



Characterizing and Aggregating Attack Graph-based Security

Metrics

MIT Lincoln Labs Seminar

July 7, 2010

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The Institute for Information Infrastructure Protection (I3P) on Security Metrics

Security metrics is considered a top **4** research &
development priority through 2019



INFOSEC Research Council (IRC) on Security Metrics

Enterprise security metrics considered a top **8** research
priority through 2015



Attack Graph-based Security Metric

- a value derived from measuring attack graph properties

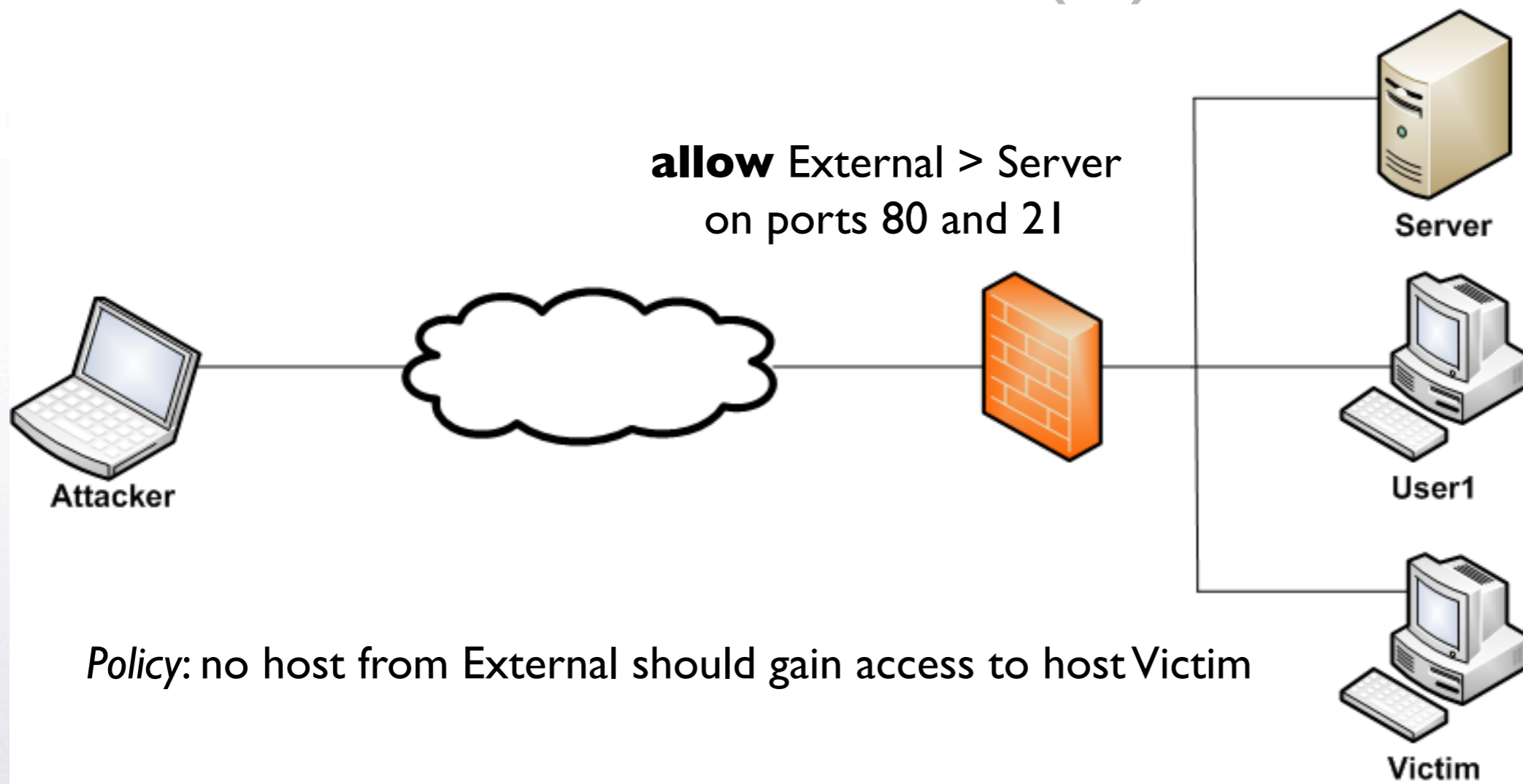


Attack Graph

- an abstraction divulging the *potential* ways an attacker can leverage interdependencies among vulnerabilities to violate a security policy

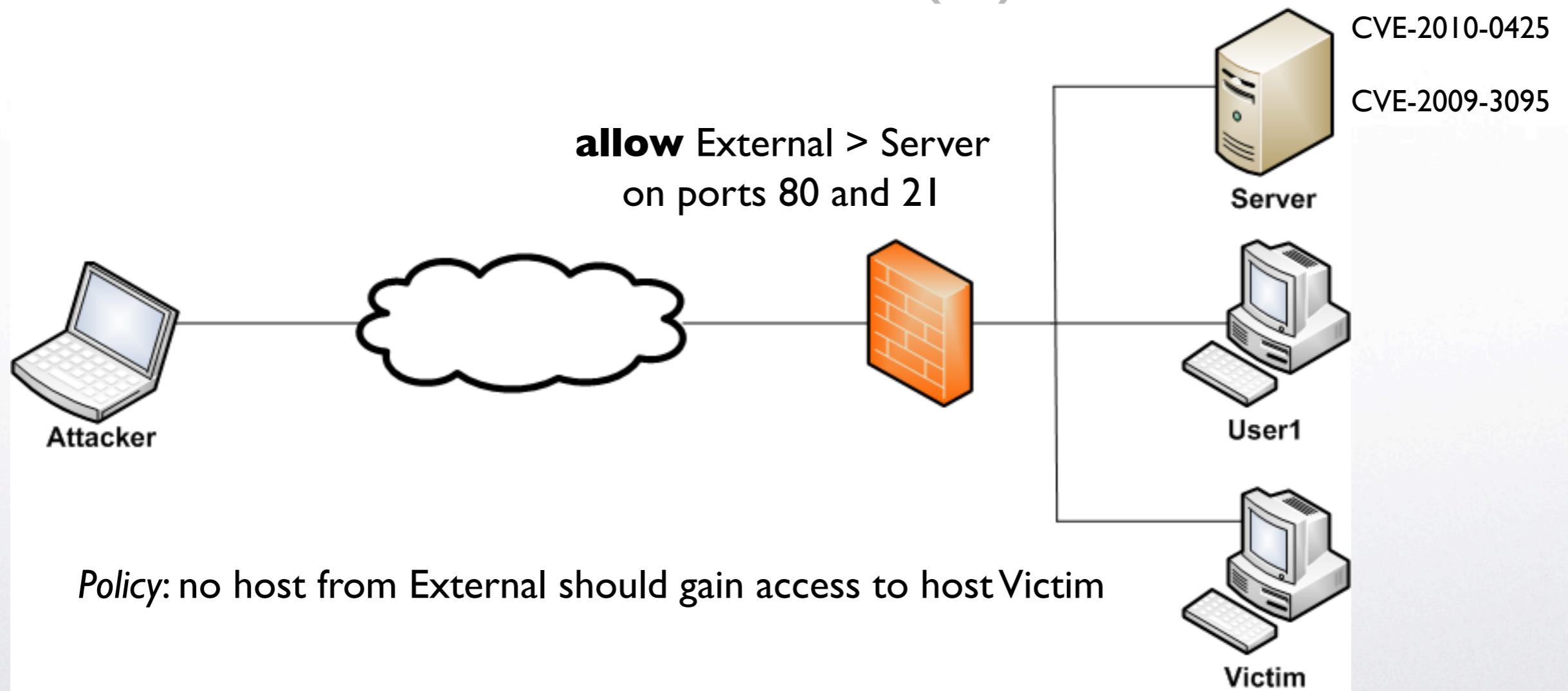


The Attack Graph Generation Process (I)



