ON THE SELF-SIMILARITY OF THE 1999 DARPA/LINCOLN LABORATORY EVALUATION DATA

Kun Huang[1], Dafang Zhang[2]
[1]*School of Computer and Communication,*[2] *School of Software,Hunan University, Changsha, Hunan 410082, P.R. China*

Keywords: Intrusion detection, Evaluation data, Network traffic, Self-similarity.

Abstract: While intrusion detection systems (IDSs) are becoming ubiquitous defence, no comprehensive and scientifically rigorous benchmark is available to evaluate their performances. In 1998 and again in 1999, the Lincoln Laboratory of MIT conducted a comprehensive evaluation of IDSs and produced the DARPA off-line evaluation data to train and test IDSs. However, there is the lack of detailed characteristics of the DARPA/Lincoln Laboratory evaluation data. This paper examines the self-similarity of the 1999 DARPA/Lincoln Laboratory evaluation data sets for training and indicates that the evaluation data clearly exhibits self-similarity during preceding tens of hours period, while not during other time periods. Also the likely causes failing self-similarity are explored. These finding results can help evaluators to understand and use the 1999 DARPA/Lincoln Laboratory evaluation data well to evaluate IDSs.

1 INTRODUCTION

Intrusion detection systems (IDSs) are an important component of defensive measures protecting computer systems and networks from rapidly growing unauthorized intrusion (Denning, 1987). Numerous different intrusion detection technologies have been developed and deployed in realistic environment.

While IDSs are becoming ubiquitous defence, no comprehensive and scientifically rigorous benchmark is available to evaluate their performances. Current evaluation data for IDSs (Puketza, 1996) can't be shared publicly due to privacy and security concerns. In 1998 and again in 1999, the Lincoln Laboratory of MIT conducted a comprehensive evaluation of IDSs and released the DARPA off-line evaluation data. The DARPA evaluation data has been a widespread public benchmark available to test both host-based and network-based IDSs, and both signature-based and anomaly-based IDSs.

IDSs under test are ultimately intended for use in real network, so it is required that the evaluation data for IDSs should be realistic. However, the DARPA evaluation data is only claimed to be similar to real network traffic, but not validated in literatures (Richard, 2000; Lippmann, 2000). Since it is shown that real network traffic captured from Local Area Networks and Wide Area Networks statistically exhibits the property of self-similarity (Leland, 1994; Paxson, 1995; Beran, 1995), the 1999 DARPA evaluation data which is attack-free network traffic data for training should also exhibit self-similarity.

McHugh (McHung, 2001) criticizes many aspects of the 1998 and 1999 DARPA/Lincoln Laboratory evaluations, including questionable collected evaluation data, attacks taxonomy, and evaluation criteria. It is criticized that there is the lack of statistical characteristics of the DARPA evaluation data and no validation of similarity to real network traffic. But the critique doesn't quantify the statistical characteristics of the synthetic evaluation data and deeply explore the raised flaws and likely causes.

This paper quantifies the statistical property of self-similarity of the 1999 DARPA/Lincoln Laboratory evaluation data and explores the likely causes failing self-similarity. Our contribution will help evaluators to understand and use the synthetic evaluation data to train and test IDSs well.

The rest of this paper is organized as follows. Section 2 overviews the 1999 DARPA evaluation data. Section 3 gives a brief background of self-similarity. In Section 4, the self-similarity of the 1999 DARPA evaluation data is explored. Finally, Section 5 draws conclusions.

Huang K. and Zhang D. (2006).
ON THE SELF-SIMILARITY OF THE 1999 DARPA/LINCOLN LABORATORY EVALUATION DATA.
In *Proceedings of the International Conference on Security and Cryptography*, pages 75-80
DOI: 10.5220/0002096900750080

2 SUMMARY OF 1999 DARPA EVALUATION DATA

In 1998 and 1999, the Lincoln Laboratory of MIT conducted a large-scale quantitative evaluation of IDSs and publicly released the DARPA evaluation data that would be a comprehensive benchmark available through the Lincoln Laboratory website. To sanitize privacy and security information and eliminate impact of the operation of real network, the Lincoln Laboratory developed a real network traffic model, and then synthesized the normal behaviours and attack scenarios in an isolated test bed network (Lippmann, 2000).

