Learning Equilibria in Stochastic Information Flow Tracking Games with Partial Knowledge

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2013 Target Corporation Data Breach

40 million credit and debit card numbers and 70 million records of personal information were stolen

September 2013	Phishing attacks against Fazio Mechanical Services
15 November 2013	Accessed Target's network and tested malware on Point of Service machines
27 November 2013	Began collection of credit card data from Point of Service machines
2 December 2013	Moved data out of Target's network

Shu, X., Tian, K., Ciambrone, A. and Yao, D., 2017. Breaking the target: An analysis of target data breach and lessons learned. *arXiv preprint arXiv:1701.04940*.

Stages of Advanced Persistant Threats (APTs)

40 million credit and debit card numbers and 70 million records of personal information were stolen

Initial Infection	Phishing attacks against Fazio Mechanical Services
Command and Control	Accessed Target's network and tested malware on Point of Service machines
Lateral Expansion	Began collection of credit card data from Point of Service machines
Data Exfiltration	Moved data out of Target's network

Shu, X., Tian, K., Ciambrone, A. and Yao, D., 2017. Breaking the target: An analysis of target data breach and lessons learned. *arXiv preprint arXiv:1701.04940*.

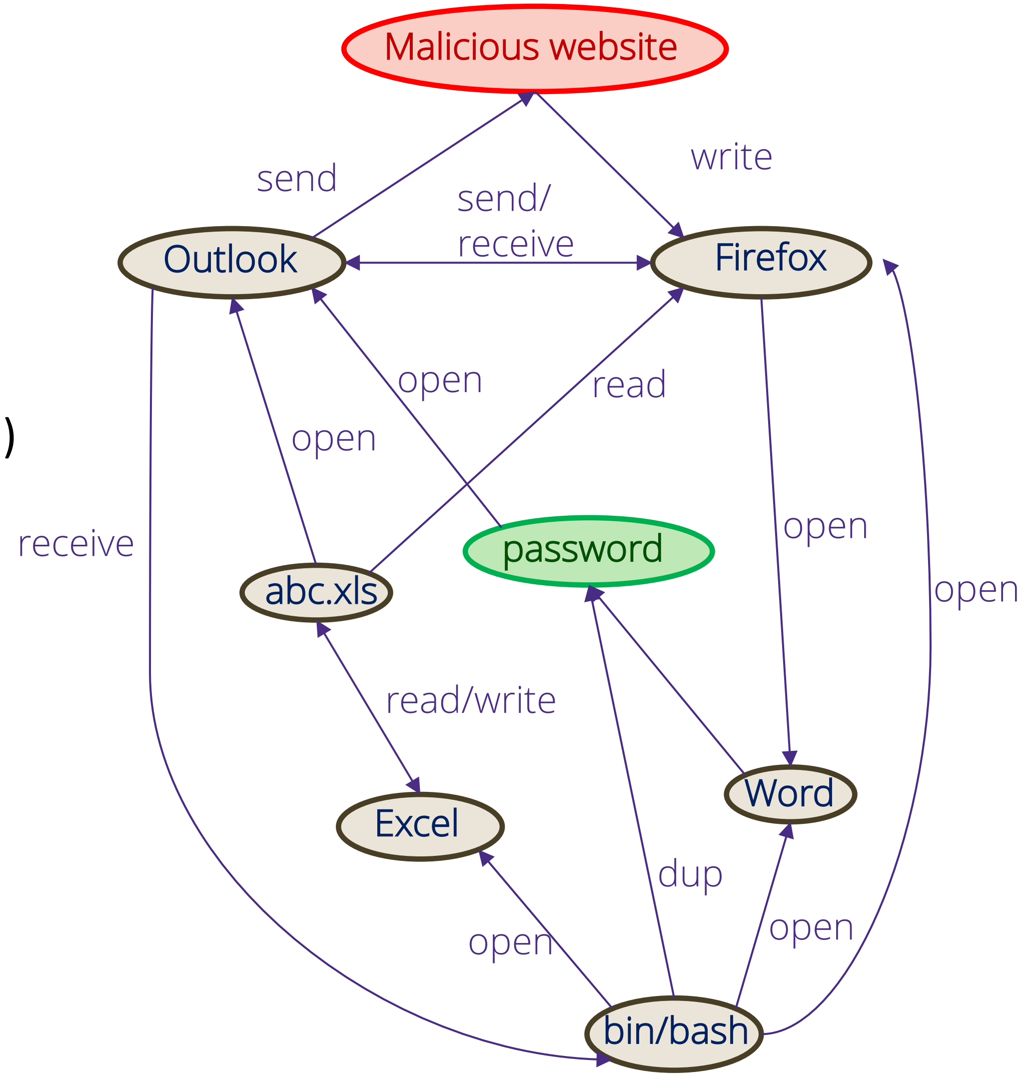
Information Flow Graphs (IFGs)

Adversary interact with system components (e.g. processes, files) using system calls (e.g. read, write, open)

Information flows (data- and control-flow commands) abstract the interactions of the adversary with various system components

Graphical representation of system-level data

- ➢ Nodes: Subjects and Objects
  - Subjects: Processes (an instance of a computer program)
  - Objects: e.g. files/memory/network sockets
- ➢ Edges: probability of transferring information flows between processes
  - System calls: e.g. read, write, open, send



