Network Diversity: A Security Metric for Evaluating the Resilience of Networks against Zero-Day Attacks

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Abstract—**Diversity has long been regarded as a security mechanism for improving the resilience of software and networks against various attacks. More recently, diversity has found new applications in cloud computing security, Moving Target Defense (MTD), and improving the robustness of network routing. However, most existing efforts rely on intuitive and imprecise notions of diversity, and the few existing models of diversity are mostly designed for a single system running diverse software replicas or variants. At a higher abstraction level, as a global property of the entire network, diversity and its effect on security have received limited attention. In this paper, we take the first step towards formally modeling network diversity as a security metric by designing and evaluating a series of diversity metrics. Specifically, we first devise a biodiversity-inspired metric based on the effective number of distinct resources. We then propose two complementary diversity metrics, based on the least and the average attacking efforts, respectively. We provide guidelines for instantiating the proposed metrics and present a case study on estimating software diversity. Finally, we evaluate the proposed metrics through simulation.**

Index Terms—**Diversity, Security Metrics, Network Security, Cloud Security, Zero Day Attacks**

I. Introduction

Protecting mission critical computer networks, such as those used in critical infrastructures and military organizations, demands more than just patching known vulnerabilities and deploying firewalls or IDSs. Improving the resilience of such networks against potential zero day attacks exploiting unknown vulnerabilities is equally important, which is evidenced by the fact that modern malware may exploit multiple unknown vulnerabilities at the same time [10]. However, dealing with unknown vulnerabilities is clearly a challenging task.

To this end, diversity has long been regarded as a security mechanism for improving the resilience of a software system against unknown vulnerabilities [24] (a more detailed review of related work will be given in Section VII). Security attacks exploiting unknown vulnerabilities may be detected and tolerated as Byzantine faults by comparing either the outputs [8] or behaviors [13] of multiple software replicas or variants [7]. Although the earlier diversity-by-design approaches usually suffer from prohibitive development and deployment cost, recent work show more promising results on employing either opportunistic diversity [14] or automatically generated diversity [4], [20], [5]. More recently, diversity has found new applications in cloud computing security [33], [44], Moving Target Defense (MTD) [18], and network routing [6]. Most of those existing efforts rely on either intuitive notions of diversity or models mostly designed for a single system running diverse software replicas or variants.

However, at a higher abstraction level, as a global property of an entire network, the concept of *network diversity* and its effect on security has received limited attention. In this paper, we take the first step towards formally modeling network diversity as a security metric, for the purpose of evaluating the resilience of networks with respect to zero day attacks. More specifically,

- First, we propose a network diversity metric by adapting well known mathematical models of biodiversity in ecology. The metric basically counts the number of distinct resources inside a network, while considering the uneven distribution of resources and varying degree of similarity between resources. This first metric is suitable for cases where all the resources are regarded as equally important, and it can also serve as a building block of other metrics. The main limitation is that it ignores potential causal relationships between resources in a network.
- Second, we design a network diversity metric based on the least attacking effort required for compromising certain important resources, while taking into account the causal relationships between resources. This metric is suitable for cases where administrators are mostly concerned about some critical assets (e.g., storage or database servers). However, by focusing on the least attacking effort, the metric only provides a partial picture about how diversity may affect security.
- Third, we devise a probabilistic network diversity metric to reflect the average attacking effort required for compromising critical assets. This metric serves as a complementary measure to the above second metric in depicting the effect of diversity on security.
- Fourth, we provide guidelines for instantiating the proposed metric models for given networks. In particular, we demonstrate how software similarity may be estimated

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through a case study on different versions of Chrome.
- Finally, we evaluate and compare the three metrics through simulation results under different use cases.

The main contribution of this paper is threefold. First, to the best of our knowledge, this is the first effort on systematically modeling network diversity as a security metric. As we will demonstrate shortly, an intuitive notion of diversity can usually cause misleading results, whereas our formal model of network diversity will enable a better understanding of the effect of diversity on security. Second, the application of biodiversity concepts to computer networks draws an interesting analogy between the two domains, and we believe there exist other opportunities for adapting existing concepts and methodologies in ecology to security. Third, by quantifying the effect of diversity on network security, the proposed metrics lay a foundation for developing better, quantitative approaches to improving network security through diversity.

The preliminary version of this paper has previously appeared in [42]. This paper has substantially improved and extended the previous version. The most significant extensions include a new probabilistic model for addressing various limitations of the previous model appearing in [42] (Section IV), discussions on how to instantiate the metrics and in particular on collecting inputs about software diversity (Section V), and finally a series of simulations for analyzing the proposed metrics under different use cases (Section VI).

The rest of this paper is organized as follows. Section II presents use cases and the biodiversity-inspired metric. Section III and Section IV propose the least and average attacking effort-based metrics, respectively. Section V discusses how to instantiate the metric models and presents a case study on estimating software similarity. Section VI gives simulation results. Section VII reviews related work, and finally Section VIII discusses limitations and concludes the paper.

II. Preliminaries

This section presents several use cases and defines a biodiversity-inspired network diversity metric.

A. Use Cases

We describe several use cases in order to motivate our study and illustrate various requirements and challenges in modeling network diversity. Some of those use cases will also be revisited in later sections.

a) Use Case 1: Stuxnet and SCADA Security: Stuxnet is one of the first malware that employ multiple (four) different zero day attacks [10]. This clearly indicates, in a mission critical system, such as supervisory control and data acquisition (SCADA) in this case, the risk of zero day attacks and multiple unknown vulnerabilities is very real, and consequently network administrators will need a systematic way for evaluating such a risk. However, this is clearly a challenging task due to the lack of prior knowledge about vulnerabilities or attacking methods.

A closer look at Stuxnet's attack strategies will reveal how network diversity may help here. Stuxnet targets the programmable logic controllers (PLCs) on control systems of gas pipelines or power plants [10], which are mostly programmed using Windows machines not connected to the network. Therefore, Stuxnet adopts a multi-stage approach, by first infecting Windows machines owned by third parties (e.g., contractors), next spreading to internal Windows machines through the LAN, and finally covering the last hop through removable flash drives [10]. Clearly, the degree of software diversity along potential attack paths leading from the network perimeter to the PLCs can be regarded as a critical metric of the network's resilience against a threat like Stuxnet. Our objective in this paper is to provide a rigorous study of such network diversity metrics.

b) Use Case 2: Worm Propagation: To make our discussion more concrete, we will refer to the running example shown in Figure 1 from now on. In this use case, our main concern is the potential propagation of worms or bots inside the network. A common belief here is that we can simply count the number (percentage) of distinct resources in the network as diversity. Although such a definition is natural and intuitive, it clearly has limitations.

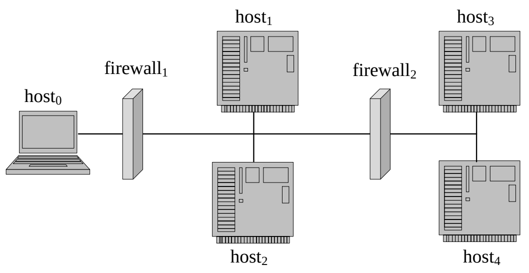


Fig. 1. The Running Example

For example, suppose host 1, 2, and 3 are Web servers running IIS, all of which access files stored on host 4. Clearly, the above count-based metric will indicate a lack of diversity and suggest replacing IIS with other software to prevent a worm from infecting all three at once. However, it is easy to see that, even if a worm can only infect one Web server after such a diversification effort, it can still propagate to all four hosts through the network share on host 4. The reason that this naive approach fails in this case is that it ignores the existence of causal relationships between resources (due to the network share). Therefore, after we discuss the count-based metric in Section II-B, we will address this limitation with a *goal oriented* approach in Section III.

c) Use Case 3: Targeted Attack: Suppose now we are more concerned with a targeted attack on the storage server, host 4. Following above discussions, an intuitive solution is to diversify resources along any *path* leading to the critical asset (host 4), e.g., between hosts 1 (or 2, 3) and host 4. Although this is a valid observation, realizing it requires a rigorous study of the causal relationships between different resources, because host 4 is only as secure as the weakest path (representing the least attacking effort) leading to it. We will propose a formal metric based on such an intuition in Section III.

