Towards Scalable Critical Alert Mining

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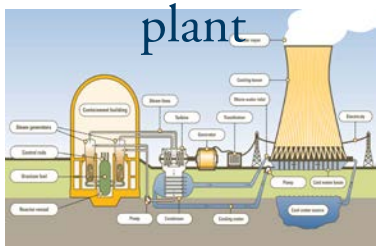
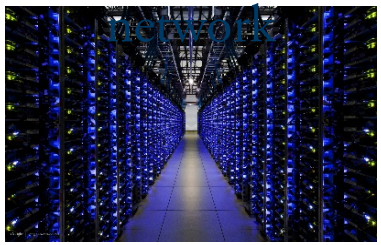
Big Data Analytics in Automated System Management

- Complex systems are ubiquitous

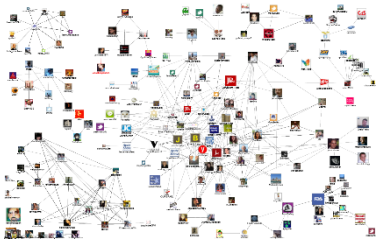
Nuclear power plant



Computer network

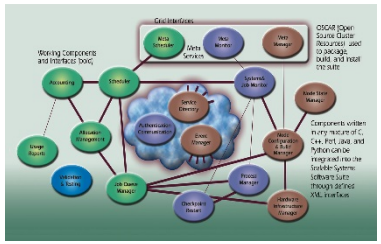


Social media



Chemical production system

Software system

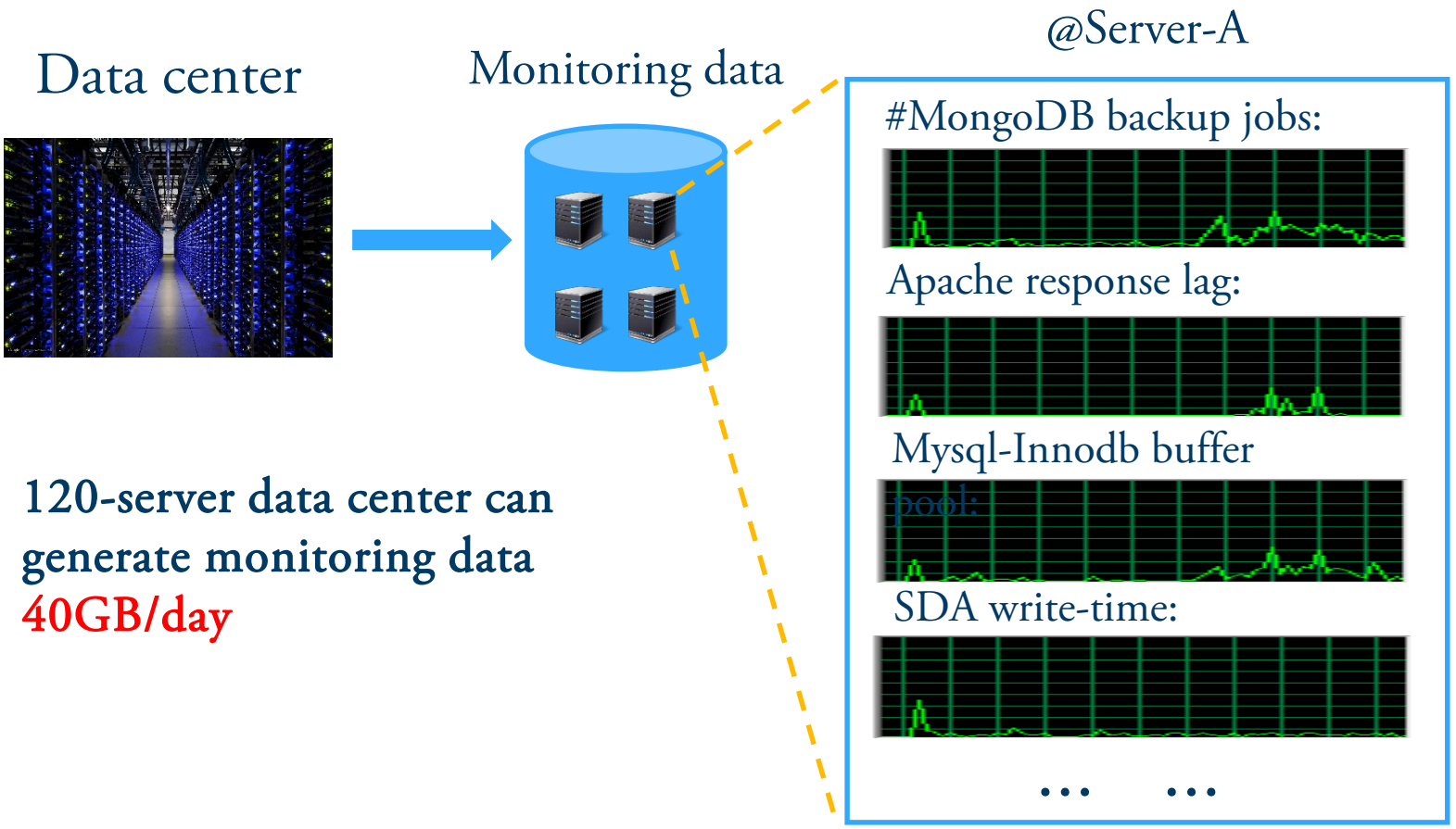


Aircraft system

- Tons of monitoring data generated from complex systems
- Big data analytics are desired to extract knowledge from massive data and automate complex system management

