Analyzing Intensive Intrusion Alerts via Correlation[†]

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Outline

1. Motivation
2. Previous work on intrusion alert correlation
3. Three utilities for interactive analysis
4. Experimental validation
5. Conclusions and future work

Motivation (cont'd)

- CERT's overview of attack trends (04-18-02)
  - Increasing automation
  - Increasing sophistication of attack tools
- "Traditional" intrusion detection systems (IDS)
  - Focus on low-level attacks or anomalies
  - Mix actual alerts with false alerts
  - Generate an unmanageable number of alerts
    - ID practitioners: "Encountering 10,000 to 20,000 alerts per day per sensor is common"
- Conclusion: we need automated tools to…

A. construct attack scenarios
B. facilitate intrusion analysis

Related Work on Alert Correlation

Method 1: Exploit similarities between alert attributes

- Ex.: Valdes and Skinner (2001), Staniford et al. (2000)
- Cannot fully discover the causal relationships between alerts

Method 2: Exploit known attack scenarios

- Ex.: Cuppens and Ortalo (2000), Dain and Cunningham (2001), Debar and Wespi (2001)
- Restricted to known attack scenarios

Method 3: Use pre- and post-conditions of attacks

- Templeton and Levitt (2000), Cuppens and Miege (2002), Ning et al (2002)

A Model for Alert Correlation

- Represent our knowledge about individual types of attacks
  - *Prerequisite*: necessary condition or system state for an intrusion to be successful
  - *Consequence*: possible outcome or system state of an intrusion
- Correlate alerts (i.e., detected attacks) by reasoning about the consequences of earlier attacks and the prerequisites of later ones
- Ex.: **if** attack A learns a vulnerable service exists, **and** attack B exploits the same vulnerable service, **then** correlate A and B

A Model (cont'd)

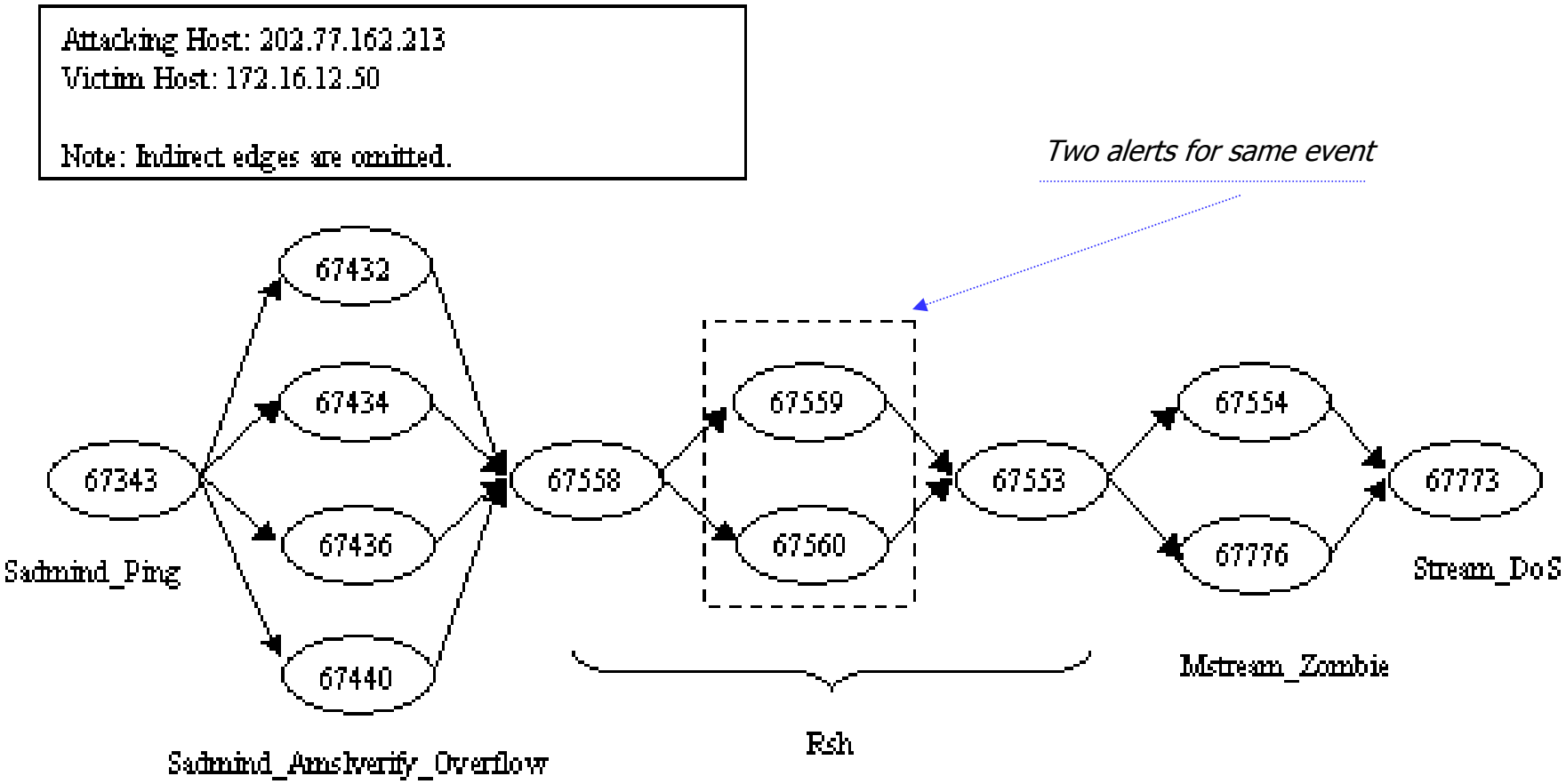
- *Hyper-alert type*: definition of a potential attack, including its prerequisites and consequences
- *Hyper-alert*: a set of occurrences of a hyper-alert type, and the times at which they occurred

