An Information-Theoretic View of Network-Aware Malware Attacks

Zesheng Chen*, *Member, IEEE,* and Chuanyi Ji, *Senior Member, IEEE*

***Abstract*—This work provides an information-theoretic view to better understand the relationships between aggregated vulnerability information viewed by attackers and a class of randomized epidemic scanning algorithms. In particular, this work investigates three aspects: (a) a *network vulnerability* as the non-uniform vulnerable-host distribution, (b) *threats*, *i.e.*, intelligent malwares that exploit such a vulnerability, and (c) *defense*, *i.e.*, challenges for fighting the threats. We first study five large data sets and observe consistent clustered vulnerable-host distributions. We then present a new metric, referred to as the *non-uniformity factor*, that quantifies the unevenness of a vulnerable-host distribution. This metric is essentially the Renyi information entropy that unifies the non-uniformity of a vulnerable-host distribution with different malware-scanning methods. Next, we draw a relationship between Renyi entropies and randomized epidemic scanning algorithms. We find that the infection rates of malware-scanning methods are characterized by the Renyi entropies that relate to the information bits in a non-unform vulnerable-host distribution extracted by a randomized scanning algorithm. Meanwhile, we show that a representative network-aware malware can increase the spreading speed by exactly or nearly a non-uniformity factor when compared to a random-scanning malware at an early stage of malware propagation. This quantifies that how much more rapidly the Internet can be infected at the early stage when a malware exploits an uneven vulnerable-host distribution as a network-wide vulnerability. Furthermore, we analyze the effectiveness of defense strategies on the spread of network-aware malwares. Our results demonstrate that counteracting network-aware malwares is a significant challenge for the strategies that include host-based defenses and IPv6.**

EDICS: SEC-NETW, MOD-ATTA, and MOD-PERF

I. Introduction

Malware attacks are a significant threat to networks. Malwares are malicious softwares that include worms, viruses, bots, and spywares. A fundamental characteristic of malwares is self-propagation, *i.e.*, a malware can infect vulnerable hosts and use infected hosts to self-disseminate. A key component of malware propagation is malware-scanning methods, *i.e.*, how effectively the malware finds vulnerable targets. Most of the real, especially old worms, such as Code Red [19], Slammer [18], and latter Witty [25], use naive random scanning [6]. Random scanning chooses target IP addresses uniformly and does not take any information on network structures into consideration. Advanced scanning methods, however, have been developed that exploit the IP address structure. For example, Code Red II [34] and Nimda [33] worms have used localized scanning [5]. Localized scanning preferentially searches for vulnerable hosts in the local sub-network. The Blaster worm [36] has used sequential scanning in addition to localized scanning [31]. Sequential scanning searches for vulnerable hosts through their closeness in the IP address space. Moreover, the AgoBot has employed a blacklist of the well-known monitored IP address space and avoided scanning these addresses to be stealthy [39]. The Samy worm has developed to make use of "friendship" in social networks to propagate across the MySpace site [40]. A common characteristic of these malwares is that they scan for vulnerable hosts by exploiting a certain structure in the IP address space. Such a structure, as we shall soon show, exhibits network vulnerabilities to defenders and advantages to attackers.

In this paper, we study the perspective of attackers who attempt to collect the information on network vulnerabilities and design intelligent malwares. By studying this perspective, we hope to help defenders better understand malware spreading, *e.g.*, the worst as well as practical malwares that utilize a certain class of randomized scanning algorithms, and better defend against malware attacks.

For attackers, an open question is how certain information can help them design fast-spreading malwares. The information can be from coarse to fine, including the number of vulnerable hosts, a distribution of vulnerable hosts, the locations of detection systems, and individual vulnerable hosts. This work focuses on aggregated information, *i.e.*, vulnerable-host distributions. The vulnerable-host distributions have been observed to be bursty and spatially inhomogeneous by Barford *et al.* [1]. A non-uniform distribution of Witty-worm victims has been reported by Rajab *et al.* [21]. A Web-server distribution has been found to be non-uniform in the IP address space in our prior work [8]. These discoveries suggest that vulnerable hosts and Web servers may be "clustered" (*i.e.*, non-uniform). The clustering/non-uniformity makes the network vulnerable since if one host is compromised in a cluster, the rest may be compromised rather quickly. Therefore, the information on vulnerable-host distributions can be critical for attackers to develop intelligent malwares.

We refer the malwares that exploit the information on the highly uneven distributions of vulnerable hosts as *network-aware* malwares. Such malwares include aforementioned localized-scanning and sequential-scanning malwares. In our prior work, we have studied *importance-scanning* malwares [8], [10], [15]. Specifically, importance scanning provides a worst-case ("what-if") scenario: When there are many ways for

Z. Chen is the Corresponding Author and is with the Department of Electrical and Computer Engineering, Florida International University, Miami, FL, 33174 USA e-mail: zchen@fiu.edu. C. Ji is with the School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA, 30332 USA e-mail: jic@ece.gatech.edu. This work was supported in part by NSF ECS 0300605.

network-aware malwares to exploit the information on vulnerable hosts, importance scanning is a worst-case threat-model and can serve as a benchmark for studying real malwares. Indeed, what has been observed is that real network-aware and importance-scanning malwares spread much faster than random-scanning malwares [21], [8]. However, it is not well understood how to characterize the relationship between the information on vulnerable-host distributions possessed by attackers and the propagation speed of network-aware malwares.

Questions arise. Does there exist a *generic* characteristic across different vulnerable-host distributions? If so, how do network-aware malwares exploit such a vulnerability? How can we defend against such malwares? Our goal is to investigate such a generic characteristic in vulnerable-host distributions, to quantify its relationship with network-aware malwares, and to understand the effectiveness of defense strategies. To achieve this goal, we investigate network-aware malware attacks in view of information theory, focusing on both the worst-case and real network-aware malwares.

A fundamental concept of information theory is the *entropy* that measures the uncertainty of outcomes of a random event. The reduction of uncertainty is measured by the amount of acquired information. We apply the *Renyi entropy*, a generalized entropy [23], to analyze the uncertainty of finding vulnerable hosts for different malware-scanning methods. As we shall soon show, the Renyi entropy is unique in relating three factors: malware-scanning methods, the information bits extracted by malwares from the vulnerable-host distribution, and malware spreading speed.

As the first step, we observe, from five large-scale measurement sets, the common characteristics of non-uniform vulnerable-host distributions. We then derive a new metric as the *non-uniformity factor* to characterize the non-uniformity of a vulnerable-host distribution. A larger non-uniformity factor reflects a more non-uniform distribution of vulnerable hosts. We obtain the non-uniformity factors from the data sets on vulnerable-host distributions and show that all data sets have large non-uniformity factors. Moreover, the non-uniformity factor is a function of the Renyi entropies of order two and zero [23]. We show that the non-uniformity factor better characterizes the unevenness of a distribution than the Shannon entropy. Therefore, in view of information theory, the non-uniformity factor provides a quantitative measure of the unevenness/uncertainty of a vulnerable-host distribution.

Next, we relate the generalized entropy with network-aware scanning methods. The class of network-aware malwares that we study all utilizes *randomized* epidemic algorithms. Hence the importance of applying the generalized entropy is that the Renyi entropy characterizes the bits of information extractable by the randomized epidemic algorithms. We develop explicit relations among the Renyi entropy, the randomized epidemic scanning methods, and the spreading speed of network-aware malwares at an early stage of propagation. A malware that spreads faster at the early stage can in general infect most of the vulnerable hosts in a shorter time. The propagation ability of a malware at the early stage is characterized by the *infection rate* [32]. We derive the infection rates of a class of network-aware malwares. We find that the infection rates of random-scanning and network-aware malwares are determined by the uncertainty of the vulnerable-host distribution or the Renyi entropies of different orders. Specifically, a random-scanning malware has the largest uncertainty (*i.e.*, Renyi entropy of order zero), and an optimal importance-scanning malware has the smallest uncertainty (*i.e.*, Renyi entropy with order infinity). Moreover, the infection rates of some real network-aware malwares depend on the non-uniformity factors or the Renyi entropy of order two. For example, compared with random scanning, localized scanning can increase the infection rate by nearly a non-uniformity factor. Therefore, the infection rates of malware-scanning algorithms are characterized by the Renyi entropies, relating the efficiency of a randomized scanning algorithm with the uncertainty on a non-uniform vulnerable-host distribution. These analytical results on the relationships between vulnerable-host distributions and network-aware malware spreading ability are validated by simulation.

Finally, we study new challenges to malware defenses posed by network-aware malwares. Using the non-uniformity factor, we show quantitatively that the host-based defense strategies, such as proactive protection [3] and virus throttling [27], should be deployed at almost all hosts to slow down network-aware malwares at the early stage. A partial deployment may invalidate such host-based defenses. Moreover, we demonstrate that the infection rate of a network-aware malware in the IPv6 Internet can be comparable to that of the Code Red v2 worm in the IPv4 Internet. This shows that having a much larger IP-address space would not alleviate malware spreading.