Massive Monitoring Data in Complex Systems

- Example: monitoring data in computer networks



120-server data center can generate monitoring data 40GB/day

System Malfunction Detection via Alerts

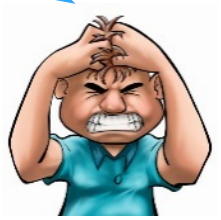
- Example: alerts in computer networks

Monitoring data

Alert @server-A

01:20am: #MongoDB backup jobs ≥ 30
01:30am: Memory usage ≥ 90%
01:31am: Apache response lag ≥ 2 seconds
01:43am: SDA write-time ≥ 10 times slower than average performance
…
09:32pm: #MySQL full join ≥ 10
09:47pm: CPU usage ≥ 85%
09:48pm: HTTP-80 no response
10:04pm: Storage used ≥ 90%
…

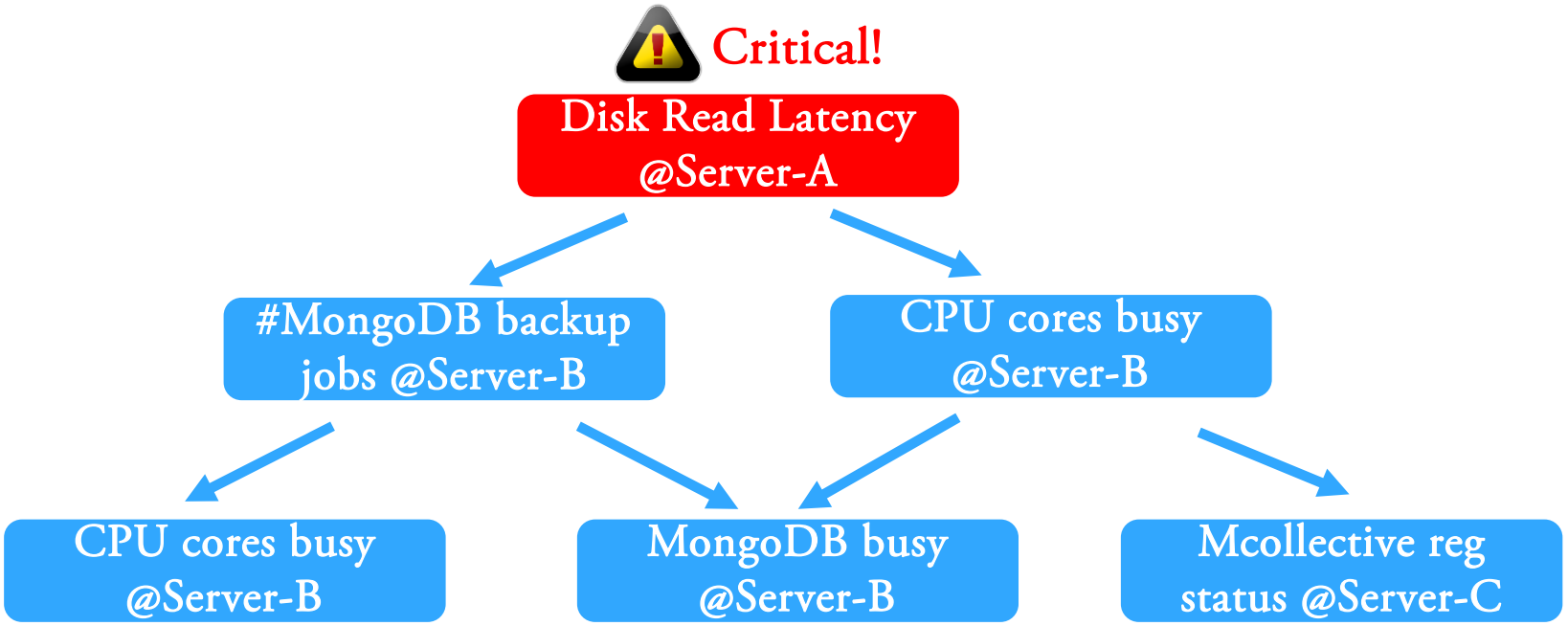
Which alert should I start with?



