國立交通大學

網路工程研究所

碩士論文

信譽基準的權重投票以減少入侵偵測的誤判漏判

Creditability-based Weighted Voting to Reduce False Positives and Negatives in Intrusion Detection

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摘　　　要

誤判和漏判發生於每台入侵偵測系統,而誤判和漏判發生的頻率和多寡被用來評估入侵偵測系統的能力。單一台入侵偵測系統的偵測能力常不理想是因為伴隨大量的誤判，再加上單單只有一台的偵測結果是無法調查其漏判的狀況。據此顯示單靠一台來偵測是有所不足和其限制，因此為了克服單一台的限制，藉由整合多台不同知識能力的入侵偵測系統為一方法,然而,在偵測同一份網路流量時，不同的偵測能力可能會產生不同的偵測結果,所以如何利用這些偵測結果來對該被偵測的網路流量做出一個好的決策是具挑戰性的難題。因此本研究提出一個信譽基準的權重投票方法,用以整合考量各家入侵偵測系統的知識能力並嘗試同時降低誤判和漏判的機會，且藉此提升多台所產生之警報處理的有效性。提出的方法主要程序為:調查各家入侵偵測系統的偵測能力並對他們建立相對應的信譽值，然後根據各信譽值分配權重給相對應的投票者,再實際對該被處理的網路流量執行決策以決定是否為惡意的。在結果中，不同的信譽數值證明不同台入侵偵測系統的偵測能力是不同的,即證明其知識能力不相同的特性。再者,在投票方法中，我們使用 Accuracy 及 Efficiency 用以評估投票演算法,本文所提出的投票方法準確性和有效性達到 95%和 94%，優於多數決的 66%和 41%。此外，本文提出的投票方法相較於各台入侵偵測系統，在平均誤判及漏判減少的百分比數值為 21%和 58%。

關鍵字：入侵偵測，誤判，漏判，警報後處理

Creditability-based Weighted Voting to Reduce False Positives and Negatives in Intrusion Detection

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Abstract

False Positive (FP) and False Negative (FN) happen to every Intrusion Detection System (IDS). How frequently they occur is used to evaluate the performance of an IDS. A large number of FPs will degrade the performance of the IDS. Furthermore, FNs cannot be investigated from one IDS's alerts. Thus, to overcome the limitation of one IDS, a way to leverage multiple IDSs' domain knowledge is used. However, due to different detection capabilities, different IDSs may have different detection results for a traffic trace. Hence, using these results to make a good decision regarding the trace's status turns out to be challenging. This work proposes a Creditability-based Weighted Voting (CWV) to reduce both FPs/FNs and increase the performance of multiple IDSs. The CWV first investigates the detection capabilities of all IDSs and models the corresponding creditabilities to them. Then, according to the creditabilities, it assigns the weights to IDSs and makes a decision concerning the trace. From the experiment results, we demonstrate the different IDSs' detection capabilities by their creditabilities. In addition, we use Accuracy and Efficiency to evaluate the CWV and the majority voting (MV). The CWV achieves the accuracy of 95% and the efficiency of 94% compared to 66% and 41% of the MV. Besides, with the CWV, the average percentages of FP/FN reduction for an IDS are 21% and 58%, respectively.

Keywords: intrusion detection, false positives, false negatives, alert post-processing

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Contents

List of Figures

List of Tables

Chapter 1 Introduction

Intrusion Detection Systems (IDSs) usually protect computer networks against intrusions. A signature-based IDS is a popular approach nowadays. It specifies signatures of intrusions and tries to detect malicious activities by matching these signatures against the traffic data, called pattern matching. IDS vendors need to set up a signature database and maintain it. There are two major challenges in the signature-based IDS's defense. One is growing and changing of malicious traffic and the other is the difficulty in the design of IDS. The former leads the signature database maintenance difficult. For instance, rules of Snort [1] are updated frequently. The latter includes runtime limitation and specificity of signatures. Runtime limitation presents that IDSs may not analyze the context of all activities in real-time. For example, a malicious activity differs only slightly from normal activities, so IDSs cannot detect it with part of content. Specificity of signatures presents that the balance between general signatures and specific ones is hard to determine. If the signatures are too general, they are easily matched in the payload, even though the payload is benign. On the other hand, if the signatures are too specific, IDSs would not detect malicious activities. Thus, because of these two challenges, *False Positives* (FPs) and *False Negatives* (FNs) of IDSs occur.

FPs and FNs are used for evaluating the performance of an IDS. One IDS is often found to be dissatisfactory with respect to either or both of a large number of FPs and FNs. To illustrate the severity of FPs and FNs, we use two views: the vendor and the user. From the vendor's view, a heavy workload of analysis happens due to a large number of FPs while FNs occur because of no corresponding signatures in the IDS. From the user's view, frequent alert messages of FPs interrupt the user while the FNs means that malicious traffic intruding the protected networks is undetected. Thus, we tend to reduce not only FPs, but also FNs because both of them are severe and non-negligible.

In order to reduce FPs and FNs, an analyst post-processes, i.e., using alerts as input and processing them to improve their accuracy, all alerts produced by an IDS to confirm whether the alerts are TPs or FPs [2]. Nevertheless, the observed problem is the limitation of one IDS. This is because an analyst can only deal with the alerts which the IDS can detect in an IDS, but cannot investigate FNs of the IDS. Furthermore, if there are a large number of FPs and FNs, an analyst will analyze alerts with heavy workload. Accordingly, it is another problem in alert post-processing.

The problem, in fact, has been estimated that up to 99% of alerts produced by an IDS are FPs [3-4]. Moreover, according to the alert management [2], i.e., an analyst post-processes all alerts for improving signature design, the limitation of one IDS is found out. To overcome the mentioned problem and limitation of one IDS, multiple IDSs are used because each has its own private and independent signature design. Based on different domain knowledge among IDSs, traffic can be recognized by leveraging IDSs' detection capabilities. The advantage of this is the malicious activities which cannot be detected by some IDS could be detected by others.

Several methods deal with alerts produced by an IDS to reduce the amount of FPs. Some of them analyze alerts to recognize high-level attack scenario for high view of attacks [5-8], some study the causes of FPs to identify root causes [4, 9, 10], and others classify alerts to TPs or FPs for reducing FPs [2, 11, 12]. However, these methods only consider one IDS to detect malicious traffic, so they still cannot evaluate FNs for the IDS. On the other hand, for solving the conflicts of detection from multiple IDSs, a *Majority Voting* (MV) algorithm [13] is proposed. MV finds potential FPs (P-FPs) and potential FNs (P-FNs) first by comparing IDSs alerts. If few IDSs generate alerts but most IDSs do not when they process the same traffic, these traces are P-FPs of the few

IDSs. In contrast, few IDSs do not generate alerts but most IDSs do, these are P-FNs of the few IDSs. Next, an analyst analyzes P-FPs and P-FNs to verify they are indeed FPs and FNs. However, in [14-15], authors found MV often leads error decision. We also find MV is not efficient enough in experiments. The reason is MV disregards different domain knowledge among IDSs that results in low percentages of P-FPs/P-FNs being FPs/FNs.

In this work, to leverage different domain knowledge among multiple IDSs, reduce FPs and FNs, and increase the efficiency of alert post-processing, we propose a *Creditability-based Weighted Voting* (CWV) algorithm. For this purpose, there are two main components of our algorithm, *Creditability Modeling* (CM) and *Weighted Voting* (WV). First, the CM identifies IDSs' detection capabilities of different types of traffic traces by investigating past detection experience to determine IDSs' corresponding creditabilities. To investigate the detection capabilities on both or either two factors comprised an alert, i.e., protocols and malicious types, the creditabilities are therefore constructed in two levels, *Protocol level* and *Alert Message level*. For instance, "HTTP" is a protocol in Protocol level. "HTTP: Attempt to Read Password File" is an alert message of HTTP protocol in Alert Message level. Second, according to the creditabilities, we assign the weights for weighted voting to decide the traffic trace malicious or benign in WV. Thus, it would result in not only reducing FPs, but also increasing TPs. In other words, it could increase TNs and reduce FNs.

The rest of this paper is organized as follows. Chapter 2 presents the background and related works. Chapter 3 states terminologies and problem statements. Chapter 4 describes the design and solution ideas of our algorithm. Chapter 5 displays the evaluation of our works. Finally, Chapter 6 concludes this work and discusses the future works.

Chapter 2 Background

This chapter describes alert post-processing and its related methods first, and then introduces the generation method of FP/FN datasets.

2.1 Methods of alert post-processing

If there are a large number of FPs and FNs, an analyst may have a heavy workload, i.e., he or she needs a long time to analyze the correctness of alerts. Accordingly, for reducing the number of FPs and FNs, a method, called alert post-processing (APP), is proposed. APP uses alerts as an input and processes them to improve their accuracy. Several researchers [2][4-12] proposed the methods to reduce the number of FPs from an IDS. These methods can be classified into three categories, i.e., alert correlation, alert clustering, alert classification, and illustrated systematically as follows.

First, alert correlation [5-8] analyzes alerts by recognizing high-level attack scenario with higher view of attacks and makes *correlated* alerts be an attack graph. For example, Ning et al. [5] presented an alert correlation approach correlating alerts based on pre-conditions and post-conditions. Two alerts are correlated when the pre-condition of a later attack is satisfied by the post-condition of an earlier attack. This approach offered a more condensed view on the security issues raised by an IDS. Unfortunately, Sadoddin and Ghorbani [8] investigated that alert correlation may not have a significant effect in reducing the number of total alerts, even the number of FPs. This is because the goal of alert correlation is providing a higher view of attacks. It is different from the goal of reducing the number of FPs and FNs even if the alert correlation may sometimes reduce the number of FPs.

Second, alert clustering [4, 9, 10] studies the causes of FPs and identifies root causes that makes an IDS alerts. It clusters the alerts with similar root causes together. For instance, Julisch [10] defined six attributes for an alert, i.e., source and destination

IP addresses, source and destination ports, alert types, and timestamps. The alerts with same six attributes are categorized to the same group, called alert cluster. Thus, the alerts in the same alert cluster, they may have the same root cause. According to the root causes, a system administrator may reduce the number of FPs of an IDS.

Third, alert classification [2, 11, 12] classifies alerts to TPs and FPs for reducing the number of FPs of an IDS. For example, the Adaptive Learner for Alert Classification (ALAC) was proposed [12], and it was an adaptive alert classifier based on the feedback of an intrusion detection analyst and machine-learning technique. Also, it had a recommender mode and an agent mode. The former was in which all alerts are labeled to TP/FP and passed to the analyst while the latter was in which some alerts are processed automatically. Intuitively, because of the goal of ALAC, it could reduce the number of FPs of the IDS. Although the agent mode reduces the analyst's workload, the recommender mode would still lead a heavy workload to the analyst.

