Draining the Water Hole: 
Mitigating Social Engineering Attacks with CyberTWEAK

Zheyuan Ryan Shi, Aaron Schlenker, Brian Hay
Daniel Bittleston, Siyu Gao, Emily Peterson, John Trezza, Fei Fang
1Carnegie Mellon University, 2Facebook, Inc., 3Security Works
ryanshi@cmu.edu, aschlenker@fb.com, bhay@securityworks.com
{dbittle, siyug, emilypet, jtrezza}@andrew.cmu.edu, feif@cs.cmu.edu

Abstract
Cyber adversaries have increasingly leveraged social engineering attacks to breach large organizations and threaten the well-being of today’s online users. One clever technique, the “watering hole” attack, compromises a legitimate website to execute drive-by download attacks by redirecting users to another malicious domain. We introduce a game-theoretic model that captures the salient aspects for an organization protecting itself from a watering hole attack by altering the environment information in web traffic so as to deceive the attackers. Our main contributions are (1) a novel Social Engineering Deception (SED) game model that features a continuous action set for the attacker, (2) an in-depth analysis of the SED model to identify computationally feasible real-world cases, and (3) the CYBERTWEAK algorithm which solves for the optimal protection policy. To illustrate the potential use of our framework, we built a browser extension based on our algorithms which is now publicly available online. The CYBERTWEAK extension will be vital to the continued development and deployment of countermeasures for social engineering.

1 Introduction
Social engineering attacks are a scourge for the well-being of today’s online user and the current threat landscape only continues to become more dangerous [Mitnick and Simon 2001]. Social engineering attacks manipulate people to give up confidential information through the use of phishing campaigns, spear phishing whaling or watering hole attacks. For example, in watering hole attacks, the attacker compromises a legitimate website and directs visitors to a malicious domain where the attacker can intrude the user’s network. The number of social engineering attacks is growing at a catastrophic rate. In a recent survey, 60% organizations were or may have been victim of at least one attack [Agari 2016]. Such cybercrime poses an enormous threat to the security at all levels – national, business, and individual.

To mitigate these attacks, organizations take countermeasures from employee awareness training to technology-based defenses. Unfortunately, existing defenses are inadequate. Watering hole attackers typically use zero-day exploits, rendering patching and updating almost useless [Sutton 2014]. Sand-boxing potential attacks by VM requires high-end hardware, which hinders its wide adoption [Farquhar 2017]. White/blacklisting websites is of limited use, since the adversary is strategically infecting trustworthy websites.

We propose a game-theoretic deception framework to mitigate social engineering attacks, and, in particular, the watering hole attacks. Deception is to delay and misdirect an adversary by incorporating ambiguity. Watering hole attackers rely on the identification of a visitor’s system environment to deliver the correct malware to compromise a victim. Towards this end, the defender can manipulate the identifying information in the network packets, such as the user-agent string, IP address, and time-to-live. Consequently, the attacker might receive false or confusing information about the environment and send incompatible exploits. Thus, deceptively manipulating employees’ network packets provides a promising countermeasure to social engineering attacks.

Our Contributions
We provide the first game-theoretic framework for autonomous countermeasures to social engineering attacks. We propose the Social Engineering Deception (SED) game, in which an organization (defender) strategically alters its network packets. The attacker selects websites to compromise, and captures the organization’s traffic to launch an attack. We model it as a zero-sum game and consider the minimax strategy for the defender.

Second, we analyze the structure and properties of the SED game, based on which we identify real-world scenarios where the optimal protection policy can be found efficiently.

Third, we propose the CYBERTWEAK (Thwart WatEring hole AttacK) algorithm to solve the SED game. CYBERTWEAK exploits theoretical properties of SED, linear program relaxation of the attacker’s best response problem, and the column generation method, and is enhanced with dominated website elimination. We show that our algorithm can handle corporate-scale instances involving over $10^5$ websites.

Finally, we have developed a browser extension based on our algorithm. The software is now publicly available on the Chrome Web Store [1]. The extension is able to manipulate the user-agent string in the network packets. We take additional steps to improve the usability and explain the output of CYBERTWEAK intuitively. We believe it will be vital to the

http://bit.ly/CyberTWEAK

Copyright © 2020, Association for the Advancement of Artificial Intelligence (www.aaai.org). All rights reserved.
mises a set of legitimate websites. Not only do these websites need to be lucrative, but the attacker also has to be strategic in this choice. For example, compromising Google.com is nearly impossible while the Polish Financial Authority, victim of the 2017 Ratankba malware attacks (Symantec 2017), cannot invest the same security resources. Indeed, in previous attacks the attacker was not observed to compromise all websites (Parliament 2018). In step 3, employees visit the compromised website and are redirected to a malicious website which scans their system environment and the present vulnerabilities. To gather this information, attackers use techniques such as analyzing the user-agent string, operating system fingerprinting, etc. In Step 4, the attacker delivers an exploit for an identified vulnerability. After these steps, the attacker can navigate the target network and access the sensitive information.

Our algorithm and browser extension introduce uncertainty in step 3 of a watering hole attack. Identifying the vulnerabilities in a visitor relies on the information gathered from reconnaissance. The extension modifies the network packets so that the attacker gets false information about the visitor. Deception is not free, though. Altering the network packet can degrade the webpage rendered, e.g., displaying for Android on a Windows desktop. Thus, the defender needs to carefully trade-off security and the quality of service.

In reality, sophisticated attackers typically do not send all exploits without tailoring to the packet information, as defense would become easier after seeing more such unknown exploits. Also, sending all exploits would be flagged as suspicious and get blocked. The attacker would need to get a new zero-day – a costly proposition. Thus, the attacker prefers scanning the system environment of the incoming traffic.

