# The Prevention Threat of Behavior-based Signature using Pitcher Flow Architecture

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**Summary**
In recent years, Intrusion Prevention System (IPS) has been widely implemented to prevent suspicious threats. Unlike the traditional Intrusion Detection System, IPS has additional features to secure the computer network system. IPS is an access control device with a prevention function, which enforces a network security policy, is a helpful device that allows for more granular blocking action.
In this paper, we propose a new prediction and prevention method with behavior-based detection, this method is called pitcher flow. We describes the habitual activity of the performance an overall network with a new algorithm for identifying and recognizing the normal behavior of user activities in the internal network. First, we define behavior activity by duration of activity conducted and active connection. Second, we categorize packets into class/type, identifying parameters by classifying the packets. Finally, we use the pitcher flow mechanism to identify and recognize suspicious threats. This paper also describes an algorithm for the complexity of the suspicious response.

***Key-words:***
Behavior-based detection, Hybrid intrusion prevention, Identify habitual activity.

## 1. Introduction

In the last few years, the Internet has experienced explosive growth. Along with the widespread evolution of newly emerging services, the quantity and impact of attacks have been continuously increasing as well. Intrusion Prevention System (IPS) has become an essential component of computer security to predict and prevent attacks. They monitor, identify and recognize all real-time packets inbound and outbound. IPS, which proactively combines the firewall technique with that of the Intrusion Detection System, prevents attacks from entering the network by examining various data records and the detection demeanor of the pattern recognition sensor, When an attack is identified, intrusion prevention blocks and logs the offending data.

According to CSI/FBI survey [9], the company business has dollar amount of loss by type of attack. Meanwhile, to secure the systems, the enterprise uses several technology security systems, and almost 69% of which use intrusion prevention to defend from threat and attack.

The signature is the primary means to identify activity in network traffic, and the host performs the detection of inbound and outbound packets and to block that activity before damage and network resources are accessed. However, IPS can effectively detect suspicious threats that are already known from a list of signatures. Common Vulnerability Exposure (cve.mitre.org) is a list of intruding products, and there are several IPS devices with proprietary standards. For this reason, many IPS vendors dedicate a large number of engineers to continuous observation of suspicious threats and update their product database with new signatures as threats arise.

From our observation, many devices are defined through the process of identifying suspicious threats and rogue activity from inbound network traffic. Unfortunately, computer misuse or malicious activity from inside the network not the main issue in past research, and it is important to understand how to identify a compromised system by inspecting outbound traffic. It is a broader term that encompasses indentifying a variety of suspicious, rogue and malicious threats in outbound user activity. They are, (i) spam e-mail, (ii) theft of intellectual property, (iii) computer zombie from inside network to trigger attack, and (iv) internal system that launches scanning and exploits until it launches a DoS attack against the host on the Internet. Therefore, this action triggers revenge action from outside.

The habitual activity between activity of higher transaction size and concurrent connection, definitely, affects the performance of the utilize overall network. In this paper, we proposed a new system architecture for IPS, named Pitcher Flow, which is a Behavior-based detection mechanism to detect, identify, recognize, and react to a suspicious threat. The proposed method also addresses how to identify common knowledge as an activity profile between new algorithms for identifying the normal behavior of user activities. Our method is expected to help security officers (IT Manager and Administrator) to be

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aware of status user profile's activities.

The rest of this article is organized as follow. Section 2, we review related work. Section 3, describes Pitcher Flow architecture and its algorithms. Section 4 includes concluding remarks.

## 2. Related Work

For detecting an intrusion based on the behavior of a user's activities, previous works have concentrated on [1], identifying application's types solely by transport layer communication patterns, excluding payload data patterns. [2] asynchronous event sequences and data pattern comparison between correlation among random order communication (e.q. bot command and windows executable file). The signature is the primary factor in intrusion prevention, because it triggers an alert. There are three trigger mechanisms : (i) pattern-based prevention, (ii) anomaly-based prevention, and (iii) behavior-based prevention [2],[3],[4].

Previous work on a method based behavior model [3] has proposed an idea for the behavior rule that uses correlations between packet/payload data patterns and communication patterns. The scenario-based intrusion detection method has similar features based on state transition machine, however, scenarios of compromise consist of not only sequential events but also random order events and certain scenarios that have to be described involved complicated correlations between communications.

Proposal [4], describes a method for anomaly intrusion detection on linear prediction and Markov chain model, they combine with signature verification to detect attacks more efficiently. They introduced a method for detecting intrusion based on the temporal behavior of applications, using dataset from University of New Mexico (cs.unm.edu/~immsec/data-sets.htm), and then they [5] proposed anomaly intrusion using temporal information of the privilege program with a method based on linear prediction and Markov chain.

