PCkAD: an unsupervised intrusion detection technique exploiting within payload n-gram location distribution

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Abstract—Signature-based and protocol-based intrusion detection systems (IDS) are employed as means to reveal content-based network attacks. Such systems have proven to be effective in identifying known intrusion attempts and exploits but they fail to recognize new types of attacks or carefully crafted variants of well known ones. This paper presents the design and the development of an anomaly-based IDS technique which is able to detect content-based attacks carried out over application level protocols, like HTTP and FTP. In order to identify anomalous packets, the payload is split up in chunks of equal length and the n-gram technique is used to learn which byte sequences usually appear in each chunk. The devised technique builds a different model for each pair of protocol of interest and packet length, in terms of number of chunks, and use them to classify the incoming traffic. Models are build by means of an unsupervised approach. Experimental results witness that the technique achieves an excellent accuracy with a very low false positive rate.

I. INTRODUCTION

Cyber security is a set of technologies, processes, means and practices tought to protect computers, data, services interconnected from attacks of various nature.

Network security is a crucial aspect of cyber security due to the ubiquitous diffusion of the Internet. Traditional protection techniques such as user authentication, data encryption, avoiding programming errors and firewalls are used as the first line of defense to improve security, but they are generally unable to protect against malicious mobile code, insider attacks and unsecured modems. Therefore, intrusion detection is required as an additional wall for protecting systems despite the prevention techniques. Intrusion detection is the process of monitoring the events occurring in a computer system or network and analyzing them for signs of possible incidents, which are violations or imminent threats of violation of computer security policies, acceptable use policies, or standard security practices.

Intrusion detection is classified into two types: misuse intrusion detection and anomaly intrusion detection. Misuse intrusion detection uses well-defined patterns of the attack that exploit weaknesses in system and application software to identify the intrusions. Anomaly intrusion detection identifies

deviations from the normal usage behavior patterns to identify the intrusion.

There exist attacks which exploit some vulnerabilities of a service or application by delivering a bad payload. It is possible to detect these attacks by inspecting the packets payload. A lot of IDS use n-grams for packets analysis.

In [1] the authors have reviewed many of such intrusion detection techniques, some of them are described in this section.

PAYL [2] uses 1-g and unsupervised learning to build a byte-frequency distribution model of network traffic payloads. A 1-g is simply a single byte with value in the range 0-255. The result of preprocessing a packet payload this way is a feature vector containing the relative frequency count of each of the 256 possible 1-grams (byte values) in the payload. The model also includes the average frequency, as well as the variance and standard deviation as other features. Separate models of normal traffic are created for each combination of destination port and length of the flow. Clustering is then used to reduce the number of models. During the detection phase a simplified Mahalanobis distance measure is used to compare the current traffic to the model, and an anomaly is raised if the distance exceeds a given threshold. Testing was performed on all attacks in the DARPA 1999 dataset using individual packets as data units (connection data units were also attempted). The overall detection rate was close to 60% at a false positive rate less then 1%.

POSEIDON [3] uses PAYL as a basis for detection, but with different preprocessing. Unlike, PAYL it does not use the length of the payload for determining whether to create a separate model, but instead uses the output of a SOM classifier. The aim of the SOM is to identify similar payloads for a given destination address and port. This improvement was shown to produce less models and higher accuracy than PAYL.

ANAGRAM [4] also builds on PAYL, but uses a mixture of high-order N-grams with N $\u0394$ 1. This reduces its susceptibility to mimicry attacks since higher order N-grams are harder to emulate in padded bytes. By contrast, PAYL can be easily evaded if normal byte frequencies are known to an attacker

since malicious payloads can be padded with bytes to match it. ANAGRAM uses supervised learning to model normal traffic by storing N-grams of normal packets into one bloom filter, and models attack traffic by storing N-grams from attack traffic into a separate bloom filter. At runtime the N-grams from incoming payloads are compared with those stored in the two bloom filters. An anomaly is raised if the N-grams either match the attack bloom filter, or do not match the normal bloom filter.

Similarly, McPAD [5] creates 2v-grams and uses a sliding window to cover all sets of 2 bytes, ν positions apart in network traffic payloads. Since each byte can have values in the range 0-255, and n = 2, the feature space is $256^2 = 65,536$. By varying ν , different feature spaces are constructed, each handled by a different classifier. The dimensionality of the feature space is then reduced using a clustering algorithm. Multiple one-class SVMs are used for classification, and a meta-classifier combines these outputs into a final classification prediction. The results of testing McPAD showed it could detect shellcode attacks in HTTP requests.