- Complex systems could have many issues
  - For the 40GB/day data generated from the 120-server data center, we will collect 20k+ alerts/day

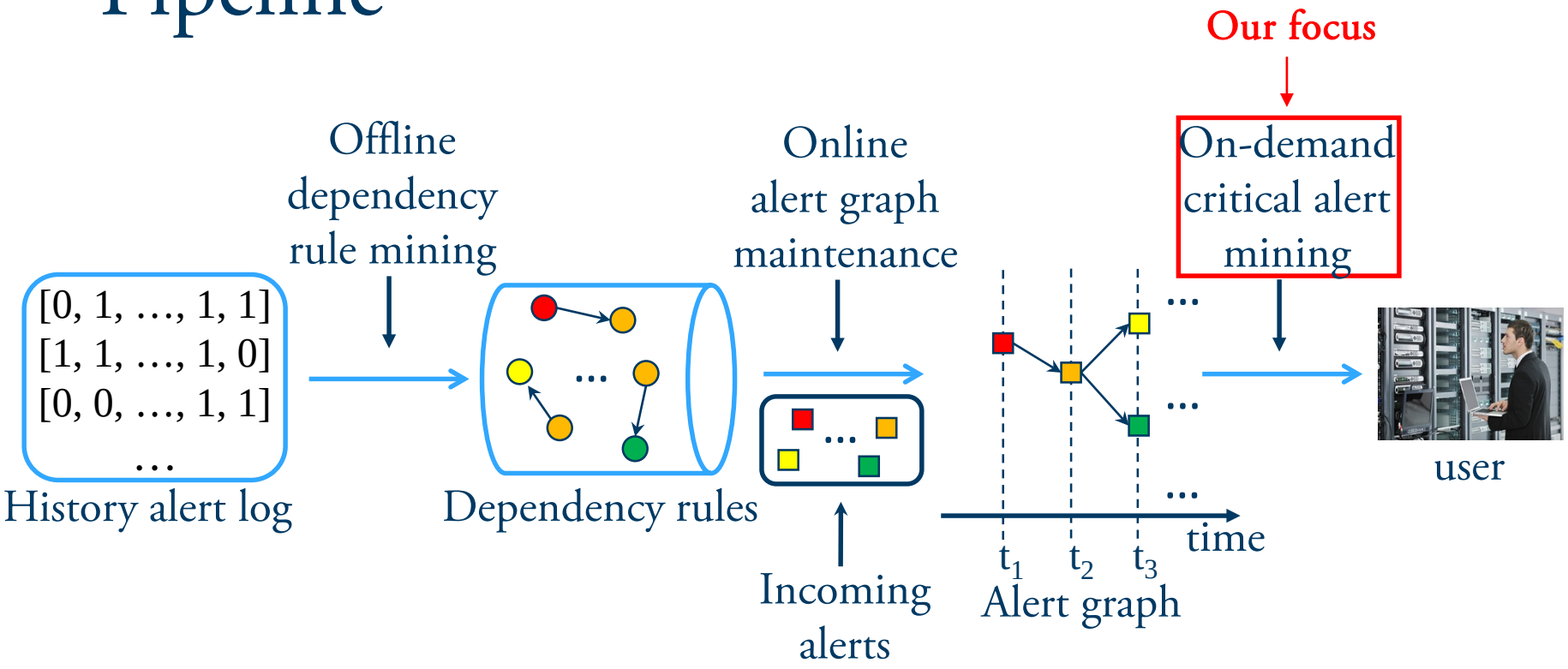
Mining Critical Alerts

- Example: critical alerts in computer networks



How to efficiently mine critical alerts from massive monitoring data?

