Some Research Directions in Automated Pentesting

Carlos Sarraute

CoreLabs & ITBA PhD program
Buenos Aires, Argentina

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Agenda outline

1. Motivation
2. The Search for an Efficient Solution
   - Two primitives
   - Using the primitives in a Network Graph
   - Integration with a Pentesting Tool
3. The Search for a Better Model
   - POMDPs
   - Penetration Testing as POMDPs
   - Experiments
4. Discussion

Agenda

What is Penetration Testing?

Penetration testing

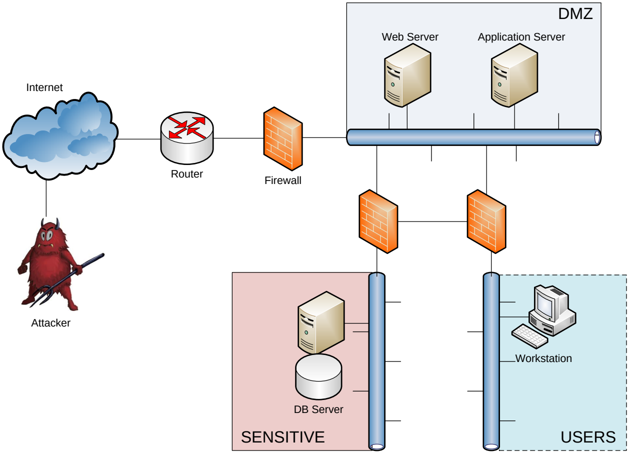
Actively verifying network defenses by conducting an intrusion in the same way an attacker would.

- Penetration testing tools have the ability to launch real exploits for vulnerabilities.
  - different from vulnerability scanners (Nessus, Retina, ...)
- Main tools available:
  - Core Impact (since 2001)
  - Immunity Canvas (since 2002)
  - Metasploit (since 2003)

Need for Automation

- Reduce human labor
- Increase testing coverage
  - Higher testing frequency
  - Broader tests trying more possibilities
- Complexity of penetration testing tools
  - More exploits
  - New attack vectors (Client-Side, WiFi, WebApps, . . .)
- Equip penetration testing tool with “expert knowledge”

Anatomy of a real-world attack



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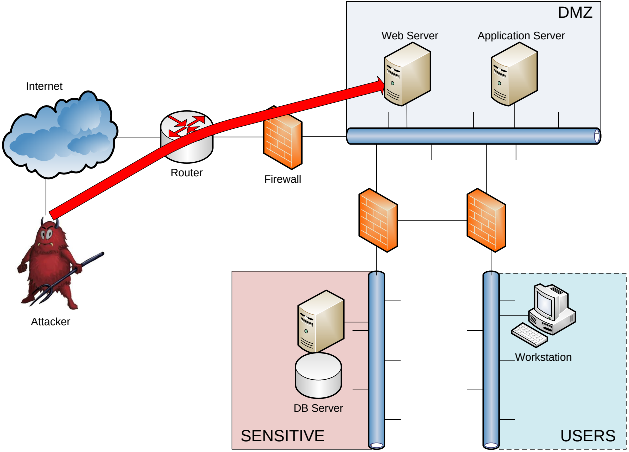

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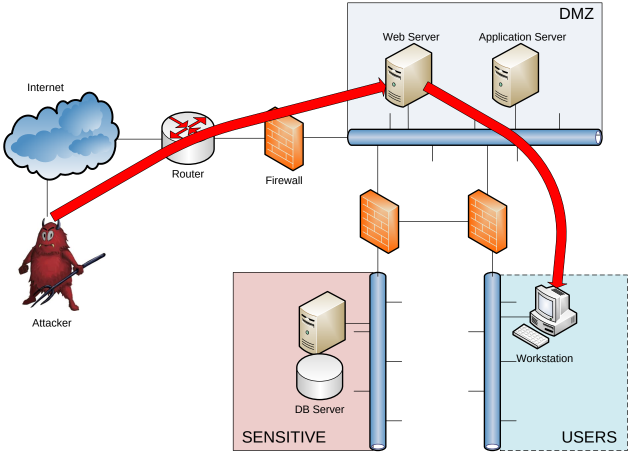