In [6], the authors also extract language features in the form of high-order N-grams from connection payloads. They use unsupervisedaA anomaly detection, so no labeled training data is required. To reduce the potential for false positives they restrict their analysis to the application layer protocol bytes. Their approach differs from others because it uses a geometric representation of high-order N-grams. N- grams and words in connection payloads are compared using vectorial similarity measures such as distance functions.

In this paper an anomaly-based intrusion detection technique is proposed, called Packet Chunk Anomaly Detector (PCkAD), which uses n-grams and a novel preprocessing step for the analysis of network packets payload. The system uses protocol knowledge to identify the relevant parts of a packet payload for the analysis and discard all the rest, subsequently the useful payload is split up in not overlapping portions, here called chunks, of equal length. The system models normal behaviour of clear and structured network contents in an automatic and unsupervised fashion. A packet payload is recognised as anomalous if it contains too many never seen n-grams or known n-grams whose distribution differs considerably from that observed during the training phase. The experiments were conducted on the dataset DARPA 1999 to test the effectiveness of the proposed technique. The system is able to get a detection rate of 100% with a false-positive rate less than 1%, for the FTP traffic.

The rest of the paper is organized as follows. Section 2 details the proposed technique. Section 3 presents the results and evaluations of the method applied to the DARPA 1999 dataset. Section 4 concludes the paper.

```
GET /people/svalente/gif/poker.dogs.jpg HTTP/1.0

Referer: http://marx.eyrie.af.mil/people/svalente/home.html

User-Agent: Mozilla/4.04 [en] (X11: I; SunOS 5.5 sun4u)

Host: marx.eyrie.af.mil

Accept: image/gif, image/x-bitmap, image/jpeg, image/pjpeg, image/png, */*

Accept-Language: en

Accept-Charset: iso-8859-1,*,utf-8
```

Fig. 1. An example of HTTP packet payload. Only the URL following the keyword GET is recognised as relevant content.

II. DESCRIPTION OF THE TECHNIQUE

This section describes the proposed technique, called PCkAD, in detail. PCkAD uses n-grams (briefly described in subsection 2.1) and a novel preprocessing step for the analysis of network packets payload (subsection 2.2). Subsequently n-grams are extracted from the contents of the network traffic (subsection 2.3) and a model of normal behaviour is built (subsection 2.4) then the resulting model is used to identify anomalous contents (subsection 2.5).

A. The n-gram technique

N-grams have been used previously in fields like information retrieval [7] and statistical natural language processing [8]. With this technique it is possible to extract sequences of symbols from a given input flow by using a sliding window of length n. At each position a sequence of length n is considered. Formally, the set S of features correspond to all possible sequences of length n and is defined by:

$$S := \{0, ..., 255\}^n. \tag{1}$$

To show how the technique works, consider the artificial payload x = "ooddod" where the set of all possible symbols is restricted to "o" and "d". If n = 2, the sequences that can be extracted are "oo", "od", "dd", "do", and "od", respectively.

The use of n-grams does not require expert domain knowledge to construct relevant features, since a model of normality can be built in an automatic fashion from the n-grams occurring in a packet payload.

B. The preprocessing phase

Every time a new packet payload is observed, the system exploits protocol knowledge to identify the relevant parts of the payload for the analysis, while all the rest is discarded. Subsequently the useful payload is split up in non-overlapping portions of equal length, here referred to as *chunks*.

More in the detail, let P_p denote a packet payload and let St_{pp} denote the set of all the basic components of the payload structure.

For instance, the basic components of the HTTP packet payload are shown in Figure 1, and correspond to the lines starting with following keywords: GET, Referer, User-agent, Host, Accept, AcceptLanguage and Accept-Charset.

By using protocol knowledge, the IDS selects the set $Sv_{pp} \subseteq St_{pp}$ of the components which are relevant for the analysis. Every component c_p in Sv_{pp} is then split up in non-overlapping sequences of length len_{ck} , in bytes, and the set

```
GET / HTTP/1.0
User-Agent: Mozilla/3.01 (Win95; I;)
Host: www.usatoday.com
Accept: image/gif, image/x-xbitmap, image/jpeg, image/pjpeg, */*
```

Fig. 2. A new HTTP packet payload is observed.