A Model (cont'd)

- Given hyper-alerts h_1 and h_2, h_1 *prepares for* h_2 if…
  - h_1 occurred before h_2 and
  - the prerequisite of h_2 implies the consequence of h_1
- For a *hyper-alert correlation graph* CG = (V, E)…
  - V represents a set of hyper-alerts
  - for all h_1, $h_2 \in V$, there is a directed edge from h_1 to h_2 if and only if h_1 prepares for h_2
  - *Note:* We usually omit transitive edges for the sake of readability

A Hyper-Alert Correlation Graph

- Example encountered in an early experiment…



Contributions of This Work

- We propose three utilities to facilitate interactive intrusion analysis
  1. Adjustable graph reduction
  2. Focused analysis
  3. Graph decomposition
- A case study of the effectiveness of the three utilities
  - Test dataset = DEFCON8 "Capture The Flag"

#1. *Adjustable Graph Reduction*

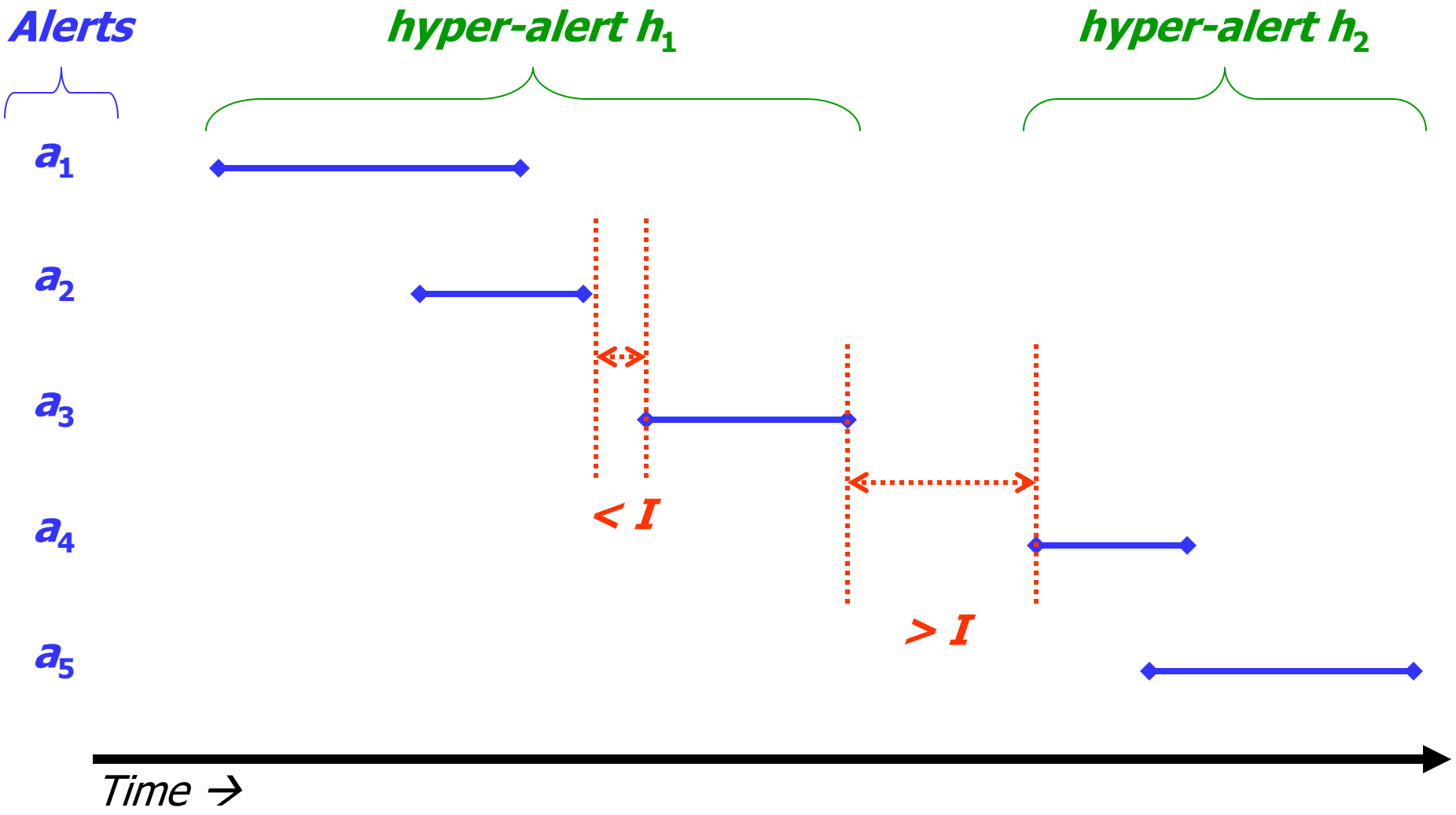
- Basic idea: Aggregate (combine) hyper-alerts of the same type only when they occur close to each other in time

- *Interval constraint*: given a time interval *I* (e.g., 3 seconds), a hyper-alert *h* satisfies interval constraint *I* if

  1) *h* has only one alert, or

  2) for every alert a_i in *h*, there is at least one other alert a_j in *h* which overlaps a_i in time, or which is separated from a_i by no more than *I* units of time

Adjustable Graph Reduction (cont'd)



#2. *Focused Analysis*

- Basic idea: Focus on the hyper-alerts of interest according to user's specification
- *Focusing constraints*
  - A *focusing constraint* is a logical combination of comparisons between attribute names and constants.
  - Example:
    srcIP = 129.174.142.2 $\vee$ *destIP* = 129.174.142.2
  - Only correlate hyper-alerts that evaluate to true w.r.t. the focusing constraint, i.e., filter out irrelevant hyper-alerts

