Automated Diagnosis of Chronic Performance Problems in Production Systems

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Motivation

- Major outages are rare in production systems
  - Such blackouts also detected by alarms

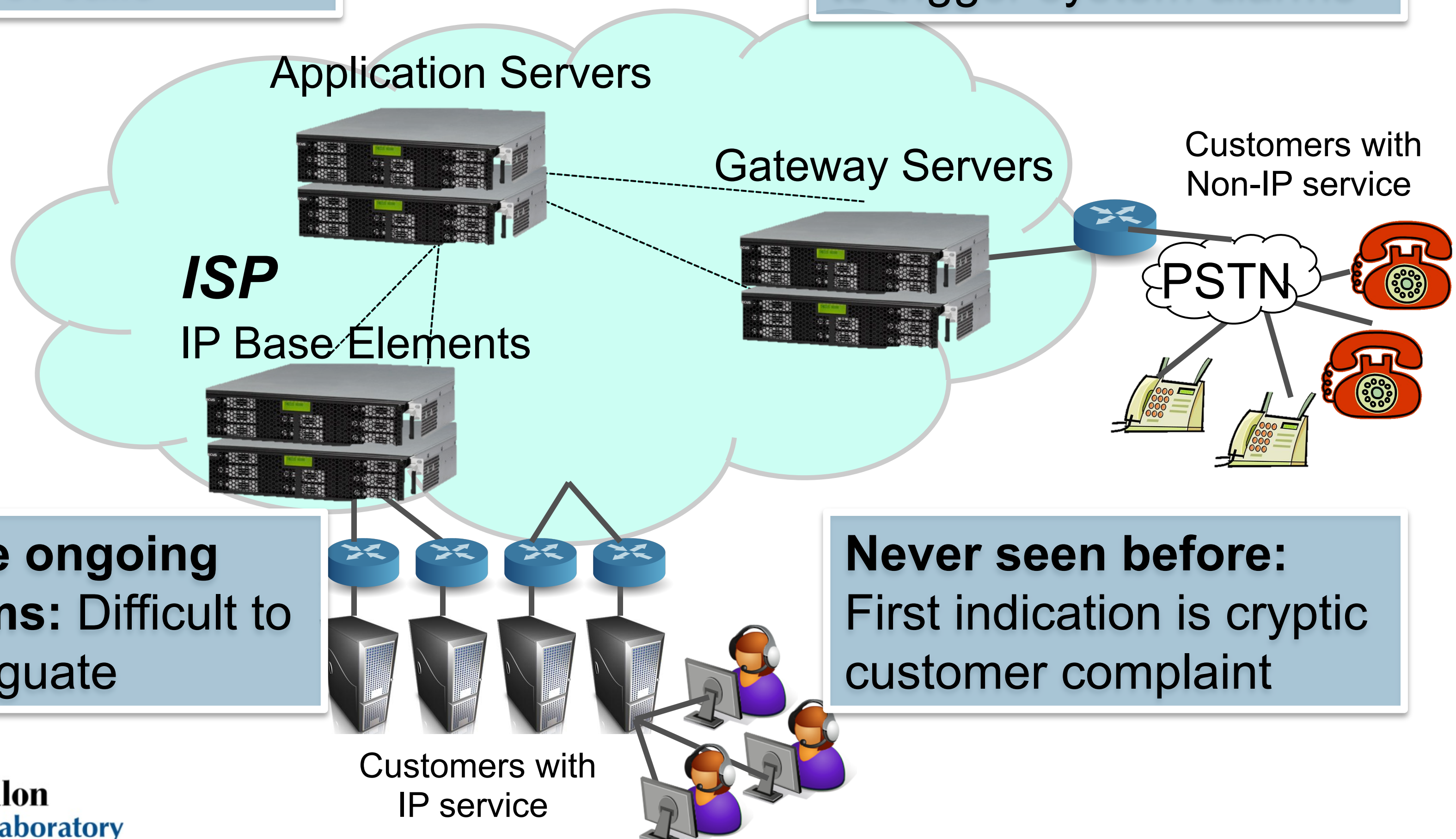
- **Chronic performance problems** (*brownouts*)
  - System still works, but with degraded performance
  - Problem typically affects subset of users/requests
  - Admins often unaware until the user complains

- Chronics are fairly common
  - Production VoIP system:
    – Source of 42% of failed calls in worst month of outages
  - Production Hadoop cluster (OpenCloud):
    – Source of 78% of reported problems in 11-month period

Challenges (1)

Scale: Thousands of network elements, millions of calls

Under radar: Symptoms often not severe enough to trigger system alarms



Multiple ongoing problems: Difficult to disambiguate

Never seen before: First indication is cryptic customer complaint

Challenges (2)

- **Labeled failure-data** not always available
  - Difficult to diagnose problems not encountered before
- **Desired level of instrumentation** might not be possible
  - Existing vendor instrumentation with limited control
  - Cost of adding instrumentation might be high
  - Instrumentation might be diverse, at different sampling rate

Outline

- Thesis statement
- Approach
  - Instrumentation
  - Anomaly detection
  - Problem localization
- Experimental evaluation
  - Fault injection
  - Case studies
- Extensions
- Conclusion

Thesis Statement

Diagnosis of chronic performance problems in production systems is possible through the analysis of common **white-box logs** to extract local behavior and system-wide dependencies, coupled with the analysis of common **black-box metrics** to identify the resource at fault.

Goals and Non-goals

- Goals of approach
  - Diagnosis using existing instrumentation in production systems
  - Anomaly detection in the absence of labeled failure-data
  - Differentiation of workload changes from anomalies

- Non-goals
  - Diagnosis of system-wide outages
  - Diagnosis of value faults and transient faults
  - Root-cause analysis at code-level

Assumptions

- Majority of the system is working correctly
- Problems manifest as observable behavioral changes
  - Exceptions or performance degradations
  - Visible to the end-user
- All instrumentation is locally time-stamped
- Clocks are synchronized to enable system-wide correlation of data
- Instrumentation faithfully captures system behavior

Target Systems for Validation

- VoIP system at large ISP
  - 10s of millions of calls per day
  - 1000s of network elements with heterogeneous hardware
  - 24x7 Ops team uses alarm correlation to diagnose outages
  - Separate team troubleshoots long-term chronics
  - Labeled traces available
- Hadoop: Open-source implementation of MapReduce
  - Diverse kinds of data-intensive workloads
    - Graph mining, language translation
  - Hadoop clusters have homogeneous hardware
    - 400-node Yahoo! M45, 64-node OpenCloud clusters
  - Controlled experiments in Amazon EC2 cluster
  - Long running jobs (> 100s): Hard to label failures

Contributions

	VoIP	HADOOP
Anomaly Detection	Heuristics-based	Peer comparison without labeled data
Problem Localization	Localize to customer/network-element/resource/error-code	Localize to node/task/resource
Types of chronics	Exceptions, performance degradation, single-source, multiple-source	Exceptions, performance degradation, single-source, multiple-source
Experimental Evaluation	Production VoIP system, 1000s of network elements	OpenCloud, 64 nodes
Publications	SLAML'11, OSR'11, DSN'12	WASL'08, HotMetrics'09, ISSRE'09, ICDCS'10, NOMS'10, CCGRID'10