 Ck_{cp} is derived. The number of chunks nck that a component can contain is defined by:

$$nck = \lceil len_p/len_{ck} \rceil, \tag{2}$$

with len_p the length of the component.

Consider again the HTTP packet of Figure 1, which corresponds to a GET request. The system recognises the URL following the keyword GET as the only relevant component (GET and HTTP 1.0 are also included). If the length of a single chunk is 15 bytes, then Ck_{cp} will contain the following chunks: "GET /people/sva", "lente/gif/poker", ".dogs.jpg HTTP/", and "1.0\r\n".

C. The extraction phase

There exist many IDSs which use the n-gram technique to analyse network packets payload, two examples are [4] [3]. The n-grams are used to model the language which characterizes a network traffic profile, since each different n-gram is interpreted as a different feature of a feature space used to represent the traffic.

Differently from the other techniques based on n-grams, PCkAD extracts n-grams from a packet payload after the preprocessing phase described in the previous subsection. The packet payload is split in chunks to learn the typical structure of a legitimate payload. By exploiting the partitioning in chunks, it is possible for the system to know which are the typical n-grams of a legitimate network traffic profile, how they are distributed, and where they are typically located inside the payload.

Only n-grams which occur in at least a chunk are taken into account. Given a chunk c and a n-gram s, s is said to occur in c if:

- either s is a subsequence of c, or
- a suffix (prefix, resp.) of s is a prefix (suffix, resp.) of c and the remaining part of s is a suffix (prefix, resp.) of the chunk preceding (succeeding, resp.) c.

The latter condition serves the purpose of taking into account also n-grams located on the border between two consecutive chunks.

Figures 2, 3 and 4 show an example of how a packet payload is processed by the IDS. In this example, each chunk has a length of 30 bytes and the entire payload is considered relevant for the analysis.

D. The model

The system models normal behaviour of network traffic in an automatic and unsupervised fashion. In oder to build the

```
0 - GET / HTTP/1.0
User-Agent: Mo
30 - zilla/3.01 (Win95; I;)
Host:
60 - www.usatoday.com
Accept: imag
90 - e/gif, image/x-xbitmap, image/
120 - jpeg, image/pjpeg, */*
```

Fig. 3. The payload is split up in chunks of equal length (30 bytes).

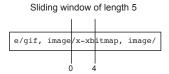


Fig. 4. The IDS extracts a 5-gram from a chunk.

model of normal behavior, an off-line learning phase working on a training dataset containing only legitimate network packets is accomplished by the IDS.

Initially, the system groups the packets in classes, based on the following two criterions:

- 1) the observed port;
- 2) the number of chunks a packet payload contains.

Subsequently, for each different class, a model is built that will be then exploited to assess the nature of never seen packets.

The first criterion is needed in order to identify network traffic profiles of different nature. Each protocol implies specific contents, so it is important to separate traffic pertaining to different protocols to capture information about specific characteristic of the network profile. Differently, the resulting classifier could exhibit a large misclassification rate.

Clearly, this strategy alone is inadequate to build accurate models. It is possible to observe very different contents in the same profile. In [2] it has been shown how the byte distribution of HTTP packets vary among different length payload.

The second criterion is used to build a model from packets with similar payload, therefore the chunks are used not only in the analysis phase but also in the learning phase.

The length of a chunk influences considerably the building process, in that the larger the size of a chunk, the smaller the number of models. In the evaluation section it is shown how the length of the chunks affects the results of the analysis.

During the learning phase, for each built model and for each observed n-gram, the average number of occurrences and the standard deviation are computed, both in the entire relevant payload and in every single chunk. The n-grams extracted and their average number of occurrences and standard deviation are stored in a *trie* data structure. A trie is essentially an N-ary tree, whose nodes are N-place vectors with components corresponding to the characters of an alphabet of size N. In this work, the trie was implemented so that each node, except the root node, maintains only a single byte of a n-gram, while the average number of occurrences and the standard deviations are stored only in the leaf nodes. Next section explains how these information are used in the analysis process.

E. Anomalous packet detection

Many methods have been assessed in order to check if a packet is anomalous or not. Some techniques of intrusion detection use a vectorial representation of the packets and the models then compute an anomaly index or score by using a distance function [6]. The n-gram representation fit well with this approach: each dimension corresponds to a distinct n-gram and its value may be the frequency. However, this approach cannot be directly applied in the proposed technique because the chunks are used. N-grams could occur in two or more chunks and for each of these chunks different statistics (mean and standard deviation) are available.