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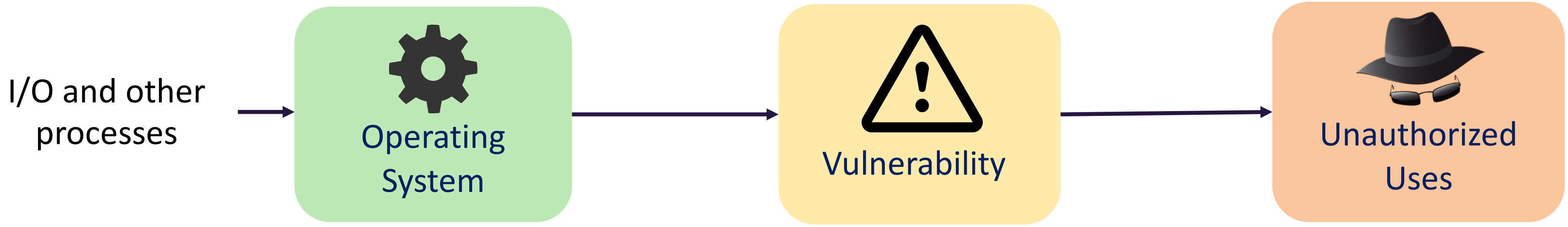
Dynamic Information Flow Tracking (DIFT)



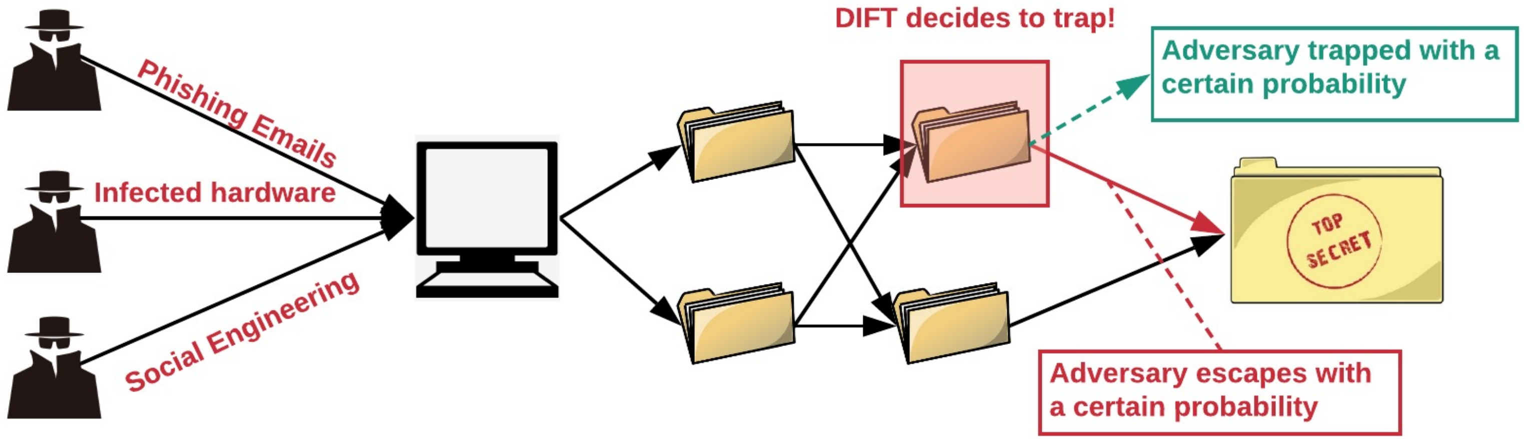
Tag suspicious data channels

Track propagation of tagged inputs based on tag propagation policy (data- and control-flow)

Trap attacks; check the authenticity of tagged flows and restrict spurious values

Suh, G. E., Lee, J. W., Zhang, D., & Devadas, S. (2004, October). Secure program execution via dynamic information flow tracking. *In ACM Sigplan Notices,*ACM

Problem Formulation



Aim

Model a DIFT-based defense mechanism against APTs that:

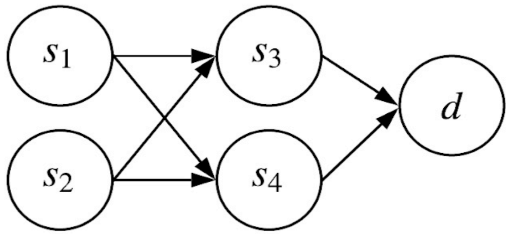
a. Captures the trade-off between detection accuracy and resource efficiency.

b. Accounts for rate of false negatives.

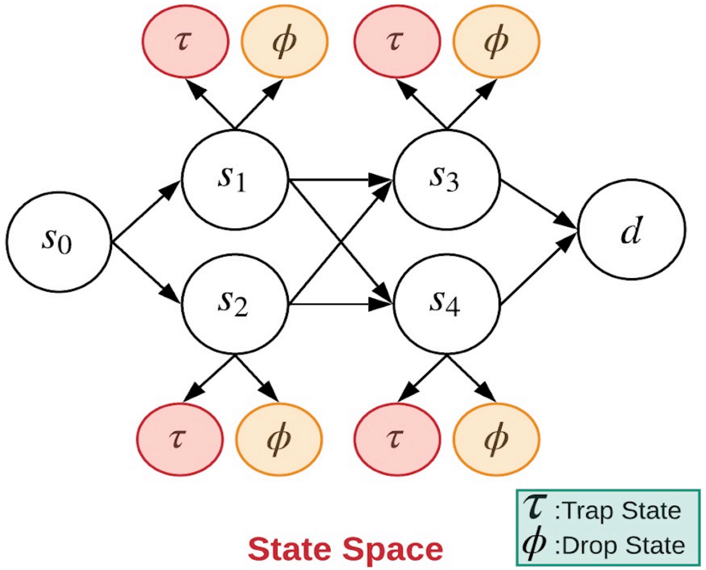
Problem Formulation

- APT **(A)** is the adversary infecting the system.
- DIFT **(D)** is the defense framework used against **A**.
- Goal of **A** is to evade detection and reach target nodes.
- Goal of **D** is to dynamically place trap locations to:
  - Maximize detection probability
  - Minimize performance overhead on system
- Strategic interactions between **D** and **A** form a game.

State space and Actions



Information Flow Graph



State Space

$$\mathbf{S} = \{s_0, \underbrace{s_1, \ldots, s_{N-1}}_{\text{Node in IFGs}}, d, \phi, \tau\}$$

Collection of entry nodes | Node in IFGs | Terminal state | Quit state | Trapped state

We assume that both players know destination node d.