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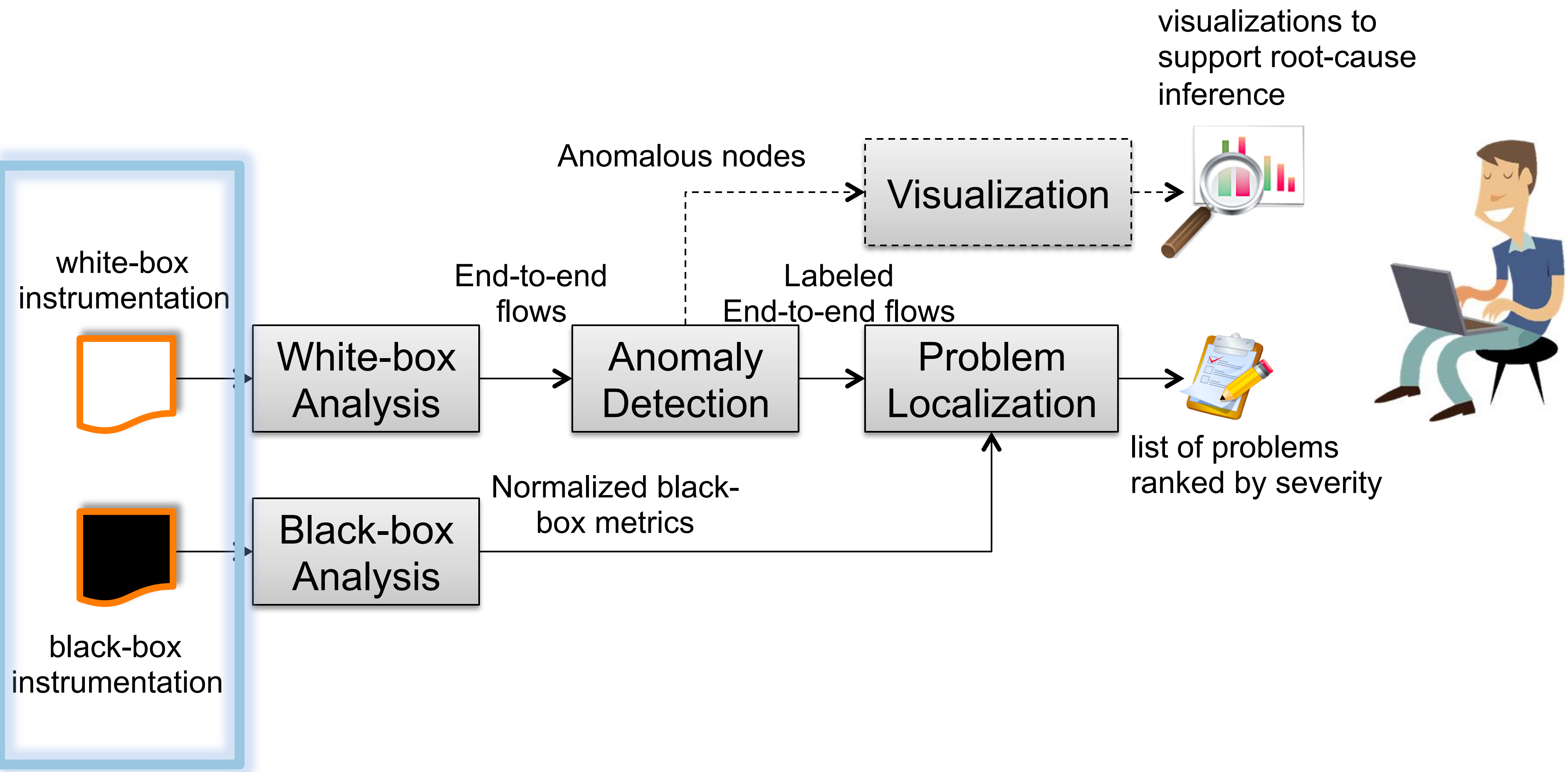
Overview of Approach



Black-Box Instrumentation

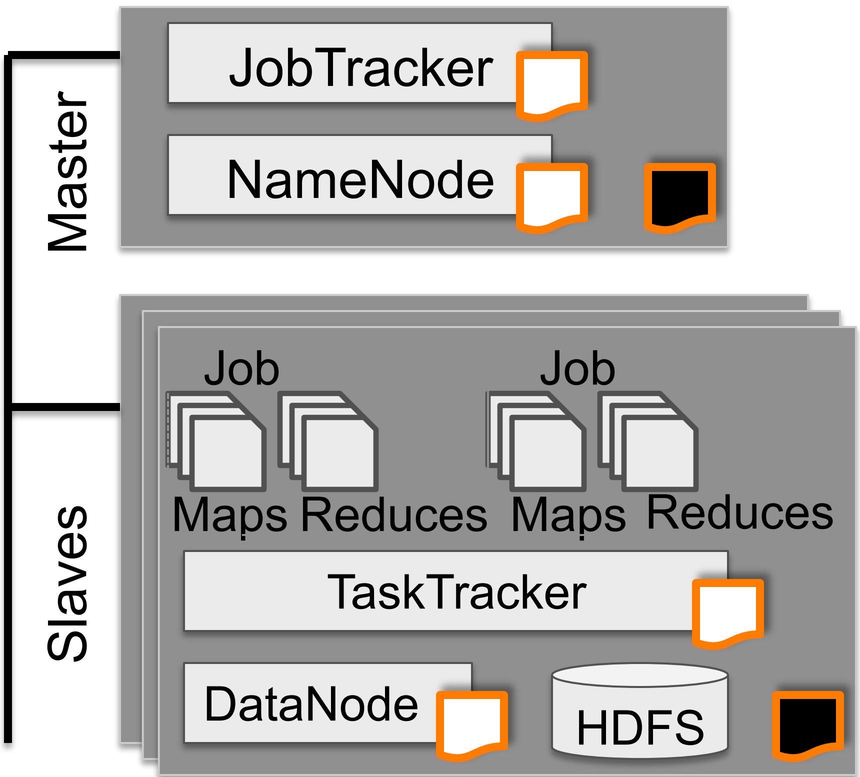
- For both Hadoop and VoIP
- Resource-usage metrics collected periodically from OS
- Monitoring interval varies from 1s to 15min
- Examples of metrics
  - CPU utilization, CPU run-queue size
  - Pages in, pages out
  - Memory used, memory free
  - Context-switches
  - Packets received, packets sent
  - Disk blocks read, disk blocks written

White-Box Instrumentation

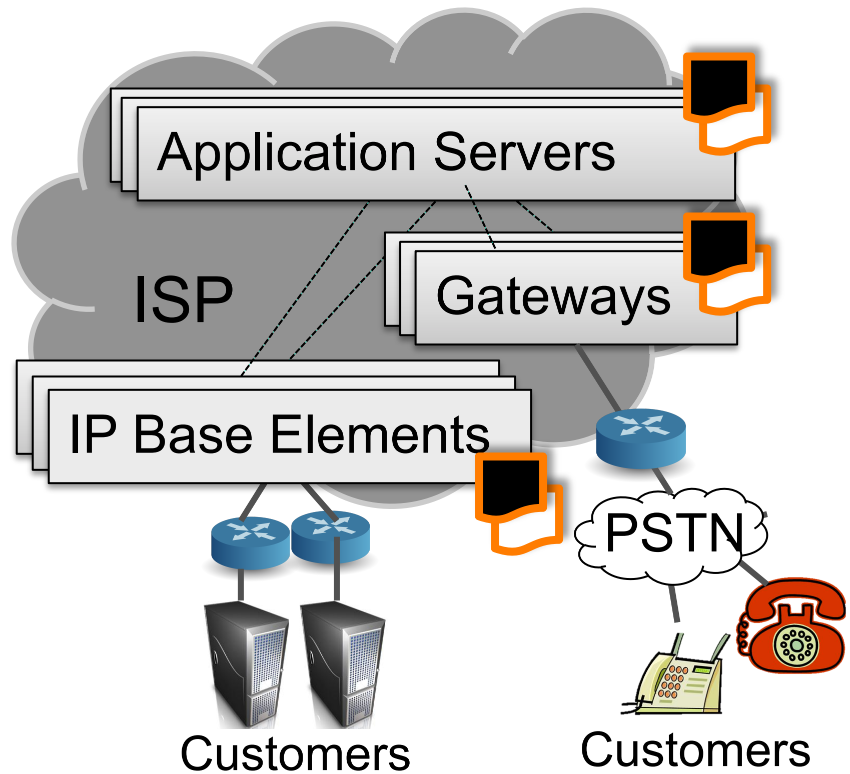
- Each node logs each request that passes through it
  - Timestamp, IP address, request duration/size, phone no., …
- Log formats vary across components
  - Application-specific parsers extract relevant attributes
- Construction of end-to-end traces
  - Extract control flow information
    - Control flow captures sequence of events executed
    - E.g., dependencies between Maps and Reduces in Hadoop
  - Extract data flow information
    - Data flow captures transfer of data between components
  - Stitch end-to-end flows using control and data flow information

Target Systems' Instrumentation

Hadoop Clusters
(OpenCloud, Yahoo! M45)