Thus, it was decided to compute the anomaly index as the percentage of anomalous n-grams recognised in the relevant packet payload. This index provides a quantitative measure of the size of anomalous portion of the payload.

As an example, consider a HTTP GET request whose relevant portion is the URL which corresponds to the GET keyword. If the total number of n-grams is 100, and 45 of them are recognised as anomalous, then the anomaly score evaluates to 45%.

The simplified Mahalanobis distance is exploited to evaluate if a known n-gram is *unusual* or *non-legitimate* within the entire payload or a single chunk. In this work it is used the simplified assumption that the bytes are statistically independent, so the Mahalanobis distance between the feature vector of a specific payload and the model associated with the same payload is defined by:

$$d(\vec{x}, \vec{M}) = \sum_{i=0}^{N-1} \frac{|\mu_i - x_i|}{\sigma_i},$$
 (3)

where N is the size of the set of all the possible n-grams, μ_i is the average number of occurrences of the i-th n-gram in the model (aka legitimate profile) \vec{M} and σ_i is its standard deviation, while x_i is the count of the i-th n-gram in the feature vector \vec{x} associated with the observed packet payload.

Notice that, if an n-gram never appears in the training samples or it appears with exactly the same frequency in each sample the standard deviation σ_i evaluates to zero. To avoid the distance to become infinite, a smoothing factor α is added up to the standard deviation, leading to the following formula:

$$d(\vec{x}, \vec{M}) = \sum_{i=0}^{N-1} \frac{|\mu_i - x_i|}{\sigma_i + \alpha}.$$
 (4)

Intuitively, the smoothing factor α reflects the statistical confidence of the sampled training data. The larger the value of α , the less the confidence the samples are truly representative of the actual distribution, and thus the byte distribution can be more variable.

Here the Mahalanobis distance is not fully used, but rather its terms are exploited separately in order to decide if an ngram is unusual or not.

In particular, consider v_{np} and v_{nc} as the feature vectors representing the normal profile for the entire relevant payload

and for each chunk c respectively and v_p and v_c as the feature vectors of a new packet payload observed for the entire payload and for each chunk c respectively. When a new packet is observed the system uses the Mahalanobis distance to compute the difference between each component of v_{np} and v_p , for the i-th n-gram:

$$d(v_{np}, v_p)_i = \frac{|\mu_i - x_i|}{\sigma_i + \alpha} \tag{5}$$

the term $d(v_{np}, v_p)_i$ is then compared with a threshold th_s : if $d(v_{np}, v_p)_i > th_s$ the *n*-gram is said to be *unusual* (aka, *non-legitimante*), otherwise it is *usual* (aka, *legitimate*). The same approach holds for v_{nc} and v_c .

An *n*-gram is recognised as *anomalous* if one of the following conditions happens:

- it has never been observed in the normal traffic: in this case all its occurrences are identified as anomalous;
- it has been observed in the normal traffic, but it is unusual in the entire relevant payload: in this case all its occurrences are identified as anomalous;
- it has been observed in the normal traffic and it is usual
 in the entire relevant payload, but it is anyway unusual
 in at least a chunk: in this case only the occurrences
 unusually distributed are considered anomalous.

For each packet payload the system computes:

- the total number of distinct n-grams, tot_{seqs} ;
- the number of anomalous n-grams, a_{seqs} .

Afterward an anomalous score, a_{score} , is computed:

$$a_{score} = \frac{a_{seqs}}{tot_{seqs}} 100 \tag{6}$$

For each analysed protocol a different threshold has been defined. If there is a low degree of variability in the contents of the network traffic of a specific protocol it is appropriate to use a low threshold, while on the contrary a higher threshold is needed to tolerate a reasonable level of variability.

III. EXPERIMENTAL RESULTS

In this section a set of experiments designed to test the effectiveness of the proposed technique is presented.

Experiments were conducted on the dataset DARPA 1999. The 1999 DARPA IDS [9] data set was collected at MIT Lincoln Labs to evaluate intrusion detection systems. All the network traffic including the entire payload of each packet was recorded in tcpdump format and provided for evaluation. In addition, there are also audit logs, daily file system dumps, and BSM (Solaris system call) logs. The data consists of three weeks of training data and two weeks of test data. In the training data there are two weeks of attack-free data and one week of data with labeled attacks. This dataset has been used in many research efforts and results of tests involving this data have been reported in many publications. Although there are problems due to the nature of the simulation environment that created the data [10], it still remains a useful set of data to compare techniques. The best results were reported by [11].

