Poseidon: a 2-tier Anomaly-based Intrusion Detection System*

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Abstract

We present Poseidon, a new anomaly based intrusion detection system. Poseidon is payload-based, and presents a two-tier architecture: the first stage consists of a Self-Organizing Map, while the second one is a modified PAYL system [22]. Our benchmarks on the 1999 DARPA data set [15] show a higher detection rate and lower number of false positives than PAYL and PHAD.

1 Introduction

Intrusion detection systems were introduced by Anderson [1] and formalized later by Denning [7]. Nowadays, there exist two main types of network intrusion detection methods: *anomaly based* and *signature based*. In signature based methods, (e.g. Snort [21]) a characteristic trait of the intrusion is developed off-line, and then loaded in the intrusion database before the system can begin to detect this particular intrusion. This usually yields good results in terms of low false positives, but has drawbacks: first, *all* new attacks will go unnoticed until the system is updated, creating a window of opportunity for attackers to gain control of the system under attack. Secondly, only known attacks can be detected, and while this could be acceptable for detecting attacks to e.g., the OS, it makes it much harder to use signature-based system for protecting web-based services, because of their ad-hoc nature. Notably, the protection of web-services is becoming a high-impact problem (see [10]).

Anomaly based systems (ABS), on the other hand, build statistical models that describe the normal behaviour of the network, and flag any behaviour that significantly deviates from the norm as an attack. This has the advantage that new attacks will be detected as soon as they take place (or – depending on the architecture – as soon as the attack has taken place). Moreover, ABS can be more easily applied also to ad-hoc networked systems such as web-based services. The disadvantage is that ABS needs an extensive model building phase: a significant amount of data (and thus a significant period of time) is needed to build accurate models of legal behaviour.

Most intrusion detections systems in use today are signature based, however, new attacks are devised with increasing frequency every day (see [10] for weekly and monthly single attack rates), so anomaly based systems become increasingly attractive.

Every intrusion detection system suffers from (1) false positives (false alarms), in which legal be-

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haviour is incorrectly flagged as an attack and (2) false negatives, or misses, in which true attacks are undetected. Anomaly based systems are more vulnerable to these problems than signature based systems because they use statistical models to detect intrusions.

ABS can extract information to detect attacks from different layers: packet headers, packet payload or both. *Header information* is mainly useful to recognize attacks aiming at vulnerabilities of the network stack implementation or probing the operating system to identify active network services. On the other hand, *payload information* is most useful to identify attacks against vulnerable applications (since the connection that carries the attack is established in a normal way) [22]. Without pretending to be globally better that other types of ABS, payload-based systems have importance of their own, as they are particularly suitable for detecting popular attacks such as those on the HTTP protocol, and worms (see Wang and Stolfo [22] for a discussion). Notably, PAYL and the system of Kruegel et al. [13] are mainly payload-based, while PHAD [16] is partly payload based.

Contribution In this paper we propose POSEIDON (Payl Over Som for Intrusion DetectiON): a two-tier intrusion detection architecture. The first tier consists of a self-organizing map (SOM), and is used exclusively to classify payload data; the second tier consists of a slight modification of the well-known PAYL system [22] (see Figure 1).

POSEIDON is payload-based: it uses only destination address and service port numbers to build a profile for each port monitored, and it does *not* consider other header features.

We have extensively benchmarked our system wrt PAYL [22] (also by replicating PAYL's experiments) and PHAD [16] using the 1999 DARPA benchmark [15]. PAYL and PHAD are the reference ABS based on payload analysis. On this dataset, our experiments show:

- a *higher* detection rate and *lower* number of false positives than PAYL and PHAD.

- a reduction on the number of profiles used wrt PAYL. This has a positive influence on the runtime efficiency of the system.

Incidentally, being payload-based, our system takes into consideration only what Mahoney and Chan [17] call the *legitimate* data of the 1999 DARPA data set, implying that we can legitimately expect that the system in real life performs as well as it does on the DARPA benchmark.