#3. *Graph Decomposition*

- Basic idea: cluster the hyper-alerts based on common features shared by them, and decompose a large graph into smaller, more meaningful graphs (clusters)
- *Clustering constraints*
  - Given sets of attribute names A_1 and A_2 for two hyper-alerts h_1 and h_2, a *clustering constraint* $C_c(A_1, A_2)$ is a logical combination of comparisons between constants and attribute names in A_1 and A_2

Graph Decomposition (cont'd)

- Example
  - $A_1 = A_2 = \{srcIP, destIP\}$
  - $C_c(A_1, A_2) =$
    $(A_1.srcIP = A_2.srcIP) \wedge (A_1.destIP = A_2.destIP)$

  → i.e., two hyper-alerts are clustered if they have the same source and destination IP addresses

Case Study of DEFCON8 Dataset

- Before applying utilities

Category	Count
Total hyper-alert types	115
Correlated hyper-alert types	95 (83%)
Uncorrelated hyper-alert types	20
Total hyper-alert instances	65,054
Correlated hyper-alert instances	9,744 (15%)
Uncorrelated hyper-alert instances	55,310

DEFCON8 Before Applying Utilities

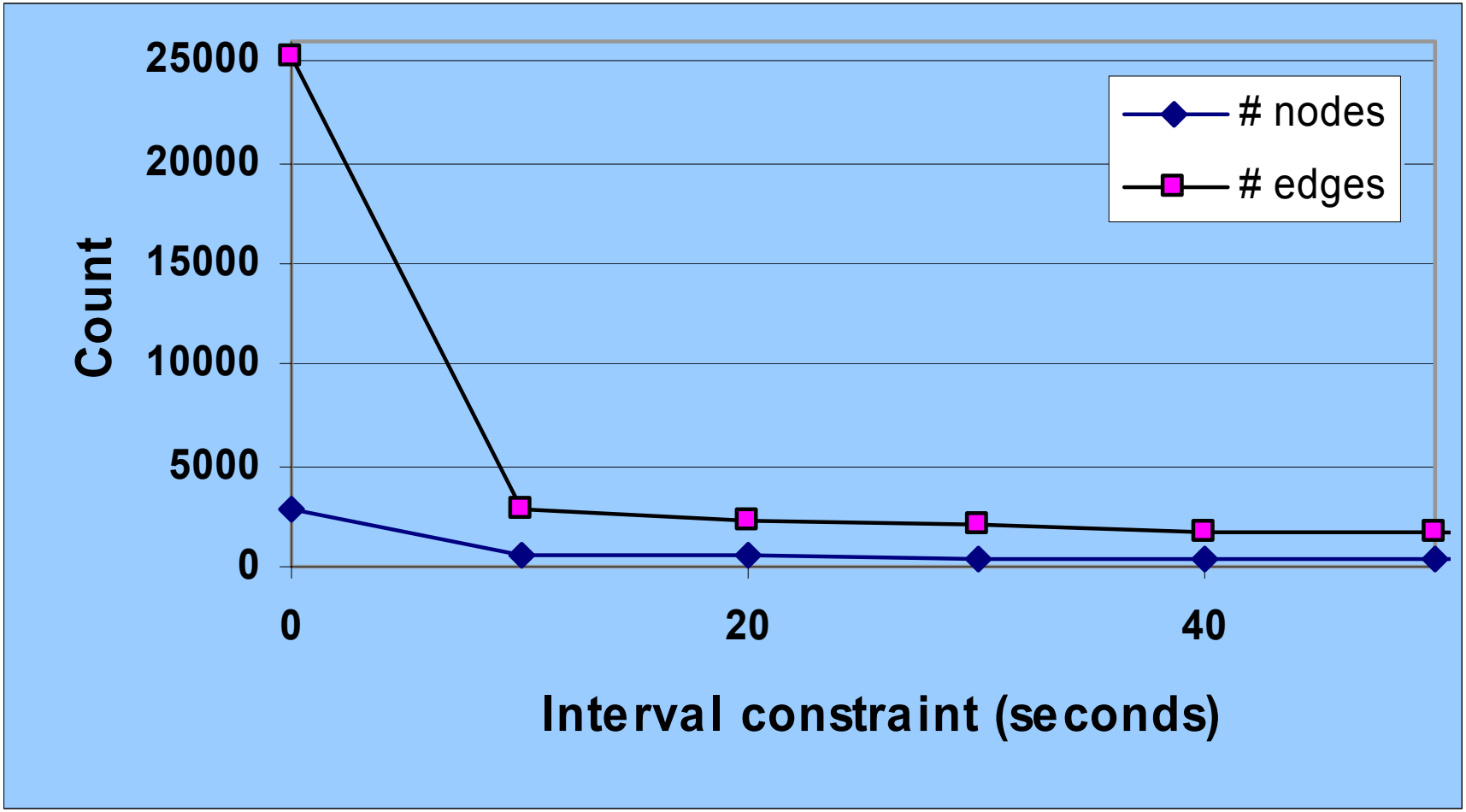
- Some hyper-alert types have many uncorrelated instances