However, the efficiency of APP is low when alerts only come from an IDS. This is because, as mentioned before, if there is only one IDS, APP only can process FP cases and cannot investigate FN ones. Hence, alert correlation, clustering, and classification cannot reduce the number of FNs due to the limitation of one IDS. Accordingly, the detection with multiple IDSs are recently noticed. For instance, Chen et al. [13] presented a particular method of APP, Majority Voting algorithm (MV), to deal with the alerts produced by multiple IDSs and reduce the number of FPs and FNs. The idea of MV is solving the conflicts of the detection of multiple IDSs. It finds FPs and FNs by comparing IDSs' alerts. If few IDSs produce alerts from specific traffic traces, the trace is likely to be an FP case of the few IDSs. On the other hand, if few IDSs do not produce alerts, it is likely to be an FN case of the few IDSs. However, Parham [15] presented that majority voting is not absolutely correct in many cases, and it would often lead to error decision. Furthermore, the key reason of the inefficiency of MV is disregarding different domain knowledge among multiple IDSs.

Although some related works, used multiple IDSs such as the sensor fusion architecture (SFA), they focused on how to model and enhance their architectures, not APP. For example, Thomas and Balakrishnan [16-17] addressed the problem of optimizing the performance of the SFA. In practice, a neural network learner was designed in the SFA in order to determine the weight of each IDS based on the reliability of that IDS in detecting a certain attack. However, this neural network learner is a black box and authors did not concretely mention how to calculate the weights.

In this work, by leveraging different domain knowledge among multiple IDSs, Creditability-based Weighted Voting (CWV) algorithm reduces both the number of FPs and FNs, and increases the efficiency of APP. CWV not only investigates the detection creditabilities of multiple IDSs to overcome the limitation of one IDS, but also reduces the number of FPs and FNs to decrease the heavy workload of analyst. According to the goals and methods of the above works, as summarized in Table 1, this work will focus on the comparison of MV and CWV and evaluate the efficiency of two algorithms.

Table 1. Comparison of methods of alert post-processing.

Approach	**Goal**	**Number of IDSs**	**FNs investigation**	**Output**	**Creditability**
Alert correlation [5-8]	•Merge alerts for a high-level view of attack	One	N/A	Attack graphs	N/A
Alert clustering [4, 9, 10]	•Identify root causes of alerts	One	N/A	Alert clusters	N/A
Alert classification [2, 11, 12]	•Reduce FP •Reduce analyst's workload	One	N/A	TP/FP	N/A
Majority Voting (MV) [13]	•Reduce FP/FN •Reduce analyst's workload	Multiple	Yes (by some IDSs)	FP/FN	N/A
Creditability-based Weighted Voting (CWV)	•Reduce FP/FN •Reduce analyst's workload	Multiple	Yes (by some IDSs)	TP/FP/TN/FN	Yes

2.2 Generation method of FP/FN datasets

In order to evaluate the detection capabilities of IDSs, the way to generate test trace datasets has been considered. Some researchers provided the real-world traffic traces for evaluating FPs and FNs to measure the accuracy of the IDSs [13, 18].

As shown in Figure 1, Lin et al. designed an Active Trace Collection (ATC) [18] to actively extract and classify suspicious traces from real-world traffic captured in the NCTU Beta Site [19]. First, in the extraction module, it uses a traffic replay tool to replay the captured traffic to multiple IDSs. If an IDS detects specific behavior in the traffic, it will trigger an alert. According to the IDSs' alerts, the ATC finds out the anchor packets that trigger the alerts by comparing five fields, i.e., source/destination IP addresses, source/destination ports, and protocols, and then processes the packet and connection association to extract each session into the packet traces. Second, in the classification module, according to the alert messages, the ATC classifies the traces into different categories by keywords. It defines ten categories, such as *Web*, *File Transfer*, *Remote Access*, etc. Each category uses the corresponding protocol names as its keywords. For example, the Web category uses HTTP as its keywords. Others can be referred to [18]. Up to now, the suspicious classified traces have been collected.

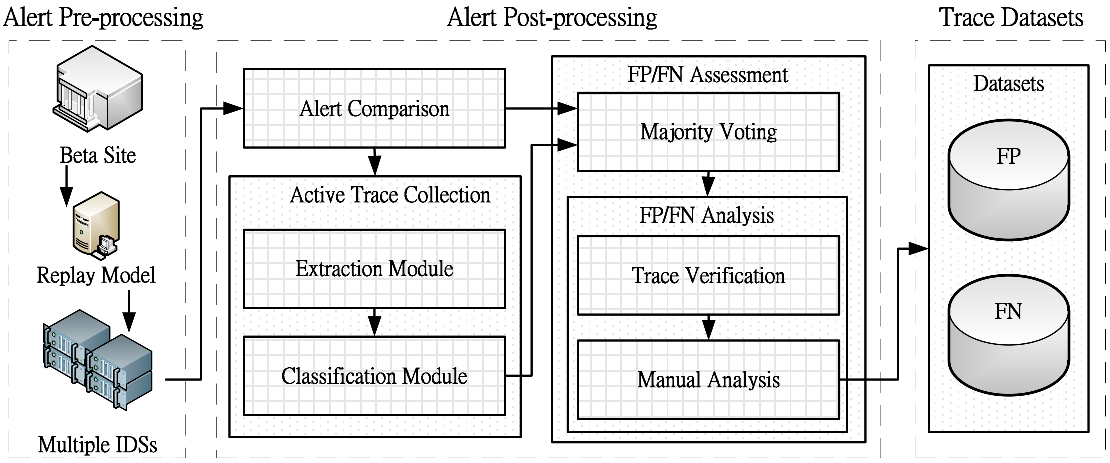


Figure 1. Generation method of FP/FN datasets.

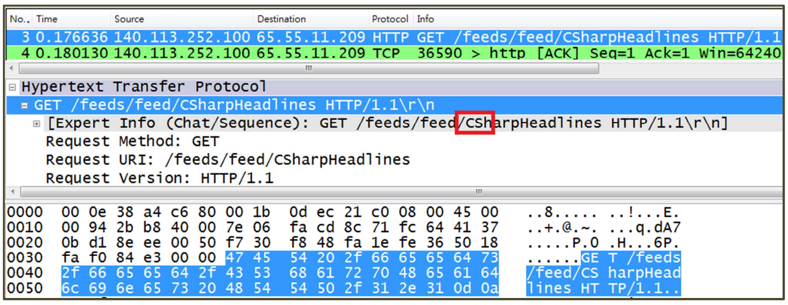
Besides, the detection of IDSs may be incorrect due to FPs and FNs. Lin et al. also proposed a FP/FN Assessment (FPNA) [18], which analyzes the FP and FN cases and investigates the causes of FPs and FNs. First, it finds out potential FPs and FNs of the IDSs with a voting algorithm (e.g., majority voting). Next, in FP/FN analysis, it replays the corresponding extracted traces based on the alerts to the IDSs. This step verifies whether the traces are reproducible to the original IDSs or not. Then, to confirm the cases which are correct FPs or FNs, the reproducible traces are manually analyzed by analysts. At the same time, the confirmed FP and FN cases and the causes of them are recorded to generate the FP/FN datasets. This work further uses the traces and the causes behind the FPs and FNs to investigate the creditabilities of IDSs.

In the following paragraphs, two case studies of the FP/FN analysis are taken as examples to show why the benign traces are detected as malicious ones and the malicious traces are not detected by IDSs. The investigation of FP/FN analysis is illustrated with the description of activity, the corresponding signature, and the cause of FP/FN, which are shown in the description, signature, and cause fields in Table 2 and Table 3, respectively. In detail, first, the description of the malicious activity is referred to Common Vulnerabilities and Exposures (CVE) [20]. Second, the corresponding signature of the malicious activity is referred to Snort rule [1] as example if it exists. Third, the cause of FP/FN is explained why the FP/FN occurs.

1) Table 2 illustrates a false positive case, “WEB-CGI csh access”, and the detail analysis with Wireshark [21] of packet content is shown in Figure 2. The execution of csh interpreter in the cgi-bin directory on a WWW site is detected by just matching the “/csh” content in the request URI field. It often results in FP because the signature design is too general and rough.

Table 2. A false positive in FP/FN analysis.

Description	
Perl, sh, csh, or other shell interpreters are installed in the cgi-bin directory on a WWW site, which allows remote attackers to execute arbitrary commands. (reference: CVE, 1999-0509)	
Signature	**Cause**
alert tcp $EXTERNAL_NET any -> $HTTP_SERVERS $HTTP_PORTS (msg:"WEB-CGI csh access"; flow:to_server,established; uricontent:"/csh"; nocase; ...)	GET /feeds/feed/CSharpHeadlines HTTP/1.1



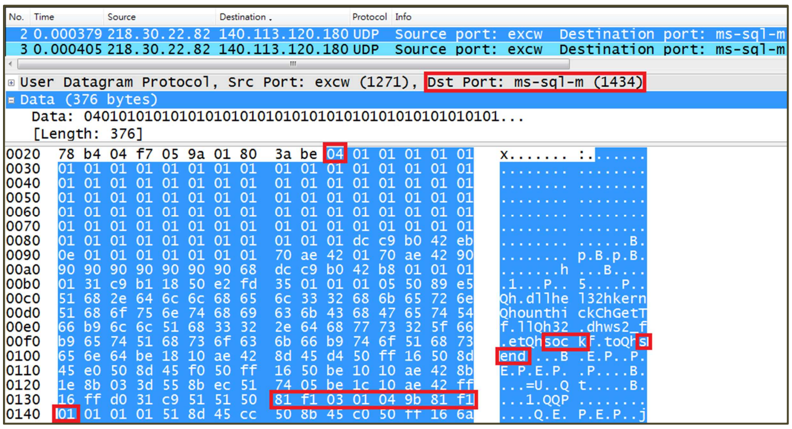
```
No.. Time     Source          Destination    Protocol Info
 3 0.176636 140.113.252.100 65.55.11.209 HTTP GET /feeds/feed/CSharpHeadlines HTTP/1.1
 4 0.180130 140.113.252.100 65.55.11.209 TCP  36590 > http [ACK] Seq=1 Ack=1 Win=64240

⊟ Hypertext Transfer Protocol
  ⊟ GET /feeds/feed/CSharpHeadlines HTTP/1.1\r\n
    ⊞ [Expert Info (Chat/Sequence): GET /feeds/feed/CSharpHeadlines HTTP/1.1\r\n]
      Request Method: GET
      Request URI: /feeds/feed/CSharpHeadlines
      Request Version: HTTP/1.1

0000  00 0e 38 a4 c6 80 00 1b  0d ec 21 c0 08 00 45 00   ..8..... ..!...E.
0010  00 94 2b b8 40 00 7e 06  fa cd 8c 71 fc 64 41 37   ..+.@.~. ...q.dA7
0020  0b d1 8e ee 00 50 f7 30  f8 48 fa 1e fe 36 50 18   .....P.0 .H...6P.
0030  fa f0 84 e3 00 00 47 45  54 20 2f 66 65 65 64 73   ......GE T /feeds
0040  2f 66 65 65 64 2f 43 53  68 61 72 70 48 65 61 64   /feed/CS harpHead
0050  6c 69 6e 65 73 20 48 54  54 50 2f 31 2e 31 0d 0a   lines HT TP/1.1..
```

Figure 2. A false positive case study in FP/FN analysis - WEB-CGI csh access.