The remainder of this paper is structured as follows. Section II provides the background on information theory. Section III presents our collected data sets. Section IV introduces a new metric called the non-uniformity factor and compares this metric to the Shannon entropy. Sections V and VI characterize the spreading ability of network-aware malwares through theoretical analyses and simulations. Section VII further studies the effectiveness of defense strategies on network-aware malwares. Section VIII concludes this paper.

II. Renyi Entropy

An entropy is a measure of the average information uncertainty of a random variable [13]. A general entropy, called the Renyi entropy [23], [4], is defined as

$$H_q(X) = \frac{1}{1-q} \log_2 \sum_{x \in \mathcal{X}} (P_X(x))^q, \text{ for } q \neq 1, \quad (1)$$

where the random variable X is with probability distribution P_X and alphabet $\mathcal{X}$. The well-known Shannon entropy is a special case of the Renyi entropy, *i.e.*,

$$H(X) = \lim_{q \to 1} H_q(X). \quad (2)$$

It is noted that

$$H_0(X) = \log_2 |\mathcal{X}|, \quad (3)$$

where $|\mathcal{X}|$ is the alphabet size; and

$$H_\infty(X) = -\log_2 \max_{x \in \mathcal{X}} P_X(x), \quad (4)$$

where $H_\infty(X)$ is a result from $\lim_{q\to\infty} H_q(X)$ and is called the min-entropy of X. In this paper, moreover, we are also interested in the Renyi entropy of order two, *i.e.*,

$$H_2(X) = -\log_2 \sum_{x\in\mathcal{X}} (P_X(x))^2. \quad (5)$$

Comparing $H_0(X)$, $H(X)$, $H_2(X)$, and $H_\infty(X)$, we have the following theorem that has been proved in [22], [4].

Theorem 1:

$$H_0(X) \geq H(X) \geq H_2(X) \geq H_\infty(X) \quad (6)$$

with equality *iff* X is uniformly distributed over $\mathcal{X}$.

III. Measurements and Vulnerable-Host Distributions

We begin our study by considering how significant the unevenness of vulnerable-host distributions is. We use five large data sets to obtain empirical vulnerable-host distributions.

A. Measurements

DShield (D1): DShield provides the information of vulnerable hosts by aggregating logs from more than 1,600 intrusion detection systems (IDSes) distributed throughout the Internet [35]. We further focus on the following ports that were attacked by worms: 80 (HTTP), 135 (DCE/RPC), 445 (NetBIOS/SMB), 1023 (FTP servers and the remote shell attacked by W32.Sasser.E.Worm), and 6129 (DameWare).

iSinks (P1 and C1): Two unused address space monitors run the *iSink* system [29]. The monitors record the unwanted traffic arriving at the unused address spaces that include a Class A network (referred to as "Provider" or P1) and two Class B networks at the campus of the University of Wisconsin (referred to as "Campus" or C1) [1].

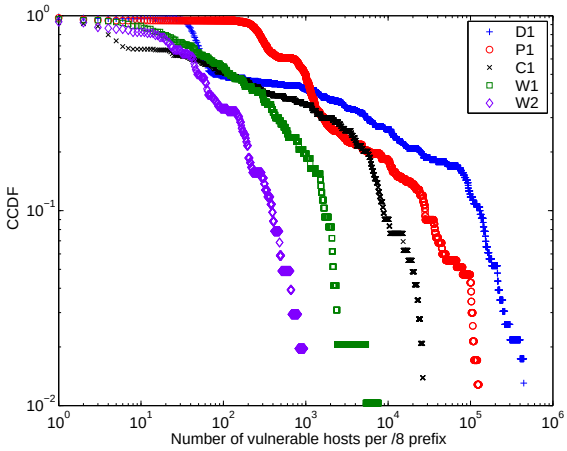
Witty-worm victims (W1): A list of Witty-worm victims is provided by CAIDA [25]. CAIDA used a network telescope with approximate 2^{24} IP addresses to log the traffic of Witty-worm victims that are Internet security systems (ISS) products.

Web-server list (W2): The IP addresses of Web servers were collected through UROULETTE [38]. UROULETTE provides a random uniform resource locator (URL) generator to obtain a list of IP addresses of Web servers.

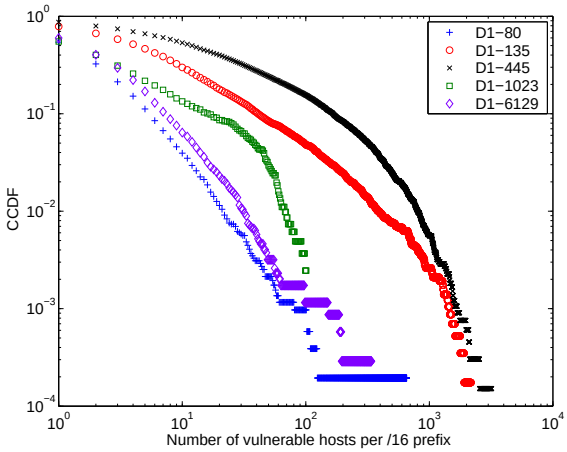
The first three data sets (D1, P1, and C1) were collected over a seven-day period from 12/10/2004 to 12/16/2004 and have been studied in [1] to demonstrate the bursty and spatially inhomogeneous distribution of malicious source IP addresses. The last two data sets (W1 and W2) have been used in our prior work [8] to show the virulence of importance-scanning malwares. The summary of our data sets is given in Table I.

TABLE I
Summary of the Data Sets.

Trace	Description	Number of unique source addresses
D1	DShield	7,694,291
P1	Provider	2,355,150
C1	Campus	448,894
W1	Witty-worm victims	55,909
W2	Web servers	13,866



(a) Population distributions in /8 subnets.



(b) Population distributions in /16 subnets.

Fig. 1. CCDF of collected data sets.

B. Vulnerable-Host Distributions

To obtain vulnerable-host group distributions, we use the classless inter-domain routing (CIDR) notation [17]. The Internet is partitioned into subnets according to the first l bits of IP addresses, *i.e.*, /l prefixes or /l subnets. In this division, there are 2^l subnets, and each subnet contains 2^{32-l} addresses, where $l \in \{0, 1, \cdots, 32\}$. For example, when $l = 8$, the Internet is grouped into Class A subnets (*i.e.*, /8 subnets); when $l = 16$, the Internet is partitioned into Class B subnets (*i.e.*, /16 subnets).

We plot the complementary cumulative distribution functions (CCDF) of our collected data sets in /8 and /16 subnets in Figure 1 in log-log scales. CCDF is defined as the fraction of the subnets with the number of hosts greater than a given value. Figure 1(a) shows population distributions in /8 subnets for D1, P1, C1, W1, and W2, whereas Figure 1(b) exhibits host distributions in /16 subnets for D1 with different ports (80, 135, 445, 1023, and 6129). Figure 1 demonstrates a wide range of populations, indicating highly inhomogeneous address structures. Specifically, the relatively straight lines, such as W2 and D1-135, imply that vulnerable hosts follow a power law distribution. Similar observations were given in [19], [18], [20], [21], [1], [8], [9], [11], [28].

IV. Non-Uniformity Factor

In this section, we derive a simple metric, called the *non-uniformity factor*, to quantify the vulnerability, *i.e.*, the non-uniformity of a vulnerable-host distribution. We show that the non-uniformity factor is a function of Renyi entropies. We then compare the non-uniformity factor with the well-known Shannon entropy.

A. Definition and Property

We consider aggregated vulnerable-host distributions. Let l ($0 \leq l \leq 32$) be an aggregation level of IP addresses as defined in Section III-B. For a given l, let $N_i^{(l)}$ be the number of vulnerable hosts in /l subnet i, where $1 \leq i \leq 2^l$. Let N be the total number of vulnerable hosts, where $N = \sum_{i=1}^{2^l} N_i^{(l)}$. Let $p_g^{(l)}(i)$ ($i = 1, 2, \cdots, 2^l$) be the probability that a randomly chosen vulnerable host is in the i-th /l subnet. Then $p_g^{(l)}(i) = \frac{N_i^{(l)}}{N}$; and $\sum_{i=1}^{2^l} p_g^{(l)}(i) = 1$. Thus, $p_g^{(l)}(i)$'s denote the group distribution of vulnerable hosts in /l subnets.

Definition: The *non-uniformity factor* in /l subnets is defined as

$$\beta^{(l)} = 2^l \sum_{i=1}^{2^l} \left(p_g^{(l)}(i) \right)^2. \tag{7}$$

Note that such a definition is not *arbitrary*. In the next section, $\beta^{(l)}$ is used to unify the analytical results on the infection speeds of different malware-scanning strategies.