Pipeline



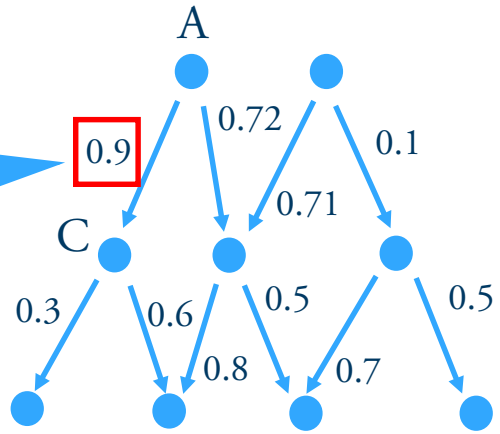
- Offline dependency rule mining
- Online alert graph maintenance
- On-demand critical alert mining

Alert Graph

- Alert graphs are directed acyclic (DAG)
- Nodes: alerts derived from monitoring data
- Edges
  - Indicate the probabilistic dependency between two alerts
  - Direction: from one older alert to another younger alert
  - Weight: the probability that the dependency holds
- Example

$p(C|A) = 0.9$ means A has probability 0.9 to be the cause of C

Alert graph G



How to measure an alert is critical?

Gain of Addressing Alerts

- If alert u is addressed, alerts caused by u will disappear
- Given a subset of alerts S are addressed, $p(u|\mathrm{S})$ is the probability that alert u will disappear

$$p(u|\mathrm{S}) = 1 - \prod_{v \in parent(u)} (1 - p(v|\mathrm{S}) \cdot p(u|v))$$

The cause of u disappears given S is

- Given a subset of alerts S are addressed, $\mathrm{Gain}(\mathrm{S})$ quantifies the benefit of addressing S

$$\mathrm{Gain}(\mathrm{S}) = \sum_{u \in \mathrm{V}} F(\mathrm{S}, u)$$

  - $F(\mathrm{S}, u)$ quantifies the impact from S to alert u
  - If $F(S, u) = p(u|\mathrm{S})$, $\mathrm{Gain}(\mathrm{S})$ is the expected number of alerts will disappear given alerts in S are addressed

Critical Alert Mining

- Input
  - An alert graph $G = (V, E)$
  - k, #wanted alerts
- Output: $S \subset V$ such that
  - $|S| = k$
  - Gain(S) is maximized

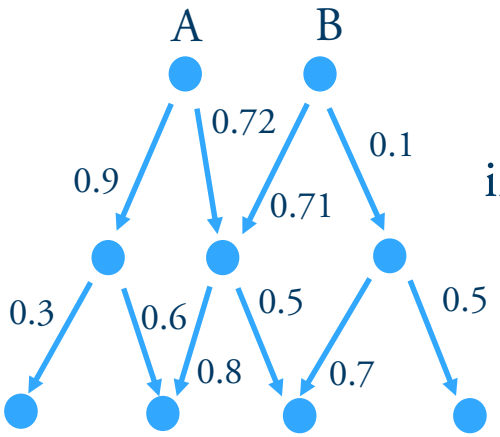
NP-hard

- Related problems
  - Critical Alert Mining is not #P hard as Influence Maximization, since alert graphs are DAGs
  - Bayesian network inference enables fast conditional probability computation, but cannot efficiently solve top-k queries