ISP's VoIP System



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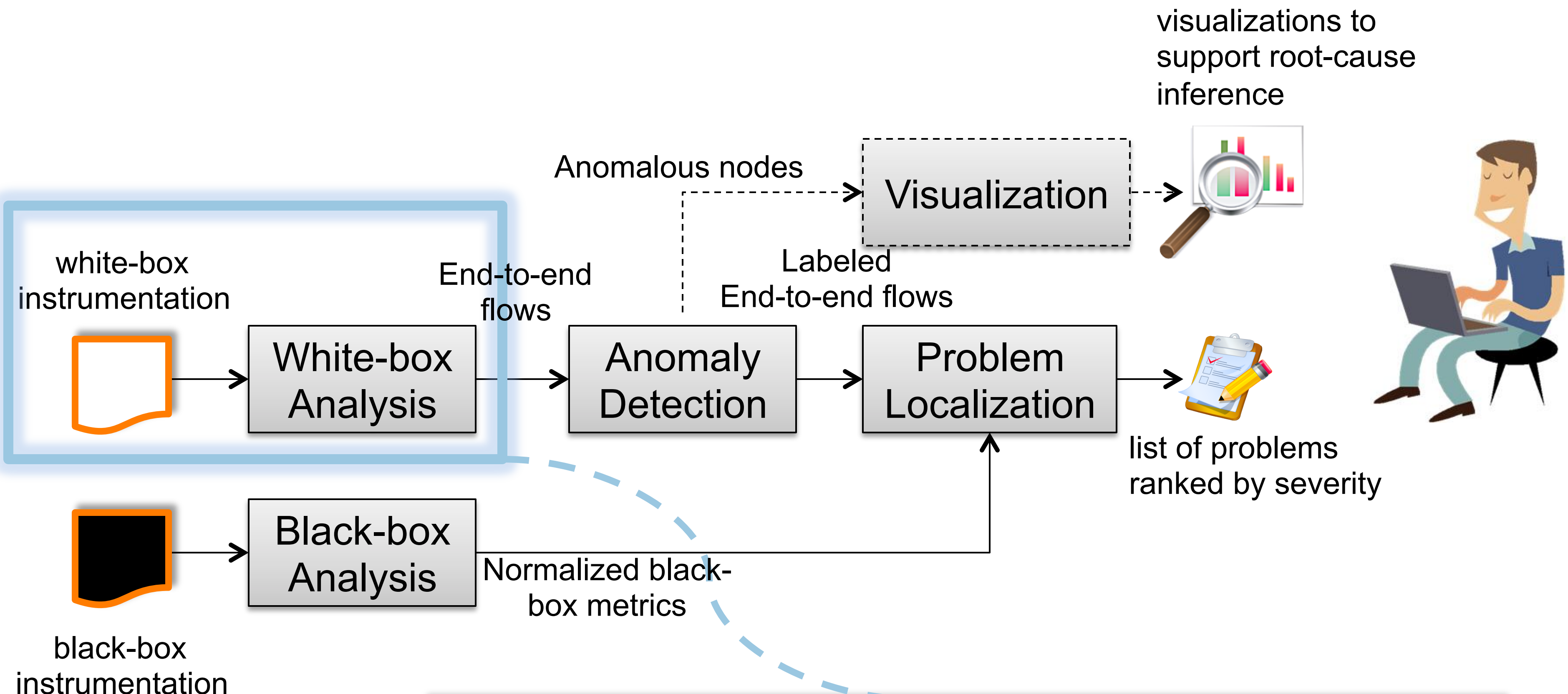
White-Box Analysis



Questions

- How do we extract local control- and data-flow?
- How do we infer dependencies with other components?
- How do we deal with missing dependency information?

White-Box Logs

Hadoop Logs

control flow

```
2011-10-12 23:59:55,625 INFO org.apache.hadoop.mapred.TaskTracker:
attempt_201106031747_9630_m_013846_0 0.027189009% Records R/W=208/1
2011-10-12 23:59:55,943 INFO org.apache.hadoop.mapred.TaskTracker: Sent
out 43000 bytes for reduce: 37 from map:
attempt_201106031747_9630_m_013677_0 given 43000
```

control and data flow

VoIP Call Detail Record

```
Mon Apr 29 07:30:14 2013
  NAS-Identifier = "other"
  Acct-Status-Type = "Accounting-off"
  NAS-IP-Address = 172.30.11.36
  Client-IP-Address = 172.30.11.36
  Acct-Input-Packets = 5
  Acct-Output-Packets = 5
  Acct-Input-Octets = 100
  Acct-Output-Octets = 2789
```

control flow

data flow

White-Box Analysis: Hadoop

1 Each node logs task (or block) info. locally

TaskTracker 6

```
10:03:59, MAP
LaunchTaskAction
task_188_m_98
```

2 Domain-specific knowledge used to extract attributes of interest

3 Infer dependency using exact key match on task ID.

TaskTracker 8

```
10:03:59, SHUFFLE
task_656_r_900
copying
task_188_m_98

10:03:59, REDUCE
task_656_r_900
192.168.22.3
```

4 Match on IP address within given time window

Datanode 34

```
10:04:01,
BLOCK_WRITE
blk_8987676
192.168.22.3 to
192.168.22.6
```

White-Box Analysis: VoIP

1 Each node logs call outcomes locally in Call Detail Record

IP Base Element 3

```
IPBE CDR
10:03:59, START
973-123-8888 to
409-555-5555
192.156.1.2 to
11.22.34.1
10:04:02, STOP
```

2 Domain-specific knowledge used to extract attributes of interest

3 Infer dependency using exact key match on phone no.

Application Server 5

```
AS CDR
10:04:05,
ATTEMPT
973-123-8888 to
409-555-5555\
```

4 Approx match on partial phone no. and time

Gateway Server 12

```
GS CDR
10:04:10,
ATTEMPT
973-123-xxxx to
409-555-xxxx
```

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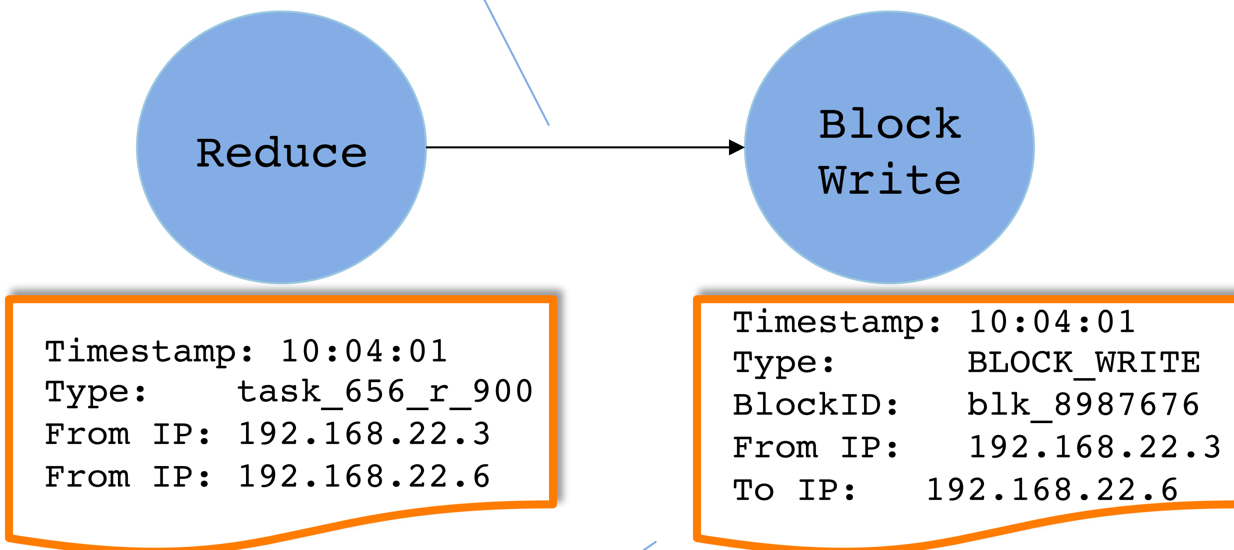
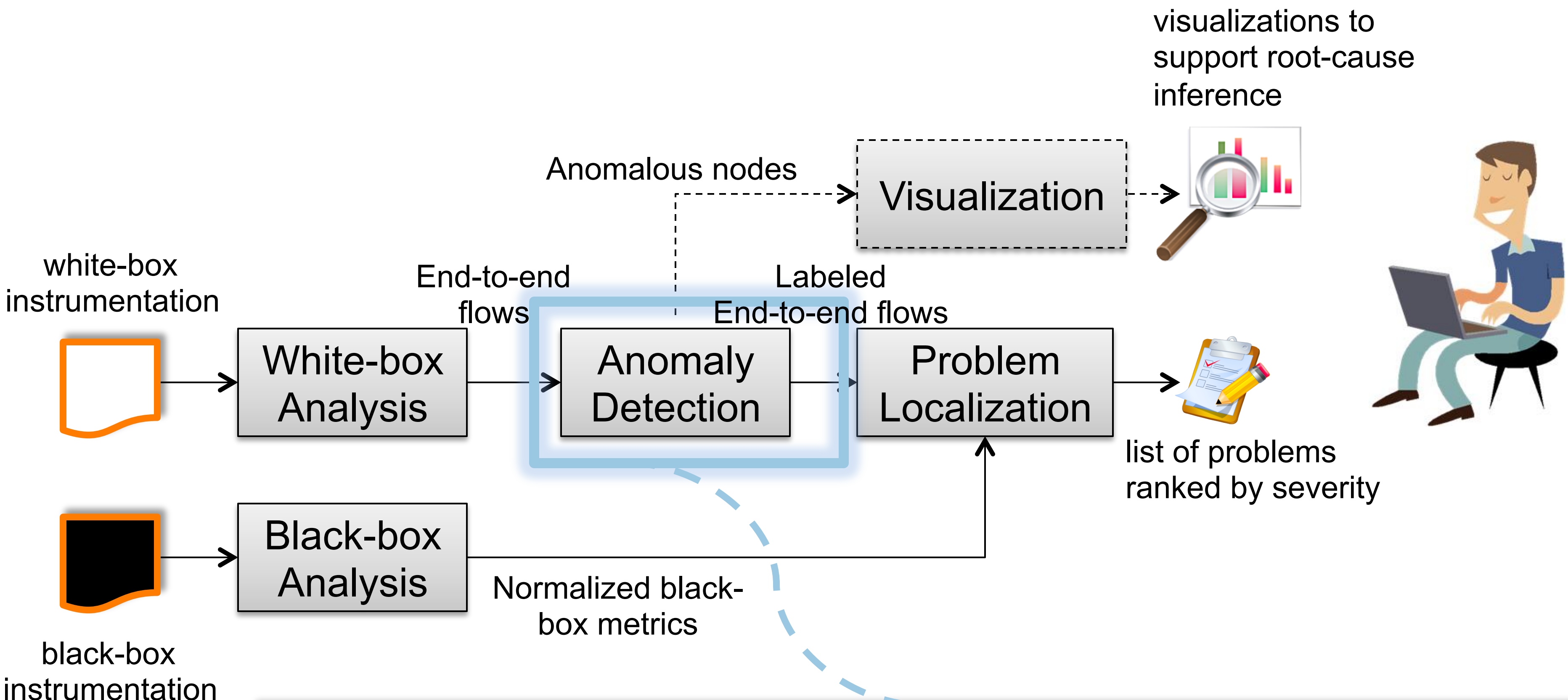
Output of White-box Analysis

