A Quantitative Framework to Model Advanced Persistent Threats*

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Abstract: In recent years, Advanced Persistent Threats (APTs) have emerged as increasingly sophisticated cyber attacks, often waged by state actors or other hostile organizations against high-profile targets. APT actors employ a diversified set of sophisticated tools and advanced capabilities to penetrate target systems, evade detection, and maintain a foothold within compromised systems for extended periods of time. Stealth and persistence enable APT actors to conduct long-term espionage and sabotage operations. Despite significant efforts to develop APT detection and mitigation capabilities, the stealthy nature of APTs poses significant challenges, and defending from such threats is still an open research problem. In particular, quantitative models to capture how APTs may create and maintain a foothold within a target system are lacking. To address this gap, we propose a quantitative framework to (i) assess the cost incurred by APT actors to compromise and persist within a target system; (ii) estimate the value they gain over time by persisting in the system; (iii) simulate how the footprint of an APT evolves over time when, to maintain stealth, attackers have constraints on the volume of potentially detectable activity they can engage in. We also propose a preliminary defender model, and results from the evaluation show that our approach is promising, thus encouraging further research in this direction.

1 INTRODUCTION

In recent years, we have witnessed the emergence of Advanced Persistent Threats (APTs), a form of increasingly sophisticated cyber attacks that are often waged by state actors, organized crime, or other hostile organizations against high-profile targets such as government agencies and large corporations. APT actors employ a vast arsenal of diverse and sophisticated tools and possess advanced capabilities to penetrate target systems, evade detection, and maintain a foothold within compromised systems for extended periods of times. Stealth and persistence enable well-resourced and driven APT actors to plan and execute long-term espionage and sabotage operations. It is not uncommon to discover and eradicate APTs months or even years after the initial compromise and after significant damage has already occurred. In 2008, an attack targeted the U.S. Department of Defense and spread to highly classified networks after an infected USB flash drive was connected to a computer. For 14 months, the malware periodically exfiltrated information, until Operation Buckshot Yankee finally eradicated it in 2009. In 2011, a successful spear phishing attack allowed attackers to remotely control over 150 computers in the French Ministry of Economy, and retrieve documents for over three months before the attack was discovered.

As shown by countless high-profile incidents, and despite significant efforts to develop APT detection and mitigation capabilities, the stealthy and sophisticated nature of APTs still poses significant challenges. In fact, defending from such threats is still an open research problem. In particular, quantitative models to capture how an APT actor may create and maintain a foothold within a target system are lacking, and traditional approaches rely on unreasonable or inaccurate assumptions about the attacker's behavior, which do not take into account the specific nature of APTs and their ability to circumvent traditional detection mechanisms. For instance, we demonstrate that attackers do not necessarily need to compromise the most valuable nodes within a network in order to maximize their rewards. APT actors weigh various incentives and deterrents when considering which nodes to target and how to move within a network.

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To address current limitations, we propose a quantitative framework to (i) assess the cost incurred by APT actors to compromise and persist within a target system; (ii) estimate the value they gain by persisting in the system over time; (iii) simulate how the footprint of an APT evolves over time when, to maintain stealth, attackers have constraints on the volume of potentially detectable activity they can perform. We also propose a preliminary defender model, and results from our evaluation indicate that our approach is effective in reducing the malware footprint.

The paper is organized as follows. Section 2 discusses background information on APTs. Section 3 presents the proposed attacker model. Then, Section 4 presents a heuristic algorithm for constructing the malware footprint, and Section 5 reports simulation results. Section 6 presents a preliminary defender model. Finally, Section 7 discusses related work, and Section 8 gives some concluding remarks.

2 BACKGROUND

In this section, we discuss the incentives and deterrents that APT actors may weigh when evaluating which nodes to target and how to move within a network. This system of incentives and deterrents is at the basis of the proposed quantitative framework.

APT Incentives. Of the 66 APTs identified by the Kaspersky Global Research and Analysis Team, 61 are classified as having the primary function of exfiltrating data, including credential theft, and cyber espionage (Kaspersky Labs,). The remaining APTs generally fall under the category of cyber sabotage, as it is the case for the renown Stuxnet APT. While perhaps not a primary function, it has been shown that many of these threats (e.g., Shamoon) also include some form of reporting function to transmit data to attacker-operated command and control (C&C) servers. Even Stuxnet, known primarily for sabotaging Iranian nuclear centrifuges, incorporated extensive features to transmit system information to the C&C infrastructure. Thus, we can conclude that the primary incentive for malicious actors to deploy APTs is represented by the ability to stealthily exfiltrate data over time. To guide the selection of nodes to be compromised and maximize the value gained from exfiltration campaigns, attackers must be able to map network resources and estimate the value of each such resource.

Temporal Dynamics. In 2017, the Ponemon Institute, in a study on organizational data breaches, concluded that organizations which required over 100 days to identify that a breach had occurred faced 36% higher costs compared to organizations which identified breaches in under 100 days (pon, 2017). A deeper analysis (Langner, 2013) of Stuxnet determined that the malware had the ability to completely destroy the existing Iranian nuclear refinement capability during the period the malware was active. However, this would have almost certainly resulted in its rapid detection and removal. The analysis determined that, as deployed, Stuxnet had an overall effect of delaying the Iranian nuclear program by 2 years. Thus, the dwell time of APT malware is critical to determine the total value it can accrue over time by persisting within the target network.

Deterrents. APT actors go to great lengths to maintain stealth. In particular, they commonly use multiple zero-day exploits. It is estimated that 50% of Stuxnet development cost was allocated to stealth-related features (Langner, 2013). Stuxnet employed five zero-day exploits. Bounties for the discovery of vulnerabilities range in the millions of dollars, and this does not even include the significant cost (Ablon and Bogart, 2017) associated with developing, testing and maintaining the exploit code over time. Furthermore, APTs employ a variety of other mechanisms to maintain stealth and can develop proxy networking schemes to reduce the overall volume of traffic, especially outbound traffic, which may otherwise alert network operators. Thus, we can conclude that defensive mechanisms aimed at increasing the cost of maintaining stealth can potentially deter attackers from compromising certain nodes and steer them towards more cost-effective targets. We capture this logic in our model, and show that an APT actor can eventually achieve better long-term benefits by forgoing some specific targets for the sake of stealth and persistence.