3 Social Engineering Deception Game

We model the strategic interaction between the organization (defender) and an adversary as a two-player zero-sum game, where the defender chooses an alteration policy and the adversary chooses which websites to compromise and decides the effort spent on scanning traffic. In everyday activities employees of a target organization O visit a set of websites W which includes legitimate sites and potential watering holes set up by an adversary. Let \( t_{w}^{all} \) denote the total amount of traffic to \( w \in W \) from all visitors and \( t_{w} \) the total traffic to \( w \) from O. The defender’s alteration policy is represented by \( x \in [0, 1]^{|W|} \) where \( x_{w} \) is the proportion of O’s traffic to website \( w \in W \) for which the network packet will be altered.

We assume a drive-by download attack will be unsuccessful if, and only if an employee’s packet is altered. However, it is easy to account for different levels of adversary and defender sophistication by adding an additional factor in Eq. (1) below. We consider a cost \( c_{w} \) to alter a single unit of traffic to \( w \). The defender is limited to a budget \( B_{d} \) on the allowable cost.

The adversary first chooses which websites to compromise, represented by a binary vector \( y \in \{0, 1\}^{|W|} \). If \( y_{w} = 1 \), i.e., they turn website \( w \) into a watering hole, they must pay a cost \( \pi_{w} \). The attacker has a budget \( B_{a} \) for compromising websites (w.l.o.g. we assume \( \pi_{w} \leq B_{a} \forall w \in W \)). The adversary then decides the scanning effort for each compromised web-

---

**2 Watering Hole Attacks**

Watering hole attacks are a prominent type of social engineering used by sophisticated attackers. Before we describe our modeling decisions, it is useful to highlight the primary steps in executing a watering hole attack, as illustrated in Fig. 1. In step 1, the attacker identifies a target organization. They use surveys and external information like specialized technical sites to understand the browsing habits of its employees. This allows the adversary to determine the most lucrative websites to compromise for maximum exposure to employees from the targeted organization. In step 2, the adversary compro-
site which can enable them to send exploits tailored to the packet information. We use $e_w$ to denote how much traffic the attacker decides to scan per week for $w$, and refer to $e$ as the effort vector. The discreet attacker has a budget $B_e$ for scanning the incoming traffic. In the special case where the scanning effort is negligible ($B_e = \infty$), all our complexity and algorithmic results to be introduced still hold.

We consider an attacker who aims to maximize the expected amount of unaltered flow from target organization $O$ that is scanned by them, as each unit of scanned unaltered flow can lead to a potential success in the social engineering attack, i.e., compromise an employee and discover critical information about $O$. We model it as a zero-sum game, and therefore the defender’s goal is to minimize this amount.

Social engineering is a complex domain which we cannot fully model. However, we build our model and assumptions so that we can formally reason about deception, and even when our assumptions are not met, our work provides a sensible solution. For example, cyber attackers may have tools to circumvent existing deception techniques. Nonetheless, our solution increases the attacker’s uncertainty about the environment as they cannot easily obtain or trust the information in the network packets. In Appendix B, we provide a detailed discussion of the generality and limitations of our work.

4 Computing Optimal Defender Strategy

In this section, we present complexity analysis and algorithms for finding the optimal defender strategy $x^*$ in this game, which is essentially the minimax strategy, i.e., a strategy that minimizes the attacker’s maximum possible expected amount of scanned unaltered flow. $x^*$ should be the solution of the following bi-level optimization problem $P_1$.

$$\mathcal{P}_1 : \min_x \max_y \sum_{w \in W} \kappa_w (1 - x_w) e_w$$

s.t. $\sum_{w \in W} e_w \leq B_e$ (1)

$$\sum_{w \in W} \pi_w y_w \leq B_a$$ (2)

$e_w \leq t_w^all \cdot y_w, \forall w \in W$ (3)

$y_w \in \{0, 1\}, \forall w \in W$ (4)

$e_w \in [0, \infty), \forall w \in W$ (5)

$$\sum_{w \in W} \pi_w x_w \leq B_d$$ (6)

$$x_w \in [0, 1], \forall w \in W$$ (7)

In objective function 1, $\kappa_w = t_w / t_w^{all}$. Since $t_w (1 - x_w)$ is the total amount of unaltered flow from the defender organization $O$ and $e_w / t_w^{all}$ is the percentage of incoming traffic that will be scanned, $\kappa_w (1 - x_w) e_w$ is the total scanned unaltered traffic to $w$. Constraint (2) describes the budget constraint for the attacker, and Constraint (3) requires that the attacker can only scan traffic for the compromised websites. Constraint (4) is the budget constraint for the defender.

Unfortunately, solving $P_1$ is challenging. It cannot be solved using any of the existing solvers directly due to the bi-level optimization structure, the mix of real-valued and binary variables and the bilinear terms in the objective function ($x_w e_w$). In fact, even the adversary’s best response problem $P_2(x)$, represented as a mixed integer linear program (MILP) below, is NP-hard as stated in Thm 1.

$$P_2(x) : \max_{y, c} \sum_{w \in W} \kappa_w (1 - x_w) e_w$$

s.t. Constraints $2 \sim 6$ (9)

Theorem 1. Finding adversary’s best response is NP-hard.

Therefore, we exploit the structure and properties of $P_1$ and design several novel algorithms to solve it. We first identify two tractable special classes of SED games which can be solved in polynomial time and discuss their real world implications. Then we present CYBERTWEAK, our algorithm for general SED games.

4.1 Tractable Classes

The first tractable class is identified based on the key observation stated in Thm 2: the optimal solutions of SED games exhibit a greedy allocation of the attacker’s effort budget. That is, for at most one website $w$, the attacker spends scanning effort neither zero nor $t_w^{all}$.

Theorem 2. Let $(x^*, y^*, e^*)$ be an optimal solution to $P_1$, $W_F = \{w : e_w^* = t_w^{all}\}, W_Z = \{w : e_w^* = 0\}, W_B = \{w : e_w^* \in (0, t_w^{all})\}$. There is an optimal solution with $|W_B| \leq 1$.

As a result, if the attacker’s scanning budget is so limited that he cannot even scan through the traffic of any website, he will use all the scanning effort on one website in the optimal solution. Thus, the optimal defender strategy can be found by enumerating the websites.