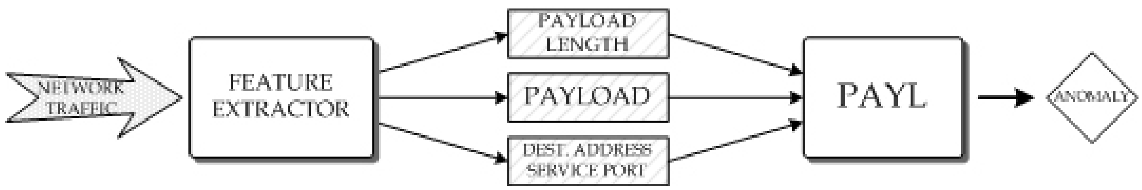
This paper is structured as follows: Section 2 presents the internals of POSEIDON and of PAYL; in Section 3 we describe benchmarking experiments and compare obtained results with PAYL and PHAD. In Section 4 we discuss other related work. Finally, in Section 5 we draw our conclusions and set the course for further developments. In the appendix we report the pseudo-code of POSEIDON.

2 Architecture

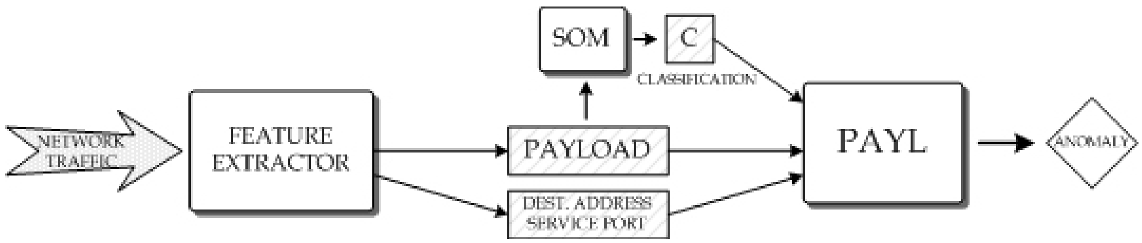
Intrusion detection system can be either *packet oriented* or *connection oriented*. In the former architecture, every packet is analysed as soon as it arrives, without trying to correlate it with previous collected data. On the other hand, connection oriented systems work either by (a) reassembling the whole connection (commonly only from client to server) - waiting until the connection is closed - to analyse the connection payload, or (b) by gathering statistics which consider, e.g., the amount of bytes transmitted and received, the duration of the connection, the protocol type and final connection status.

POSEIDON, like most intrusion detection systems, is packet oriented. This architecture presents two main advantages: firstly, POSEIDON can identify and block an attack *while* it is taking place (intrusion prevention); in connection-based systems the attack is seen only *after* it has taken place. Secondly, connection-based systems are computationally more expensive, in particular they require a huge amount of memory resources to keep all the segments to analyse. This makes connection-based system more suitable for off-line analysis. On the other hand, connection-based systems support a finer-grained analysis.

Our starting point is the PAYL architecture. Our algorithm receives as input a packet and *classifies* the packet, without prejudice of any of its properties, such as length, destination port or application data semantics. The idea is that the classifier keeps



(a) PAYL



(b) POSEIDON

Figure 1: PAYL and POSEIDON architectures

as much information as possible about packets (e.g. high-dimensional data) for the anomaly detection phase: we also want the classifier to operate in an unsupervised manner. This is a typical clustering problem which can be properly tackled using neural networks in general and Self-Organizing Maps (SOM) [12] in particular. In fact, SOMs have been widely used in the past both to classify network data and to find anomalies. Here, we use them for pre-processing.

In fact, our architecture combines a SOM with a modified PAYL algorithm. Figure 1 shows a comparison between our architecture and PAYL's.

We now give a high-level description of the algorithms underlying our system, a more formal description is reported in the appendix. We first describe the SOM. Later in the section, we introduce PAYL, focusing on the main differences between our approach and the PAYL approach towards classification of network data.

2.1 SOM classification model

Self organizing maps are defined as topology-preserving single-layer maps in which the topological structure, imposed on the nodes in the network, is not changed during classification (preserving neighbourhood relations) and there is only one layer of nodes. A SOM is suitable to analyse high-dimensional data and belongs to the category of competitive learning networks [12]. Nodes are also called *neurons*, to remind us of the artificial intelligence nature of the algorithm. Each neuron n has a *vector of weights* w_n associated to it: the dimension of the weights arrays is equal to the length of longest input data. These arrays (also referred as *reference vectors*) determine the SOM behaviour.