3 ATTACKER MODEL

In this section, we present a model to capture the behavior of an APT actor, whose overall goal is to maximize the value accrued from gaining and maintaining a position within the target network, while minimizing the likelihood of being detected. We first present some preliminary definitions and discuss our assumptions in Section 3.1. Then, in Section 3.2, we present the proposed cost-reward model in detail.

3.1 Preliminaries and Assumptions

We represent a network as a graph $G = (V, E)$, where V is a set of network elements – such as routers and end hosts – and E captures the connectivity between them. As mentioned earlier, APT actors continue to

accrue value as they persist within the target network. To capture the temporal dynamics of APTs, and without loss of generality, we discretize time as a a finite sequence of integers $\mathcal{T} = \langle t_0, t_1, \ldots, t_m \rangle \subseteq \mathbb{N}^m$, with $m \in \mathbb{N}$ and $t_i < t_{i+1}$ for each $i \in [1, m]$. We then define $reward(t_i)$, with $i \in [1, m]$, as the value gained by an APT actor at time t_i, or, more precisely, during the time interval $\Delta t_i = [t_{i-1}, t_i]$. Therefore, the value accrued by the attacker over the entire time horizon $\mathcal{T}$ can be simply defined as $Reward = \sum_{k=1}^{m} reward(t_i)$.

Due to the sophisticated nature of APTs, the amount of resources that threat actors invest in researching their targets, and the potential exploitation of zero-day vulnerabilities, it is reasonable to assume that APTs are always successful in compromising a target node. Additionally, we assume a strong adversarial model in which attackers have full knowledge of the network topology, the location of various assets – including data items – and their respective value.

3.2 Cost-reward Model

The value an APT actor gains from a target network during a given time interval depends on the number and nature of the compromised nodes. We model the malware footprint within the network as an overlay tree, rooted at the attacker's entry point into the network. The choice of using a tree overlay is justified by the following reasoning. As mentioned previously, APT actors are highly determined to ensure that their actions are stealthy in order to maintain persistence and accrue more value over time. To achieve this goal, they seek to avoid detection by minimizing the number of communication channels, as observed in several instances of existing malware (Symantec Security Response, 2011; Symantec Security Response, 2015). This behavior can be captured by modeling communication links as the edges of an overlay tree. However, there are other means an attacker can use to minimize detectability. Jafarian *et al.* introduce the notion of *quantifying detectability* by measuring malware activity during a given time window (Jafarian et al., 2014). Leveraging this concept, we assume that the need to maintain stealth constrains attackers to minimize detectability. We model this constraint as a *detectability budget B*, representing the attacker's level of risk tolerance within any time interval Δt_i.

3.2.1 Cost

Attacker interactions with network nodes incur a *detectability* cost, which quantifies the risk of those interactions being detected. As mentioned earlier, the cost an attacker is willing to incur during any time interval Δt_i is bounded by B. Detectability costs for individual nodes can be determined based on several characteristics of those nodes, as described below.

- **Role:** Intuitively, nodes with more mission-critical roles, such as a database server, would undergo more scrutiny and would be more heavily monitored than typical user workstations. For example, staff may routinely check the status of a critical database, whereas a user workstation may only be examined when there is an apparent issue.
- **Operating System:** Newer operating systems inherently incorporate additional protection mechanisms which render attacks designed for older systems ineffective. Furthermore, security monitoring options are typically more robust and diversified on these operating systems, resulting in more effective detection of malicious activity. As a result, newer operating systems generally force attackers to resort to *noisier* attacks, which defenders can more readily detect.
- **Deployed Defense Mechanisms:** Defenders often deploy additional defense mechanisms to provide another layer of defense on top of baseline operating system features. These may include host-based antivirus software, host-based intrusion detection systems, file integrity monitoring systems, and other similar defenses.

The detectability cost of a node is also affected by the level of attacker's effort necessary to compromise the node and maintain it in the malware footprint. The attacker's effort includes activities that can be broadly classified in the following two categories:

- **Compromise and Acquisition:** activities performed to establish the attacker's presence and control on the target node, including activities such as scanning and reconnaissance, initial compromise, and privilege escalation.
- **Operation-on-target and Maintenance:** activities performed to carry out the attacker's objectives on a compromised node, including activities such as exfiltrating information, downloading malware updates, and routing attack traffic.

Another important consideration is that the malware footprint within a network may not be composed solely of compromised nodes. An attacker may leverage standard network mechanisms to forward malicious traffic through several nodes – such as routers – without necessarily compromise them. If such nodes are on the path between two compromised nodes, they can be considered part of the malware footprint. Compromising every node within the malware footprint is impractical for a variety of reasons. Assuming

that the attacker has the capability to do so, leveraging such capability may not be cost-effective. For instance, compromising a router may give the attacker additional benefits, but the risk of detection would also be much higher. In this case, it may be more cost-effective for the attacker to compromise nodes hosting sensitive data and use the router to forward exfiltration traffic originating at the compromised nodes. Intuitively, including non-compromised nodes in the malware footprint enables APT actors to more efficiently allocate their detectability budget and gain more value from the target network by using the budget to compromise more desirable and cost-effective nodes.

To account for this type of scenario, we consider two classes of nodes in our overlay model, namely *compromised nodes* and *traffic-forwarding nodes*. The latter are nodes that pass malicious traffic, but are not compromised by the attacker. As these nodes are only used to passively forward traffic, the attacker incurs a lower cost to maintain them in the malware footprint. However, there is still a small risk associated with these nodes, as malicious traffic passing through them can be potentially detected. Formally, we define the notion of *APT Malware Footprint* as follows.