One property of $\beta^{(l)}$ is that

$$\beta^{(l)} \geq \left(\sum_{i=1}^{2^l} p_g^{(l)}(i) \right)^2 = 1. \tag{8}$$

The above inequality is derived by the Cauchy-Schwarz inequality. The equality holds if and only if $p_g^{(l)}(i) = 2^{-l}$, for $i = 1, 2, \cdots, 2^l$. In other words, when the vulnerable-host distribution is uniform, $\beta^{(l)}$ achieves the minimum value 1. On the other hand, since $p_g^{(l)}(i) \geq 0$,

$$\beta^{(l)} \leq 2^l \cdot \left(\sum_{i=1}^{2^l} p_g^{(l)}(i) \right)^2 = 2^l. \tag{9}$$

The equality holds when $p_g^{(l)}(j) = 1$ for some j and $p_g^{(l)}(i) = 0$, $i \neq j$, *i.e.*, all vulnerable hosts concentrate on one subnet. This means that when the vulnerable-host distribution is extremely non-uniform, $\beta^{(l)}$ obtains the maximum value 2^l. Moreover, assuming that vulnerable hosts are uniformly distributed in the first n ($1 \leq n \leq 2^l$) /l subnets, *i.e.*, $p_g^{(l)}(i) = \frac{1}{n}$, $i = 1, 2, \cdots, n$; and $p_g^{(l)}(i) = 0$, $i = n+1, \cdots, 2^l$, we have $\beta^{(l)} = \frac{2^l}{n}$. Therefore, $\beta^{(l)}$ characterizes the non-uniformity of a vulnerable-host distribution. A larger non-uniformity factor reflects a more non-uniform distribution of vulnerable hosts.

The non-uniformity factor is indeed related to a distance between a vulnerable-host distribution and a uniform distribution. Consider L_2 distance between $p_g^{(l)}(i)$ and the uniform distribution $p_u^{(l)}(i) = \frac{1}{2^l}$ for $i = 1, 2, \cdots, 2^l$, where

$$||p_g^{(l)} - p_u^{(l)}||_2{}^2 = \sum_{i=1}^{2^l} \left(p_g^{(l)}(i) - \frac{1}{2^l} \right)^2, \tag{10}$$

which leads to

$$\beta^{(l)} = 2^l \cdot ||p_g^{(l)} - p_u^{(l)}||_2{}^2 + 1. \tag{11}$$

For a given l, 2^l is a constant and is the size of the sample space of /l subnets. Hence, $\beta^{(l)}$ essentially measures the deviation of a vulnerable-host group distribution from a uniform distribution for /l subnets.

How does $\beta^{(l)}$ vary with l? When $l = 0$, $\beta^{(0)} = 1$. In the other extreme where $l = 32$,

$$p_g^{(32)}(i) = \begin{cases} \frac{1}{N}, & \text{address } i \text{ is vulnerable to the malware;} \\ 0, & \text{otherwise,} \end{cases} \tag{12}$$

which results in $\beta^{(32)} = \frac{2^{32}}{N}$. More importantly, the ratio of $\beta^{(l)}$ to $\beta^{(l-1)}$ lies between 1 and 2, as shown below.

Theorem 2:

$$\beta^{(l-1)} \leq \beta^{(l)} \leq 2\beta^{(l-1)}, \tag{13}$$

where $l \in \{1, \cdots, 32\}$.

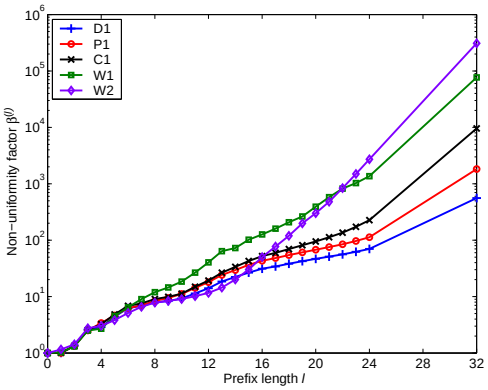
The proof of Theorem 2 can be found in [7]. An intuitive explanation of this theorem is as follows. For /l and /$(l-1)$ subnets, group i ($i = 1, 2, \cdots, 2^{l-1}$) of /$(l-1)$ subnets is partitioned into groups $2i-1$ and $2i$ of /l subnets. If vulnerable hosts in each group of /$(l-1)$ subnets are equally divided into the groups of /l subnets (*i.e.*, $p_g^{(l)}(2i-1) = p_g^{(l)}(2i) = \frac{1}{2} p_g^{(l-1)}(i)$, $\forall i$), then $\beta^{(l)} = \beta^{(l-1)}$. If the division of vulnerable hosts is extremely uneven for all groups (*i.e.*, $p_g^{(l)}(2i-1) = 0$ or $p_g^{(l)}(2i) = 0$, $\forall i$), then $\beta^{(l)} = 2\beta^{(l-1)}$. Excluding these two extreme cases, $\beta^{(l-1)} < \beta^{(l)} < 2\beta^{(l-1)}$. Therefore, $\beta^{(l)}$ is a non-decreasing function of l. Moreover, the ratio of $\beta^{(l)}$ to $\beta^{(l-1)}$ reflects how unevenly vulnerable hosts in each /$(l-1)$ subnet distribute between two groups of /l subnets. This ratio is indicated by the slope of $\beta^{(l)}$ in a $\beta^{(l)} \sim l$ figure.

B. Estimated Non-Uniformity Factor

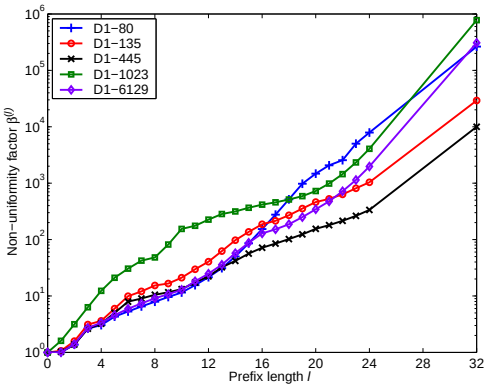
Figure 2 shows the non-uniformity factors estimated from our data sets. The non-uniformity factors increase with the prefix length for all data sets. Note that the y-axis is in a *log* scale. Thus, $\beta^{(l)}$ increases *almost exponentially* with a wide range of l. To gain intuition on how large $\beta^{(l)}$ can be, $\beta^{(8)}$ and $\beta^{(16)}$ are summarized for all data sets in Table II. It can be observed that $\beta^{(8)}$ and $\beta^{(16)}$ have large values, indicating the significant unevenness of collected distributions.

TABLE II
$\beta^{(8)}$ AND $\beta^{(16)}$ OF COLLECTED DISTRIBUTIONS.

$\beta^{(l)}$	D1	P1	C1	W1	W2
$\beta^{(8)}$	7.9	8.4	9.0	12.0	7.8
$\beta^{(16)}$	31.2	43.2	52.2	126.7	50.2
$\beta^{(l)}$	D1-80	D1-135	D1-445	D1-1023	D1-6129
$\beta^{(8)}$	7.9	15.4	10.5	48.2	9.1
$\beta^{(16)}$	153.3	186.6	71.7	416.3	128.9

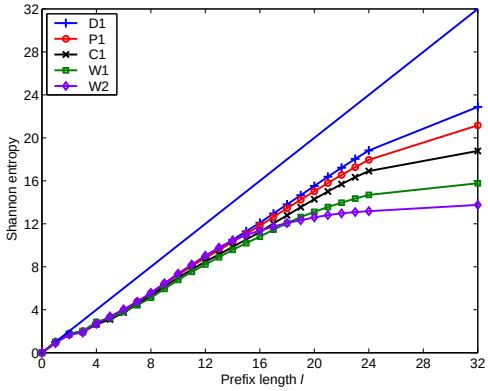


(a) Five data sets.

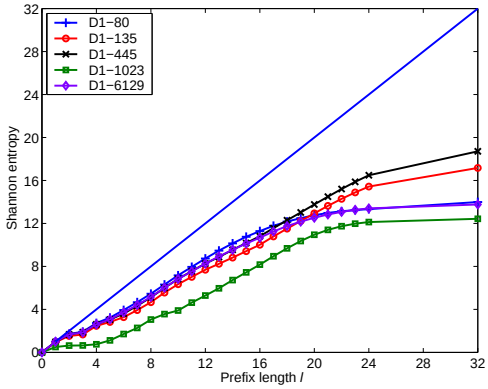


(b) D1 with different ports.

Fig. 2. Non-uniformity factors of collected data sets. Note that the y-axis uses a *log* scale.



(a) Five data sets.



(b) D1 with different ports.

Fig. 3. Shannon entropies of collected data sets.