Corollary 1. (Small Effort Budget) If $0 < B_e \leq t_w^{all}, \forall w$, the optimal solution can be found in polynomial time.

The second tractable class roots in the fact that if the scanning effort is negligible (or equivalently, $B_e = \infty$) the attacker only needs to reason about which websites to compromise. Further, if the attacker has a systematic way of compromising a website which makes the cost $\pi_w$ uniform across websites, then the attacker only needs to greedily choose the websites with the highest unaltered incoming traffic and the defender can greedily alter traffic in the top websites. We provide details about these algorithms in the appendix.

Theorem 3. (Uniform Cost + Unlimited Effort) If $\pi_w = 1, \forall w \in W$ and $B_e = \infty$, the defender’s optimal strategy can be found in polynomial time.

4.2 CyberTWEAK

For the general SED games, we propose a novel algorithm CYBERTWEAK (Alg 1). It first computes an upper bound for $P_1$ leveraging the dual problem of the linear program (LP) relaxation of $P_2(x)$. As a byproduct, the computation provides a heuristic defender strategy $\hat{x}^*$ (Line 2). It then runs an optimality check (Line 3) to see if $\hat{x}^*$ is optimal for $P_1$. When optimality cannot be verified, it solves the original problem $P_1$ by converting $P_1$ to an equivalent LP and applying column generation (Gillmore and Gomory 1961), an iterative approach to compute the optimal strategy (Line 4).

https://arxiv.org/abs/1901.00586
We further improve the scalability by identifying and eliminating dominated website as pre-processing (Line 1). Next we provide details about these steps.

**Upper Bound for** $\hat{P}_1$ Let $\hat{P}_2(x)$ be the LP relaxation of $P_2(x)$ and denote the dual variables of the (relaxed) constraints $\{7\} \sim \{9\}$ as $\lambda_1, \lambda_2, \nu, \eta$. We then include the variable $x$ for the defender strategy along with the dual problem, and obtain the minimization problem $\hat{P}_1$.

$$\begin{align*}
\hat{P}_1 & : \min_{x, \lambda_1, \lambda_2, \nu, \eta} B_e \lambda_1 + B_a \lambda_2 + \sum_{w \in W} \eta_w \\
& \text{s.t. } \kappa_w (1 - x_w) \leq \lambda_1 + \nu_w, \quad \forall w \in W \\
& \quad \pi_w \lambda_2 - \pi_w^\text{all} \nu_w + \eta_w \geq 0, \quad \forall w \in W \\
& \quad \sum_{w \in W} c_w t_w x_w \leq B_d \\
& \quad x_w \in [0, 1], \lambda_1, \lambda_2, \nu_w, \eta_w \geq 0, \quad \forall w \in W
\end{align*}$$

$\hat{P}_1$ is an LP which can be solved efficiently. In addition, $\hat{x}^*$ in the optimal solution for $\hat{P}_1$ is a feasible defender strategy in the original problem $P_1$. Therefore, solving $\hat{P}_1$ leads to a heuristic defender strategy as well as bounds for the optimal value of $P_1$. Denote the optimal value of a problem $P$ as $\text{OPT}(P)$. We formalize the bounds below.

Theorem 4. If $B_e \geq \max_u t_u^\text{all}$, $\text{OPT}(\hat{P}_1) \leq 3 \text{OPT}(P_1)$.

Theorem 5. Let $x^*$, $\hat{x}^*$ be an optimal solution to $P_1$, $\hat{P}_1$.

$$\text{OPT}(P_1) \leq \text{OPT}(\hat{P}_2(\hat{x}^*)) \leq \text{OPT}(\hat{P}_1) \leq \text{OPT}(\hat{P}_2(x^*))$$

Optimality Conditions for $\hat{x}^*$ We present a sufficient condition for optimality, which leverages the solution of the following LP $P_3(\hat{x}^*)$.

$$\hat{P}_3(\hat{x}^*) : \min_{\hat{x}} v$$

$$\text{s.t. } v \geq \sum_{w \in W} \kappa_w (1 - x_w) c_w, \quad \forall e \in e^{P_2(\hat{x}^*)}$$

$$\sum_{w \in W} |x_w - \hat{x}^*| \leq \epsilon$$

Constraints $\{7\} \sim \{9\}$

$\epsilon$ is an arbitrary positive number and $e^{P_2(\hat{x}^*)}$ denotes the set of optimal effort vectors in $P_2(\hat{x}^*)$. The following claim shows the optimality condition.

Claim 1. Given $\hat{x}^*$, an optimal solution to $\hat{P}_1$, $\hat{x}^*$ is optimal for $P_1$ if $\text{OPT}(P_2(\hat{x}^*)) \leq \text{OPT}(\hat{P}_3(\hat{x}^*))$.

Clearly, when $\epsilon$ is large, $\text{OPT}(\hat{P}_3(\hat{x}^*))$ is lower and it is harder to satisfy the condition, so in CYBERTWEAK, we use a small enough $\epsilon$ in $\hat{P}_3(\hat{x}^*)$.

**Column Generation** Define $\hat{e}^A$ as the set of all max effort vectors which satisfy $\sum_{w \in W} e_w = B_e$ and $|W| \leq 1$. According to Thm 2 restricting the attacker to only choose strategies from $\hat{e}^A$ will not impact the optimal solution for the defender. As a result, $\hat{P}_1$ is equivalent to the following LP denoted as $\hat{P}_1^\text{LP}(\hat{e}^A)$, when $e^A = \hat{e}^A$.

$$\hat{P}_1^\text{LP}(\hat{e}^A) : \min_{x, v} v$$

$$\text{s.t. } v \geq \sum_{w \in W} \kappa_w (1 - x_w) c_w, \quad \forall e \in e^A$$

Constraints $\{7\} \sim \{9\}$

Although existing LP solvers can solve $\hat{P}_1^\text{LP}(\hat{e}^A)$, the order of $\hat{e}^A$ is prohibitively high, leading to poor scalability. Therefore, CYBERTWEAK instead uses an iterative algorithm based on the column generation framework to incrementally generate constraints of the LP. Instead of enumerating all of $\hat{e}^A$, we keep a running subset $e^A \subseteq \hat{e}^A$ of max effort vectors and alternate between solving $\hat{P}_1^\text{LP}(e^A)$ (referred to as the master problem) and finding a new max effort vector to be added to $e^A$ (slave problem). In the slave problem, we solve the adversary’s best response problem $P_2(x)$ where $x$ is the latest defender strategy found. This process repeats until no new effort vectors are found for the adversary. Recall that we get $\hat{x}^*$ and $e^{P_2(\hat{x}^*)}$ when finding upper bound and verifying optimality of $\hat{x}^*$, which can serve as the initial set of strategies for column generation.