Definition 1 (APT Malware Footprint)**.** *The footprint of an APT malware in a network $G = (V,E)$ is a tree $T = (C \cap F, root)$, where*

- *$C \subseteq V$ is a set of compromised nodes;*
- *$F \subseteq V$ is a set of non-compromised non-leaf traffic-forwarding nodes;*
- *$root \in C$ is the root of the tree.*

We model detectability as two separate cost functions, namely $cost_c : V \times \mathcal{T} \rightarrow \mathbb{R}$ and $cost_f : V \times \mathcal{T} \rightarrow \mathbb{R}$. Specifically, $cost_c(v,t_i)$ is the detectability cost incurred by the APT malware for compromising node v and maintaining the compromise at time t_i. Similarly, $cost_f(v,t_i)$ is the detectability cost incurred by the APT malware for forwarding traffic through node v at time t_i. As discussed previously, the detectability cost of compromising a node is higher than the cost of forwarding traffic through the same node, therefore $\forall v \in V, \forall t_i \in \mathcal{T}, cost_c(v,t_i) \geq cost_f(v,t_i)$. Additionally, $\forall v \in V$, $cost_c(v,t_0) = 0$ and $cost_f(v,t_0) = 0$ by definition. The total cost at time t_i can be computed as

$$cost(t_i) = \sum_{v \in C} cost_c(v,t_i) + \sum_{v \in F} cost_f(v,t_i), \forall i \in [1,m]$$

It must be noted that, once a node v has been compromised at time t_j, the cost for the attacker to maintain v in its footprint during subsequent time intervals is lower than the cost sustained for the initial compromise. Formally, the cost function $cost_c$ for a node v compromised at time t_j can be defined as

$$cost_c(v,t_i) \begin{cases} = 0 & \text{if } t_i < t_j \\ = c_v & \text{if } t_i = t_j \\ < c_v & \text{if } t_i > t_j \end{cases}$$

where c_v is a constant representing the one-time cost sustained by the attacker to compromise node v.

3.2.2 Reward

APT malware gains value from information extracted from target systems. Many prior approaches use the concept of one or more *target nodes* (Albanese et al., 2012; Albanese and Jajodia, 2018), which an attacker seeks to compromise. In these approaches, target nodes may represent *crown jewels*, such as critical databases or email servers, which would severely impact an organization, if compromised. While these targets are undoubtedly critical, these approaches do not account for other valuable information which may reside on other nodes within the network, nor for the intrinsic value those nodes may have for an attacker who seeks to maintain persistence within the network.

An attacker may choose to forgo these targets entirely in favor of more lightly-defended options. This approach may be especially enticing if the network defenses are densely concentrated around critical resources and relatively sparse in other regions of the network. In such a situation, an attacker can compromise a larger proportion of the network without exceeding its detectability budget. Accruing value in a more incremental fashion may in fact be a more effective strategy for an attacker aiming to evade detection. For example, an attacker may forgo an organization's heavily-guarded email server and instead compromise the organization's lightly-secured user workstations. Depending on the organizational security policy, the attacker may be able to extract not only email messages that could have been otherwise retrieved from the server at a much higher risk, but also additional locally-stored information.

To model the value of nodes throughout the network, we use two separate *reward* functions, namely $reward_c : V \times \mathcal{T} \rightarrow \mathbb{R}$ and $reward_f : V \times \mathcal{T} \rightarrow \mathbb{R}$. Specifically, $reward_c(v,t_i)$ is the reward gained by the APT malware for compromising node v or controlling the compromised node at time t_i. Similarly, $reward_f(v,t_i)$ is the reward gained by the APT malware for forwarding traffic through node v at time t_i. As discussed previously, the reward gained from a compromised node is higher than the reward from a non-compromised node used solely for forwarding traffic, therefore $\forall v \in V, \forall t_i \in \mathcal{T}, reward_c(v,t_i) \geq$

$reward_f(v,t_i)$. Additionally, $\forall v \in V$, $reward_c(v,t_0) = 0$ and $reward_f(v,t_0) = 0$ by definition. Finally, the total reward at time t_i, with $i \in [1,m]$, which was introduced earlier in Section 3.1, can be computed as

$$reward(t_i) = \sum_{v \in C} reward_c(v,t_i) + \sum_{v \in F} reward_f(v,t_i)$$

4 TREE FORMATION PROBLEM

The long-term attacker's objective is to construct an overlay tree $T = (C \cap F, root)$ that maximizes total rewards over the time horizon $\mathcal{T} = \langle t_0, t_1, \ldots, t_m \rangle$, subject to cost constraints.

$$\begin{aligned} \underset{T}{\text{maximize}} \quad & \sum_{i=1}^{m} reward(t_i) \\ \text{subject to} \quad & cost(t_i) \leq B, \forall i \in [1,m] \end{aligned}$$

However, as the above optimization problem would be unpractical for the attacker to solve, it is reasonable to assume that a more realistic objective is to construct, during each time interval Δt_i, a partial tree $T_i = (C_i \cap F_i, root)$ that reuses – either partially or totally – the tree T_{i-1} generated during the previous time interval and maximizes the rewards, subject to the detectability budget B.

$$\begin{aligned} \underset{T_i}{\text{maximize}} \quad & \sum_{v \in C_i} reward_c(v,t_i) + \sum_{v \in F_i} reward_f(v,t_i) \\ \text{subject to} \quad & \sum_{v \in C_i} cost_c(v,t_i) + \sum_{v \in F_i} cost_f(v,t_i) \leq B \end{aligned}$$

As formulated, this problem is closely related to the class of Steiner Tree Problems (Johnson et al., 2000). In particular, this problem closely models the Prize-Collecting Steiner Tree Problem (PCST) and, more specifically, the Node-Weighted Prize-Collecting Steiner-Tree Problem (NW-PCST), for which a number of approximation algorithms exist (Bateni et al., 2013; Sadeghian Sadeghabad, 2013). These approximation algorithms include rooted variants, where a specific root node is required to exist in the tree. These variants would accurately model an entry or extraction point for the malware. However, all variants of this problem are generally considered NP-Hard, and the budgeted variants are shown to be at least as hard to approximate as the maximum coverage problem (Moss and Rabani, 2007).