Inferred dependencies between components



Unstructured logs transformed into structured log

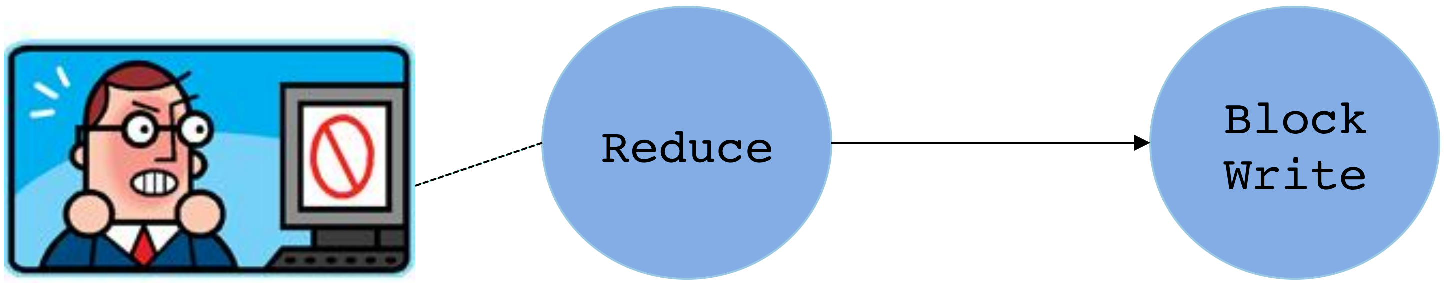
Anomaly Detection



Questions

- How to detect performance problems in the absence of labeled data?
- How to distinguish legitimate application behavior vs. problems?

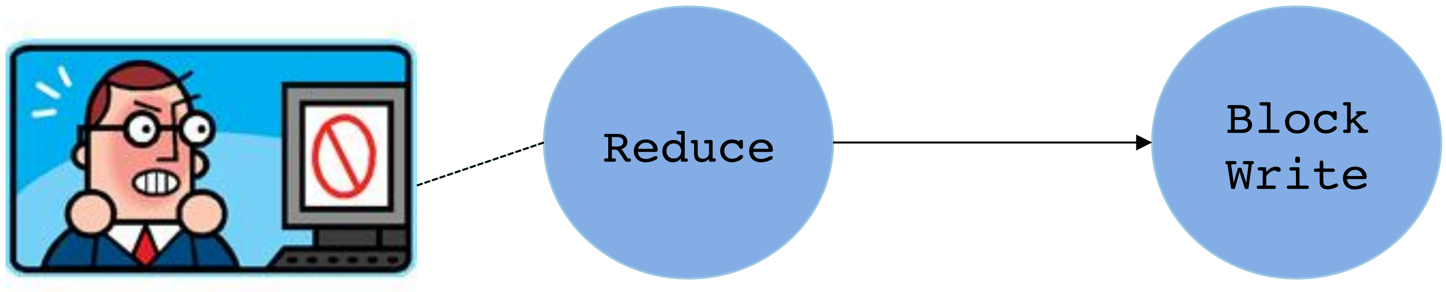
Anomaly Detection



- Some user-visible problems manifest as errors
  - Detected by extracting error codes from failed flows, or
  - Apply domain-specific heuristics
- Performance problems can be harder to detect
  - Exploit the notions of “peers” to detect performance problems
  - Determine what system behaviors can be considered equivalent (“peers”) under normal conditions
  - Significant deviation from “peers” is regarded anomalous

rika (Swahili), *noun*. peer, contemporary, age-set, undergoing rites of passage (marriage) at similar times.

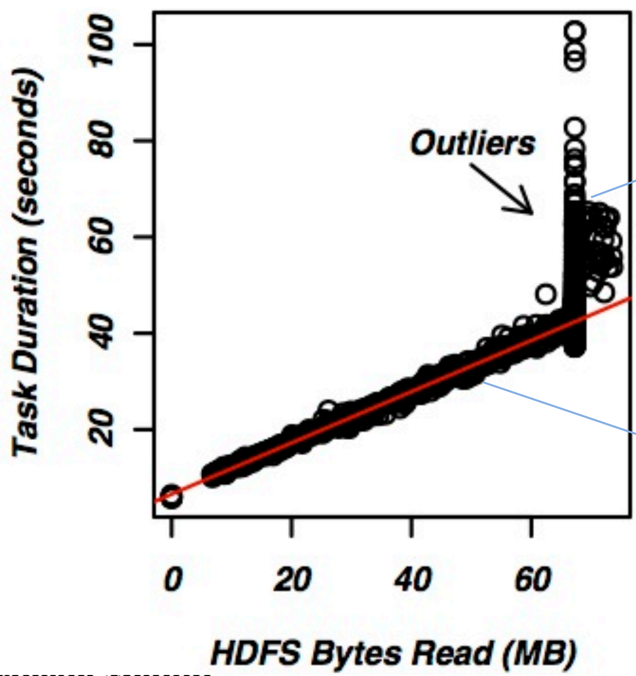
Anomaly Detection: Hadoop (1)



- Extract exceptions from failed and canceled tasks
- Detect performance problems using “peers”
  - Empirical analysis of production data to identify peers
    - 219,961 successful jobs (Yahoo! M45 and OpenCloud)
    - 89% of jobs had low variance in their Map durations
    - 65% of jobs had low variance in their Reduce durations
  - Designate tasks belonging to the same job as peers

Anomaly Detection: Hadoop (2)

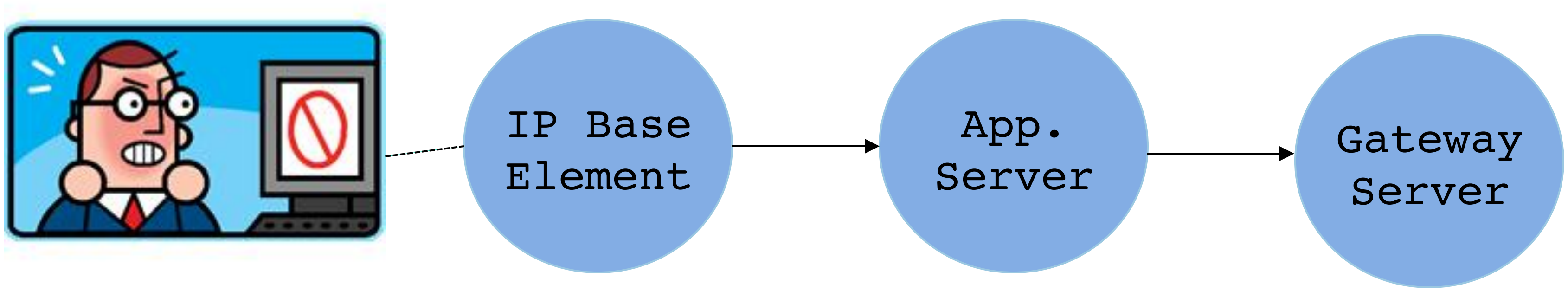
- At the same time, behavior amongst peers can legitimately diverge due to various application factors
  - Identified 12 such factors on OpenCloud
  - Example: HDFS bytes written/read