To accomplish the classification, SOM goes through three phases: initialization, training and classification.

Initialization First of all, some system parameters (nodes number, learning rate and radius) have to be fixed by e.g. the IDS technician. The number of nodes directly determines the classification given by the SOM: a small network will classify different data inputs in the same node while a large network will produce a too sparse classification. Afterwards, the array of node weights is initialized, usually with random values (in the same range of input values).

Training The training phase consists of a number of iterations (also called *epochs*). At each iteration one input vector x is processed as follows: x is compared to all neuron weights arrays w_n with a distance function (Euclidean or Manhattan): the most similar node (also called *best matching unit*, BMU) is then identified.

After the BMU has been found, the neighbouring neurons and the BMU itself are updated. The following update parameters are used: the neighbourhood is governed by the *radius* parameter (r) and the magnitude of the attraction is affected by the *learning rate* (α).

During this phase, the map tends to converge to a stationary distribution, which approximates the probability density function of the high-dimensional input data.

As the learning proceeds and new input vectors are given to the map, the learning rate and radius values gradually decrease to zero.

Classification During the classification phase, the first part of the training phase is repeated for each sample: the input data is compared to all the weight arrays and the most similar neuron determines the classification of the sample (but weights are not updated). The winning neuron is then returned.

2.2 PAYL classification model

PAYL, is a n-gram [6] analysis algorithm, and uses a classification method based on clustering of packet payload data length.

PAYL classifies packets on the *length of the payload*. During the training phase, for a given training data set, PAYL computes a set of *models* M_{ij}. For each incoming packet, with destination port j and payload length i, M_{ij} stores incrementally the average byte frequency and the standard deviation of each byte frequency. During the detection phase, the same values are computed for incoming packets and then compared to model values: a significant difference from the norm produces an alert. To compare models, PAYL uses a simplified version of the Mahalanobis distance, which has the advantage of taking into account not only the average value but also its variance and the covariance of the variables measured.

The maximum amount of space required by PAYL is: $p * l * k$, where p is the total number of ports monitored (each host may have different ports), l is the length of the longest payload and k is a constant representing the space required to keep the mean and the variance distribution values for each payload byte (PAYL uses a fixed value of 512).

To reduce the otherwise large number of models to be computed, PAYL organizes models in clusters. After comparing two neighbouring models using the Manhattan distance, if the distance is smaller than a given threshold t, models are merged: the means and variances are updated to produce a new combined distribution. This process is repeated until no more models can be merged. Experiments with PAYL show [22] that a reduction in the number of model of up to a factor of 16 can be achieved.

Modification to PAYL Our modification to PAYL works as follows: we pre-process each packet, using the SOM. Afterwards PAYL uses the class value given by the SOM (*winning neuron*) instead of the payload length. Technically PAYL, instead of using model M_{ij}, uses the model M_{nj} where j is the usual destination port and n is the classification derived from the neural network. Then, mean and variance values are computed as usual.

Having added SOM to the system we must allow for both the SOM and PAYL to be trained separately. Regarding resource consumption, we have to revise the required amount of space to: $p * n * k$, where the new parameter n indicates the amount of SOM network nodes.

3 Tuning and Experiments

In this section, we show the results of our benchmarks and compare the performance of POSEIDON with PAYL and PHAD. PAYL and PHAD are the two reference ADS based on payload. Unsurprisingly, they are the only two ABS based on payload which have published their detection rate on the DARPA 1999 dataset.

3.1 SOM parameters tuning

The SOM algorithm needs several parameters on start-up: the total number of network nodes, the function used to compute the distance between vectors and the values of the *learning rate* and *update radius*. For the sake of transparency, we report here the values used in our experiments.

Concerning the number of neurons, a small network would yield a too course classification, while

		PAYL	PAYL_exp	POSEIDON
Number of profiles used		4065	(11312 - unclustered)	1622
HTTP	DR	89,00%	90,00%	100,00%
	FP	0,17%	0,73%	0,0016%
FTP	DR	95,50%	94,74%	100,00%
	FP	1,23%	11,41% (1,21%*)	11,31% (0,93%*)
Telnet	DR	54,17%	53,65%	95,12%
	FP	4,71%	4,94%	6,72%
SMTP	DR	78,57%	73,34%	100,00%
	FP	3,08%	8,35%	3,69%
Overall DR with FP < 1%		58,8% (57/97)		73,2% (71/97)*

Table 1: Comparison between PAYL, our implementation of PAYL (PAYL_exp) and POSEIDON; DR stands for detection rate, while FP is the false positive rate

a large network will produce a sparse classification. In addition, it is worth bearing in mind that the computational load increases quadratically with the number neurons.