Example 1 (APT Malware Footprint)**.** *Figure 1 illustrates the concept of APT Malware Footprint using a simple network and different values, ranging from 40 to 130, for the attacker's detectability budget. In this example, we assume that all nodes in the footprint, marked with a bold red outline, are compromised. In the figure, which capture a snapshot of the network at time t_1, each node v is labeled with its respective reward $r = reward_c(v,t_1)$ and cost $c = cost_c(v,t_1)$. In this example, V_1 is the root node. The figure clearly shows that an increased detectability budget allows the attacker to access a larger proportion of the target network and gain a larger reward. Note that, in Figures 1(a) and 1(b), the attacker selects V_4 as the budget does not allow compromising other more rewarding nodes. However, as shown in Figure 1(c), with a larger budget, the attacker chooses to forgo $V4$ in favor of V_7, which allows a more efficient use of the available budget and leads to a larger overall reward. In Figure 1(d), the attacker budget is so large that nearly the entire network is compromised. However, it should be noted that the one node which is not compromised, V_5, has the single highest value in the entire graph. However, due to also having the highest associated cost – indicating the presence of more sophisticated defense mechanisms – including this node would not lead to the largest possible aggregate reward for this budget level. Other threat modeling approaches focusing on target nodes would likely designate V_5 as a primary target for the attacker, thus steering even more defensive resources towards it. This example demonstrates that an attacker does not necessarily need to compromise nodes with the highest value in order to maximize the reward.*

4.1 Algorithm

In this section we propose an algorithm to model how an APT actor may build its footprint in the target network. To ensure practical runtimes and to scale to large networks, we propose an iterative, greedy approach. At a conceptual level, the algorithm starts from a root node – which represents the attacker's entry point into the network – and, during each time interval Δt_i, it enumerates routes to potential target nodes originating from any of the current leaf nodes. Each route includes a target node, which the attacker seeks to compromise, and possibly a number of intermediate *forwarding* nodes. Note that, for each such route to be added to the malware footprint, the route's terminal node must be compromised for the attacker to be able to control that route. The length of routes is controlled by the parameter hop_{max}. Each route has an associate reward and cost, which correspond to the aggregated reward and cost of all the nodes that comprise the route.

When the attacker selects a route, the route is added to the malware footprint and the attacker may

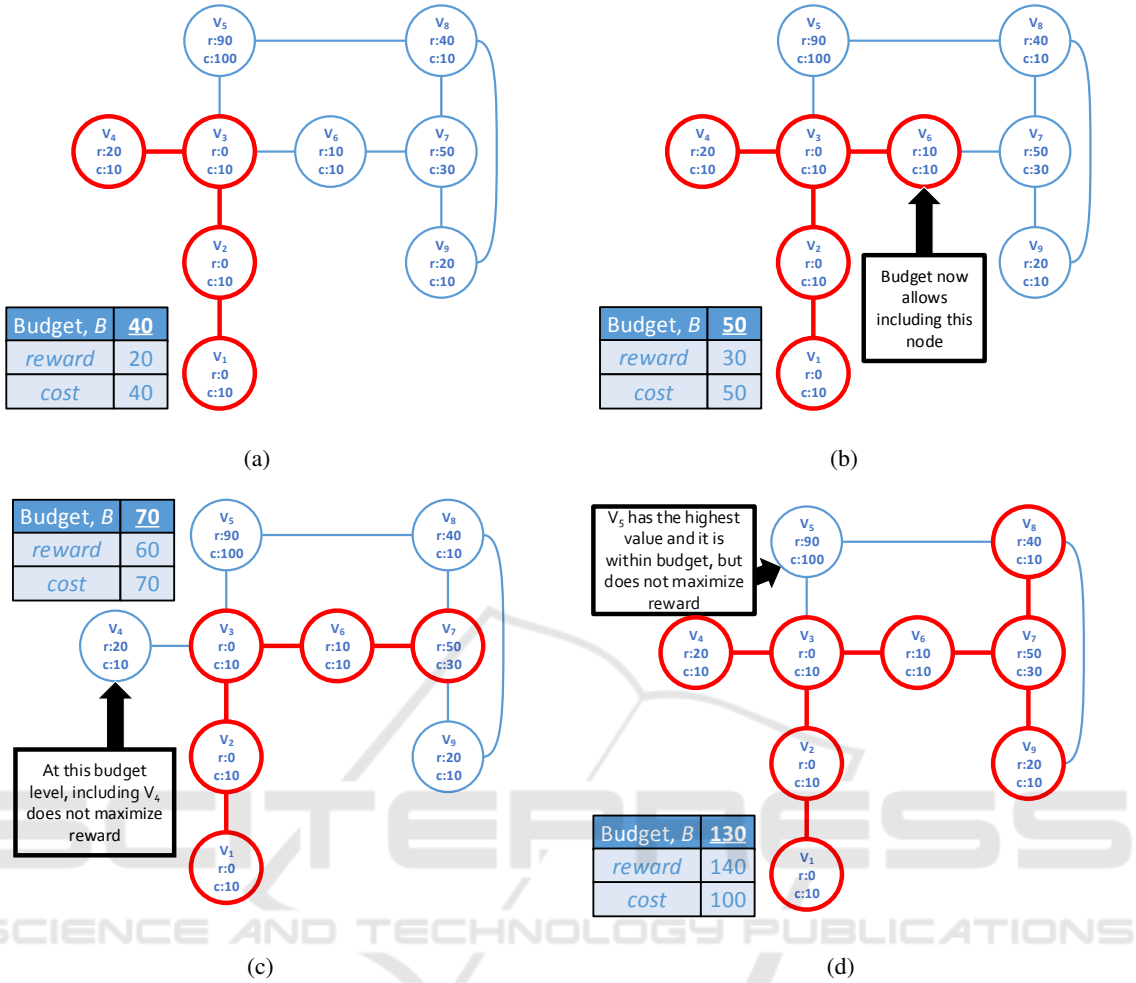


Figure 1: Basic example of APT malware footprint for different values of the budget.

enumerate new routes originating from any of the currently compromised nodes. The attacker selects routes in this iterative manner until the budget B is exhausted or there are no more viable routes to consider. Different strategies may be employed by the attacker to select a route amongst the available ones. We have considered three possible *route selection strategies*: (i) Greatest_Reward, which selects the route that maximizes reward; (ii) Lowest_Cost, which chooses the route that minimizes cost; and (iii) Cost_Effective, which chooses the route that optimizes the cost/reward ratio.