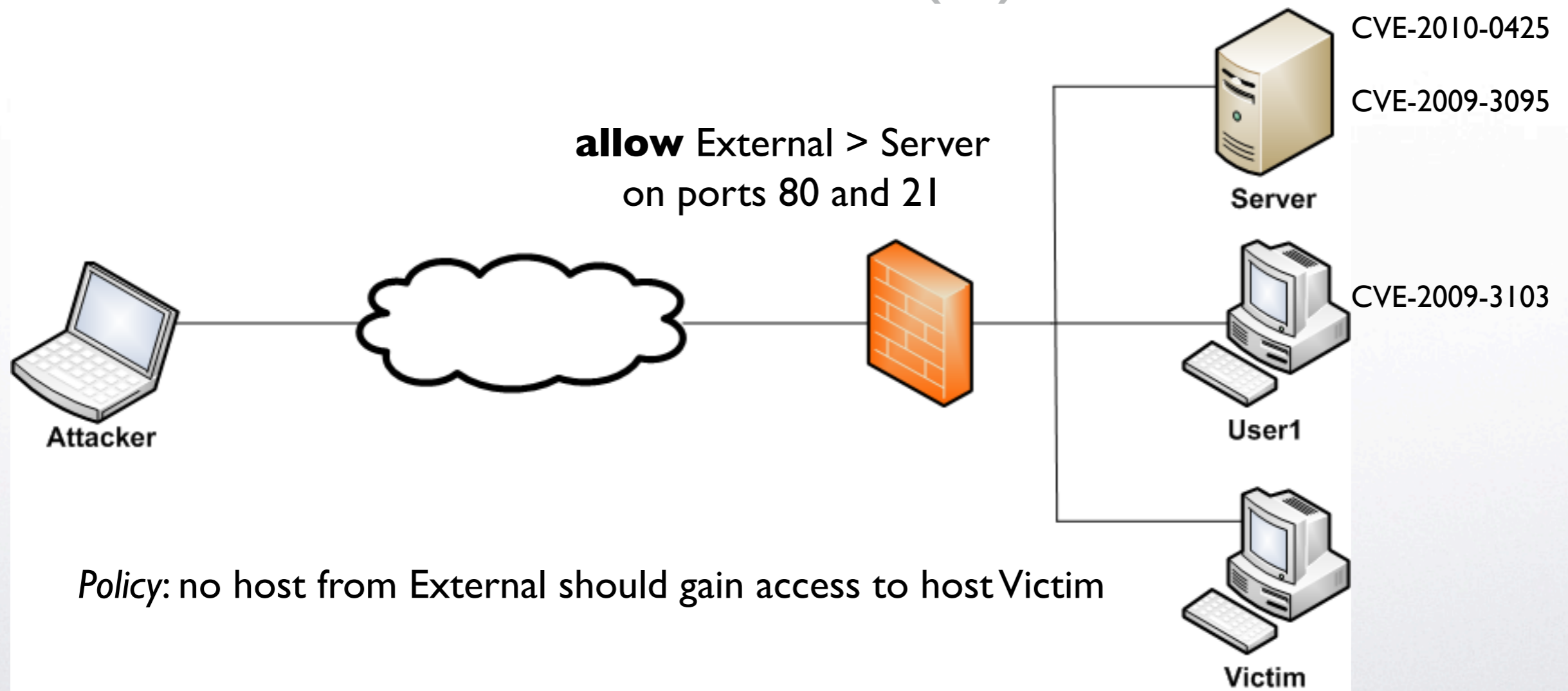


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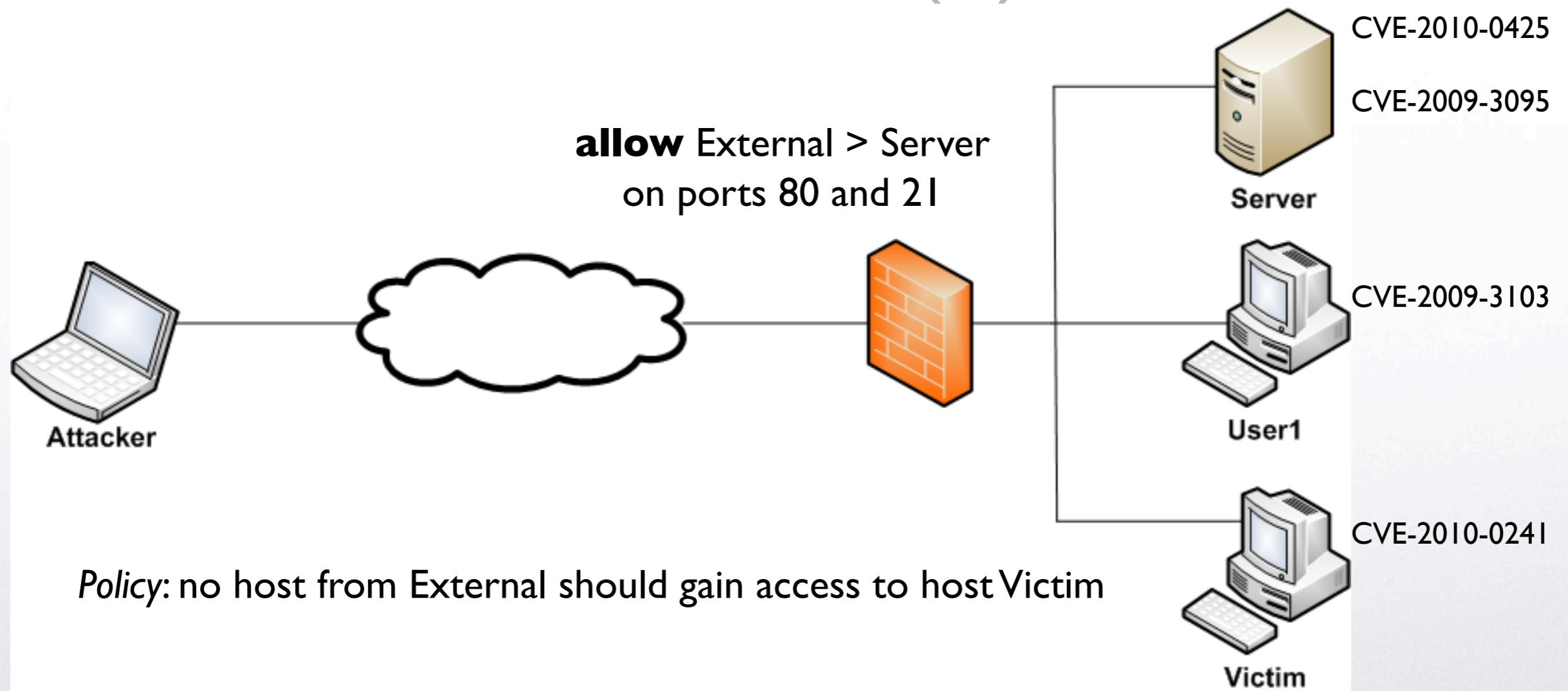


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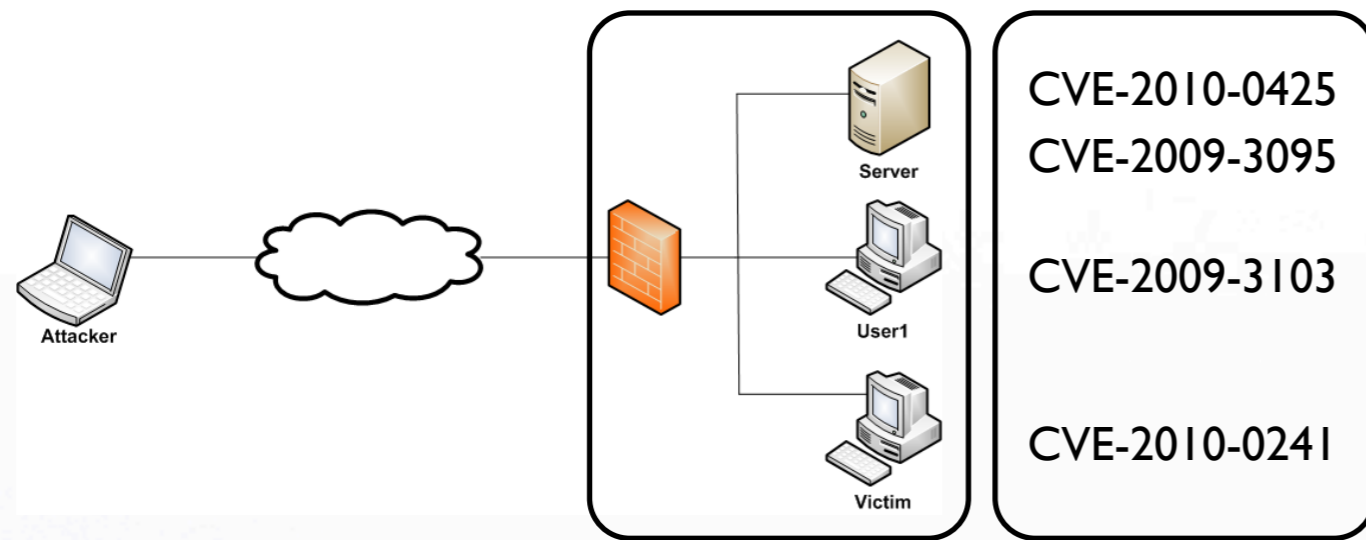