Flag tasks which do not fit regression model as anomalous

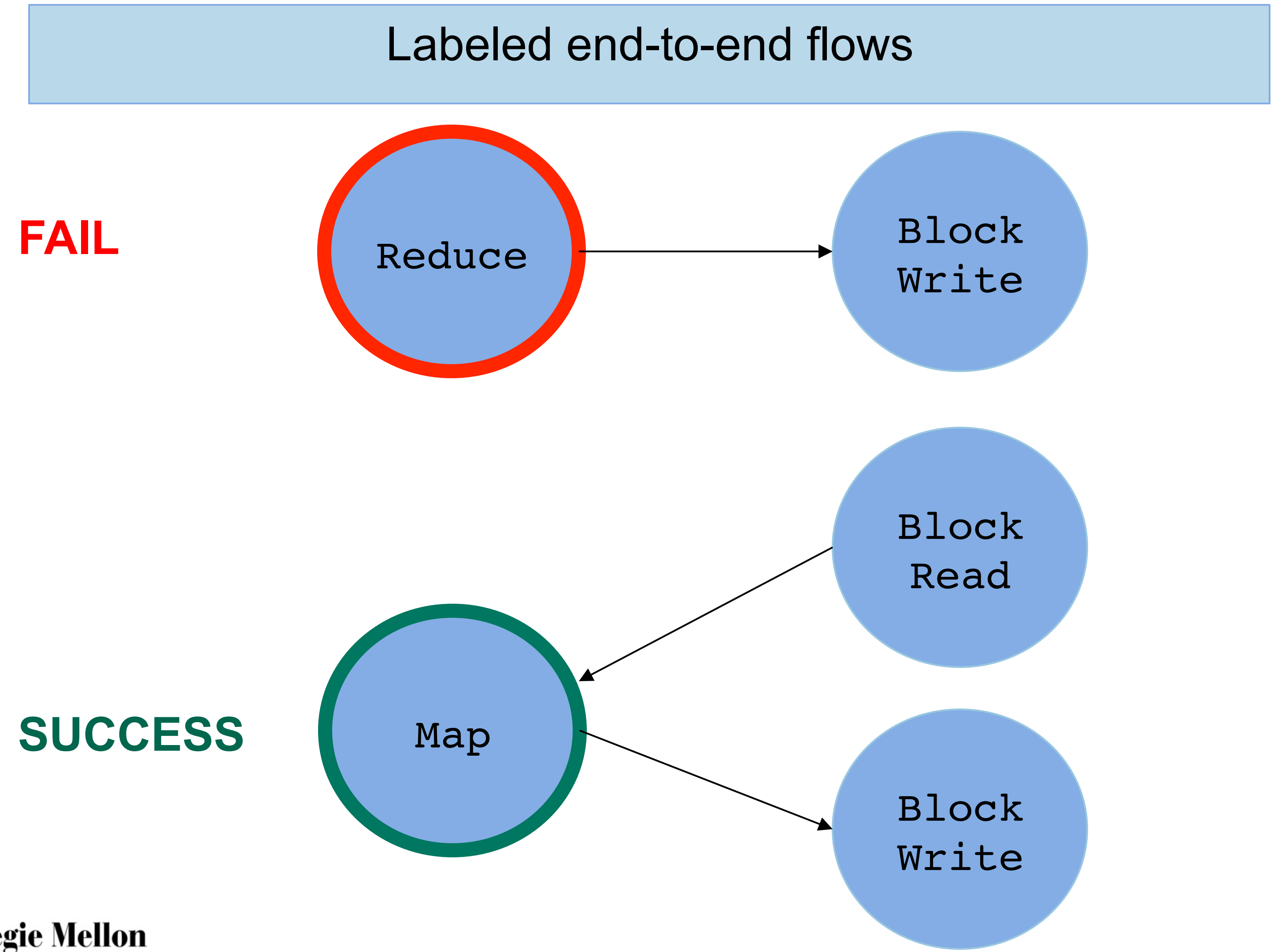
Exploit regression to automatically learn factors influencing task durations

Anomaly Detection: VoIP

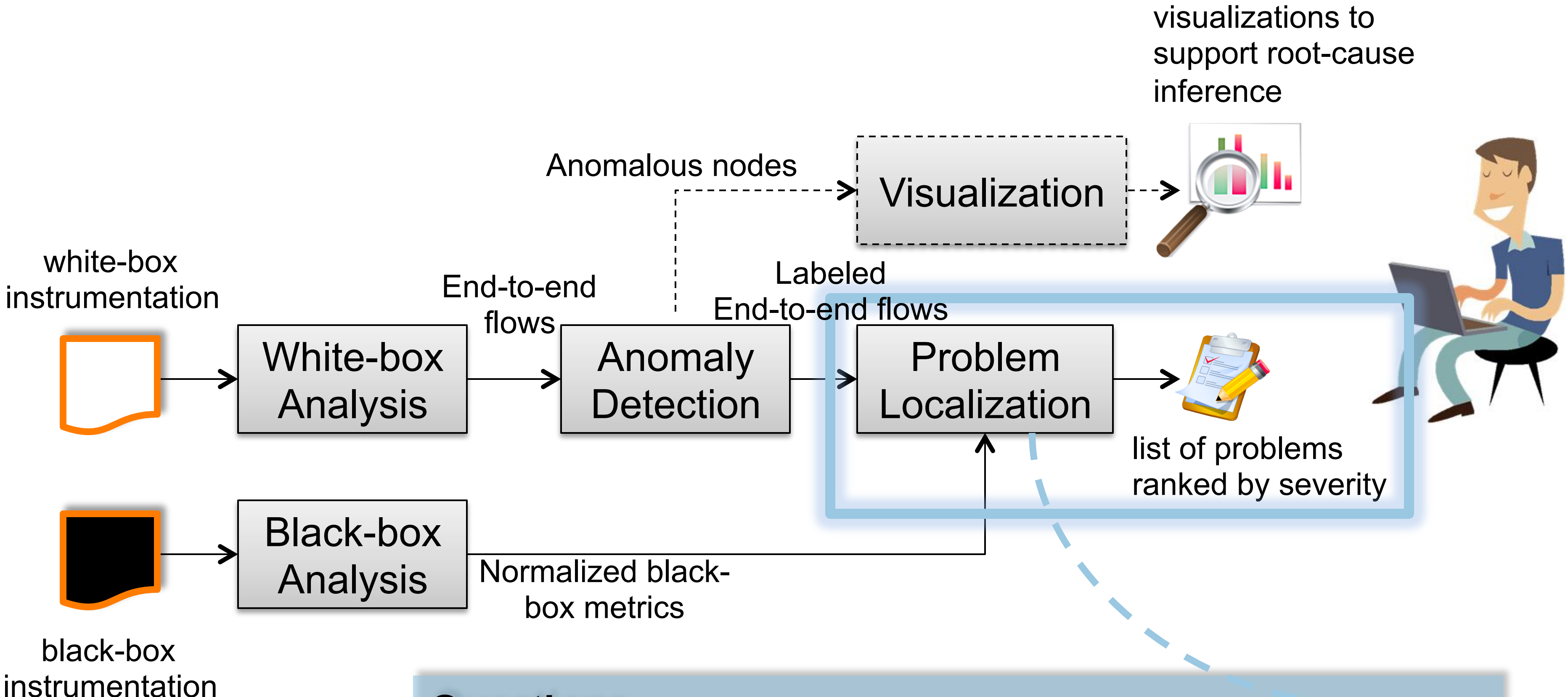


- Detecting blocked or dropped calls
  - Extract defect codes (e.g., timeout) from failed calls
  - Exploit domain-specific heuristics to detect problems
    - Examples: Callback soon after call end, zero talk-time
- Detecting performance problems
  - Designate peers to be calls belonging to the same service
  - Simple statistical technique to detect peers when deviate
    - Packet loss exceeds 90^{th} percentile of calls

Output of Anomaly Detection



Problem Localization



Questions

- How to identify problems due to combination of factors?
- How to distinguish multiple ongoing problems?
- How to find resource that caused the problem?
- How to handle “noise” due to flawed anomaly detection?

Identify Suspect Attributes (1)

STEP 1: Find individual attributes most likely to occur in failed flows

Labeled end-to-end traces generated by anomaly-detection

```
Task1: 09:31am,SUCCESS, Server1, Map2, BlockRead3,
Task2: 09:32am,FAIL, Server1, Map3, Server8, BlockRead5,
       :
       :
```

10s of thousands of attributes

10s of millions of flows

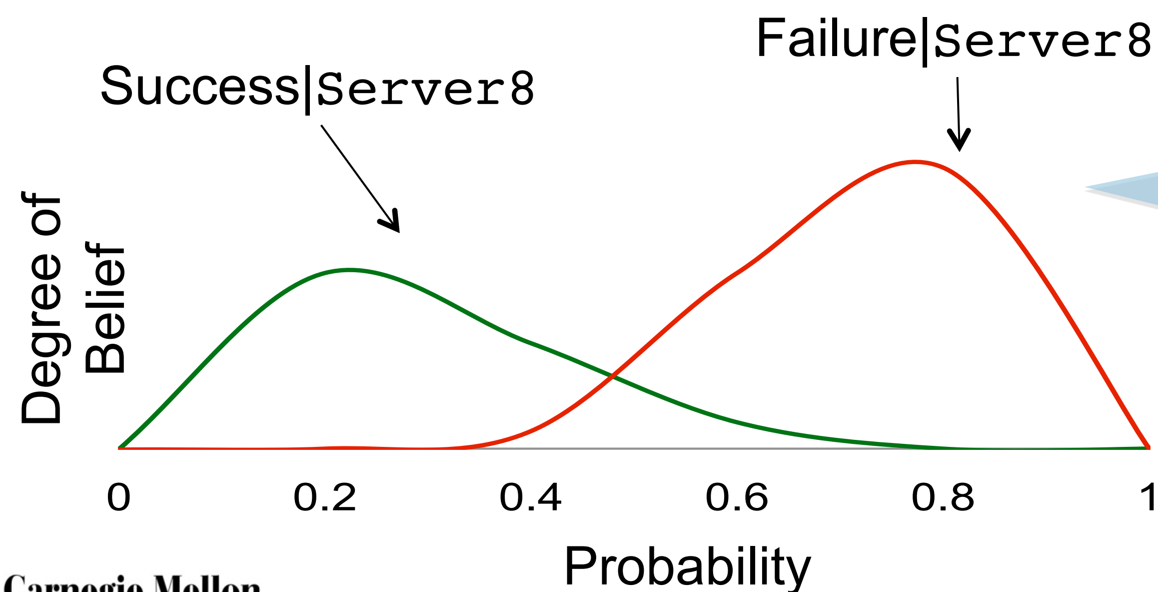
	Server1	Server8	Map2	Map3	Outcome
Task1	1	0	1	0	SUCCESS
Task2	1	1	0	1	FAIL

Binary representation supports scalable representation of attributes as sparse table.