We also consider two different tree evolution approaches. In the *conservative* approach, the attacker maintains any node that was compromised during previous time intervals. In this case, a fraction of the budget B for the current time interval goes toward maintaining the compromised nodes. As discussed earlier, the maintenance cost is lower than the cost to compromise, so the remaining portion of the budget can be used to expand the tree. In the *dynamic* strategy, the attacker may forgo some of the previously compromised nodes and have a larger portion of the budget available to compromise new nodes if this choice leads to better values of the chosen objective function.

Pseudo-code for the proposed *treeConstruction* algorithm and for the auxiliary *findRoutes* algorithm is shown in Algorithm 1 and Algorithm 2 respectively.

Example 2 (Malware Footprint Evolution)**.** *To illustrate how the malware footprint evolves over time, consider again the simple example discussed earlier. In this example, the budget remains constant over time ($B = 55$ for each time interval). However, as shown in Figure 2, during each time interval, the attacker compromises a larger proportion of the network due to the cost of maintaining compromised nodes being lower than the cost of the original compromise. In this example, node detectability costs are reduced by 50% in the time intervals after initial compromise. By incorporating the temporal dynamics of detectability*

Algorithm 1: $treeConstruction(G,T,B,hop_{max})$.

Input: Graph $G=(V,E)$, current tree $T=(C\cap F,root)$, budget B, and parameter hop_{max}.
Output: An updated tree T.

```
// Initialize
R ← ∅
runningBudget ← 0
r ← ∅
// Bootstrap R with root
findRoutes(G, T, r, root, R, runningBudget, 0, B, hop_max)
while R ≠ ∅ do
    // selectRoute selects route depending on route selection strategy, e.g. Greatest_Reward
    r ← selectRoute(R)
    // final destination node is compromised, other nodes in the route are traffic-forwarding nodes
    addRoute(T, r)
    for all routes ∈ R do
        // remove invalid routes (routes with the final destination not compromised)
        // update costs and rewards for remaining routes which share nodes with r
    end for
    // Find routes using the newly compromised node
    findRoutes(G, T, finalDest, r, R, B, runningBudget, rCost, rReward, hop_max)
end while
return T
```

cost, the threat model reflects the progressive nature of APT malware behavior, slowly expanding through the network to avoid detection.

5 SIMULATIONS

In this section, we study the performance of our algorithm for large networks. For each network size, we generated 30 different network topologies and the results were averaged over different network settings. To the best of our knowledge, there are no existing models that capture the connectivity of an enterprise network at both layer 2 and layer 3. Therefore, in order to generate different network topologies, we used scale-free networks and synthesized enterprise network topologies of different sizes. Such networks are known to accurately capture the connectivity in ISP networks at the router level (Spring et al., 2002). We used the NetworkX 2.0 library to generate these networks in an incremental fashion, using the Holme and Kim algorithm, a variant of the Barabási-Albert (BA) model. In the BA model, new nodes are added to the network one at a time and each new node is connected to one of the existing nodes with a probability that is proportional to the current degree of that node. Therefore, a node with a higher degree has a higher probability of becoming the new node's neighbor. The Holme and Kim algorithm tends to generate networks with more clusters than typical BA networks, which is intended to more closely model enterprise networks.

Reward. Figure 3 reports the total reward accrued by the attacker over a time horizon $\mathcal{T}=\{t_1,\ldots,t_m\}$, with $m=10$, and for all three route selection strategies, when using the dynamic approach. As expected, the malware gains greater reward from larger networks, and the cost-effective strategy yields the best results among all the strategies considered.

Malware Footprint. Figure 4 reports the percentage of nodes that are compromised by the malware at time t_m, for different network sizes. The Lowest_Cost strategy achieves the best results because it tends to compromise a large number of low-cost but low-reward nodes, whereas the Greatest_Reward tends to include high-reward, but also high-cost, nodes, thus exhausting its budget sooner.

Runtime. Fig. 5 illustrates the average runtime for different network sizes. It can be seen that the total runtime increases linearly with the network size. Instead, Figure 6 compares the runtime of the dynamic and conservative approaches for different network sizes. The dynamic approach requires roughly twice as much time to compute.

Conservative vs. Dynamic Approach. Figure 7 reports the reward accrued by the malware over time as a percentage of the total value of all network assets. The chart compares the dynamic and conservative approaches, and reports values averaged over of all network sizes considered (100,200,300,400,500). During the first time interval, the two approaches yield the same reward, but then they start to diverge. As the dynamic approach may reconsider the choice of target nodes made during previous time intervals, it is likely to achieve results that are closer to the optimal solution, as confirmed by the set of charts discussed in the following paragraph.

Algorithm 2: $findRoutes(G, T, v, r, R, B, runningBudget, rCost, rReward, hop_{max})$.