The objective of this survey [6] is to study perceptions on information security related to your information and computer (laptop and/or home computer) and related behavior. Results provide support for the many hypothesized relationship, and this study provides an initial step toward understanding of the applicability the applicability of social cognitive theory in the new domain of information security.

Unfortunately, in previous work, researchers focus on the signature system, without discussing how to analyze and recognize normal activity of trusted users inside the network.

## 3. The Proposed Architecture

In this section we propose a new architecture for accurate, recognition of suspicious activity as shown in Figure 1. We employ pitcher flow as the new architecture to detect, identify and react before damage and network resources are accessed.

### 3.1 Pitcher Flow : The Signature, Accuracy and Logging System

The pitcher flow mechanism is described as follows. First, the sensor with the algorithm mechanism captures real-time traffic from the activity host and forwards the captured traffic traces to access control / sensor control system, by comparing the signatures between log of data records to identify and recognize the suspicious packet. Second, we can notice when some attacks log at a certain system, meanwhile, the algorithm identifies and compares with a list suspicious of data record, and the risk rating will collect it. After that a list will be save and identifies as suspicious threat. Risk rating is the quantitative measure of a network's suspicious threat level before event response mitigation. Finally, when an attack is identified, the response is to block action of the event response.

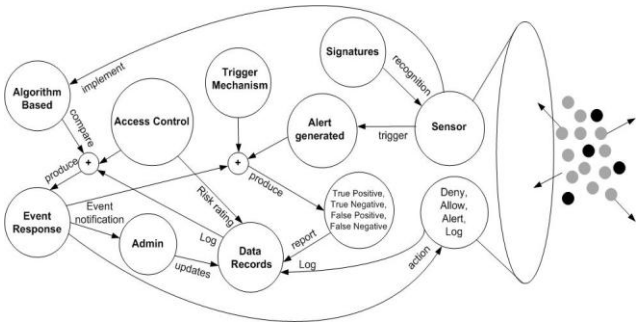


Figure 1 : The Pitcher Flow

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The alert generated by the sensor, which is the situation trigger alarm (valid and invalid but feasible) from the sensor, there are four alerts : (i) The true negative, which is normal user traffic and no alarm is generated, (ii) true positive, which is generated alarm after attack traffic, (iii) false negative, which will be silent no alarm is generated at attack traffic, meanwhile, (iv) the false positive produces an alert if it identifies normal activity traffic, to reduce false positive alert the main focus.

### 3.2 Behavior-based Flow

The main problem in behavior-based detection is recognizing and identifying suspicious threat activity. To

better illustrate and identify suspicious activity, in Figure 2, we present the behavior-based flow with algorithm detection mechanism.

In this section, according to [6], from the result survey, we combine it between our dataset from capturing data activity. Wherein audit records contain information such as frame protocol (source and destination IP address between port address). Both data stream real-traffic from machine contain over a 100, 000 audit data records.

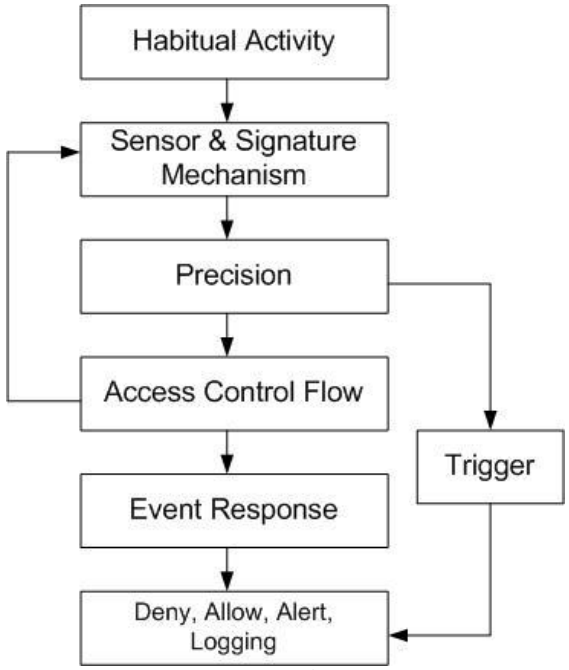



Figure 2 : The flowchart

Meanwhile, the suspicious threat attack from valid inside user is constrained. The emphasis is character behavior activity, however, the composite pattern detection and anomaly-based detection increases the detection demeanor of pattern recognition sensor.