Identify Suspect Attributes (2)

STEP 1: (contd)

- Estimate conditional probability distributions
  - *Prob*(Success|Attribute) vs. *Prob*(Failure|Attribute)
- Update belief on distribution with each flow seen



Anomaly score: Distance between distributions

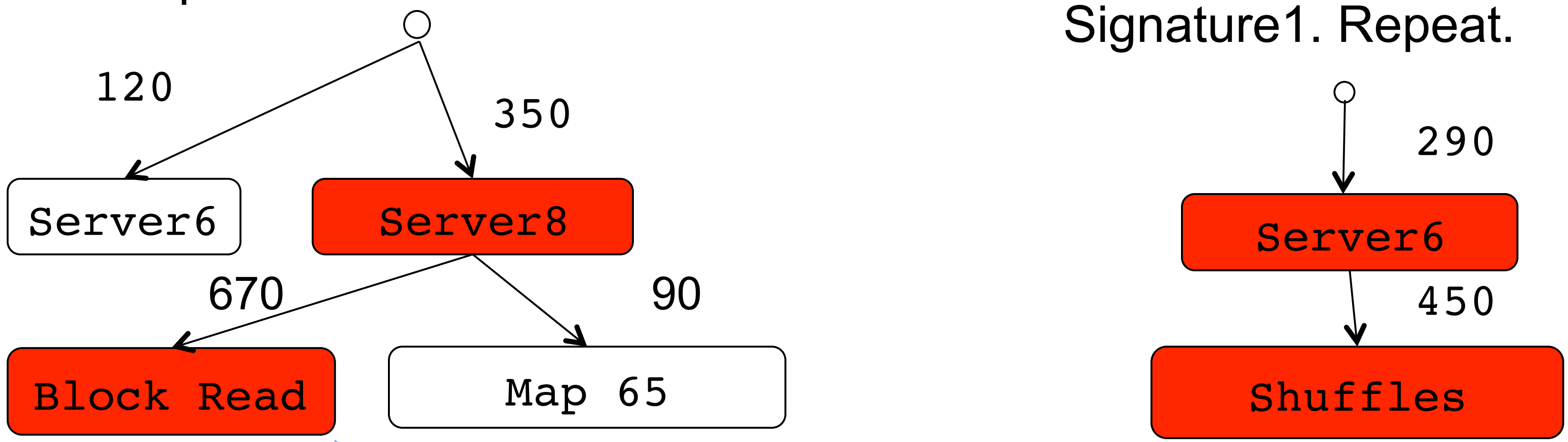
Find Attribute Combinations

STEP 2: Determine if chronic is triggered by combination of factors

- Find attribute combinations that maximize anomaly score
  - Greedy, iterative search limits combinations explored

Step 1: All flows

Step 2: Remove all flows that match Signature1. Repeat.



Indict path with highest anomaly score

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Rank Problems by Severity

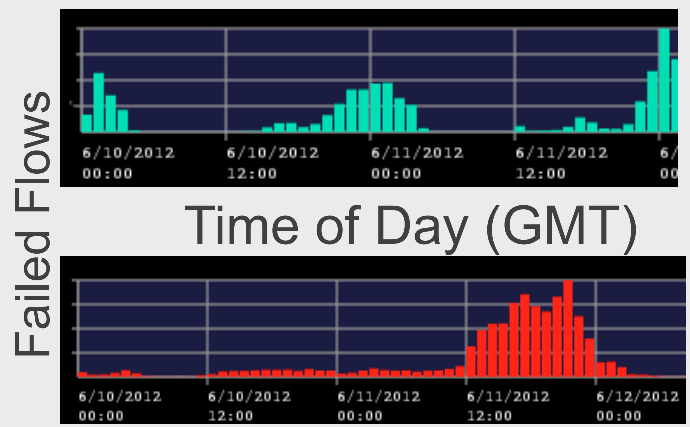
STEP 3: Rank list of identified problems by severity

- Rank problems based on number of flows affected
  - Spurious attributes introduced by noise receive low-rank

UI: Ranked list of chronics identified

1. Chronic signature1
`Server8`
`BlockRead`

2. Chronic signature2
`Server64`



Visualization allows operators to identify recurrent problems

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Fusing Black-box Metrics

STEP 4: Determine if resource-usage metrics affected

Annotate flows associated with culprit nodes (and peers)

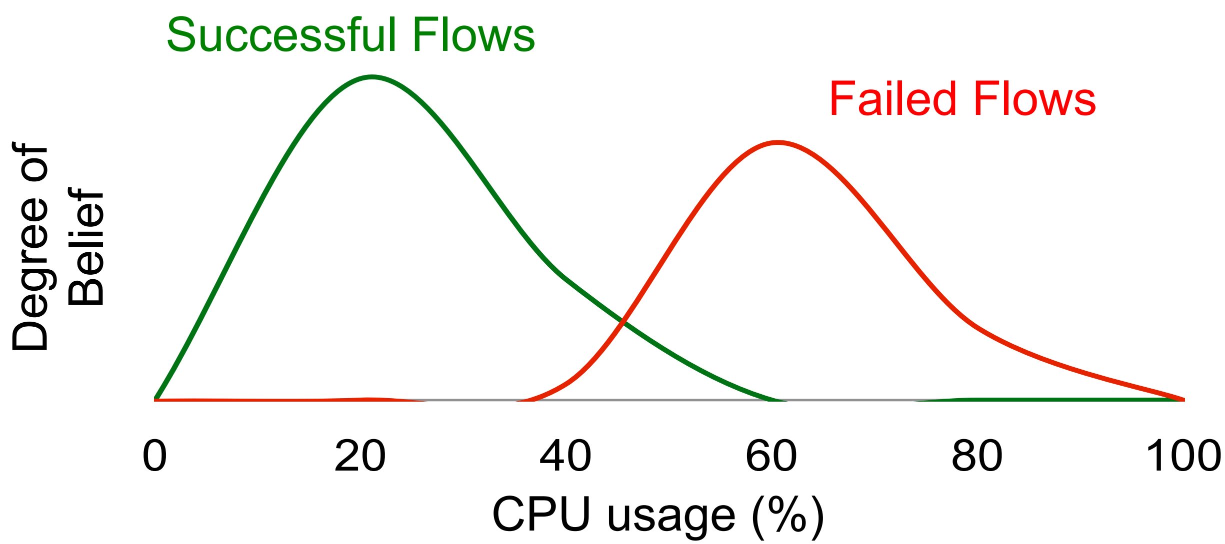
Culprit Node	Peer	Peer
Server 8	**Server 10**	**Server 13**
Time: 10:03:59, Map ID: task_188_m_98 Bytes Read: 7867 Duration: 25 seconds Status: FAILED	Time: 10:03:59, Map ID: task_188_m_76 Bytes Read: 7867 Duration: 3 seconds Status: SUCCESS	Time: 10:03:59, Map ID: task_188_m_85 Bytes Read: 6863 Duration: 2 seconds Status: SUCCESS
Mean CPU: 70.4% Mean Memory: 500MB Mean DiskUtil: 30KB	Mean CPU: 12.4% Mean Memory: 430MB Mean DiskUtil: 32KB	Mean CPU: 15.4% Mean Memory: 480MB Mean DiskUtil: 23KB

Mean resource-usage on node during event duration

Culprit Black-Box Metrics

STEP 4: (contd)