2) Table 3 illustrates a false negative case, “SQL Worm propagation attempt”, and the detail analysis of packet content is shown in Figure 3. The SQL Worm would result in buffer overflow in the Microsoft Windows server service. The worm loads Kernel32.dll and WS2_32.dll and then calls GetTickCount to continuously send 376 bytes UDP packet of exploit and propagation code across port 1434 until the SQL Server process is shut down. However, it sometimes results in FN since some IDSs miss the signature to detect it.

Table 3. A false negative in FP/FN analysis.

Description	
Buffer overflow in the Server Service in Microsoft Windows 2000 SP4, XP SP1 and SP2, and Server 2003 SP1 allows remote attackers, including anonymous users, to execute arbitrary code via a crafted RPC message. (reference: CVE, 2002-0649)	
Signature	**Cause**
alert udp $EXTERNAL_NET any -> $HOME_NET 1434 (msg:"SQL Worm propagation attempt"; flow:to_server; content:"|04|"; depth:1; content:"|81 F1 03 01 04 9B 81 F1 01|"; fast_pattern:only; content:"sock"; content:"send"; …)	Signature content doesn’t exist.



```
No. Time     Source        Destination .   Protocol Info
 2 0.000379 218.30.22.82 140.113.120.180 UDP  Source port: excw  Destination port: ms-sql-m
 3 0.000405 218.30.22.82 140.113.120.180 UDP  Source port: excw  Destination port: ms-sql-m

⊞ User Datagram Protocol, Src Port: excw (1271), Dst Port: ms-sql-m (1434)
⊟ Data (376 bytes)
    Data: 0401010101010101010101010101010101010101010101010101...
    [Length: 376]

0020  78 b4 04 f7 05 9a 01 80  3a be 04 01 01 01 01 01   x....... :.......
0030  01 01 01 01 01 01 01 01  01 01 01 01 01 01 01 01   ........ ........
0040  01 01 01 01 01 01 01 01  01 01 01 01 01 01 01 01   ........ ........
0050  01 01 01 01 01 01 01 01  01 01 01 01 01 01 01 01   ........ ........
0060  01 01 01 01 01 01 01 01  01 01 01 01 01 01 01 01   ........ ........
0070  01 01 01 01 01 01 01 01  01 01 01 01 01 01 01 01   ........ ........
0080  01 01 01 01 01 01 01 01  01 01 01 dc c9 b0 42 eb   ........ ......B.
0090  0e 01 01 01 01 01 01 01  70 ae 42 01 70 ae 42 90   ........ p.B.p.B.
00a0  90 90 90 90 90 90 90 68  dc c9 b0 42 b8 01 01 01   .......h ...B....
00b0  01 31 c9 b1 18 50 e2 fd  35 01 01 01 05 50 89 e5   .1...P.. 5....P..
00c0  51 68 2e 64 6c 6c 68 65  6c 33 32 68 6b 65 72 6e   Qh.dllhe l32hkern
00d0  51 68 6f 75 6e 74 68 69  63 6b 43 68 47 65 74 54   Qhounthi ckChGetT
00e0  66 b9 6c 6c 51 68 33 32  2e 64 68 77 73 32 5f 66   f.llQh32 .dhws2_f
00f0  b9 65 74 51 68 73 6f 63  6b 66 b9 74 6f 51 68 73   .etQhsoc kf.toQhs
0100  65 6e 64 be 18 10 ae 42  8d 45 d4 50 ff 16 50 8d   end....B .E.P..P.
0110  45 e0 50 8d 45 f0 50 ff  16 50 be 10 10 ae 42 8b   E.P.E.P. .P....B.
0120  1e 8b 03 3d 55 8b ec 51  74 05 be 1c 10 ae 42 ff   ...=U..Q t.....B.
0130  16 ff d0 31 c9 51 51 50  81 f1 03 01 04 9b 81 f1   ...1.QQP ........
0140  01 01 01 01 51 8d 45 cc  50 8b 45 c0 50 ff 16 6a   ....Q.E. P.E.P..j
```

Figure 3. A false negative case study in FP/FN analysis - SQL Worm propagation attempt.

Chapter 3 Problem Statement

3.1 Terminologies

Table 4 defines a confusion matrix to represent the types of trace datasets with IDSs' detection. The rows represent the actual trace behavior such as malicious and benign, and the columns represent the detection alarms such as alert or non-alert. According to the corresponding relation between row and column elements, there are four types of traces, *True Positive* (TP), *False Positive* (FP), *True Negative* (TN), and *False Negative* (FN). TP and FP represent the IDS produces alert for malicious and normal activities, respectively. Similarly, TN means the IDS does not produce alert for a normal activity while FN does for a malicious activity.

Table 4. Confusion matrix definition.

		Detected	
		Alert	Non-alert
Actual	Malicious	True Positive (TP)	False Negative (FN)
	Benign	False Positive (FP)	True Negative (TN)

Table 5 defines the notations used in this algorithm. M and $\neg M$ respectively denote malicious and benign. Based on the IDS detection, A and $\neg A$ denote the presence or absence of an intrusion alarm, i.e., alert or non-alert, separately. Then, n means the number of detected traces, i.e., how many traces marked with A there are. N presents the number of IDSs involved in detection, and these N IDSs are a set V. Moreover, whether all N IDSs having the voting rights depends on the voting algorithm. According to the detection results, one of four types illustrated in Table 4 would occur, i.e., TP, FP, TN, or FN. Besides, suppose there are different k previous alert messages of the j-th IDS under the protocol P, and $m_{k,P}^{j}$ records these messages. Furthermore, a notation S is used to present a set of these messages. After the records, in order to investigate the creditabilities, we use probability to model the rate of type of traces of the *j*-th IDS under each protocol by $Type^{j}_{\mathrm{rate},P}$. However, maybe not all IDSs are creditable enough, so two thresholds τ_d and τ_a are used to choose parts of IDSs with suitable creditability. The set of the chose IDSs is a subset of V and it is denoted as V_r. τ_d is the detection threshold whereas τ_a is the abnormality threshold. Then, according to each IDS's creditability, its corresponding weight w^{j}_{i} is assigned. d^{j}_{i} and msg^{j}_{i} are detection result and alert message of the *j*-th IDS for *i*-th trace. Based on the above notations and definitions, CMD_i can be calculated for malicious tendency of *i*-th trace. Finally, based on the CMD_i, DR_i represents a decision result for *i*-th trace, i.e., if the trace is malicious, benign, or unknown.

Table 5. The notations used in Creditability-based Weighted Voting.

Notations	**Descriptions**
$M, \neg M$	Trace behavior, i.e., malicious and benign.
$A, \neg A$	Intrusion alarm, i.e., alert and non-alert.
n	Number of detected traces.
N	Number of IDSs.
$V:\{1, 2, ..., N\}$	Set of voters, i.e., set of IDSs.
$Type:\{TP, FP, TN, FN\}$	Types of the trace dataset.
$m^{j}_{k,P}$	Previous alert message m_k of the *j*-th IDS under the protocol *P*.
k	Alert message type index.
j	IDS index.
$P:\{HTTP, FTP, ...\}$	Protocol type of classified traces.
$S:\{m^{j}_{k,P}\}$	Set of previous alert messages.
$Type^{j}_{\mathrm{rate},P}$	Rate of the type of trace of the *j*-th IDS under the protocol *P*.
V_r	Set of the remaining voters. A subset of *V*.
$r, r \le N$	Number of elements of V_r.
τ_d	Detection threshold measured the correctness of detection.
τ_a	Abnormality threshold measured the abnormality of alert frequency.
w^{j}_{i}	Weight of the *j*-th IDS for *i*-th trace, which is assigned according to the creditabilities.
d^{j}_{i}	Detection result produced by the *j*-th IDS for *i*-th trace.
msg^{j}_{i}	Alert message of the *j*-th IDS for *i*-th trace.
i	Trace index.
CMD_i	Creditability Malicious Decision function calculated the malicious tendency for *i*-th trace with creditabilities.
$DR_i:\{A', \neg A', Unknown\}$	Decision result with voting algorithm for *i*-th trace.

3.2 Problem description

In APP, on the one hand, the efficiency is low when alerts only come from one IDS, as explained in Chapter 1. On the other hand, when alerts come from multiple IDSs, the efficiency may also be low if APP disregards the different domain knowledge among multiple IDSs. Moreover, due to the different domain knowledge, different IDSs may have different detection results for a traffic trace. Hence, how to efficiently use these results to make a good decision on the processed traffic trace is a problem.

The above description can be formulated as follows.

Given: (1) a training dataset T, (2) N IDSs, (3) sets of alerts produced by N IDSs, (4) n corresponding processed traces.

Suppose: (1) the weight of *j*-th IDS is w^j, (2) the alert produced by *j*-th IDS for *i*-th trace is a_i^j.

Objectives: (1) model a series of weights $\{w^1, w^2, w^3, ..., w^N\}$ according to T, (2) design a function $f_i(w^j, a_i^j)$ to make a decision on each trace.

To maximize the number of correct decisions, the number of FPs and FNs are minimized and the efficiency of APP is maximized accordingly.

Chapter 4 Creditability-based Weighted Voting

This chapter details the Creditability-based Weighted Voting algorithm which includes four components. The first component is the *Creditability Modeling*, which investigates and models the IDSs' creditabilities according to the past experience of detection. Second, the *Authority Selecting* selects authorities of detection if they exist. Third, the *Voter Excluding* excludes voters that cannot often perform well in detection. Lastly, the *Weighted Voting* determines a trace where it belongs to.

