Towards Scalable Cluster Auditing through Grammatical Inference over Provenance Graphs

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NDSS Symposium 2018
Feb 20, 2018

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Notable Data Breach in 2017

Forbes

Security / #CyberSecurity

SEP 7, 2017 @ 10:42 PM 41,538

Equifax Data Breach Impacts 143 Million Americans

EQUIFAX

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Equifax, Apache Struts, & CVE-2017-5638 Vulnerability

Written by Fred Bals | Senior Content Writer/Editor | Sep 15, 2017

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We recently discovered a cybersecurity incident involving consumer information. Once discovered, we acted immediately to stop the intrusion.

6:20 PM - 7 Sep 2017

Notable Data Breach in 2017

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Equifax Data Breach Timeline 2017

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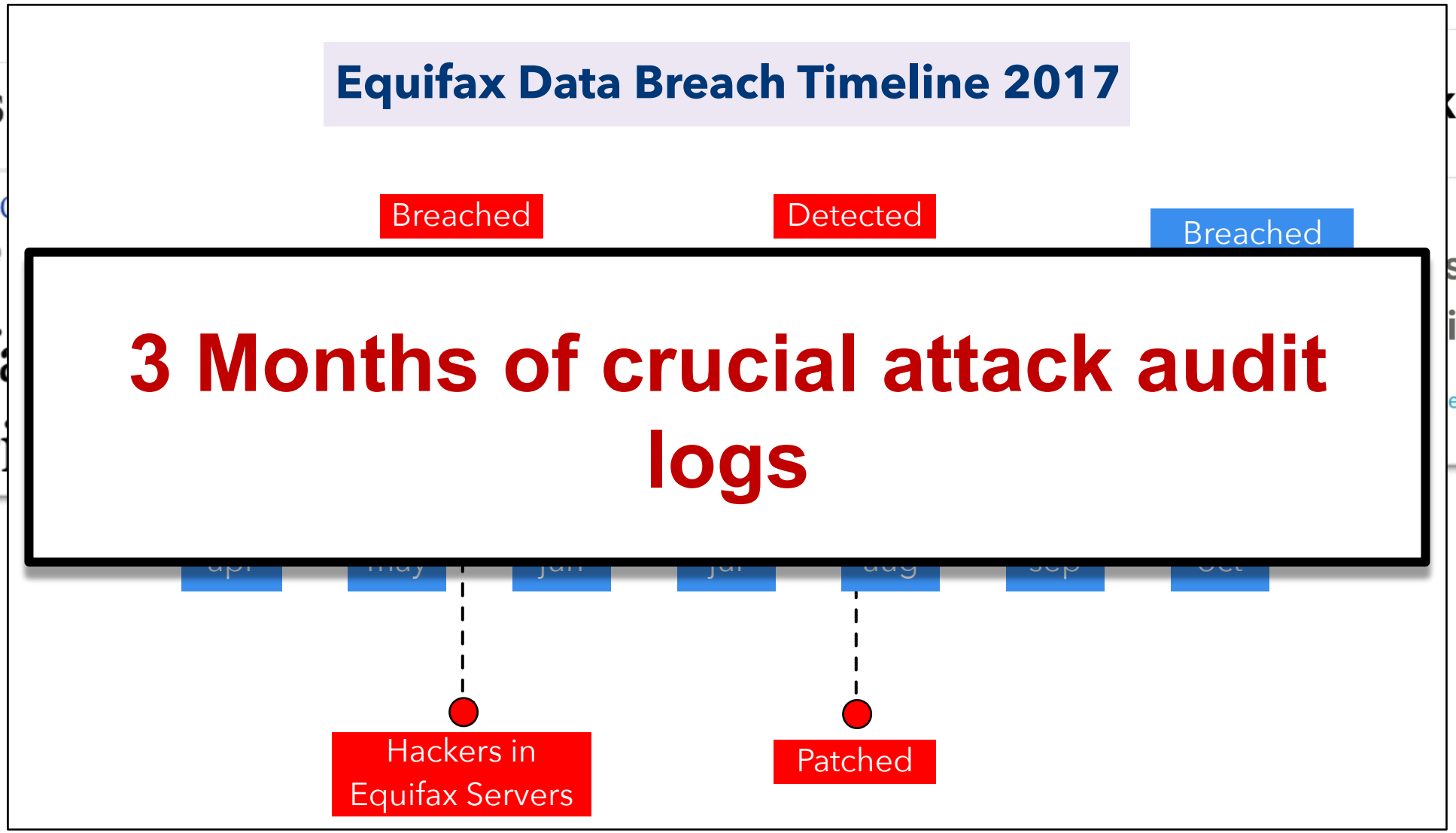
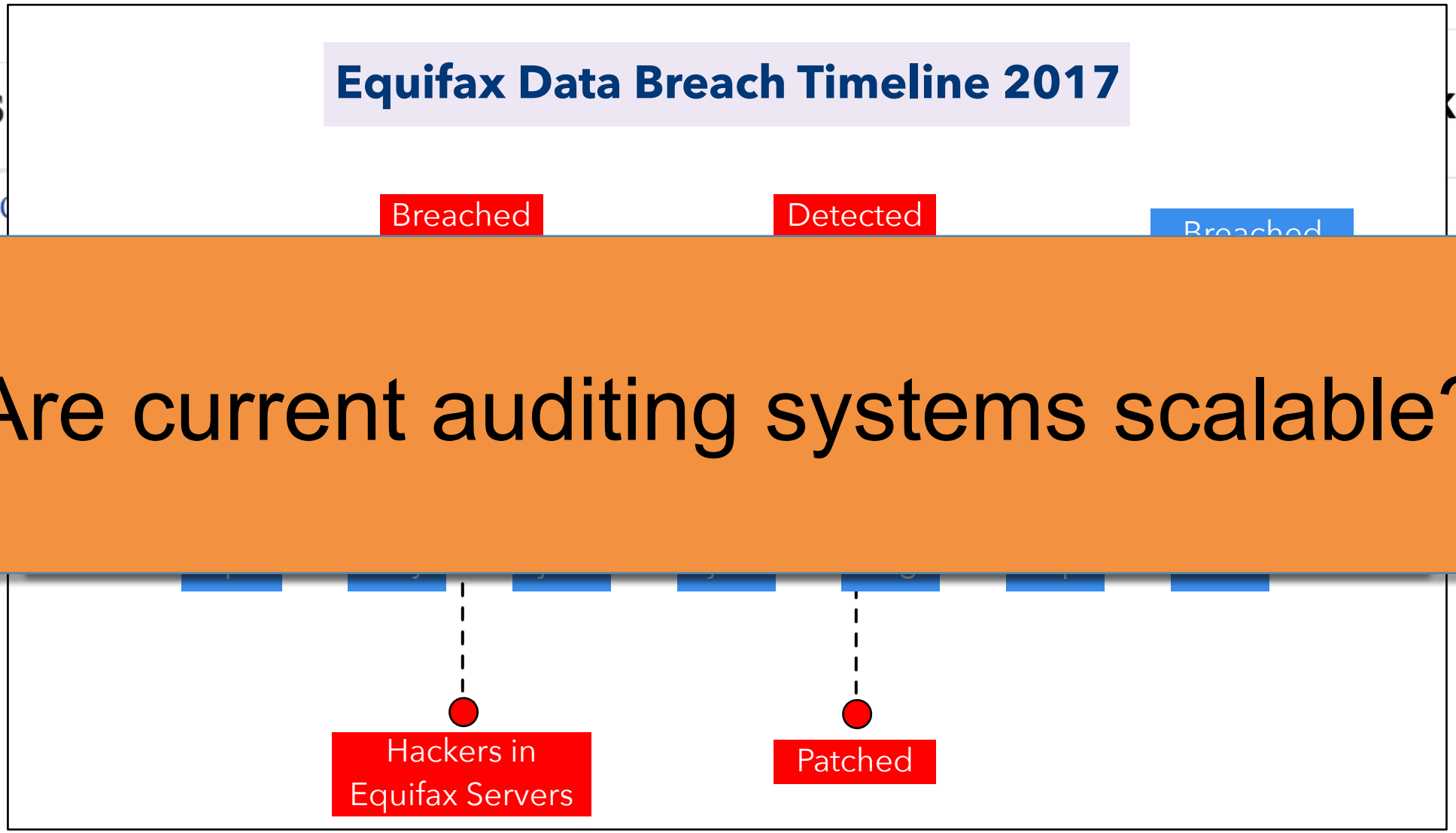
Notable Data Breach in 2017