Naive Greedy Algorithm

- Greedy search strategy

Alert graph G



Find the alert u such that S ∪ $\{u\}$ has the largest incremental gain

S

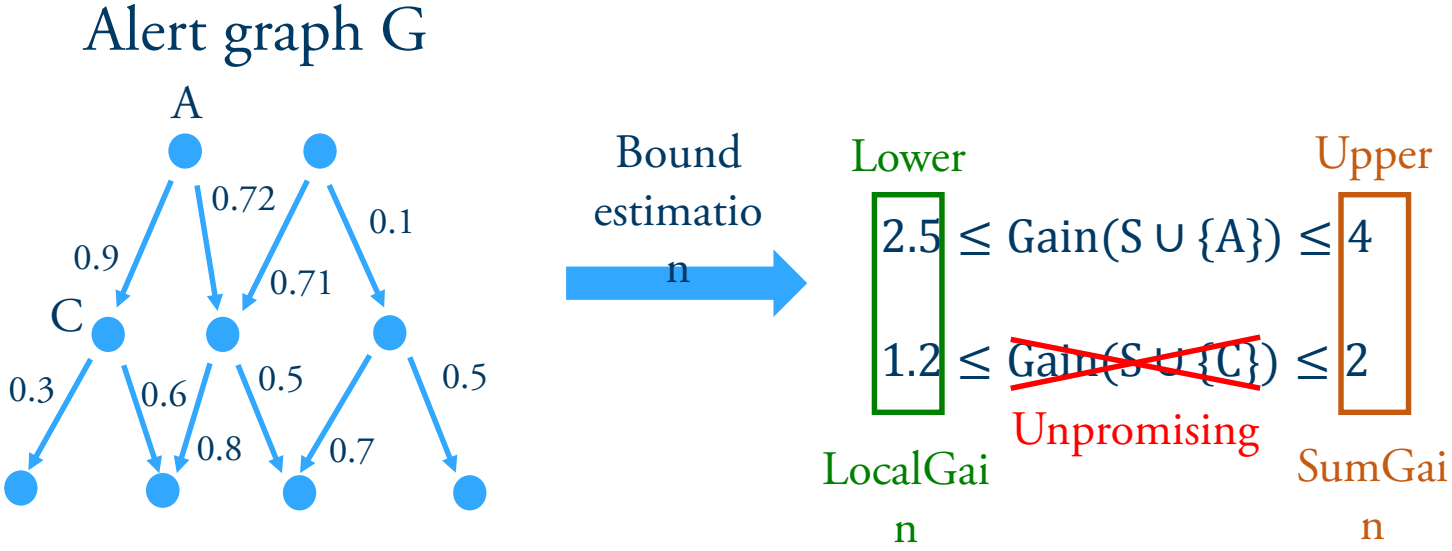
{ A B }

- Greedy algorithms have approximation ratio $1 - \frac{1}{e}$ (≈0.63)
- Efficiency issue: time complexity $O(k|V||E|)$

How to speed up greedy algorithms?

Bound and Pruning Algorithm (BnP)

- Pruning unpromising alerts by upper and lower bounds



- Drawback: pruning might not always work

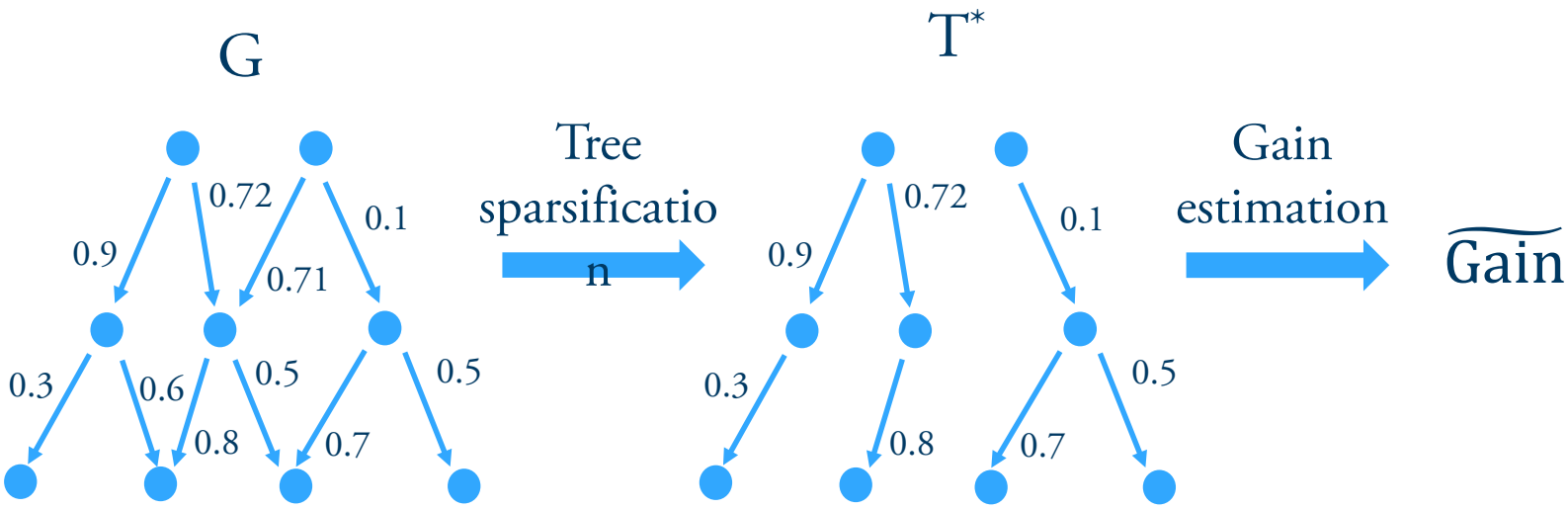
Can we trade a little approximation quality for better efficiency?