In the experiments only the inside HTTP and FTP network traffic data which was captured between the router and the victims was used. It is important to notice that not all the types of payloads are suitable to be analysed with n-grams. If n-grams are blindly constructed from all packet payloads including encrypted and unstructured data, then a huge range of n-grams would be created and the resulting model would not be able to discriminate between normal and anomalous traffic. Therefore only clear and structured payloads are considered.

The inbound TCP traffic to the ports 80 and 21 of the hosts 172.016.xxx.xxx was examined, since it contains most of the victims. Each packet in the dataset was used as the data unit.

The configuration set up is similar to that chosen to evaluate PAYL [2] and POSEIDON [3], two other intrusion detection techniques, so that a comparison with PCkAD could be done. The system was trained on the DARPA dataset using week 1 (5 days, attack free) and week 3 (7 days, attack free). The detector was then evaluated on weeks 4 and 5, which contain 201 instances of 58 different attacks, 177 of which are visible in the inside tcpdump data. In the experiments only the HTTP and FTP traffic is considered, so the attacks using protocols TCP, UDP, ICMP, ARP (address resolution protocol) and IP are not treated here.

Hence, examples of the attacks not considered are: smurf (ICMP echo-reply flood), ping-of-death (over-sized ping packets), UDPstorm, selfping, ipsweep.

Different port traffic has different byte variability. For example, the payloads to port 80 (HTTP requests) are usually less variable than those of port 25 (email). Hence, different thresholds were set for each protocol, in particular, their values has been derived empirically so that the false-positive rate would be less than 1%. It was set a threshold of 40% for FTP and a threshold of 30% for HTTP. Other configuration parameters are:

- the smoothing factor α : it was set to 0.1, a reasonable value for this dataset;
- the length of a single chunk, in bytes;
- the value of n, for the n-grams.

The experiments were set up to assess how the chunks and the n-grams affect the system performance. The reported results concern only the analysis of the FTP traffic because most of the attacks directed towards HTTP-based application where recognised because of the following reasons:

- the IDS identifies malformed HTTP requests easily by using protocol knowledge, like the crashiis attack which sends "GET ../.." as a request;
- there exist many attack packets whose characteristics are very different from those observed in the legitimate packets of the training data set, so it does not exist a model for the packet classification. This means that the system automatically classify these packets as anomalous. An example of such attack is apache2, a DoS attack, which sends requests with a lot of repeated "User-Agent:sioux\r\n".

During the analysis of the FTP traffic, about 3000 FTP packets

sent by the same source host, which is sending FTP commands in a way that is typical of the Telnet protocol (one character per packet, with the TCP flag PUSH set), were found. Although it is normal traffic, this behaviour was never observed in the training data set. Currently the system is not able to handle payloads containing only one character, because it uses high order n-grams. Therefore these packets were not taken into account to assess the effectiveness of PCkAD. The treatment of this aspect is planned for future work. The same consideration holds for POSEIDON too [3], while PAYL [2] works with 1-grams so it should be able to handle this scenario.

It is possible to set up the system so that the chunks are disabled during the analysis phase. The variant of the technique with chunks disabled is used as baseline for the evaluation.

Table 1 reports the results about the influence of the length of a single chunk on the analysis process, with n=3. len_{ck} , dr_{ck} , dr_w , fpr_{ck} and fpr_w denote respectively: the length of a chunk (in bytes), the detection rate with chunks enabled, the detection rate with chunks disabled, the false-positive rate with chunks enabled and the false-positive rate with chunks disabled.

len_{ck}	dr_{ck}	dr_w	fpr_{ck}	fpr_w
7	84,2%	78,9%	0,682%	0,591%
15	100%	73,7%	0,584%	0,55%
20	84,2%	84,2%	0,518%	0,518%
25	73,7%	73,7%	0,522%	0,493%
39	63,1%	63,1%	0,353%	0,353%

TABLE I
RESULTS OF N-GRAMS ANALYSIS OF FTP NETWORK TRAFFIC WITH AND
WITHOUT CHUNKS.