Experimenting with different initialization parameters and using the *quantization error* method [12] to evaluate the classification given by the network, we found the best SOM with the following parameters:

- Number of neurons: 96 (rectangular network of 12 by 8).
- Learning rate: 0.1.
- Update radius: 4.
- Distance function: Manhattan.

3.2 Experiments

We have benchmarked POSEIDON against PAYL (also by replicating the experiment on PAYL) and PHAD, using the same data used by PAYL and PHAD: the DARPA 1999 dataset [15]. This standard dataset is used as reference by a number of researchers (e.g. [16, 19, 22]), and offers the possibility of comparing the performance of various IDS. This dataset has been criticized because of the environment in which data were collected [18]; as explained by Mahoney and Chan [17], it is possible to tune an IDS in such a way that it scores particularly well on this particular data set: some attributes – specifically: remote client address, TTL, TCP options and TCP window size – have a small range in the DARPA simulation, but have a large and growing range in real traffic. IDS which take into account the above-mentioned attributes are likely to score much better on the DARPA set than in real life. Since our system does not consider these attributes, we can legitimately expect that the system in real life performs as well as it does on the DARPA benchmark.

To compare our model with PAYL, we apply the same restrictions and conditions used by Wang and Stolfo [22]: we focus only on inbound TCP packets, with data payload, directed to hosts 172.016.0.0/16 and ports 1-1024.

We train the SOM clustering algorithm using internal network traffic of week 1 and week 3 (12 days, 2.444.591 packets, attack free): for each different protocol we use a different SOM. Then, we use the same data to build PAYL models taking advantage of the classification given by the neural network.

After this double training phase, it is possible to use the testing weeks (4 and 5) to benchmark the intrusion detection algorithm. This data contains several attack instances (97 payload-based attacks are detectable applying the same traffic filter mentioned above), as well as legal traffic, directed against different hosts of the internal network: the attack source can be situated both inside and outside the network.

Figure 2 shows a detailed comparison of PAYL and POSEIDON in terms of percentage of true negatives (reported on the y axis) wrt the percentage false positives (x axis). Table 1 reports a summary of these results: the first columns we have PAYL's