**Dominated Websites** Not all websites are equally valuable for an organization as some are especially lucrative for an adversary to target. In a Polish bank, many employees may visit the Polish Financial Authority website daily, while perhaps a CS conference website is rarely visited by a banker. Intuitively, attackers will not compromise the conference website and thus, the bank may not need to alter traffic to it. Identifying such websites in pre-processing could greatly reduce the size of our problem. A website $w$ is dominated by another website $u$ if the attacker would not attack $w$ unless they have used the maximum effort on $u$, i.e. $e_u = t_u^{\text{all}}$, regardless of the defender’s strategy. Thm 6 presents sufficient conditions for a website to be dominated and leads to an algorithm (Alg 6) to find dominated website to be eliminated.

Theorem 6. Consider websites $u, w \in W$. If the following conditions hold, the website $w$ is dominated by $u$:

$$x_u^{\text{max}} := B_d / (c_u t_u) \leq 1, \quad \kappa_w \leq \kappa_u (1 - x_u^{\text{max}}),$$

$$\pi_w \geq \pi_u,$$

$$t_w^{\text{all}} \leq t_u^{\text{all}}.$$

We conclude the section with the following claim.

Claim 2. CYBERTWEAK terminates with optimal solution.

In light of the hardness of the attacker’s best response problem (Thm 7), we also design a variant of CYBERTWEAK, which uses a greedy heuristic to find a new max effort vector to be added in each iteration of column generation (denoted as GREEDYTEWAK). The algorithm allocates the adversary’s budget to websites in decreasing order of
Algorithm 2: FIND-DOMINATED-WEBSITES

1 Define $U = \{ w \in W : c_w t_w \geq B_d \}$. Let $D = \emptyset$.
2 Calculate $x_u^{\text{max}} = B_d / c_u t_u, \forall u \in U$.
3 foreach website $w \in W$ do
4    Set $U_w = \{ u \in U : \kappa_w \leq \kappa_u (1 - x_u^{\text{max}}) \}$
5    if exists $U'_w \subseteq U_w$ such that
6        \( (1) \sum_{u \in U'_w} \pi_u \leq \pi_w, (2) \sum_{u \in U'_w} t_u^{\text{all}} \geq t_w^{\text{all}}, \) and
7        \( (3) \sum_{u \in U'_w} t_u^{\text{all}} \geq B_c \) then $D = D \cup \{ w \}$
8 return set of dominated websites $D$

$r_w = \kappa_w (1 - x_w) \alpha_w$, where $\alpha_w$ is a tuning parameter. Another variant uses an exact dynamic programming algorithm for the slave problem. Details about these variants can be found in Appendix A. Also, we note that the SED problem is related to recent work on bi-level knapsack with interdiction (Caprara et al. 2010). However, our outer problem of $P_1$ is continuous rather than discrete, and the added dimension of adversary’s effort makes the inner problem $P_2(x)$ more complicated than that being studied in this work.

5 Experiments
We developed and tested CYBERTWEAK to match the scalability required of large-scale deployment. Unless otherwise noted, problem parameters are described in details in Appendix B. All results are averaged over 20 instances; error bars represent standard deviations of the mean.

First, we run experiments on the polynomial time tractable cases (Corollary 1 and Theorem 3). Fig. 2a shows that in both cases, our solution can easily handle $10^3$ websites, applicable to real-world corporate-scale problems.

Moving on to the general SED games, we test 3 algorithms (CYBERTWEAK, GREEDYTWEAK, and RELAXEDLP) with two other baselines, MAXEFFORT and ALLACTIONS. RELAXEDLP refers to solving $P_1$. MAXEFFORT solves $P_1^{\text{LP}}(e^A)$ directly without column generation. ALLACTIONS decomposes SED into subproblems, each assuming some adversary’s effort vector is a best response. Its details can be found in Appendix A. We test the algorithms with different problem scales. In small and medium sized instances, we skip dominated website elimination (DWE) step (Line 3) and optimality check (OC) step (Line 5) in Alg. 1 as the problem size is small enough, making these steps unnecessary. We use solid lines to represent methods with optimality guarantee and dotted lines for others (RELAXEDLP based methods).

For small instances (Fig. 2b), both baselines become impractical even on problems with less than 12 websites. However, CYBERTWEAK is able to find the optimal solutions rather efficiently. GREEDYTWEAK slightly improves over CYBERTWEAK. RELAXEDLP yields the fastest running time, despite a solution gap above 6% as shown in Table 1.

For medium-sized instances (Fig. 2c), baseline algorithms cannot run and GREEDYTWEAK stops being helpful, mainly because the “better” effort vectors generated in GREEDYTWEAK far outnumbers the “best” effort vectors in CYBERTWEAK (Fig. 2d) despite the saved time in each iteration. RELAXED LP has negligible running time and often solves the problem optimally (Table 1).

For large instances (Fig. 2e), CYBERTWEAK with both DWE and OC steps is able to handle $10^5$ websites in 10 seconds. When we remove (denoted as “w/o”) DWE and/or OC step, runtime increases significantly, showing the efficacy of these steps. Compared to RELAXEDLP or RELAXEDLP enhanced with DWE step, which can also efficiently handles $10^5$ websites, CYBERTWEAK has optimality guarantee.

