

# General Sum Markov Games for Strategic Detection of Advanced Persistent Threats using Moving Target Defense in Cloud Networks

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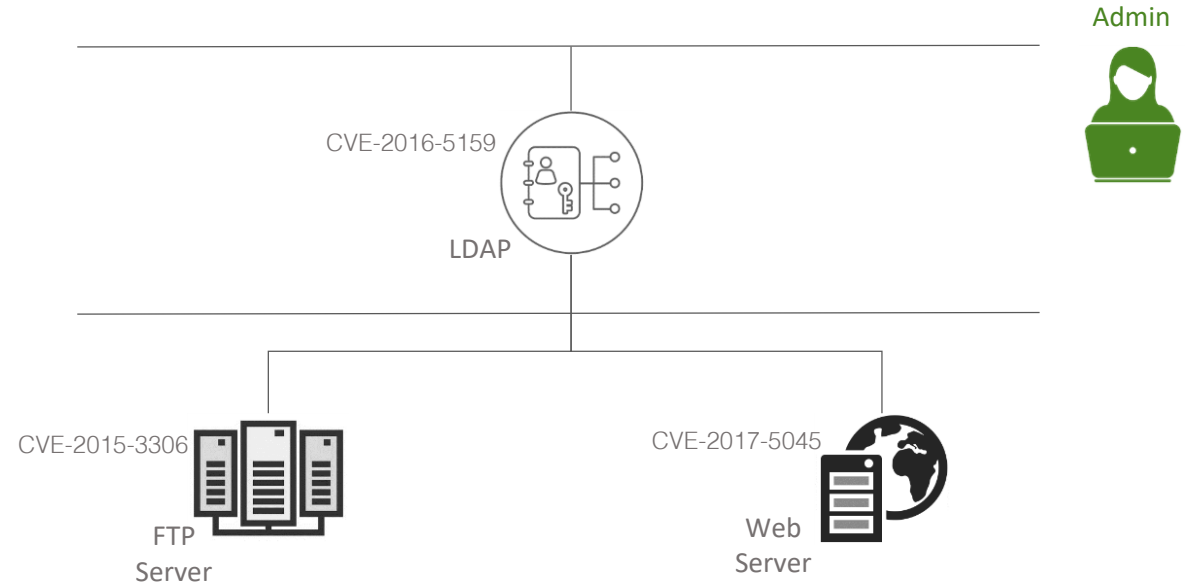
Yochan AI Lab

**SNAC**

Secure Networking and  
Computing Lab

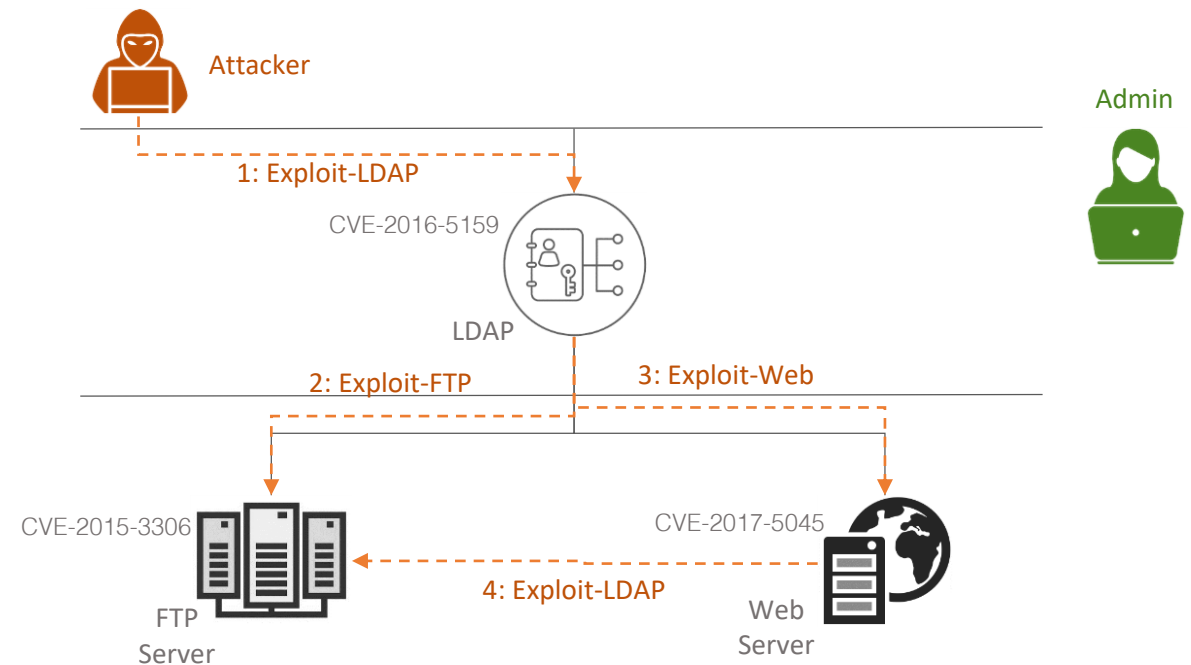
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- Cloud service providers provide computing and network resources to third parties for business.
- Attackers seek to attack such systems leading to a loss of Confidentiality, Availability and/or Integrity.
- Defenders can choose to monitor attacks on these systems using intrusion detection systems.



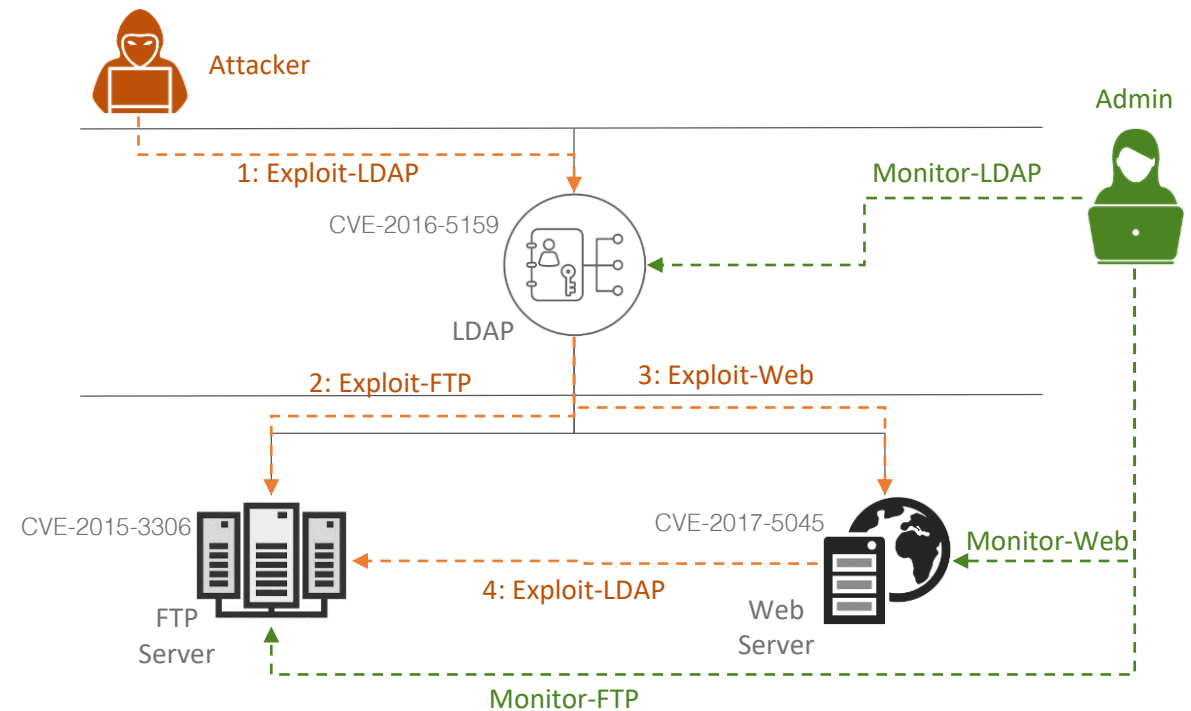
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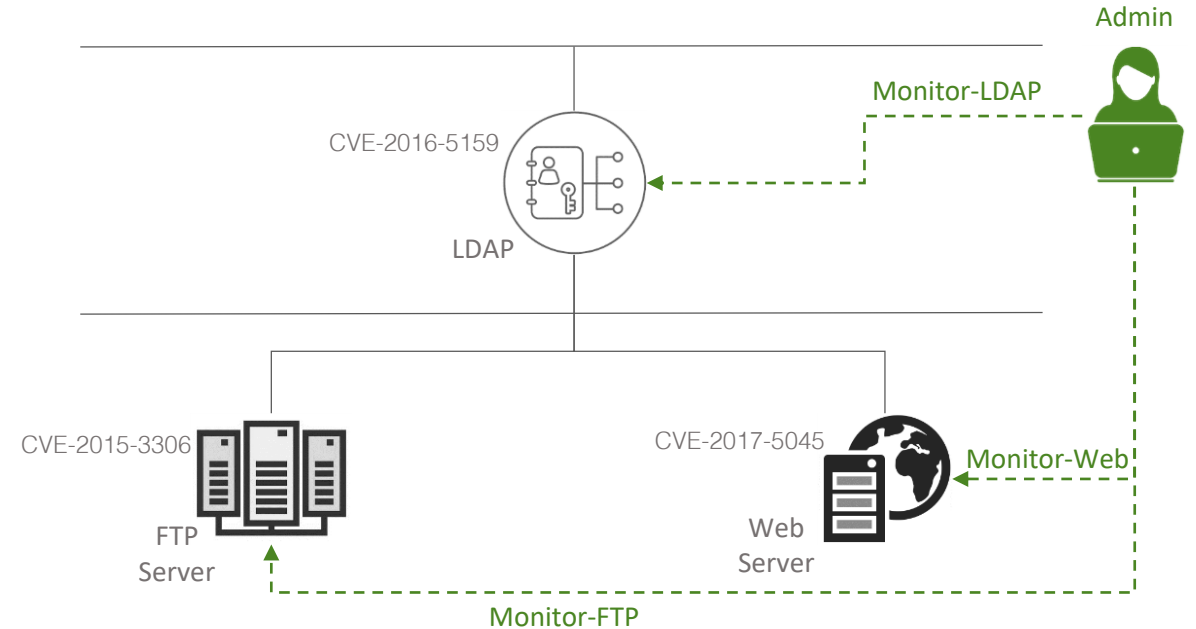
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# Detection of Threats in Cloud Networks