ACTIONS:

- **A** (a_t): {Transitioning to a out-neighboring state, Quit}
- **D** (d_t). **:** {Trap, no Trap}
- No actions are allowed for D at nodes in the set $\{s_0, \phi, \tau\}$

Transition Structure

DIFT (D)

$$p_D = \{p_D(s) : s \in \mathbf{S}, s \notin \{s_0, d, \phi, \tau\}\}$$

$p_D(s)$: Probability of trapping in *s*

$1 - p_D(s)$: Probability of not trapping in *s*

APT (A)

For $s \notin \{s_0, d, \tau, \phi\}$

$$p_A(s) = \{p(s, s'): s \in \mathbf{S}, s' \in N(s)\}$$

$p_A(s)$: Probability distribution of all possible actions in state *s*.

False negatives of DIFT ($FN(s_i)$) depends on:

- Number of security rules
- Strength security rules

Given actions $a_t = s_{i'}$ and $d_t = 1$. The next state is given by:

$$s_{t+1} = \begin{cases} s_{i'} & w.p. \quad FN(s_i) \\ \tau & w.p. \quad 1 - FN(s_i) \end{cases}$$

We assume policies of both players to be stationary

Payoff Structure

DIFT (D)

$$r_D(s,d,a)\begin{cases}\alpha_D > 0, if\ s=\tau & \text{Reward for detecting}\\ \beta_D < 0, if\ s=d & \text{Penalty for evading detection}\\ \sigma_D \geq 0, if\ s=\phi & \text{Reward for dropping out}\\ C_D(s) < 0, if\ s \in S\ and\ d=1 & \text{Resource cost}\\ 0, otherwise\end{cases}$$

APT (A)

$$r_A(s,d,a)\begin{cases}\alpha_A < 0, if\ s=\tau & \text{Penalty for getting detected}\\ \beta_A > 0, if\ s=d & \text{Reward for reaching destination}\\ \sigma_A \leq 0, if\ s=\phi & \text{Penalty for dropping out}\\ 0, otherwise\end{cases}$$

Payoff Structure

$$U_A(p_D, p_A) = p_\tau^{(T)}\alpha_A + p_R^{(T)}(d)\beta_A + p_\phi^{(T)}\sigma_A$$

$$U_D(p_D, p_A) = \sum_{v_i \in V_{(G)}} (p_D(s_i)\mathcal{C}_D(v_i)) + p_\tau^{(T)}\alpha_D + p_R^{(T)}(d)\beta_D + p_\phi^{(T)}\sigma_D$$

$p_\tau^{(T)}$: Probability of being in the trapped state at terminal time T

$p_R^{(T)}$: Probability of reaching the destination at terminal time T

$p_\phi^{(T)}$: Probability of being drop state at terminal time T

Terminating Conditions

1. The adversary is trapped by the defender.
2. The adversary reaches the destination.
3. The adversary quits the game.

Payoff Structure

$$U_A(p_D, p_A) = p_\tau^{(T)}\alpha_A + p_R^{(T)}(d)\beta_A + p_\phi^{(T)}\sigma_A$$

$$U_D(p_D, p_A) = \sum_{v_i \in V(G)} (p_D(s_i)\mathcal{C}_D(v_i)) + p_\tau^{(T)}\alpha_D + p_R^{(T)}(d)\beta_D + p_\phi^{(T)}\sigma_D$$

$$p_\tau(s_i) = p_D(s_i)FN(s_i)$$

$$p_R(s_i) = \sum_{s_i \in S} p_A(s_j, s_i)p_R(s_i)(1 - p_\tau(s_j))$$

$$p_\phi(s_i) = p_A(s_i, \phi)p_R(s_i)(1 - p_\tau(s_j))$$

Terminating Conditions

1. The adversary is trapped by the defender.
2. The adversary reaches the destination.
3. The adversary quits the game.

Properties of APT vs. DIFT game

Nonzero-sum

Defender payoff:

Reward, penalty, cost of tagging

Adversary payoff:

Reward, penalty

Stochastic

Uncertainty in both players' actions

Imperfect Information

Defender cannot distinguish between benign and malicious flow

Incomplete Information

Unknown rate of false negatives

Solution Concept

Strategy pair $(p_A^*, p_D^*) \in \mathbf{P}_A \times \mathbf{P}_D$ *forms a Nash equilibrium in stochastic stationary strategies for any* $\epsilon > 0$ *and for all* $p_A \in \mathbf{p}_\mathrm{A}$ *and* $p_D \in \mathbf{p}_\mathrm{D}$ *if*

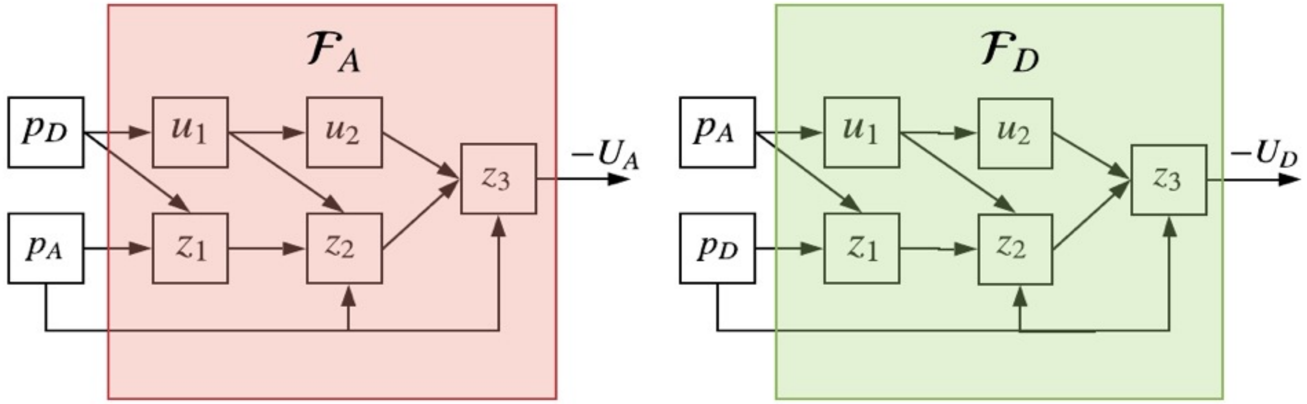
$$U_A\,(p_A^*, p_D^*) \geq (p_A, p_D^*)$$
$$U_D(p_A^*, p_D^*) \geq (p_A^*, p_D\ )$$