On the other hand, the least attacking effort by itself only provides a partial picture. Suppose now host 1 and 2 are diversified to run IIS and Apache, respectively, and firewall

2 will only allow host 1 and 2 to reach host 4. Although the least attacking effort has not changed, this diversification effort has actually provided attackers more opportunities to reach host 4 (by exploiting either IIS or Apache). That is, misplaced diversity may in fact hurt security. This will be captured by a probabilistic metric in Section IV.

d) Use Case 4: MTD: In this case, suppose host 1 and 2 are Web servers, host 3 an application server, and host 4 a database server. A Moving Target Defense (MTD) approach attempts to achieve better security by varying in time the software components at different tiers [18]. A common misconception here is that the combination of different components at different tiers will increase diversity, and the degree of diversity is equal to the product of diversity at those tiers. However, this is usually not the case. For example, a single flaw in the application server (host 3) may result in a SQL injection that compromises the database server (host 4) and consequently leaks the root user's password. Also, similar to the previous case, more diversity over time may actually provide attackers more opportunities to find flaws. The lesson here is again that, an intuitive observation may be misleading, and formally modeling network diversity is necessary.

B. Biodiversity-Inspired Network Diversity Metric

Although the notion of network diversity has attracted limited attention, its counterpart in ecology, *biodiversity*, and its positive impact on the ecosystem's stability has been investigated for many decades [9]. While many lessons may potentially be borrowed from the rich literature of biodiversity, in this paper we will focus on adapting existing mathematical models of biodiversity for modeling network diversity.

Specifically, the number of different species in an ecosystem is known as *species richness* [32]. Similarly, given a set of distinct resource types (we will consider similarity between resources later) R in a network, we call the cardinality $\mid R \mid$ the *richness* of resources in the network. An obvious limitation of this richness metric is that it ignores the relative abundance of each resource type. For example, the two sets $\{r_1, r_1, r_2, r_2\}$ and $\{r_1, r_2, r_2, r_2\}$ have the same richness of 2 but clearly different levels of diversity.

To address this limitation, the Shannon-Wiener index, which is essentially the Shannon entropy using natural logarithm, is used as a *diversity index* to group all systems with the same level of diversity, and the exponential of the diversity index is regarded as the *effective number* metric [15]. The effective number basically allows us to always measure diversity in terms of the number of equally-common species, even if in reality those species may not be equally common. For example, the second set $\{r_1, r_2, r_2, r_2\}$ will yield an effective number of 1.75, which means this set has the same amount of diversity as a set with 1.75 equally-common resources. Therefore, this set is less diversified than the first set (which yields an effective number of 2). In the following, we borrow this concept to define the effective resource richness and our first diversity metric.

Definition 1 (Effective Richness and d_1-Diversity): In a network G with the set of hosts $H = \{h_1, h_2, \ldots, h_n\}$, set of resource types $R = \{r_1, r_2, \ldots, r_m\}$, and the resource mapping $res(.) : H \rightarrow 2^R$, let $t = \sum_{i=1}^{n} \mid res(h_i) \mid$ (total number of resource instances), and let $p_j = \frac{|\{h_i : r_j \in res(h_i)\}|}{t} (1 \leq i \leq n, 1 \leq j \leq m)$ (relative frequency of each resource). We define the network's diversity as $d_1 = \frac{r(G)}{t}$, where $r(G)$ is the network's effective richness of resources, defined as

$$r(G) = \frac{1}{\prod_1^n p_i^{p_i}}$$

One limitation of the effective number-based metric is that similarity between different resource types is not taken into account and all resource types are assumed to be entirely different, which is not realistic (e.g., the same application can be configured to fulfill totally different roles, such as NGinx as a reverse proxy or a web server, respectively, in which case these should be regarded as different resources with high similarity). Therefore, we borrow the similarity-sensitive biodiversity metric recently introduced in [22] to re-define resource richness. With this new definition, the above diversity metric d_1 can now handle similarity between resources.

Definition 2 (Similarity-Sensitive Richness): In Definition 1, suppose a similarity function is given as $z(.) : [1, m] \times [1, m] \rightarrow [0, 1]$ (a larger value denoting higher similarity and $z(i, i) = 1$ for all $1 \leq i \leq m$), let $zp_i = \sum_{j=1}^{m} z(i, j) p_j$. We define the network's effective richness of resources, considering the similarity function, as

$$r(G) = \frac{1}{\prod_1^n zp_i^{p_i}}$$

The effective richness-based network diversity metric d_1 is only suitable for cases where all resources may be treated equally, and causal relationships between resources either do not exist or may be safely ignored. On the other hand, this metric may also be used as a building block inside other network diversity metrics, in the sense that we may simply say "the number of distinct resources" without worrying about uneven distribution of resource types or similarity between resources, thanks to the effective richness concepts given in Definition 1 and 2.

III. Least Attacking Effort-Based Network Diversity Metric

This section models network diversity based on the least attacking effort. Section III-A defines the metric, and Section III-B discusses the complexity and algorithm.

A. The Model

In order to model diversity based on the least attacking effort while considering causal relationships between different resources, we first need a model of such relationships and possible zero day attacks. Our model is similar to the *attack graph* model [35], [2], although our model focuses on remotely accessible resources (e.g., services or applications that are reachable from other hosts in the network), which will be regarded as placeholders for potential zero day vulnerabilities instead of known vulnerabilities as in attack graphs.

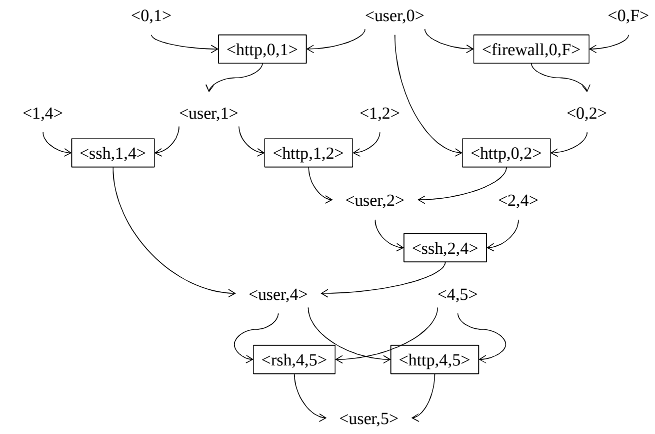


Fig. 2. An Example Resource Graph

To build intuitions, we revisit Figure 1 by making following assumptions. Accesses from outside firewall 1 are allowed to host 1 but blocked to host 2; accesses from host 1 or 2 are allowed to host 3 but blocked to host 4 by firewall 2; hosts 1 and 2 provide $http$ service; host 3 provides ssh service; Host 4 provides both $http$ and rsh services.

Figure 2 depicts a corresponding *resource graph*, which is syntactically equivalent to an attack graph, but models zero day attacks rather than known vulnerabilities. Each pair in plaintext is a self-explanatory security-related condition (e.g., connectivity $\langle source, destination\rangle$ or privilege $\langle privilege, host\rangle$), and each triple inside a box is a potential exploit of resource $\langle resource,\ source\, host, destination\, host\rangle$; the edges point from the pre-conditions to a zero day exploit (e.g., from $\langle 0, 1\rangle$ and $\langle user, 0\rangle$ to $\langle http, 0, 1\rangle$), and from that exploit to its post-conditions (e.g., from $\langle http, 0, 1\rangle$ to $\langle user, 1\rangle$). Exploits or conditions involving firewall 2 are omitted for simplicity.

We simply regard resources of different types as entirely different (their similarity can be handled using the effective resource richness given in Definition 2). Also, we take the conservative approach of considering all resources (services and firewalls) to be potentially vulnerable to zero day attacks. Definition 3 formally introduces the concept of resource graph.

Definition 3 (Resource Graph): Given a network with the set of hosts H, set of resources R with the resource mapping $res(.) : H \to 2^R$, set of zero day exploits $E = \{\langle r, h_s, h_d\rangle \mid h_s \in H, h_d \in H, r \in res(h_d)\}$ and their pre- and post-conditions C, a resource graph is a directed graph $G(E \cup C, R_r \cup R_i)$ where $R_r \subseteq C \times E$ and $R_i \subseteq E \times C$ are the pre- and post-condition relations, respectively.