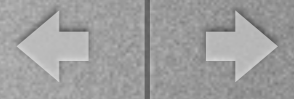
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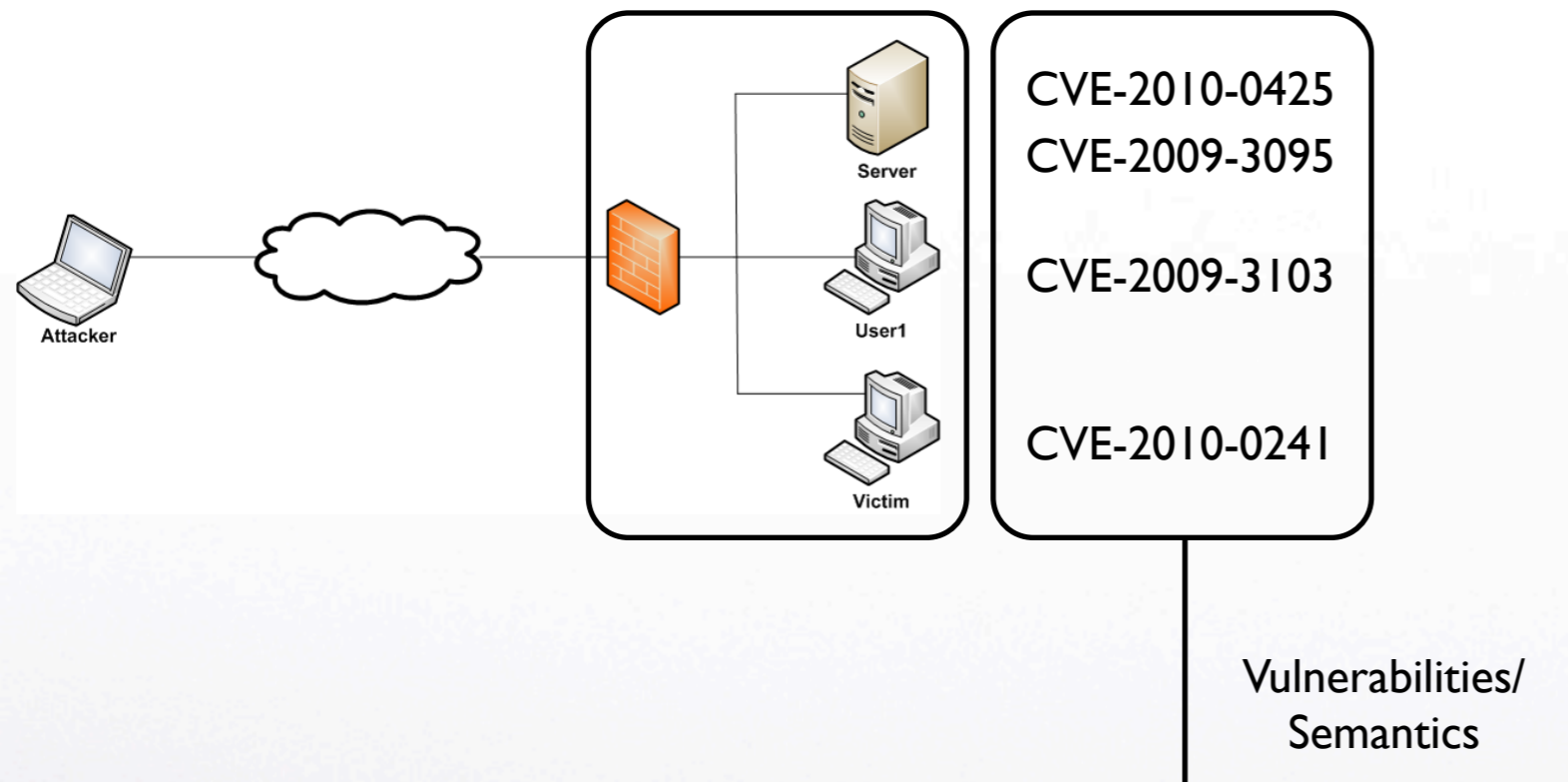


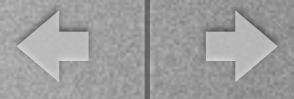
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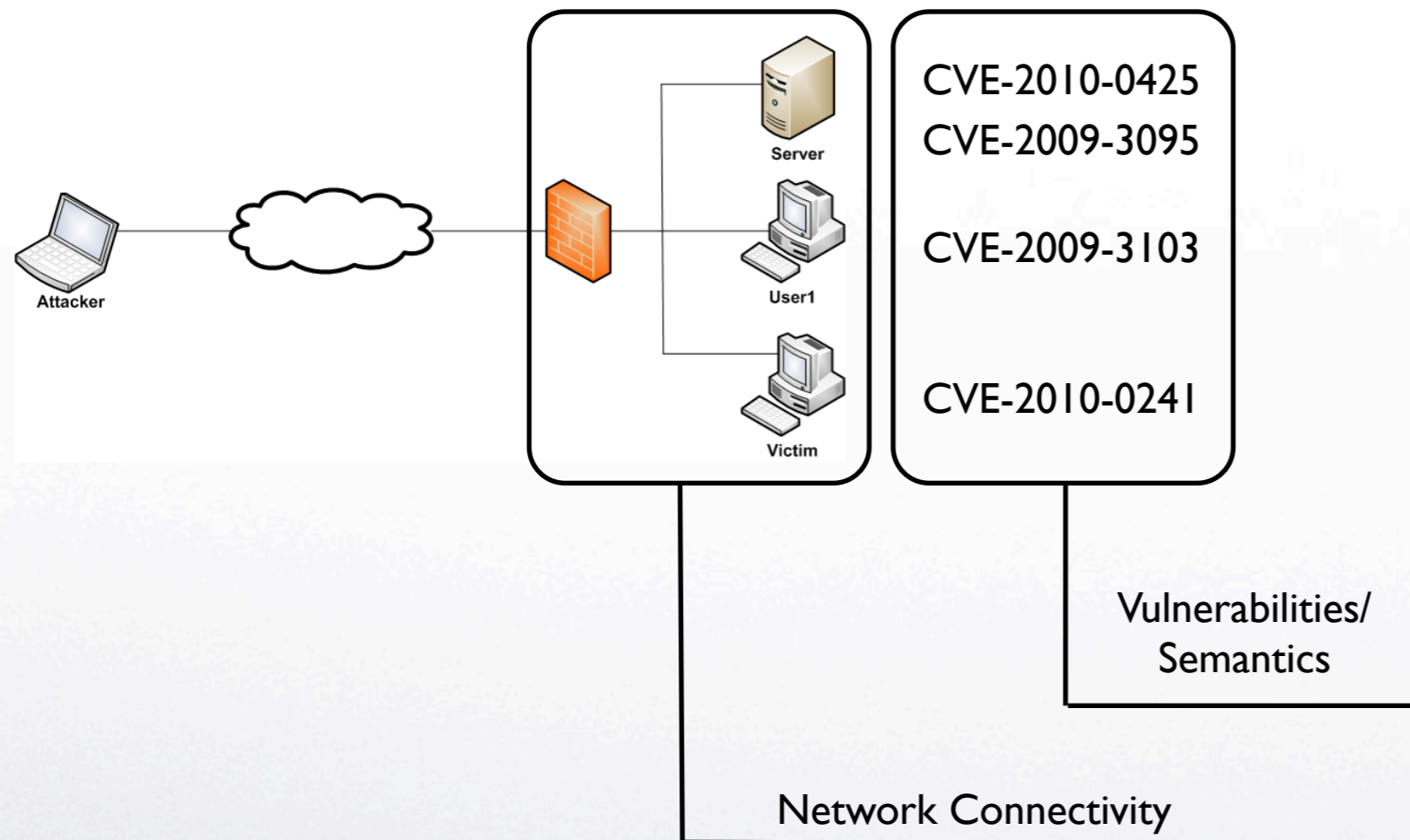


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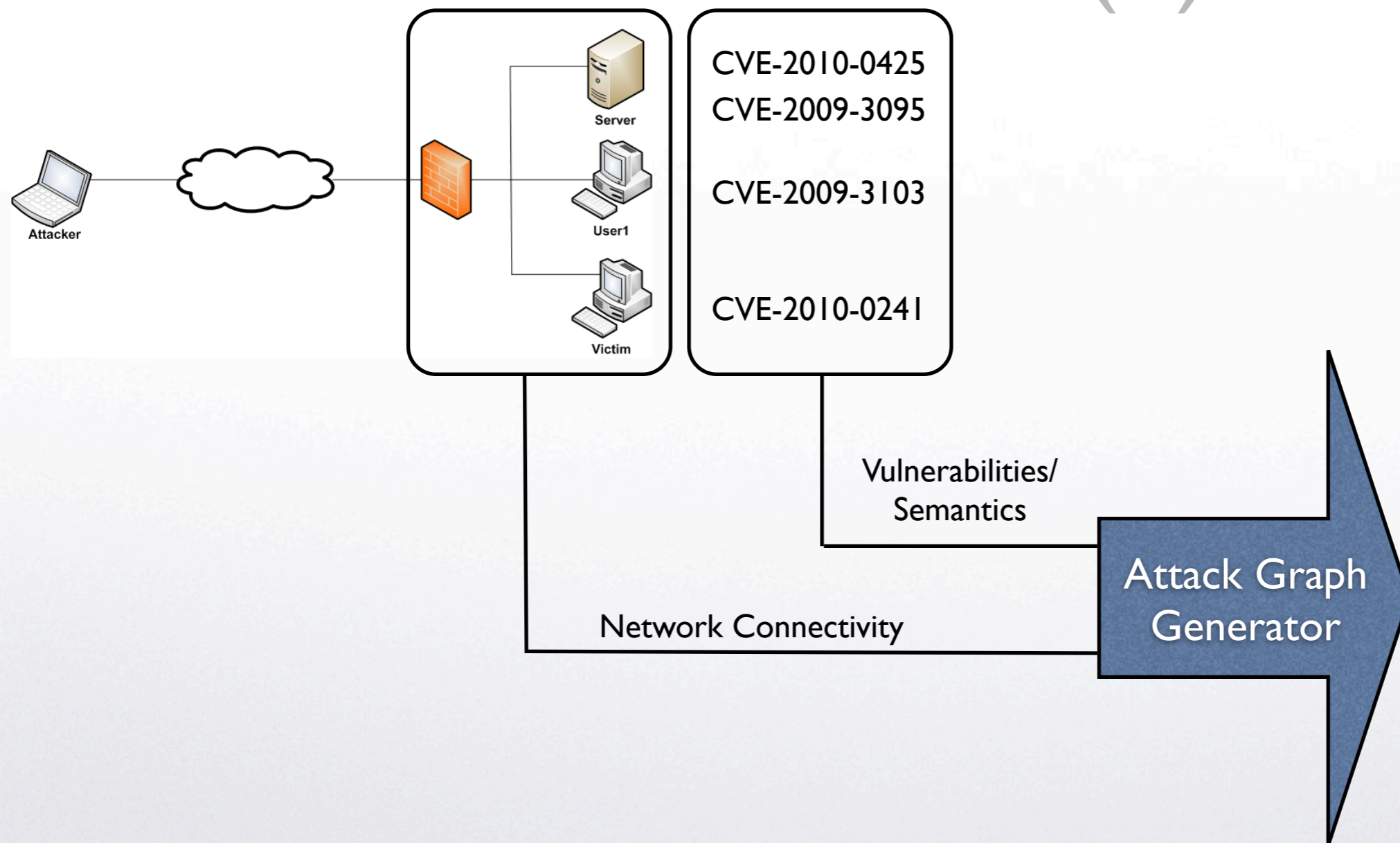