4.1 Overview

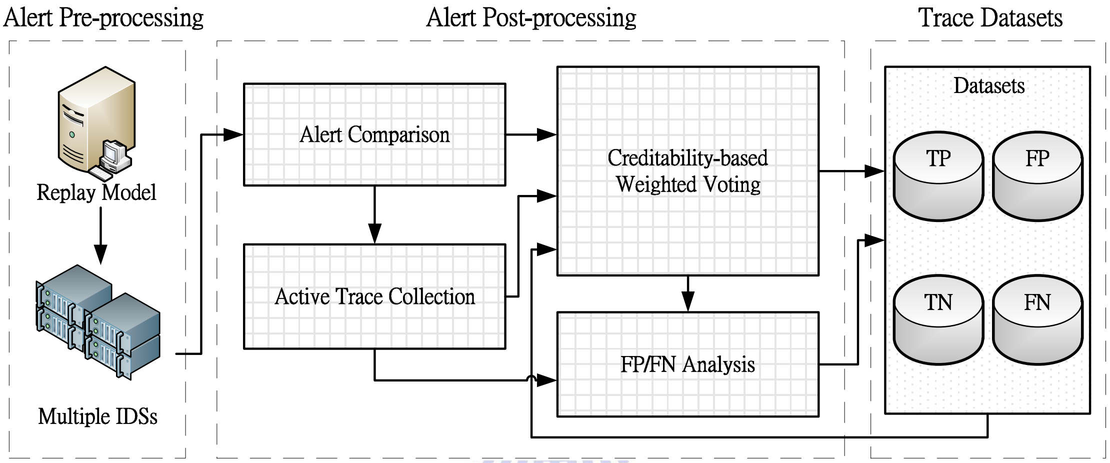


Figure 4. Architecture of our system.

The goal of this work is to increase the efficiency of alert post-processing when alerts come from multiple IDSs, that is, to increase the accuracy of the corresponding processed traces which actually belong to TP, FP, TN, or FN cases. Accordingly, the generated TP/FP/TN/FN datasets can be not only used by IDS vendors to improve their signature design, but also used to accumulate our knowledge of alerts.

For this goal, as shown in Figure 4, the Active Trace Collection collects and classifies the suspicious traffic traces which are replayed to multiple IDSs by comparing the alerts produced by IDSs. Since the detection of IDSs could be incorrect, i.e., FP and FN, the FP/FN Analysis investigates the causes of FPs/FNs using the collected traces and records the confirmed TP/FP/TN/FN traces into Datasets as the ground truth. Based on the Datasets and the accumulated knowledge of alerts, this work therefore proposes a *Creditability-based Weighted Voting* to make a decision on the suspicious traffic trace more accurately.

Creditability-based Weighted Voting

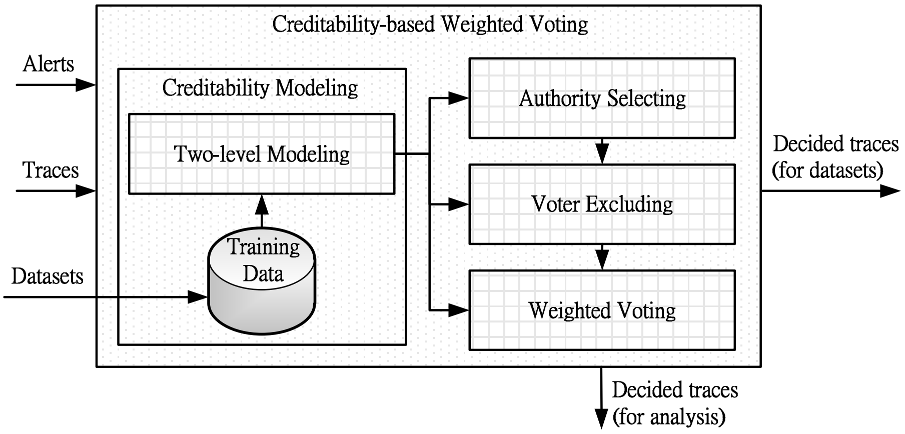


Figure 5. Architecture of Creditability-based Weighted Voting.

The key idea of the *Creditability-based Weighted Voting* to increase the efficiency of alert post-processing is investigating the IDSs' creditabilities and deciding the traces more accurately with the corresponding creditabilities.

Hence, the *Creditability-based Weighted Voting* is constructed with some components. As shown in Figure 5, from the Datasets, the *Creditability Modeling* selects the significant types of traces to set up the *Training Data* and uses the *Two-level Modeling* to model the IDSs' corresponding creditabilities for different types of traces. Since each IDS could not perform well on all types of traces, we consider that some IDS performs well or not on some type of trace or some alert. Therefore, investigating the creditabilities only for all types of traces is not enough. However, based on the creditabilities, first, the *Authority Selecting* selects the IDS with high detection capability to be an authority if it exists. Secondly, the *Voter Excluding* excludes the voter that cannot usually detect the malicious traffic in detection. Third, the *Weighted Voting* decides the trace where it tends to, i.e., malicious, benign, or unknown, with proper voters and weights.

4.2 CM: Creditability Modeling

Since each IDS could not perform well on each alert or each type of trace, the CM is designed to investigate and model the detection capabilities of IDSs for different types of traffic with two levels. The two-level is especially designed in terms of the categorization of signature definition. An alert message, the description of a suspicious activity in a signature, comprises both or either two factors, i.e., protocols and malicious types. Hence, investigating the alert can consider both two factors. Besides, based on the protocol, which is the most common categorization, the detection capability on protocol factor can also be investigated. Thus, it is reasonable to make use of two levels to model the creditability. As shown in Figure 5, the CM includes two components. One is *Training Data* and the other is *Two-level Modeling*.

TD: Training Data

According to the TP/FP/TN/FN traces confirmed from the FP/FN analysis, the CM selects the significant types of traces to set up the TD. The selection policies are based on the proportion of appearances in traffic and the number of corresponding defined signatures. If both of them are high, the CM will identify the types of traces as significant ones and select them into TD.

TLM: Two-level Modeling

Based on the TD, the TLM counts two detection capabilities for an IDS. One is for *Alert Message level* (AML) and the other is for *Protocol level* (PL). Just as the name implies, each AML's detection capability depends on the correctness of an alert message and the detection capability of PL is based on some protocol. Therefore, the conditional probability of each element of the confusion matrix can be calculated as follows.

First, in AML, the correct rate of a previous alert message analyzed by FP/FN analysis can be calculated as $P_j(M \mid m_{k,P}^j)$ with conditional probability,

$$P_j(M \mid m_{k,P}^j) = \frac{c(m_{k,P}^j)}{t(m_{k,P}^j)}, \quad j \in [1, N], \tag{1}$$

where $t(m_{k,P}^j)$ and $c(m_{k,P}^j)$ are the total number and the correct number of $m_{k,P}^j$.

Second, in PL, we define the successful detection rate and successful ignorance rate as $P_j(M \mid A)$ and $P_j(\neg M \mid \neg A)$ to mean the correct detected malicious traces and ignored benign ones, respectively. Based on (1), the successful detection rate is calculated as

$$P_j(M \mid A) = P_j(M \mid m_{1,P}^j, m_{2,P}^j, \ldots, m_{h,P}^j) = \frac{\sum_{k=1}^{h} c(m_{k,P}^j)}{\sum_{k=1}^{h} t(m_{k,P}^j)}, \quad j \in [1, N], \tag{2}$$

where h is the number of all alert message types of j-th IDS under the protocol P. Besides, according to the Bayes' theorem and $Type_{\text{rate},\,P}^j$, the successful ignorance rate is calculated as

$$P_j(\neg M \mid \neg A) = \frac{P(\neg M) \cdot TN_{\text{rate},\,P}^j}{P(\neg M) \cdot TN_{\text{rate},\,P}^j + P(M) \cdot FN_{\text{rate},\,P}^j}, \quad j \in [1, N]. \tag{3}$$

As a result, for each IDS, it has a creditability table which comprises three vectors, i.e., $P_j(M \mid m_{k,P}^j)$, $P_j(M \mid A)$ and $P_j(\neg M \mid \neg A)$.

4.3 AS: Authority Selecting

Selecting authorities with relatively low FP and FN

Based on the investigation of detection capabilities of IDSs for different types of traces, the AS finds that sometimes some IDSs have much higher creditabilities than others. In other words, the lower FP and FN rates could result in higher creditabilities. Thus, comparing with other IDSs, if the creditabilities of some IDSs are high enough for some type of trace, the AS assumes that these IDSs can be the authorities of detection and selects these IDSs to be authorities.

The procedure of the AS includes three steps. First, for each type of trace, the AS sorts the FP and FN rates of every IDS from high to low respectively. Then, the AS separately calculates the average values L_1 and L_2 of FP and FN rates of the IDSs listed after three-quarters of all IDSs since the concept of mean in Statistics. Third, the IDSs will be selected to be the authorities of detection by the AS when their FP and FN rates are both lower than L_1 and L_2.

Deciding traces by authorities if they exist

Finally, there are three cases: no authority, one authority, or multiple authorities. If no authority occurs, the CWV will enter the Voter Excluding and then Weighted Voting. When there is one authority, the traces will be decided directly by that authority. Otherwise, the CWV will enter the Weighted Voting and the traces will be decided by the multiple authorities.

4.4 VE: Voter Excluding

The VE is designed to exclude the voters which cannot usually perform well in detection. Based on the concept, the VE excludes the voters according to two views. One is the TP/FP rates and the other is alert frequency.

Excluding voters with low TP and high FP

First, according to the TP and FP rates, the VE excludes the voters which have TP is less than detection threshold τ_d while FP is more than τ_d. The reason is that some IDSs produce more incorrect detection than correct detection. The VE then assumes that the IDSs are not strong enough and excludes them.

Excluding voters with abnormal alert frequency

Second, based on the alert frequency, the VE assumes that the IDSs having the abnormal alert frequency are unusual. The reason is that some IDSs always produce alert or not on detecting the specific type of trace. For example, when processing the same type of trace, some IDS does not produce any alert while others do. Moreover, the IDS, which has the detection function in the type of trace, does not produce any alert that means its corresponding signature design is doubted. Thus, when every IDS processes the same type of trace, if either the alert rate or the non-alert rate is more than τ_a, the IDSs will be excluded by the VE.