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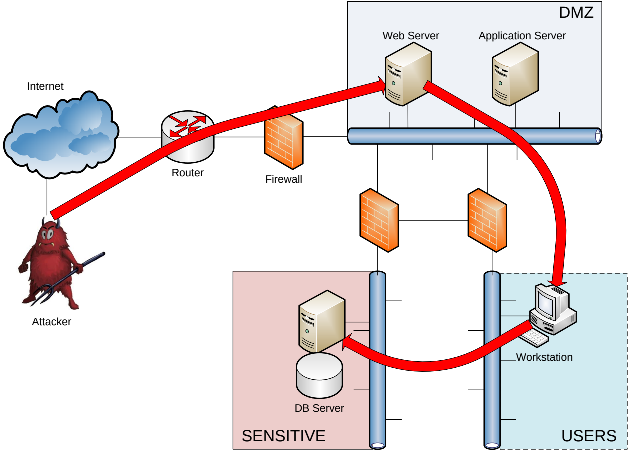

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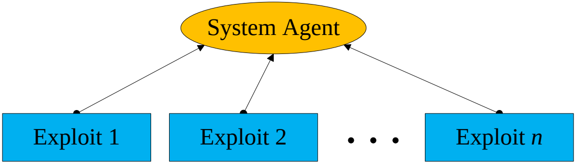
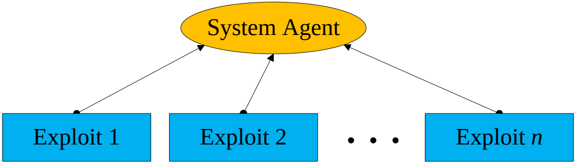
The **Choose** primitive



Problem

$\{A_1, \ldots, A_n\}$ independent actions that result in a goal $\mathfrak{g}$.
Each A_k has probability of success p_k and running time t_k.
Task: Find order of execution to minimize total running time.

The **Choose** primitive



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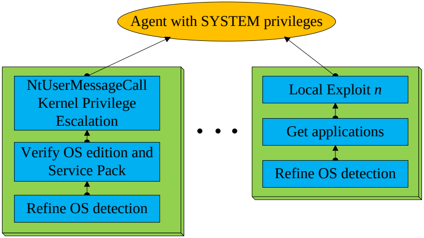
Solution

Order actions according to t_k/p_k (in increasing order).

The **Combine** primitive



Definition

We call *strategy* a group of actions that are executed in a fixed order.

Problem

$\{G_1, \ldots, G_n\}$ are strategies that result in a goal $\mathfrak{g}$.
Task: Minimize total time.

Expected probability and time

If the actions of G are $\{A_1, \ldots, A_n\}$ then:
The expected running time of G is

$$T_G = t_1 + p_1\, t_2 + p_1\, p_2\, t_3 + \ldots + p_1\, p_2 \ldots p_{n-1}\, t_n$$

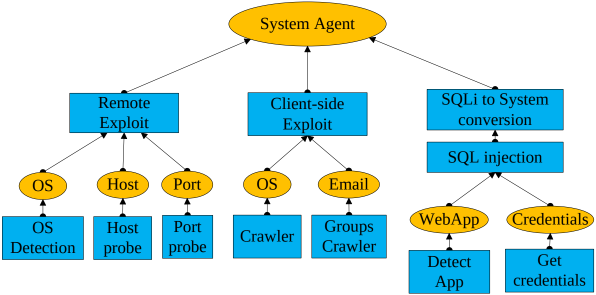
The probability of success is simply

$$P_G = p_1\, p_2 \ldots p_n$$

Solution

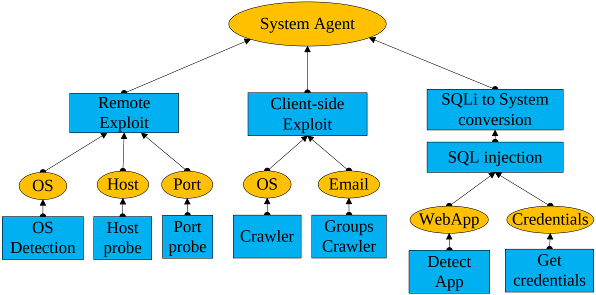
Sort the strategies according to T_G / P_G.
In each group, execute actions until one fails or all the actions are successful.
Complexity of planning: $\mathcal{O}(n \log n)$

The **Combine** primitive (cont)



Groups of actions with an AND relation (order is not specified).

The **Combine** primitive (cont)



Groups of actions with an AND relation (order is not specified).

Idea

In each group, order actions according to $t_k/(1-p_k)$.

Intuitively, actions with higher probability of failure have priority.