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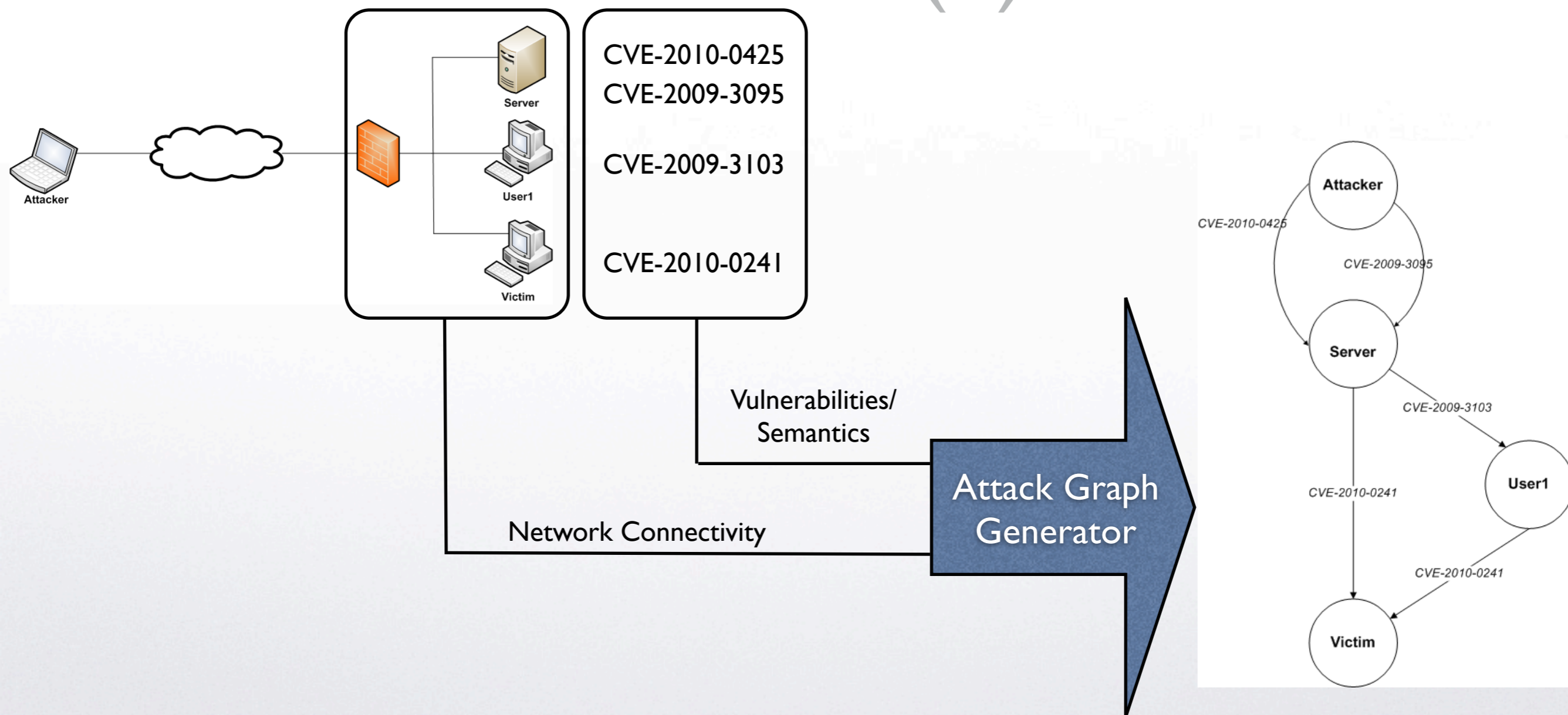


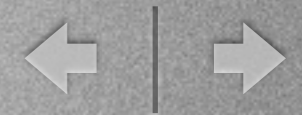
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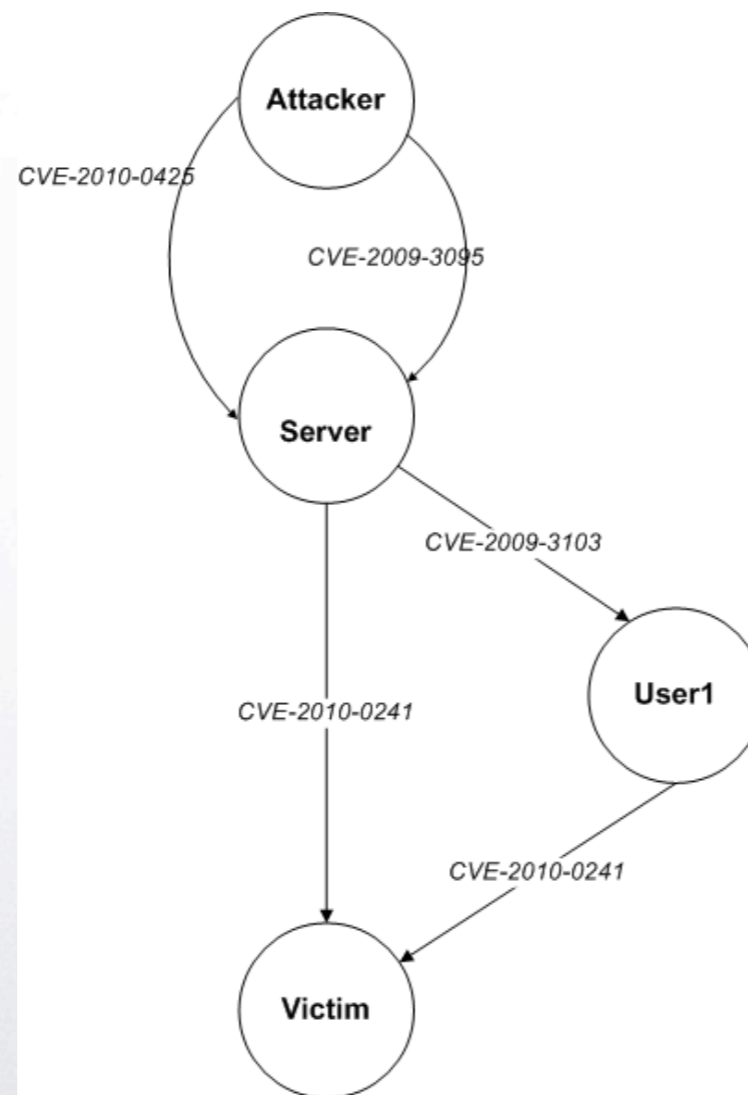
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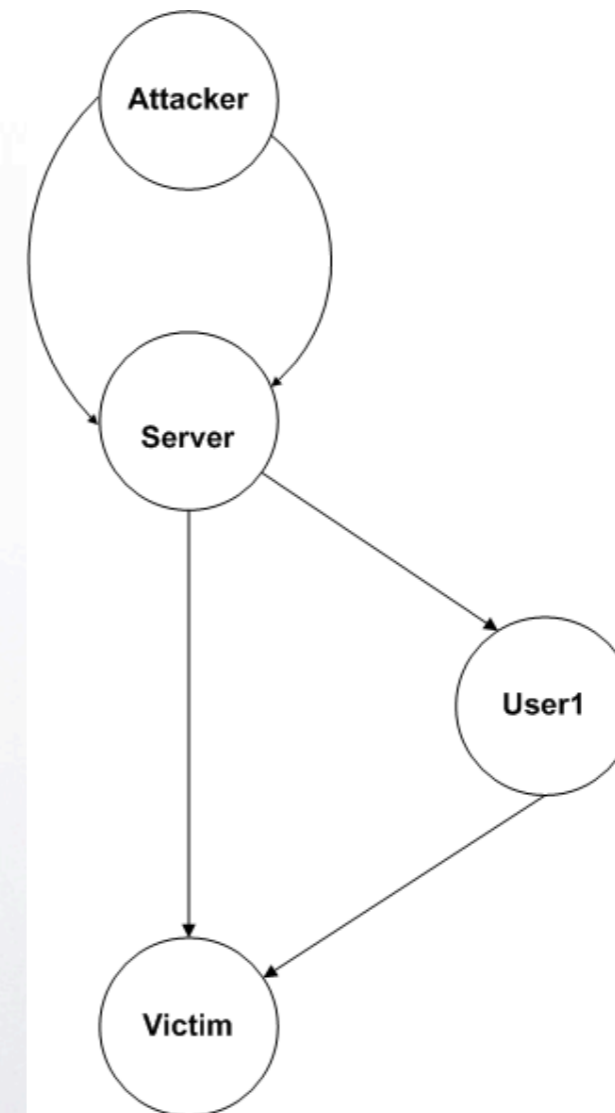


Condition-oriented Attack Graphs

Labeled-edge attack graph



Label-free-edge attack graph





Overview

- Modeling Attack Path Complexity
- Aggregating Attack Graph-based Security Metrics When Comparing Networks
- Providing an Efficient Computation of the Number of Paths Metric
- Using Multiple Attack Graph-based Security Metrics for Network Hardening



Modeling Attack Path Complexity



A Kolmogorov Complexity- inspired Approach



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- Kolmogorov Complexity claims that the complexity of a string is equal to the smallest program that can produce this string