4.5 WV: Weighted Voting

Calculating the malicious tendency

After the VE excludes some voters, or there are multiple authorities, the WV is processed with proper voters. The WV assigns the weights to the corresponding voters according to the creditabilities. Then, when processing the traces one by one, the WV designs a *Creditability Malicious Decision Function*, *CMD* to calculate the degree of tendency towards malicious activity. For *i*-th trace, its *CMD$_i$* is calculated as

$$T_{i,j} = \begin{cases} P_{i,j}(M \mid msg_i^j), & if\ (d_i^j = A) \wedge (msg_i^j \in S) \\ P_j(M \mid A), & if\ (d_i^j = A) \wedge (msg_i^j \notin S) \\ 1 - P_j(\neg M \mid \neg A), & if\ (d_i^j = \neg A) \end{cases}, \quad j \in V_r, i \in [1, n], \tag{4}$$

$$CMD_i(T_{i,j}) = \frac{1}{r} \sum_{j \in V_r} T_{i,j}, \quad i \in [1, n]. \tag{5}$$

In (5), the *CMD$_i$* has three conditions to calculate $T_{i,j}$ respectively. The first condition is the *j*-th IDS produces an alert and the corresponding alert message belongs to the previous alert message set. It can be detailed to AML with $P_{i,j}(M \mid msg_i^j)$. Secondly, the *j*-th IDS produces an alert but the alert message does not belong to the previous alert message set. It can only be calculated in PL with $P_j(M \mid A)$. Third, the *j*-th IDS does not produce an alert. It is calculated in PL with $P_j(\neg M \mid \neg A)$.

Making a decision with the malicious tendency

Finally, the WV makes a decision on *i*-th trace with *DR$_i$* to decide the trace is malicious, benign or unknown. The *DR$_i$* is malicious if the *CMD$_i$* is more than α while the DR_i is benign if the CMD_i is less than β. Hence, the DR_i is formulated as

$$DR_i = \begin{cases} A', & if\ \ CMD_i(T_{i,\,j}) > \alpha \\ \neg A', & if\ \ CMD_i(T_{i,\,j}) < \beta, \quad i \in [1, n],\, 0 < \alpha, \beta < 1,\ \beta \le \alpha\ , \\ Unknown, & otherwise \end{cases} \tag{6}$$

where A' means the i-th trace is decided as malicious trace while $\neg A$' means the i-th trace is decided as benign one.

4.6 Example of Creditability-based Weighted Voting

Assume there are seven IDSs (i.e., N = 7), which detect the same traffic and produce the corresponding alerts. By comparing the alerts, the HTTP traces can be collected and are taken as examples here. After the FP/FN analysis, the TP/FP/TN/FN datasets can be set up. Next, the CM set up the TD according to the datasets and then uses the TLM to model the seven IDSs' corresponding creditabilities respectively. It first calculates $TP^{j}_{\text{rate},\ HTTP}$, $FP^{j}_{\text{rate},\ HTTP}$, $TN^{j}_{\text{rate},\ HTTP}$, and $FN^{j}_{\text{rate},\ HTTP}$. Then, in AML, the S is set up with the correct rates of the previous alert messages which are calculated as $P_j(M \mid m^{j}_{k,HTTP})$. Next, in PL, it calculates the successful detection rate $P_j(M \mid A)$ and successful ignorance rate $P_j(\neg M \mid \neg A)$, which are shown in Table 6.

After the CM, the other three components of the procedure of the CWV can process with the two-level creditabilities. First, in AS, the L_1 and L_2 are 0 and 0.51 separately. By comparing every IDS's $FP^{j}_{\text{rate},\ HTTP}$ and $FN^{j}_{\text{rate},\ HTTP}$ with L_1 and L_2 respectively, there is no authority in detection. Second, in the VE, the 3-rd IDS is excluded according to the TP/FP rates. The 1-th, 4-th, 5-th and 6-th IDSs are excluded according to the abnormal alert frequency. Hence, after the VE, the remaining voters are the 2-nd and the 7-th IDSs. Finally, in the WV, when processing the 87-th trace, the 2-nd IDS produces an alert and the alert message is "IBM Lotus Domino Accept-Language Buffer Overflow" which is an element of S, while the 7-th IDS does not produce any alert. Besides, the creditability of the 2-nd IDS of the alert message in AML, $P_{87,2}(M \mid msg_{87}^{2})$ is 0.83. The creditability of the 7-th IDS of the non-alert in PL, $P_{7}(\neg M \mid \neg A)$ is 0.80. Therefore, the CMD_{87} is calculated as (0.83+(1-0.80))/2, that is, the result of the CMD_{87} is 0.52. Because the value is larger than 0.5 (α = 0.5), the DR_{87} is A' which means the 87-th trace is decided as malicious one.

Table 6. Two-level creditabilities results of example run.

Creditabilities	**IDS1**	**IDS2**	**IDS3**	**IDS4**	**IDS5**	**IDS6**	**IDS7**
$P_{j}(M \mid A)$	-	0.46	0.03	-	1.00	-	0.51
$P_{j}(\neg M \mid \neg A)$	0.71	0.78	0.52	0.71	0.75	0.71	0.80
$P_{87,\,j}(M \mid msg_{87}^{j})$	N/A	0.83	N/A	N/A	N/A	N/A	N/A

Chapter 5 Evaluation and Observation

In this chapter, the detection capabilities of multiple IDSs and the performance of the CWV are evaluated. First, the IDSs' corresponding creditabilities of different types of traffic traces modeled by the CM are illustrated. Second, the Accuracy, TPR, TNR and Efficiency are used to evaluate the voting algorithms.

5.1 Trace selection and experiment environment

Trace selection

As mentioned in Chapter 4.2, the selection policies are based on the rates of appearances in traffic and the rates of number of corresponding signatures. If both of them of some type of trace are significant, this type of trace will be selected. First, according to the ten categories classified by ATC [18], we investigate the traffic in Beta Site [19] during the period from September 1, 2010 to February 1, 2011 to understand the frequent appearance categories in traffic. Second, we take the rule version 2.9 of Snort as example to investigate the signature classification and distribution. The investigation result of the above policies is shown in Table 7. It obviously represents that Web, File Transfer, and Network are significant types. Moreover, Remote Access is more familiar than VoIP to us in our experience. In addition, the signatures in Chat are usually chat programs detection which used to be against corporate policy in normal traffic [1]. Furthermore, in Web, File Transfer, Network and Remote Access, we select the most popular protocol, respectively. Hence, we decide the four types of traces, i.e., HTTP, FTP, NetBIOS and TELNET.

Table 7. Investigation result of trace selection.

Category	Web	File Sharing	Chat	File Transfer	Net-work	Remote Access	VoIP	Encryp-tion	Email	Strea-ming
% of traffic	35.86	32.69	8.82	7.07	4.84	4.05	3.14	2.79	0.49	0.22
% of signature	81.78	0.14	0.57	2.13	8.80	0.66	1.41	0.00	4.48	0.04

Experiment environment

The real-world traffic is captured from the NCTU Beta Site [19], during the period from September 1, 2010 to February 1, 2011. It then uses a traffic replay tool (e.g., tcpreplay) to replay captured raw traffic to multiple IDSs. Seven IDSs are involved in the classification, which are shown in Table 8. Table 9 presents the number of four selected types of traces. The ratio of malicious traces to benign ones is about 4 to 6. The benign traces rate is not so expected high since we expect to avoid a flood of the benign traces dominating the results in this experiment. During the period, the two dominant types of trace are HTTP and NetBIOS. In the HTTP traffic, 39% of the traces are malicious, meaning HTTP applications are frequently exploited. In the NetBIOS traffic, 62% of the traces are malicious, meaning the vulnerabilities of NetBIOS are usually targeted by attacker. Here, we choose the traces collected in the first two months to be the training data while the traces of the latter three months to be the processing data. The former is as input for the CM to set up the TD, and the latter is as input for the CWV one by one.

Table 8. Seven IDSs Information.

Vendor name	BroadWeb	D-Link	Fortinet	McAfee	TippingPoint	Trend Micro	ZyXEL
Device name	NetKeeper7K	DFL-1600	FortiGate-110c	M-1250	5000E	TDA2	ZyWALL USG 1000

The parameters in the CWV are set as follows. In the VE, the detection threshold τ_d is set 0.5 while the abnormality threshold τ_a is set 0.9. In the WV, the values of α and β are both set 0.5. Moreover, we discuss these parameters in Chapter 5.3.

Table 9. Statistics of number of traffic traces.

(a) Training data

Type	**Malicious**	**Benign**	**Total**
HTTP	46	72	118
FTP	22	74	96
NetBIOS	66	47	113
TELNET	4	31	35
Total	138	224	362

(b) Processing data

Type	**Malicious**	**Benign**	**Total**
HTTP	57	86	143
FTP	29	77	106
NetBIOS	87	46	133
TELNET	5	42	47
Total	178	251	429

5.2 Experiment results of investigation of creditabilities

In the CM evaluation, this work takes seven IDSs, which are called IDS1, IDS2, …, and IDS7, respectively, as examples to represent the IDSs' corresponding creditabilities of different types of traffic traces in two levels.

Protocol level

As mentioned in Chapter 4.2, the successful detection rate and successful ignorance rate are defined as $P_j(M \mid A)$ and $P_j(\neg M \mid \neg A)$, respectively, to represent the detection capabilities for PL. As shown in Table 10 (a), first, the value of detection rate is '-' that means uncalculated, that is, the IDS does not produce any alert for the type of traces. Secondly, some values of detection rate are 0.00 since the alerts result from common commands used, i.e., the traffic are always benign. For example, some alerts produced by the IDS5 for FTP traces result from FTP common command used. Third, some values of detection or ignorance rates are 1.00. The observed reason is the definition of signature for the type of traces is more precise. For instance, the type of alerts produced by the IDS5 for TELNET traces is only one and is correct in our investigation. Besides, the IDSs' detection capabilities for different protocols are different. In our investigation, for HTTP, the IDS2, IDS5 and IDS7 have higher creditabilities. Then, for FTP, the IDS5, IDS6 and IDS7 have higher creditabilities. Next, for NetBIOS, the IDS1, IDS4, IDS5 and IDS6 have higher creditabilities. Finally, for TELNET, the IDS3 and IDS5 have higher creditabilities. Generally, the IDS5 achieves appreciable successful rates under each protocol.

Alert Message level

As mentioned in Chapter 4.2, the correctness of a previous alert message is defined as $P_j(M \mid m^j_{k,P})$ to represent the detection capability for AML. Table 10 (b) shows the top ten accurate alert messages, i.e., the alert messages have higher creditabilities, in our investigation. Besides, some of them result from the same traffic with same suspicious activity, and therefore, these are grouped into one to represent.