Next consider how attackers may potentially attack a critical network asset, modeled as a goal condition, with the least effort. In Figure 2, by following the simple rule that an exploit may be executed if all the pre-conditions are satisfied, and executing that exploit will cause all the post-conditions to be satisfied, we may observe six *attack paths*, as shown in Table I (the second and third columns can be ignored for now and will be explained shortly). Definition 4 formally introduces the concept of attack path.

Definition 4 (Attack Path): Given a resource graph $G(E \cup C, R_r \cup R_i)$, we call $C_I = \{c : c \in C, (\nexists e \in E)(\langle e, c\rangle \in R_i)\}$ the set of initial conditions. Any sequence of zero day exploits $e_1, e_2, \ldots, e_n$ is called an attack path in G, if $(\forall i \in [1, n])(\langle c, e_i\rangle \in R_r \to (c \in C_i \vee (\exists j \in [1, i-1])(\langle e_j, c\rangle \in R_i)))$, and for any $c \in C$, we use $seq(c)$ for the set of attack paths $\{e_1, e_2, \ldots, e_n : \langle e_n, c\rangle \in R_i\}$.

We are now ready to consider how diversity could be defined based on the least attacking effort (the shortest path). There are actually several possible ways for choosing such shortest paths and for defining the metric, as we will illustrate through our running example in the following.

- First, as shown in the second column of Table I, path 1 and 2 are the shortest in terms of the *steps* (i.e., the number of zero day exploits). Clearly, those do not reflect the least attacking effort, since path 4 may actually take less effort than path 1, as attackers may reuse their exploit code, tools, and skills while exploiting the same $http$ service on three different hosts.
- Next, as shown in the third column, path 2 and 4 are the shortest in terms of the number of distinct resources (or effective richness). This seems more reasonable since it captures the saved effort in reusing exploits. However, although path 2 and 4 have the same number of distinct resources (2), they clearly reflect different diversity.
- Another seemingly valid solution is to base on the minimum ratio $\frac{\#\, of\, resources}{\#\, of\, steps}$ (which is given by path 4 in this example), since such a ratio reflects the potential improvements in terms of diversity (e.g., the ratio $\frac{2}{4}$ of path 4 indicates 50% potential improvement in diversity). However, we can easily imagine a very long attack path minimizing such a ratio but does not reflect the least attacking effort (e.g., an attack path with 9 steps and 3 distinct resources will yield a ratio of $\frac{1}{3}$, less than $\frac{2}{4}$, but clearly requires more effort than path 4).
- Finally, yet another option is to choose the shortest path that minimizes both the number of distinct resources (path 2 and 4) and the above ratio $\frac{\#\, of\, resources}{\#\, of\, steps}$ (path 4). However, a closer look will reveal that, although path 4 does represent the least attacking effort, it does not represent the maximum amount of potential improvement in diversity, because once we start to diversify path 4, the shortest path may change to be path 1 or 2.

Based on these discussions, we define network diversity by combining the first two options above. Specifically, the network diversity is defined as the ratio between the minimum number of distinct resources on a path and the minimum number of steps on a path (note these can be different paths). Going back to our running example above, we find path 2 and 4 to have the minimum number of distinct resources (two), and also path 1 and 2 to have the minimum number of steps (three), so the network diversity in this example is equal to $\frac{2}{3}$ (note that it is a simple fact that this ratio will never exceed 1). Intuitively, the numerator 2 denotes the network's current level of robustness against zero day exploits (no more than 2 different attacks) , whereas the denominator 3 denotes the network's maximum potential of robustness (tolerating no more than 3 different attacks) by increasing the amount of diversity (from $\frac{2}{3}$ to 1). More formally, we introduce our second network diversity metric in Definition 5 (note that,

Attack Path	# of Steps	# of Resources
1. $\langle http, 0, 1\rangle \rightarrow \langle ssh, 1, 4\rangle \rightarrow \langle rsh, 4, 5\rangle$	3	3
2. $\langle http, 0, 1\rangle \rightarrow \langle ssh, 1, 4\rangle \rightarrow \langle http, 4, 5\rangle$	3	2
3. $\langle http, 0, 1\rangle \rightarrow \langle http, 1, 2\rangle \rightarrow \langle ssh, 2, 4\rangle \rightarrow \langle rsh, 4, 5\rangle$	4	3
4. $\langle http, 0, 1\rangle \rightarrow \langle http, 1, 2\rangle \rightarrow \langle ssh, 2, 4\rangle \rightarrow \langle http, 4, 5\rangle$	4	2
5. $\langle firewall, 0, F\rangle \rightarrow \langle http, 0, 2\rangle \rightarrow \langle ssh, 2, 4\rangle \rightarrow \langle rsh, 4, 5\rangle$	4	4
6. $\langle firewall, 0, F\rangle \rightarrow \langle http, 0, 2\rangle \rightarrow \langle ssh, 2, 4\rangle \rightarrow \langle http, 4, 5\rangle$	4	3

TABLE I
[illegible]

for simplicity, we only consider a single goal conditio representing the given critical asset, which is not a limit since multiple goal conditions can be easily handled thr adding a few dummy conditions [1]).

Definition 5 (d_2-Diversity): Given a resource graph G $C, R_r \cup R_i)$ and a goal condition $c_g \in C$, for each c and $q \in seq(c)$, denote $R(q)$ for $\{r : r \in R, r$ appears i the network diversity is defined as (where $min(.)$ return minimum value in a set)

$$d_2 = \frac{min_{q \in seq(c_g)} \mid R(q) \mid}{min_{q' \in seq(c_g)} \mid q' \mid}$$

B. The Complexity and Algorithm

Since the problem of finding the shortest paths (in t of the number of exploits) in an attack graph (whic syntactically equivalent to a resource graph) is known t NP-hard [35], not surprisingly, the problem of determinin network diversity d_2 is also NP-hard, as stated in Theor (the proof is omitted and can be found in [42]).

Theorem 1: Given a resource graph $G(E \cup C, R_r \cup$ determining the network diversity d_2 is NP-hard.

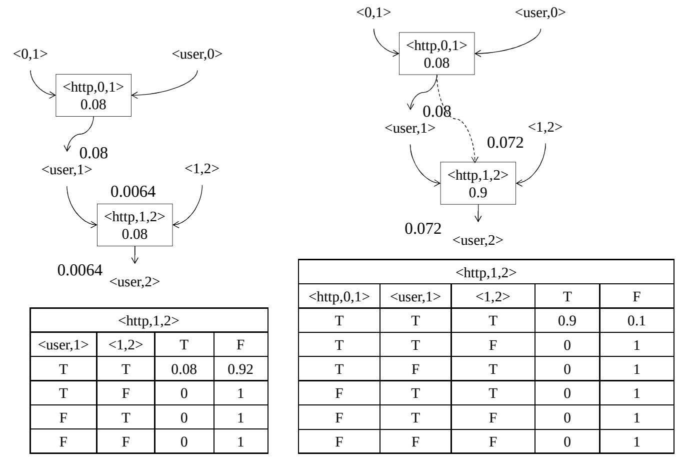
Although determining d_2 in general is computatio infeasible, it may be estimated within a reasonable time u heuristics. In particular, we have proposed an algorithm employs the heuristic of only maintaining a limited nu of local optima at each step in order to keep the compl manageable [42]. The algorithm is shown to run in polyno time under the assumption that each exploit has a con number of pre- and post-conditions. The simulation re also confirm that the algorithm provides accurate en estimation of d_2 in an acceptable amount of time.

IV. Probabilistic Network Diversity

In this section, we develop a probabilistic metric to ca the effect of diversity based on average attacking effo combining all attack paths. The preliminary version of paper [42] has proposed a probabilistic metric model fo purpose. We will first identify important limitations in model, and then provide a redesigned model to address them.