The 1999 DARPA evaluation data includes three weeks of training data with background traffic and labeled attacks for tuning IDSs, and two weeks of test data with background traffic and unlabeled attacks. Every week of the evaluation data has five weekdays and every day has about 22 hours from 8 AM to 6 AM of the next day, except for Thursday of week 3 stopping at about 4 AM and Friday in week 3 ending at about 1 AM. Of the five weeks, only weeks 1 and 3 are attack-free network traffic data and the rest have been mixed with background traffic (attack-free traffic) and injected attack traffic. So this paper focuses on the attack-free background traffic of weeks 1 and 3.

In week 1 and 3, the network traffic predominantly occurred during between 8 AM to 6 PM every weekday, while hardly during the rest time. Over IP layer, TCP and UDP packets dominate the overall network traffic per day, while other protocols packets are also generated. It's noted that the inside network traffic is nearly the same with the outside network traffic.

3 BRIEF BACKGROUND OF SELF-SIMILARITY

3.1 Definition and Properties of Self-similarity

The most common way that a stochastic process is called self-similarity with self-similarity parameter (that is, Hurst parameter H), if the rescaled process, with an appropriate rescaling factor, and the original process have identical finite-dimensional distributions (Leland, 1994).

Let $X=\{X_t, t=0,1,2,\cdots\}$ be wide-sense stationary stochastic process with mean μ , variance σ^2, and autocorrelation function $r(k), k\geq 0$ and let $X^{(m)}=\{X_k^{(m)}, k=1,2,3,\cdots\}$ denote the aggregated time series process obtained by averaging the original time series X over adjacent, non-overlapping blocks of size $m, (m=1,2,\cdots)$, i.e. $X^{(m)}$ is given by $X_k^{(m)}=(X_{(k-1)m}+\cdots+X_{km-1})/m$. The process X is called self-similarity if the distribution of each of the corresponding aggregated process $X^{(m)}, m\geq 1$ is equal or approximately equal to that of the original process X (Leland, 1994).

There are four main properties of self-similarity process: Hurst effect, slowly decaying variance, long-range dependence, and $1/f$ noise (Rose, 1996).

3.2 Estimating the Hurst Parameter

Various estimators of the Hurst parameter H are used to examine whether a stochastic process exhibits self-similarity and/or long-range dependence. There are the following estimation methods (Rose, 1996).

Variance-time Plots The variance of aggregated time series process $X^{(m)}, m\geq 1$ is given by $\mathrm{var}(X^{(m)})\sim cm^{-\beta}$, or $\log(X^{(m)})\sim -\beta\log(m)+\log(c)$ as $m\to\infty$, where c is some positive constant and $0<\beta<1$. In the log-log plot of the sample variance versus the aggregation level, a straight line with slope $-\beta$ would be estimated, thus since $H=1-\beta/2$, H can be estimated.

R/S Analysis The R/S statistics are shown by $E[R(m)/S(m)]\sim cm^H$, or $log(E[R(m)/S(m)])\sim H\log(m)+\log(c)$ as $m\to\infty$, where $0.5<H<1$. In the log-log plot of the R/S statistics versus the number of points of the aggregated series, the slope of the straight line would be an estimation of the Hurst parameter H .

Periodogram Method This method plots the logarithm of the spectral density of a time series process versus the logarithm of the frequencies, that is $\log(f(\lambda))\sim(-\gamma)\log(\lambda)+\log(c)$ as $\lambda\to 0$, where $0<\gamma<1$, $H=(1+\gamma)/2$ and c is some positive constant, and the slope of the straight line is estimated for Hurst parameter. The periodogram is given by $I(\lambda)=|\sum_{j=1}^{N}X(j)e^{ij\lambda}|^2/(2\pi N)$, where λ is the frequency, N is the length of the time series and X is the actual time series. The periodogram $I(\lambda)$ is an asymptotically unbiased estimate of the spectral density $f(\lambda)$.

