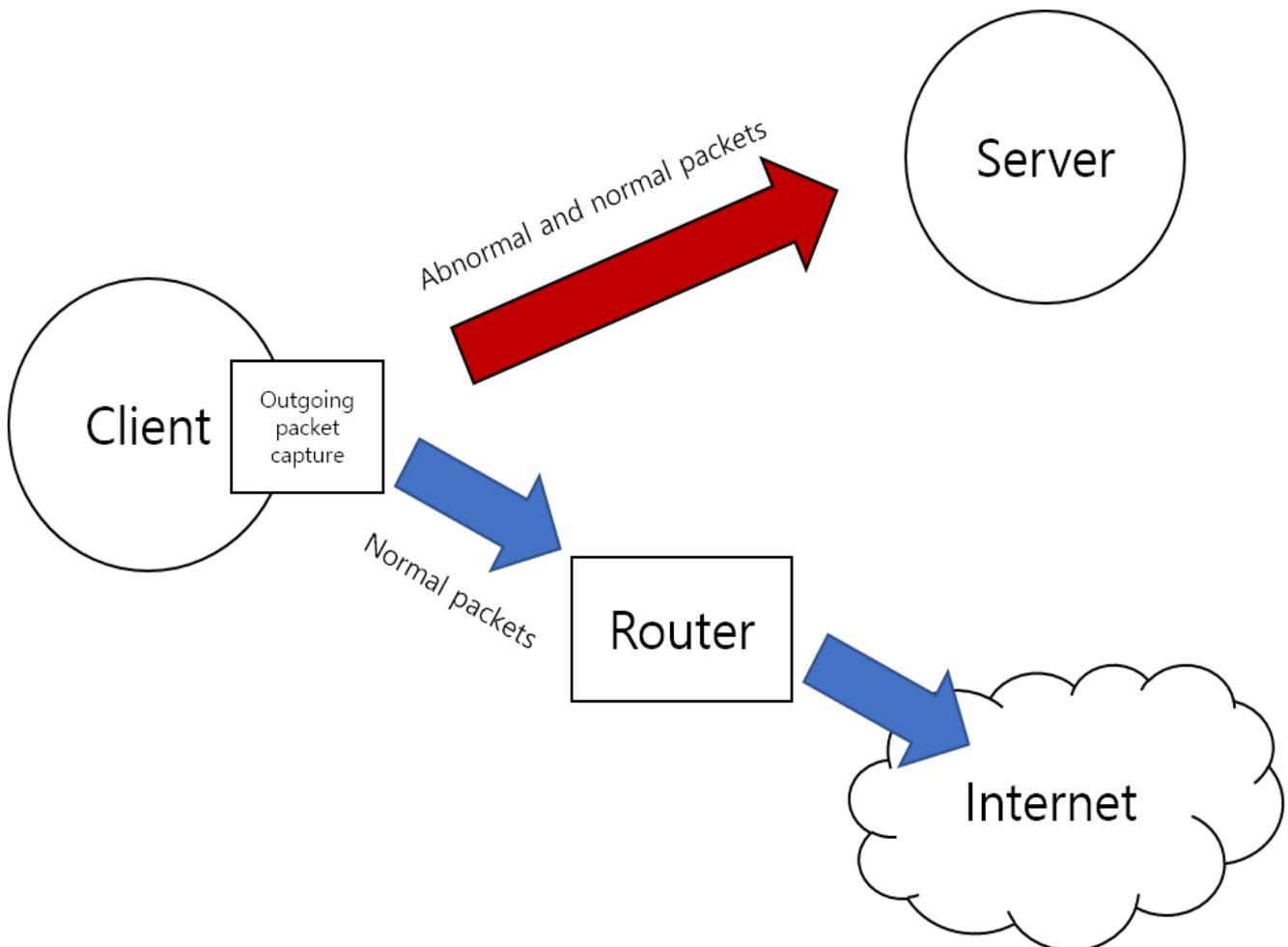
| Attribute           | Description                                   |
|---------------------|---|
| connection_duration | elapsed time since connection                 |
| header_size         | ip packet header size                         |
| cumulative_size     | Cumulative size of transmitted packets        |
| connected_port      | the number of connected port to the same host |
| service             | Network service on the destination            |
| flags               | normal or error status of the connection      |
| protocol            | type of the protocol                          |

Connection\_duration and cumulative\_size can provide information to detect DDoS attack since most DDoS attacks continuously transmit massive packets to a victim server, the client side must keep an eye on the size of the accumulated packets over the time of the connection.