A. Overview

This section first reviews the probabilistic model of network diversity introduced in [42] and then points out its limitations. This model defines network diversity as the ratio between two probabilities, namely, the probability that given critical assets may be compromised, and the same probability but with an additional assumption that all resource instances are



<http,1,2>			
<user,1>	<1,2>	T	F
T	T	0.08	0.92
T	F	0	1
F	T	0	1
F	F	0	1

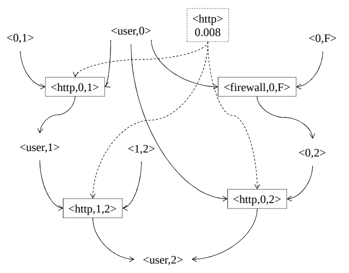
<http,1,2>				
<http,0,1>	<user,1>	<1,2>	T	F
T	T	T	0.9	0.1
T	T	F	0	1
T	F	T	0	1
F	T	T	0	1
F	T	F	0	1
F	F	F	0	1

Fig. 3. Modeling Network Diversity Using Bayesian Networks

distinct (which means attackers cannot reuse any exploit). Both probabilities represent the *attack likelihood* with respect to goal conditions, which can be modeled using a Bayesian network constructed based on the resource graph [11].

For example, Figure 3 demonstrates this model based on our running example (only part of the example is shown for simplicity). The left-hand side represents the case in which the effect of reusing an exploit is not considered, that is, the two $http$ service instances are assumed to be distinct. The right-hand side considers that effect and models it as the conditional probability that the lower $http$ service may be exploited given that the upper one is already exploited (represented using a dotted line). The two conditional probability tables (CPTs) illustrate the effect of reusing the $http$ exploit (e.g., probability 0.9 in the right CPT), and not reusing it (e.g., probability 0.08 in the left CPT), respectively. The network diversity in this case will be calculated as the ratio $d_3 = \frac{0.0064}{0.072}$.

In the above model, modeling the effect of reusing exploits as a conditional probability (that a resource may be exploited given that some other instances of the same type are already exploited) essentially assumes a total order over different instances of the same resource type in any resource graph, which comprises a major limitation. For example, in Figure 4 (the dashed line and box, and the CPT table may be ignored for the time being), although the reused $http$ exploit $\langle http, 1, 2\rangle$ (after exploiting $\langle http, 0, 1\rangle$) may be handled using the above model by adding a dotted line pointing to it from its ancestor $\langle http, 0, 1\rangle$, the same method will not work for the other potentially reused $http$ exploit $\langle http, 0, 2\rangle$, since there does not exist a definite order between $\langle http, 0, 1\rangle$ and $\langle http, 0, 2\rangle$,



<http,1,2>				
<http>	<user,1>	<1,2>	T	F
T	T	T	0.9	0.1
T	T	F	0	1
T	F	T	0	1
F	T	T	0	1
F	T	F	0	1
F	F	F	0	1

Fig. 4. The Redesigned Model

which means an attacker may reach $\langle http, 0, 2\rangle$ before, or after, reaching $\langle http, 0, 1\rangle$. Therefore, we cannot easily assume one of them to be exploited first. Considering that the resource graph model is defined based on a Bayesian network, which by definition requires acyclic graphs, we cannot add bi-directional dotted lines between exploits, either.

Another related limitation is that, once exploits are considered to be partially ordered, the attack likelihood will not necessarily be the lowest when all the resources are assumed to be distinct. For example, in Figure 4, an attacker may reach condition $\langle user, 2\rangle$ through two paths, $\langle http, 0, 1\rangle \rightarrow \langle http, 1, 2\rangle$ and $\langle firewall, 0, F\rangle \rightarrow \langle http, 0, 2\rangle$. Intuitively, the attack likelihood will actually be higher if the $http$ exploits in the two paths are assumed to be distinct, since now an attacker would have more choices in reaching the goal condition $\langle user, 2\rangle$. Those limitations will be addressed in following sections through a redesigned model.

B. Redesigning d_3 Metric

To address the aforementioned limitations of the original d_3 metric [42], we redesign the model of reusing exploits of the same resource type. Intuitively, what allows an attacker to more likely succeed in exploiting a previously exploited type of resources is the knowledge, skills, or exploit code he/she has obtained. Therefore, instead of directly modeling the casual relationship between reused exploits, we explicitly model such advantages of the attacker as separate events, and model their effect of increasing the likelihood of success in subsequent exploits as conditional probabilities.

More specifically, a new parent node common to exploits of the same resource type will be added to the resource graph, as demonstrated in Figure 4 using dashed lines and box. This common parent node represents the event that an attacker has the capability to exploit that type of resources. However, unlike nodes representing initial conditions, which will be treated as evidence for calculating the posterior probability of the goal condition, the event that an attacker can exploit a type of resources will not be considered observable. Adding a common parent node to exploits of the same resource type will introduce probabilistic dependence between the children nodes such that satisfying one child node will increase the likelihood of others, which models the effect of reusing exploits.

For example, in Figure 4, the dashed line box indicates a new node $\langle http\rangle$ representing the event that an attacker has the capability to exploit $http$ resources. The dashed lines represent conditional probabilities that an attacker can exploit each $http$ instance, and the CPT table shows an example of such conditional probability for $\langle http, 1, 2\rangle$. The marginal probability 0.08 assigned to $\langle http\rangle$ represents the likelihood that an attacker has the capability of exploiting $http$ resources, and the conditional probability 0.9 assigned to $\langle http, 1, 2\rangle$ represents the likelihood for the same attacker to exploit that particular instance. The existence of such a common parent will introduce dependence between those $http$ exploits, such that satisfying one will increase others' likelihood.

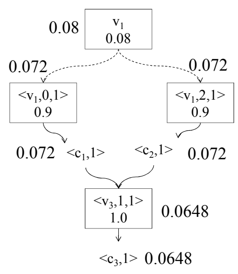
Formally, Definition 6 characterizes network diversity using this approach. In the definition, the second set of conditional probabilities represent the probability that an attacker is capable of exploiting each type of resources. The third and fourth sets together represent the semantics of a resource graph. Finally, the fifth set represents the conditional probability that an exploit may be executed when its pre-conditions are satisfied (including the condition that represents the corresponding resource type).

Definition 6 (d_3 Diversity): Given a resource graph $G(E \cup C, R_r \cup R_i)$, let $R' \subseteq R$ be the set of resource types each of which is shared by at least two exploits in E, and let $R_s = \{(r, \langle r, h_s, h_d\rangle) : r \in R', \langle r, h_s, h_d\rangle \in E\}$ (that is, edges from resource types to resource instances). Construct a Bayesian network $B = (G'(E \cup C \cup R', R_r \cup R_i \cup R_s), \theta)$, where G' is obtained by injecting R' and R_s into the resource graph G, and regarding each node as a discrete random variable with two states T and F, and θ is the set of parameters of the Bayesian network given as follows.

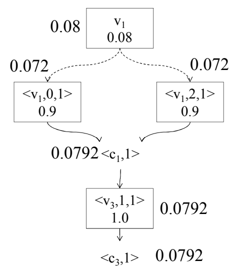
1) $P(c = T) = 1$ for all the initial conditions $c \in C_I$.
2) $P(r = T)$ are given for all the shared resource types $r \in R'$.
3) $P(e \mid \exists c_{\langle c,e\rangle \in R_r} = F) = 0$ (that is, an exploit cannot be executed until all of its pre-conditions are satisfied).
4) $P(c \mid \exists e_{\langle e,c\rangle \in R_i} = T) = 1$ (that is, a post-condition can be satisfied by any exploit alone).
5) $P(e \mid \forall c_{\langle c,e\rangle \in R_r \cup R_s} = T)$ are given for all $e \in E$ (that is, the probability of successfully executing an exploit when its pre-conditions have all been satisfied).

Given any $c_g \in C$, the network diversity d_3 is defined as $d_3 = \frac{p'}{p}$ where $p = P(c_g \mid \forall c_{c \in CI} = T)$ (that is, the conditional probability of c_g being satisfied given that all the initial conditions are true), and p' denotes the minimum possible value of p when some edges are deleted from R_s (that is, the lowest attack likelihood by assuming certain resource types are no longer shared by exploits).