C. Shannon Entropy

To further understand the importance of the non-uniformity factor, we now turn our attention on the Shannon entropy for comparison. It is well-known that the Shannon entropy can be used to measure the non-uniformity of a probability distribution [13]. The Shannon entropy in /l subnets is defined as

$$H\left(P^{(l)}\right) = -\sum_{i=1}^{2^l} p_g^{(l)}(i) \log_2 p_g^{(l)}(i), \tag{14}$$

where $P^{(l)} = \{p_g^{(l)}(1), p_g^{(l)}(2), \cdots, p_g^{(l)}(2^l)\}$.

It is noted that

$$0 \leq H\left(P^{(l)}\right) \leq l. \tag{15}$$

If a distribution is uniform, $H\left(P^{(l)}\right)$ achieves the maximum value l. On the other hand, if a distribution is extremely non-uniform, *e.g.*, all vulnerable hosts concentrate on one subnet, $H\left(P^{(l)}\right)$ obtains the minimum value 0.

Furthermore, we compare $H\left(P^{(l)}\right)$ with $H\left(P^{(l-1)}\right)$ and find that their difference is between 0 and 1, as shown in the following theorem.

Theorem 3:

$$H\left(P^{(l-1)}\right) \leq H\left(P^{(l)}\right) \leq H\left(P^{(l-1)}\right) + 1, \tag{16}$$

where $l \in \{1, \cdots, 32\}$.

The proof of Theorem 3 can be found in [7]. Figure 3 shows the Shannon entropies of our empirical distributions from the data sets. $H\left(P^{(l)}\right) = l$ is denoted by the diagonal line in the figure. It can be seen that the curves for our collected data sets are similar.

D. Non-Uniformity Factor, Renyi Entropy, and Shannon Entropy

To quantify the difference between the non-uniformity factor and the Shannon entropy, we note that the non-uniformity factor directly relates to the Renyi entropies of order two and zero, as shown in the following equation:

$$\beta^{(l)} = 2^{l - H_2\left(P^{(l)}\right)} = 2^{H_0\left(P^{(l)}\right) - H_2\left(P^{(l)}\right)}, \tag{17}$$

where $P^{(l)} = \{p_g^{(l)}(1), p_g^{(l)}(2), \cdots, p_g^{(l)}(2^l)\}$. Therefore, the non-uniformity factor is essentially a Renyi entropy. Hence, the non-uniformity factor corresponds to a generalized entropy of order 2, whereas the Shannon entropy is the generalized entropy of order 1.

Why do we choose the non-uniformity factor rather than the Shannon entropy? We compare these two metrics in terms of characterizing a vulnerable-host distribution and find the following fundamental differences. First, in Figure 2, when a distribution is uniform, $\beta^{(l)} = 1$. Hence, the distance between $\beta^{(l)}$ and the horizontal access 1 measures the degree of unevenness. Similarly, the distance between $H\left(P^{(l)}\right)$ and 0 in Figure 3 reflects how uniform a distribution is. A larger

$H\left(P^{(l)}\right)$ corresponds to a more even distribution, whereas a larger $\beta^{(l)}$ corresponds to a more non-uniform distribution. In addition, if two distributions have different prefix lengths, we can directly apply the non-uniformity factor (or the Shannon entropy) to compare the unevenness (or evenness) between them. Therefore, the Shanon entropy provides a better measure for describing the evenness of a distribution, while the non-uniformity factor gives a better metric for characterizing the non-uniformity of a distribution. Second, from Theorem 1 and Equation (17), we have $\beta^{(l)} > 2^{l-H\left(P^{(l)}\right)}$ when the non-zero $p_g^{(l)}$'s are not all equal. Meanwhile, evidenced by Figures 2 and 3, the non-uniformity factor magnifies the unevenness of a distribution. Therefore, $\beta^{(l)}$ depends more on the large $p_g^{(l)}$'s. Finally, a more important aspect of using the non-uniformity factor is its relation to some real randomized epidemic algorithms (*e.g.*, localized scanning and sequential scanning). Such a relationship cannot be drawn using the Shannon entropy but can be related to Renyi entropies and thus information bits.

V. Information Bits and Network-Aware Malware Spreading

In this section, we explicitly relate the speed of malware propagation with the information bits extracted by random-scanning and network-aware malwares.

A. Collision Probability, Uncertainty, and Information Bits

Now consider a malware or an adversary that searches for vulnerable hosts. An adversary often does not have the complete knowledge on the locations of vulnerable hosts. Hence, malwares make a random guess on which $/l$ subnets are likely to have most vulnerable hosts. This results in a class of randomized epidemic algorithms for malwares to scan subnets. Let $q_g^{(l)}(i)$ $(i = 1, 2, \cdots, 2^l)$ be the probability that a malware scans the i-th $/l$ subnet. Thus, $q_g^{(l)}(i)$'s characterize the virulence of randomized epidemic scanning algorithms.

We then define three important quantities: the collision probability, uncertainty, and information bits. Consider a randomly chosen vulnerable host Y. The probability that this host is in the $/l$ subnet i is $p_g^{(l)}(i)$. Imagine that a malware guesses which subnet host Y belongs to and chooses a target $/l$ subnet i with the probability $q_g^{(l)}(i) = p_g^{(l)}(i)$. Thus, the probability for the malware to make a correct guess is $p_h = \sum_{i=1}^{2^l}\left(p_g^{(l)}(i)\right)^2$. This probability is called the *collision probability* and is defined in [4]. Such a probability of success is reflected in our designed non-uniformity factor and corresponds to a scenario that the malware knows the underlying vulnerable-host group distribution. Intuitively, the more non-uniform a vulnerable-host distribution is, the larger the probability of success is, *i.e.*, the easier it is for a scan to hit a vulnerable host, the more vulnerable the network is, and the less uncertainty there is in a vulnerable-host distribution.

We now extend the concept of the collision probability and define p_h as the probability that a malware scan hits a subnet where a randomly chosen vulnerable host locates, *i.e.*,

$$p_h = \sum_{i=1}^{2^l} p_g^{(l)}(i) q_g^{(l)}(i). \tag{18}$$

Then two important quantities can be defined:

- $-\log_2 p_h$ as the *uncertainty* exhibited by the vulnerable-host distribution $p_g^{(l)}(i)$'s.
- $H_0\left(P^{(l)}\right) - [-\log_2 p_h]$ as the number of *information bits* extracted by a randomized epidemic scanning algorithm using $q_g^{(l)}(i)$'s.

Here $-\log_2 p_h$ is regarded as the uncertainty on the vulnerable-host distribution in view of the malware, similar to self-information [41]. For example, if a malware has no information about a vulnerable-host distribution and has to use random scanning, it has the largest uncertainty $H_0\left(P^{(l)}\right) = l$ and extracts zero information bit from the distribution. Likewise, the number of information bits extracted by a network-aware malware can be measured as the reduction of the uncertainty and thus equals to $H_0\left(P^{(l)}\right) - [-\log_2 p_h]$. For example, $\log_2 \beta^{(l)} = H_0\left(P^{(l)}\right) - H_2\left(P^{(l)}\right)$ is the information bits extractable by an adversary that chooses $q_g^{(l)}(i) = p_g^{(l)}(i)$.

B. Infection Rate

We characterize the spread of a network-aware malware at an early stage by deriving the infection rate. The infection rate, denoted by α, is defined as the average number of vulnerable hosts that can be infected per unit time by one infected host during the early stage of malware propagation [32]. The infection rate is an important metric for studying network-aware malware spreading ability for two reasons. First, since the number of infected hosts increases exponentially with the rate $1 + \alpha$ during the early stage, a malware with a higher infection rate can spread much faster at the beginning and thus infect a large number of hosts in a shorter time [8]. Second, while it is generally difficult to derive a close-form solution for dynamic malware propagation, we can obtain a close-form expression of the infection rate for different malware scanning methods.

Let R denote the (random) number of vulnerable hosts that can be infected per unit time by one infected host during the early stage of malware propagation. The infection rate is the expected value of R, *i.e.*, $\alpha = E[R]$. Let s be the scanning rate or the number of scans sent by an infected host per unit time, N be the number of vulnerable hosts, and Ω be the scanning space (*i.e.*, $\Omega = 2^{32}$).

C. Random Scanning

Random scanning (RS) has been used by most real worms and is the simplest randomized epidemic algorithm. For RS, an infected host sends out s random scans per unit time, and the probability that one scan hits a vulnerable host is $\frac{N}{\Omega}$. Thus, R follows a Binomial distribution B(s, $\frac{N}{\Omega}$)[1], resulting in

$$\alpha_{RS} = E[R] = \frac{sN}{\Omega}. \tag{19}$$

[1]In our derivation, we ignore the dependency of the events that different scans hit the same target at the early stage of malware propagation.