Type	# Correlated	# Uncorrelated
IPHalfScan	958	33,745
Windows_Access_Error	0	11,657
HTTP_Cookie	0	2,119

- 450 hyper-alert correlation graphs
- Largest graph: 2,940 nodes and 25,321 edges
- Average graph: 22 nodes and 311 edges

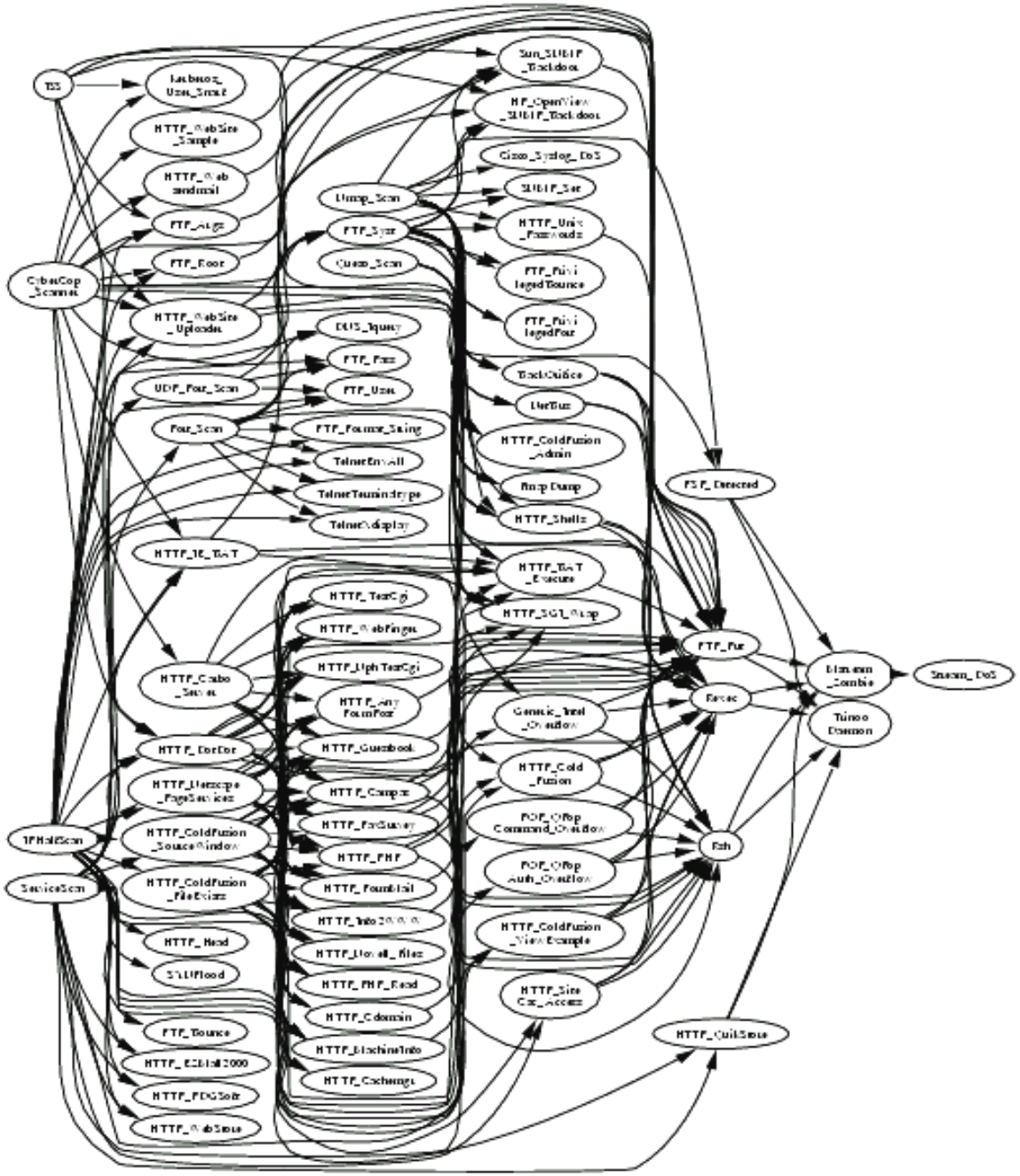
Using Adjustable Graph Reduction

- Most hyper-alerts of the same type are close to each other in time in the DEFCON8 dataset