Figure 5 shows two simple examples in which the first depicts a conjunction relationship between the two exploits (in the sense that both upper exploits must be executed before the lower exploit can be reached), whereas the second a disjunction relationship (any of the two upper exploits can alone lead to the lower exploit). In both cases, assuming



<v₃,1,1>			
<v₁,0,1>	<v₁,2,1>	T	F
T	T	1	0
T	F	0	1
F	T	0	1
F	F	0	1



<v₃,1,1>			
<v₁,0,1>	<v₁,2,1>	T	F
T	T	1	0
T	F	1	0
F	T	1	0
F	F	0	1

Fig. 5. Two Examples of Applying d_3

$c_g = \langle c_3, 1\rangle$, the probability $p = P(c_g \mid \forall c_{c \in CI} = T)$ is shown in the figure. We now consider how to calculate the normalizing constant p'. For the left-hand side case, the probability $p = P(c_g \mid \forall c_{c \in CI} = T)$ would be minimized if we delete both edges from the top node (v_1) to its two children (that is, those two exploits no longer share the same resource type). It can be calculated that $p' = 0.0064$, and hence the diversity $d_3 = \frac{0.0064}{0.0648}$ in this case. The right-hand case is more interesting, since it turns out that p is already minimized because deleting edges from the top node (v_1) will only result in a higher value of p (since an attacker would have two different ways for reaching the lower exploit), which can be calculated as 0.1536. Therefore, diversity in this case is $d_3 = \frac{0.0792}{0.0792}$, that is, improving diversity will not enhance (in fact it hurts) security in this case. This example also confirms our earlier observation that assuming all resources to be distinct does not necessarily lead to the lowest attack likelihood.

The above example also leads to the observation that the normalizing constant p' may not always be straightforward to calculate since finding the case in which p is minimized essentially means we need to optimize a network's diversity for improving its security, which itself comprises an interesting future direction. Instead, we propose an approximated version of normalizing constant p' based on following observations from the above example. In Figure 5, we can see that the right-hand side contains two attack paths leading to the goal condition $\langle c_3, 1\rangle$ (since each of the upper exploits alone is sufficient to lead to the lower exploit). We have shown previously that deleting dashed lines will only increase the probability p (of reaching the goal condition). However, we can easily see that, whether we delete the dashed lines or not, the probability p would always be minimized if there were only one path (e.g., by deleting $\langle v_1, 2, 1\rangle$ from the figure). Note that, for the left-hand side, there is already only one path since both upper exploits are required to reach the lower exploit, so p is minimized when the two upper exploits are assumed to be distinct. Intuitively, the network's security can never exceed the case in which only the shortest path (in terms of the number of steps) remains in the resource graph, with no resource being shared along the path. This intuition leads to following result.

Proposition 1: The normalizing constant p' in Definition 6 always satisfies $p' \geq p''$ where p'' is the probability $P(c_g \mid \forall c_{c \in C_I} = T)$ calculated on the shortest attack path in terms of steps (see Section III-A).

Proof (Sketch): We prove the result by mathematical induction on i, the number of steps in the shortest path. The base case $i = 1$ is trivial. For the inductive case, suppose the result holds for any resource graph with shortest path no longer than k. Given a resource graph G whose shortest path has $k + 1$ steps, let the set of exploits that are directly adjacent to the goal condition c_g be E_{k+1}. Clearly, $P(c_g \mid \forall c_{c \in CI} = T) \geq P(e \mid \forall c_{c \in CI} = T)$ holds for all $e \in E_{k+1}$ since c_g can be satisfied by any exploit in E_{k+1} (and the probability of the disjunction of events cannot be smaller than the probability of any event). Without loss of generality, suppose $e_{k+1} \in E_{k+1}$ is the exploit next to c_g on the shortest path, and we have $P(c_g \mid \forall c_{c \in CI} = T) \geq P(e_{k+1} \mid \forall c_{c \in CI} = T)$. Let E_k be the set of exploits closest to e_{k+1}, $E \subseteq E_k$ be the set of exploits on the shortest path, and $e_k \in E$ be the exploit next to e_{k+1}. There cannot be any conjunctive relationships between the exploits in E and any other exploit in $E_k \setminus E$ with respect to e_{k+1}, because otherwise the shortest path would have more than $k + 1$ steps, contradicting our assumption. Therefore, we have that $P(c_g \mid \forall c_{c \in CI} = T) \geq P(e_{k+1} \mid \forall c_{c \in CI} = T) \geq P(e_k \mid \forall c_{c \in CI} = T) \cdot P(e_{k+1} \mid \forall c_{\langle c,e\rangle \in R_r \cup R_s} = T)$. Then by our inductive hypothesis, we have that $P(e_k \mid \forall c_{c \in CI} = T)$ must be no less than the same probability calculated on the shortest path (of length k), and hence conclude the proof. □

The above result simplifies the application of d_3 since the shortest path can be easily obtained using the algorithm mentioned in Section III-B. We apply the approach to our running example, as shown in Figure 2. Based on Table I, the first and second attack paths have the lowest number of steps. The left-hand side of Figure 6 depicts the first path. The normalizing constant can be calculated based on this path as $p' = 5.12 * 10^{-4}$. The right-hand side depicts the application of our model for reusing exploits, which adds a common parent for the same type of resources, represented using dotted lines and boxes. There are two types of resources that are reused in this resource graph, *http* and *ssh*. By applying the method described above, we obtain the attack likelihood $p = 0.0052$, and therefore the network diversity can be calculated as $d_3 = \frac{p'}{p} = \frac{5.12*10^{-4}}{0.0052}$.

V. Applying the Network Diversity Metrics

The network diversity metrics we have proposed so far are based on abstract models of networks and attacks. How to instantiate such models for a given network is equally important. This section discusses various practical issues in applying the metrics, such as collecting input information and determining software diversity.

A. Instantiating the Network Diversity Models

To apply the proposed network diversity metrics, necessary input information need to be collected. We describe how such inputs may be collected from a given network and discusses the practicality and scalability.

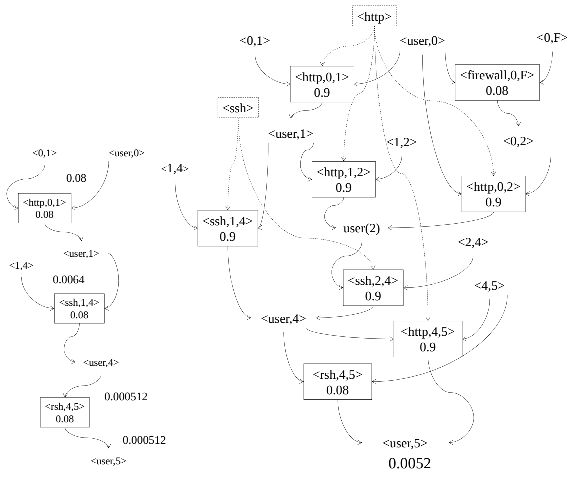


Fig. 6. Applying d_3 on the Running Example

1) The d_1 Metric: To instantiate d_1, we need to collect information about

- hosts (e.g., computers, routers, switches, firewalls),
- resources (e.g., remotely accessible services), and
- similarity between resources.

Information about hosts and resources is typically already available to administrators in the form of a network map. A network scanning will assist in collecting or verifying information about active services. A close examination of host configurations (e.g., the status of services and firewall rules) may also be necessary since a network scanning may not reveal services that are currently disabled or hidden by security mechanisms (e.g., firewalls) but may be re-enabled once the security mechanisms are compromised.

Collecting and updating such information for a large network certainly demand substantial time and efforts. Automated network scanning or host-based tools exist to help simplify such tasks. Moreover, focusing on remotely accessible resources allows our model to stay relatively manageable and scalable, since most hosts typically only have a few open ports but tens or even hundreds of local applications. A challenge is to determine the similarity of different but related resources, which will be discussed in further details in Section V-B.

2) The d_2-Diversity Metric: To instantiate the least attacking effort-based d_2 network diversity metric, we need to collect the following, in addition to what is already required by d_1,

- connectivity between hosts,
- security conditions either required for, or implied by, the resources (e.g., privileges, trust relationships, etc.), and
- critical assets.

The connectivity information is typically already available as part of the network map. A network scanner may help to verify such information. A close examination of host configurations (e.g., firewall rules) and application settings (e.g., authentication policies) is usually sufficient to identify the requirements for accessing a resource (pre-conditions), and an assessment of privilege levels of applications and the strength of isolation around such applications will reveal the consequences of compromising a resource (post-conditions). Critical assets can be identified based on an organization's needs and priority.