Single-Tree Approximation

- If an alert graph is a tree, a $(1 - \frac{1}{e})$-approximation algorithm runs in $O(k|V|)$
- Intuition: sparsify alert graphs into trees, preserving most information
- Maximum directed spanning trees are trees in an alert graph
  - Span all nodes in an alert graph
  - Sum of edge weights is maximized

Single-Tree Approximation (cont.)

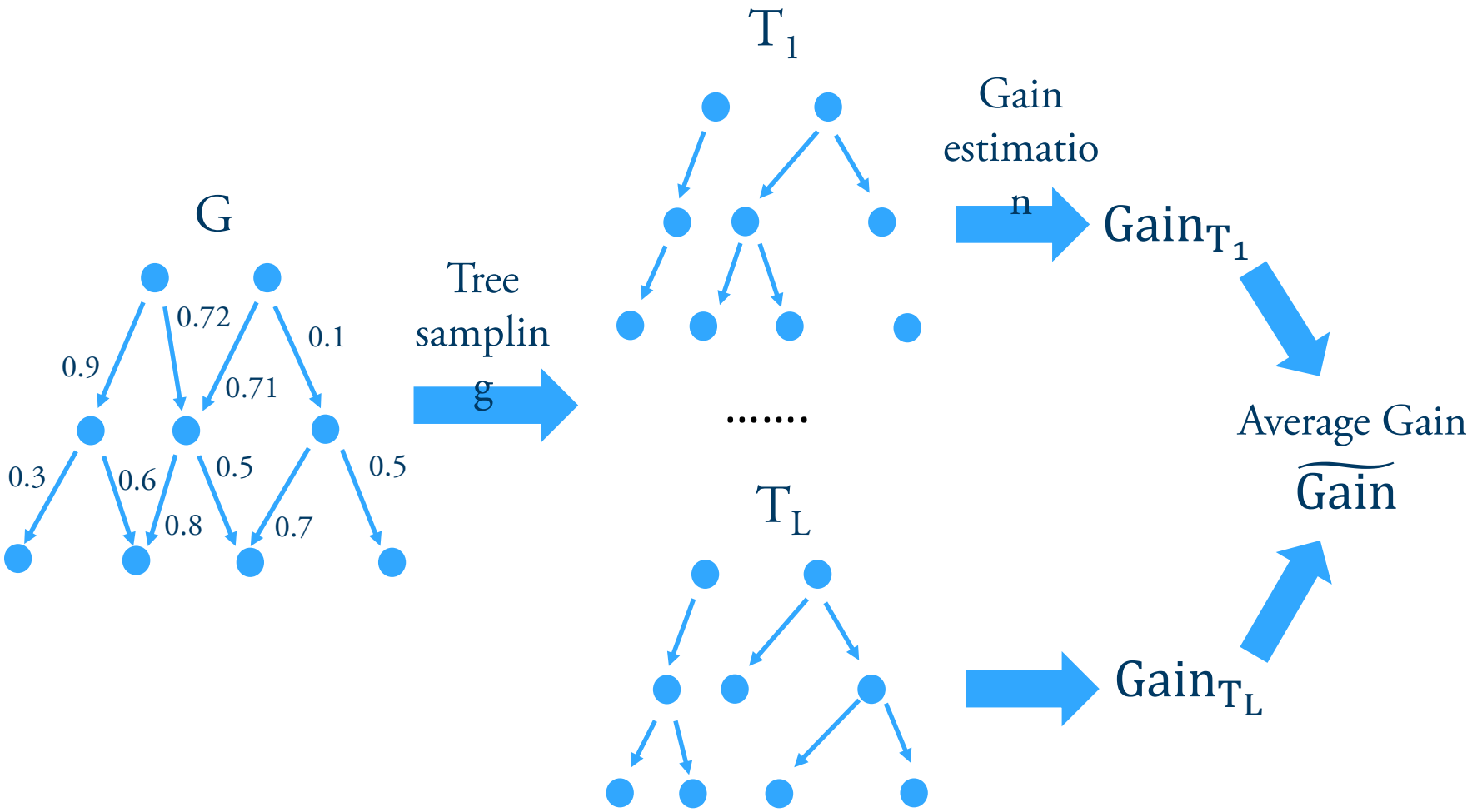
- Linear-time algorithm to search maximum directed spanning tree