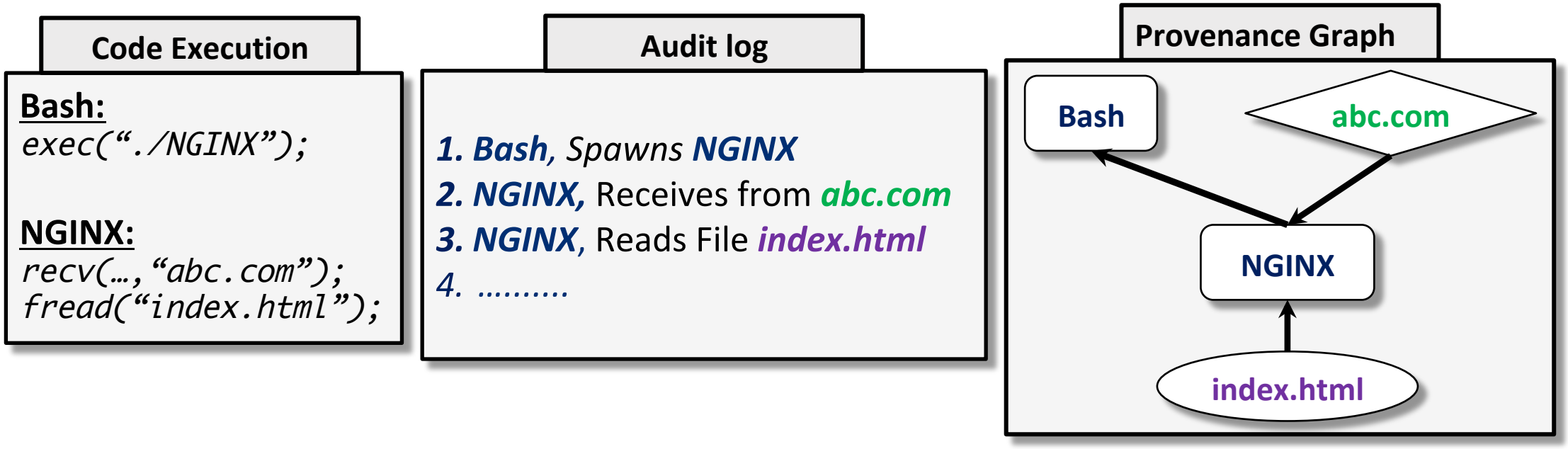
Notable Data Breach in 2017



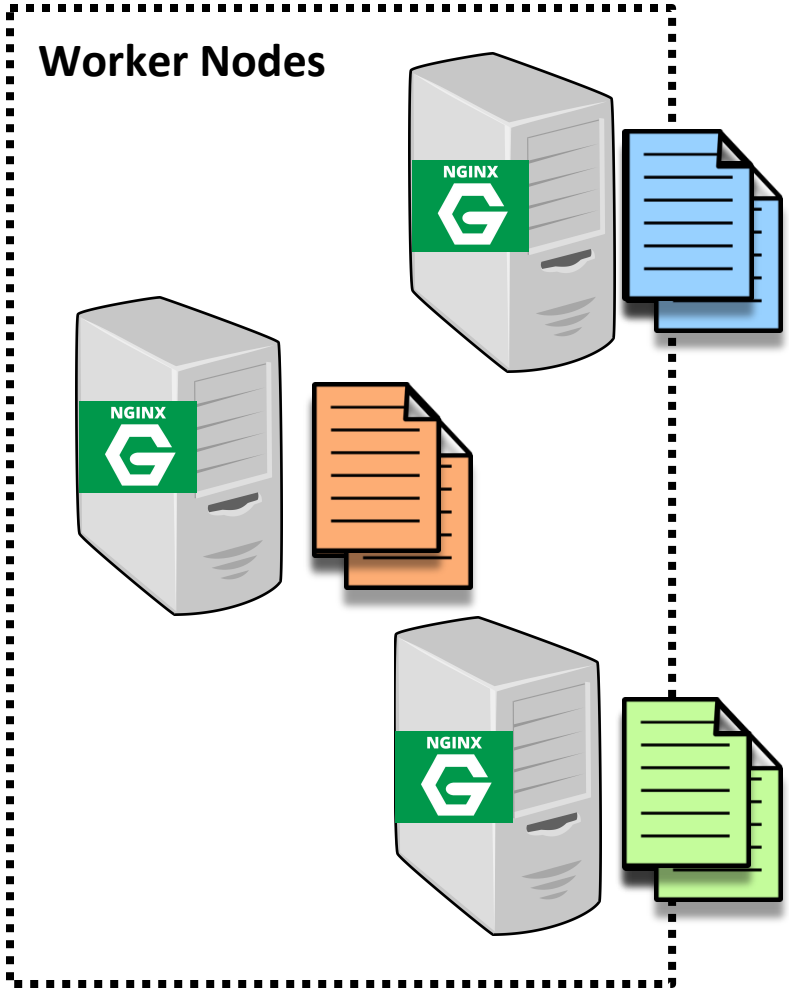
Are current auditing systems scalable?

Data Provenance aka Audit log

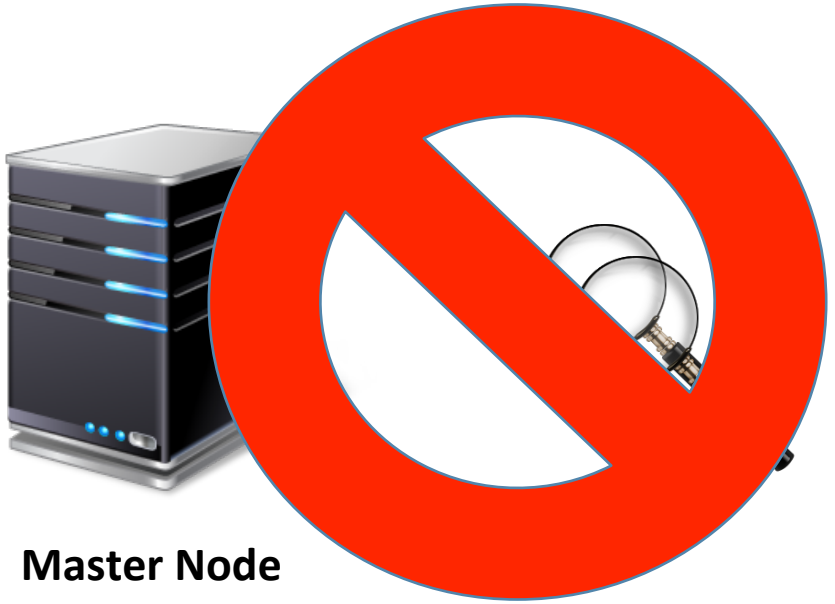
- Lineage of system activities
- Represented as Directed Acyclic Graph (DAG)
- Used for forensic analysis



Data Provenance in a Cluster



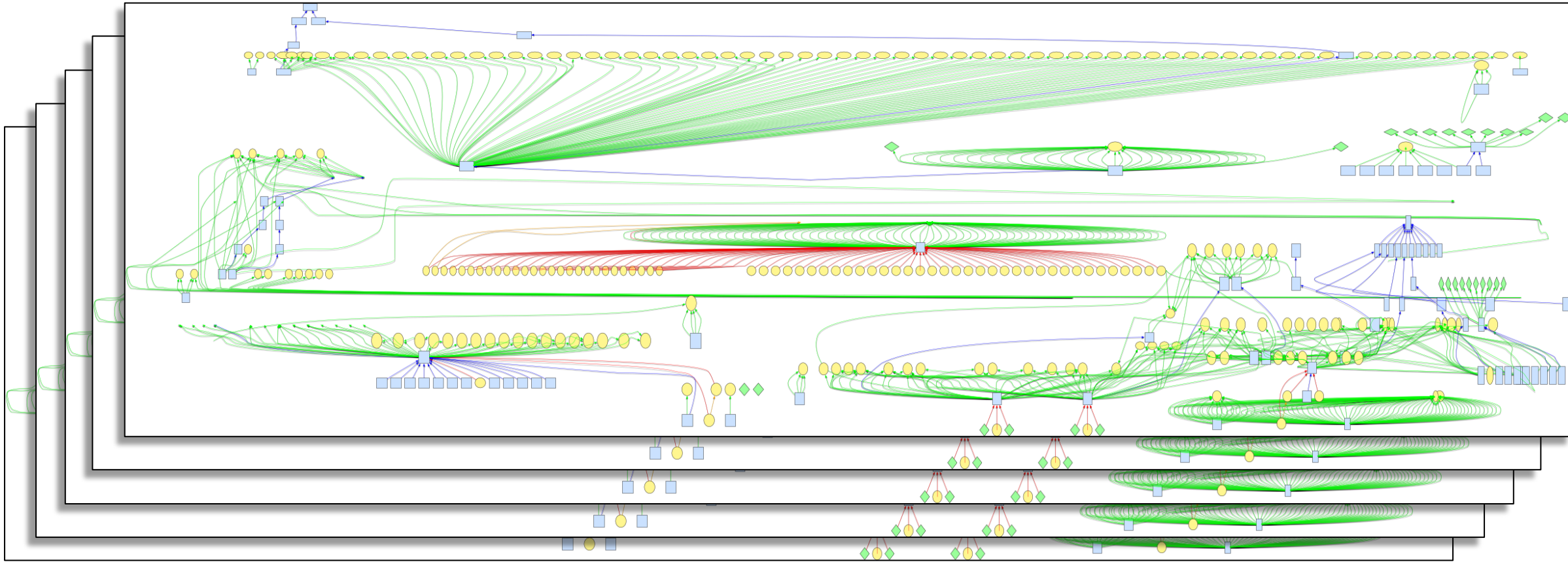
Centralized auditing not practical due to two limitations