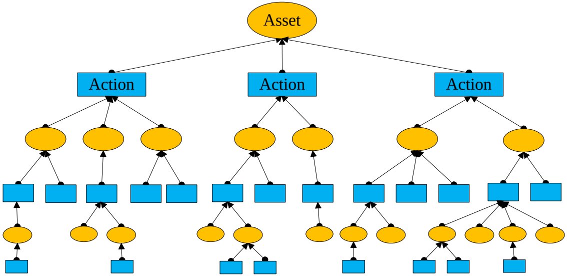
References (for this section)

- [Sar09a] New Algorithms for Attack Planning
  - *FRHACK Conference, France. Sept 7/8, 2009.*
- [Sar09b] Probabilistic Attack Planning in Network + WebApps Scenarios
  - *H2HC Conference, Sao Paulo, Brazil. Nov 28/29, 2009.*

Agenda

First level: fixed source and target

Given a source machine and a target machine, the problem is to find a path in an Attack Tree:



1. *Action node:* connected by AND relation with its requirements $\longrightarrow$ use *Combine* primitive.
2. *Asset node:* connected by OR relation with the actions that provide that asset $\longrightarrow$ use *Choose* primitive.

Second level: graph of machines

Use First level procedure to compute $Time(u,v)$ and $Prob(u,v)$ for all $u, v \in \mathcal{V}$ and then ...

Algorithm 1 Modified Dijkstra's algorithm

$T[s] = 0,\ P[s] = 1$
$T[v] = +\infty,\ P[v] = 0 \quad \forall v \in \mathcal{V}, v \neq s$
$S \leftarrow \emptyset$
$Q \leftarrow \mathcal{V}$ (where Q is a priority queue)
while $Q \neq \emptyset$ **do**
  $u \leftarrow \arg\min_{x \in Q} T[x]/P[x]$
  $Q \leftarrow Q \backslash \{u\},\ S \leftarrow S \cup \{u\}$
  for all $v \in \mathcal{V} \backslash S$ adjacent to u **do**
    $T' = T[u] + P[u] \times Time(u,v)$
    $P' = P[u] \times Prob(u,v)$
    if $T'/P' < T[v]/P[v]$ **then**
      $T[v] \leftarrow T'$
      $P[v] \leftarrow P'$
return $\langle T, P \rangle$

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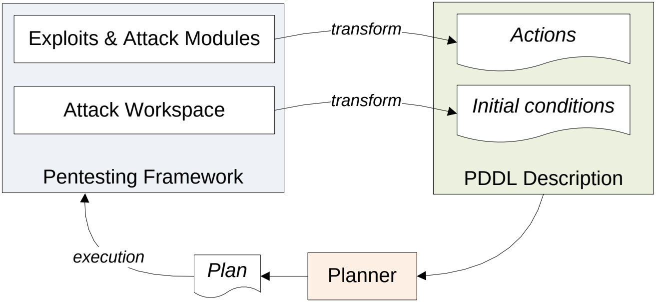
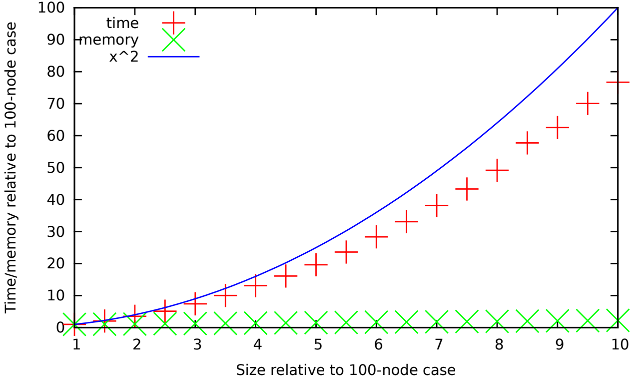
Anatomy of a planning-based attack

Attack Planning, as used in Core Insight Enterprise

[LSR10]; a.k.a. “Cyber Security Domain” [BGHH05]



Experimental results



- Scales up to 1000 machines.
- Planner running time is cuadratic
- Memory consumption is linear.