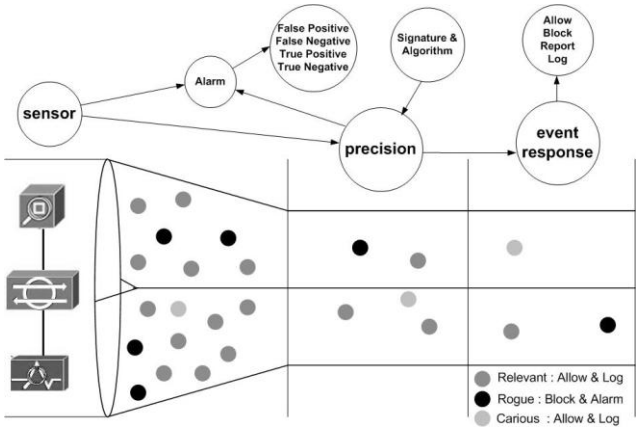



Figure 3. Identify and Recognizing Suspicious Mechanism

Furthermore, from our observations, there are two habitual behavior activities : (i) media rich with activity higher transaction size, and (ii) transactional with activity concurrent connection, as follows :

Table 1. Example behavior activity level of higher transaction size, between more transactions per connection

| Activity | Applications |
|---|---|
| WWW | Browsers, http |
| Collaborative Workspaces | Google Apps, Google Readers, blogs. |
| Download - Upload | P2P, FTP, updates process : System Operation, Anti Virus, Applications |
| Streaming video | You Tube, Realtime, Quick time, YM Webcam. |
| Data Replication | Backup data, mirroring data in other sites. |
| Remote Login | SSH access, WinSCP, Putty |
| Remote VNC | (Remote desktop), to other remote PCs in network. |
| Mail | SMTP, POP, IMAP |
| Spamming mail | Many mails sent to address |

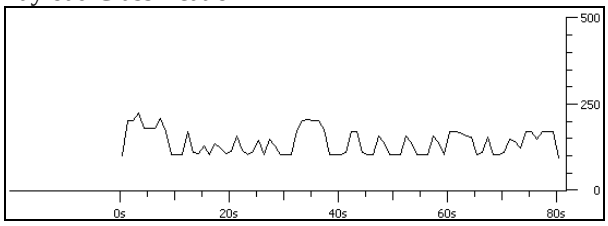
Table 2. Example behavior activity level of concurrent connection, between higher connection rates

| Activity | Applications |
|---|---|
| E-Commerce | https |
| Internet Messaging | YM!, mIRC, ICQ, Pidgin, Adium, GTalk, Skype. |
| VoIP | Skype, YM Voice. |
| Game online | Ragnarok, HalfLife, Age of Empires, Ayo Dances. |
| Scanning | Scanning port using script tools |

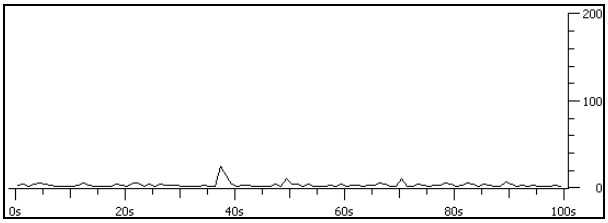
### (a) Sensor & Signature Mechanism

From real-traffic, we distinguish between normal activity and malicious activity, such as P2P BitTorrent, and Slammer worm. The similarities are often minimum utilization Ethernet packets.

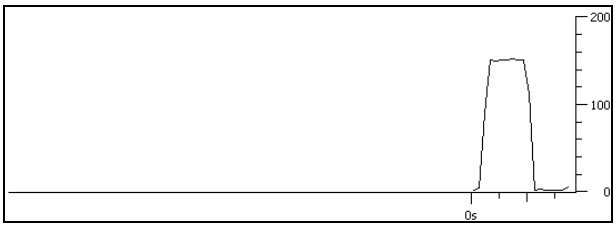
Payload Classification




(a) Bit Torrent P2P. Ethernet : 100%, IP : 100%, TCP : 0.38%, Data : 0.38%, UDP : 99.62%, Data : 99.54%




(b) Slammer worm. Ethernet : 97.43%, IP : 84.16%, TCP : 45.77%, Data : 0.37%, UDP : 36.86%, Data : 0.28%, NetBios session : 32.69%, ARP : 13.27%




(c) Normally activity, containing a few JPEG. Ethernet : 100%, IP : 98.97%, TCP : 0.17 %, UDP : 98.81%, ARP : 0.48%

Figure 4, application-specific bit string of the payload, (a) Bit Torrent P2P, with capture file of two torrent clients communicating without DHT or peer exchange, (b) Slammer worm, sending a DCE RPC packet, (c) Normal activity, a simple capture containing a few JPEG pictures one can reassemble and save to a file.