Master Node

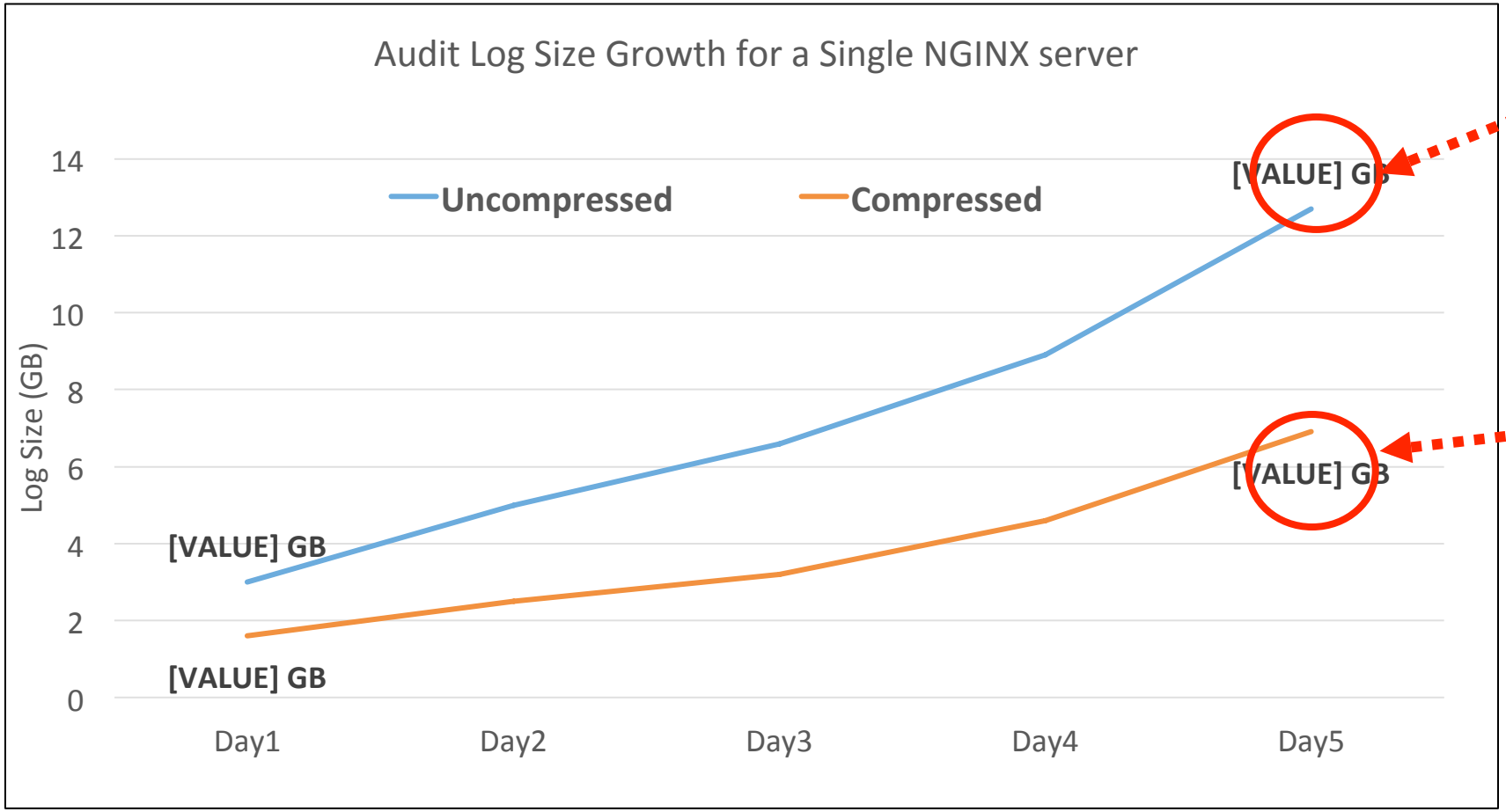
Limitation#1: Graph Complexity

- NGINX and MySQL running for 5 mins on a single machine



Limitation#2: Storage overhead

- Leads to network overhead as logs are transferred to master node

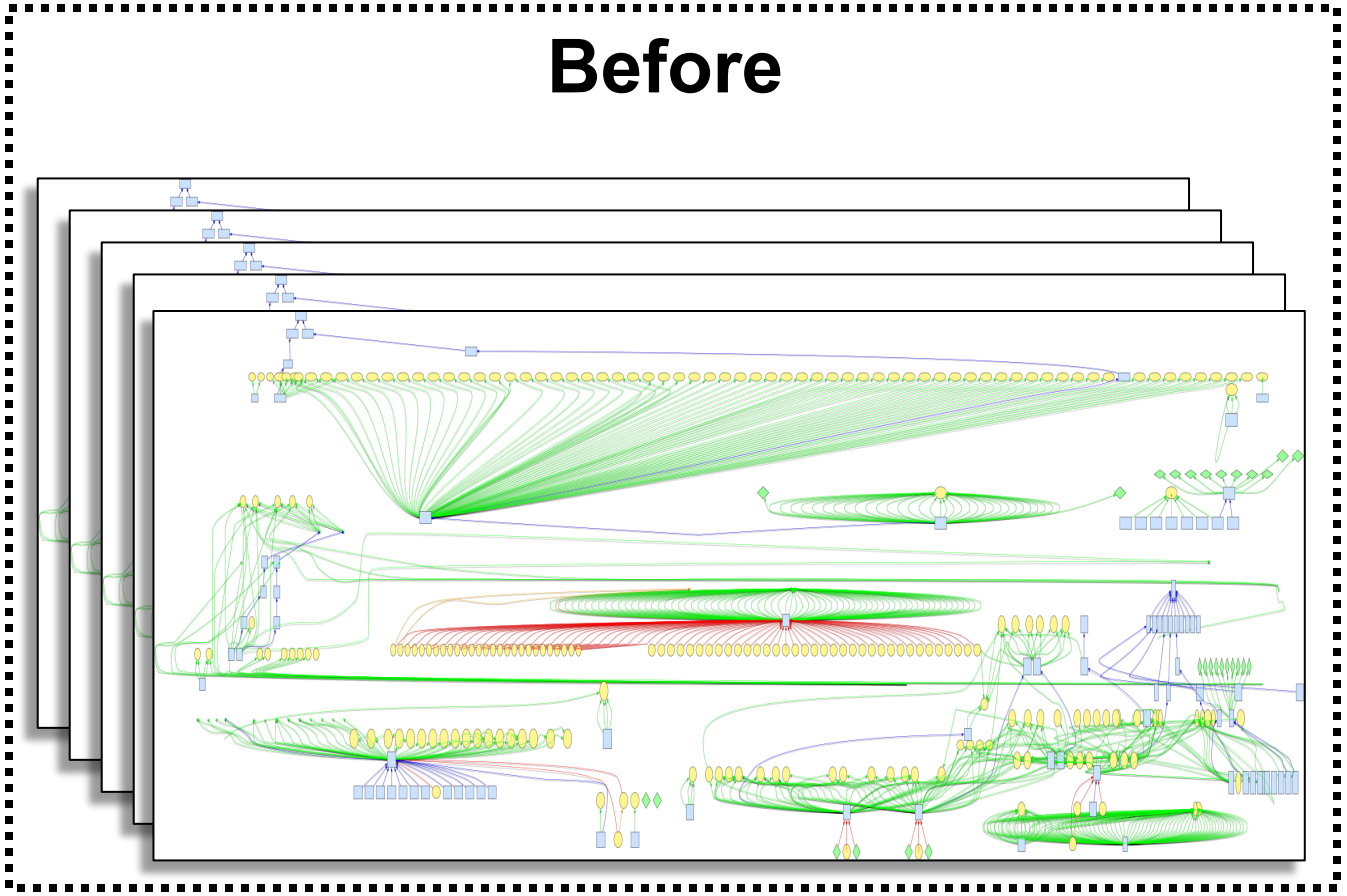


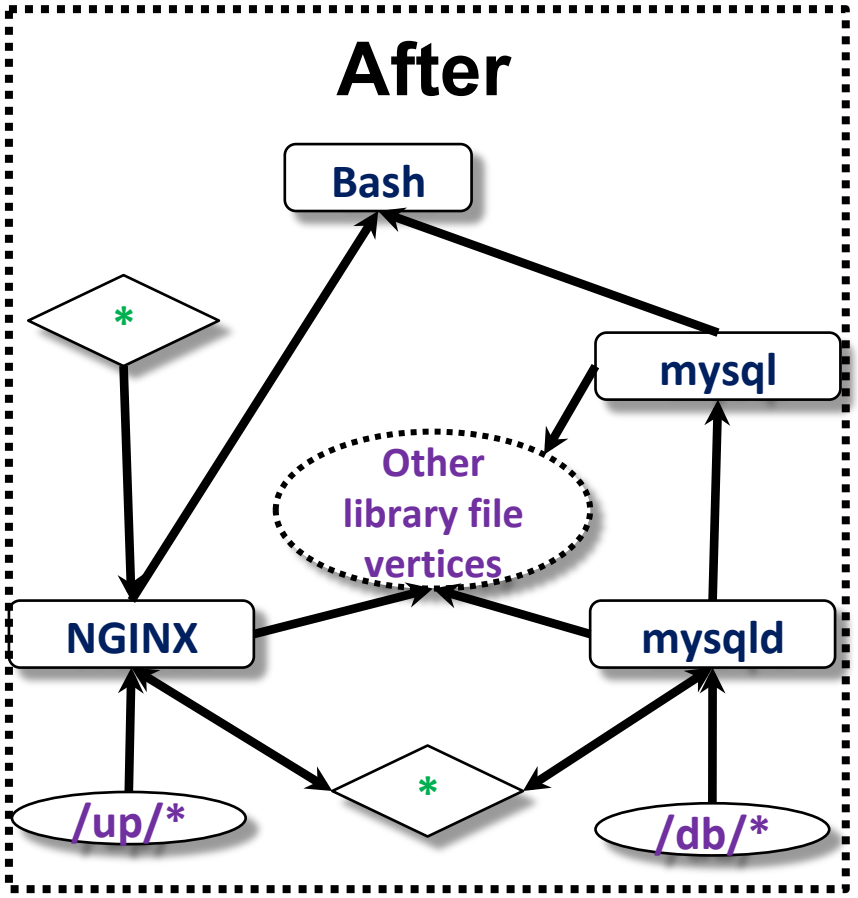
Winnower

- Cluster applications are replicated in accordance with microservice architecture principle
- Replicated apps produce highly homogeneous provenance graphs
  - core execution behaviour is similar

Key Idea:
Remove redundancy from provenance graphs across cluster before sending to **master node**