The amount of additional information required for applying d_2 is comparable to that required for d_1, since a resource typically has a small number of pre- and post-conditions. Once such information is collected, we can construct a resource graph using existing tools for constructing traditional attack graphs due to their syntactic equivalence, and the latter is known to be practical for realistic applications [31], [19].

3) The d_3-Diversity Metric: To instantiate the probabilistic network diversity metric d_3, we need to collect the following, in addition to what is already required for d_2,

- marginal probabilities of shared resource types, and
- conditional probabilities that resources can be compromised when all the pre-conditions are satisfied.

Both groups of probabilities represent the likelihood that attackers have the capability of compromising certain resources. A different likelihood may be assigned to each resource type, if this can be estimated based on experiences or reputations (e.g., the history of past vulnerabilities found in the same or similar resource). When such an estimation is not possible or desirable (note that any assumption about attackers' capabilities may weaken security if the assumption turns to be invalid), we can assign the same nominal value as follows. Since a zero day vulnerability is commonly interpreted as a vulnerability not publicly known or announced, it can be characterized using the CVSS base metrics [28], as a vulnerability with a remediation level *unavailable*, a report confidence *unconfirmed*, and a maximum overall base score (and hence produce a conservative metric value). We therefore obtain a nominal value of 0.8, converting to a probability of 0.08. For reference purpose, the lowest existing CVSS score [30] is currently 1.7, so 0.08 is reasonably low for a zero day vulnerability. Once the probabilities are determined, applying d_3 amounts to constructing Bayesian networks and making probabilistic inferences based on the networks, which can be achieved using many existing tools (e.g., we use OpenBayes [12]). Although it is a well known fact that inference using Bayesian networks is generally intractable, our simulation results have shown that the particular inference required for applying the d_3 metric can actually be achieved under reasonable computational cost [42].

B. Determining Software Similarity

A challenge in applying the network diversity metrics is to determine the similarity of different but related resources, such as different versions of the same software. Although a practical approach might be to simply disregard any small differences among such similar resources and treat them equally, this section presents a case study to demonstrate that it is sometimes possible and necessary to take software similarity into account.

Recall that the similarity-sensitive richness model (Definition 2) provides an abstract model to factor software similarity into the network diversity metric, if such similarity can be quantified as a similarity function $z(.)$. To demonstrate how such a model may be instantiated for realistic applications, we examine 10 different versions of the Chrome browser, whose details are given in Table II. The first row of the table shows the latest version, 42.0.2283.5 (published Thu Jan 22 06:24:31 2015), which will be used as the benchmark for further comparison. We observe that chrome has two branches under development at the same time, one starting with 41 and the other with 42.

# Index	# Version	# Publish Time
0	42.0.2283.5	Thu Jan 22 06:24:31 2015
1	41.0.2272.28	Thu Jan 22 06:15:29 2015
2	42.0.2283.4	Thu Jan 22 05:52:05 2015
3	41.0.2272.27	Thu Jan 22 01:06:09 2015
4	41.0.2272.26	Wed Jan 21 23:15:50 2015
5	42.0.2283.3	Wed Jan 21 22:47:20 2015
6	42.0.2283.2	Wed Jan 21 20:39:39 2015
7	42.0.2283.1	Wed Jan 21 20:07:26 2015
8	42.0.2283.0	Wed Jan 21 20:01:55 2015
9	41.0.2272.25	Wed Jan 21 16:00:53 2015
10	41.0.2272.16	Wed Jan 21 02:44:41 2015

TABLE II
DIFFERENT VERSIONS OF CHROME

It might be expected that, with such small differences in terms of version numbers, there would not be much difference in the software, either. Taking the first two versions, 42.0.2283.5 and 41.0.2272.28, as an example, the total number of source files is quite similar (75136 and 73596 files, respectively). However, our study shows that totally 9338 files have been modified between those two versions. Moreover, we find that there are 767,987 insertions and 190,943 deletions between those two versions (for reference purpose, the total number of lines in those two versions are 14,750,264 and 15,330,677, respectively). Those numbers show that there may exist significant differences between different versions of the same software, both at file level and at line level. Therefore, we measure the similarity between different versions at those two levels, that is, the *file-level similarity* is defined as the ratio between the number of unchanged files and that of all files, and the *modification-level similarity* as the ratio between the number of unchanged lines and that of all lines.

In Figure 7, the two lines depict the number of differences in terms of files and modifications, respectively, for the ten versions (represented using the same indices in Table II). Version 42.0.2283.5 is used as a benchmark for comparison. Clearly, the trends at those two different levels are very similar, that is, the difference among versions belonging to the same version branch (e.g., 42) is very small, whereas the difference from another branch (e.g., 41) can be significant.

Table III shows a more detailed view for four selected versions. We can see that, the number of changes (*F-#* for file level and *M-#* for modification level) between versions on the same branch is almost negligible. For versions on different branches, the number of changes can reach almost 10,000 at file level and 1,000,000 at modification level. The last two columns of the table show the calculated similarity scores at two levels (*F-Similarity* for file-level similarity and *M-Similarity* for modification-level similarity).

Next we apply the calculated similarity results to our

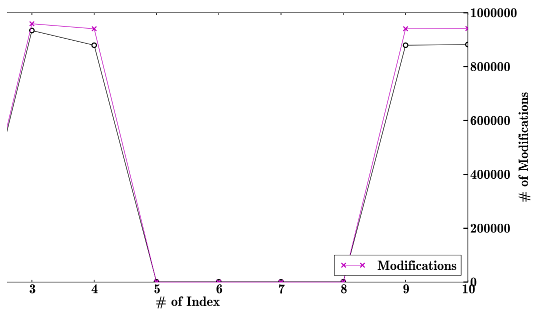


Fig. 7. Trends of File-Level and Modification-Level Differences

Index	Version	F-#	M-#	F-Similarity	M-Similarity
0	42.0.2283.5	0	0	1	1
1	41.0.2272.28	9338	959044	0.875	0.937
2	42.0.2283.4	3	6	0.9999	0.999999
3	41.0.2272.27	9341	959114	0.875	0.937
4	41.0.2272.26	8795	940662	0.883	0.938

TABLE III
DETAILED RESULTS

richness-based network diversity metric d_1. Assume a network is installed with the four different versions shown in Table III. Clearly, if we take the simplistic approach of disregarding any small differences between the four versions, there would be only one resource type. By Definition 1, the diversity of a network with four instances of such a resource (without considering any other resources) would be $d_1 = 0.25$, as shown in the third column of Table IV. The last column of the table shows the same d_1 results, but with similarity taken into consideration (that is, the effective richness is now calculated based on Definition 2). We can see that, as the two rows show, for four versions from different branches, the d_1 result is about one percent different with or without considering similarity, whereas the same result is almost identical for the same branch. Therefore, software similarity may indeed have a meaningful impact on network diversity, and we leave more detailed study to future work.

Branch	Version	d_1	d_1 with Similarity
Different	1. 42.0.2283.5	0.25	0.262239095954
	2. 41.0.2272.28		
	4. 41.0.2272.27		
	5. 41.0.2272.26		
Same	1. 41.0.2272.28	0.25	0.250018751406
	2. 41.0.2272.27		
	3. 41.0.2272.26		
	4. 41.0.2272.25		

TABLE IV
THE EFFECT OF SIMILARITY ON d_1

VI. SIMULATION

In this section, we study the three proposed metrics by applying them to different use cases through simulations. All simulation results are collected using a computer equipped with a 3.0 GHz CPU and 8GB RAM in the Python environment under Ubuntu 12.04 LTS. The Bayesian network-based metric is implemented using OpenBayes [12]. To generate a large number of resource graphs for simulations, we first construct a small number of seed graphs based on real networks, and then generate larger graphs from those seed graphs by injecting new hosts and assigning resources in a random but realistic fashion (e.g., we vary the number of pre-conditions of each exploit within a small range to reflect the fact that most real world exploits have a small number of pre-conditions, as evidenced in public vulnerability databases [30]).