1) The first two “URL.DirectoryTraversal.Suspicious” and “HTTP: Attempt to Read Password File” alerts result from the same traffic with the request URI string “../../../../../../../etc/passwd”. The former alert results from the string “../../”. The latter alert results from the string “/etc/passwd”. These malicious activities could obtain the private information or access the files on the file system.

2) The “FTP: MKDIR Command Used” alert results from the FTP MKD command used. The observed malicious activity is the MKD and CWD commands are used alternately, which means the intruder creates a directory, changes the working directory to the created directory, and then creates the same directory alternately.

3) The “specifiers.BolinTech.DreamFTPServer.Format.String” alert results from the malicious FTP request containing embedded format string specifiers, i.e., “user %n”, “pass %n”, “retr %n” or “%n”.

4) The “SOLARIS.TELNETD.AUTHENTICATION.EXP”, “Telnet: Login Bypass (General)”, and “Solaris Telnetd Authentication Bypass Vulnerability” alerts result from the argument injection via USER environment variable. The Solaris telnet daemon misinterprets "-f" sequences as valid requests to skip the authentication. However, the alert may be FP when the target is a non-Solaris telnet server.

5) The “NetPathCanonicalize.SRVSVC.MicrosoftWindows.MS08-067.Buffer.Overflow” alert results from the RPC API NetPathCanonicalize() function exploited with a crafted path. The successful overflow exploit could allow a remote attacker to execute arbitrary code or crash the service. However, the alert may be FP when the path does not include the buffer overflow code.

6) The “IBM Lotus Domino Accept-Language Buffer Overflow” alert results from the long length of Accept-Language field, e.g., 100. The observed malicious activity is the duplicated language code appears frequently, while the alert may be FP when the abnormal language code does not exist.

7) The “WEB-MISC robots.txt access” alert results from the file robots.txt accessed directly. The malicious activity could gather the information about the target site. However, the alert may be FP when some search engine’s robot checks robots.txt for information about the site.

Table 10. Experiment results of investigation of creditabilities.

(a) Protocol level – successful detection and ignorance rates for each IDS.

Types / IDSs	HTTP		FTP		NetBIOS		TELNET	
	$P_j(M\|A)$	$P_j(\neg M\|\neg A)$	$P_j(M\|A)$	$P_j(\neg M\|\neg A)$	$P_j(M\|A)$	$P_j(\neg M\|\neg A)$	$P_j(M\|A)$	$P_j(\neg M\|\neg A)$
IDS1	-	0.71	-	0.92	0.95	0.69	0.28	0.99
IDS2	0.46	0.78	-	0.92	-	0.33	-	0.98
IDS3	0.03	0.52	0.00	0.78	0.66	0.33	1.00	0.99
IDS4	-	0.71	-	0.92	0.68	1.00	-	0.98
IDS5	1.00	0.75	0.74	0.98	0.88	0.83	1.00	0.99
IDS6	-	0.71	0.69	1.00	0.67	0.68	0.00	0.98
IDS7	0.51	0.80	0.70	0.95	0.41	0.31	0.01	0.72

(b) Alert Message level – top ten accurate alert messages.

Rank	**Alert messages**	$P_j(M \mid m^j_{k,P})$
1	URL.DirectoryTraversal.Suspicious	1.00
1	HTTP: Attempt to Read Password File	1.00
1	FTP: MKDIR Command Used	1.00
1	specifiers.BolinTech.DreamFTPServer.Format.String	1.00
1	SOLARIS.TELNETD.AUTHENTICATION.EXP	1.00
1	Telnet: Login Bypass (General)	1.00
7	NetPathCanonicalize.SRVSVC.MicrosoftWindows.MS08-067.Buffer.Overflow	0.89
8	IBM Lotus Domino Accept-Language Buffer Overflow	0.83
9	Solaris Telnetd Authentication Bypass Vulnerability	0.80
10	WEB-MISC robots.txt access	0.75

5.3 Accuracy, TPR, TNR, and Efficiency of voting algorithms

Evaluation metrics

Let TP_{traces} be the number of malicious traces which are correctly determined, FN_{traces} be the number of malicious traces which are not determined, TN_{traces} be the number of benign traces which are correctly classified, FP_{traces} be the number of benign traces which are incorrectly determined as malicious ones.

This work uses the *Accuracy*, *TPR*, and *TNR* metrics [22] for the voting algorithm in the evaluation. The *Accuracy* is evaluated with the percentage of whole traces that are determined precisely. This is a commonly used metric for overall view of evaluation.

$$Accuracy = \frac{TP_{traces} + TN_{traces}}{TP_{traces} + FP_{traces} + TN_{traces} + FN_{traces}} \times 100\% .$$

In detail, the *TPR* is evaluated with the percentage of malicious traces that are correctly caught as malicious ones, while the *TNR* is evaluated with the percentage of benign traces that are correctly passed as benign ones.

$$TPR = \frac{TP_{traces}}{TP_{traces} + FN_{traces}} \times 100\% , \qquad TNR = \frac{TN_{traces}}{TN_{traces} + FP_{traces}} \times 100\% .$$

There is a tradeoff between *TPR* and *TNR*. It is required to evaluate the performance of voting algorithm on both *TPR* and *TNR*. Like the F1 score [23] which is a measure of a test's accuracy, this work defines a similar measure for the efficiency of voting algorithm. The *Efficiency* takes the harmonic mean of *TPR* and *TNR*, given by:

$$Efficiency = \frac{2}{\frac{1}{TPR} + \frac{1}{TNR}} \times 100\% .$$

Higher value of *Efficiency* indicates that the voting algorithm performs better on not only *TPR*, but also *TNR*.

Experimental evaluation results

Improving accuracy by leveraging the domain knowledge among IDSs

Figure 6 shows the whole accuracy of CWV and MV. It is observed that each accuracy of CWV is higher than that of MV. The total accuracy of CWV and MV are 95% and 66%, while the average accuracy of them are 96% and 71%. It is observed that the CWV is improved by about 1.4 times of percentage as the MV. The result demonstrates that the weights of IDSs should be different for leveraging the different domain knowledge among IDSs when multiple IDSs involve detection.

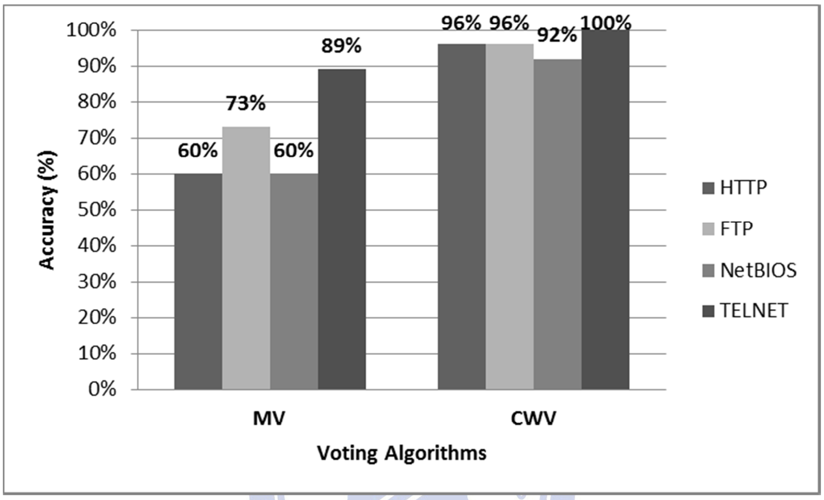


Figure 6. Accuracy of the voting algorithms.

Increasing both TPR and TNR with two-level creditability modeling

Figure 7 and Figure 8 compare the TPR and TNR of CWV with MV. The results mainly demonstrate the effect on two-level creditability modeling. First, the average TPR of CWV and MV are 93% and 14% that means the FN rate of the former is lower than the latter. The observed reason is the FNs of some IDS could be avoided by leveraging other IDSs' correct detection with corresponding creditabilities. Second, the average TNR of CWV and MV are 98% and 93% that means the FP rate of the former is lower than the latter. The main reason is the FPs of some IDS could be filtered with the creditabilities especially in AML. Third, in the CWV, the TNR are higher than the TPR since the correctness of alert message itself is investigated in AML. Thus, alert message with frequent FP would be filtered. Lastly, the TPR and TNR of MV for HTTP, FTP, and TELNET are 0% and 100%, respectively. In this case, the reason is only few IDSs produce alerts, which means most IDSs occur FNs or the few ones occur FPs. No matter which situation it is, the MV decides the result directly from IDSs with the same weight, that is, may ignore some IDSs which have noticeable creditabilities, could result in insignificant results, especially most of them are FNs.

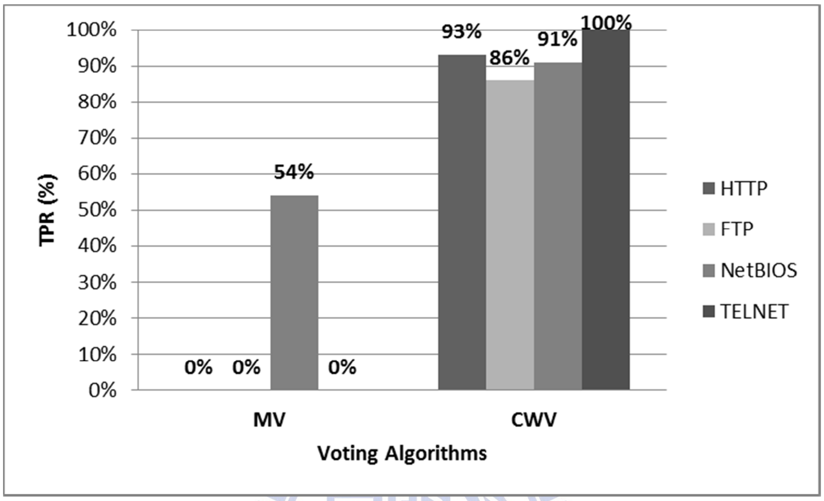


Figure 7. TPR of the voting algorithms.