- Place all possible Network and Host-Based Intrusion Detection Systems.
- ☺ Every known attack can be detected.
- ☹ Network Performance and Computing Resources are used up for security leading to lower Quality of Service (QoS) for actual customers.
- ☺ Place a sub-set of them.
- ☹ Deterministic placement is bad!



# Moving Target Defense Security



Shift the attack surface so that an attacker's attack, designed based on reconnaissance, is no longer valid at attack time.

## **Attack Surface Shifting**

Manadhata et. al. 2013  
Zhu and Bashar 2013  
Carter et. al. 2014  
Prakash and Wellman 2015  
Sengupta et. al. 2016, 2017  
Chowdhury et. al. 2016  
B. Bohara 2017

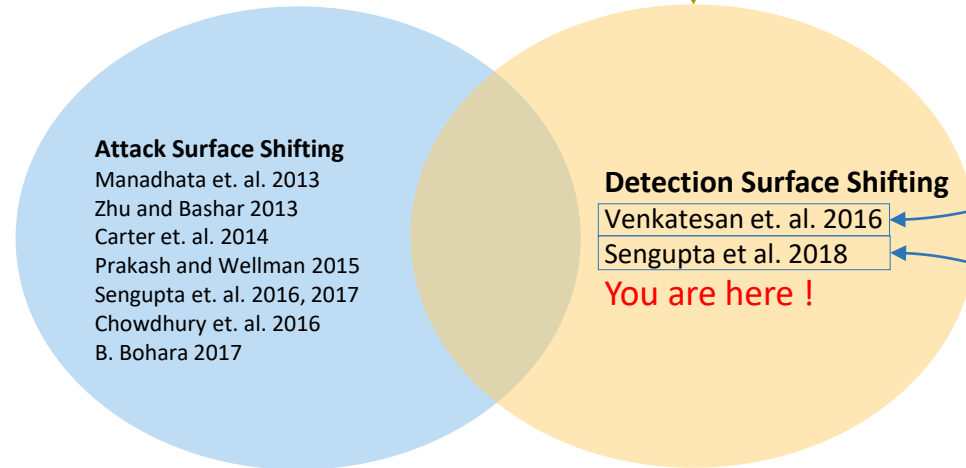
# Moving Target Defense

## Security vs. Quality of Service



Shift the attack surface so that an attacker's attack, designed based on reconnaissance, is no longer valid at attack time.

Shift the detection surface to maximize security with limited number of resources. Helps improve QoS metrics.



Hot topic for physical security

Uses centrality based measures.

- Higher centrality node sees more attack traffic.
- Strategy optimizes performance by moving IDS between HCNs.

Uses Stackelberg Security Games.

- Attacks are either successful or detected with 100% accuracy.
- Does not model multi-stage attacks.
- Attacker has capability to attack any node on the system as opposed to planning an attack path.

# Agenda

- Formulating the problem as a General Sum Markov Game
  - Attack Graphs
  - Common Vulnerabilities and Exploits (CVEs)
  - Common Vulnerability Scoring System (CVSS)
  - MiniNET simulations
- Placement Strategies
  - Stackelberg Equilibria in Markov Games
  - Anytime solutions with Dynamic Programming
- Experimental results
  - Simulation
  - Emulation