References (for this section)

- [SRL11] An Algorithm to find Optimal Attack Paths in Nondeterministic Scenarios
  - C. Sarraute, G. Richarte, J. Lucangeli
  - *AISec workshop, ACM CCS, Chicago. October 21, 2011.*

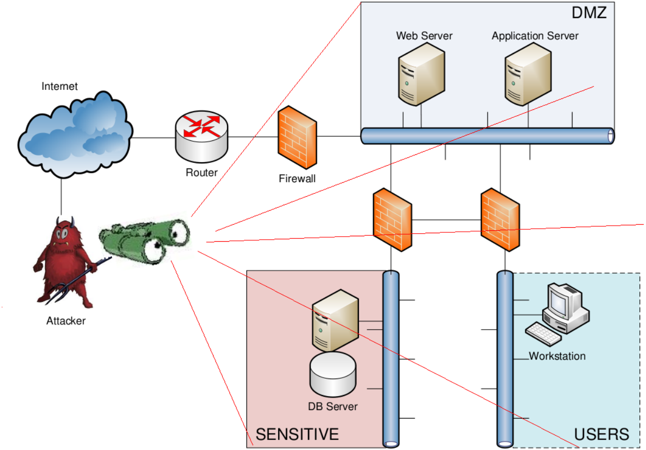
Agenda

Anatomy of a real-world attack w/o uncertainty

What's the problem?

Anatomy of a real-world attack w/o uncertainty

What's the problem? **PDDL & Planner w/o Uncertainty!**



Penetration Testing w/ uncertainty

What kind of uncertainty?

Penetration testing has insider knowledge. But can't know *everything!* OS versions, applications installed, ...

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  (I) gather information (run scans); (II) attack (run exploits)
  - Still simplified: scans don't yield perfect knowledge
  - Exhaustive scans expensive (runtime, traffic)

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- **Our solution:** explicit model of uncertainty in POMDP
  - POMDP plans intelligently mix (I) and (II)
  - Grounds attack planning w/ uncertainty in formal framework
  - Only related work: neither of these [SRL11]

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  - POMDP plans intelligently mix (I) and (II)
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  - Only related work: neither of these [SRL11]
  - And, yes, it doesn't scale . . . (to be continued)

Agenda

Markov Decision Process (MDP)

Definition

An *MDP* is a tuple $\langle \mathcal{S}, \mathcal{A}, T, r \rangle$ where:

- $\mathcal{S}$ is the state space
- $\mathcal{A}$ is the action space
- $T : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \rightarrow [0, 1]$ is the transition function
  - $T(s, a, s')$ is the probability of coming to state s' when executing action a in state s
- $r : \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$ is the reward function

Definition

Solution: policy $\pi : \mathcal{S} \rightarrow \mathcal{A}$
Objective: maximize expected reward $E\left[\sum_{t=0}^{\infty} r_t \middle| \pi\right]$

Partially Observable MDP (POMDP)

Definition

A POMDP is a tuple $\langle \mathcal{S}, \mathcal{A}, T, r, \mathcal{O}, O, b_0 \rangle$ where:

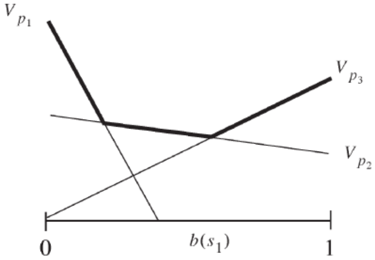
- $\langle \mathcal{S}, \mathcal{A}, T, r \rangle$ is a Markov decision process
- $\mathcal{O}$ is the space of observations
- $O : \mathcal{S} \times \mathcal{A} \times \mathcal{O} \to [0, 1]$ is the observation function
  - $O(s, a, o)$ is the probability of making observation o when executing action a in state s
- b_0 is the initial belief (probability distribution over $\mathcal{S}$)

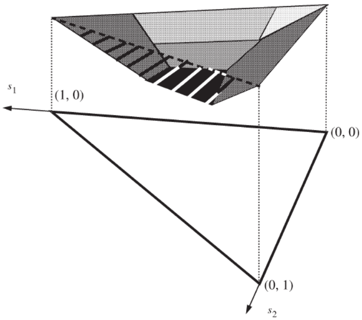
POMDP Policies

Definition

Solution: policy $\pi : \mathcal{H} \to \mathcal{A}$ ($\mathcal{H}$: action/observation histories)

Objective: maximize expected reward $E\left[\sum_{t=0}^{\infty} r_t \middle| b_0, \pi\right]$





Equivalent: policy $\pi : \mathcal{B} \to \mathcal{A}$ where $\mathcal{B} = \Pi(\mathcal{S})$

Solving POMDPs

- **Is it hard?**
  - $\mathcal{S}$: all states (= all possible configurations)
  - Belief states *b*: probability distributions over $\mathcal{S}$
  - ...and we need to *reason* about this stuff!
- **How to do it?**
  - Here: SARSOP [KHL08]
  - Approximate belief value based on selected belief states (get hyperplane for each, compute upper envelope)
- **What about scaling??**
  - Bad
  - Long-term proposal: use in “1-machine case”, design global solution by decomposition + approximation