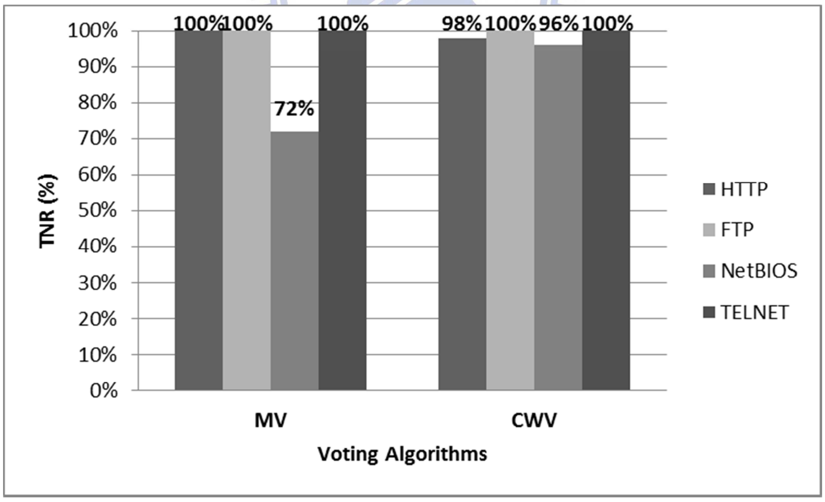


Figure 8. TNR of the voting algorithms.

Figure 9 shows the efficiency of voting algorithms. The efficiency of MV is 41%, while that of CWV is as high as 94%. The CWV can maintain about 2.3 times of percentage as the MV on efficiency. This means the CWV can maintain both TPR and TNR well.

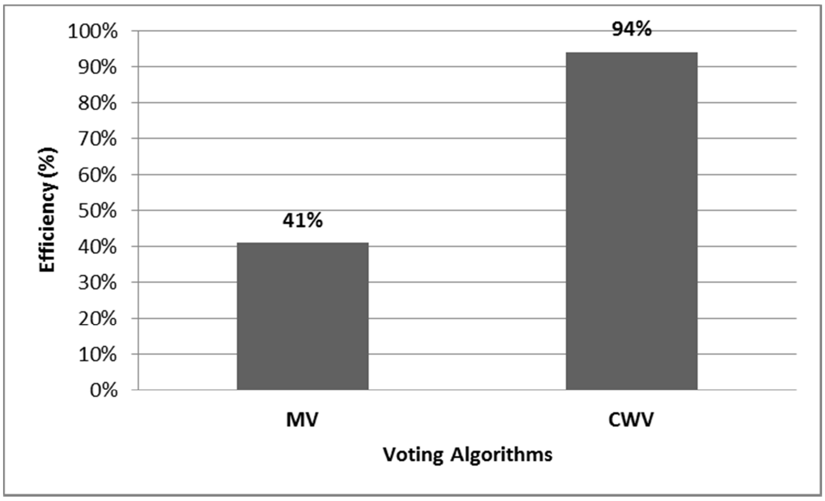


Figure 9. Efficiency of the voting algorithms.

Discussion of important parameters in CWV

In the VE, the detection threshold τ_d is set 0.5 that means the halved correct detection, i.e., the probability of intuition is one over two. Based on this value, we experiment with various abnormality threshold values from 0.6 to 1.0 and the results are shown in Figure 10. The values, smaller than 0.5, are not used in this experiment because they result in no involved voters. It does not make sense when there are no voters in a voting. From Figure 10, we can observe that when the abnormality threshold is 0.9, the CWV has the highest efficiency. Therefore, we use this value in all experiments of this thesis.

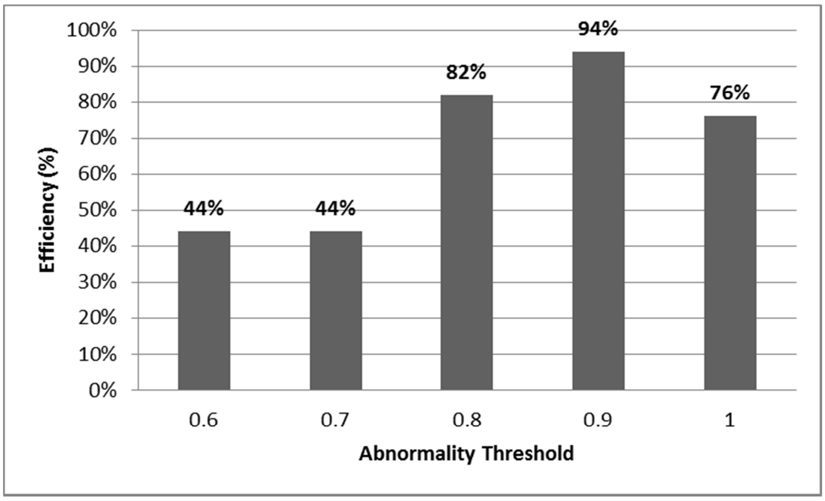


Figure 10. Efficiency under various abnormality thresholds of CWV.

Similarly, in the WV, we change α and β from 0.1 to 0.9 and find that the accuracy can be 100% when the values of α and β are 0.7 and 0.1, respectively. However, the range between α and β is large, 0.6 (= 0.7 – 0.1), so the number of unknown cases is up to 55% of that of total processed traffic traces. Hence, α and β can be tuned according to the tradeoff between the accuracy of decided traces and the number of unknown traces that need to be analyzed manually.

5.4 Differences between CWV and each IDS in percentages at FP and FN

Table 11 shows the percentages of FP and FN of CWV and each IDS for different types of traces. Some IDSs have FP and FN values with 0% and 100% since these IDSs do not produce alert for this type of traces. This also means these IDSs miss the signatures. Secondly, the FP of IDS3 is 100% because the alerts result from common command used, such as “FTP GET command”. Third, the FP and FN of IDS5 are 0%. The observed reason is the type of alerts produced by IDS5 is only one, and the message is “SOLARIS.TELNETD.AUTHENTICATION.EXP” that is a precise signature in our investigation, i.e., the creditability of the message is 1.0. Actually, the corresponding traces are always malicious ones in analysis. Besides, for NetBIOS traces, most IDSs produce many alerts that result in more FPs for each IDS, while for other types of traces, some IDSs produce alerts that result in more FNs.

Table 11. Percentages of FP and FN of CWV and each IDS.

	HTTP		**FTP**		**NetBIOS**		**TELNET**	
	FP	*FN*	*FP*	*FN*	*FP*	*FN*	*FP*	*FN*
IDS1	0	100	0	100	63.04	5.17	0	100
IDS2	26.74	94.74	0	100	0	100	0	100
IDS3	63.95	100	100	86.21	80.43	1.15	2.38	40.00
IDS4	0	100	0	100	25.53	7.58	0	100
IDS5	0	98.25	0	48.28	52.17	9.20	0	0
IDS6	0	100	0	13.79	67.39	1.15	0	100
IDS7	9.30	5.26	0	48.28	39.13	82.76	97.62	80.00
CWV	2.33	7.02	0	13.79	4.35	9.20	0	0

Furthermore, the differences between CWV and each IDS in percentages at FP and FN are shown in Table 12. First, some IDSs detect better than the CWV partially because the value of FP or FN in percentage is negative, but no IDS can individually detect well in both FP and FN. Second, the CWV performs well in most cases for all types of traces by leveraging different detection capabilities among IDSs which are shown in different values of FP and FN. It is demonstrated that the average percentages of FP and FN reduction between CWV and each IDS are 21% and 58%.

Table 12. Differences between CWV and each IDS in percentages at FP and FN.

	HTTP		**FTP**		**NetBIOS**		**TELNET**	
	FP	*FN*	*FP*	*FN*	*FP*	*FN*	*FP*	*FN*
IDS1	-2.33	92.98	0	86.21	58.69	-4.08	0	100
IDS2	24.41	87.82	0	86.21	-4.35	90.8	0	100
IDS3	61.62	92.98	100	72.42	76.08	-8.05	2.38	40.00
IDS4	-2.33	92.98	0	86.21	21.18	-1.62	0	100
IDS5	-2.33	91.23	0	34.49	47.82	0	0	0
IDS6	-2.33	92.98	0	0	63.04	-8.05	0	100
IDS7	6.97	-1.76	0	34.49	34.78	73.56	97.62	80.00
Average	11.95	78.44	14.29	57.15	42.46	20.37	14.29	74.29

5.5 Case studies

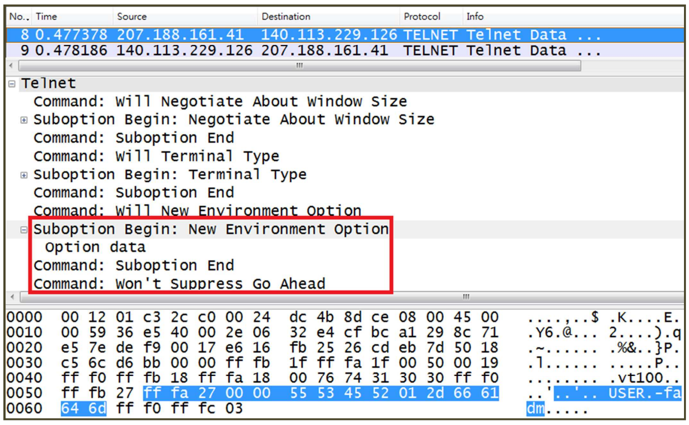
In this section, two case studies in the experiment are taken as examples to show the TP case in CWV and FN in MV, and the TN case in CWV and FP in MV.

Case study I: TP case in CWV and FN in MV

In this case, the alert messages and the corresponding creditabilities are shown in Table 13, while the trace content is illustrated in Figure 11. It is observed that the attacker uses the command “USER –fadm” as the argument injection via USER environment variable in environment option to attempt to bypass the authentication. More information about Telnet environment option can be found in [24]. Furthermore, the malicious content in hexadecimal is “ff fa 27 00 00 55 53 45 52 01 2d 66 61 64 6d” obviously. However, this malicious trace can be correctly determined by the CWV because of the high creditabilities in AML, while it is missed by the MV because only few voters can detect it.