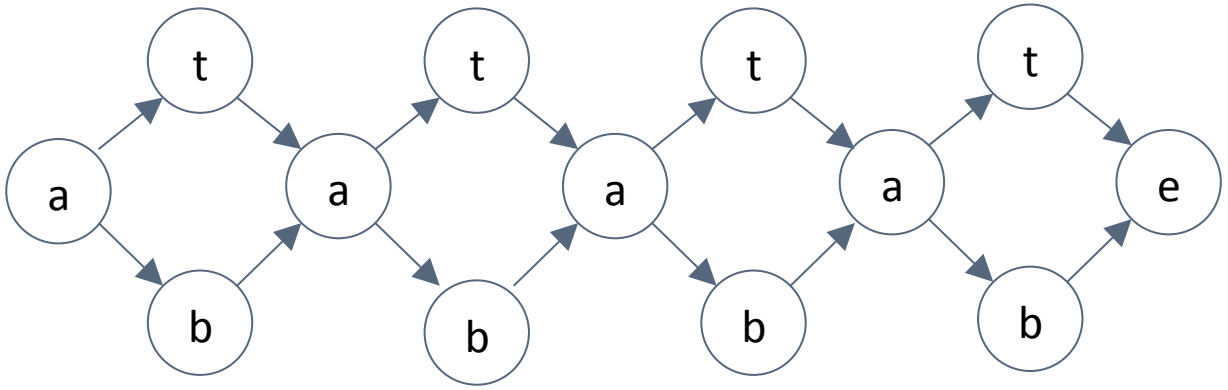
Master Node View with Winnower



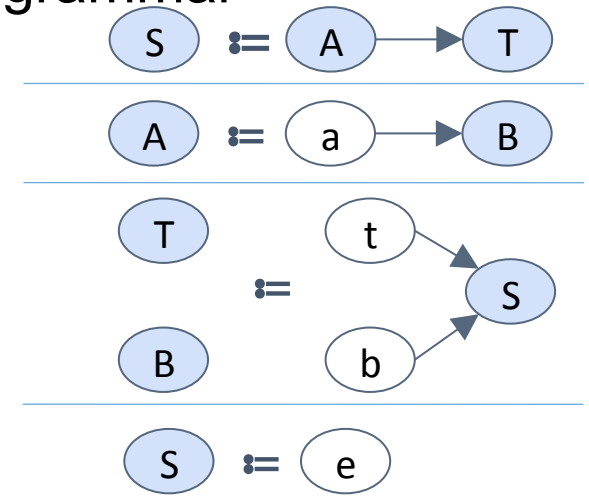


Winnower

- Build consensus model across cluster using graph grammars
- Like string grammar, graph grammars provide rule-based mechanisms
  - For generating, manipulating and analyzing graphs
  - *Induction* – produce grammar from a given graph
  - *Parsing* – membership test of a given graph is in a grammar