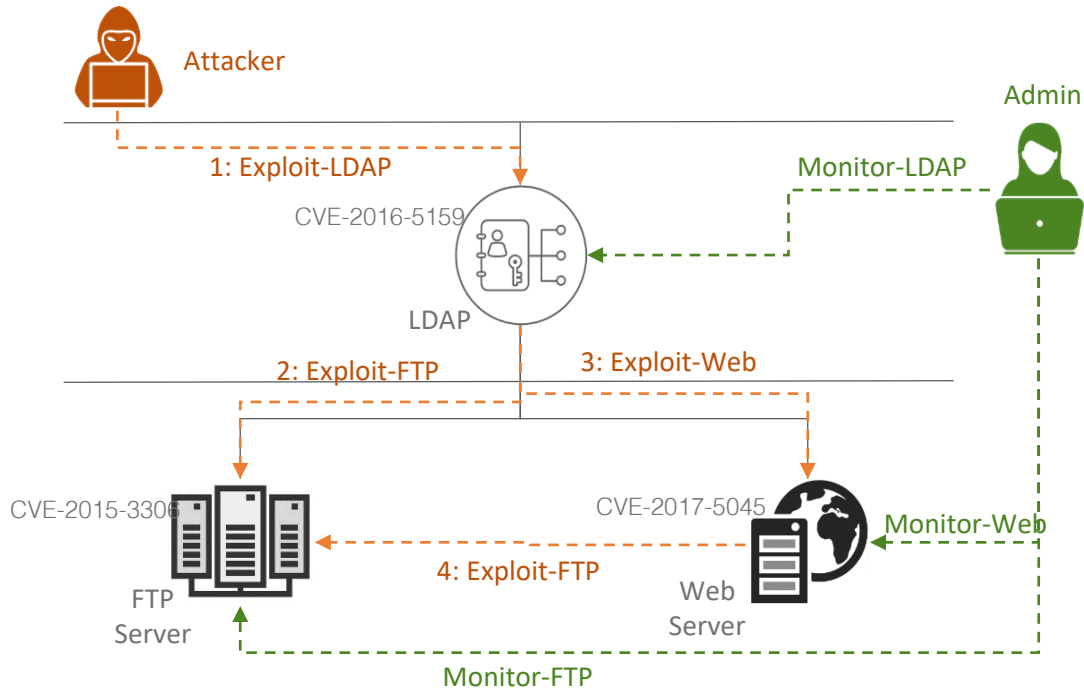


# General Sum Markov Games

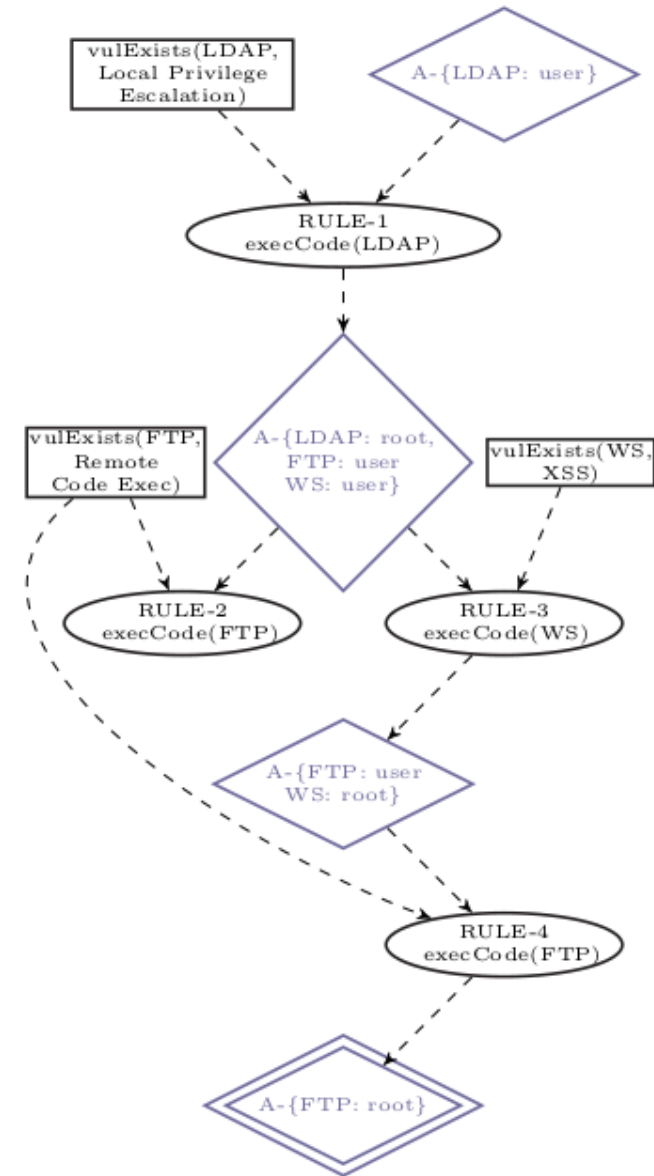
**Markov Game** (Shapley 1953) for two players  $P_1$  and  $P_2$  can be defined by the tuple  $(S, A_1, A_2, \tau, R, \gamma)$  where,

- $S = \{s_1, s_2, s_3, \dots, s_k\}$  are finite states of the game,
- $A_1 = \{a_1^1, a_1^2, \dots, a_1^m\}$  represents the possible finite action sets for  $P_1$ ,
- $A_2 = \{a_2^1, a_2^2, \dots, a_2^n\}$  are finite action sets for  $P_2$ ,
- $\tau(s, a_1, a_2, s')$  is the probability of reaching a state  $s' \in S$  for state  $s$  if  $P_1$  and  $P_2$  take actions  $a_1$  and  $a_2$  respectively,
- $R^i(s, a_1, a_2)$  is the reward obtained by  $P_i$  if in state  $s$ ,  $P_i$  and  $P_{-i}$  take the actions  $a_1$  and  $a_2$  respectively, and
- $\gamma \mapsto [0, 1)$  is discount factor for future discount rewards.

# Attack Graphs

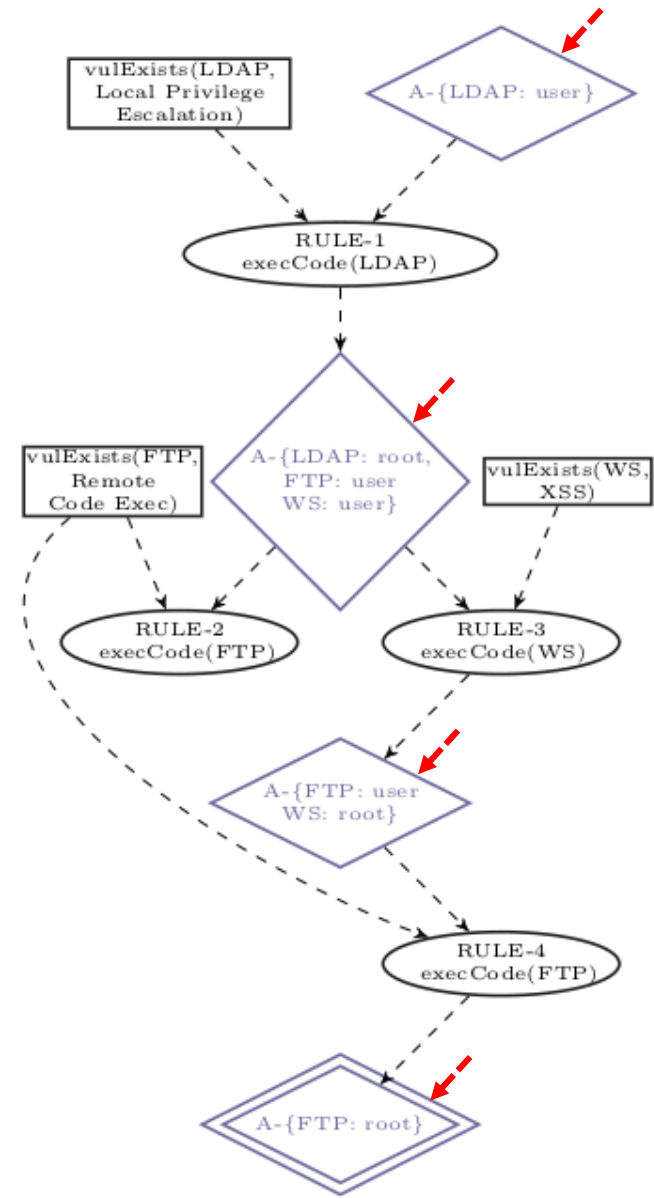
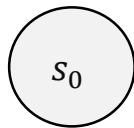
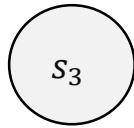
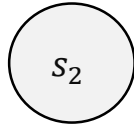
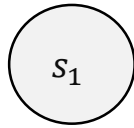