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Birds-Eye View

- **States**
  - Network structure static and fully known
  - Combinations of configuration parameters . . .
  - . . . as relevant to modeled exploits!
- **Actions**
  - Exploits: succeed/fail depending on state
  - Scans: return observation depending on state
  - Both are deterministic!
- **Rewards**
  - $r = V - T - D$: value of computer, runtime, detection risk
  - V: human decision; T, D: estimate using statistics
- **Initial belief**
  - Probability distribution over configurations
    $\Longrightarrow$ uncertainty from point of view of pentesting tool

Example: Actions

```
actions :

Probe-M0-p445
OSDetect-M0

Exploit-M0-win2000-SMB
Exploit-M0-win2003-SMB
Exploit-M0-winXPsp2-SMB

Terminate
```

"Terminate" action: give planner the choice to "give up" if expected costs outweigh expected reward

Example: States (1 Machine)

```
states :

M0-win2000
M0-win2000-p445
M0-win2000-p445-SMB
M0-win2000-p445-SMB-vuln
M0-win2000-p445-SMB-agent

M0-win2003
M0-win2003-p445
M0-win2003-p445-SMB
M0-win2003-p445-SMB-vuln
M0-win2003-p445-SMB-agent

M0-winXPsp2
M0-winXPsp2-p445
M0-winXPsp2-p445-SMB
M0-winXPsp2-p445-SMB-vuln
M0-winXPsp2-p445-SMB-agent

M0-winXPsp3
M0-winXPsp3-p445
M0-winXPsp3-p445-SMB

terminal
```

Example: Scans – Port Scan

```
O: Probe-M0-p445: M0-win2000                  : closed-port 1
O: Probe-M0-p445: M0-win2000-p445             : open-port 1
O: Probe-M0-p445: M0-win2000-p445-SMB         : open-port 1
...
O: Probe-M0-p445: M0-win2003                  : closed-port 1
O: Probe-M0-p445: M0-win2003-p445             : open-port 1
O: Probe-M0-p445: M0-win2003-p445-SMB         : open-port 1
...
O: Probe-M0-p445: M0-winXPsp2                 : closed-port 1
O: Probe-M0-p445: M0-winXPsp2-p445            : open-port 1
O: Probe-M0-p445: M0-winXPsp2-p445-SMB        : open-port 1
...
O: Probe-M0-p445: M0-winwinXPsp3              : closed-port 1
O: Probe-M0-p445: M0-winXPsp3-p445            : open-port 1
O: Probe-M0-p445: M0-winXPsp3-p445-SMB        : open-port 1
```

Example: Scans – OS Detection

```
O: OSDetect-M0: M0-win2000                    : win 1
O: OSDetect-M0: M0-win2000-p445               : win 1
...
O: OSDetect-M0: M0-win2003                    : win 1
O: OSDetect-M0: M0-win2003-p445               : win 1
...

O: OSDetect-M0: M0-winXPsp2                    : winxp 1
O: OSDetect-M0: M0-winXPsp2-p445               : winxp 1
...
O: OSDetect-M0: M0-winXPsp3                    : winxp 1
O: OSDetect-M0: M0-winXPsp3-p445               : winxp 1
...
```

Example: Exploit SAMBA Server on Port 445

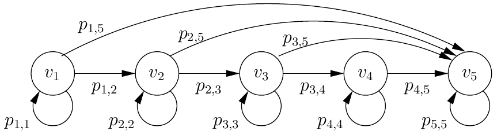
```
T: Exploit-M0-win2003-SMB identity
T: Exploit-M0-win2003-SMB: M0-win2003-p445-SMB-vuln
                                 : * 0
T: Exploit-M0-win2003-SMB: M0-win2003-p445-SMB-vuln
                                 : M0-win2003-p445-SMB-agent 1

O: Exploit-M0-win2003-SMB: * : * 0
O: Exploit-M0-win2003-SMB: * : no-agent 1
O: Exploit-M0-win2003-SMB: M0-win2003-p445-SMB-agent
                                 : agent-installed 1
```

What is our "Initial Belief"??

- **Regular penetration testing**
  - Run tests every T time units (days)
  - Possibly changed OS, applications (versions), ...