Table 13. Alert messages and corresponding creditabilities in case study I.

msg_i^j	$P_{i,j}(M \mid msg_i^j)$
SOLARIS.TELNETD.AUTHENTICATION.EXP	1.00
Solaris Telnetd Authentication Bypass Vulnerability	0.80



```
No.. Time     Source             Destination        Protocol  Info
 8 0.477378 207.188.161.41   140.113.229.126 TELNET Telnet Data ...
 9 0.478186 140.113.229.126 207.188.161.41  TELNET Telnet Data ...

⊟ Telnet
    Command: Will Negotiate About Window Size
  ⊞ Suboption Begin: Negotiate About Window Size
    Command: Suboption End
    Command: Will Terminal Type
  ⊞ Suboption Begin: Terminal Type
    Command: Suboption End
    Command: Will New Environment Option
  ⊟ Suboption Begin: New Environment Option
      Option data
    Command: Suboption End
    Command: Won't Suppress Go Ahead

0000  00 12 01 c3 2c c0 00 24  dc 4b 8d ce 08 00 45 00   .......$ .K....E.
0010  00 59 36 e5 40 00 2e 06  32 e4 cf bc a1 29 8c 71   .Y6.@... 2....).q
0020  e5 7e de f9 00 17 e6 16  fb 25 26 cd eb 7d 50 18   .~...... .%&..}P.
0030  c5 6c d6 bb 00 00 ff fb  1f ff fa 1f 00 50 00 19   .l...... .....P..
0040  ff f0 ff fb 18 ff fa 18  00 76 74 31 30 30 ff f0   ........ .vt100..
0050  ff fb 27 ff fa 27 00 00  55 53 45 52 01 2d 66 61   ..'..'.. USER.-fa
0060  64 6d ff f0 ff fc 03                               dm.....
```

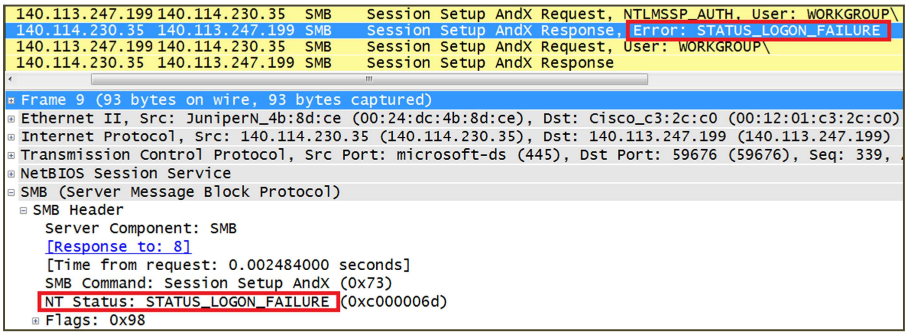
Figure 11. Trace content in case study I.

Case study II: TN case in CWV and FP in MV

In this case, the alert messages and the corresponding creditabilities are shown in Table 14, while the trace content is illustrated in Figure 12. It is observed that the signature designs are not specific enough. Hence, the general signature is easily matched in the payload even though the payload is benign. Obviously, logon/login failure is general that often occurs in normal activities. It is demonstrated that the corresponding creditabilities are low in our investigation. Therefore, this benign trace can be correctly determined as benign one by the CWV, while it is incorrectly classified to malicious one by the MV because most voters detect it.

Table 14. Alert messages and corresponding creditabilities in case study II.

msg_i^j	$P_{i,j}(M \mid msg_i^j)$
netbios: SMB.Login.Failure	0.26
SMB: Windows Logon Failure	0.12
EXPLOIT Server Service Remote Code attack	0.62
NETBIOS-SS: NULL Credentials Login	0.50



```
140.113.247.199 140.114.230.35   SMB    Session Setup AndX Request, NTLMSSP_AUTH, User: WORKGROUP\
140.114.230.35  140.113.247.199  SMB    Session Setup AndX Response, Error: STATUS_LOGON_FAILURE
140.113.247.199 140.114.230.35   SMB    Session Setup AndX Request, User: WORKGROUP\
140.114.230.35  140.113.247.199  SMB    Session Setup AndX Response

⊞ Frame 9 (93 bytes on wire, 93 bytes captured)
⊞ Ethernet II, Src: JuniperN_4b:8d:ce (00:24:dc:4b:8d:ce), Dst: Cisco_c3:2c:c0 (00:12:01:c3:2c:c0)
⊞ Internet Protocol, Src: 140.114.230.35 (140.114.230.35), Dst: 140.113.247.199 (140.113.247.199)
⊞ Transmission Control Protocol, Src Port: microsoft-ds (445), Dst Port: 59676 (59676), Seq: 339,
⊞ NetBIOS Session Service
⊟ SMB (Server Message Block Protocol)
  ⊟ SMB Header
      Server Component: SMB
      [Response to: 8]
      [Time from request: 0.002484000 seconds]
      SMB Command: Session Setup AndX (0x73)
      NT Status: STATUS_LOGON_FAILURE (0xc000006d)
    ⊞ Flags: 0x98
```

Figure 12. Trace content in case study II.

Chapter 6 Conclusions and Future Works

This work proposes the Creditability-based Weighted Voting (CWV) to reduce both FPs and FNs and increase the efficiency of alert post-processing with multiple IDSs. The CM leverages the domain knowledge among multiple IDSs by investigating the detection capabilities of all IDSs and models the corresponding creditabilities to them. From the experiment results of investigation of creditabilities, we demonstrate the different IDSs' detection capabilities by their creditabilities. In detail, we observe that the signature design is the main factor on the correctness of detection. Some IDS has more specific signature that results in fewer number of alerts and FPs, while some IDS has more general signature that results in more number of alerts and FPs. On the other hands, some IDS misses the signature, leading to FNs.

This work uses Accuracy, TPR, TNR, and defines Efficiency to evaluate two voting algorithms, the CWV and the MV. The CWV can achieve the accuracy and the efficiency up to 95% and 94%, which are much higher than the MV in comparison. Besides, between the CWV and each IDS, the CWV performs well in most cases for all types of traffic traces. It is demonstrated that the average percentages of FP and FN reduction between the CWV and each IDS are 21% and 58%.

However, the CWV could make an incorrect decision in some situations. For example, when processing the trace which triggers the new alert of some IDS, the CWV only can use the corresponding creditability in PL of the IDS to determine the trace. The incorrect result could then occur. Besides, if some IDS significantly updates or modifies its signature database, which means the detection capability changes greatly, the corresponding creditability would be almost useless. The WV could make an incorrect decision on the trace. Hence, the frequency and the duration of updating training data are issues in the future. Furthermore, another goal in the future is the automation because it could increase the productivity and practicability of this system. In foreground, the CWV keeps processing traffic traces one by one, while in background, the creditability table for each IDS is updated with considering the above issue to maintain the reliance on creditability.

References

[1] "Rule of Snort," available at: http://www.snort.org/vrt.

[2] T. Pietraszek, "Alert classification to reduce false positives in intrusion detection," July 2006.

[3] S. Axelsson, "The base-rate fallacy and the difficulty of intrusion detection," *ACM Transactions on Information and System Security* (*TISSEC*), vol. 3, no. 3, pp. 186-205, 2000.

[4] K. Julisch, "Clustering Intrusion Detection Alarms to Support Root Cause Analysis," *ACM Transactions on Information and System Security* (*TISSEC*), vol. 6, no. 4, pp. 443–471, November 2003.

[5] P. Ning, Y. Cui, and Douglas S. Reeves, "Constructing Attack Scenarios through Correlation of Intrusion Alerts," *Proc. 9th ACM Conference on Computer & Communications Security* (*CCS 2002*), pp. 245-254, Washington D.C., November 2002.

[6] P. Ning, D. Xu, C. Healey, and R. St. Amant, "Building Attack Scenarios through Integration of Complementary Alert Correlation Methods," *Proc. 11th Annual Network and Distributed System Security Symposium*, February 2004.

[7] P. Ning and D. Xu, "Learning Attack Strategies from Intrusion Alert," *Proc. ACM Conference on Computer and Communication Security* (*CCS '03*), October 2003.

[8] R. Sadoddin, and A. Ghorbani, "Alert correlation survey: framework and techniques," *Proc. 2006 international Conference on Privacy, Security and Trust: Bridge the Gap between PST Technologies and Business Services*, vol. 380, November 2006.

[9] K. Julisch, "Using root cause analysis to handle intrusion detection alarms," Ph.D. dissertation, University of Dortmund, 2003.

[10] K. Julisch, "Mining Alarm Clusters to Improve Alarm Handling Efficiency," *Proc. 17th Annual Computer Security Applications Conference* (*ACSAC*), pp. 12–21, December 2001.

[11] T. Pietraszek, and A. Tanner, "Data mining and machine learning-Towards reducing false positives in intrusion detection," *Information Security Technical Report*, 10:169–183, 2005.

[12] T. Pietraszek, "Using Adaptive Alert Classification to Reduce False Positives in Intrusion Detection," *Lecture Notes In Computer Science*, pp. 102-124, 2004.

[13] I. W. Chen, P. C. Lin, C. C. Luo, T. H. Cheng, Y. D. Lin, Y. C. Lai and F. C. Lin, "Extracting Attack Sessions from Real Traffic with Intrusion Prevention Systems," *Proc. IEEE Intl. Conference on Communications* (*ICC*), June 2009.

[14] G. Latif-Shabgahi, J. M. Bass, and S. Bennett, “A taxonomy for software voting algorithm used in safety-critical systems,” *IEEE Trans. on Reliability*, vol. 53, no. 3, pp. 319-328, September 2004.

[15] B. Parham, “Voting Algorithms,” *IEEE Trans. on Reliability*, vol. 43, no. 4, pp. 617-629, 2002.

[16] C. Thomas and N. Balakrishnan, “Improvement in Intrusion Detection With Advances in Sensor Fusion,” *IEEE Transactions on Information Forensics and Security*, vol. 4, no. 3, pp. 542-551, 2009.

[17] C. Thomas and N. Balakrishnan, “Advanced sensor fusion technique for enhanced intrusion detection,” in *IEEE Int. Conf. Intelligence and Security Informatics*, Taipei, Taiwan, June 2008.

[18] Y. D. Lin, P. C. Lin, S.H. Wang, and I. W. Chen, “Extracting, Classifying, and Anonymizing Packet Traces with Case Studies on False Positives/Negatives Assessment,” *IEEE Journal on Selected Areas in Communications*, Submit.

[19] Y. D. Lin, I. W. Chen, P. C. Lin, C. S. Chen, and C.H. Hsu, “On Campus Beta Site: Architecture Designs, Operational Experience, and Top Product Defects,” *IEEE Communication Magazine*, vol. 48, pp. 83-91, 2010.

[20] “Common Vulnerabilities and Exposures (CVE),” available at: http://cve.mitre.org/.

[21] “Wireshark,” available at: http://www.wireshark.org/.

[22] S. X. Wu and W. Banzhaf, “The use of computational intelligence in intrusion detection systems : A review,” *Applied Soft Computing*, vol. 10, pp. 1-35, 2010.

[23] C. J. Rijsbergen, Information retrieval, Butterworths, London, 1979.

[24] S. Alexander, Editor, “Telnet Environment Option”, RFC 1572, Lachman Technology, Inc., January 1994.