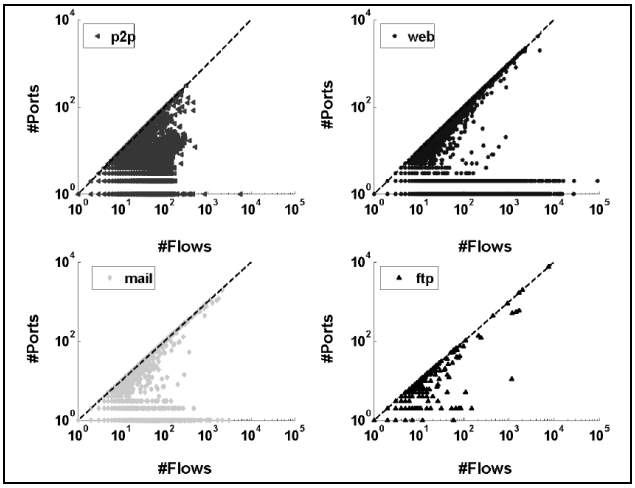



Figure 5. Number of source port versus number of flows per source IP address [10].

To quantify how the number of used source ports may distinguish client from server behavior, the examine the distribution of the source port a host uses in the traces [10]. Figure 5, plots number of flows (x-axis) vs the number of source port (y-axis) that each source IP uses for 15 minutes.

Figure 5. Number of source ports vs number of flows per source IP address in the UN1 trace for a 15 – minute interval for four different applications [10]. In the client-server application (Web, FTP, mail), most points fall on the diagonal or horizontal line for small values in the y-axis (number of used ports). In P2P, point are clustered in between the diagonal and the x-axis.

Table 3 : The notations of parameters used in sensor and signature

| **Notations** | **Descriptions** |
|---|---|
| $S_1$ | source IP address |
| $S_2$ | source Port address |
| $Des_1$ | destination IP address |
| $Des_2$ | destination port number |
| *TCP/UDP* | protocol uses |
| *PY* | Payload |
| *RG* | Regex |
| $MAC_1$ | MAC source address |
| $MAC_2$ | MAC destination address |
| *LE* | Length of packet |
| *URL* | URL address |
| *FR* | Frame |
| *FL* | Flags |
| *WS* | Windows size |

Previous research has shown that anomalous behavior may be determined by simply inspecting the size of the packet, the identifying the type of attack based on payload size [7]. In this experiment, the payloads were a determined to be a constant size, The applications have a payload classification from their characteristics (string, port, flag, protocol, payload and Regex) that can be examined by a sensor. Table 4 presents sample data of a string payload :

Table 4. Sample data string

| Application | String | Protocol |
|---|---|---|
| Bit Torrent | 0000000d0600\0x13 | TCP/UDP |
| eDonkey2000 | 0xe319010000 | TCP/UDP |
| MSN Messenger | “PNG” 0x0d0a | TCP |
| IRC | “USERHOST” | TCP |
| YM! | “ymsgr” | TCP |
| nntp | “ARTICLE” | TCP |
| SSH | “SSH” | TCP |

In Table 5, we define regular expressions (Regex) that can be used in selectors to define ranges of values instead of defining each possible value separately. Regex can match with pattern recognizing in layer 7 application. Therefore, this approach can be to combined with a global signatures database, which is an real-time anomaly analyzer system, proposed by [8].

Tabel 5. Sample data regex

| Suspicious | Regex String |
|---|---|
| HTTP Overflow | pcre:"/(\w+)\s*=\s*('\|")[^\2]*\[\[[^\2]*\][^\2]*\2\s*\;.*new\s+RegExp\s*\(\s*\1\|new\s+RegExp\(('\|")[^\3]*\[\[[^\3]*\]/smi"; |
| BitTorrent | .*[Ii][Nn][Ff][Oo]_[Hh][Aa][Ss][Hh]=.* |
| eDonkey2000 | ^[\C5\D4\E3-\E5].\?.\?.\?.\?([ABCABCDEF[ABCE\A0\A1\A2\A3\A4]\|.....\?[ -~]\|....$) |
| MSN Messenger | ^(ver [ -~]*msnftp\x0d\x0aver msnftp\x0d\x0ausr\|method msnmsgr:) |
| IRC | ^(nick[\x09-\x0d -~]*user[\x09-\x0d -~]*:\|user[\x09-\x0d -~]*:[\x02-\x0d -~]*nick[\x09-\x0d -~]*\x0d\x0a) |
| YM! | ^(ymsg\|ypns\|yhoo).?.?.?.?.?.?.?[lwt].*\xc0\x80? |
| nntp | ^20[01][\x09-\x0d -~]*\x0d\x0a[\x09-\x0d -~]*AUTHINFO USER\|20[01][\x09-\x0d -~]*news |
| SSH | ([A-Za-z0-9._-]+) sshd\[([0-9]+)\]: \[[^]]+\] |