A Kolmogorov Complexity- inspired Approach

- Kolmogorov Complexity claims that the complexity of a string is equal to the smallest program that can produce this string
- We use a modified language of Regular Expressions to model attack path complexity



Language for Attack Path Complexity (I)

- **Alphabet**
 - A corresponds to the vulnerabilities found in all attack graphs being considered
- **Constants**
 - ϵ corresponds to the empty string
 - $v_i \in A$ denotes a vulnerability from one of the attack graphs being considered
 - \emptyset corresponds to the empty set



Language for Attack Path Complexity (2)

Let S and T be two strings comprised of characters from A

- **Operations**
 - ST evaluates to the concatenation of string S and T
 - $()$ provides priority ordering of evaluation
 - $(S)^+$ the expression S may repeat more than one time but must appear once
 - S^k repeat S k times



Language for Attack Path Complexity (3)

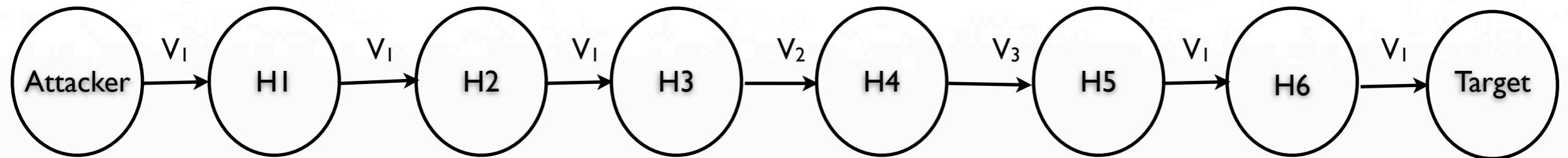
● Operations

Let E_1 and E_2 be expressions of the language

- $E_1^{[m]}E_2$ evaluates to inserting E_1 at index m in E_2
- $E_1^{[m_1],[m_2],\dots,[m_n]}E_2$ evaluates to inserting E_1 into indices m_1 through m_n of E_2
- $E_1^{k[m]}E_2$ evaluates to inserting E_1^k at index m in E_2
- $E_1^{k,[m]}E_2$ evaluates to concatenating E_1^k to E_2 , and inserting E_1 into index m of E_2
- $E_1^{k,[m_1],[m_2],\dots,[m_n]}E_2$ evaluates to concatenating E_1^k to E_2 , and inserting E_1 into indices m_1 through m_n of E_2

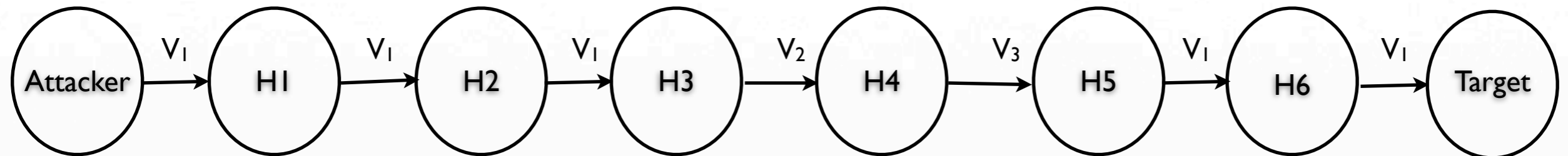


Kolmogorov Complexity Example





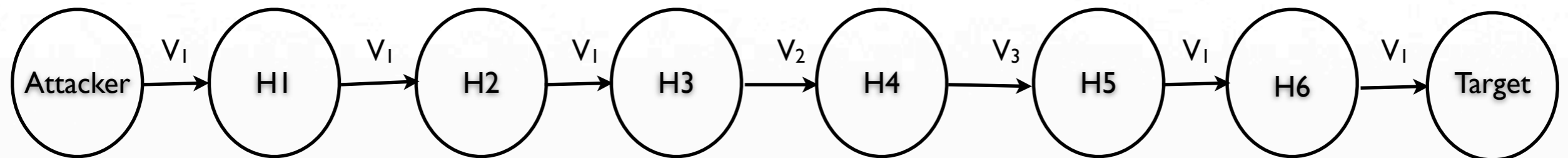
Kolmogorov Complexity Example



A Qualitative Representation: $v_1^{3,[2]}v_2v_3v_1$



Kolmogorov Complexity Example



A Qualitative Representation: $v_1^{3,[2]}v_2v_3v_1$

The Quantitative Representation: $v_1v_1v_1v_2v_3v_1v_1$



Aggregating Attack Graph-based Security Metrics



Previously Proposed Attack Graph-based Security Metrics



Previously Proposed Attack Graph-based Security Metrics

- **Capability Metrics - in terms of attacker capability**
 - Number of Paths (Ortalo et al. '99), Weakest Adversary (Pamula et al. '06), Network Compromise Percentage (Lippmann et al. '06)



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- **Complexity Metrics - in terms of attack effort**
 - Shortest Path (Phillips & Swiler '98), Mean of Path Lengths (Li & Vaughn '06)



A Critical Issue Attack Graph-based Security Metrics Miss



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- Security is a *multidimensional* entity



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 - Combine metrics measuring distinct attributes of network security



A Critical Issue Attack Graph-based Security Metrics Miss

- Security is a *multidimensional* entity
- All proposed security metrics are *unidimensional*
- Our approach for comparing 2 networks
 - Combine metrics measuring distinct attributes of network security
 - Resolve conflicts by measuring *relevant subsets of attack paths*



Assistive Metrics

- Mean of Path Lengths (MPL)
- *Standard Deviation of Path Lengths (SDPL)*
- *Median of Path Lengths (MePL)*
- *Mode of Path Lengths (MoPL)*



Decision Metrics

- *K-step Capability Accumulation (KCA)*
- *Normalized Mean of Path Lengths (NMPL)*
- Shortest Path (SP), Number of Paths (NP), Network Compromise Percentage (NCP), Weakest Adversary (WA)