Largest Correlation Graph after Maximum Graph Reduction

- Nodes: 2,940→77 (97% reduction)
- Edges: 25,321→347 (99% reduction)



Using Graph Decomposition

- $A_1 = A_2 = \{srcIP, destIP\}$

best choice

- $C_{c1}(A_1, A_2) :=$
  $A_1.destIP = A_2.destIP$

  →Generated 12 clusters

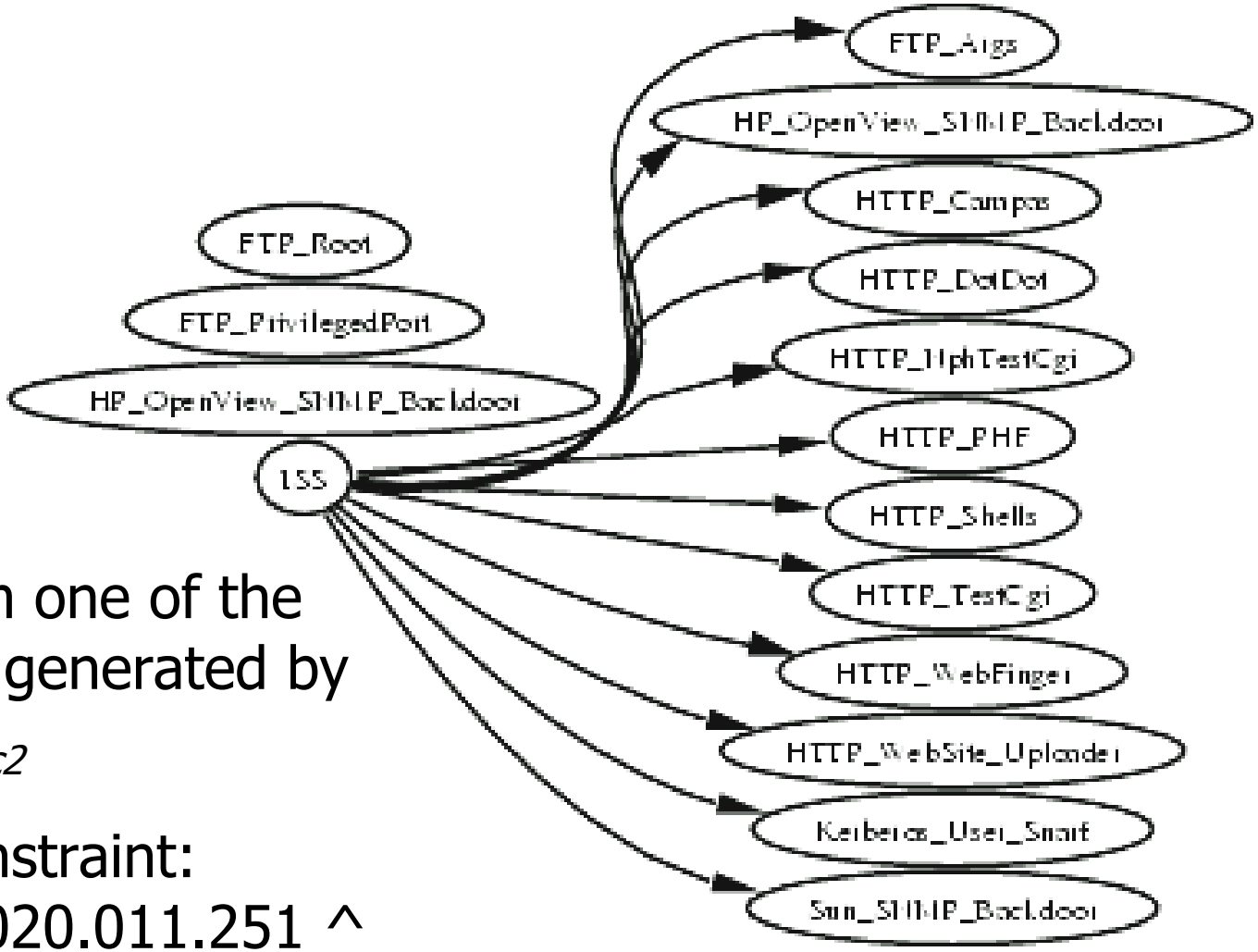
- $C_{c2}(A_1, A_2) :=$
  $(A_1.srcIP = A_2.srcIP) \wedge (A_1.destIP = A_2.destIP)$