Compare distribution of each black-box metric for successful/failed flows



Indict metric if difference between distributions is statistically significant

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Experimental Evaluation

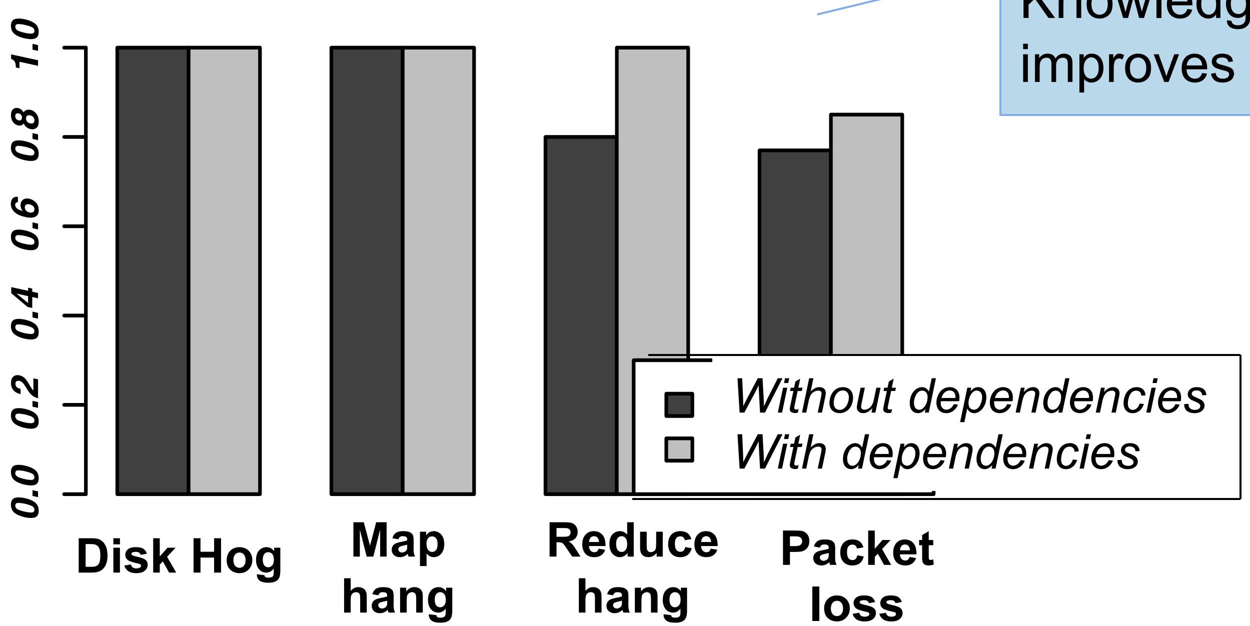
		HADOOP	VOIP
FAULT INJECTION	Workload	Gridmix cluster benchmark	One-week of ISP's call logs
	Injected faults	Resource hogs/Task hangs 10 iterations per fault	Server/Customer problems 1000 simulated faults in total
	Experimental setup	10-node EC2 cluster 2 1.2GHz cores, 7GB RAM	1 simulation node 2 2.4GHz cores, 16GB RAM
CASE STUDIES	Production Sytem	OpenCloud	Production VoIP system at ISP
	Status	Post-mortem offline analysis of real incidents	Used in production for 2 years since 2011

Expt #1: Impact of Dependencies

QUESTION: Does knowledge of dependencies affect diagnosis?

METHOD: Hadoop EC2 cluster, 10 nodes, fault injection.

- Apply problem localization with white-box metrics.
- Compare against approach without knowledge of dependencies.



Knowledge of dependencies improves diagnosis

Expt #2: Impact of Fusion

QUESTION: Does fusion of metrics provide insight on root-cause?

METHOD: Hadoop EC2 cluster, 10 nodes, fault injection.

- Apply problem localization with fused white/black-box metrics.

	Top Metrics Indicted		Insight on root-cause
Fault Injected	**White box**	**Black-box**	
Disk hog	Maps	Disk	✓
Packet-loss	Shuffles	-	✗
Map hang (Hang1036)	Maps	-	✓
Reduce hang (Hang1152)	Reduces	-	✓

Fusion of metrics provides insight on most injected faults

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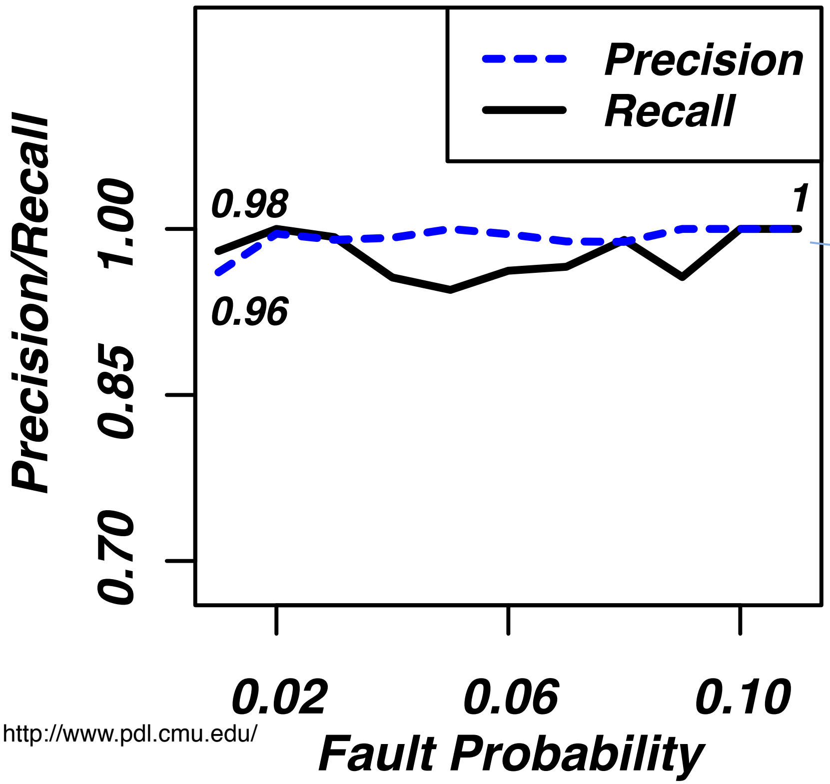
Expt #3: Impact of Fault Probability

QUESTION: Can we effectively diagnose low-probability faults?

METHOD: One week of ISP's call logs, 1 node, fault simulation.

- Randomly label 1-10% of flows with attributes of interest as faulty.
- Apply problem localization with white-box metrics.



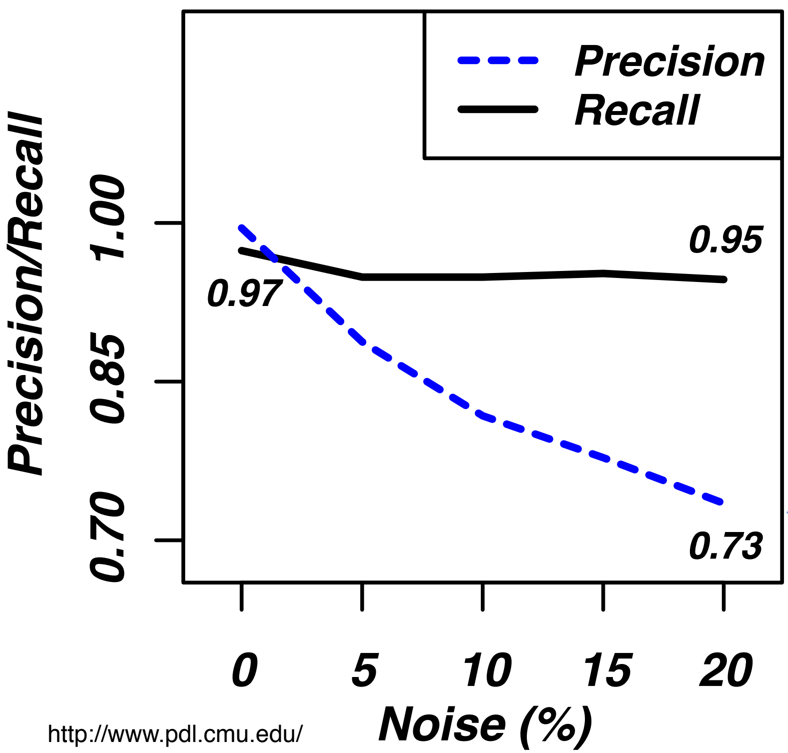
Robust to changes in fault probability

Expt #4: Impact of Noise

QUESTION: Does flawed anomaly-detection (noise) impact diagnosis?

METHOD: One week of ISP's call logs, 1 node, fault simulation.

- Mislabel 5-20% of failed flows.
- Apply problem localization with white-box metrics



Recall robust to noisy labels.

Precision drops due to spurious attributes.

Case #1: Multiple Hardware Issues

INCIDENT: Multiple hardware problems in OpenCloud cluster

- User experiences multiple job failures with cryptic exceptions.
- Administrators initially suspected memory configuration issue.
- Took a week to resolve. Bad disk and bad NIC on two nodes.

DIAGNOSIS APPLIED

- Apply problem-localization approach with white-box metrics.
- Correctly identified nodes with bad hardware in top-10 ranked list

Identified multiple simultaneous problems affecting user's job.

Case #2: Quality (QoS) Violations

INCIDENT: Calls in VoIP system experiencing high packet-loss

- Operators suspect issue with network elements at ISP.
- Took a weeks to resolve.