Result 1:

The APT vs. DIFT game satisfies the following:

1. The game terminates in at most $N + 3$ number of steps.
2. There exists a Nash Equilibrium (NE) for the game.
3. For a given strategy pair (p_A, p_D) computation of $p_R^{(T)}$, $p_\tau^{(T)}$ and $p_\phi^{(T)}$ has complexity **linear** in the number of states and edges in S.

Modified Partially Input Convex Neural Networks (PICNNs)

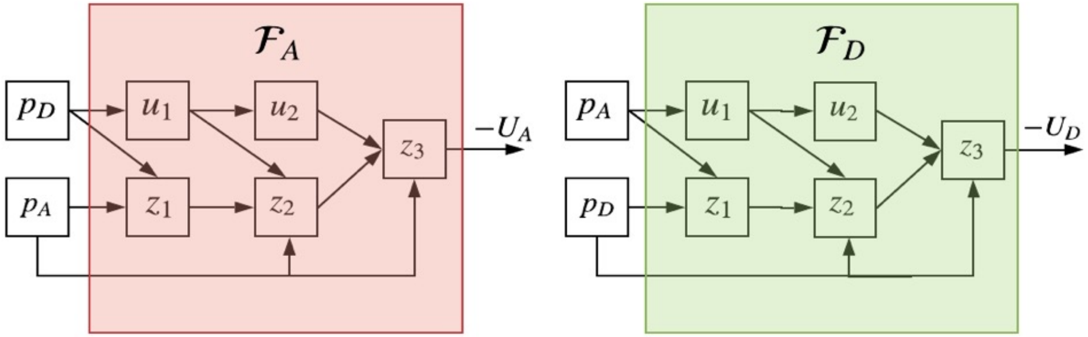


The modified PICNN model defines a neural network with k layers over output y by implementing the following architecture for i = 0,….,k

$$z_{i+1} = g_i\left(W_i^{(z)} z_i + W_i^{(y)} y + W_i^{(u)} u_i + b_i\right), f(y;\theta) = z_k, u_0 = x$$

B. Amos, L. Xu, and J. Z. Kolter, "Input convex neural networks," in Proceedings of the 34th International Conference on Machine Learning, vol. 70. JMLR. org, 2017, pp. 146–155.

Results



$$z_{i+1} = g_i\left(W_i^{(z)} z_i + W_i^{(y)} y + W_i^{(u)} u_i + b_i\right), f(y;\theta) = z_k, u_0 = x$$

Result 2:

The function $\mathcal{F}$ is convex in y provided that all $W_{(1:k-1)}^{(z)}$ are non-negative, and all functions g_i are convex and non-decreasing.

B. Amos, L. Xu, and J. Z. Kolter, "Input convex neural networks," in Proceedings of the 34th International Conference on Machine Learning, vol. 70. JMLR. org, 2017, pp. 146–155.

Supervised Learning for Games

Data Generation → **Training Partial Input Convex Neural Networks (PICNN)** → **Alternating Optimization**

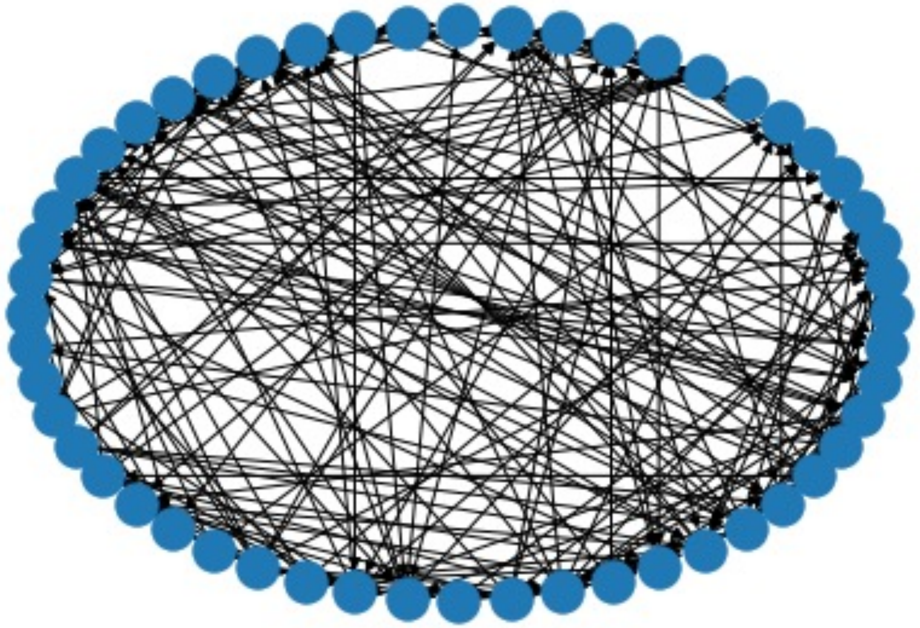
Generate training samples (p_A, p_D) and corresponding labels U_A, U_D

Train two partially input convex neural networks, $\mathcal{F}_A, \mathcal{F}_D$ to predict U_A, U_D respectively for a given (p_A, p_D)