We apply the three network diversity metrics to different use cases, as presented in section II-A. Our objective is to evaluate the three metrics through numerical results and to examine those results together with statistically expected results represented by different attack scenarios.

The first two simulations compare the results of all three metrics to examine their different trends as graph sizes increase and as diversity increases. First of all, to convert the Bayesian network-based metric d_3 to a comparable scale of the other two, we use $\frac{\log_{0.08}(p')}{\log_{0.08}(p)}$ (i.e., the ratio based on equivalent numbers of zero day exploits) instead of d_3. In the left-hand side of Figure 8, the scatter points marked with X in the red color are the individual values of d_2. The blue points marked with Y are the values of d_3 (converted as above). Also shown are their average values, and the average value of the effective richness-based metric d_1. While all three metrics follow a similar trend (diversity will decrease in larger graphs since there will be more duplicated resources), the Bayesian network-based metric d_3 somehow reflects an intermediate result between the two other extremes (d_1 can be considered as the average over all resources, whereas d_2 only depends on the shortest path). The right-hand side of Figure 8 shows the average value of the three metrics in increasing number of distinct resources for resource graphs of a fixed size. All three metrics capture the same effect of increasing diversity, and their relationships are similar to that in the previous simulation.

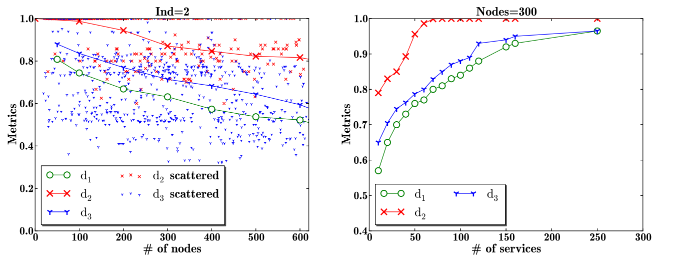


Fig. 8. Comparison of Metrics (Left) and the Effect of Increasing Diversity (Right)

Next we examine the metric results under different use cases, as described in Section II-A. The first use case considers worms, which are characterized as follows. First, each worm can only exploit a small number of vulnerabilities. In our implementation, we randomly choose one to three resource types as the capability of each worm. Second, the goal of a worm is infecting as many hosts as possible, without specific targets. Although some worms or bots may indeed have a target in the reality, it is usually still necessary for them to first compromise a large number of machines before the target can be reached (e.g., Stuxnet [10]). In Figure 9, the X-axis is the ratio of the number of resource types to the number of resource instances, which roughly represents the level of diversity in terms of richness (it can be observed that d_1 is close to a straight line). Y-axis shows the results of the three metrics as well as the ratio of hosts that are not infected by the simulated worms. The four lines represent the three metrics (marked with d_1, d_2, and d_3) and the ratio of hosts uninfected by simulated worms (marked with S_1). The left and right figures correspond to different percentage of first-level exploits (the exploits that only have initial conditions as their pre-conditions) among all exploits, which roughly depicts how well the network is safeguarded (e.g., 50% means a more vulnerable network than 10% since initially attackers can reach half, or five times more, exploits). For each configuration, we repeat 500 times to obtain the average result of simulated worms.

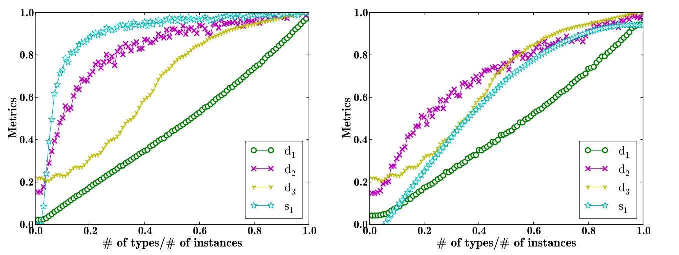


Fig. 9. Worm Propagation (Left 10% Initially Satisfied Exploits, Right 50% Initially Satisfied Exploits)

In this simulation, we can make following observations. First of all, all three metrics still exhibit similar trends and relationships as discussed above. The left figure shows that, when the network is better safeguarded (with only 10% of exploits initially reachable), the effect of increasing diversity on simulated worms shows a closer relationship with the d_2 metric than the other two, both of which indicate that increasing diversity can significantly increase the percentage of hosts uninfected by worms. Intuitively, in such well guarded networks, many hosts cannot be reached until the worms have infected other adjacent hosts, so increasing diversity can more effectively mitigate worm propagation. In comparison, the right figure shows a less promising result where both three metrics and the percentage of uninfected hosts all tend to follow a similar trend. Intuitively, in such less guarded networks where half of the exploits may be reached initially, the effect of diversity on worms is almost proportional to the richness of resources (d_1), and all three metrics tend to yield similar results.

The second use case is about targeted attack (Section II-A). We simulate attackers with different capabilities (sets of resources they can compromise) and the level of such capabilities (that is, the number of resources they can compromise) follows the Gamma distribution [27]. Similarly, we also repeat each experiment 500 times and we examine two different cases corresponding to different percentages of first-level exploits. In Figure 10, S_2 is the result of simulated attacker, which means the percentages of attackers who cannot reach the randomly selected goal condition. From the results we can observe similar results as with the simulated worms. Specifically, increasing diversity can more effectively mitigate the damage caused by simulated attackers for well guarded networks (the left figure) than for less guarded networks (the right figure). Also, in the left figure, the simulated attackers' results are closer to that of d_2 than the other two metrics, whereas it is closer to both d_2 and d_3 in the right figure. In addition, by comparing the results in Figure 10 (targeted attack) to that in Figure 9 (worm), we can see that the same level of diversity can more effectively mitigate worm than it can do to simulated attackers. This can be explained by the fact that a worm is assumed to have much less capability (set of resources it can compromise) than a simulated attacker.

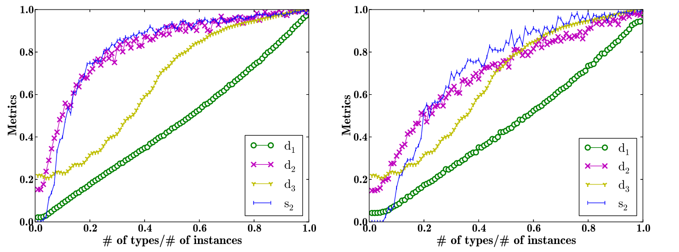


Fig. 10. Targeted Attack (Left 10% Initially Satisfied Vulnerabilities, Right 50% Initially Satisfied Vulnerabilities)

We now study the third use case, the Moving Target Defense (MTD). The MTD approach attempts to achieve better security by varying in time the configurations of networks, in which diversity plays a critical role. Our goal here is to study the effect of varying diversity on the effectiveness of MTD, and also on evaluating our metric when applied to MTD. To the best of our knowledge, this is among the first efforts on studying MTD using simulations (another similar effort by Zhuang et al. [45] also employs simulation results, but our goal is to evaluate the proposed network diversity metric under MTD applications, which is different from their study). Our simulations are based on following assumptions.

- We assume attackers do not initially have full details about the network but may gradually learn about such details as the configuration is changed over time. Specifically, attackers can learn about the change of a configuration (e.g., either through the failure of their attacks, or by observing special features of a configuration).
- We assume attackers' capabilities, which are sets of resources they can compromise, follow gamma distribution. Moreover, having the capabilities does not mean the attacker can immediately compromise the resource, since he/she may still need certain amount of time to actually implement the attack on specific instances of the resource. Therefore, in our simulations, we assign each resource an attack window, and only a resource whose duration of appearing inside a configuration is longer than the corresponding attack window may be compromised by attackers who have the capability.
- We assume the MTD approach employs dynamically changing network configurations. Specifically, the network topology remains the same but resources of each host may change. Also, we assume a fixed frequency of changes in our simulations (e.g., in Figure 11, the left figure shows the frequency of configuration change is 1 configuration/per day). We leave other ways for changing network configurations, such as using a varying frequency, as future work.