DIAGNOSIS APPLIED

- Flag calls whose packet-loss exceeds 85th percentile as faulty.
- Apply problem-localization approach with white-box metrics.
- Showed most QoS issues were tied to specific customers.

Operators alerted customers' of problem on their site.
Customer fixed problem and QoS violation resolved.

Case #3: Performance Problem

INCIDENT: Intermittent performance problem in VoIP system

- Intermittent performance problem with two application servers.
- Affected 0.1% of all calls passing through application servers.

DIAGNOSIS APPLIED

- Apply problem-localization using white/black-box metrics.
- Post-mortem analysis confirmed issue with application servers.
- Also flagged anomalous CPU and memory usage.

Successfully identified low-severity fault affecting multiple servers.

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Lessons Learned (1)

- Synthesis of end-to-end causal traces possible
  - Local logs capture local control- and data-flow info
  - Approximate-matching infers implicit dependencies
- In absence of labeled data, peer-comparison is feasible approach for anomaly detection
  - Peers can be tasks (Hadoop), end-to-end flows, calls within the same service (VoIP)
- Regression can help to differentiate between
  - Legitimate application behavior (more bytes read/written) vs.
  - Anomalous behavior (task taking longer to run for other unexplained reasons)

Lessons Learned (2)

- Important to analyze both successful and failed flows
  - Limiting analysis to only failed flows might elevate common elements over causal elements
- Fusion of white+black-box data can provide more insight into source of problem
- Ranking problems by severity helps tolerate noise
  - Spurious labels receive lower ranking

Limitations

- No diagnosis for the Master node of a Hadoop cluster
  - Problems at master typically result in system-wide issues
- Peer-groups are defined statically
  - Need to automate identification of peers
- False positives occur if root-cause not in logs
  - Algorithm tends to implicate adjacent network elements
  - Need to incorporate more data to improve visibility
- Does not detect dormant problems that do not impact user-perceived system behavior
  - Examples: Blacklisted nodes in Hadoop

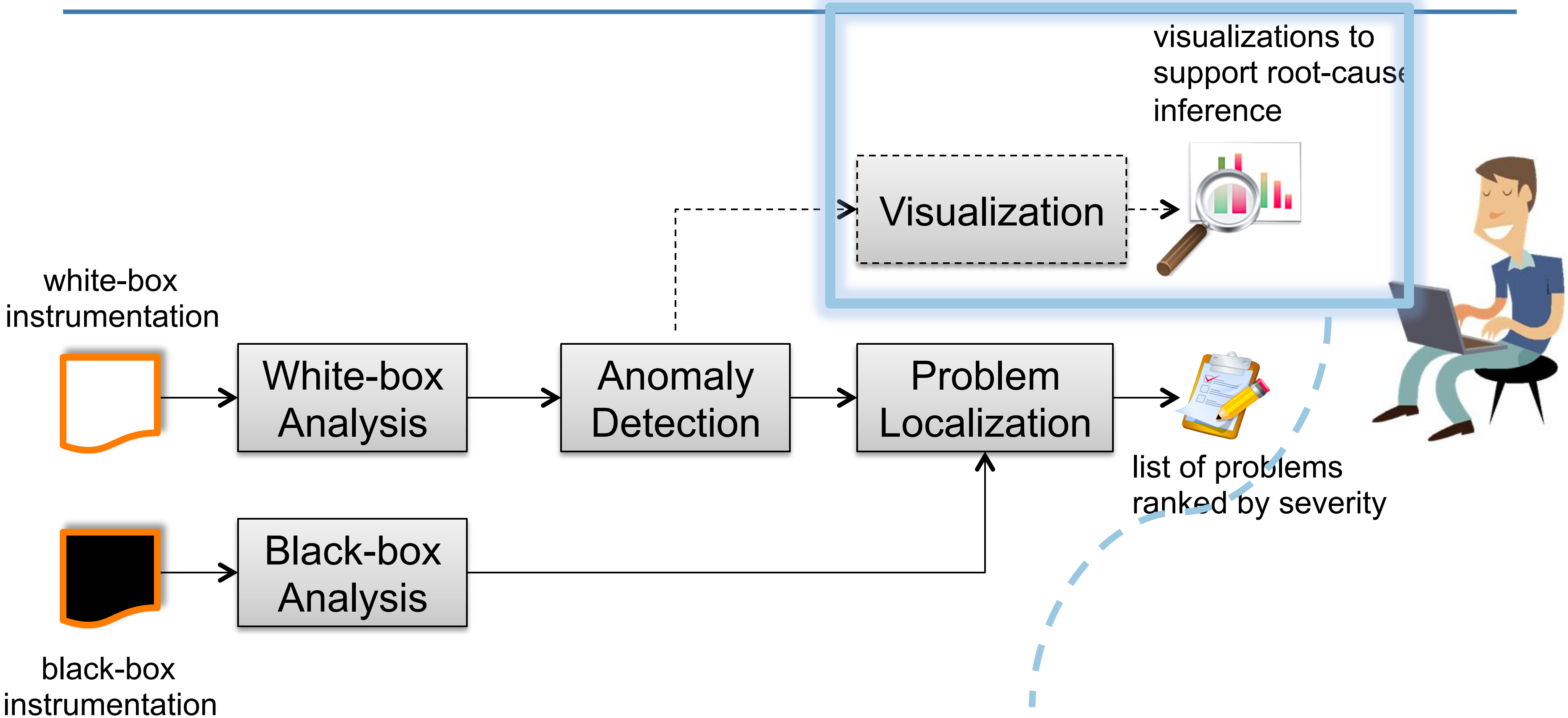
Extensions (Future Work)

- Visualization in heterogeneous systems
  - ✓ User study on diagnosis interfaces in Hadoop [CHIMIT11]
  - ✓ Visual signatures of problems in Hadoop [LISA12]
  - ✗ Visual signatures of problems in heterogeneous systems
  - ✗ Extensible visualization framework for diagnosis

Future Work

- Online monitoring and diagnosis
  - ✓ Generic framework for monitoring and diagnosis [WADS09]
  - ✓ Streaming implementation of problem-localization [DSN12]
  - ✗ Scalable monitoring and diagnostic framework

Visualization

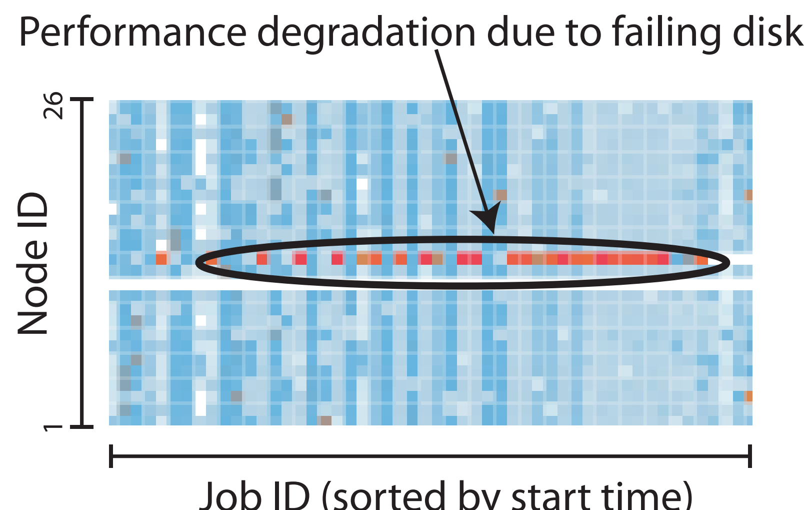


Questions

- How to develop compact visualizations for large clusters?
- Can visualizations help spot/discriminate different anomalies?

Theia: Visual Signatures of Problems

- Maps anomalies observed to broad problem classes
  - Hardware failures, application issue, data skew
- Supports interactive data exploration
  - Users drill-down from cluster- to job-level displays
  - Hovering over the visualization gives more context
- Compact representation for scalability
  - Can support clusters with 100s of nodes



*USENIX LISA 2012 Best Student-Paper Award

Conclusion

- Approach for diagnosis of chronic problems
  - Amenable for use in production systems
  - Infers dependencies from existing white-box logs
  - Uses heuristics and peer-comparison to detect anomalies
  - Localizes source of problem using statistical approach
  - Incorporates both white-box and black-box logs
- Demonstrated for two production systems
  - VoIP system at ISP (approach deployed for 2 years now)
  - OpenCloud Hadoop cluster
- Initial progress on extensions (visualization)

Collaborators & Thanks

- VoIP (AT&T)
  - **Matti Hiltunen**, Kaustubh Joshi, Scott Daniels
- Hadoop visualization
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- OpenCloud
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- Hadoop diagnosis
  - Jiaqi Tan, Xinghao Pan, Rajeev Gandhi, Keith Bare, Michael Kasick, Eugene Marinelli

Publications (1)

Diagnosis in VoIP

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Visualization, User studies, Surveys

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Questions?


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