    $\Longrightarrow$ Uncertainty in b_0, function of T

- **How to derive $b_0(T)$?**
  - In general: *formal model of system evolution ...*
  - Here: (a) individual updates; (b) perfect knowledge at $T = 0$



"each day: either no change, or upgrade, or upgrade to latest version"

Agenda

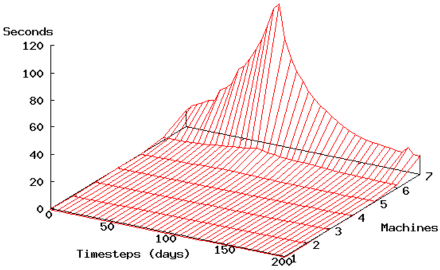
Test Examples

Problem generator with 3 parameters:

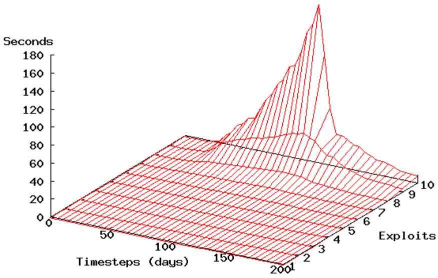
- Number M of machines in network
  Agent on machine M_0, M "behind" M_0 in fully connected network
- Number E of exploits considered
  $E \geq M$, distributed evenly across machines
- Time delay T (days) since last pentest
  Update parameters estimated by hand

Here: $1 \leq M \leq 7$; $1 \leq E \leq 50$; $0 \leq T \leq 200$

Scaling T

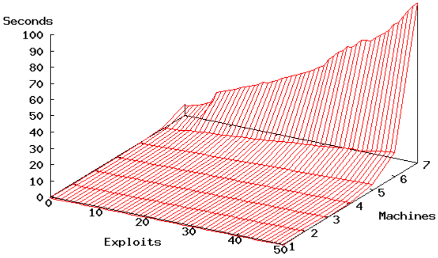


Scaling T against M

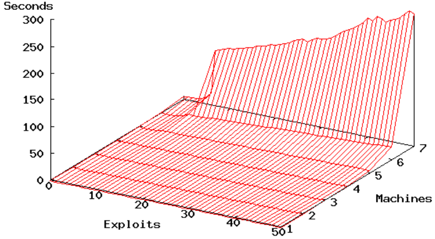


Scaling T against E

Scaling E and M



Scaling E against M; $T = 10$



Scaling E against M; $T = 80$

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Joint work with researchers at INRIA (Nancy, France)

Jörg Hoffmann, author of FF [Hof01] and Metric-FF [Hof02], reference tools for “classical” planning.

Olivier Buffet, author of books and tools on Markov decision process [SB10].

- [SBH11] Penetration Testing == POMDP Solving?
  - *SecArt’11 (Workshop on Intelligent Security), IJCAI’11 Conference, Barcelona. July 16-22, 2011.*

Agenda

Probabilistic Planner: Summary

First direction . . . We have presented:

- An **attack model** based on exploits metrics:
  - Average running time
  - Probability of success
  - Details of the vulnerable platform (OS and application versions)
  - Connectivity requirements.
- An efficient planning solution, **integrated** to a penetration testing framework.
- An **evaluation of our implementation** that shows the feasability of planning and verifying attacks in **real-life scenarios**.

POMDP model: Is it worth it?

Second direction . . . POMDPs make better hackers!

(a) Beliefs: likelihood of particular vulnerabilities
$\Longrightarrow$ order exploits by promise

(b) Belief transitions: update “promise” as more information comes in
$\Longrightarrow$ order exploits dynamically

(c) Belief transitions vs. rewards (time/risk): trade-off observation gain against its cost
$\Longrightarrow$ apply scans only where needed/profitable

POMDP model: What have we gained?

- More accurate model of attack planning w/ uncertainty
- Scales “Ok” in 1-target-machine case
- Can deliver better plans thus more effective pentesting
  - Policy = stronger notion of plan
  - Contemplates all possible histories of actions / observations.
- No independence assumptions
  - Understand the limits of what can be done with state-of-the-art POMDP planners

Bridging the language gap

- Separate the problem from potential solutions.
- Communicate our problem to the AI / Planning community $\longrightarrow$ they're looking for practical applications!
- Solving: PoC implementation shows feasibility
  Scaling to large networks $\implies$ decompose/approximate with 1-target-machine cases
- Basic AI: these POMDPs have particular properties ...
  $\longrightarrow$ open path for further research

That's all folks!

Thanks for your attention!
Questions?

carlos @ coresecurity . com
http://corelabs.coresecurity.com/

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An algorithm to find optimal attack paths in nondeterministic scenarios.
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