Sample Network scenario

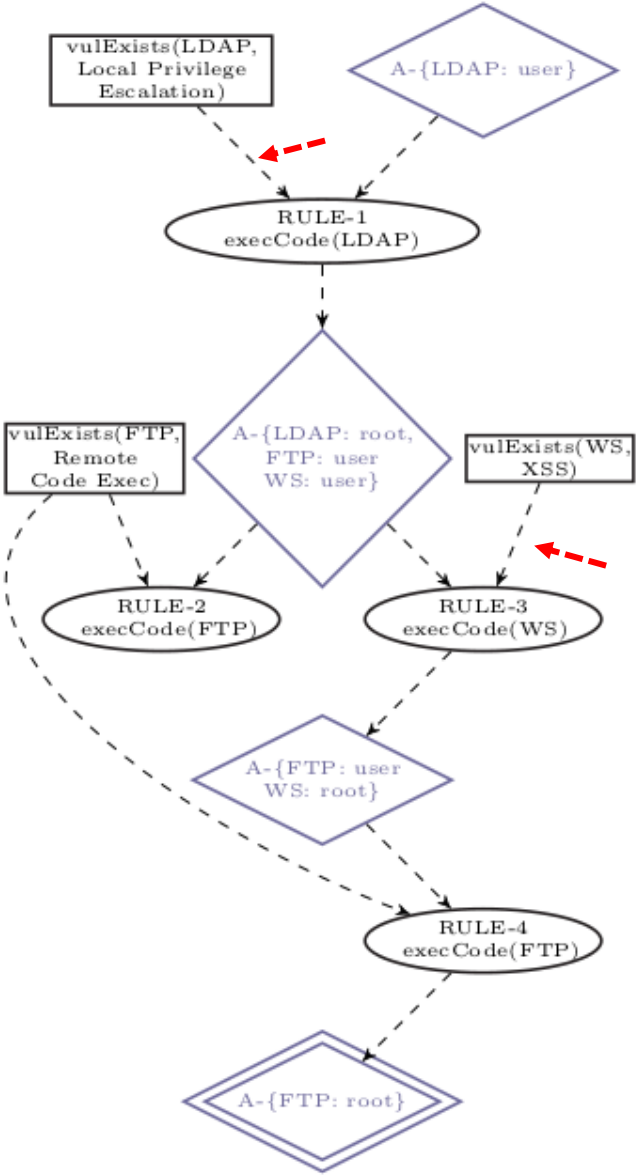
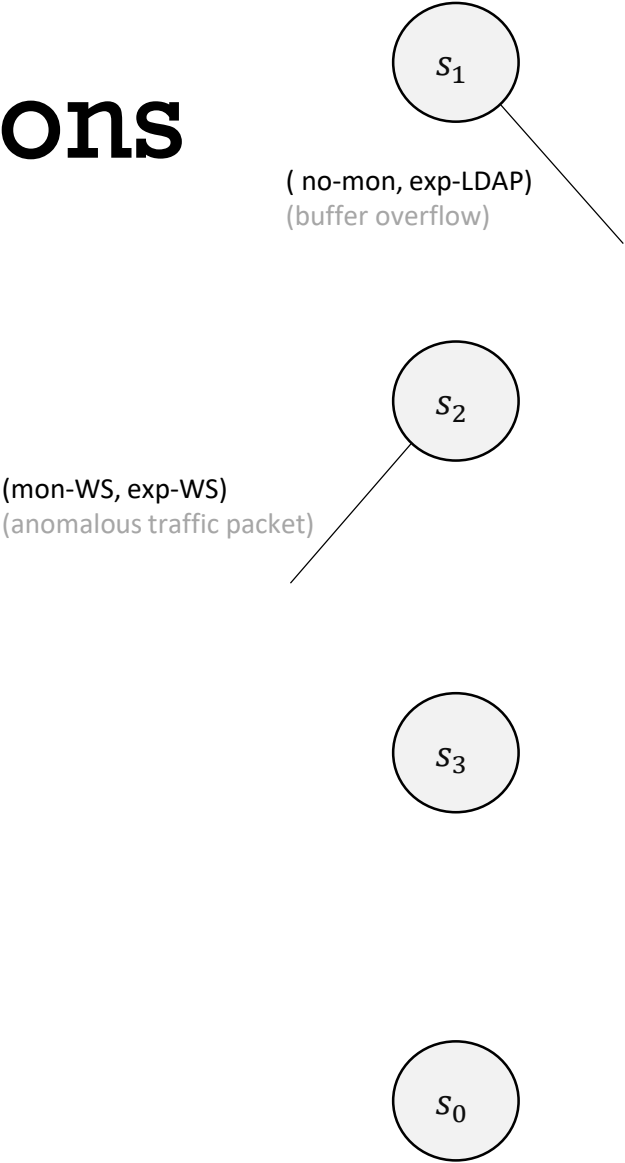


Corresponding Attack Graph

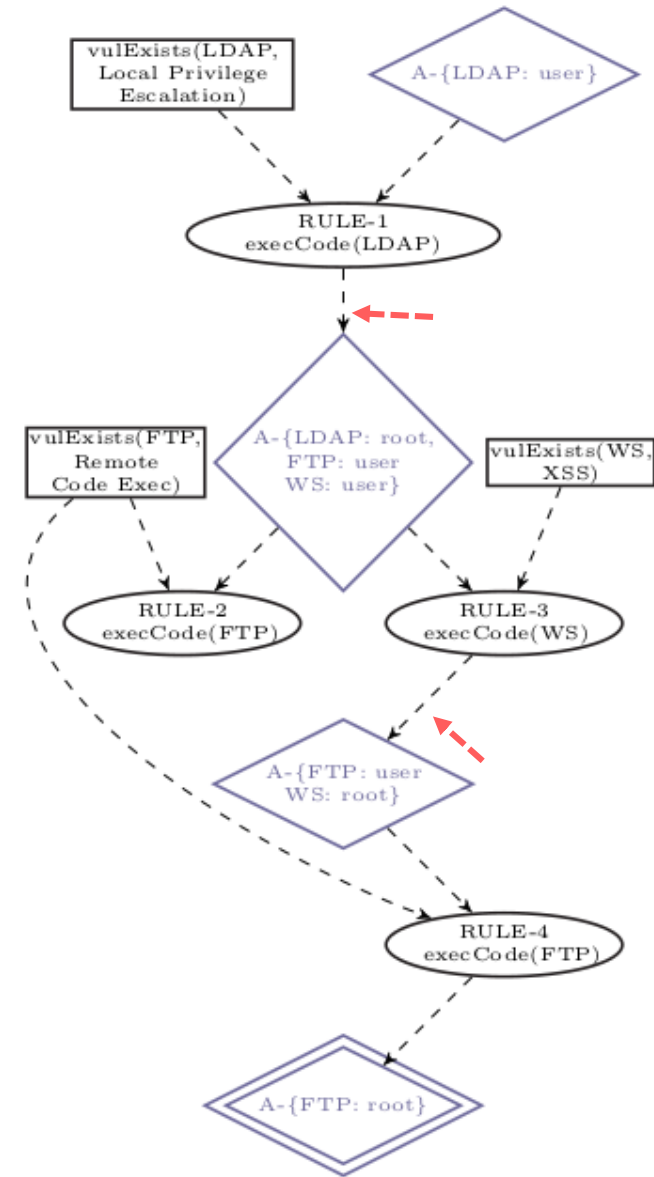
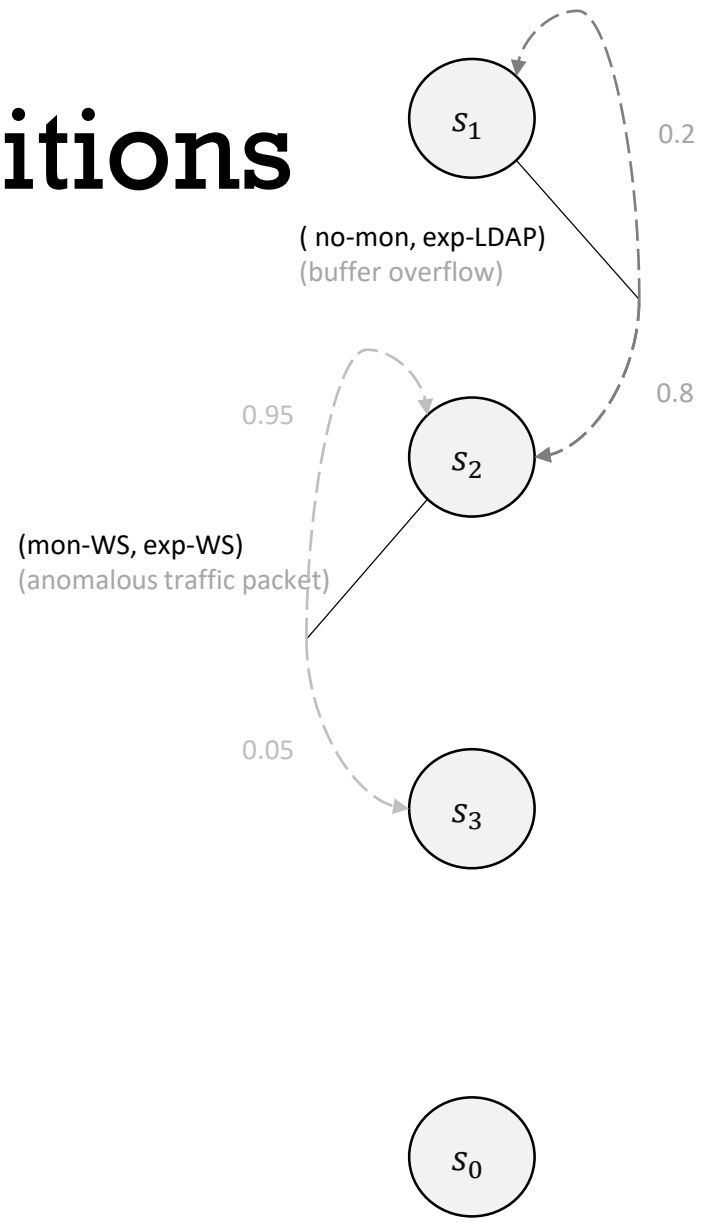
# States