K-step Capability Accumulation Metric

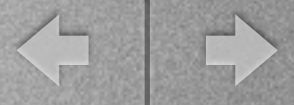
$$Cap_h(G) = \cup_h capabilities(n)$$



K-step Capability Accumulation Metric

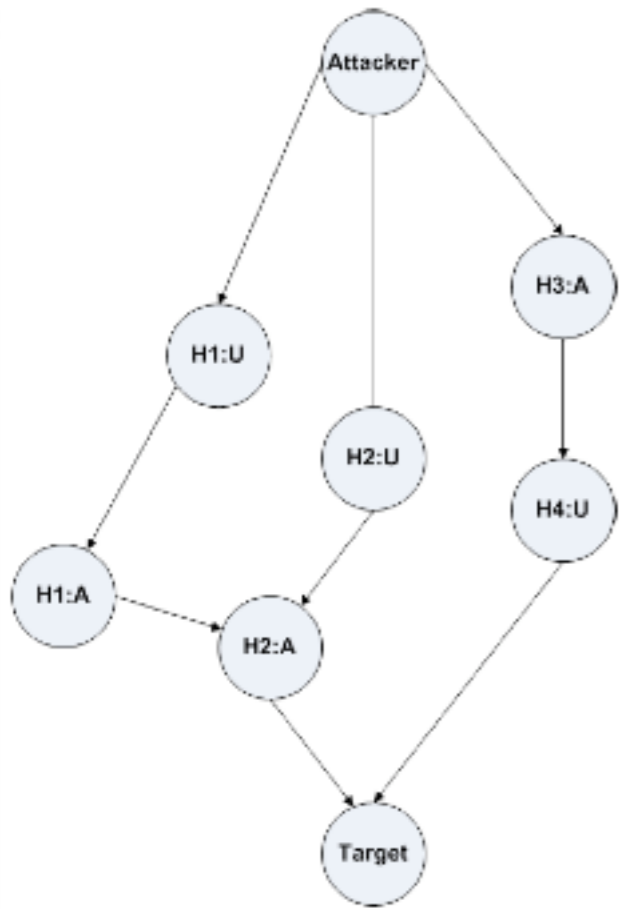
$$Cap_h(G) = \cup_h capabilities(n)$$

$$KCA_k(G) = \cup_{i=0}^k Cap_i(G)$$



K-step Capability Accumulation Metric

G_1



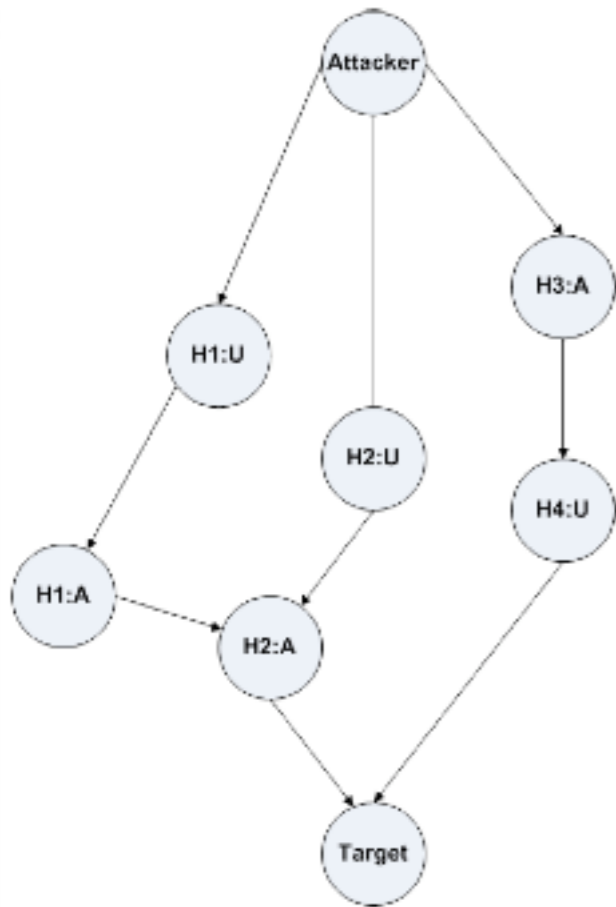
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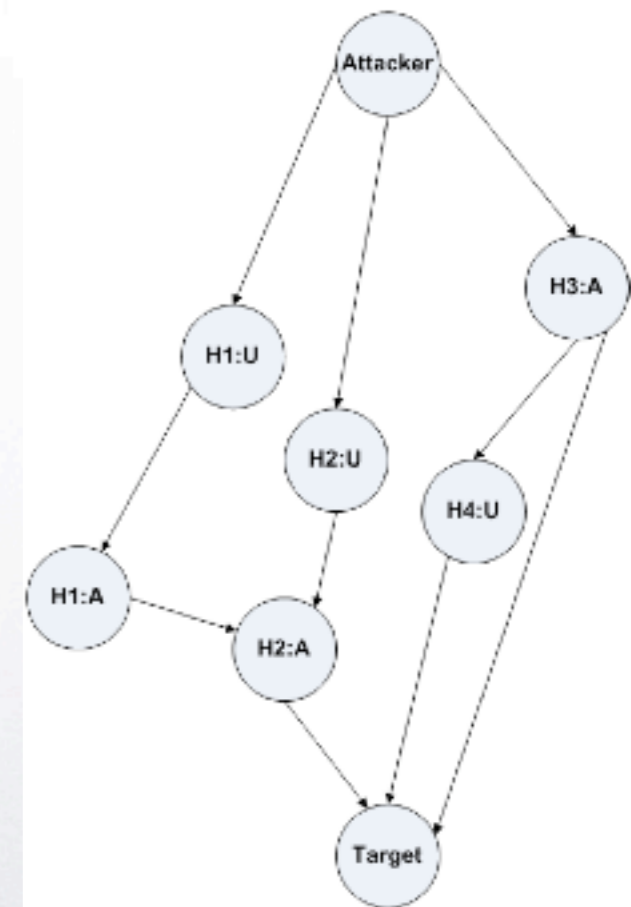
G₁



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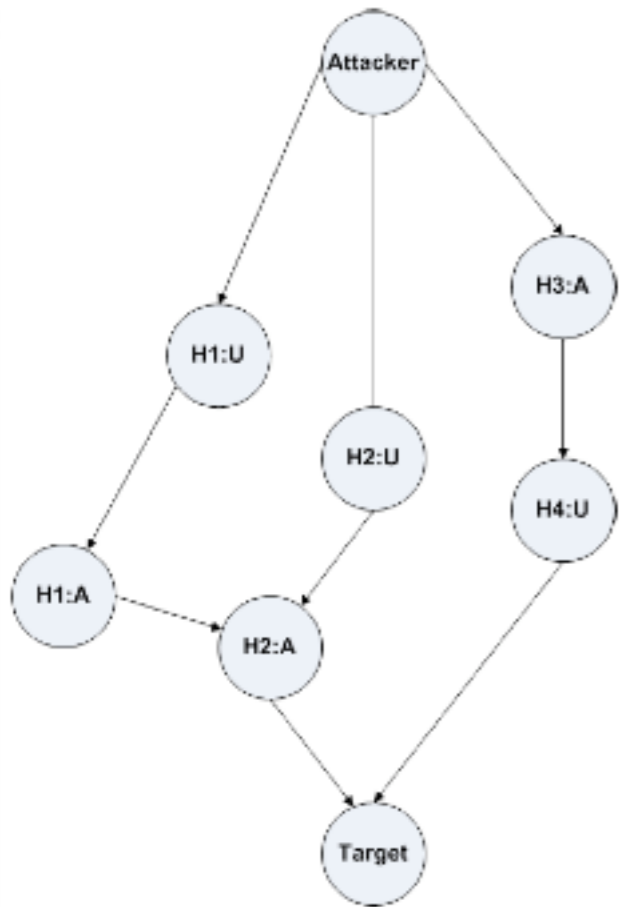
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K-step Capability Accumulation Metric

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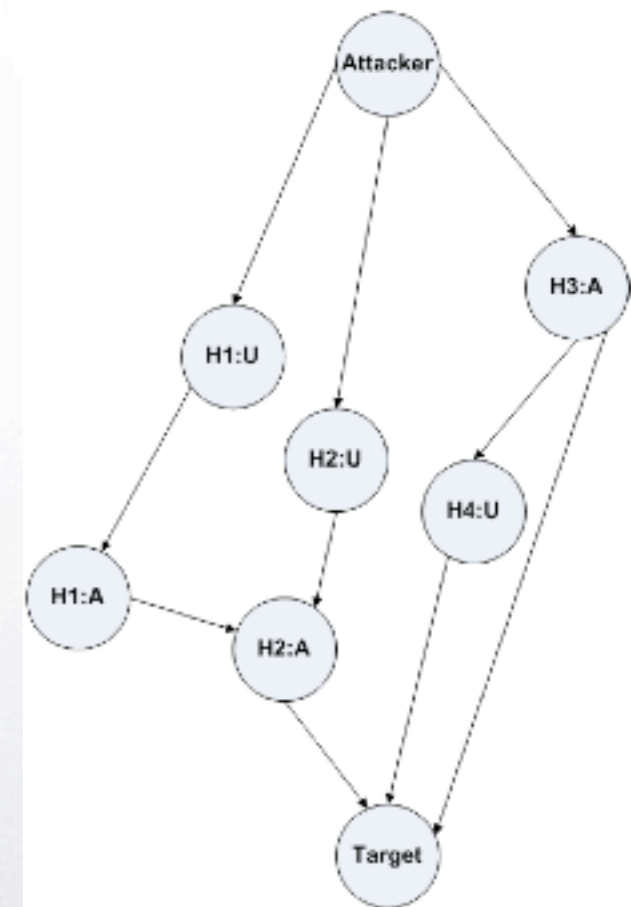


$$Cap_h(G) = \cup_h capabilities(n)$$

$$KCA_k(G) = \cup_{i=0}^k Cap_i(G)$$

$$KCA_1(G_1) = KCA_1(G_2)$$

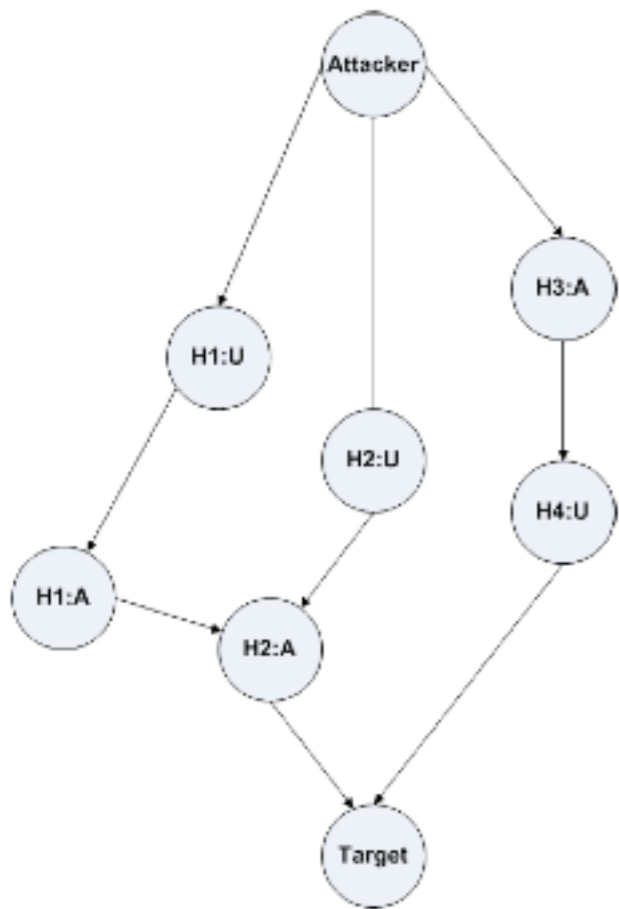
G₂





K-step Capability Accumulation Metric

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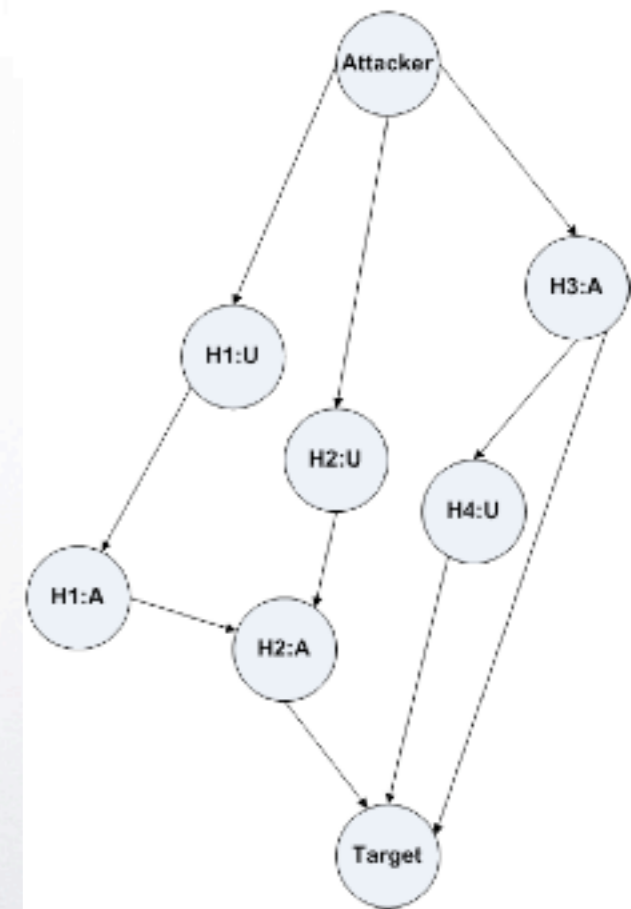
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$$KCA_2(G_1) < KCA_2(G_2)$$