1. Update the strategy of each player by fixing the strategy of the opponent.

2. Optimize player strategy by maximizing the corresponding payoff function.

Case Study: Synthetic Graph

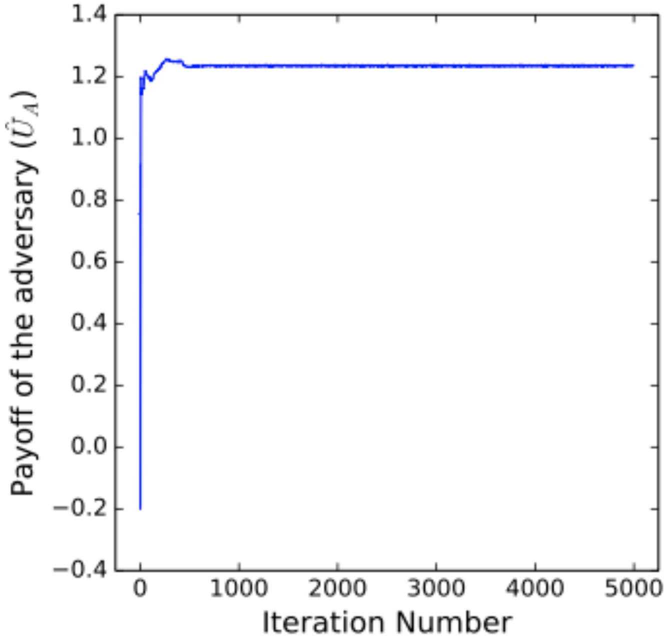


- Number of nodes = 50
- Erdös Renyi graph with directed edge probability p = 0.2
- Destination node (d) is the 50th node.
- Resource cost is generated from a uniform distribution [0,10].

Simulation Results

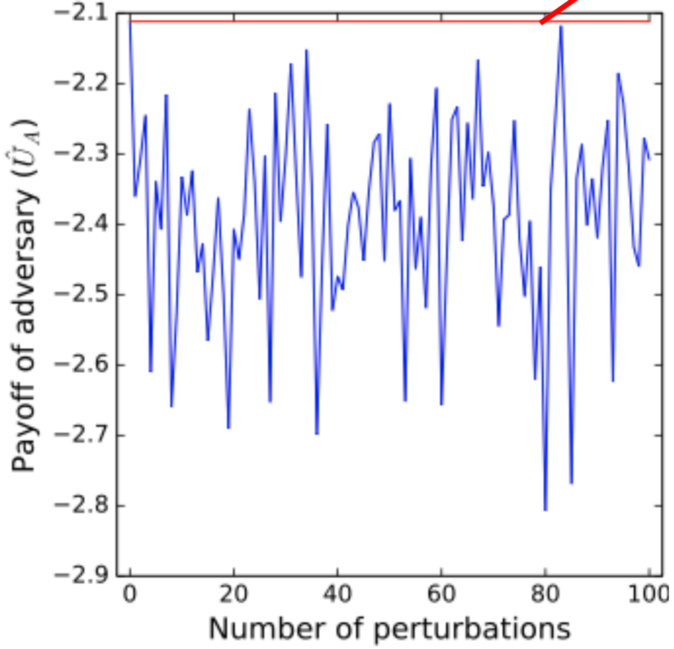
Payoff received from at the ϵ-NE obtained from the algorithm