- Drawback: accuracy loss in Gain estimation
  - Edge of the highest weight is always selected
  - Edges of similar weight never get selected

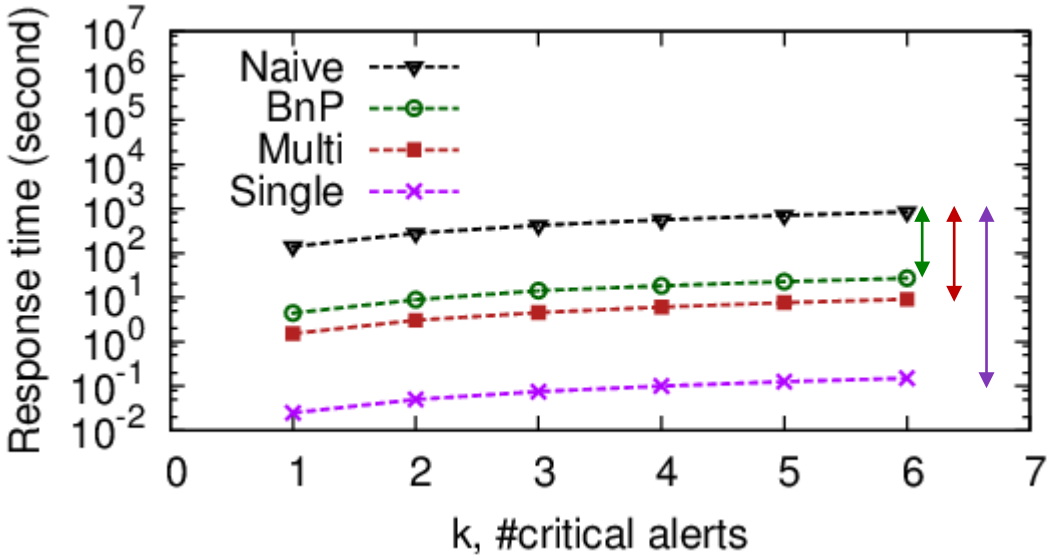
Multi-Tree Approximation

- Sample multiple trees from an alert graph



Experimental Results

- Efficiency comparison on LogicMonitor alert graphs



- BnP is 30 times faster than the baseline
- Multi-tree approximation is 80 times faster with 0.1 quality loss
- Single-tree approximation is 5000 times faster with 0.2 quality loss

Conclusion

- Critical alert mining is an important topic for automated system management in complex systems
- A pipeline is proposed to enable critical alert mining
- Tree approximation practically works well for critical alert mining
- Future work
  - Critical alert mining with domain knowledge
  - Alert pattern mining
    - if two groups of alerts follow the same dependency pattern, they might result from the same problem
  - Alert pattern querying
    - if we have a solution to a problem, we apply the same solution when we meet the problem again

Questions?