Whittle's Maximum Likelihood Estimator (MLE) Since the periodogram is not appropriate to estimate the spectral density, the Whittle's MLE is used to estimate the spectral density by minimizing an approximate log-likelihood function applied to the spectral density, thus to obtain the estimation of Hurst parameter and produce the confidence interval. The more detailed description of MLE is seen in (Rose, 1996). However, it is noted that Whittle's MLE only make a accurate estimation if it is known that the process is self-similar.

Abry-Veitch Wavelet-based Analysis This method computes the Discrete Wavelet Transform, averages the sequences of the coefficients of the transform, and then performs a linear regression on the logarithm of the average, versus the log of j, the scale parameter of the transform. The result should be directly proportional to H. The more detailed description is seen in (Rose, 1996).

4 EXPERIMENTAL RESULTS

Self-similarity of attack-free training data of the 1999 DARPA/Lincoln evaluation data set is examined using above five estimation methods of Hurst parameters. Since the last two methods are used to provide an accurate estimate if the process is self-similar, the preceding three methods are used to check whether the process is self-similar or not and the last two methods are used to estimate Hurst parameter accurately.

It is assumed that H_{var}, $H_{R/S}$, $H_{Whittle}$, and $H_{Abry\text{-}Veith}$ represent the estimated Hurst parameter by respectively using variance-time plots, R/S analysis, periodogram method, Whittle's MLE and Abry-Veitch Wavelet-based analysis, and H_{avg} represents the average of estimated Hurst parameters. If $0.5<(H_{var}+ H_{R/S} + H_{Whittle})/3<1$, H_{avg} is the average of above five estimated Hurst parameters; otherwise $H_{avg} =(H_{var}+ H_{R/S} + H_{Whittle})/3$.

4.1 Examining Self-similarity

The total counts of frame arrival are recorded in each 0.3-second interval. Thus above five estimation methods are used to estimate the Hurst parameters and compute the average values during each 1 hour with 12 000 sample points. The Hurst estimates of frame counts arrival process of week 1 on the inside and outside network are shown in Figure 1 (a) and (b) respectively. Similarly, Figure 2 shows the Hurst estimates of frame counts arrival process of week 3 on the inside and outside network.

It is denoted by Figure 1 that the evaluation data clearly exhibits self-similarity during all of 08 AM to 09 PM periods every weekday of week 1 on the both inside and outside network. Figure 2 also shows that the evaluation data clearly exhibits self-similarity during all of 08 AM to 07 PM periods every weekday of week 3 on the inside network and during all of 08 AM to 10 PM periods every weekday of week 3 on the outside network. During the other time of week 1 and 3, the 1999 DARPA evaluation data can't clearly exhibits the property of self-similarity, and especially the Hurst parameter values are undulated, which means that sometimes the evaluation data exhibits self-similarity and sometimes it fails. Table 1 shows these periods of week 1 and 3 when the evaluation data fails self-similarity.

At the same time, Figure 1, Figure 2 and Table 1 show that except on Monday of week 1, and on Tuesday and Wednesday of week 3, the evaluation data on the inside network exhibits different self-similarity from that on the outside network, although synthetic traffic is generated to intercommunicate and pass through both the inside and outside network.

4.2 Investigating the Likely Causes Failing Self-similarity

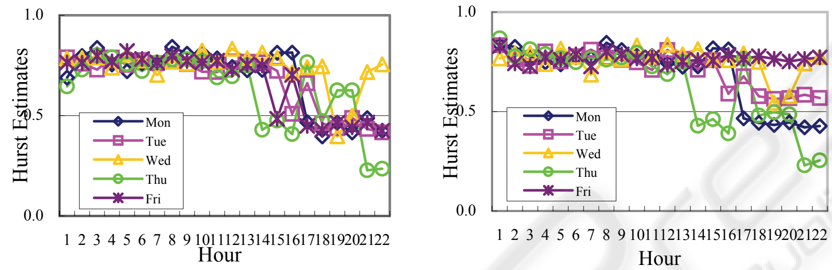
For those periods listed by Table 1, which fail to exhibit self-similarity, the likely causes are investigated as follows.