APT's payoff vs. iteration



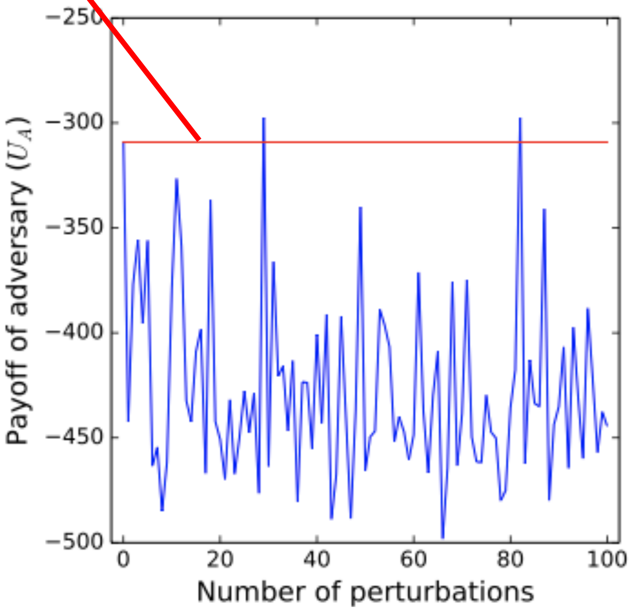
Payoff Convergence

APT's payoff for 100 perturbed strategies



Convex Approximation

APT's payoff for 100 perturbed strategies

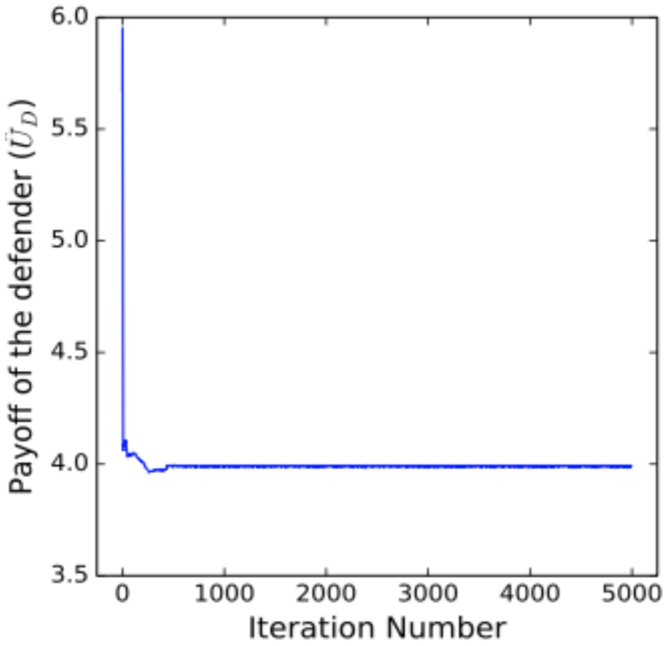


Original Function

Simulation Results

Payoff received from at the ϵ-NE obtained from the algorithm

DIFT's payoff vs. iteration



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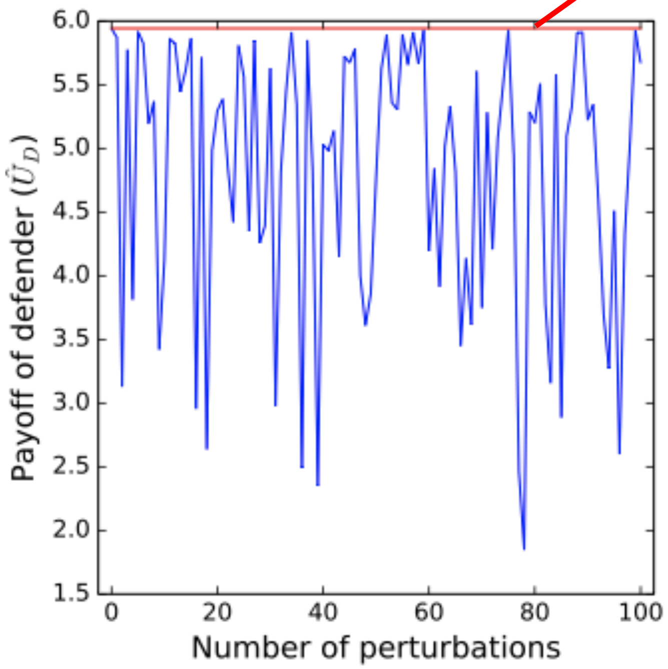

Convex Approximation

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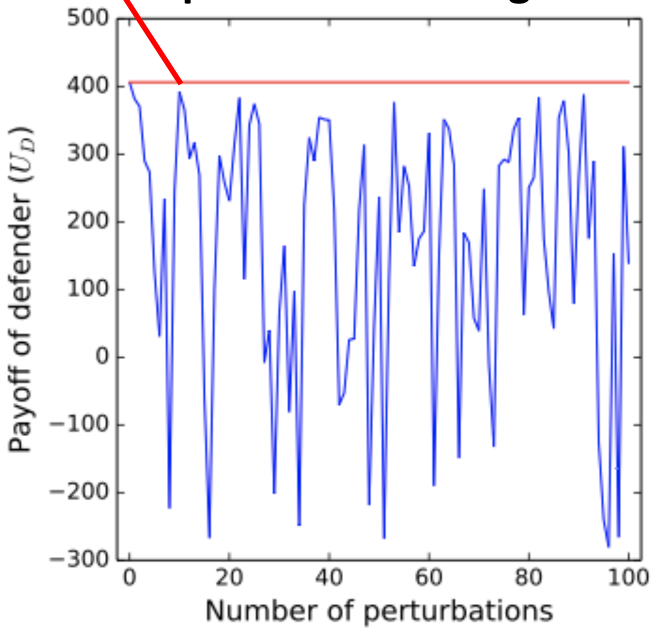
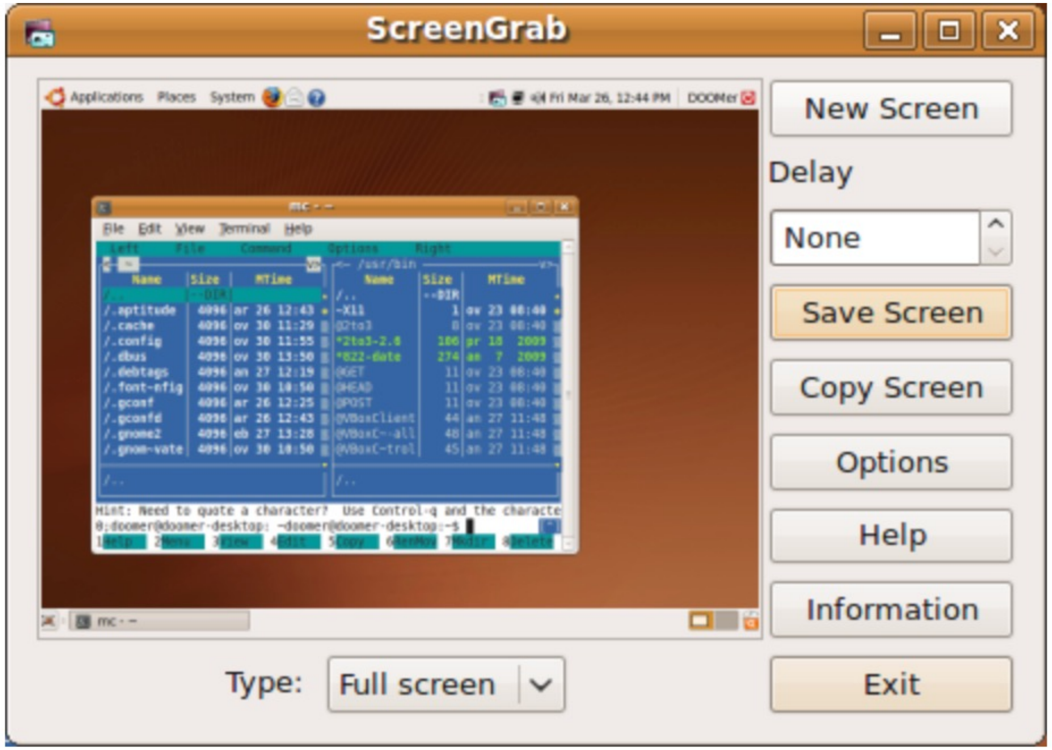