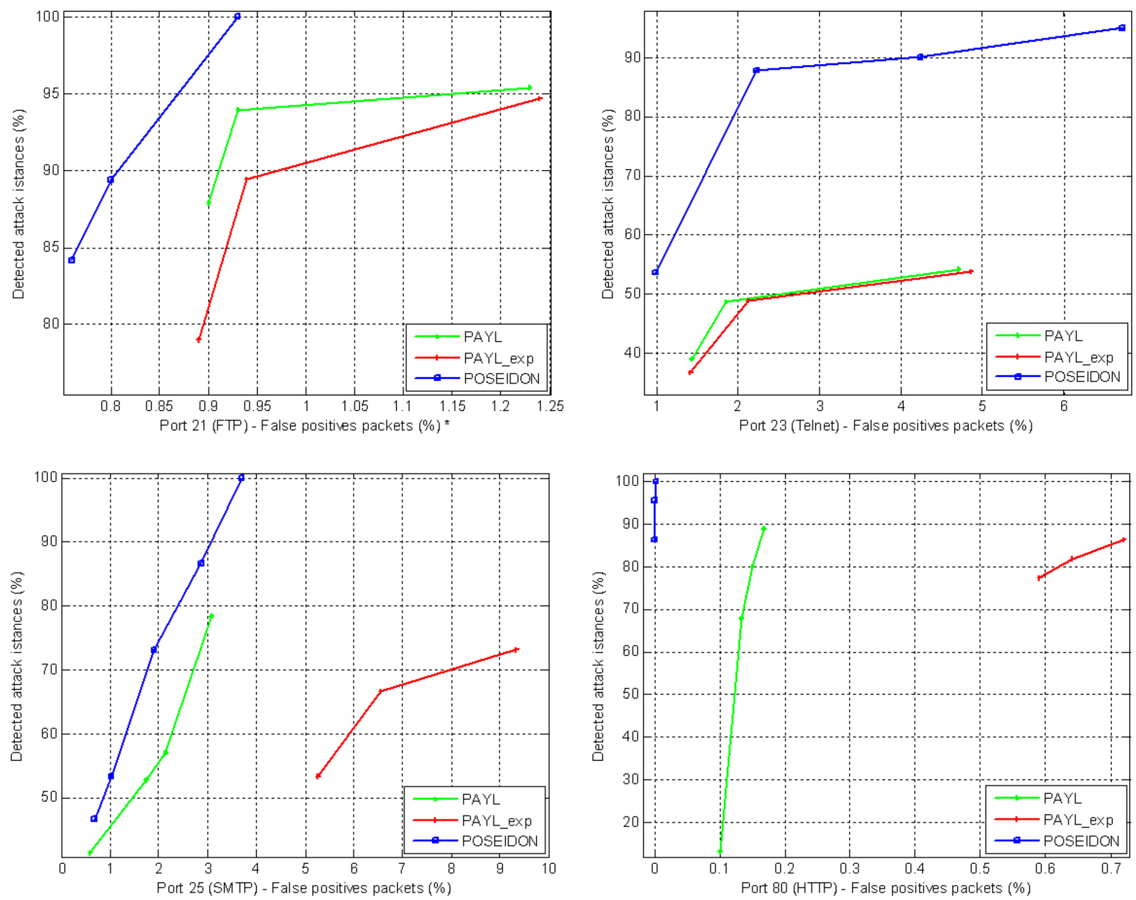


Figure 2: Detection rates for ports 21 (FTP), 23 (Telnet), 25 (SMTP) and 80 (HTTP): the x-axis and y-axis present false positive rate and detection rate respectively. POSEIDON presents always a higher detection rate compared with PAYL at the same false positive rate. For the graph relative to port 21 see Remark 3.2.

statistics as we have inferred them from the graphics reported in Wang and Stolfo [22]. The second column reports the figures we obtained by replicating Wang and Stolfo's benchmarks. For the sake of correctness, to replicate PAYL experiments we used an un-clustered architecture, which yields on one hand to a higher number of profiles, and on the other hand to a better classification. The third column reports POSEIDON's result.

Remark During FTP protocol benchmarks we found a high rate of false positives (more than 3000 packets) both with PAYL and with POSEIDON: all these packets are 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). These packets are marked as an attack because the training model does not contain this kind of traffic over the FTP control channel port, although it is normal traffic. During our experiments with PAYL we found the same behaviour: for this reason we decided to present benchmarks results of PAYL and POSEIDON also without taking into account these packets (the figures with a star * in Table 1 and the graph in Figure 2).

Table 2 compares our results with PHAD: it is not possible to make a full comparison between the two systems, because of the restrictions used by

PHAD authors (they restrict to a maximum total amount of 100 false positives during 10 days of testing). Nonetheless, we could legitimately compare the two systems on the HTTP protocol, on which POSEIDON meets the restrictions above.

Unfortunately, there is no other public available data set suitable to compare our approach with previous researches on anomaly intrusion detection: many authors use the KDD 99 data set [2] in which regrettably payload data is discarded. Because we use payload information, we can not use this data set to benchmark POSEIDON and models that use this data set are not directly comparable with ours.

Concluding, we believe that the significant achieved improvement over PAYL is determinated by a better distribution of mean and variance value within categories, obtained with introduction of a new classification algorithm (SOM).

4 Related work

Intrusion detection systems based on anomaly detection have been widely studied for two decades. We recall that anomaly detection systems can operate in various manners, sometimes extracting features from packet headers and sometimes from payload data.

In this section we report on related work. First we describe other neural network-based systems then we address statistical-based systems.

4.1 Neural networks based systems

We start by presenting other neural-network based IDS. We cannot benchmark these systems wrt POSEIDON because their authors use either private data sets (Cannady [3], Labib and Vemuri [14] and Ramadas et al. [20]), or data sets that do not contain payload information (Depren et al. [8]) or do not provide precise statistics (Nguyen [19]).