Another way to derive the infection rate of RS is as follows. Consider a randomly chosen vulnerable host Y. The probability that this host is in the /l subnet i is $p_g^{(l)}(i)$. An RS malware can make a successful guess on which subnet host Y belongs to with collision probability $p_h = \frac{1}{2^l} = 2^{-H_0\left(P^{(l)}\right)}$. A scan from the RS malware can be regarded as first selecting the /l subnet randomly and then choosing the host in the subnet at random. Hence the probability for the malware to hit host Y is $\frac{1}{2^{32-l}} \cdot 2^{-H_0\left(P^{(l)}\right)} = 2^{-H_0\left(P^{(l)}\right)-(32-l)}$. Since there are N vulnerable hosts, the probability for a malware to hit a vulnerable host is $N \cdot 2^{-H_0\left(P^{(l)}\right)-(32-l)}$. Thus, R follows a Binomial distribution B(s, $N \cdot 2^{-H_0\left(P^{(l)}\right)-(32-l)}$), resulting in

$$\alpha_{RS} = E[R] = \frac{sN}{2^{32-l}} \cdot 2^{-H_0\left(P^{(l)}\right)}. \tag{20}$$

Therefore, for the RS malware, the uncertainty on the vulnerable-host distribution is $-\log_2 p_h = H_0\left(P^{(l)}\right)$, *i.e.*, the number of information bits on vulnerable hosts extracted by RS is $H_0\left(P^{(l)}\right) - H_0\left(P^{(l)}\right) = 0$.

D. Optimal Importance Scanning

Importance scanning (IS) exploits the non-uniform distribution of vulnerable hosts. In our prior work, we show that IS corresponds to the worst-case malware attacks given a vulnerable-host distribution [8]. In this work, we derive the infection rate of IS and relate that to information bits. An infected host scans /l subnet i with the probability $q_g^{(l)}(i)$. Consider a randomly chosen vulnerable host Y. The probability for this host being in /l subnet i is $p_g^{(l)}(i)$. An IS malware can make a successful guess on which subnet host Y belongs to with collision probability $p_h = \sum_{i=1}^{2^l} p_g^{(l)}(i) q_g^{(l)}(i)$. Thus, the probability for the malware to hit the host Y is $\frac{1}{2^{32-l}} \sum_{i=1}^{2^l} p_g^{(l)}(i) q_g^{(l)}(i)$. Similar to RS, R of IS follows a Binomial distribution B(s, $\frac{N}{2^{32-l}} \sum_{i=1}^{2^l} p_g^{(l)}(i) q_g^{(l)}(i)$), which leads to[2]

$$\alpha_{IS} = E[R] = \frac{sN}{2^{32-l}} \sum_{i=1}^{2^l} p_g^{(l)}(i) q_g^{(l)}(i). \tag{21}$$

Therefore, the uncertainty of the vulnerable-host distribution for an IS malware is $-\log_2 \sum_{i=1}^{2^l} p_g^{(l)}(i) q_g^{(l)}(i)$, and the number of information bits on vulnerable hosts extracted by IS is $H_0\left(P^{(l)}\right) + \log_2 \sum_{i=1}^{2^l} p_g^{(l)}(i) q_g^{(l)}(i)$.

Note that importance scanning can choose $q_g^{(l)}(i)$'s to maximize the infection rate, resulting in a "worst-case" scenario for defenders or /l optimal IS (/l OPT_IS) for attackers [8], *i.e.*,

$$\alpha_{OPT\_IS}^{(l)} = \max\{\alpha_{IS}\} = \frac{sN}{2^{32-l}} \max_i \{p_g^{(l)}(i)\}. \tag{22}$$

That is,

$$\alpha_{OPT\_IS}^{(l)} = \frac{sN}{2^{32-l}} 2^{-H_\infty\left(P^{(l)}\right)} = \alpha_{RS} \cdot 2^{H_0\left(P^{(l)}\right) - H_\infty\left(P^{(l)}\right)}. \tag{23}$$

Therefore, the uncertainty on the vulnerable-host distribution for /l OPT_IS is $H_\infty\left(P^{(l)}\right)$; and the number of information bits on vulnerable hosts extracted by this scanning method is $H_0\left(P^{(l)}\right) - H_\infty\left(P^{(l)}\right)$.

[2]The same result was derived in [8] but by a different approach.

E. Suboptimal Importance Scanning

As shown in our prior work [8], the optimal IS is difficult to implement in reality. Hence we consider a special case of IS, where the group scanning distribution $q_g^{(l)}(i)$ is chosen to be proportional to the number of vulnerable hosts in group i, *i.e.*, $q_g^{(l)}(i) = p_g^{(l)}(i)$. This results in suboptimal IS [8], called /l IS. Thus, the infection rate derived in this work is

$$\alpha_{IS}^{(l)} = \frac{sN}{2^{32-l}} \sum_{i=1}^{2^l} \left(p_g(i)\right)^2 = \frac{sN}{2^{32-l}} \cdot 2^{-H_2\left(P^{(l)}\right)} = \alpha_{RS} \cdot \beta^{(l)}. \tag{24}$$

Therefore, the uncertainty on the vulnerable-host distribution for /l IS is $H_2\left(P^{(l)}\right)$; and the corresponding number of information bits extracted is $H_0\left(P^{(l)}\right) - H_2\left(P^{(l)}\right)$ or $\log_2 \beta^{(l)}$. Moreover, compared with RS, this /l IS can increase the infection rate by a factor of $\beta^{(l)}$. On the other hand, RS can be regarded as a special case of suboptimal IS when $l = 0$.

F. Localized Scanning

Localized scanning (LS) has been used by such real worms as Code Red II and Nimda. LS is a simpler randomized algorithm that utilizes only a few parameters rather than an underlying vulnerable-host group distribution. We first consider a simplified version of LS, called /l LS, which scans the Internet as follows:

- p_a ($0 \le p_a \le 1$) of the time, an address with the same first l bits is chosen as the target,
- $1 - p_a$ of the time, an address is chosen randomly from an entire IP address space.

Hence, LS is an oblivious yet local randomized algorithm where the locality is characterized by parameter p_a. Assume that an initially infected host is randomly chosen from the vulnerable hosts. Let I_g denote the subnet where an initially infected host locates. Thus, $P(I_g = i) = p_g^{(l)}(i)$, where $i = 1, 2, \cdots, 2^l$. For an infected host located in /l subnet i, a scan from this host probes globally with the probability of $1 - p_a$ and hits /l subnet j ($j \neq i$) with the likelihood of $\frac{1-p_a}{2^l}$. Thus, the group scanning distribution for this host is

$$q_g^{(l)}(j) = \begin{cases} p_a + \frac{1-p_a}{2^l}, & \text{if } j = i; \\ \frac{1-p_a}{2^l}, & \text{otherwise,} \end{cases} \tag{25}$$

where $j = 1, 2, \cdots, 2^l$. Given the subnet location of an initially infected host (*i.e.*, /l subnet i), the *conditional* collision probability or the probability for a malware scan to hit a subnet where a randomly chosen vulnerable host locates can be calculated based on Equation (18), *i.e.*,

$$p_h(i) = p_a p_g^{(l)}(i) + \frac{1 - p_a}{2^l}. \tag{26}$$

Therefore, we can compute the collision probability as

$$p_h = \sum_{i=1}^{2^l} P(I_g = i) p_h(i) = p_a \sum_{i=1}^{2^l} p_g^2(i) + \frac{1 - p_a}{2^l}, \tag{27}$$

resulting in

$$\alpha_{LS}^{(l)} = \alpha_{RS}\left(1 - p_a + p_a\beta^{(l)}\right). \quad (28)$$

Therefore, the number of information bits extracted from the vulnerable-host distribution by /l LS is $\log_2\{1-p_a+p_a\beta^{(l)}\}$, which is between 0 and $H_0\left(P^{(l)}\right) - H_2\left(P^{(l)}\right)$.

Moreover, since $\beta^{(l)} > 1$ ($\beta^{(l)} = 1$ is for a uniform distribution and is excluded here), $\alpha_{LS}^{(l)}$ increases with respect to p_a. Specifically, when $p_a \to 1$, $\alpha_{LS}^{(l)} \to \alpha_{RS}\beta^{(l)} = \alpha_{IS}^{(l)}$. Thus, /$l$ LS has an infection rate comparable to that of /l IS. In reality, p_a cannot be 1. This is because an LS malware begins spreading from one infected host that is specifically in a subnet; and if $p_a = 1$, the malware can never spread out of this subnet. Therefore, we expect that the optimal value of p_a should be large but not 1.

Next, we further consider another LS, called two-level LS (2LLS), which has been used by the Code Red II and Nimda worms [34], [33]. 2LLS scans the Internet as follows:

- p_b ($0 \le p_b \le 1$) of the time, an address with the same first byte is chosen as the target,
- p_c ($0 \le p_c \le 1 - p_b$) of the time, an address with the same first two bytes is chosen as the target,
- $1 - p_b - p_c$ of the time, a random address is chosen.