Input: Graph $G = (V, E)$, current tree $T = (C \cap F, root)$, node v, node list r, current set of viable routes R, budget B, $runningBudget$, $rCost$, $rReward$, and parameter hop_{max}

Output: The set of viable routes, R, is updated.

```
1: // Determines if v is suitable for serving as final route destination (compromised node)
2: nodeInfectCost ← detectability cost for malware to compromise v
3: if v ∉ C then
4:     if runningBudget + rCost + nodeInfectCost < B then
5:         // Update the r with node data and add to R
6:         newRCost ← rCost + nodeInfectCost
7:         nodeInfectReward ← malware reward from the compromise of v
8:         newRReward ← rReward + nodeInfectReward
9:         newRoute ← deep copy of r, v
10:        newRouteOption ←+ newRoutw, newRCost, newRReward
11:        R ←+ newRouteOption
12:    end if
13: end if
14: // Determines if v could be a forwarding node
15: if length(r) < hop_max then
16:    neighbors ← neighbors of n
17:    for all neighbor ∈ neighbors do
18:        if neighbor ∉ routeOptions then
19:            nodeForwardCost ← detectability cost for malware to forward traffic though v
20:            if runningBudget + routeCost + nodeForwardCost < B then
21:                newRouteCost ← routeCost + nodeForwardCost
22:                nodeForwardReward ← any malware reward when forwarding traffic through v
23:                newRouteReward ← routeReward + nodeForwardReward
24:                newRouteList ← deep copy of routeList, v
25:                findRoutes (G, T, neighbor, newRouteList, routeOptions, B, runningBudget, newRouteCost, newRouteReward, hop_max)
26:            end if
27:        end if
28:    end for
29: end if
```


Approximation Ratio. To evaluate the approximation ratio of the proposed algorithm, we compared the rewards gained over time using the three route selection strategies with the rewards corresponding to the optimal solution, which was computed by exhaustively exploring the search space with a brute-force approach. Figures 8(a) and 8(b) show how the approximation ratio – for the conservative and the dynamic approach respectively – converges to 100% as the route length increases. As expected, the dynamic approach converges more rapidly than the conservative one. Results presented here were generated using networks of 25 nodes, as computation of the optimal solution for larger graphs is prohibitive.

6 DEFENDER MODEL

The goal of the defender is to minimize the attacker's reward. As the attacker is invested in solving the rooted tree problem discussed above, and success during earlier time intervals implies an increased effective budget for the current interval, a maximally effective defender will be one that disrupts the attacker's effort to maintain a tree, thus forcing the attacker to continually compromise new nodes, which results in inefficient use of the detectability budget.

We assume that the defender has sufficient resources to actively defend $k < n$ nodes, where $n = |V|$ is the number of network nodes. In real world scenarios, such nodes might receive more frequent security upgrades or be more heavily monitored. The parameter k reflects the organization's capacity for processing alerts and allocating analyst time. We refer to such actively defended nodes as *watched*, and we refer to the process by which the defender selects a k-subset $S \subseteq V$ as the defender's *strategy*. A watched node's cost increases by a multiplicative factor $\alpha > 1$.

This increase in cost reflects the additional risk an attacker takes by trying to compromise a node that is subject to increased monitoring. In each interval Δt_i, the defender selects a set $S_i \subseteq V$ according to one of a family of strategies. Let S_{i-1} be the set of watched nodes from the previous interval. For each $v \in S_i \setminus S_{i-1}$ – the newly watched nodes – $cost_c(v, t_i)$ is increased by a factor of α. For each node $v \in S_{i-1} \setminus S_i$,