Original Function

Case Study: ScreenGrab Attack



- ScreenGrab: Linux program to take screenshots.
- Adversary wants to gain access to ScreenGrab process
- Fraction of flows traversing through each process ($Prob(s)$) extracted from RAIN log data

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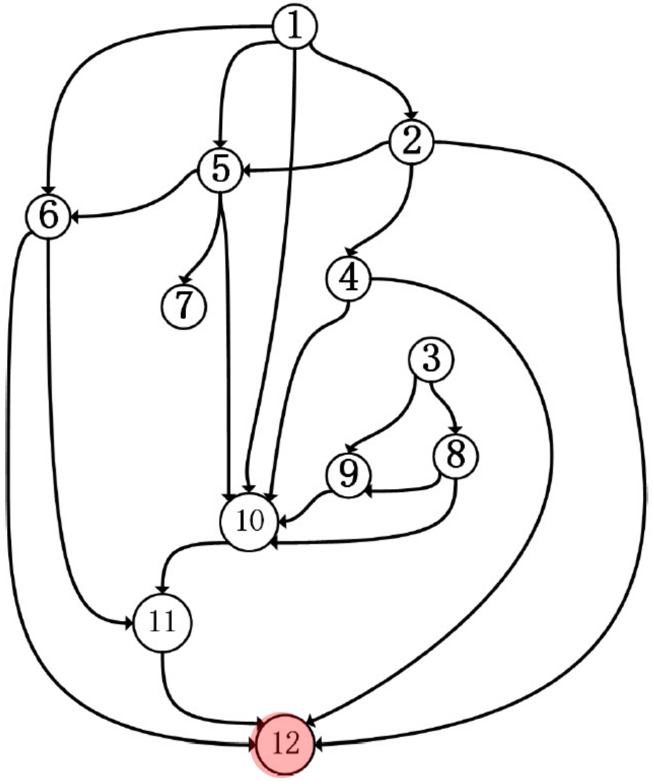
Case Study: ScreenGrab Attack

Pruned IFG for the ScreenGrab Attack



- ScreenGrab: Linux program to take screenshots.
- Adversary wants to gain access to ScreenGrab process (node 12)
- Fraction of flows traversing through each process ($Prob(s)$) extracted from RAIN log data

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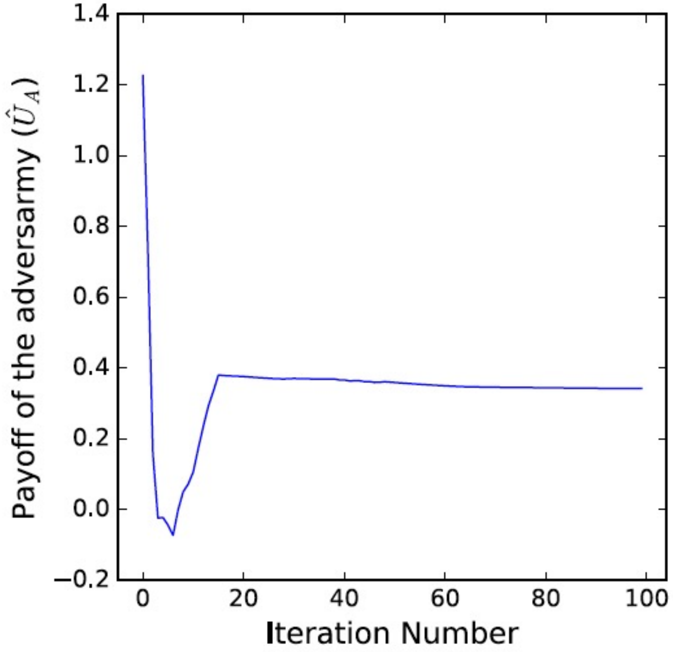
APT's payoff vs. iteration



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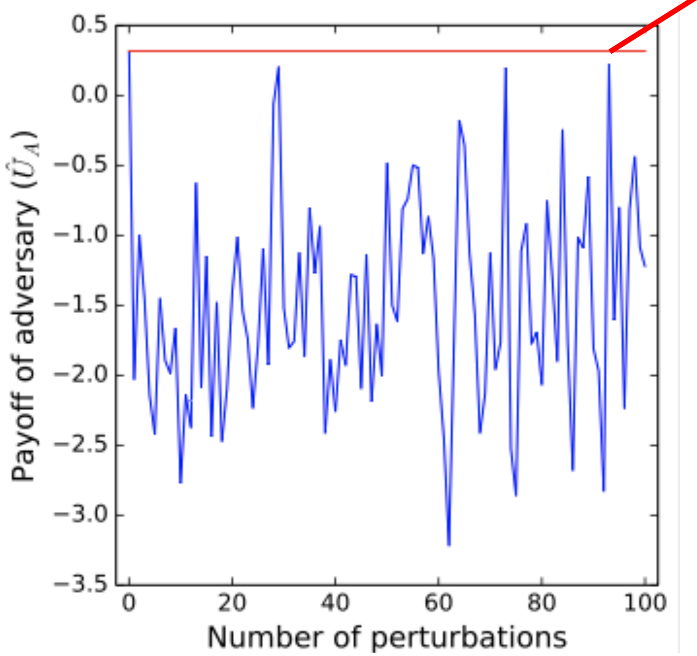
APT's payoff for 100 perturbed strategies