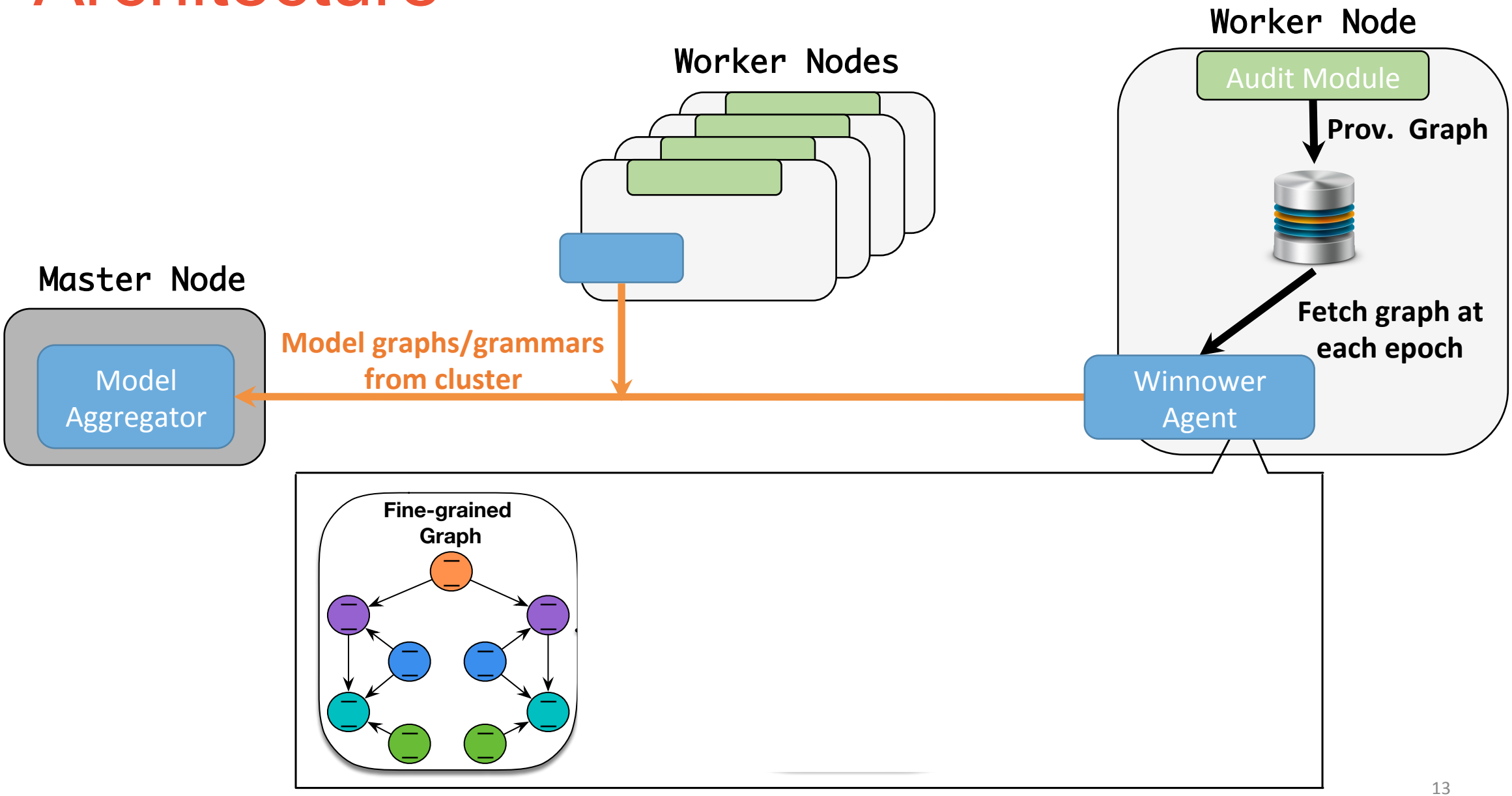


Graph

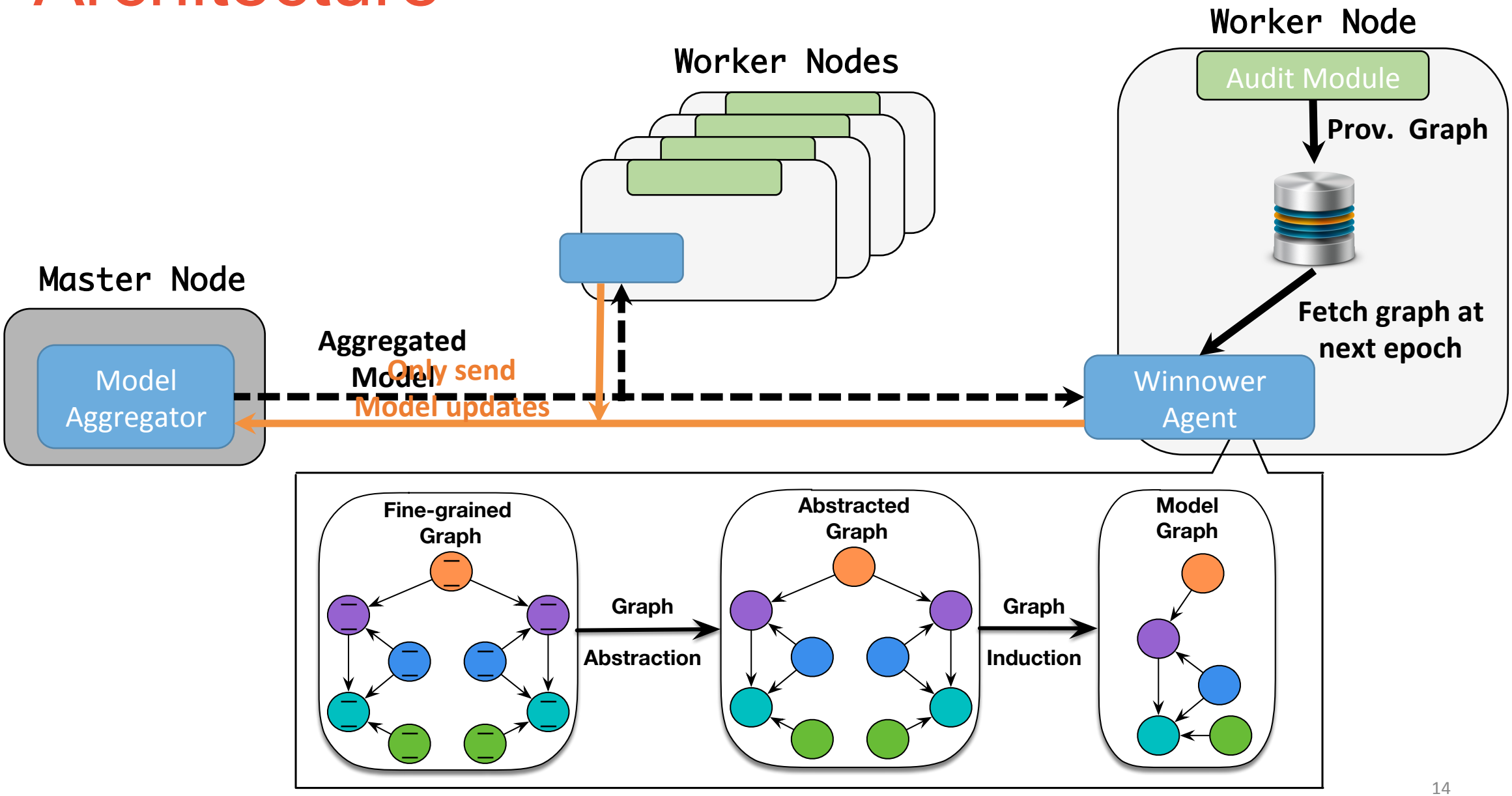


Graph Grammar

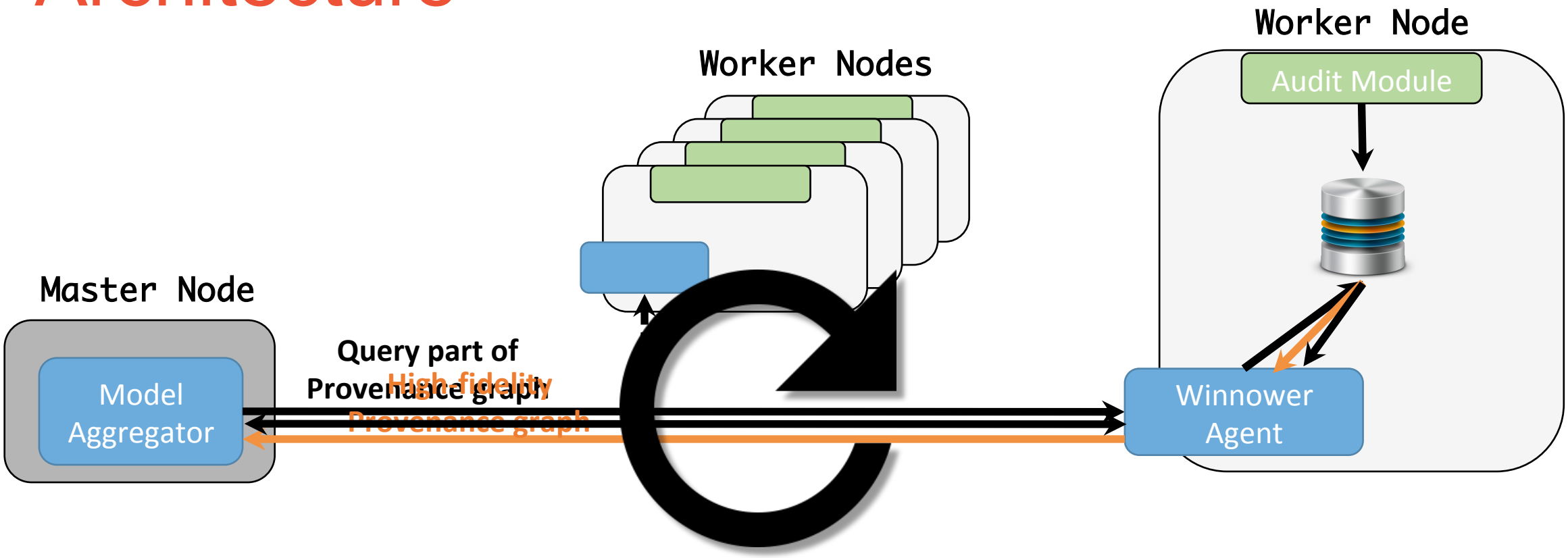
Architecture



Architecture

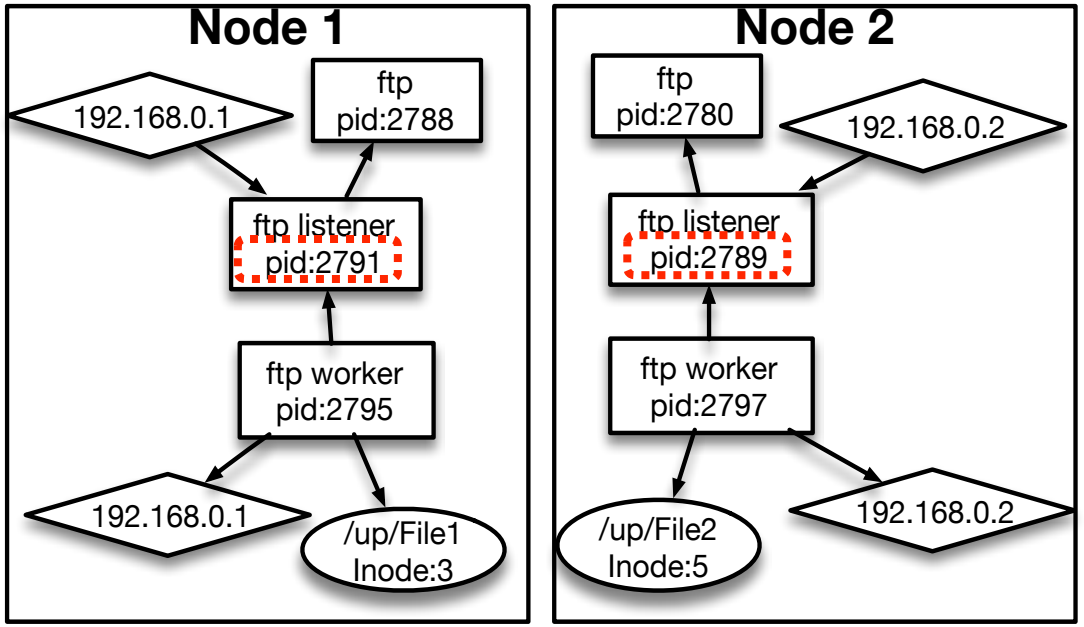


Architecture



Provenance Graph Abstraction

- Graph Induction process builds a model/grammar that concisely describe the whole graph
- However, instance-specific fields frustrate any attempts to build a generic application behaviour model

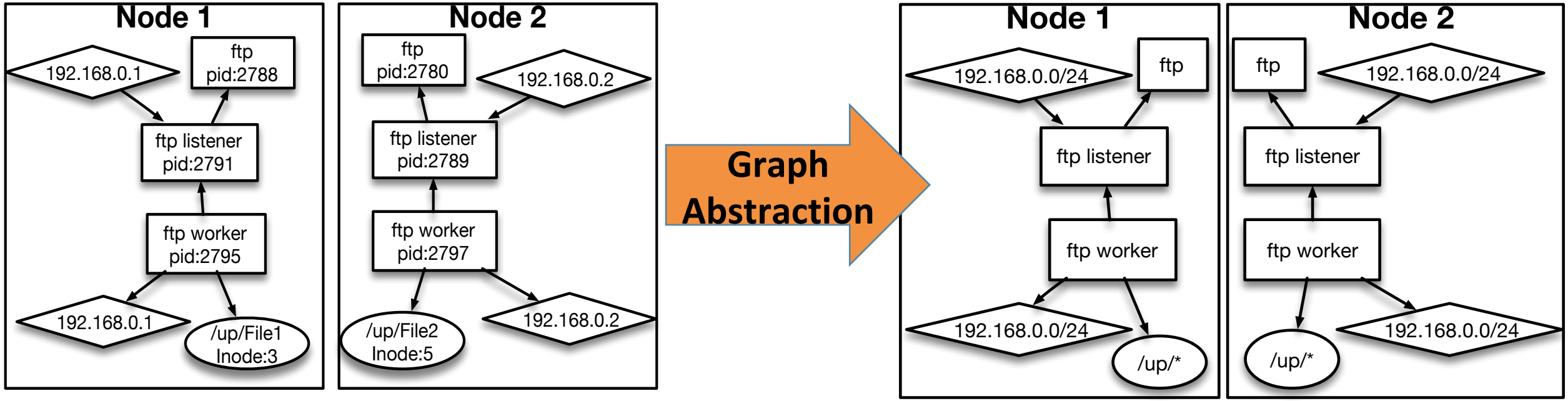


Graph Induction

No General model as instance specific information such PID is different among graphs

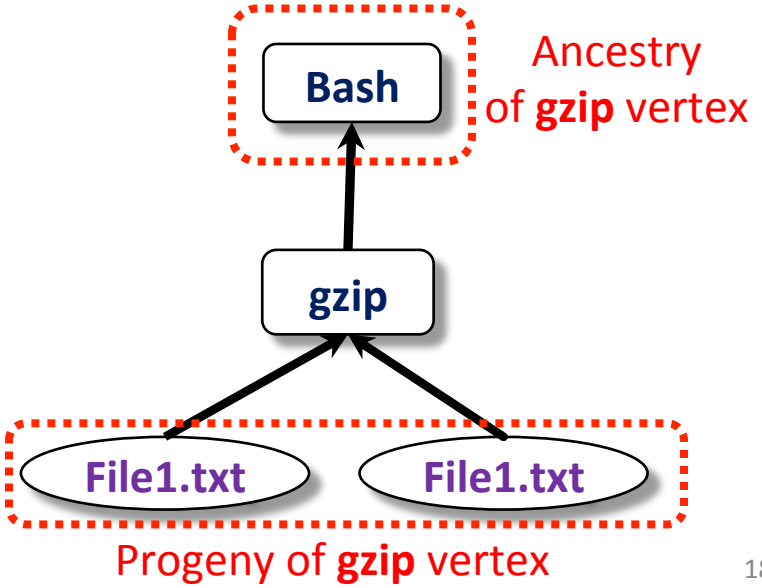
Provenance Graph Abstraction

- Provenance graph vertices have well defined fields
  - E.g. *pid:1234*, *FilePath:/etc/ld.so*
- Defined rules manually that remove or generalize these fields