Finally, we consider the trade-off between the risk exposure and degradation in rendering websites, represented by the objective $OPT(P_1)$ and defender’s budget $B_d$, respectively. With budget $B_d = \sum_{w \in W} c_w t_w$, the attacker would have zero utility. With zero defender budget, the attacker would get maximum utility $U$. Fig. 2f shows how the utility ratio $OPT(P_1)/U$ changes with the budget ratio $B_d/B_d$. As the organization increases the tolerance for service degradation, its risk exposure drops at a decreasing rate.

The impact of DWE varies significantly across instances and relies heavily on the distribution of traffic. In less than 4 of the 20 instances DWE did not reduce the problem size by much. We report in Fig. 2g the majority group where DWE eliminated a significant number of websites. We provide further discussion in Appendix D.
6 Deployment

Based on CYBERTWEEK, we developed a browser extension (available on the Google Chrome Web Store[1]). It can modify the user-agent string sent to websites automatically during browsing which contains information such as the operating system, browser, and services running on the user’s machine. The extension receives from the user the websites visited W, number of visits per week t_w, the cost to alter the user-agent string c_w and budget B_d. The total traffic t_w^' and attack cost π_w are estimated from the Cisco Umbrella 1 Million list (Cisco 2019). The attacker’s budgets are set in scale with the previously mentioned parameters. The extension runs CYBERTWEEK to set the probability of altering the user-agent string for each website. Note that it is the relative magnitudes, rather than the exact values, that matter.

The extension takes additional steps to make our algorithm more usable and interpretable. First, some users may find it hard to specify the cost of altering user-agent string c_w and budget B_d. Our extension will adjust the values based on the qualitative feedback provided by users about whether the degradation of the website’s rendering is acceptable when they visit a website using the modified user-agent, as shown in Fig. 3. Second, in addition to showing the computed altering probabilities, the extension also displays a personalized “risk level” for each website, to help the user understand the algorithm’s output. Less popular websites frequented more often by the user have higher risk, as shown in Fig. 3.

As mentioned in Section 3, advanced cyber attackers might sometimes circumvent the existing deception methods. Future versions of the extension will leverage the latest advances in anti-fingerprinting techniques, which entail manipulating more than the user-agent string.

We believe this CYBERTWEEK extension is vital to the continued study and development of the countermeasure we develop for this domain and large scale deployments.

Acknowledgments

Co-authors Z. R. Shi and F. Fang are supported in part by the U.S. Army Combat Capabilities Development Command Army Research Laboratory under Cooperative Agreement Number W911NF-13-2-0045 (ARL Cyber Security CRA).

References

[Caprara et al. 2016] Caprara, A.; Carvalho, M.; Lodì, A.; and Woeginger, G. J. 2016. Bilevel knapsack with interdiction constraints. INFORMS Journal on Computing.

[Cisco 2019] Cisco. 2019. Cisco Umbrella Popularity List.

[Durkota et al. 2015] Durkota, K.; Lişy, V.; Bosansky, B.; and Kiekinthvel, C. 2015. Optimal network security hardening using attack graph games. In IJCAI.

[Farquhar 2017] Farquhar, D. 2017. Watering hole attack prevention.

[Gilmore and Gomory 1961] Gilmore, P. C., and Gomory, R. E. 1961. A linear programming approach to the cutting-stock problem. Operations research 9(6):849–859.

[Jajodia et al. 2017] Jajodia, S.; Park, N.; Pierazzi, F.; Pugliese, A.; Serra, E.; Simari, G. I.; and Subrahmanian, V. 2017. A probabilistic logic of cyber deception.

[Laszka, Vorobeychik, and Koutsoukos 2015] Laszka, A.; Vorobeychik, Y.; and Koutsoukos, X. D. 2015. Optimal personalized filtering against spear-phishing attacks.

[Mitnick and Simon 2001] Mitnick, K. D., and Simon, W. L. 2001. The art of deception: Controlling the human element of security. Parliament 2018. Parliament. 2018. Watering Hole Attacks.

[Schlenker et al. 2018] Schlenker, A.; Thakoor, O.; Xu, H.; Tambe, M.; Vayanos, P.; Fang, F.; Tran-Thanh, L.; and Vorobeychik, Y. 2018. Deceiving cyber adversaries: A game theoretic approach. In AAMAS.

[Sutton 2014] Sutton, M. 2014. How to protect against watering hole attacks.

Symantec 2017 Symantec. 2017. Attackers target dozens of global banks with new malware.

Whittaker 2013 Whittaker, Z. 2013. Facebook, Apple hacks could affect anyone: Here’s what you can do.

| W  | Gap   | # Exact | W  | Gap   | # Exact |
|----|-------|---------|----|-------|---------|
| 4  | 13.19%| 27/20   | 50 | 2e-6  | 18/20   |
| 8  | 8.11% | 5/20    |    | 8e-10 | 19/20   |
| 12 | 6.63% | 8/20    | 50 | 2e-3  | 17/20   |
| 100| 8e-9  | 19/20   | 50 | 2e-8  | 18/20   |

Table 1: Solution quality of RELAXEDLP, with the number of instances where RELAXEDLP solves the problem exactly.
Draining the Water Hole: Mitigating Social Engineering Attacks with CyberTWEAK

Appendix

A Deferred Algorithms

A.1 Attacker’s Better Response Heuristic

In light of the hardness of finding the adversary’s best response, we consider a greedy heuristic. Leveraging Theorem 2, GREEDY (Alg. 3) allocates the adversary’s budget to websites in decreasing order of the ratio \( r_w = \frac{t_w(1-x_w)/t_{w\text{all}}}{\alpha_w} \), where \( \alpha_w \) is a tuning parameter. We replace the MILP for \( \mathcal{P}_2(x) \) in CYBERTWEAK with Alg. 3 to find an adversary’s better response. If it does not yield a new effort vector, the MILP is called. The column generation process terminates if the MILP again does not find a new effort vector. We refer to this entire procedure as GREEDY\_TWEAK. Note that GREEDY\_TWEAK also terminates with the optimal solution. Although GREEDY (Alg. 3) does not provide an approximation guarantee, it performs well in practice. As we show in the experiment section, in practice the accuracy of its solution improves as the size of the problem grows. We also considered a dynamic programming algorithm which is exact and runs in pseudo-polynomial time. However, its practical performance is unsatisfactory.