Also, DDoS attacks such as SYN flood can be suspected when many ports are assigned to the same server. In addition, IP header information including header\_size, service, flags and protocol are used for classifying normal and abnormal status.

We use SVM method to create a model for normal and abnormal binary classification with a limited amount of training set for detecting DDoS attack on the client.

The experiment was carried out in the following manner. All outgoing packets including normal and attack packets from a client were captured over three days for data collection. We installed a Tomcat web server on another PC, and the client performed DDoS attack to the server using DDoS attack tools, stacheldraht and tfin (tribe flood network) at some specific times. Figure 1 shows our DDoS attack scenario.



**Figure1.** A DDoS attack scenario for collecting data.

Afterwards, the captured packet information is converted into the values for the attribute defined above and marked with normal and attack packets. We randomly selected 100,000 datasets from the total data, used 70,000 and 30,000 of them training set and test set respectively. Of the 100,000 data sets, only about 15% of the data was marked as attack. The method used for DDoS attack is shown in Table 5

**Table 5.** Attack name and the number of data used for the attack

| Attack Name          | The number of data for training set | The number of data for test set |
|----------------------|-------------------------------------|---------------------------------|
| stacheldraht_ICMP    | 1774                                | 713                             |
| stacheldraht_UDP     | 1962                                | 802                             |
| stacheldraht_TCP_SYN | 1483                                | 689                             |
| tfn_TCP              | 1502                                | 643                             |
| tfn_UDP              | 1621                                | 832                             |
| tfn_TCP_SYN          | 2054                                | 894                             |

## RESULTS AND DISCUSSION

We generate a model to detect DDoS attack using SVM and Bayesian networks with 10,396 training sets and then performed performance analysis using test sets. The results are shown in Table 6 and Table 7.

**Table 6.** Accuracy of SVM and Bayesian networks with proposed attributes

| Method            | Detection Rate (%) | False Positive Rate (%) |
|-------------------|--------------------|-------------------------|
| SVM               | 99.94              | 0.143                   |
| Bayesian Networks | 98.57              | 0.106                   |

**Table 7.** Computational time evaluation for SVM and Bayesian networks with proposed attributes

| Method            | Training (s) | Test (s) |
|-------------------|--------------|----------|
| SVM               | 0.54         | 0.15     |
| Bayesian Networks | 1.43         | 0.32     |

From the results in the above two tables, SVM performs better than the Bayesian network in accuracy and computational time because the total number of data sets and the number of attributes are not large. Thus, SVM provides good performance even with a small number of data sets. However, the attack methods used in this experiment are not sophisticated or complicated enough as they are applied in practice, and the number of attributes is small and these attributes may not key attributes in detecting DDoS attacks as arbitrarily selected. Therefore, the reliability of this experiment may be lacked and it is necessary to design the experiment to increase the reliability in the future. Also, it may be reasonable to obtain the raw data packets of the various clients used in the actual DDoS attack and to use it for the performance evaluation. Furthermore, the key attributes extraction, such as client's network usage pattern or other network-related attributes, applicable to the client to increase the DDoS attack detection performance through the various studies will be additionally needed

## CONCLUSION

In this paper, we have proposed some attributes and a method for detecting variant of DDoS attack on the client side using SVM. However, the attack methods used in this experiment are not sophisticated or complicated enough as they are applied in practice, and the number of attributes is small and these attributes are arbitrarily selected. Since the number of attributes and effectiveness for detection are very important for machine learning, it is necessary to use user's network usage pattern or other network-related attributes for practical applications. Also, obtaining the raw data packets of the various clients used in the actual DDoS attack is needed to reliable performance evaluation.

Furthermore, future research will be needed to optimize performance using dimension reduction such as Information Gain, Chi-square statistics and PCA (principal component analysis).

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