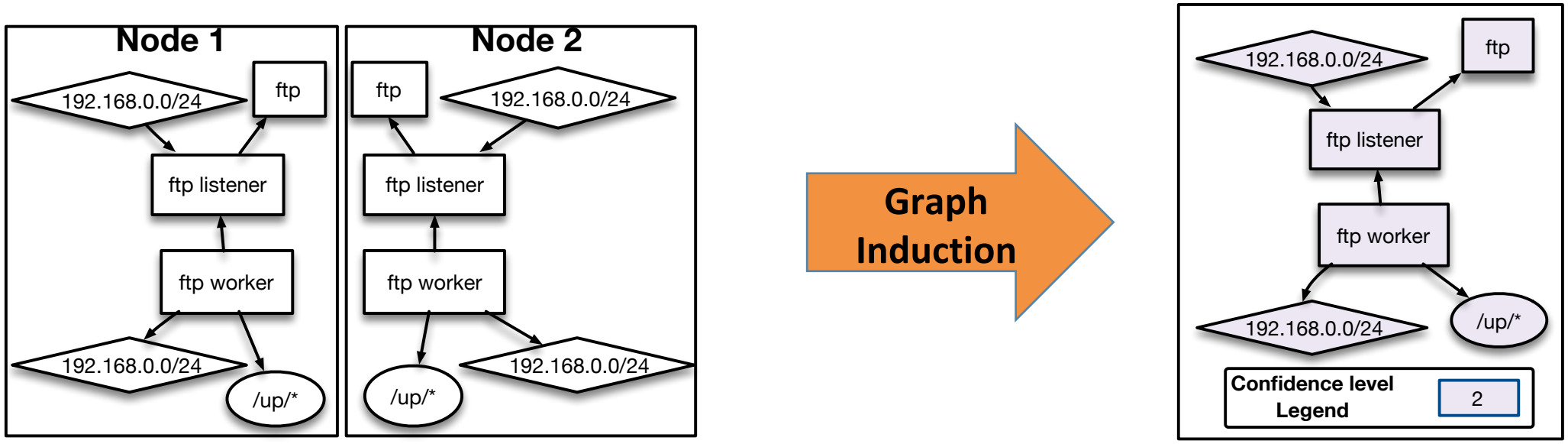
Provenance Graph Induction

- Deterministic Finite Automata (DFA) Learning to generate grammar
  - Encodes the causality in generated models
- In DFA learning the present state of a vertex includes the path taken to reach the vertex (provenance ancestry)
  - Winnower extends it to remember descendants (provenance progeny)
- State of each vertex consist of three items:
  1. Label
  2. Provenance ancestry
  3. Provenance progeny



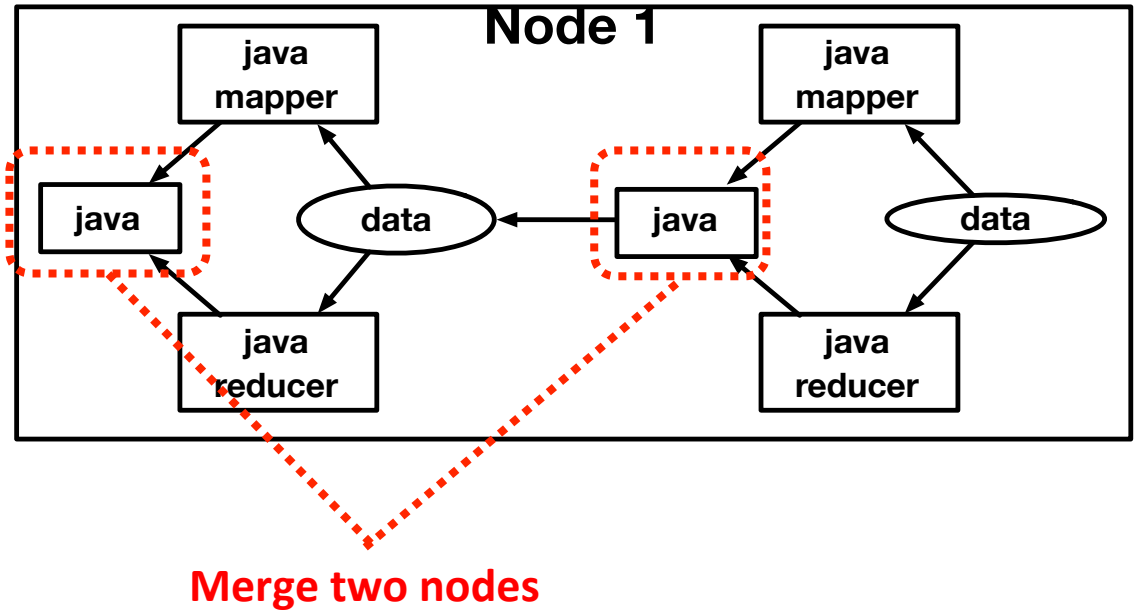
Provenance Graph Induction

- Finds repetitive patterns using standard implicit and explicit state merging algorithm
- Implicit state merging combines two subgraphs if states of each vertex are same in both subgraphs



Explicit State Merging

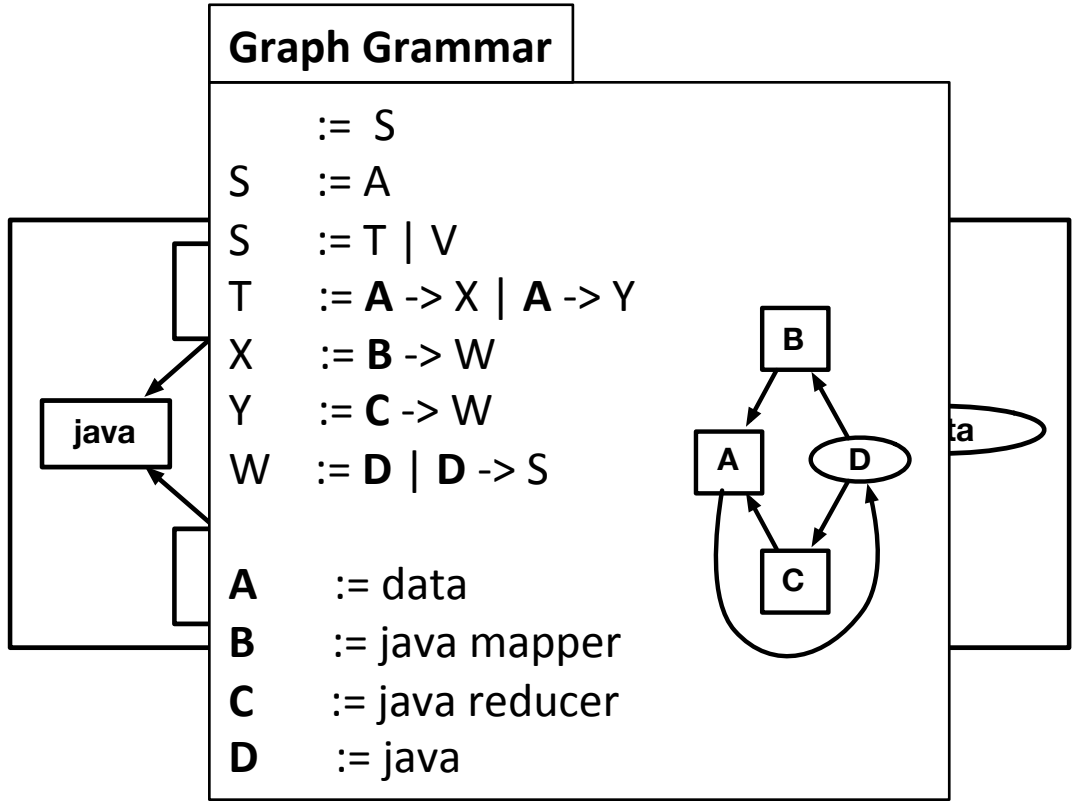
- At high-level explicit state merging
  - Picks two nodes and make their states same
  - Check if subgraph can be merged implicitly
- Consider a chained map reduce job



Graph Grammar

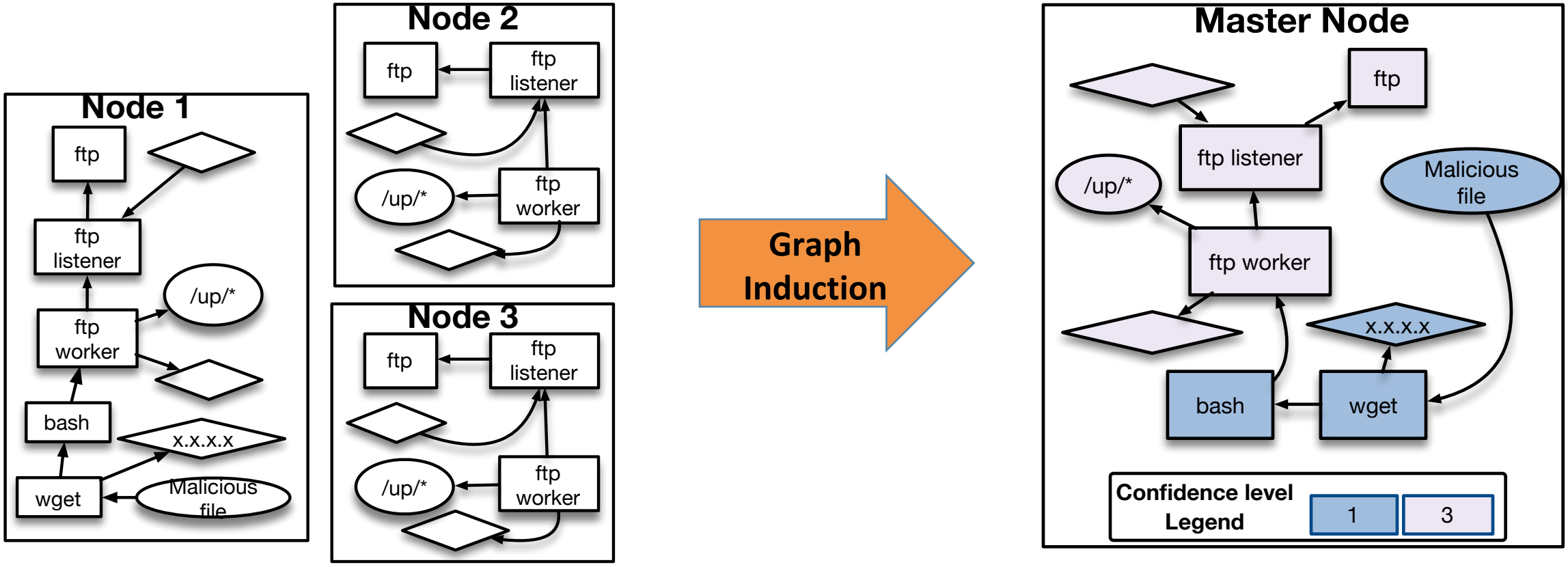
:= S
S := A
S := T | V
T := **A** -> X | **A** -> Y
X := **B** -> W
Y := **C** -> W
W := **D** | **D** -> S