\[
\text{Algorithm 3: GREEDY}
\]

1. Sort the websites in decreasing order of \( r_w = \frac{t_w(1-x_w)/t_{w\text{all}}}{\alpha_w} \).
2. foreach website \( w \) in the sorted order do
   3. if remaining attack budget \( \geq \) attack cost \( \pi_w \) then
      4. Attack this website \( w \) with maximum effort allowed
   5. if running out of budget then break

A.2 Baseline Algorithm for \( \mathcal{P}_1 \)

We show the details of one of our baseline algorithms, All Actions, in Alg. 4. Let \( \mathcal{A} \) denote the set of actions available to the adversary such that the budget constraint is satisfied. Each action \( a^* \in \mathcal{A} \) is a set of websites being compromised. According to Theorem 2, among all the websites \( w \) compromised in \( a^* \), the adversary puts “partial” effort \( e_w \in (0, t_{w\text{all}}] \) on at most one website \( w^* \). Therefore, the action-website pairs \( (a^*, w^*) \) fully characterize the adversary’s strategies. Alg. 4 works by finding the optimal defender strategy, assuming each action-website pair is the optimal strategy for the adversary.

\[
\text{Algorithm 4: ALL ACTIONS}
\]

1. foreach \( (a^*, w^*) \in \mathcal{A} \times W \) where \( w^* \in a^* \) do
   2. foreach website \( w \in W \) do
      3. if \( w = w^* \) then
         4. Define \( z_w = \min\{B_e - \sum_{w^* \in a^*,w \neq w^*} t_{w\text{all}}, t_{w\text{all}} \} \)
      else if \( w \in a^* \) then
         6. Define \( z_w = t_{w\text{all}} \)
      else
         7. Define \( z_w = 0 \)
      8. Define \( k_w = \frac{t_{w\text{all}}}{t_w} z_w \)
   9. foreach \( (\hat{a}, \hat{w}) \in \mathcal{A} \times W \) where \( \hat{w} \in \hat{a} \) do
      10. Define \( \hat{k}_w \) similarly as above, for each \( w \in W \).
      11. Add to \( BR(a^*, w^*) \) the following linear constraint
         \[
         \sum_{w^* \in a^*,k \in \hat{a}} k_w (1 - x_w) \geq \sum_{w \in \hat{a}} \hat{k}_w (1 - x_w)
         \]
      12. Solve the following LP
         \[
         \min_{x,v} \quad v \\
         \text{s.t.} \quad v \geq \sum_{w \in W} k_w (1 - x_w) \\
         \text{linear constraints in } BR(a^*, w^*) \\
         \sum_{w \in W} e_w t_w x_w \leq B_d \\
         x_w \in [0, 1], \quad \forall w \in W
         \]
      13. Select the best solution out of all the LPs.

B Deferred Proofs

B.1 Proof of Theorem 1

We reduce from the knapsack problem. In the knapsack problem, we have a set \( W \) of items each with a weight \( \omega_w \) and value \( p_w \) \( \forall w \in N \), and aim to pick items of maximum possible value subject to a capacity \( B \). We now create an instance of the SED problem. Create a website for each item \( w \) in \( W \) with organization traffic and total traffic \( t_w = t_{w\text{all}} = p_w \) and attack cost \( \omega_w \). Assume that \( x = 0^T \). Next, set \( B_a = B \) and \( B_e = \infty \). Notice that the objective function becomes \( \sum_{w \in W} e_w \) where \( \sum_{w \in W} e_w \leq \infty \) and \( e_w \leq p_w y_w \). Hence, \( e_w = p_w \) whenever \( y_w = 1 \). Then, the adversary’s best response problem is given by:

\[
\max \quad \sum_{w \in W} p_w y_w \\
\text{s.t.} \quad \omega_w y_w \leq B \\
y_w \in \{0, 1\}, \quad \forall w \in W
\]

This is exactly the knapsack problem described above. \( \square \)
B.2 Proof of Theorem 2
For each \( w \in W \), let \( k_w = t_w(1 - x_w)/t_w^{all} \). Suppose there exist some \( w_1, w_2 \in W_B \), and w.l.o.g assume \( k_{w_1} \geq k_{w_2} \). Let \( \Delta e = e_w^* - e_w \). Consider the solution \( (x^*, y^*, \hat{e}) \) where \( \hat{e}_{w_1} = e_{w_1} + \Delta e, \hat{e}_{w_2} = e_{w_2} - \Delta e \) and \( \hat{e}_w = e_w^* \) for all other websites \( w \in W \). This is a feasible solution, and the objective increases by \( (k_{w_1} - k_{w_2})\Delta e \geq 0 \) compared to \((x^*, y^*, e^*)\). Furthermore, at least one of \( w_1 \) and \( w_2 \) is removed from \( W_B \). We can apply this argument repeatedly until \(|W_B| \leq 1\). 