Second, certain application layer protocol (i.e., HTTP) generated by Poisson model absolutely dominates the whole traffic packet distribution of the evaluation data failing self-similarity. Figure 3 (b) shows that during from 03 AM to 04 AM period on Wednesday of week 3 HTTP packets dominate the TCP services. Since HTTP activities are generated by Poisson model, the whole packets trend to exhibit Poisson model and fails self-similarity.

Final, UDP dominates the whole traffic and dilutes the effect of TCP that maintains the property of self-similarity. Figure 3 (c) shows that during from 00 AM to 06 AM on Monday of week 1, UDP dominates the whole traffic on the inside network. Since it is indicated by Park (Park, 1996) that the reliable TCP serve to maintain the self-similarity and the unreliable and no-flow-controlled UDP results in showing little self-similarity. So UDP dominates the whole traffic and dilutes the effect of TCP, which results in failing self-similarity.

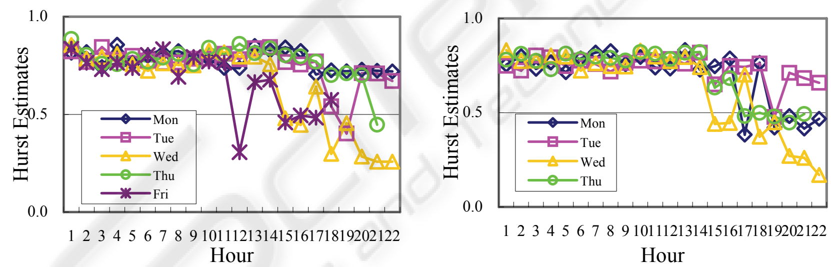
Table 1: Periods of week 1 and 3 that fail to exhibit self-similarity.

Week 1	Mon	Tue	Wed	Thu	Fri
Inside Network	00 A.M.~ 06 A.M.			21 P.M. ~ 00 A.M. 01 A.M.~ 06 A.M.	
Outside Network	00 A.M.~ 06 A.M.	01 A.M. ~ 06 A.M.	02 A.M.~ 04 A.M.	21 P.M. ~ 00 A.M. 01 A.M ~ 02 A.M. 04 A.M. ~ 06 A.M.	22 P.M. ~ 23 P.M. 00 A.M. ~ 06 A.M.
Week 3	**Mon**	**Tue**	**Wed**	**Thu**	**Fri**
Inside Network		02 A.M. ~ 03 A.M.	22 P.M. ~ 00 A.M. 01 A.M. ~ 06 A.M.	04 A.M. ~ 05 A.M.	19 P.M. ~ 20 P.M. 22 P.M. ~ 01 A.M.
Outside Network	00 A.M. ~ 01 A.M. 02 A.M. ~ 06 A.M.	02 A.M. ~ 03 A.M.	22 P.M. ~ 00 A.M. 01 A.M. ~ 06 A.M.	00 A.M. ~ 05 A.M.	



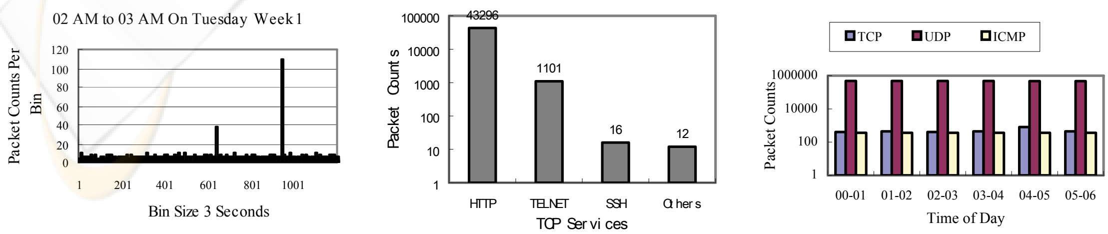
(a) Inside network (b) Outside network

Figure 1: Hurst estimates of frame counts process in week 1 on the inside and outside network.



(a) Inside network (b) Outside network

Figure 2: Hurst estimates of frame counts process in week 3 on the inside and outside network.



(a) Traffic rates (b) Application protocol distribution (c) TCP, UDP, ICMP packet distribution

Figure 3: The likely causes failing self-similarity are investigated.