A := data
B := java mapper
C := java reducer
D := java



Provenance Graph Induction

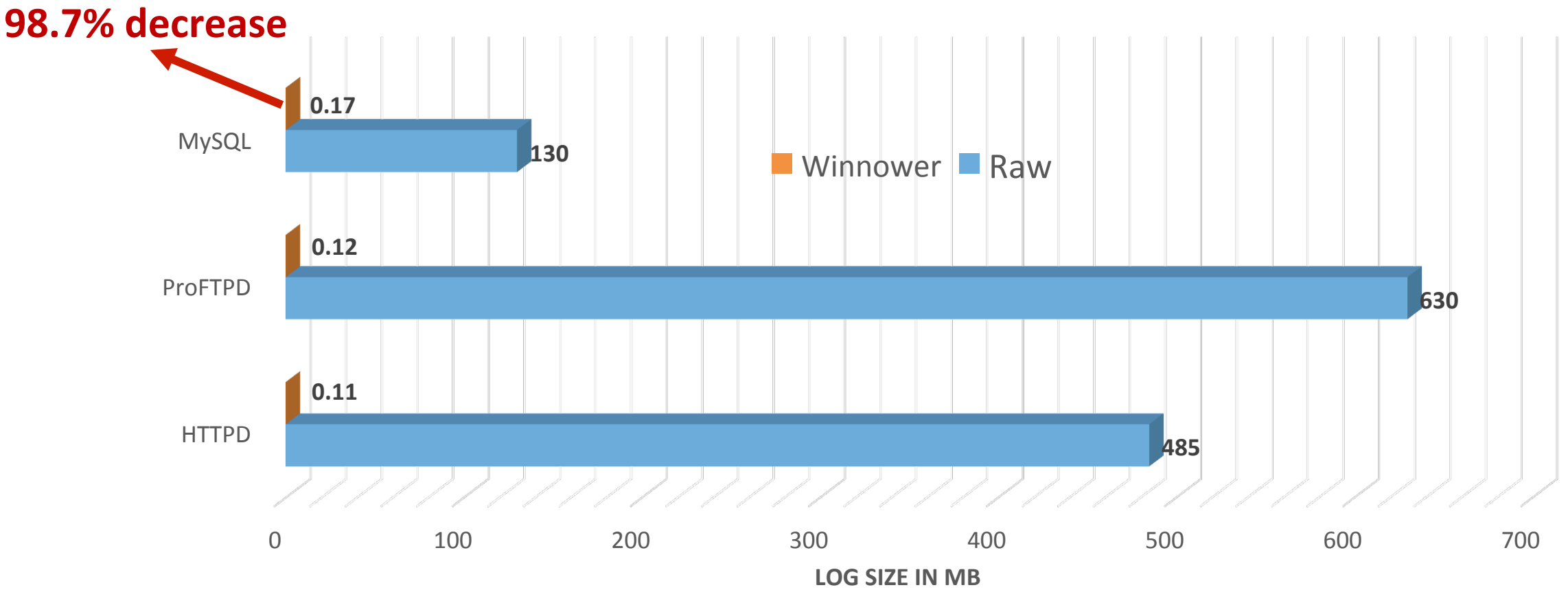
- Consider a graph with a malicious activity
- Malicious behavior is visible in the final model



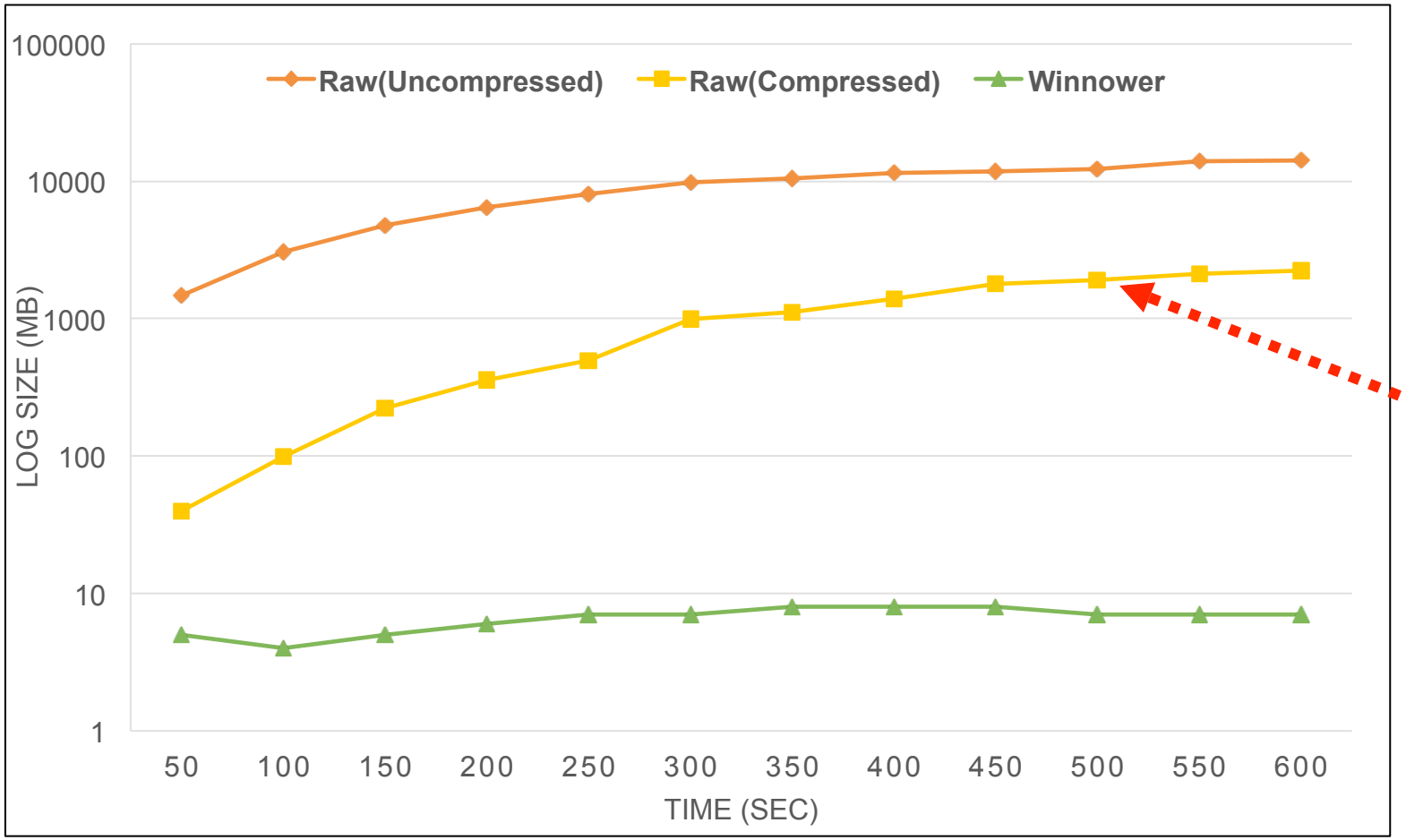
Evaluation Setup

- Setup
  - 1 VM as master node, 4 VMs as worker nodes
  - SPADE and Docker Swarm
  - Epoch size 50 sec
- Metrics
  - Storage Overhead
  - Computational Cost
  - Effectiveness

Storage Overhead on Master Node



Storage Reduction on Master Node

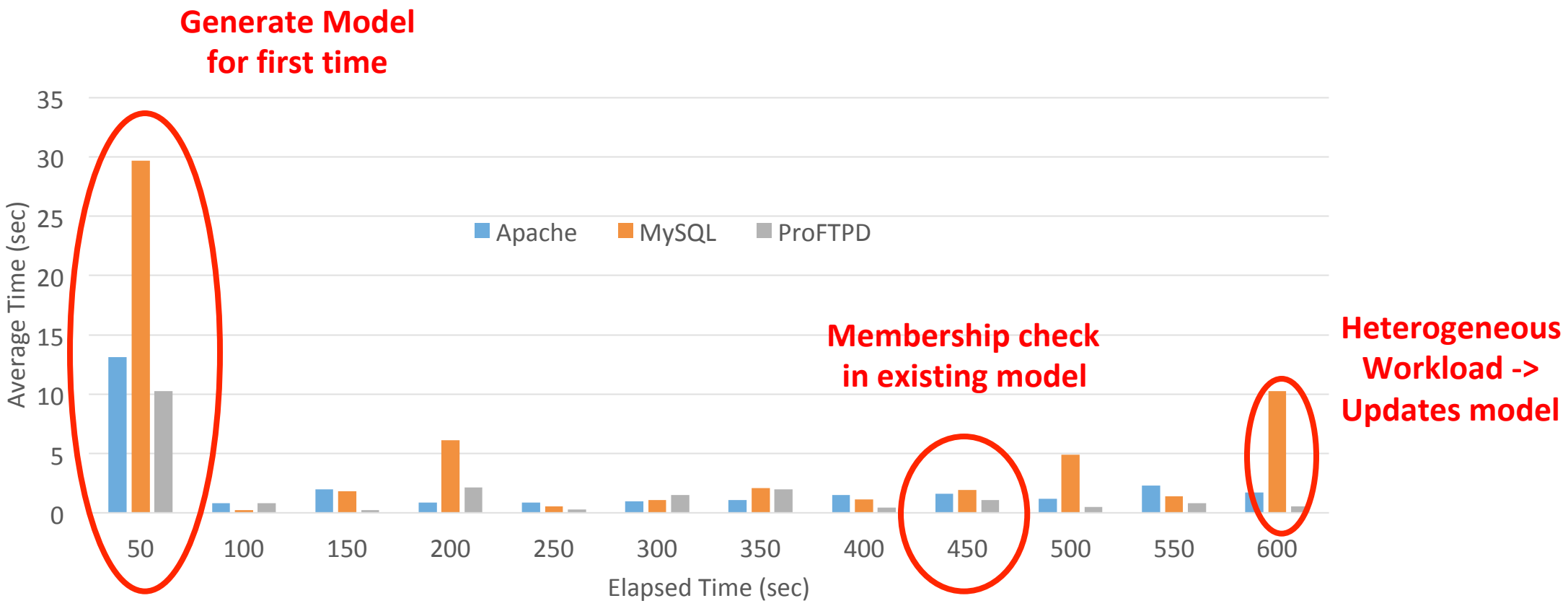


- Apache Webserver with moderate workload
- Note the log scale on y-axis

7z compression is not suitable:
- **No global view of cluster**
- **Oblivious to previous batch**