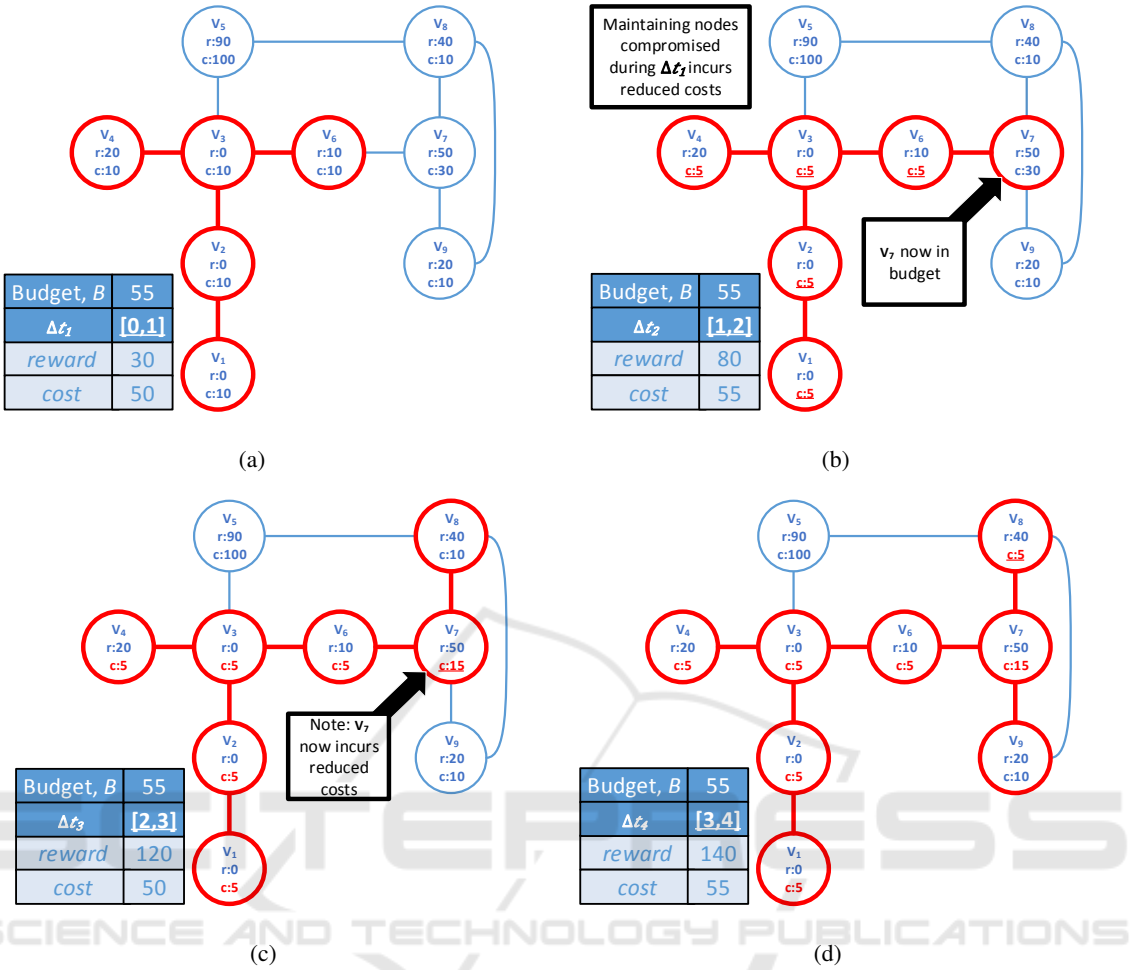


Figure 2: Evolution of malware footprint over time.

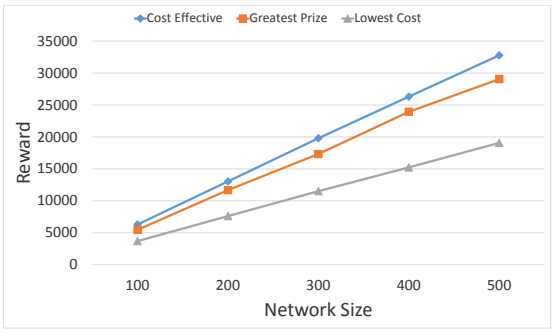


Figure 3: Reward vs. Network Size.

Figure 4: Footprint vs. Network Size.

$cost_c(v,t_i)$ is decreased by a factor of α, bringing the cost back to its normal value. These nodes are no longer watched. The cost for nodes $v \in S_i \cup S_{i-1}$ is unchanged, as they continue to be watched.

We now discuss several defender strategies. Two simple strategies are the *uniform* and the *cost-effective* strategy. A defender using the uniform strategy selects a set of k nodes uniformly at random from V during each interval. This is a very simple, low-overhead strategy that does not consider any structural properties of the graph, nor any of the node weights.

We define the cost-effectiveness of a node $v \in V$ as $e(v,t_i) = reward_c(v,t_i)/cost_c(v,t_i)$. Very cost-effective nodes are those who offer great rewards at a relatively low cost. A defender adopting the cost-effective strategy selects a set $S_i \subseteq V$ of k nodes,

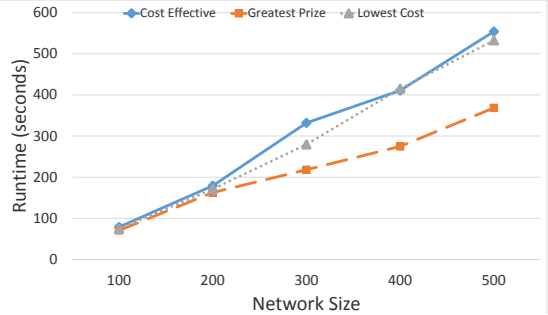


Figure 5: Runtime vs. Network Size.

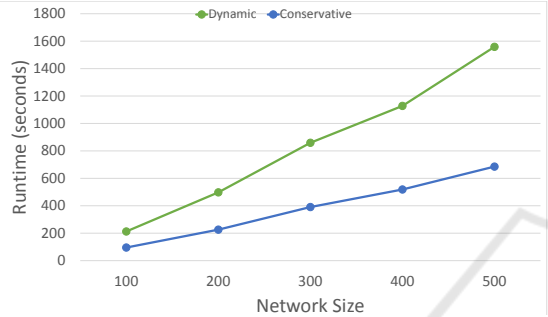


Figure 6: Conservative vs. dynamic approach: runtime.

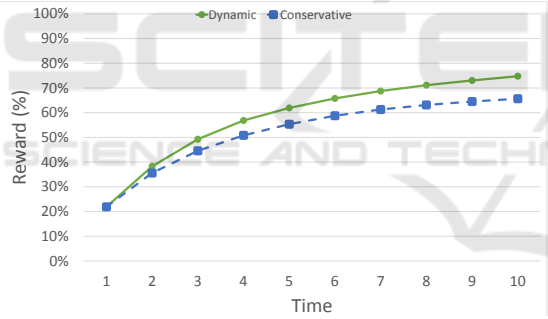


Figure 7: Conservative vs. dynamic approach: reward.

where each node $v \in S_i$ is sampled with probability $p(v,t_i) = e(v,t_i)/\sum_{u \in V} e(u,t_i)$. The cost-effective strategy is a generalization of the uniform strategy that maintains its simplicity. However, the cost-effective strategy takes more information into account when deciding the allocation of resources. A more sophisticated strategy is the betweenness strategy, which is described in the following subsection.

6.1 Betweenness Strategy

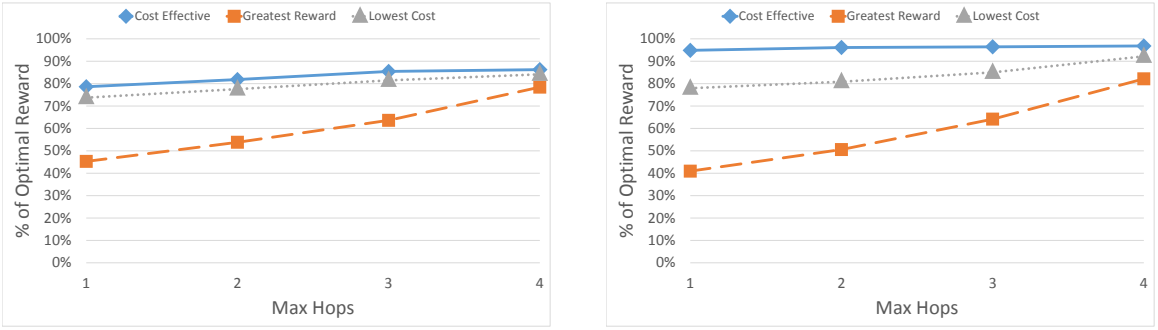
Betweenness centrality is a fundamental measure of a node's relative importance, and it is well-studied in network analysis. The betweenness centrality of a node is defined in terms of the proportion of shortest paths that pass through it. Thus, a node with high betweenness is one that connects many other nodes to one another – such as a boundary node connecting tightly-clustered subgraphs. This property is a natural measure of importance in many types of networks, including power, communication, and disease transmission (Brandes, 2001). For $u, v, w \in V$, suppose that $\lambda_{v,w}$ is the number of shortest paths from v to w, and $\lambda_{v,w}(u)$ is the number of such paths that include u. Then the betweenness centrality of u is calculated as