Cannady [3] proposes a SOM-based IDS in which network packets are first classified according to nine features and then presented to the neural network. Attack traffic is generated using a security audit tool. The author extends this work in Cannady [4, 5].

Nguyen [19] uses a one-tier architecture, consisting of a SOM, to detect two attacks in the 1999 DARPA data set: the first one (*mailbomb*) against the SMTP service, and the other one (*guessftp*) against FTP.

Labib and Vemuri [14] use a SOM to identify Denial of Service attacks. They discard information about payload and use only packet header information; their data is collected from a private network (described in a general way) and is not publicly available.

Ramadas et al. [20] use a SOM to detect attacks against DNS and HTTP services (using a private data set): they use a pre-processor to summarize some connection parameters (source and destination host and port) and then add several values to track connections behaviour: the information is then merged in a data structure used to fire events related to the connection and to feed the neural network.

Depren et al. [8] present a hybrid IDS based on self-organizing maps and benchmark it on the KDD 99 data set [2]. They feed the neural networks (one for each protocol type) with six features extracted from each connection (duration, protocol type, service type, status, total bytes sent and received) and then use the quantization error method to detect anomalies. The system is connection oriented, therefore attacks can be detected only when the connection is completely re-assembled. Regarding their architecture, the authors state that the SOM used to model TCP connections uses 1515 neurons; which in our opinion is quite large, if compared with the ones used by our system.

4.2 Statistical-based systems

In addition to ADS based on neural networks, there exist ADS employing statistical models to detect anomalous behaviour. We now report on them. Again, we cannot benchmark them against POSEIDON because they either use only headers information (Hoagland [9], Javitz and Valdes [11]) or employ benchmarking data that is not publicly available (Kruegel et al. [13]).

The SPADE [9], NIDES [11] and PHAD [16] systems rely on statistical models computed on normal network traffic: they work by extracting features from the packet header fields and fire alarm when they recognize a significant deviation from the normal model; most of the features extracted are related to IP addresses (source and destination), destination service port and TCP connection

Type	Attack	PHAD	POSEIDON
Probe	ntinfoscan	66,67% (2/3)	100% (3/3)
Denial of Service	apache2	100% (3/3)	100% (3/3)
	back	0% (0/4)	100% (4/4)
	crashiis	71,43% (5/7)	100% (7/7)
Remote to Local	phf	66,67% (2/3)	100% (3/3)
	ppmacro	33,34% (1/3)	100% (3/3)
Overall detection rate		65% (13/20)	100% (20/20)

Table 2: Comparison between PHAD and POSEIDON detection rates.

state (PHAD uses up to 34 attributes coming from Ethernet, IP and application layer protocols packets). Our approach differs from the one mentioned here in the following aspects: (a) it is payload-based: we use only destination address and service port numbers to build a profile for each port monitored, without taking care of other header features (of the above systems only PHAD considers payload information, we have compared it with our system in the previous section). (b) We have a two-tier architecture in which the SOM is used only to pre-process information.

Shifting to payload-based systems, Kruegel et al. [13] show that is is possible to find the description of a system that computes payload bytes distribution and combines this information with extracted packet header features: they first sort the resultant ASCII characters by frequency and then aggregate them into six groups. As argued in [22], this leads to a very course classification of the payload.

PAYL works in a way similar to Kruegel et al. [13] but models the full byte distribution based on payload data length and operates a clustering phase to cover possible missing lengths. The PAYL architecture is made up of a single tier, while our architecture has two different layers: the first one, made up by a SOM, is delegated to classify packets only using payload data information, without using payload length value. The second layer is a modified version of PAYL that computes byte distribution models using the classification information coming from the first layer and extracting destination IP address and service port from packets header.

5 Conclusion

We present an approach to Intrusion Detection that involves the combination of two different techniques: a self-organizing map and the PAYL architecture. We modify the original PAYL to take advantage of the unsupervised classification given by the SOM, which then functions as pre-processing stage.

Our experiments on the DARPA set show that our approach reduces the number of profiles used by PAYL (payload length can vary between 0 and 1460 in a Local Area Network, while the SOM neural network used in our experiments has less than one hundred nodes). In our experiments PAYL without SOM required 3 times as many profiles as with the SOM pre-processing (see Table 1).