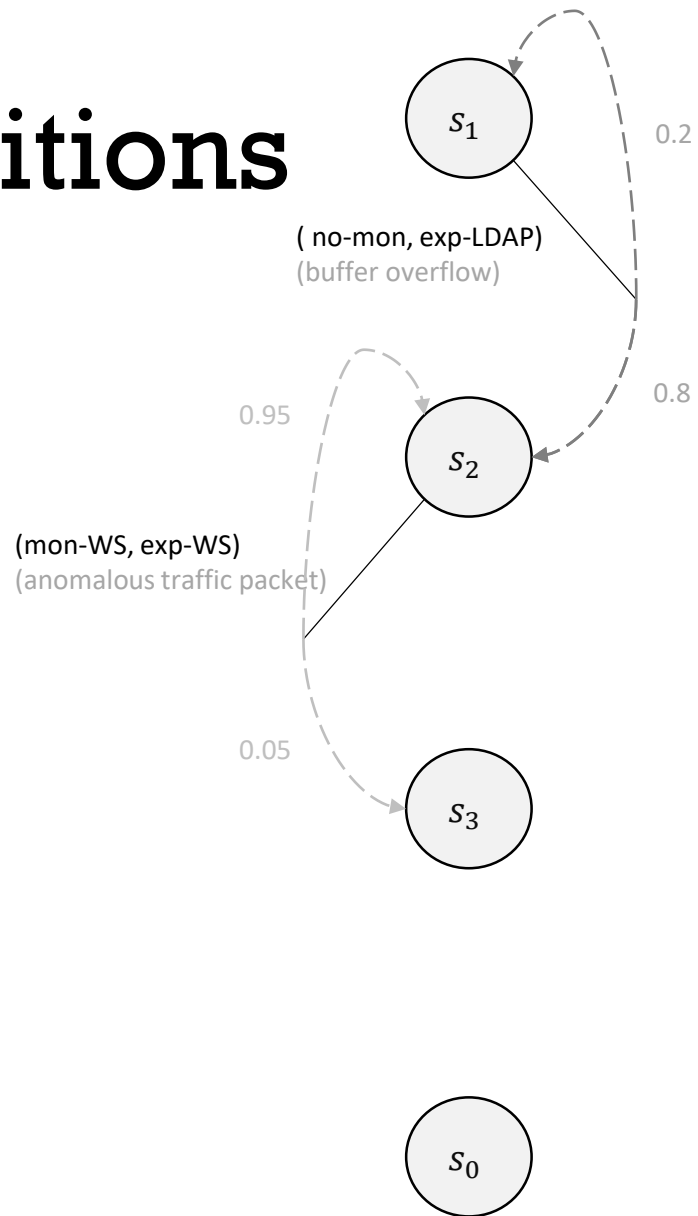
# Actions



# Transitions



# Transitions



## Exploitability score of a Common Vulnerability and Exposures (CVE)

Assumption is based on the fact that a random attacker is more likely to succeed if the attack is easy to exploit.

*Chung et. al. 2013* shows how Exploitability Scores can be used in attack graphs for calculating the probability of an attacker being able to successfully exploit an attack.

Accuracies of ML-based monitoring systems can be used to calculate the probability of when an attack succeeds even when a monitoring system is deployed.

# Reward Modeling

## Impact Score of a Common Vulnerability and Exposures (CVE)

Assumptions that the reward structure results in a zero-sum game is an unreasonable one because an attacker does not care about defenders performance metrics or QoS to legitimate users.

How to find a value for the effect on QoS given that a monitoring system is deployed?

- Venkateshan et. al. 2016 and Sengupta et. al. 2018 uses centrality measure of the nodes as a heuristic to estimate this value.
- We run MiniNET simulations– flood the network with traffic and run resource exhaustive processes with and without the IDS deployed. Measure the reduction in bandwidth or spike in cpu usage.

	no-mon	mon-FTP
no-act	0, 0	0, -2
exp-FTP	10, -10	-8, 6

$S_3$

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# Optimal IDS placement policy

Mix max computation when game is zero sum.

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## Algorithm 1

---

```
1: procedure GIVEN  $(S, M, E, \tau, U^D, U^A, \gamma^D = \gamma^A = \gamma)$ ,  
2: OUTPUT  $(V^i(s), \pi^i(s) \forall i \in \{A, D\})$   
3:    $V(s) = 0 \forall s$   
4:   loop:  $i == k$  break;  
5:   // Update Q-values  
6:   Update  $Q^D(s, m, e)$  and  $Q^A(s, m, e) \forall s \in S, m \in M(s), e \in E(s)$   
7:     using  $U^D, U^A$  and  $V(s)$ .  
8:   // Do value and policy computation  
9:   Calculate  $V^i(s)$  and  $\pi^i(s)$  for  $i \in \{A, D\}$  using the values  $Q^i(s, m, e)$   
10:   $i \leftarrow i + 1$   
11:  goto loop.  
12: end procedure
```

---

# Optimal IDS placement policy

In General-sum Games, the notion of Nash and Stackelberg Equilibria may differ.

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### Weaker threat model

Attacker has no idea about defender's placement strategy  $\rightarrow$  NE

### Stronger threat model

Attacker has knowledge about defender's placement strategy  $\rightarrow$  SSE

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In General-sum Games, the notion of Nash and Stackelberg Equilibria may differ.

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Let us consider a set of IDS systems that the defender can choose to deploy. If every subset of this set can also be covered by the defender, the Set of Subsets Are Sets (SSAS) property holds. [Korzhyk et. al. 2011](#)

**Lemma 1.** If in each state of the Markov Game, SSAS holds,  $SSE \subset NE$

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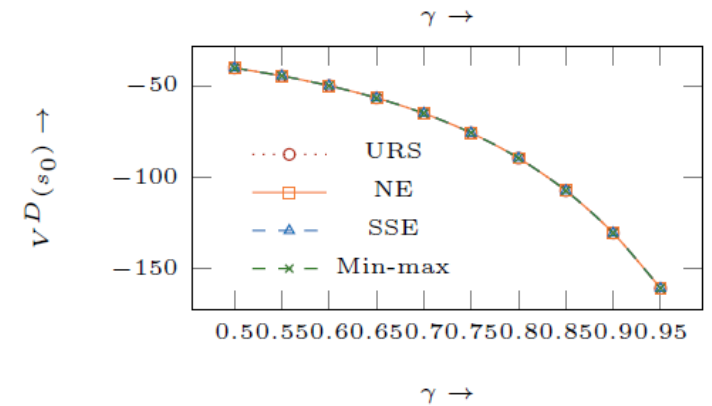
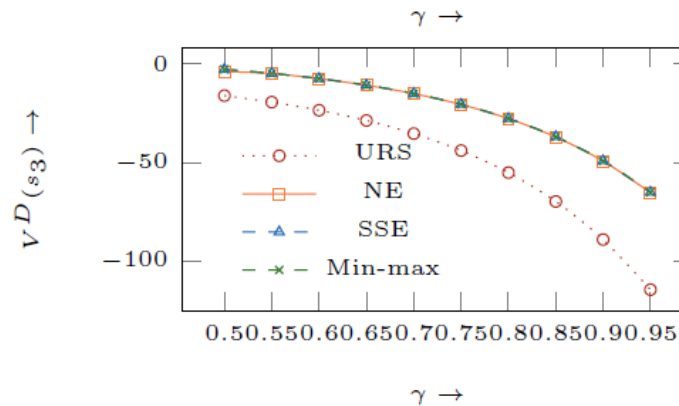
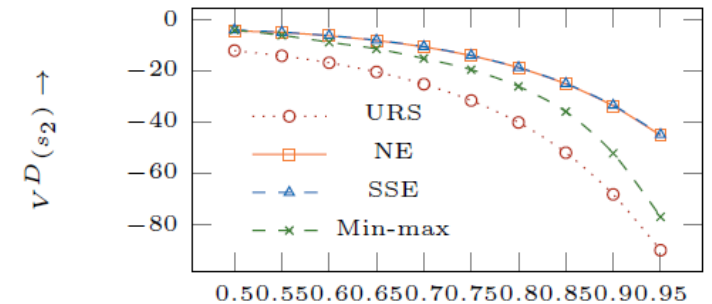
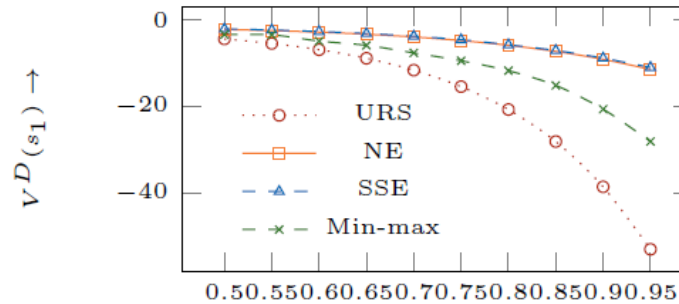
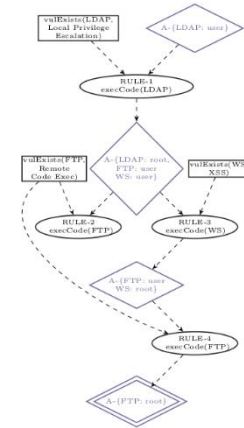
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# Experimental Results