For example, for the Code Red II worm, $p_b = 0.5$ and $p_c = 0.375$ [34]; for the Nimda worm, $p_b = 0.25$ and $p_c = 0.5$ [33]. Using the similar analysis for /l LS, we can derive the infection rate of 2LLS:

$$\alpha_{2LLS} = \alpha_{RS}\left(1 - p_b - p_c + p_b\beta^{(8)} + p_c\beta^{(16)}\right). \quad (29)$$

Similarly, the number of information bits extracted from the vulnerable-host distribution by the 2LLS malware is $\log_2\{1 - p_b - p_c + p_b\beta^{(8)} + p_c\beta^{(16)}\}$, which is between 0 and $H_0\left(P^{(16)}\right) - H_2\left(P^{(16)}\right)$.

Since $\beta^{(16)} \ge \beta^{(8)} \ge 1$ from Theorem 2, α_{2LLS} holds or increases when both p_b and p_c increase. Specially, when $p_c \to 1$, $\alpha_{2LLS} \to \alpha_{RS}\beta^{(16)} = \alpha_{IS}^{(16)}$. Thus, 2LLS has an infection rate comparable to that of /16 IS. Moreover, $\beta^{(16)}$ is much larger than $\beta^{(8)}$ as shown in Table II for the collected distributions. Hence, p_c is more significant than p_b for 2LLS.

G. Modified Sequential Scanning

The Blaster worm is a real malware that exploits sequential scanning in combination with localized scanning. A *sequential-scanning* malware studied in [31], [16] begins to scan addresses sequentially from a randomly chosen starting IP address and has a similar propagation speed as a random-scanning malware. The Blaster worm selects its starting point locally as the first address of its Class C subnet with probability 0.4 [36], [31]. To analyze the effect of sequential scanning, we do not incorporate localized scanning. Specifically, we consider our /l modified sequential-scanning (MSS) malware, which scans the Internet as follows:

- Newly infected host A begins with random scanning until finding a vulnerable host with address B.
- After infecting the target B, host A continues to sequentially scan IP addresses $B+1$, $B+2$, $\cdots$ (or $B-1$, $B-2$, $\cdots$) in the /l subnet where B locates.

Such a sequential malware-scanning strategy is in a similar spirit to the *nearest neighbor rule*, which is widely used in pattern classification [12]. The basic idea is that if the vulnerable hosts are clustered, the neighbor of a vulnerable host is likely to be vulnerable also.

Such a /l MSS malware has two stages. In the first stage (called MSS_1), the malware uses random scanning and has an infection rate of α_{RS}, *i.e.*, $\alpha_{MSS\_1} = \alpha_{RS}$. In the second stage (called MSS_2), the malware scans sequentially in a /l subnet. The fist l bits of a target address are fixed, whereas the last $32-l$ bits of the address are generated additively or subtractively and are modulated by 2^{32-l}. Let I_g denote the sunbet where B locates. Thus, $P(I_g = i) = p_g^{(l)}(i)$, where $i = 1, 2, \cdots, 2^l$. Since an MSS_2 malware scans only the subnet where B locates, the conditional collision probability $p_h(i) = p_g^{(l)}(i)$, which leads to $p_h = \sum_{i=1}^{2^l}\left(p_g^{(l)}(i)\right)^2$. Thus, the infection rate is

$$\alpha_{MSS\_2} = \alpha_{RS} \cdot \beta^{(l)}. \quad (30)$$

Therefore, the uncertainty on vulnerable hosts for /l MSS is between $H_0\left(P^{(l)}\right)$ and $H_2\left(P^{(l)}\right)$. Moreover, the infection rate of /l MSS is between α_{RS} and $\alpha_{RS}\beta^{(l)}$.

H. Summary

The information bits extractable by the network-aware malwares relates the entropy on a vulnerable-host distribution and the malware propagation speed, as shown in the following equation:

$$\text{Information bits} = H_0\left(P^{(l)}\right) - [-\log_2 p_h] = \log_2\left\{\frac{\alpha}{\alpha_{RS}}\right\}, \quad (31)$$

where p_h is the collision probability and α is the infection rate of the malware.

When /l subnets are considered, RS has the largest uncertainty $H_0\left(P^{(l)}\right)$, while optimal IS has the smallest uncertainty $H_\infty\left(P^{(l)}\right)$. Moreover, infection rates of all three network-aware malwares (suboptimal IS, LS, and MSS) can be far larger than that of an RS malware, depending on the non-uniformity factors (*i.e.*, $\beta^{(l)}$) or the Renyi entropy in the order of two (*i.e.*, $H_2\left(P^{(l)}\right)$). The infection rates of all these scanning algorithms are characterized by the Renyi entropies, relating the efficiency of a randomized scanning algorithm with the information bits in a vulnerable-host distribution.

Hence, we relate the information theory with the network-aware malware propagation through the Renyi entropy. The uncertainty of a vulnerable-host group probability distribution, which is quantified by the Renyi entropy, is important for an attacker to design a network-aware malware. If there is no uncertainty about the distribution of vulnerable hosts (*e.g.*, either all vulnerable hosts are concentrated on a subnet or all information about vulnerable hosts is known), the entropy is minimum, and the malware that uses the information on the distribution can spread fastest by employing the optimal importance scanning. On the other hand, if there is maximum uncertainty (*e.g.*, vulnerable hosts are uniformly distributed), the entropy is maximum. For this case, the best a malware

TABLE III
UNCERTAINTY ON THE VULNERABLE-HOST DISTRIBUTION, INFORMATION BITS, AND INFECTION RATES OF DIFFERENT SCANNING METHODS.

Scanning method	RS	/16 OPT_IS	/16 IS	/16 LS	2LLS	/16 MSS_2
Uncertainty (analytical result)	16	7.9266	10.2940	10.6999	11.1620	10.2940
Information bits (analytical result)	0	8.0734	5.7060	5.3001	4.8380	5.7060
Infection rate (analytical result)	0.0105	2.8152	0.5456	0.4118	0.2989	0.5456
Infection rate (sample mean)	0.0103	2.7745	0.5454	0.4023	0.2942	0.5489
Infection rate (sample variance)	0.0010	0.2597	0.0543	0.2072	0.1053	0.3186

can take an advantage from a uniform distribution is to use random scanning. In general, when an attacker obtains more information about a non-uniform vulnerable-host distribution (*e.g.,* larger l), the resulting malware can spread faster.

VI. SIMULATION AND VALIDATION

We now validate our analytical results through simulations using the collected data sets.

A. Infection Rate

We first focus on validating infection rates. We apply the discrete event simulation to our experiments [24]. Specifically, we simulate the searching process of a malware using different scanning methods at the early stage. We use the C1 data set for the vulnerable-host distribution. Note that the C1 distribution has the non-uniformity factors $\beta^{(8)} = 9.0$ and $\beta^{(16)} = 52.2$, and $\max_i\{p_g^{(l)}(i)\} = 0.0041$. The malware spreads over the C1 distribution with $N = 448,894$ and has a scanning rate $s = 100$. The uncertainty on the vulnerable-host distribution and the information bits extractable for different scanning methods are shown in Table III. The simulation stops when the malware has sent out 10^3 scans for RS, /16 OPT_IS, /16 IS, /16 LS, and 2LLS, and 65,535 scans for /16 MSS_2. Then, we count the number of vulnerable hosts hit by the malware scans and compute the infection rate. The results are averaged over 10^4 runs. Table III compares the simulation results (*i.e.*, sample mean) with the analytical results (*i.e.*, Equations (20), (22), (24), (28), (29), and (30)). Here, a /16 LS malware uses $p_a = 0.75$, whereas a 2LLS malware employs $p_b = 0.25$ and $p_c = 0.5$. We observe that the sample means and the analytical results are almost identical.

We observe that network-aware malwares have much larger infection rates than random-scanning malwares. LS indeed increases the infection rate with nearly a non-uniformity factor and approaches the capacity of suboptimal IS. This is significant as LS only depends on one or two parameters (*i.e.*, p_a for /l LS and p_b, p_c for 2LLS), while IS requires the information of the vulnerable-host distribution. On the other hand, LS has a larger sample variance than IS as indicated by Table III. This implies that the infection speed of an LS malware depends on the location of initially infected hosts. If the LS malware begins spreading from a subnet containing densely populated vulnerable hosts, the malware would spread rapidly. Furthermore, we notice that the MSS malware also has a large infection rate at the second stage, indicating that MSS can indeed exploit the clustering pattern of the distribution. Meanwhile, the large sample variance of the infection rate of MSS_2 reflects that an MSS malware strongly depends on the initially infected hosts. We further compute the infection rate of a /16 MSS malware that includes both random-scanning and sequential-scanning stages. Simulation results are averaged over 10^6 runs and are summarized in Table IV. These results strongly depend on the total number of malware scans. When the number of malware scans is small, an MSS malware behaves similar to a random-scanning malware. When the number of malware scans increases, the MSS malware spends more scans on the second stage and thus has a larger infection rate.