We benchmark POSEIDON extensively against the PAYL algorithm and data sets showing a higher detection rate and lower false positives rate.

A Appendix: POSEIDON inner functions

In this section we describe the inner mathematical functions and algorithms used by POSEIDON.

A.1 SOM algorithm

DATA TYPE

$RR = [0.0..255.0]$
/* Reals (Double) between 0.0 and 255.0 */
l = *length of the longest packet payload*
$PAYLOAD$ = *array* $[1..l]$ *of* $[0..255]$

DATA STRUCTURE

```
N = non − empty finite set of neurons

for each n ∈ N let
    w_n := array [1..l] of RR
            /* array of weights associated */
            /* to each neuron n */
α_0 ∈ ℝ   /* Initial learning rate */
α := α_0  /* Current learning rate */
r_0 ∈ ℝ   /* Initial radius */
r := r_0  /* Current radius */
τ ∈ ℕ     /* Number of training epochs */
k ∈ ℕ     /* Smoothing factor */

INIT PHASE

for each n ∈ N
    for i := 1 to l
        w_n[i] := random(RR)
            /* Initialize with values in RR */

TRAINING PHASE

INPUT:
    x_t : PAYLOAD

for t := 1 to τ
    /* Find winning neuron */
    win_dist := +∞
    win_neuron := n_0

    for each n ∈ N do
        dist := manhattan_dist(x_t, w_n)
        if (dist ≤ win_dist) then
            win_dist := dist
            win_neuron := n
        end if
    done(for)

    /* Process neighbouring neurons */
    N_n = {n ∈ ℕ | trig_dist(n, win_neuron) ≤ r}

    for each n_n ∈ N_n
        for i := 1 to l
            w_{n_n}[i] := w_{n_n}[i] + α * (w_{n_n}[i] − x_t[i])

    α := α_0 * k/(k+t)
    r := r_0 * (τ−t)/τ
done(for)

CLASSIFICATION PHASE

INPUT:
    x : PAYLOAD

OUTPUT:
    win_neuron ∈ ℕ

win_dist := +∞
dist := win_dist
win_neuron := n_0

for each n ∈ N do
    dist := manhattan_dist(x, w_n)
    if (dist < win_dist) then
        win_dist := dist
        win_neuron := n
    end if
done(for)

return win_neuron
```

A.2 PAYL algorithm

```
DATA TYPE

feature vector = RECORD [
        mean = array [1..256] of Real,
            /* average byte frequency */
        stdDev = array [1..256] of Real
            /* standard deviation of each */
            /* byte frequency */
    ]

profile = RECORD [
        p ∈ ℕ, /* destination service port */
        ip ∈ ℕ, /* destination host address */
        fv = finite set of n feature vectors
    ]
    /* for each port monitored a profile */
    /* with n feature vectors is associated */

DATA STRUCTURE

P = set of finite profiles
threshold ∈ ℝ
    /* numeric value used for anomaly */
    /* detection given by user */

TRAINING PHASE
```

INPUT:
x : *PAYLOAD*
n : *SOM classification*
ip : *IP address* $\in \mathbb{N}$
sp : *service port* $\in \mathbb{N}$

```
for each p ∈ P do
    if (p.ip = ip and p.sp = sp) then
        fv = p.getFV(n)
        /* get feature vector with index n */
        fv.update(x)
        /* update byte frequency distributions */
    end if
done(for)
```

TESTING PHASE

INPUT:
x : *PAYLOAD*
n : *SOM classification*
ip : *IP address* $\in \mathbb{N}$
sp : *service port* $\in \mathbb{N}$

OUTPUT:
isAnomalous : *BOOLEAN*
/* is the packet anomalous ? */

```
dist := +∞
isAnomalous := FALSE

for each p ∈ P do
    if (p.ip = ip and p.sp = sp) then
        fv := p.getFV(n)
            /* get feature vector with index n */
        dist := fv.getDistance(x)
            /* get the distance between input */
            /* data and associated profile */
    end if
done(for)

if (dist ≤ threshold) then
    isAnomalous := TRUE
end if

return isAnomalous
```

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