As can be seen in the table, sometimes the chunks have a positive influence on the analysis process, although typically the system produces a greater number of false-positive when they are enabled, however this increase is very small so the results can be considered positive. Without chunks, with $len_{ck}=7$, the system is not able to recognise properly a specific attack instance so the detection rate goes down slightly. With $len_{ck}=15$ the detection rate increases from 73,7% to 100% using chunks, while the false-positive rate goes up imperceptibly. In the remaining configurations the chunks affect the results a little or nothing at all. It may happen that the system is able to recognise anomalous packets only due to never seen n-grams, in this scenario the chunks have a very low influence.

The effectiveness of the chunks depends on the nature of the models, so the length of a chunk has a great importance in the training phase. Too low values lead to the production of many models, this means that a lot of packets with similar payloads are split up in different classes. On the other hand, too high values would have the opposite effect, many packets with different payloads would be grouped together. Another experiment was set up to assess if the n-grams are able to influence the analysis process as well. If the value is too low then the set of all possible n-grams the system can learn is

relatively small, so it would be harder to recognise attack instances. With high values it is easier for the system to recognise anomalous packets, but it is also easier to produce a greater number of false-positive. In the previous experiment only 3-grams have been used; next 2-grams and 5-grams will be evaluated. Tables 2, 3 and 4 show the results with 2-grams and 5-grams. Table 2 and 3 do not report the false-positive rates because they were always below the 1%.

soglia	dr_{ck}	dr_w
40%	0%	0%
30%	10,5%	10,5%
25%	21,1%	21,1%
15%	78.9%	78.9%

TABLE II RESULTS OF 2-GRAMS ANALYSIS OF FTP NETWORK TRAFFIC, WITH $len_{ck}=20.$

soglia	dr_{ck}	dr_w
30%	31,6%	26,3%
25%	36,8%	31,6%
15%	84.2%	68.4%

TABLE III RESULTS OF 2-GRAMS ANALYSIS OF FTP NETWORK TRAFFIC, WITH len_{ck} – 15

soglia	dr_{ck}	dr_w	fpr_{ck}	fpr_w
40%	100%	100%	1,29%	1,22%
50%	100%	100%	1,05%	1,03%
60%	100%	100%	0,917%	0,888%

TABLE IV RESULTS OF 5-GRAMS ANALYSIS OF FTP NETWORK TRAFFIC, WITH len_{ck} = 15.

When n is set to 2 it is difficult for the system to detect attack instances, while for n = 5 the detection rate is very high, but the false-positive rate also goes up. These results confirm the previous considerations. In the light of the results observed, it is reasonable to say that greater values of nwould lead to higher false-positive rate while with 1-grams it would be even more difficult for the system to recognise attack instances. In the first case it would be required a large amount of resources for system administrators to check the alarms generated from the IDS, instead in the second case the falsenegative rate would goes up. Table 5 compares the PCkAD's performance with those of PAYL and POSEIDON. PAYL and POSEIDON are described in more details in the introduction. It is interesting to note that PCkAD is able to get a detection rate of 100%, like POSEIDON and better than PAYL and it is able to get the smallest false-positive rate among the three techniques.

IV. CONCLUSIONS AND FUTURE WORK

In this paper it was presented an anomaly-based intrusion detection technique, called Packet Chunk Anomaly Detector

	PAYL	POSEIDON	PCkAD
DR	94,7%	100%	100%
FPR	1,23%	0,93%	0,584%

TABLE V

Comparison among PCkAD (n = 3, len_{ck} = 15), PAYL and POSEIDON; DR stands for detection rate, while FPR is the false-positive rate.

(PCkAD), which uses n-grams and a novel preprocessing step for the analysis of network packets payload. The system models the normal behaviour of network traffic profile, in an automatic and unsupervised fashion. The resulting models are used to classify unseen packets.

Two experiments were set up to assess the effectiveness of the proposed technique and the DARPA 1999 dataset was used. The system is able to get a detection rate of 100% with a false-positive rate less than 1%, for the FTP traffic. A comparison among PCkAD, PAYL and POSEIDON is reported; PCkAD and POSEIDON share the same detection rate, which is the highest, moreover PCkAD has got the lowest false-positive rate.

A lot of efforts need to be done to improve PCkAD, first of all it is necessary to decrease even more the false-positive rate and secondly its robustness has to be assessed, also by considering other experimental scenarios. Another relevant direction of research is being currently taking into account is the handling of concept drift by means of weighted ensembles of classifiers exploiting the basic strategy here presented.

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