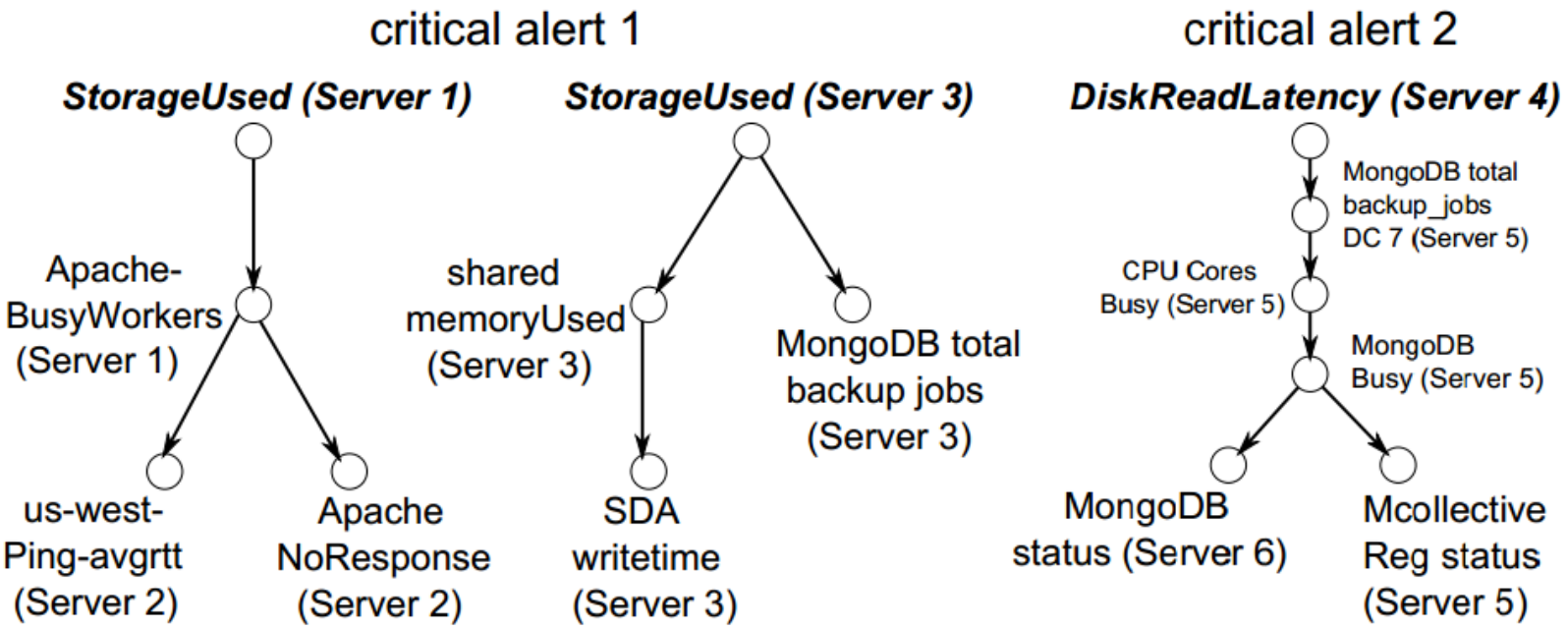
Thank you!

Experiment Setup

- Real-life data from LogicMonitor

  - 50k performance metrics from 122 servers
  - Spans 53 days
- Offline dependency rule mining
  - Training data: the latest 7 consecutive days
  - Mined 46 set of rules (starting from the 8th day)
  - Learning algorithm: Granger causality
- Alert graphs
  - Constructed 46 alert graphs
  - #nodes: 20k ~ 25k
  - #edges: 162k ~ 270k

Case study


critical alert 1
StorageUsed (Server 1)
Apache-
BusyWorkers
(Server 1)
us-west-
Ping-avgrtt
(Server 2)
Apache
NoResponse
(Server 2)
StorageUsed (Server 3)
shared
memoryUsed
(Server 3)
SDA
writetime
(Server 3)
MongoDB total
backup jobs
(Server 3)
critical alert 2
DiskReadLatency (Server 4)
MongoDB total
backup_jobs
DC 7 (Server 5)
CPU Cores
Busy (Server 5)
MongoDB
Busy (Server 5)
MongoDB
status (Server 6)
Mcollective
Reg status
(Server 5)