TABLE IV
INFECTION RATES OF A /16 MSS MALWARE.

# of malware scans	10	100	1000	10000	50000
Sample mean	0.0108	0.0190	0.0728	0.2866	0.4298
Sample variance	0.1246	0.1346	0.1659	0.2498	0.2311

B. Dynamic Malware Propagation

An infection rate only characterizes the early stage of malware propagation. We now employ the analytical active worm propagation (AAWP) model and its extensions to characterize the entire spreading process of malwares [6]. Specifically, the spread of RS and IS malwares is implemented as described in [8], whereas the propagation of LS malwares is modeled according to [21]. The parameters that we use to simulate a malware are comparable to those of the Code Red v2 worm. Code Red v2 has a vulnerable population $N = 360,000$ and a scanning rate $s = 358$ per minute [30]. We assume that the malware begins spreading from an initially infected host that is located in the subnet containing the largest number of vulnerable hosts. We show the propagation speeds of network-aware malwares for the same vulnerable-host distribution from data set D1-80. From Section V, we expect that a network-aware malware can spread much faster than an RS malware. Figure 4 demonstrates such an example on a malware that uses different scanning methods. It takes an RS malware 10 hours to infect 99% of vulnerable hosts, whereas a /8 LS malware with $p_a = 0.75$ or a /8 IS malware takes only about 3.5 hours. A /16 LS malware with $p_a = 0.75$ or a 2LLS malware with $p_b = 0.25$ and $p_c = 0.5$ can further reduce the time to 1 hour. A /16 IS malware spreads fastest and takes only 0.5 hour.

VII. EFFECTIVENESS OF DEFENSE STRATEGIES

What are new requirements and challenges for a defense system to slow down the spread of a network-aware malware? We conduct an initial study on the effectiveness of defense strategies through non-uniformity factors.

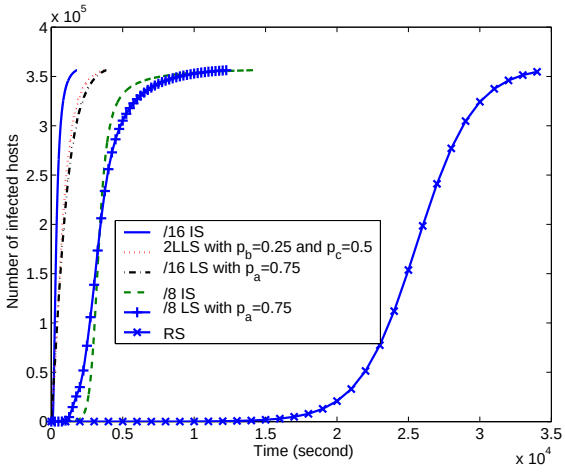


Fig. 4. A network-aware malware spreads over the D1-80 distribution.

A. Host-Based Defenses

Host-based defenses have been widely used for random-scanning malwares. Proactive protection and virus throttling are examples of host-based defense strategies. A *proactive protection* (PP) strategy proactively hardens a system, making it difficult for a malware to exploit vulnerabilities [3]. Techniques used by PP include address-space randomization, pointer encryption, instruction-set randomization, and password protection. Thus, a malware requires multiple trials to compromise a host that implements PP. Specifically, let p $(0 \leq p \leq 1)$ denote the protection probability or the probability that a single malware attempt succeeds in infecting a vulnerable host that implements PP. On the average, a malware should make $\frac{1}{p}$ exploit attempts to compromise the target. We assume that hosts with PP are uniformly deployed in the Internet. Let d $(0 < d \leq 1)$ denote the deployment ratio of the number of hosts with PP to the total number of hosts.

To show the effectiveness of the PP strategy, we consider the infection rate of a /l IS malware. Since now some of the vulnerable hosts implement PP, Equation (24) changes to

$$\begin{aligned} \alpha_{IS}^{(l)} &= \frac{sN}{2^{32-l}} \sum_{i=1}^{2^l} \left[dp \left(p_g^{(l)}(i) \right)^2 + (1-d) \left(p_g^{(l)}(i) \right)^2 \right] \\ &= \alpha_{RS} \beta^{(l)} (1 - d + dp). \end{aligned} \tag{32}$$

To slow down the spread of a suboptimal IS malware to that of a random-scanning malware, $\beta^{(l)}(1-d+dp) \leq 1$, resulting in

$$p \leq \frac{1 - (1-d)\beta^{(l)}}{d\beta^{(l)}}. \tag{33}$$

When PP is fully deployed, *i.e.*, $d = 1$, p can be at most $\frac{1}{\beta^{(l)}}$. On the other hand, if PP provides perfect protection, *i.e.*, $p = 0$, d should be at least $1 - \frac{1}{\beta^{(l)}}$. Therefore, when $\beta^{(l)}$ is large, Inequality (33) presents high requirements for the PP strategy. For example, if $\beta^{(16)} = 50$ (most of $\beta^{(16)}$'s in Table II are larger than this value), $p \leq 0.02$ and $d \geq 0.98$. That is, a PP strategy should be almost fully deployed and provide a nearly perfect protection for a vulnerable host.

We next consider the *virus throttling* (VT) strategy [27]. VT constrains the number of outgoing connections of a host and can thus reduce the scanning rate of an infected host. We find that Equation (32) also holds for this strategy, except that p is the ratio of the scanning rate of infected hosts with VT to that of infected hosts without VT. Therefore, VT also requires to be almost fully deployed for fighting network-aware malwares effectively.

From these two strategies, we have learned that an effective strategy should reduce either α_{RS} or $\beta^{(l)}$. Host-based defenses, however, are limited in such capabilities.

B. IPv6

IPv6 can decrease α_{RS} significantly by increasing the scanning space [32]. But the non-uniformity factor would increase the infection rate if the vulnerable-host distribution is still non-uniform. Hence, an important question is whether IPv6 can counteract network-aware malwares when both α_{RS} and $\beta^{(l)}$ are taken into consideration.

We study this issue by computing the infection rate of a network-aware malware in the IPv6 Internet. As pointed out by [2], a smart malware can first detect some vulnerable hosts in /64 subnets containing many vulnerable hosts, then release to the hosts on the hitlist, and finally spread inside these subnets. Such a malware only scans the local /64 subnet. Thus, we focus on the spreading speed of a network-aware malware in a /64 subnet. From Figure 2, we extrapolate that $\beta^{(32)}$ in the IPv6 Internet can be in the order of 10^5 if hosts are still distributed in a clustered fashion. Using the parameters $N = 10^8$ proposed by [14] and $s = 4,000$ used by the Slammer worm [18], we derive the infection rate of a /32 IS malware in a /64 subnet of the IPv6 Internet: $\alpha_{IS}^{IPv6} = \frac{sN}{2^{64}} \cdot \beta^{(32)} = 2.2 \times 10^{-3}$. α_{IS}^{IPv6} is larger than the infection rate of the Code Red v2 worm in the IPv4 Internet, where $\alpha_{RS}^{CR} = \frac{360{,}000 \times 358/60}{2^{32}} = 5 \times 10^{-4}$. Therefore, IPv6 can only slow down the spread of a network-aware malware to that of a random-scanning malware in IPv4. To defend against the malware effectively, we should further consider how to slow down the increase rate of $\beta^{(l)}$ as l increases when IPv4 is updated to IPv6.

C. Discussions

Defending against network-aware malwares is challenging also due to the unknown causes of vulnerable-host distributions. That is, why the vulnerable-host distribution is highly non-uniform in the IPv4 address space. An answer to this question would involve other studies that are beyond the scope of this work. Nevertheless, we hypothesize several possible reasons. First, no vulnerable hosts can exist in reserved or multicast address ranges [37]. Second, different subnet administrators may make different use of their own IP address space. For example, an administrator may intend to use NATs extensively, whereas another administrator would consider to distribute the global IP addresses first. Third, a subnet intends to have many computers with the same operating systems and applications for easy management [26], [6]. Last, some subnets are more protected than others [1], [21]. Studying these issues may provide insights on new defense strategies, which can be considered as a future direction.

VIII. Conclusions

In this paper, we have derived a simple metric, known as the non-uniformity factor, to quantify an uneven distribution of vulnerable hosts. The non-uniformity factor, shown as a function of the Renyi entropies of order two and zero, better characterizes the uneven feature of a distribution than the Shannon entropy. Moreover, we have drawn a relationship between Renyi entropies and randomized epidemic scanning algorithms. Specifically, we have related the information bits extracted by malwares from a vulnerable-host distribution with the propagation speed of network-aware malwares. Furthermore, we have evaluated the effectiveness of several commonly used defense strategies on network-aware malwares. The host-based defenses, such as proactive protection or virus throttling, require to be almost fully deployed to slow down malware spreading at the early stage. This implies that host-based defenses would be weakened significantly by network-aware scanning. More surprisingly, different from previous findings, we have shown that network-aware malwares can be zero-day malwares in the IPv6 Internet if vulnerable hosts are still clustered. These findings present a significant challenge to malware defenses: Entirely different strategies may be needed for fighting network-aware malwares.