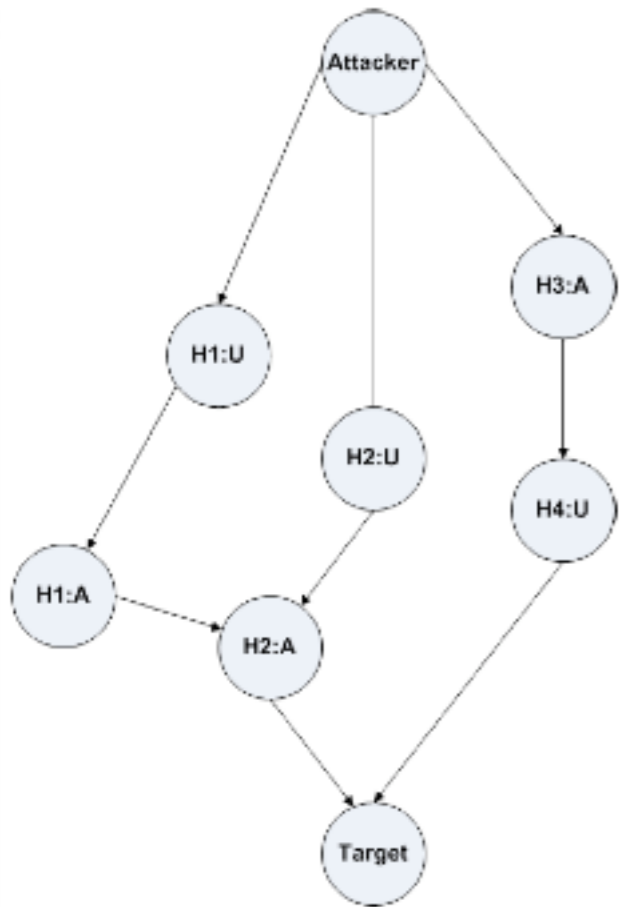
G₂





K-step Capability Accumulation Metric

G₁



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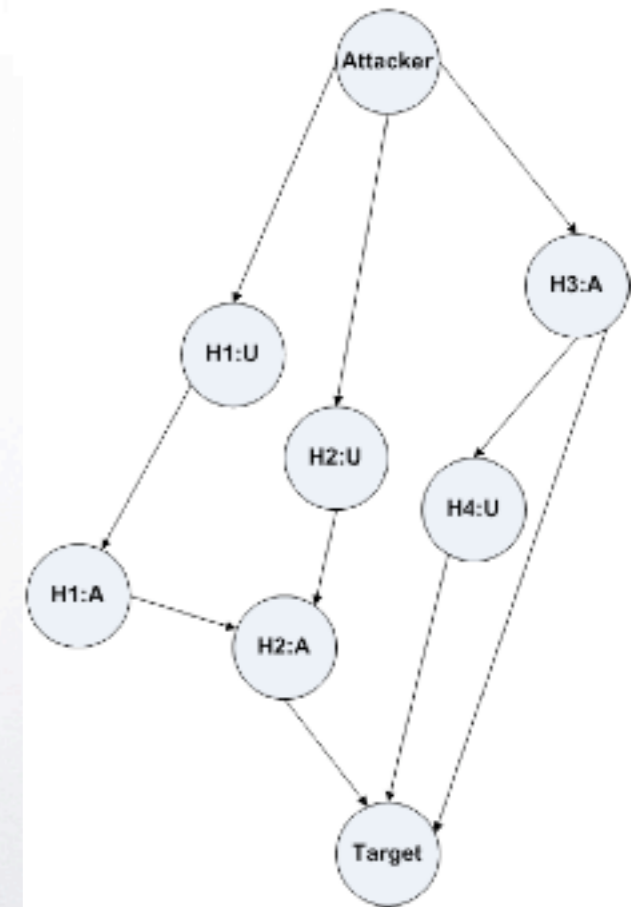
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G₁ is more secure than **G₂**

G₂





NMPL: A Problem with MPL



G_1

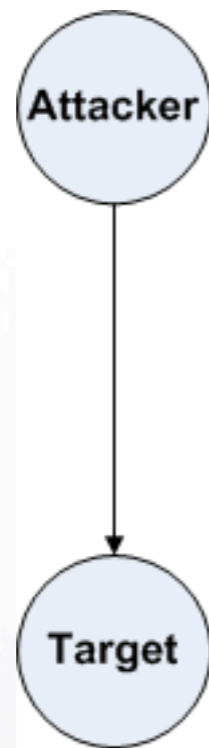
MPL claims G_1 & G_2 are **equal**



G_2



NMPL: A Problem with MPL



G_1

MPL claims G_1 & G_2 are **equal**



G_2

$NMPL(G_1) = 1$ edge and $NMPL(G_2) = 0.2$ edges
Thus, NMPL claims G_1 is more secure



Aggregation Algorithm (I)

```
for each decision metric  $m_d$  in  $M$  do  
   $R_d \cup \text{eval}((x, y, m_d) = \text{apply}(m_d, G_1, G_2))$   
end for
```

```
if  $\text{strictly\_dominates}(R_d)$ ,  $\text{majority\_dominates}(R_d)$ , or  $\text{ties}(R_d)$  then  
  Done  
else  
   $\text{enlist\_assistive\_metrics}(G_1, G_2, M)$   
end if
```

We use SP, NP, and NMPL for decision metrics



Aggregation Algorithm (2)

```
for each  $m_d$  in  $M$  do  
  if  $m_d$  equals  $SP$  then  
     $R_a \cup \text{eval}((x, y, m_d) = \text{apply}(m_d, \text{extract}(G_1, \text{MoPL}), \text{extract}(G_2, \text{MoPL}))$   
     $R_a \cup \text{eval}((x, y, m_d) = \text{apply}(m_d, \text{extract}(G_1, \text{SDPL}), \text{extract}(G_2, \text{SDPL}))$   
  else if  $m_d$  equals  $NP$  then  
     $\text{MePL}' = \min(\text{MePL}(G_1), \text{MePL}(G_2))$   
     $R_a \cup \text{eval}((x, y, m_d) = \text{apply}(m_d, \text{extract}(G_1, \text{MePL}'), \text{extract}(G_2, \text{MePL}'))$   
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  end if  
end for  
  
if  $\text{strictly\_dominates}(R_a)$ ,  $\text{majority\_dominates}(R_a)$ , or  $\text{ties}(R_a)$  then  
  Done else Undecided  
end if
```



Assumptions for Algorithm Evaluation

- The number of paths in the attack graph vary more in value than attack path length values
 - Number of paths range: 1 - 2000
 - Attack path lengths range: 1 - 50



Algorithm Evaluation

	SP, NP	SP, NMPL	NP, NMPL	SP, NP, NMPL
% Decided	48.4	78	99.9	99.9
% Strictly Dominated	4	4	99	4
% Majority Dominated	0	0	0	95
% Equal	0.4	0	0	0
% Strictly Dominated ⁺	10	10	0.1	0.1
% Majority Dominated ⁺	34	64	0.8	0.8
% Equal ⁺	0	0	0	0