B.3 Proof of Corollary 1
Since \( B_e \leq t_w^{all} \) \( \forall w \in W \), we know \(|W_F| \leq 1 \) for any feasible solution. If \(|W_F| = 1 \), then we have \(|W_Z| = n - 1 \) and \(|W_B| = 0 \). If \(|W_F| = 0 \), by Theorem 2 we have \(|W_B| = 1 \) and \(|W_Z| = n - 1 \). In either case, there is only website \( w^* \) such that \( e_{w^*} > 0 \). It follows that \( w^* \in \arg \max_{w \in W} t_w(1-x_w)\) given a defender strategy \( x \). The optimal defender strategy can be found by solving the following LP:

\[
\begin{align*}
\min_{x, v} & \quad v \\
\text{s.t.} & \quad v \geq \frac{t_w(1-x_w)B_e}{t_w^{all}} \quad \forall w \in W \\
& \quad \sum_{w \in W} c_w t_w x_w \leq B_d \\
& \quad x_w \in [0, 1] \quad \forall w \in W
\end{align*}
\]

B.4 Proof of Theorem 3
Under these assumptions, the problem \( \mathcal{P}_1 \) becomes

\[
\begin{align*}
\min_{x} & \quad \max_{y, e} \sum_{w \in W} t_w(1-x_w)y_w \\
\text{s.t.} & \quad \sum_{w \in W} y_w \leq B_a \\
& \quad \sum_{w \in W} c_w t_w x_w \leq B_d \\
x_w \in [0, 1], y_w \in \{0, 1\} \quad \forall w \in W
\end{align*}
\]

The constraint \( \sum_{w \in W} y_w \leq B_a \) must be satisfied with equality because \( t_w(1-x_w) \geq 0 \) for all \( w \in W \). The defender’s problem is to minimize the sum of \( B_a \) largest linear functions \( t_w - t_w x_w \) among the \( n = |W| \) of them, subject to the polyhedral constraints on \( x_w \). This problem can be solved as a single LP (Ogryczak and Tamir 2003) as follows.

\[
\begin{align*}
\min_{d^+, x, z} & \quad B_a z + \sum_{w \in W} d^+_w \\
\text{s.t.} & \quad d^+_w \geq t_w - t_w x_w - z \quad \forall w \in W \\
& \quad \sum_{w \in W} c_w t_w x_w \leq B_d \\
x_w \in [0, 1], d^+_w \geq 0 \quad \forall w \in W
\end{align*}
\]

B.5 Proof of Theorem 4
Let \( x^* \) be the optimal solution to \( \mathcal{P}_1 \). Consider the problem \( \mathcal{P}_2(x^*) \). At optimal solution, the inequality \( e_w \leq t_w^{all} \) \( \forall w \) in \( \mathcal{P}_2(x^*) \) is satisfied with equality, as if \( e_w < t_w^{all} \) \( \forall w \), then we can decrease \( y_w \) without changing the objective value and violating any constraints. Then, we can eliminate the variables \( e_w \) and \( \mathcal{P}_2(x^*) \) becomes a standard two-dimensional fractional knapsack problem \( \mathcal{P}_4(x^*) \). It is well-known that there exists an optimal solution to \( \mathcal{P}_4(x^*) \) which has at most 2 fractional values \( y_{w_1} \) and \( y_{w_2} \) (Kellerer, Pferschy, and Pisinger 2004). We have

\[
\begin{align*}
\text{OPT}(\mathcal{P}_1) \leq \text{OPT}(\mathcal{P}_2(x^*)) = \text{OPT}(\mathcal{P}_4(x^*)) \\
\leq \text{OPT}(\mathcal{P}_2(x^*)) + t_w(1-x_w^*) + t_w(1-x_w^*) \\
\leq 3\text{OPT}(\mathcal{P}_2(x^*)) = 3\text{OPT}(\mathcal{P}_1)
\end{align*}
\]

Note that if \( B_e = \infty \), \( \mathcal{P}_1 \) is a 2-approximation.

B.6 Proof of Theorem 5
Since \( \hat{x}^* \) and its best response calculated by \( \mathcal{P}_2(\hat{x}^*) \) form a feasible solution to \( \mathcal{P}_1 \), the first inequality holds. For any defender strategy \( x \), \( \text{OPT}(\mathcal{P}_2(x)) \leq \text{OPT}(\mathcal{P}_2(x^*)) \) as adversary can choose fractional \( y_w \)'s in \( \mathcal{P}_2(x) \). For \( x^* \) specifically, we have \( \text{OPT}(\mathcal{P}_2(x^*)) = \text{OPT}(\mathcal{P}_1) \), since \( \mathcal{P}_1 \) is, by strong duality, equivalent to \( \mathcal{P}_1 \) except that the adversary is allowed to choose fractional \( y_w \)'s. This establishes the second inequality. The last inequality holds because \( x^* \) and its fractional best response calculated by \( \mathcal{P}_2(x^*) \) form a feasible solution to \( \mathcal{P}_1 \).

B.7 Proof of Theorem 6
From conditions (1) and (2), we know that for the same amount of effort, the attacker will be better off attacking website \( u \) than \( w \), regardless of the defender’s strategy.

Suppose \( e_w > 0 \) and \( e_u = 0 \) (consequently \( y_w = 1, y_u = 0 \)). Then we could let \( e'_w = 0 \) and \( e'_u = e_w \). This is possible because from condition (4), \( e_u \leq t_u^{all} \leq t_w^{all} \) so we have \( e'_u \leq t_u^{all} \). Doing this does not increase the attack cost because now \( y'_w = 0 \) and \( y'_u = 1 \) and \( y'_w \geq y'_u \) from condition (3).

Suppose \( e_w > 0 \) and \( e_u > 0 \) (consequently \( y_w = y_u = 1 \)). Let \( e'_w = e_w - \min\{e_w, t_u^{all} - e_u\} \) and \( e'_u = e_u + \min\{e_w, t_u^{all} - e_u\} \). We know that if \( e'_w > 0 \), then \( e'_u \leq t_u^{all} \). Of course, the attack cost does not increase as well.

B.8 Proof of Claim 1
Suppose \( (\hat{x}^*, \text{OPT}(\mathcal{P}_2(\hat{x}^*))) \) is not an optimal solution for the LP \( \mathcal{P}_1^{LP}(\hat{x}^*) \) which is equivalent to \( \mathcal{P}_1 \). Thus, equivalently \( \hat{x}^* \) not optimal for \( \mathcal{P}_1 \). Any of its neighborhood with radius \( \epsilon \) contains some \( (\hat{x}', \hat{y}') \) as a better solution, meaning \( \hat{y}' < \text{OPT}(\mathcal{P}_2(\hat{x}^*))) \). This solution \( (\hat{x}', \hat{y}') \) satisfies constraint (20), which is strictly stronger than constraint (17). Therefore \( (\hat{x}', \hat{y}') \) is feasible for \( \mathcal{P}_3(\hat{x}^*) \); this contradicts \( \text{OPT}(\mathcal{P}_3(\hat{x}^*)) \geq \text{OPT}(\mathcal{P}_2(\hat{x}^*)) \).