  →Generated 185 clusters

- $C_{c3}(A_1, A_2) :=$
  $(A_1.srcIP = A_2.srcIP) \vee (A_1.destIP = A_2.destIP) \vee$
  $(A_1.srcIP = A_2.destIP) \vee (A_1.destIP = A_2.srcIP)$

  →Generated 2 clusters

Using Focused Analysis



- Starting from one of the 185 clusters generated by constraint C_{c2}
- Focusing constraint: *srcIP* =010.020.011.251 ^ *destIP* = 010.020.001.010

Additional Results

- Some common attack strategies were easily identified
  - e.g., Nmap_Scan → PmapDump → ToolTalk_Overflow
  - e.g., HTTP-based attack from 010.020.011.074 to 010.020.001.014, 010.020.001.015, 010.020.001.019…
- Another observation
  - There were many BackOrifice and NetBus alerts
  - i.e., attackers were coordinating multiple machines during their attacks
  - Makes correlation and attack identification more difficult!

Conclusions

- Developed three utilities for interactive intrusion alert analysis
  1. Adjustable graph reduction
  2. Focused analysis
  3. Graph decomposition
- Studied the effectiveness of these utilities through a case study
  - Utilities simplified the analysis of huge number of alerts
- Caution! The results produced by these utilities are distillations of what really happened

Future Work

- Automate analysis process
  - Currently, skill is required to choose the right interval, focusing, and clustering constraints
- Integrate with other complementary correlation methods
- Identify attacks missed by most IDSs
- Use for attack prediction

Software Available

http://discovery.csc.ncsu.edu/software/correlator/ver0.2/iac.html

Some Previous Results

- We implemented a DBMS based intrusion alert correlator
  - http://discovery.csc.ncsu.edu/software.html.
- Validated it with the 2000 DARPA intrusion detection scenario datasets
  - Completeness: At least 93.18% related alerts are correlated in LLDOS 1.0, at least 62.5% related alerts are correlated in LLDOS 2.0.2
  - Soundness: At least 92.3% correlated alerts are indeed related