At the start of each time period  $t$ ,

- URS – Uniformly select an IDS system out of  $n$ -monitoring actions at random.
- Min-max – Defender’s reward is negative of the attacker’s reward. Zero-sum Markov Game strategy.



# Experimental Results

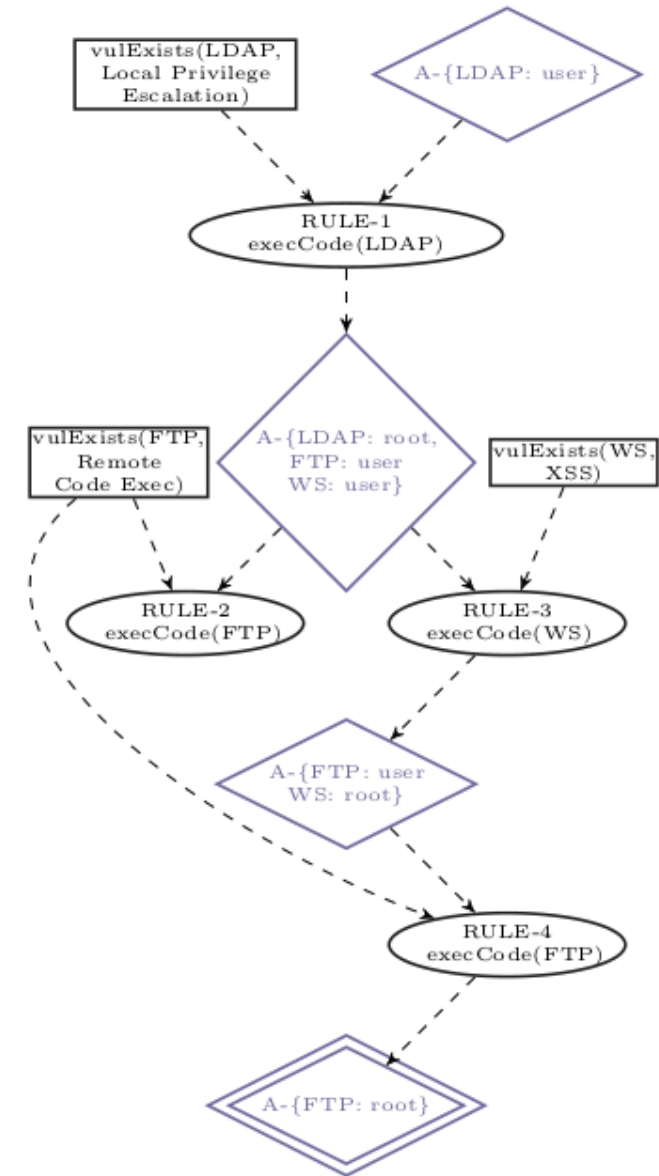
- For states further away from the goal, don't need to monitor at times to enhance performance QoS.

$$\pi_{MG-SSE}(s_1) : \{no-mon: 0.097, mon-LDAP: 0.903\}$$

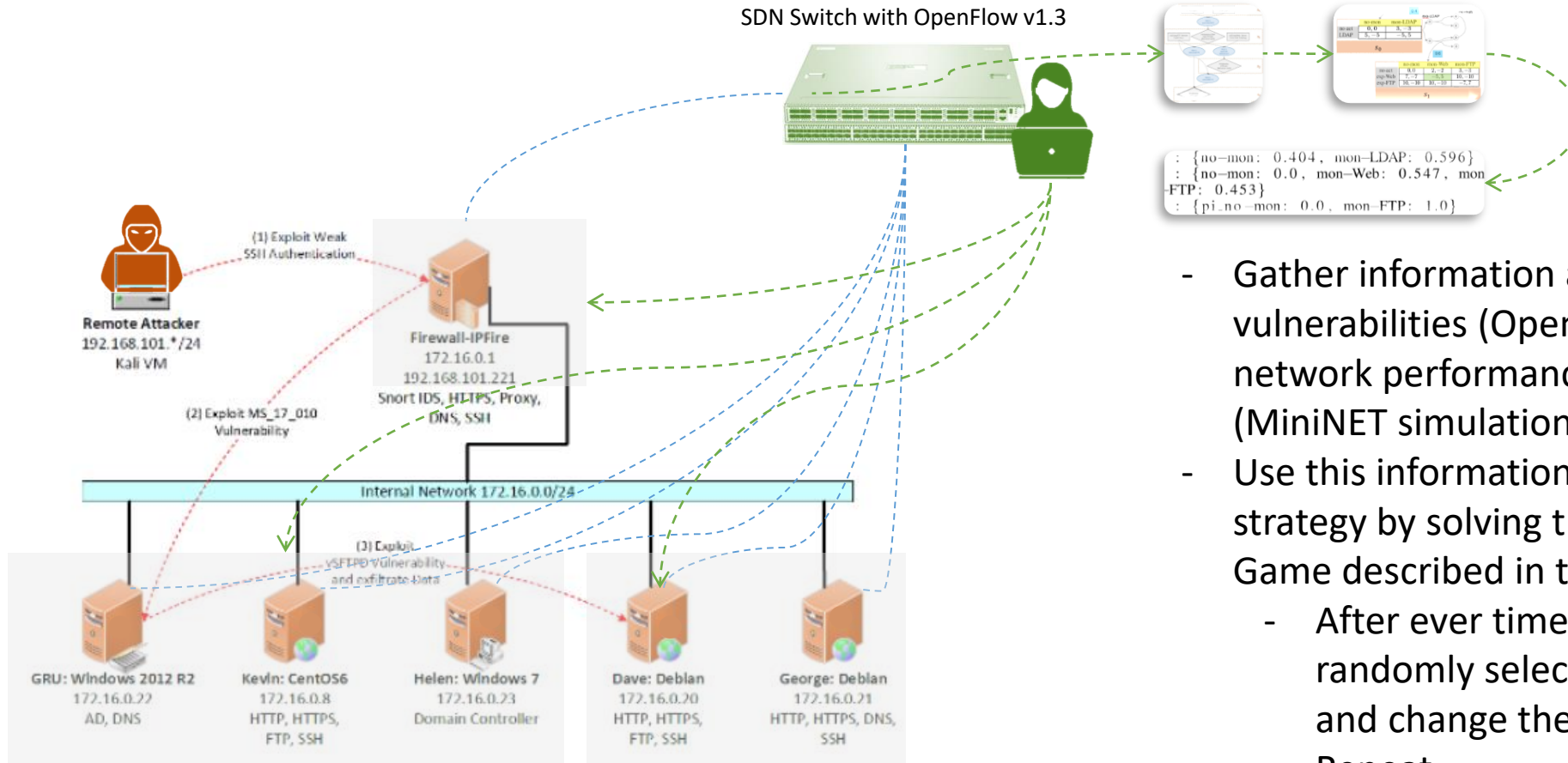
$$\pi_{MG-SSE}(s_2) : \{no-mon: 0.0, mon-Web: 0.539, mon-FTP:0.461\}$$

$$\pi_{MG-SSE}(s_3) : \{pi\_no-mon: 0.0, mon-FTP: 1.0\}$$

- For states closer to the goal, not monitoring is not an option. Security becomes more important than performance.