Regex are specified using a keyword the keywoard PCRE, which stand for Perl Compatible Regular Expression. PCRE is more powerful and complicated, than regex. The regex attribute always contains just a single pattern, not lists of patterns. We observe that identifying suspicious activity, on receiving packet, in Figure 1, system it receives an identification field from each packet header, including $S_{1,}$ $S_{2,}$ $Des_{1,}$ $Des_{2,}$ $MAC_{1,}$ $MAC_{2,...}$, and classifies them into classes/types, Identifying parameters by comparing the packets.

Furthermore, we wish to distinguish normal or curious activity by classes/types, such as (i) IP Address between MAC Address, (ii) number of connection, (i.e. 1 to 1 connections, 1 to N connection or N to 1 connection), and (iii) payload. After classifying a packet, it sends the packet to the precision section. Algorithm 1 lists the details.

**Algorithm 1 : Identification & declaration Packet data**

```
type packet_data record, Parameters on table 1
precision⇐ identification result
    r_r⇐ risk rating
    packet_data = 1    // input data between real-time detection
    while packet_data <> 0 do
            identification (precision)
            risk_rating (precision, rr)
            trigger (precision)
            event_response (precision, r_r)
    end while
```

**(b) Precision**

In this section, we describe the process of recognizing a detailed suspicious threat. We identify the habitual activity in the previous section, based on Table 1 and Table 2, which are the behavior activity levels, and next a process identifies the payload, shown in Table 4. Algorithm 2, lists the logic of how identification allows, blocks, logs and reports, respectively.

**Algorithm 2 : Identification and recogniztione**

```
Procedure Identification (precision)
        read (packet_data) // refers from figure 3,table 4& Algorithm 1
        if packet_data = rule then
            precision is block
        else if packet_data ≠ rule then
            precision is allow
        else if packet_data ≠ rule and suspect then
            precision is log
        else
            precision is report
        end if
    end procedure
```

The set of signatures affects the number of attack identifying detected. The accuracy affects the correctness of deciding whether an attack exists in real-traffic, notifying the logging system of an attack based on the list in the database. The sensor trigger alert produces an alarm, which is a False Positive (FP), False Negative (FN), True Negative (TN) or True Positive (TP) in every IPS, the main focus is to analyze the alarm and tune out FPs. The session that generates the through Algorithm 3 is described as follows.

**Algorithm 3 : Alarm set**

```
procedure trigger (precision)
    read (precision)
    if precision= allow then
            alarm = TN
else precision = block then
            alarm = TP
    else if precision = log then
            alarm = FP
    else
            alarm = FN
    end if
end procedure
```

**(c) Access Control Flow**

In this section, the list data set from the previous section uses the input in the access control and the risk rating to create the result (information, low, medium, or high). The risk rating then collects and lists it, in this section. The output from this section is the form of rules to generate event response or send it back to sensor for the sensor mechanism to identify. Algorithm 4 lists the details.

**Algorithm 4 : Access System**

```
Procedure risk_rating (precision, r_r) // to pitcher flow
   filter precision
   if precision = block then
            r_r is high
      else if precision = log then
            r_r is medium or r_r is low
      else precision = report then
            r_r is low or r_r is information
      end if
    end procedure
```

**(d) Event Response**

The event response, in response to the traffic by performing actions, such as : deny, alert, block, and log

**Algorithm 6 : Response**

```
procedure  event_response (precision, r_r)
    read (precision, r_r)
    if precision = allow or r_r = information or r_r  = low then
            response is allow
    else if r_r = medium then
            response is allow and log
    else if r_r = high then
            response is block
    end if
end Procedure
```

## 4. Conclusion

The Behavior-based detection is a complex, multiple problems to identify real-time traffic from internal users, under a variety of normal activities. In this paper, a new model has been proposed for identification and recognition through the behavior-based detection and prevention of an attack, with analyze real-traffic from habitual activity of internal users. This approach use the pitcher flow with signatures, accuracy, and logging systems to identify, recognize and react before threat damage and access network resources. The results indicate that this approach can be to combine with other defense systems such as firewall and network monitoring. In the future, we will experiment with a benchmark algorithm in a real-traffic network.

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