In Figure 11, the left figure shows the average success rates of attackers after 40 days of exposure to the network in the number of days before a configuration changes (e.g., 5 day means there is one configuration change per five days). We can see that a more frequent change of network configurations does not necessarily equal to better security (lower success ratio), since too fast or too slow changes can both increase the exposure of a resource and hence increase an attacker's chance in compromising that resource. In fact, the left figure indicates no clear trend in the success rate as the number of days for a change increases. The small drops in both lines indicate that the lowest success rates coincident with the average size of attack windows (in this case we assume 10 or 15 days are required to compromise a resource), which may not be meaningful in reality since different resources may have different attack windows. The right figure shows the attack success rates (the left Y-axis represents the success rate of worms and the right for targeted attacks) in the number of days since the network is exposed, with the frequency of changes set at one configuration change per day. We can see that, before 15 days, there is zero success rate for both worm propagation and targeted attack, due to the assumed 10 to 15 days of attack windows. After 15 days, there is a jump in both lines, which means, with accumulated efforts, both worms and attackers will be able to compromise more and more resources, and the success rates do not change much after about 20 days since now they will depend more on the capability of worms (attackers).

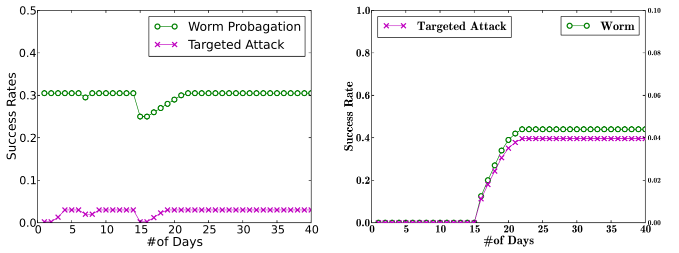


Fig. 11. Success Rate of Attacks in Frequency of Changes (Left) and in Time (Right)

In Figure 12, we only apply the d_1 metric to MTD since all three metrics will show similar trendsx1 as discussed above. In the left figure, we can see that if the set of resources types remains at a relatively small size (e.g., $\frac{\#of Resources}{\#of Days} < 20\%$), then our d_1 metric stays almost flat when the frequency of configuration changes is relatively high, and it then drops more dramatically when the frequency is lower (around one change per 20 days). This indicates that, with limited number of resource types, a higher frequency of configuration changes does not provide much security gain, unless if the frequency is too low. The left figure also indicates that, when the number of days per change increases over 20, diversity drops while success rate increases, which means our diversity metric effectively capture the effectiveness of MTD. The right figure shows similar results under larger set of resources ($\frac{\#of Resources}{\#of Days} > 80\%$). The successful rate and d_1 shows corresponding (reversed) trends. However, now with a large enough set of resources to choose from, less frequent changes in configurations mean lower diversity and hence less security.

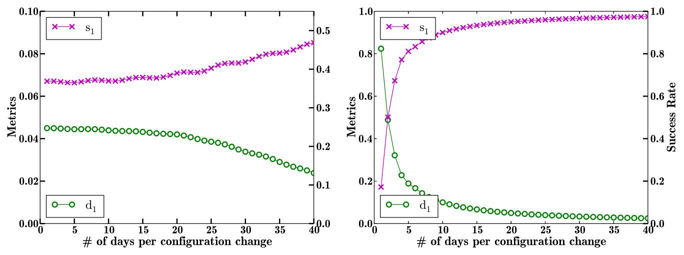


Fig. 12. d_1 in Frequency of Changes, under Less Resource Types (Left) and More Resource Types (Right)

In this last simulation, we study the relationship between cost and security in MTD, as shown in Figure 13. For worm propagation, we assign monetary values to all hosts, with critical assets (goal conditions) having higher values, whereas for targeted attack, we only assign a value to critical assets. The red and green dashed lines on top of the figure shows the total value for each scenario. Each time when worms or attackers compromise a resource, its assigned value is considered lost. Such lost value is the first part of overall cost. The other part is the cost of changing configurations in MTD (e.g., administrative cost of purchasing new software or performance cost of delaying a client's request). Figure 13 depicts the total cost (lost value due to compromised resources plus cost of configuration changes) in the number of days for a change of configuration. The results show that the overall cost will first decrease and then increase. The optimal setting of frequency is about one configuration change per 5 days, which best balances the cost of changing new configuration with lost values of compromised resources. Note that, according to our discussions above, the optimal frequency will also depend on the number of available resources.

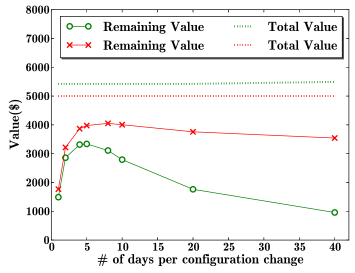


Fig. 13. Total Cost in Frequency of Changes

VII. Related Work

The research on security metrics has attracted much attention lately. Unlike existing work which aim to measure the amount of network security [17], [41], this paper focuses on diversity as one particular property of networks which may affect security. Nonetheless, our work borrows from the popular software security metric, attack surface [25], the general idea of focusing on interfaces (remotely accessible resources) rather than internal details (e.g., local applications). Our least attacking effort-based diversity metric is derived from the k-zero day safety metric [39], [38], and our probabilistic diversity metric is based on the attack likelihood metric [11], [40]. Another notable work evaluates security metrics against real attacks in a controlled environment [16], which provides a future direction to better evaluate our work. One limitation of our work lies in the high complexity of analyzing a resource graph; high level models of resource dependencies [21] may provide coarser but more efficient solutions to modeling diversity.

The idea of using design diversity for fault tolerance has been investigated for a long time. The N-version programming approach generates $N \geq 2$ functionally equivalent programs and compares their results to determine a faulty version [3], with metrics defined for measuring the diversity of software and faults [29]. The main limitation of design diversity lies in the high complexity of creating different versions, which may not justify the benefit [23]. The use of design diversity as a security mechanism has also attracted much attention [26]. The general principles of design diversity is shown to be applicable to security as well in [24]. The N-Variant system extends the idea of N-version programming to detect intrusions [8], and the concept of behavioral distance takes it beyond output voting [13]. Different randomization techniques have been used to automatically generate diversity [4], [20], [36], [5].

In addition to design diversity and generated diversity, recent work employ opportunistic diversity which already exists among different software systems. The practicality of employing OS diversity for intrusion tolerance is evaluated and the feasibility of using opportunistic diversity already existing between different OSes to tolerate intrusions is demonstrated in [14]. Diversity has also been applied to intrusion tolerant systems which usually implement some kinds of Byzantine Fault Tolerant (BFT) replication as fault tolerance solutions [7]. A generic architecture for implementing intrusion-tolerant Web servers based on redundancy and diversification principles is introduced in [34]. Components-off-the-shelf (COTS) diversity is employed to provide an implicit reference model, instead of the explicit model usually required, for anomaly detection in Web servers [37]. Diversity could play an important role in addressing various security issues in cloud computing [33], such as using diverse authorities for efficient decryption and revocation in cloud storage [44] and using diverse access policies for increasing the security of cloud data [43].

VIII. Conclusion

In this paper, we have taken a first step towards formally modeling network diversity as a security metric for evaluating networks' robustness against zero day attacks. We first devised an effective richness-based metric based on the counterpart in ecology. We then proposed a metric based on the least attacking effort required for compromising critical assets to address causal relationships between resources, and a second metric based on probabilistic models of repeated resources to reflect the average attacking effort. We provided guidelines for instantiating the proposed metrics and discussed how software diversity may be estimated. Finally, we evaluated our algorithms and metrics through simulations. Our study has shown that an intuitive notion of diversity could easily cause misleading results, and the proposed formal models provided better understanding of the effect of diversity on network security.

The main limitations of this work and corresponding future directions are as follows.

- First, although we have applied several existing biodiversity metrics, we believe more lessons could potentially be borrowed from biodiversity and related areas for improving network security, which comprises an interesting future direction.
- Second, obtaining various inputs for instantiating the proposed metrics can be challenging in practice. In addition to the guidelines and case study presented in Section V, our future work will develop practical tools for gathering the inputs, e.g., estimated measures of software diversity.
- Third, we have focused on modeling diversity in this paper, while diversity may also depend on other related factors, such as the cost (in terms of deployment and maintenance). Our future work will extend existing effort on modeling the effect of those factors on diversity.

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