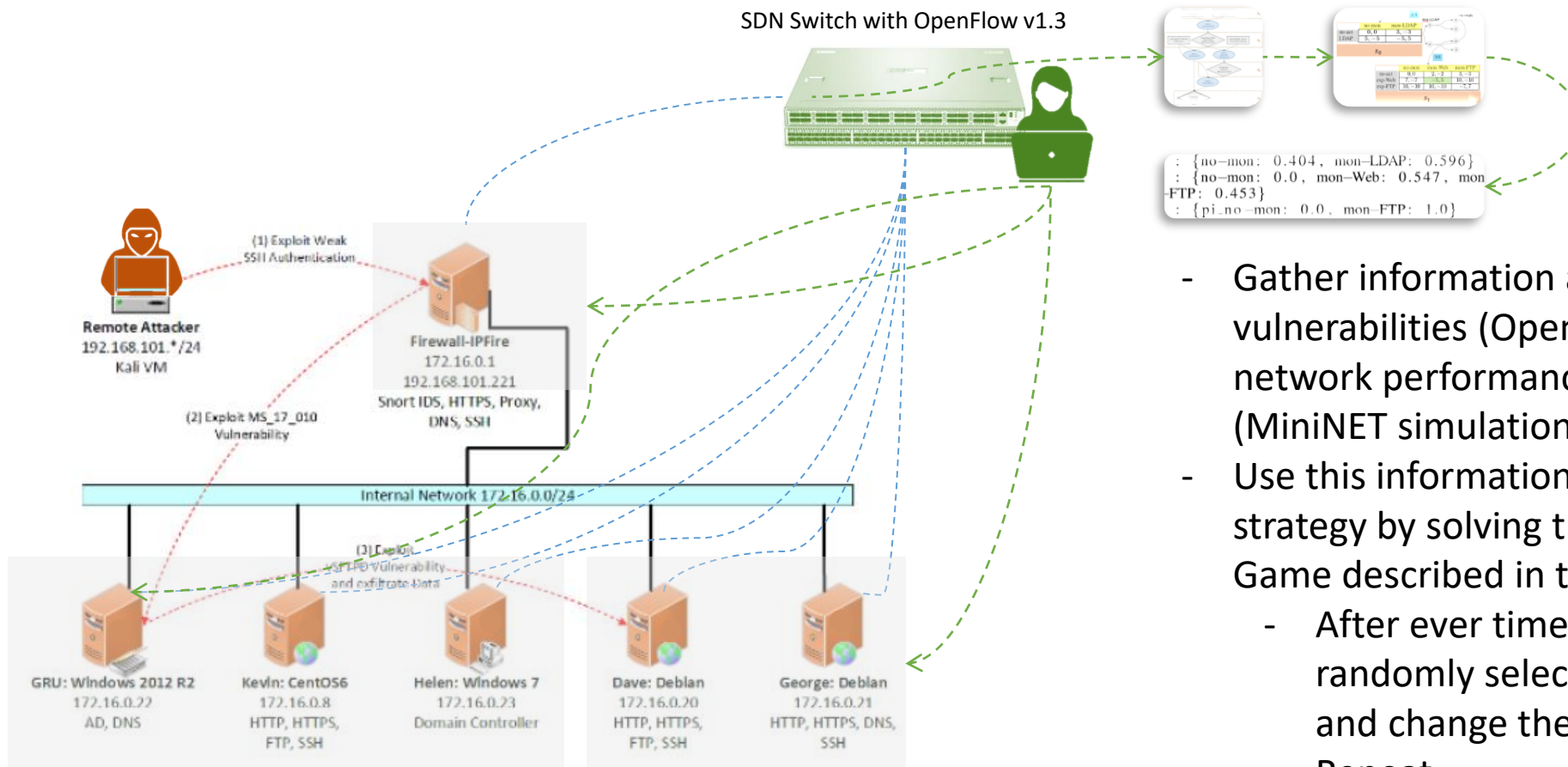


# Implementation in ThothLab



- Gather information about new vulnerabilities (OpenVAS) and average network performance over a time period  $T$  (MiniNET simulations).
- Use this information to precompute a strategy by solving the formulated Markov Game described in this work.
  - After every time period  $t \ll T$ , randomly select switching strategy and change the IDS deployment.
  - Repeat.