\]
Table 2: Solution gaps of different greedy heuristics for the adversary best response problem. Results are averaged over 5 runs on different problem sizes $|W| = 100, 200, \ldots, 500.$

\[
\begin{array}{l|l}
\alpha_w & \text{OPT} - \text{OPTGreedy} \\
\hline
\pi_w & 0.0079 \\
\pi_w / B_\alpha + 1 / B_c & 0.0285 \\
1 & 0.0082 \\
\end{array}
\]

Table 3: Parameter distributions for the experiment on large instances.

| Variable | Distribution | Variable | Distribution |
|----------|--------------|----------|--------------|
| $p_{wa}$ | $U(350, 750)$ | $t_w$ | $U(50, 100)$ |
| $t_w$ | $U(1, 4)$ | $c_w$ | $U(30, 54)$ |
| $\pi_w$ | $U(0.11 \sum_{w \in W} c_w t_w / t_w, 0.71 \sum_{w \in W} c_w t_w)$ | $B_d$ | $U(0.1 \sum_{w \in W} \pi_w, 0.8 \sum_{w \in W} \pi_w)$ |
| $B_q$ | $U(0.2 \sum_{w \in W} t_w^* / |W|, 0.8 \sum_{w \in W} t_w^* / |W|)$ | $B_a$ | $U(0.1 \sum_{w \in W} \pi_w, 0.8 \sum_{w \in W} \pi_w)$ |
| $B_e$ | $U(0.3 \sum_{w \in W} t_w^* / |W|)$ | $B_a$ | $U(2, 6)$ |
| $\pi_w$ | $U(13)$ |

Table 4: Parameter distributions for the experiment on large instances.

For large scale instances, we set different websites to have different importance, motivated by the fact that people do not visit all websites with equal frequency. We split $W$ into $W_1, W_2$ with $|W_1| : |W_2| = 1 : 9.$ Websites in $W_1$ have a large portion of traffic from the organization and those in $W_2$ have a smaller portion. Thus, $W_1$ and $W_2$ follow different distributions (Table 3). The attacker has a uniform cost of attack. In less than 4% of the 20 instances DWE did not reduce the problem size by much. We report in Fig. 2c the majority group where DWE eliminated a significant number of websites. $|W_1| / |W_2|$ could be a lot smaller in reality, and our algorithms with DWE would run even faster.

C Deferred Experiments

We present additional experiments on the adversary’s best response problem. In the Greedy algorithm (Alg. 3), the adversary selects websites based on a decreasing order of $r_w = t_w (1 - x_w) / \pi_w.$ Here, $\alpha_w$ is the tuning parameter. With different choices of $\alpha_w,$ we compute the output value $\text{OPTGreedy}$ of Greedy with the optimal value OPT obtained by solving the MILP $P_2(x).$ Table 2 shows the solution gap $\text{OPT} - \text{OPTGreedy}.$ We observe that $\alpha_w = \pi_w$ yields the smallest solution gap. We also tested other choices for $\alpha_w$ such as $(\pi_w / B_\alpha)^p + (1 / B_c)^q$ for different powers $p$ and $q,$ yet they do not yield better optimization gaps. Hence we fix $r_w = \frac{t_w (1 - x_w) / \pi_w}{10}.$

Fig. 4b shows Greedy’s solution gap decreases to near zero as the problem size grows. In addition, Greedy typically runs within 1% of the time of the MILP.

D Experiment Parameters

Table 4 shows the distribution from which the parameters are generated in most of our experiments. In Table 3 we detail the parameters used in the experiment in Fig. 2c.

In addition, in the case of small effort budget, $B_e$ is generated uniformly between 1 and $\min_{w \in W} t_w^*.$

E Discussion

Assumptions and Generality

We assumed that the attack will succeed if and only if the network packet is unaltered. If the attacker can obtain the true system information with probability $p_w$ even if the packet is altered, we may modify the objective in Eq. (1) to \[ \sum_w t_w (1 - x_w (1 - p_w)) e_w / t_w^* \]

If the organization has other countermeasures (e.g. Bromium browser VMs), the attack may fail with probability $q_w$ even if the packet is unaltered, the objective then becomes \[ \sum_w t_w (1 - x_w) (1 - q_w) e_w / t_w^* \]. Thus, our algorithm can account for different levels of adversary and defender sophistication.

We do not attempt to claim that altering the network packets is a panacea to all watering hole attacks. Cyber attackers have many tools to circumvent existing deception techniques. Nonetheless, the proposed deception technique increases their uncertainty about the true nature of the environment, which leads to more cost on them, e.g. technical complexity and increased exposure. This uncertainty ties into our consideration of the attacker’s scanning effort $e_w$ and budget $B_e,$ as
the attacker cannot easily obtain or trust the basic information in the network packets.

**Limitations** The generality notwithstanding, we acknowledge a few limitations of our work and potential problems in large-scale deployment. First, if an organization is the sole user of our method and if the attacker has (possibly imperfect) clue about the source of traffic from the start, randomizing network packet information might serve as an unintended signal to the attacker, reducing the effort needed to identify traffic from the targeted organization. Second, by manipulating the web traffic, the organization is effectively monitoring its employees’ internet activities. Although in many jurisdictions this is allowed when doing properly, the potential ethical issues must be carefully addressed.

**References**

[Ogryczak and Tamir 2003] Ogryczak, W. and Tamir, A., 2003. Minimizing the sum of the $k$ largest functions in linear time. Information Processing Letters, 85(3), pp.117-122.

[Kellerer, Pferschy, and Pisinger 2004] Kellerer, H., Pferschy, U. and Pisinger, D., 2004. Knapsack problems. Springer, Berlin, Heidelberg.