$$C(u) = \sum_{v,w \in V \mid u \notin \{v,w\} \wedge \lambda_{v,w} \neq 0} \frac{\lambda_{v,w}(u)}{\lambda_{v,w}}$$

Selecting the nodes with the highest betweenness centrality may result in a redundant set of nodes when there is significant overlap among the shortest paths that contribute to the centrality of two of more selected nodes. To avoid this problem, we can compute the list of top k nodes with respect to betweenness centrality adaptively, removing all edges incident to a previously selected node and recomputing the centrality of the all other nodes before selecting the next node. We refer to this method of finding the top k nodes as the *adaptive-k* betweenness strategy. Fortunately, there exist online polynomial time algorithms for computing the betweenness centrality over a graph that is subject to the addition and removal of nodes (Kourtellis et al., 2015). Furthermore, there exist online approximate adaptive betweenness centrality algorithms intended to scale to very large graphs (Yoshida, 2014).

A defender implementing the betweenness strategy interprets the undirected, unweighted graph $G = (V,E)$ as a directed, weighted graph $G' = (V,E',w)$, where $(u,v),(v,u) \in E'$ for every $(u,v) \in E$ and for every $(u,v) \in E'$, $w(u,v) = cost_c(v)/reward_c(v)$. In this graph, the weight of an edge connecting nodes u to v is the inverse of the cost-efficiency of v. That is, the more cost-effective (and therefore attractive to the attacker) v is, the more likely shortest paths are to go through it due to the weighting on the nodes. Hence, the more cost-effective a node, the more likely it is to have high betweenness centrality. This disproportionately skews in favor of cost-effective nodes that have high betweenness centrality in the unweighted version of the problem. Hence, the defender computes the adaptive betweenness centrality of the graph G' and selects the top k nodes in each time interval.

Figure 9(a) compares the malware footprint before and after the deployment of a defender's strategy. In this example, the attacker employs the cost-effective strategy, whereas the defender selects k nodes to watch using the adaptive-k betweenness strategy, where k is set to 10% of the number of nodes in the network. These nodes increase their cost for a time interval by a factor $\alpha = 10$, resulting in a 20%

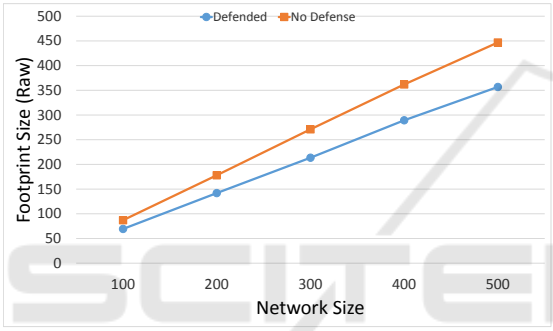


(a) Conservative approach

(b) Dynamic approach

Figure 8: Approximation ratio.

reduction in the number of compromised nodes, and a 15% reduction in attacker's reward across all network sizes, as shown in Figure 9(b).



(a) Comparison of number of compromised nodes

(b) Reduction in attacker's reward

Figure 9: Impact of defensive actions on malware.

7 RELATED WORK

Since the emergence of APTs, there has been a significant body of research in this field. Earlier work often examined the failure of existing intrusion detection systems (Chen et al., 2014) and studied the characteristics of APT malware that allowed attackers to circumvent existing defenses. Later, most research in the field focused on the detection of APT malware, primarily through various anomaly detection, network event correlation, flow-based analysis, and other big data approaches (Marchetti et al., 2016; Friedberg et al., 2015). These approaches generally require organizations to devote significant resources to the collection and processing of event logs. Other approaches rely on the use of honeypots and honeytraps to detect APTs (Virvilis et al., 2014).

While these efforts are still ongoing, other models have recently emerged as more instances of APT malware have been detected and studied. These approaches include the use of Petri Nets (Jasiul et al., 2014), Markov models (Gore et al., 2017), and game-theoretic models (Fang et al., 2014).

8 CONCLUSIONS

In recent years, Advanced Persistent Threats (APTs) have emerged as increasingly sophisticated cyber attacks, often waged by state actors or other hostile organizations against high-profile targets. As discussed, APT actors have at their disposal a diversified set of sophisticated tools and advanced capabilities to penetrate target systems, evade detection, and maintain a foothold within compromised systems for extended periods of time. Stealth and persistence enable APT actors to carry on long-term espionage and sabotage operations. Despite significant efforts to develop APT detection and mitigation capabilities, the stealthy nature of APTs poses significant challenges, and defending from such threats is still an open research problem. In particular, quantitative models to capture how an APT actor may create and maintain a foothold within a target system are lacking. To address this gap we have proposed a quantitative framework to (i) assess the cost incurred by APT actors to compromise and persist within a target system; (ii) estimate the value they gain over time by persisting in the system;

(iii) simulate how the footprint of an APT evolves over time when, to maintain stealth, the attackers have constraints on the amount of potentially detectable activity they can engage in. In our model, an attacker must weigh the value of a given target node against the probability of detection, which would impair the attacker's ability to persist within the target network. Results from our evaluation have shown that the proposed approach is promising and encourage further research in this direction.

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