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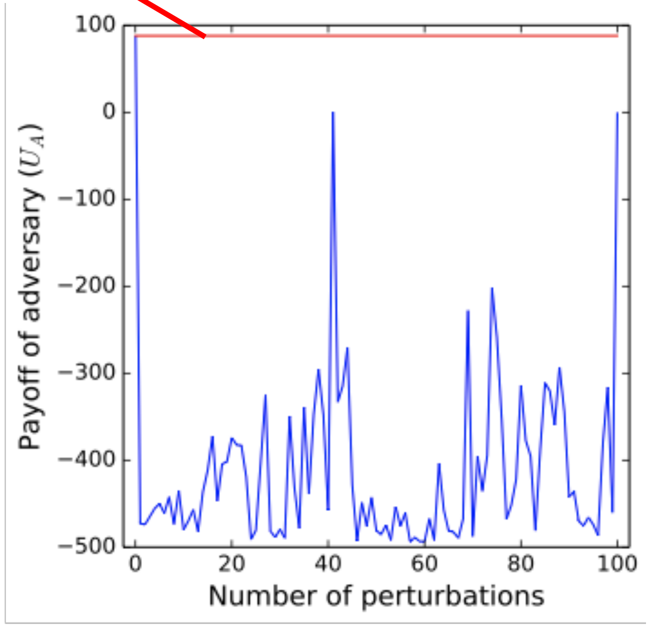
APT's payoff for 100 perturbed strategies



Original Function

Simulation Results

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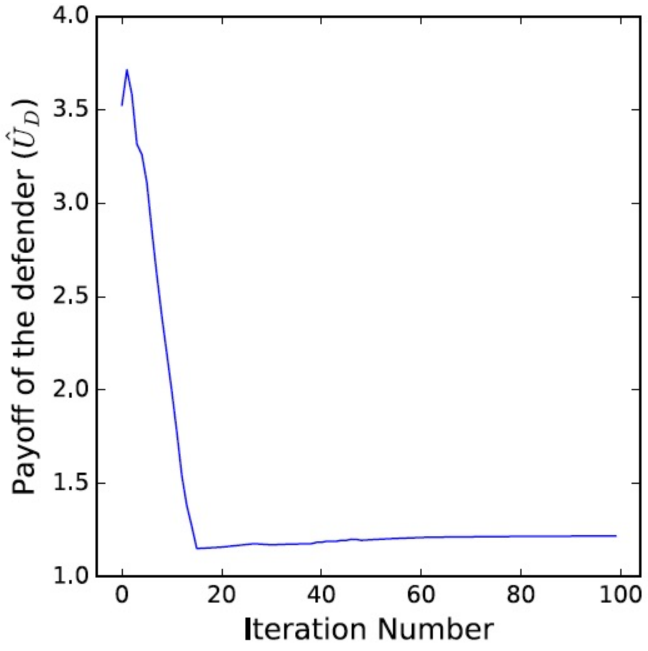
DIFT's payoff vs. iteration



Payoff Convergence

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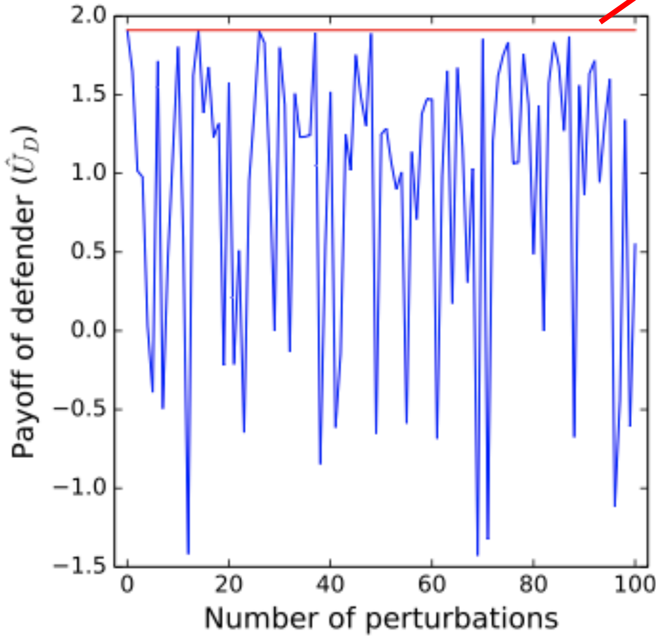

Convex Approximation

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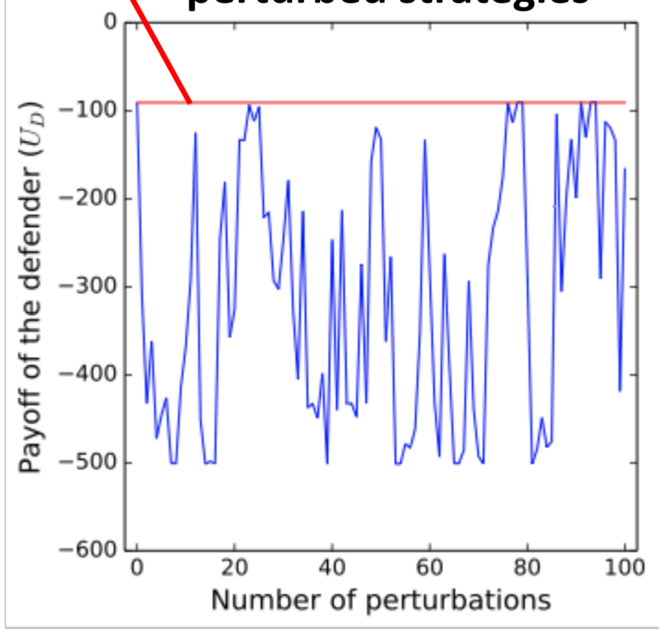

Original Function

Conclusion

- Formulated the interaction between APTs and DIFT as a two-player, multi-stage stochastic game with incomplete and imperfect information.
- Presented a supervised learning-based algorithm to learn an approximate Nash equilibrium for the game when the transition probabilities are unknown.

Future Work

- Characterize the convex approximation factor for the payoff functions of both players.
- Analyze the trade-off between obtaining a good convex approximation vs. the accuracy of the partial input convex neural networks.
- Investigate and apply the supervised learning approach to other types of games.

Thank You !

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Project ADAPT website: https://adapt.ece.uw.edu/