As part of our ongoing work, we plan to study in more depth relationships between information theory and dynamic malware attacks and develop effective detection and defense systems that exploit vulnerable-host distributions.

References

[1] P. Barford, R. Nowak, R. Willett, and V. Yegneswaran, "Toward a model for sources of Internet background radiation," in *Proc. of the Passive and Active Measurement Conference (PAM'06)*, Mar. 2006.

[2] S. M. Bellovin, B. Cheswick, and A. Keromytis, "Worm propagation strategies in an IPv6 Internet," *;login:*, vol. 31, no. 1, Feb. 2006, pp. 70-76.

[3] D. Brumley, L. Liu, P. Poosankam, and D. Song, "Design space and analysis of worm defense strategies," in *ACM Symposium on InformAtion, Computer and Communications Security (ASIACCS)*, Mar. 2006.

[4] C. Cachin, "Entropy measures and unconditional security in cryptography," *Ph.D thesis*, Swiss Federal Institute of Technology, Zurich, 1997.

[5] Z. Chen, C. Chen, and C. Ji, "Understanding localized-scanning worms," in *Proc. of 26th IEEE Int'l Performance Computing and Communications Conf. (IPCCC'07)*, New Orleans, LA, Apr. 2007, pp. 186-193.

[6] Z. Chen, L. Gao, and K. Kwiat, "Modeling the spread of active worms," in *Proc. of INFOCOM'03*, vol. 3, San Francisco, CA, Apr. 2003, pp. 1890-1900.

[7] Z. Chen and C. Ji, "An information-theoretical view of network-aware malware attacks," *technical report, arXiv:0805.0802v2*, 2008 [Online]. Available: http://arxiv.org/abs/0805.0802.

[8] Z. Chen and C. Ji, "Optimal worm-scanning method using vulnerable-host distributions," *International Journal of Security and Networks: Special Issue on Computer and Network Security*, vol. 2, no. 1/2, 2007.

[9] Z. Chen and C. Ji, "Measuring network-aware worm spreading ability," in *Proc. of INFOCOM'07*, Anchorage, AK, May 2007.

[10] Z. Chen and C. Ji, "A self-learning worm using importance scanning," in *Proc. ACM/CCS Workshop on Rapid Malcode (WORM'05)*, Fairfax, VA, Nov. 2005, pp. 22-29.

[11] Z. Chen, C. Ji, and P. Barford, "Spatial-temporal characteristics of malicious sources," in *Proc. of INFOCOM'08 Mini-Conference*, Phoenix, AZ, Apr. 2008.

[12] T. M. Cover and P. E. Hart, "Nearest neighbor pattern classification," *IEEE Trans. on Information Theory*, vol. IT-13, no. 1, Jan. 1967, pp. 21-27.

[13] T. M. Cover and J. A. Thomas, *Elements of Information Theory*. New York: Wiley, 1991.

[14] H. Feng, A. Kamra, V. Misra, and A. D. Keromytis, "The effect of DNS delays on worm propagation in an IPv6 Internet," in *Proc. of INFOCOM'05*, vol. 4, Miami, FL, Mar. 2005, pp. 2405-2414.

[15] G. Gu, Z. Chen, P. Porras, and W. Lee, "Misleading and defeating importance-scanning malware propagation," in *Proc. of the 3rd International Conference on Security and Privacy in Communication Networks (SecureComm'07)*, Nice, France, Sept. 2007.

[16] G. Gu, M. Sharif, X. Qin, D. Dagon, W. Lee, and G. Riley, "Worm detection, early warning and response based on local victim information," in *Proc. 20th Ann. Computer Security Applications Conf. (ACSAC'04)*, Tucson, AZ, Dec. 2004.

[17] E. Kohler, J. Li, V. Paxson, and S. Shenker, "Observed structure of addresses in IP traffic," in *ACM SIGCOMM Internet Measurement Workshop*, Marseille, France, Nov. 2002.

[18] D. Moore, V. Paxson, S. Savage, C. Shannon, S. Staniford, and N. Weaver, "Inside the Slammer worm," *IEEE Security and Privacy*, vol. 1, no. 4, July 2003, pp. 33-39.

[19] D. Moore, C. Shannon, and J. Brown, "Code-Red: a case study on the spread and victims of an Internet worm," in *ACM SIGCOMM Internet Measurement Workshop*, Marseille, France, Nov. 2002.

[20] Y. Pryadkin, R. Lindell, J. Bannister, and R. Govindan, "An empirical evaluation of IP address space occupancy," *Technical Report ISI-TR-2004-598*, USC/Information Sciences Institute, Nov. 2004.

[21] M. A. Rajab, F. Monrose, and A. Terzis, "On the effectiveness of distributed worm monitoring," in *Proc. of the 14th USENIX Security Symposium (Security'05)*, Baltimore, MD, Aug. 2005, pp. 225-237.

[22] A. Renyi, "Some fundamental questions of information theory," *Selected Papers of Alfred Renyi, Akademiai Kiado, Budapest*, vol. 2, 1976, pp. 526-552.

[23] A. Renyi, *Probability Theory*. North-Holland, Amsterdam, 1970.

[24] S. M. Ross, *Simulation*, 3rd Edition. Academic Press, 2002.

[25] C. Shannon and D. Moore, "The spread of the Witty worm," *IEEE Security and Privacy*, vol. 2, no. 4, Jul-Aug 2004, pp. 46-50.

[26] S. Staniford, V. Paxson, and N. Weaver, "How to 0wn the Internet in your spare time," in *Proc. of the 11th USENIX Security Symposium (Security'02)*, San Francisco, CA, Aug. 2002.

[27] J. Twycross and M. M. Williamson, "Implementing and testing a virus throttle," in *Proc. of the 12th USENIX Security Symposium (Security'03)*, Washington, DC, Aug. 2003, pp. 285-294.

[28] M. Vojnovic, V. Gupta, T. Karagiannis, and C. Gkantsidis, "Sampling strategies for epidemic-style information dissemination," in *Proc. of INFOCOM'08*, Phoenix, AZ, Apr. 2008.

[29] V. Yegneswaran, P. Barford, and D. Plonka, "On the design and utility of Internet sinks for network abuse monitoring," in *Proc. of Symposium on Recent Advances in Intrusion Detection (RAID'04)*, 2004.

[30] C. C. Zou, L. Gao, W. Gong, and D. Towsley, "Monitoring and early warning for Internet worms," in *10th ACM Conference on Computer and Communication Security (CCS'03)*, Washington DC, Oct. 2003.

[31] C. C. Zou, D. Towsley, and W. Gong, "On the performance of Internet worm scanning strategies," *Elsevier Journal of Performance Evaluation*, vol. 63. no. 7, July 2006, pp. 700-723.

[32] C. C. Zou, D. Towsley, W. Gong, and S. Cai, "Advanced routing worm and its security challenges," *Simulation: Transactions of the Society for Modeling and Simulation International*, vol. 82, no. 1, 2006, pp.75-85.

[33] CERT Coordination Center, CERT Advisory CA-2001-26 Nimda Worm [Online]. Available: http://www.cert.org/advisories/CA-2001-26.html (Dec./2008 accessed).

[34] CERT Coordination Center, "'Code Red II:' another worm exploiting buffer overflow in IIS indexing service DLL," CERT Incident Note IN-2001-09 [Online]. Available: http://www.cert.org/incident_notes/IN-2001-09.html (Dec./2008 accessed).

[35] Distributed Intrusion Detection System (DShield) [Online]. Available: http://www.dshield.org/ (Dec./2008 accessed).

[36] eEye Digital Security, "ANALYSIS: Blaster worm," [Online]. Available: http://research.eeye.com/html/advisories/published/AL20030811.html (Dec./2008 accessed).

[37] Internet Protocol V4 Address Space. http://www.iana.org/assignments/ipv4-address-space (Dec./2008 accessed).

[38] UROULETTE [Online]. Available: http://www.uroulette.com/ (Dec./2008 accessed).

[39] Wikipedia, "Agobot (computer worm)," [Online]. Available: http://en.wikipedia.org/wiki/Agobot_(computer_worm) (Dec./2008 accessed).

[40] Wikipedia, "Samy (XSS)," [Online]. Available: http://en.wikipedia.org/wiki/Samy_(XSS) (Dec./2008 accessed).

[41] Wikipedia, "Self-information," [Online]. Available: http://en.wikipedia.org/wiki/Self-information (Dec./2008 accessed).