4.3 Related Work

Allen and Marin (Allen, 2003) examine the attack-free training data for the presence of self-similarity in various time periods by using periodogram method and Whittle's MLE. Their finding results show that the 1999 DARPA evaluation data exhibits self-similarity during from 08 AM to 06 PM periods, while our results show that the evaluation data does during from 08 AM to 09 PM periods of week 1 on both inside and outside network, and during from 08 AM to 07 PM periods of week 3 on the inside network and from 08 AM to 10 PM periods on the outside network.

Compared with (Allen, 2003), we provide more accurate and detailed Hurst parameter values by using more estimation methods, and consider the difference of the evaluation data on the inside network from that on the outside network.

5 CONCLUSIONS

This paper examines the self-similarity of the 1999 DARPA/Lincoln Laboratory evaluation data by using five estimation methods of Hurst parameter. The experimental results denote that the evaluation data clearly exhibits self-similarity during from 08 AM to 09 PM periods of week 1 on both inside and outside network, and during from 08 AM to 07 PM periods of week 3 on the inside network and during from 08 AM to 10 AM periods on the outside network, while during other time periods it fails self-similarity.

Three likely causes failing self-similarity are explored as follows: (1) traffic rate is too lower (2) certain application-level protocol (i.e., HTTP) generated by Poisson model absolutely dominates the whole traffic;(3) UDP dominates the whole traffic and dilutes the effect of TCP, which result in showing little self-similarity. Our findings would help evaluators to use the evaluation data well to evaluate IDSs.

ACKNOWLEDGEMENTS

This work is supported by the National Natural Science Foundation of China under Grant No60473031.

REFERENCES

Denning, D.E., 1987.An intrusion-detection model. IEEE Transactions on Software Engineering, Vol.13, pp.222-232

Puketza, N., Zhang, K., Chung, M., et al, 1996. A methodology for testing intrusion detection systems. IEEE Transactions on Software Engineering, Vol.22, pp. 719-729

Richard, P., Lippmann, R., Fried, D., et al, 2000. Evaluating intrusion detection systems: the 1998 DARPA off-line intrusion detection evaluation. Proc. of the 2000 DARPA Information Survivability Conference and Exposition, Hilton Head, South Carolina, pp.12-26

Lippmann, R., Haines, J., Fried, D., et al, 2000.The 1999 DARPA off-line intrusion detection evaluation. Computer Networks, Vol.34, pp.579-595

Lippmann, R., Haines, J., Fried, D., et al, 2000.Analysis and results of the 1999 DARPA off-line intrusion detection evaluation, Proc. of Third International Workshop on Recent Advances in Intrusion Detection, Toulouse, France 162-182

McHung, J., 2001.Testing intrusion detection systems: a critique of the 1998 and 1999 DARPA intrusion detection system evaluations as performed by Lincoln laboratory. ACM Transactions on Information and System Security, Vol.3, ppt.262-294

Leland, W., Taqqu, M., Willinger, W., et al, 1994.On the self-similar nature of Ethernet traffic. IEEE/ACM Transactions on Networking, Vol.2, pp.1-15

Paxson, V., Floyd, S., 1995.Wide-area traffic: the failure of Poisson modeling. IEEE/ACM Transactions on Networking, Vol.3, pp.226-244

Beran, J., Sherman, R., Taqqu, M., et al, 1995 .Long-range dependence in variable bit-rate video traffic. IEEE Transaction on Communications, Vol.43, pp.556-1579

MIT Lincoln Laboratory, 2003.Intrusion detection evaluation web site. http://www.ll.mit.edu/IST/ideval

Rose, O., 1996. Estimation of the hurst parameter of long-range dependent time series. Technical Report No.137, Institute of Computer Science, University of Würzburg

Park, K., Kim, G., Crovella, M., 1996.On the relationship between file sizes, transport protocols, and self-similar network traffic. In: Proc. of 4th International Conference on Network Protocol, pp.171-180

Allen, W. H., Marin, G. A., 2003.On the self-similarity of synthetic traffic for the evaluation of intrusion detection. Proc. of the 2003 Symposium Applications and the Internet, pp.242-248