Generated two disjoint sets of 1000 attack graphs each:
1 million comparisons

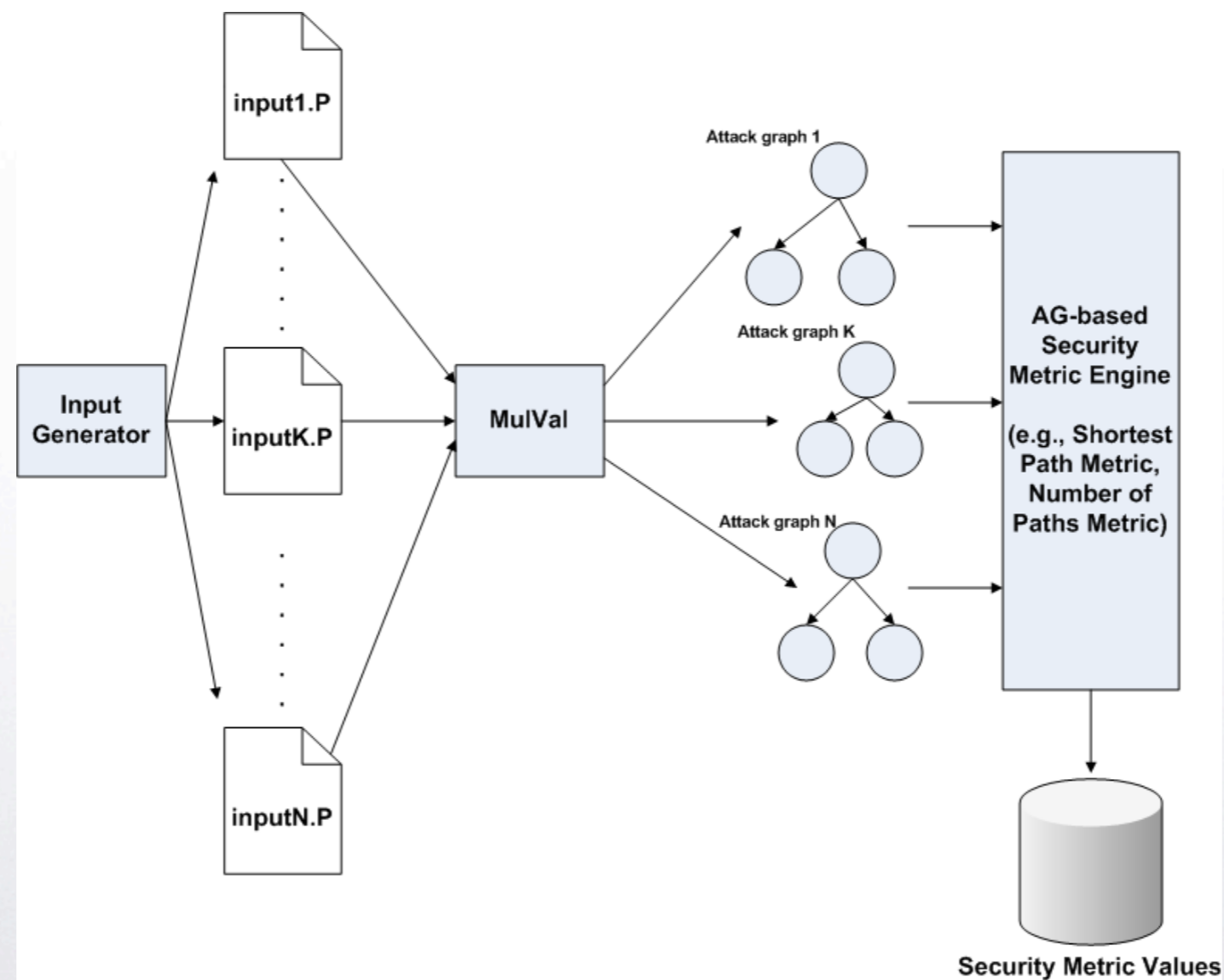
+ = enlisting the use of assistive metrics



Providing an Efficient Computation for the Number of Paths Metric



Experiment Setup





Extracted Equation for Number of Paths Metric on a Flat Network

$$NP(G_t) = \begin{cases} v_t & \text{if } t = 1, \\ v_t NP(G_{t-1}) + NP(G_{t-1}) & t > 1. \end{cases}$$



Extracted Equation for Number of Paths Metric on a Flat Network

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A Deterministic Version

When $v_t = c$, $NP(G_t) = c(c + 1)^{t-1}$ for $t \geq 1$.



Practical Issue



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- 15 host network, 1 target, single remotely exploitable vulnerability on each host



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$$\mathbf{NP(G)} = 2^{14}$$



Using Multiple Metrics for Network Hardening



Network Hardening

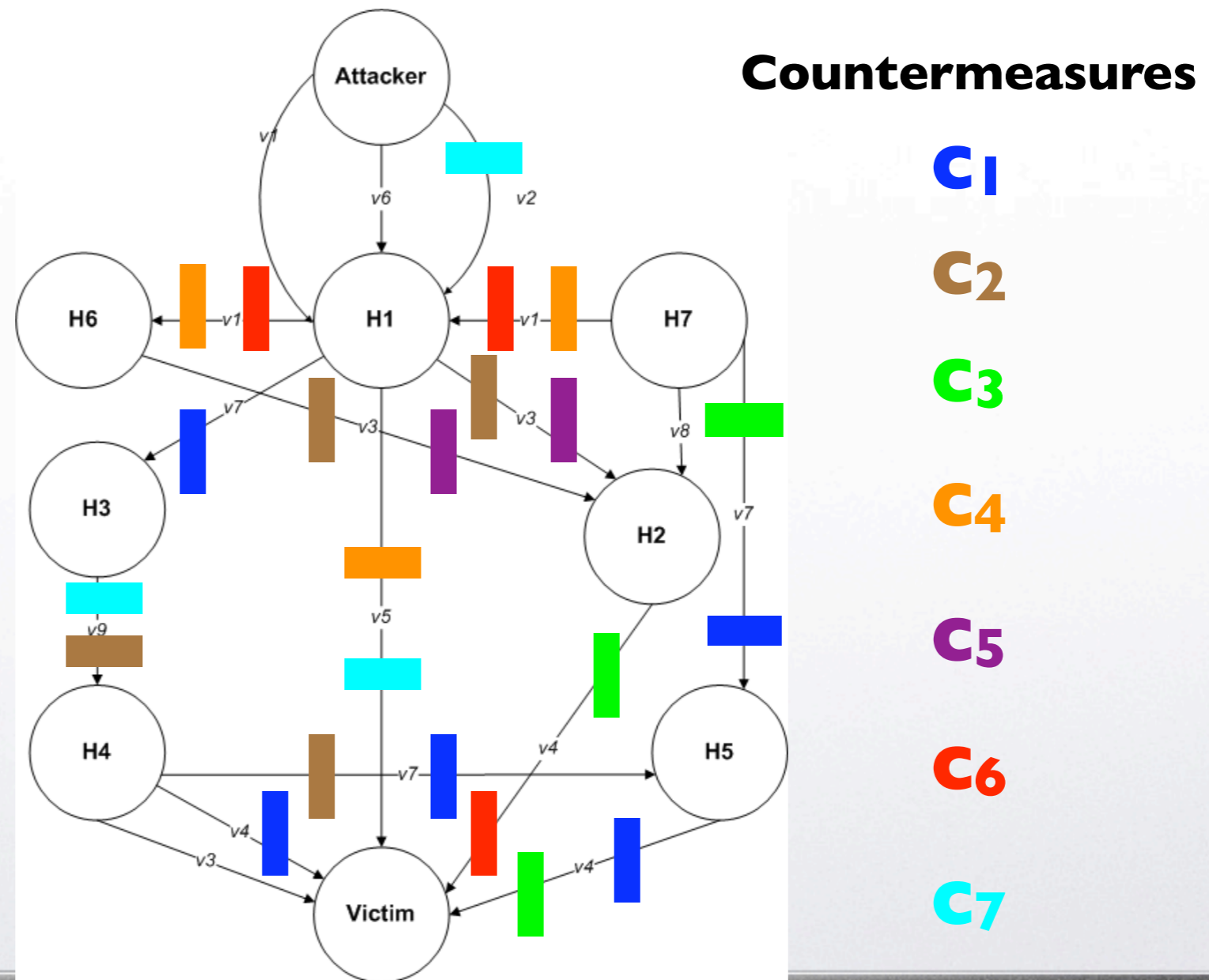


Network Hardening

- The Goal
 - Choose some subset of possible countermeasures to implement that will provide optimal protection to the network



A Reason Why Network Hardening Can Be Difficult?





Previous Approaches



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- **Eliminate all vulnerabilities**



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 - Lippmann et al., “Validating and restoring defense in depth using attack graphs” 2006



Our Approach

- Determine budget
- Determine attack graph-based security metrics of interest
- Generate attack graph
- Determine the cost of implementing each countermeasure noting vulnerabilities each mitigates
- Apply Dynamic Programming (DP) algorithm



Relevant DP Algorithm Variables

- Countermeasures are labeled 1 to N
- Each countermeasure (j) has a cost (q_j) and security benefit (m_j)

R_l^j = maximum security possible with $x \subseteq \{1,2,3,\dots,j\}$ with a cost equal exactly to l .

$$R_l^j = \begin{cases} R_l^{j-1} & \text{if } q_j > l; \\ \max\{R_l^{j-1}, R_{l-q_j}^{j-1} + m_j\} & \text{otherwise.} \end{cases}$$



Maximizing Multiple Metrics



Maximizing Multiple Metrics

- **Aggregate Objective Function**



Maximizing Multiple Metrics

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 - an increasing value = security improvement



Maximizing Multiple Metrics

- **Aggregate Objective Function**
- **Translate each metric such that:**
 - each metric is on the same scale
 - an increasing value = security improvement
 - an decreasing value = security degradation



Metric Translations

- $SP(G)_r = SP(G)/\text{maxLength}(G)$
- $NP(G)_r = NP(G)^{-1}$
- $NMPL(G)_r = NMPL(G)/(\text{maxLength}(G)NP(G)_r)$
- $NCP(G)_r = 1 - (NCP(G)/100)$
- $WA(G)_r = \text{weakestSet}(C)/|C|$, where C is the set of all attacker attributes
- $KCA(G)_r = 1 - \text{attained}(B)/|B|$, where B is the set of all network capabilities



Using Metric Translations

$$R_l^j = \begin{cases} R_l^{j-1} & \text{if } q_j > l; \\ \max\{R_l^{j-1}, R_{l-q_j}^{j-1} + m_j\} & \text{otherwise.} \end{cases}$$

$$m_j = w_1 SP(G_{l-q_j}^{j-1})_r + w_2 NP(G_{l-q_j}^{j-1})_r + w_3 NMPL(G_{l-q_j}^{j-1})_r + w_4 NCP(G_{l-q_j}^{j-1})_r + w_5 WA(G_{l-q_j}^{j-1})_r + w_6 KCA(G_{l-q_j}^{j-1})_r$$



Using Metric Translations

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How should they be weighted?



Thank You. Questions?