Evaluation: Computation Cost

- Average time spent in induction and membership test at each epoch

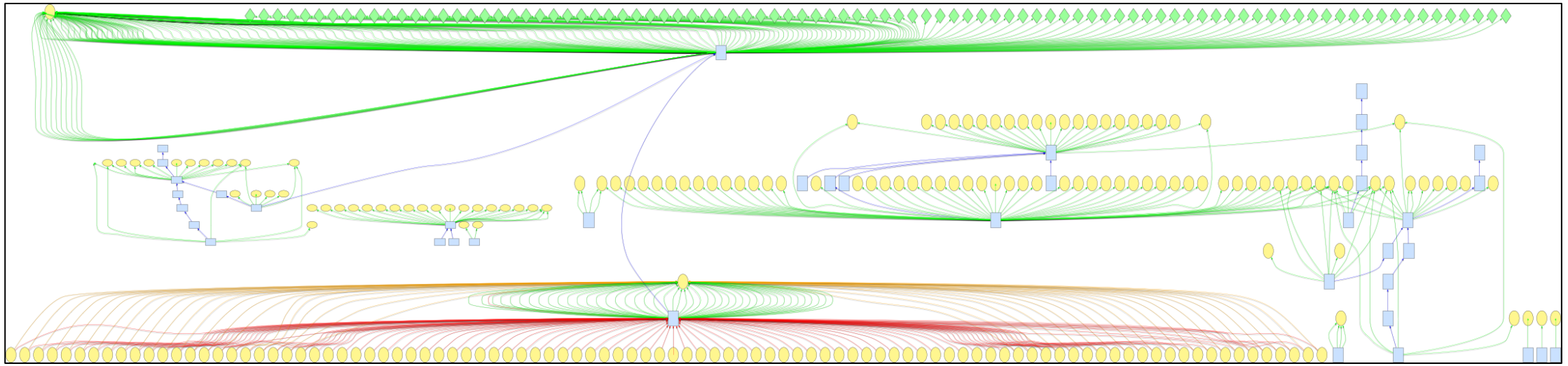


Case Study: Ransomware Attack

- Attacker exploits Redis database server vulnerability version < 3.2
- Vulnerability allows attacker to change SSH key and log in as Root
- Attacker deletes the database and left a note using vim to send bitcoins get database back

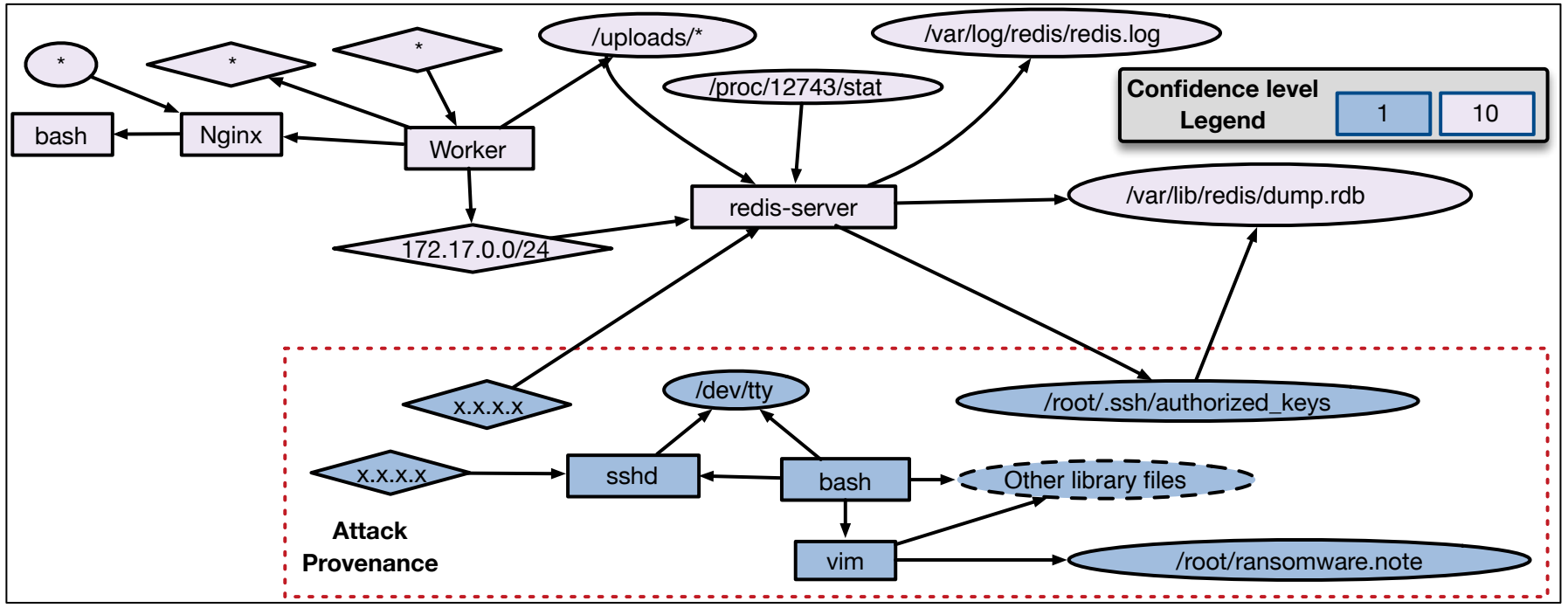
Traditional Graph of Attack

- 10 instances of redis running in the cluster
- ~80k vertices and ~83K edges with 161 MB size
- Part of provenance graph shown below



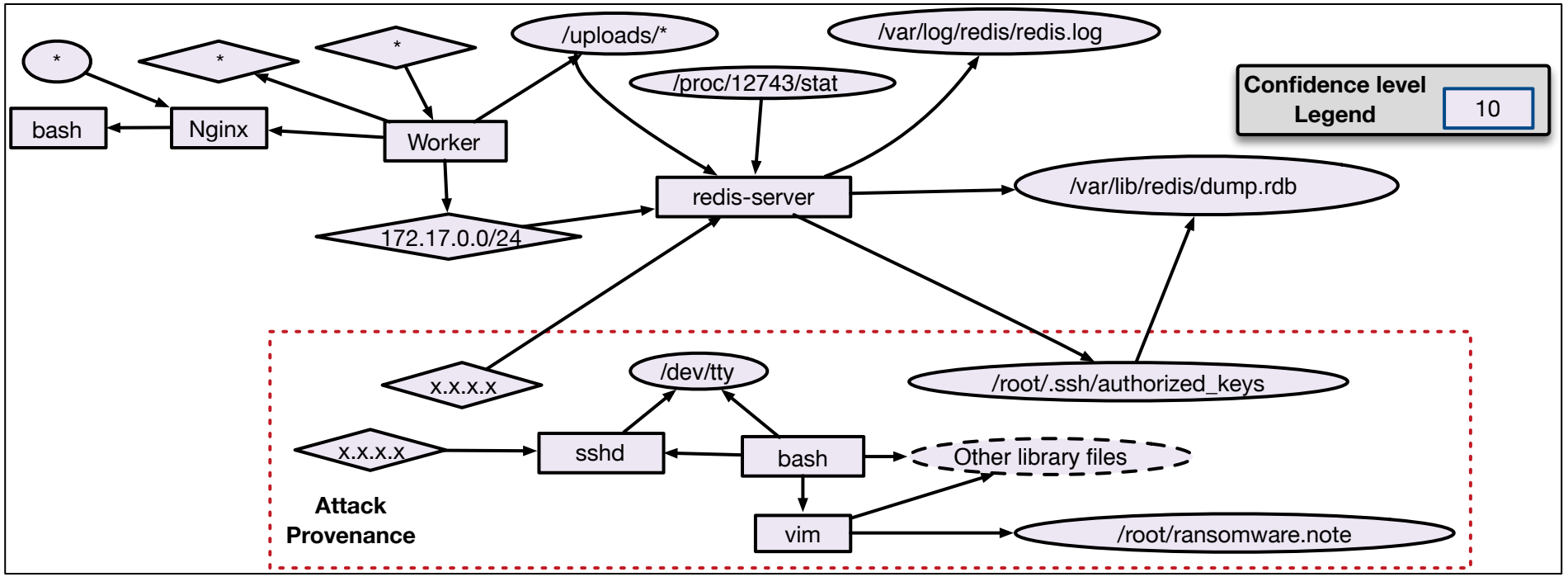
Winnower Generated Provenance graph

- 54 vertices and 68 edges with 0.7 MB size
- Part of graph is shown below:



Winnower Generated Provenance graph

- What happens if we attack all the nodes in the cluster



Conclusion

- Winnower is the first practical system for provenance-based auditing of clusters at scale with low overhead
- Winnower significantly improves attack identification and investigation in a large cluster

Questions

Thank you for your time.

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Backup Slides

Threat model

- Assumptions
  - Winnower only tracks user-space attacks i.e. trusts the OS
  - Log integrity is maintained
- Attack surface
  - Distributed application replicated on Worker nodes
- Attacker’ motive
  - Gain control over worker node by exploiting a software vulnerability in the distributed application

Online Learning