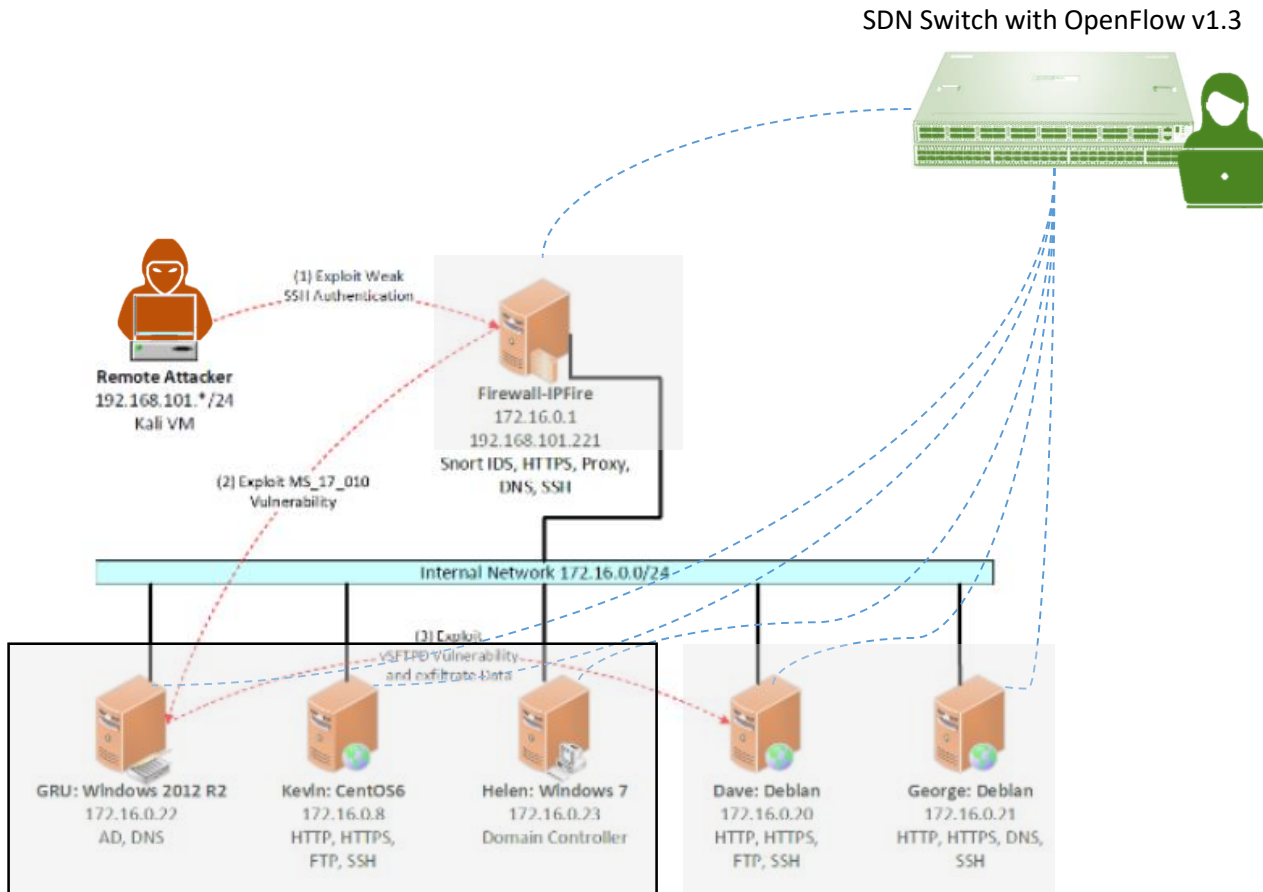
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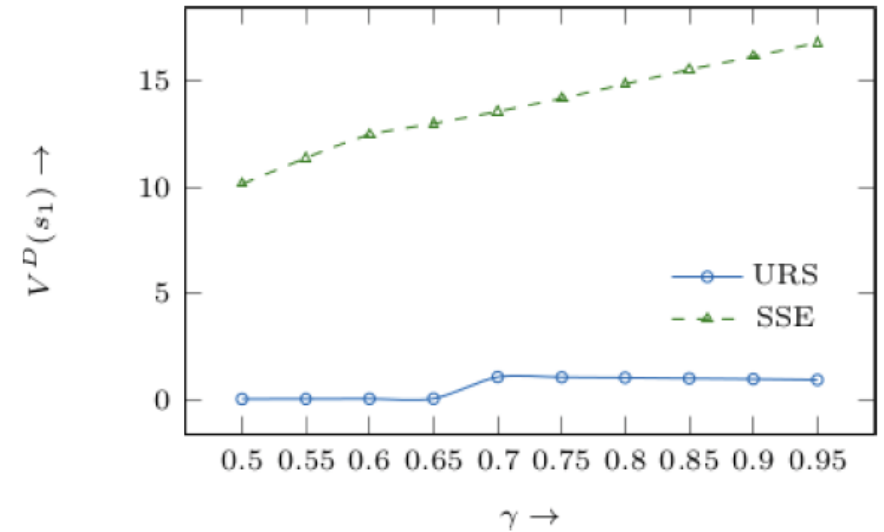
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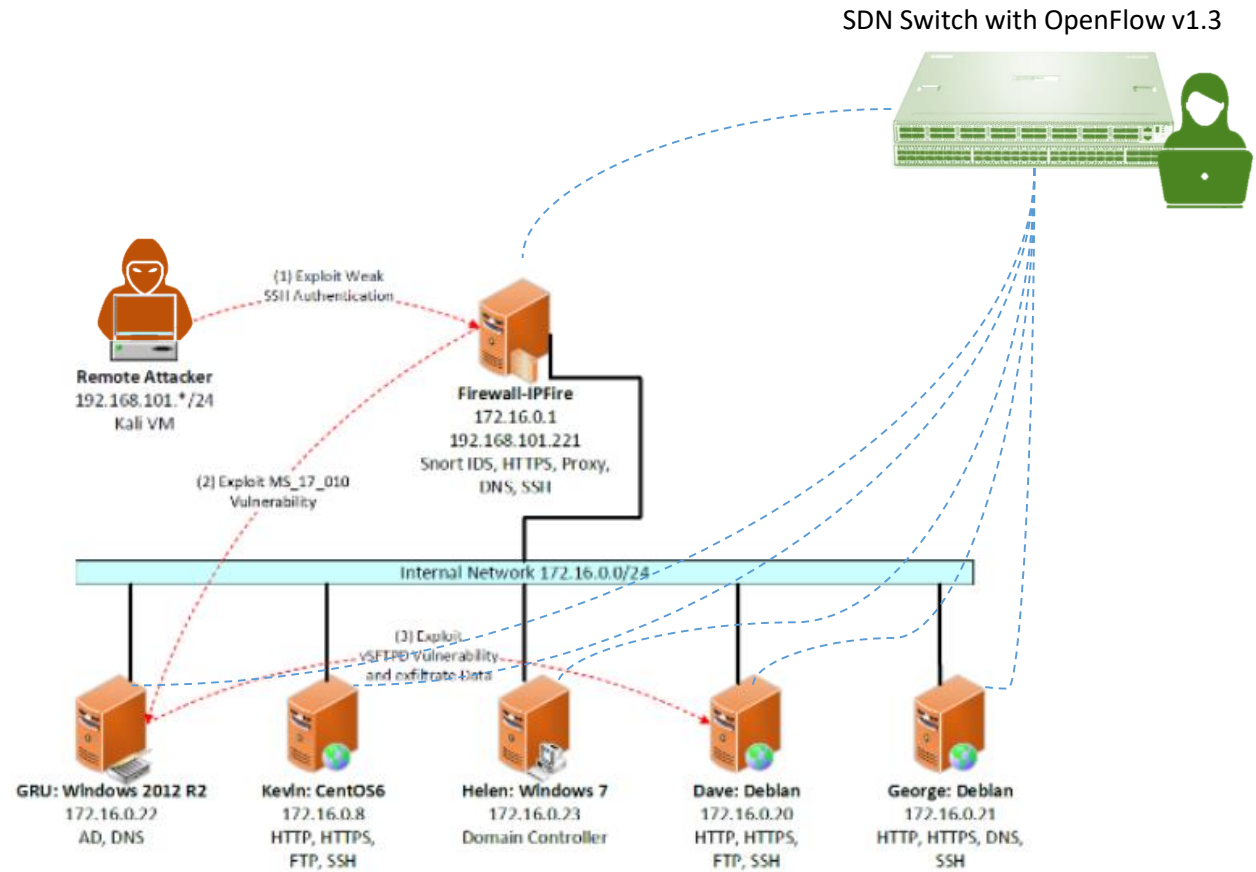


5 vulnerabilities (1H, 2M, 2L)  
2 IDSs can be placed



**Fig. 6.** Defender's value for the state  $s_1$  as discount factor increases from 0.5 to 1.

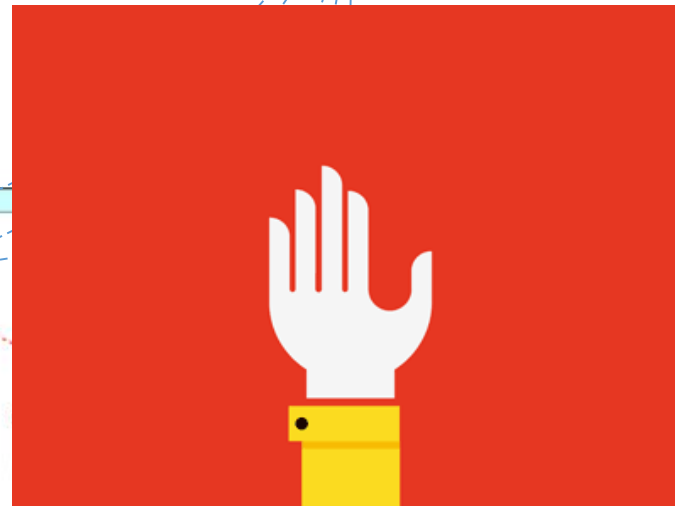
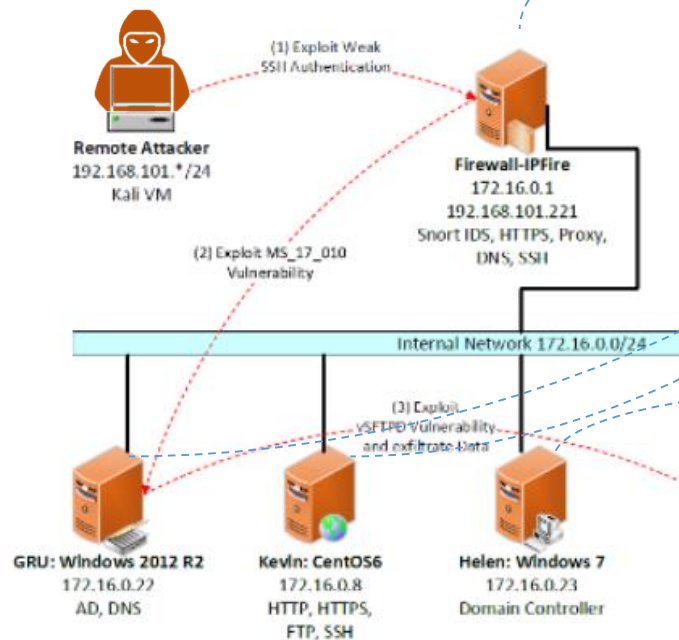
# Conclusion & Future Work



- We formulated the placement of IDS systems in the cloud as a General Sum Markov Game. We found strategies for efficient detection surface shifting which allows the defender to trade-off between Security and Quality of Service. We showed its effectiveness on simulated data and emulation environments.

- We hope to relax a set of assumptions we made in this work in the future—
  - Game states are visible to both the players?
  - What happens when this is simulated in a real-world cloud network? How to obtain real-world attack data?
  - How does the incomplete knowledge of existing attacks and irrationality of attackers affect the quality of solution?
  - How does one reason about the zero day attacks – incomplete knowledge of the defender about the attacks?

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