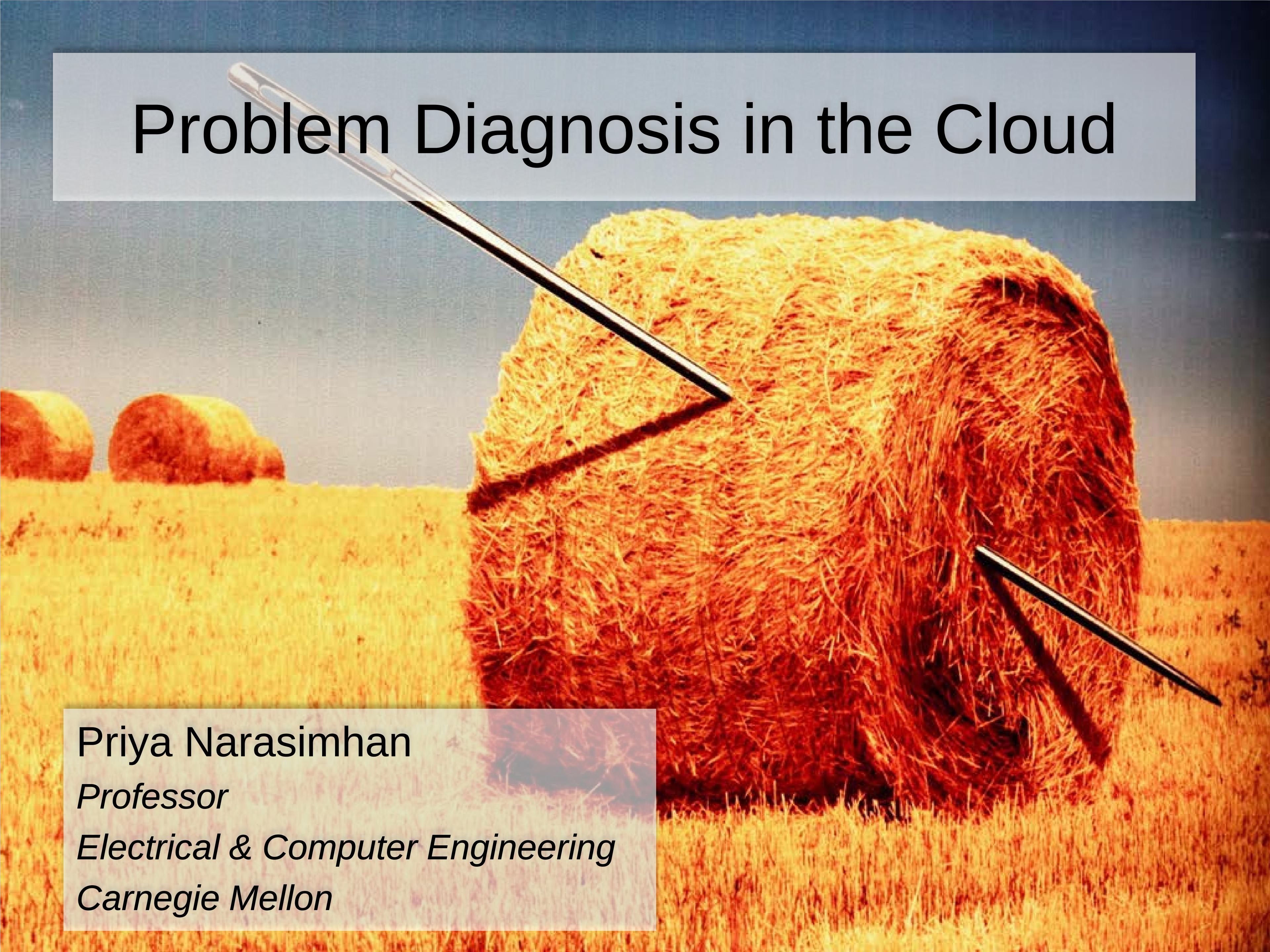

Problem Diagnosis in the Cloud

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Motivation

- Diagnosing problems
  - Creates major headaches for administrators
  - Worsens as scale and system complexity grows

- Goal: automate it and get proactive
  - Failure detection and prediction
  - Problem determination ("automated fingerpointing")
  - Problem visualization

- How: Instrumentation plus statistical analysis

Explorations

- Current explorations
  - *Hadoop*
    - [HotCloud 09, HotMetrics 09, WASL 08, SysML 08, NOMS 10, ISSRE 09, CCGrid 10, ICDCS 10, USENIX LISA 12, ICAC 13]
  - *PVFS*
    - High-performance file system (Argonne National Labs) [FAST 10]
  - *Lustre*
    - High-performance file system (Sun Microsystems) [FAST 10]

- Studied
  - Various types of problems
  - Various kinds of instrumentation
  - Various kinds of data-analysis techniques
  - Various kinds of visualization

Goals & Non-Goals

- Diagnose faulty Master/Slave node to user/admin
- Target production environment
  - Don't instrument Hadoop or applications additionally
  - Use Hadoop logs as-is (*white-box strategy*)
  - Use OS-level metrics (*black-box strategy*)
- Work for various workloads and under workload changes
- Support online and offline diagnosis
- Enable visualization of job progress for root-cause analysis

- Non-goals (for now)
  - Tracing problem down to offending line of code
  - Diagnosis of value faults

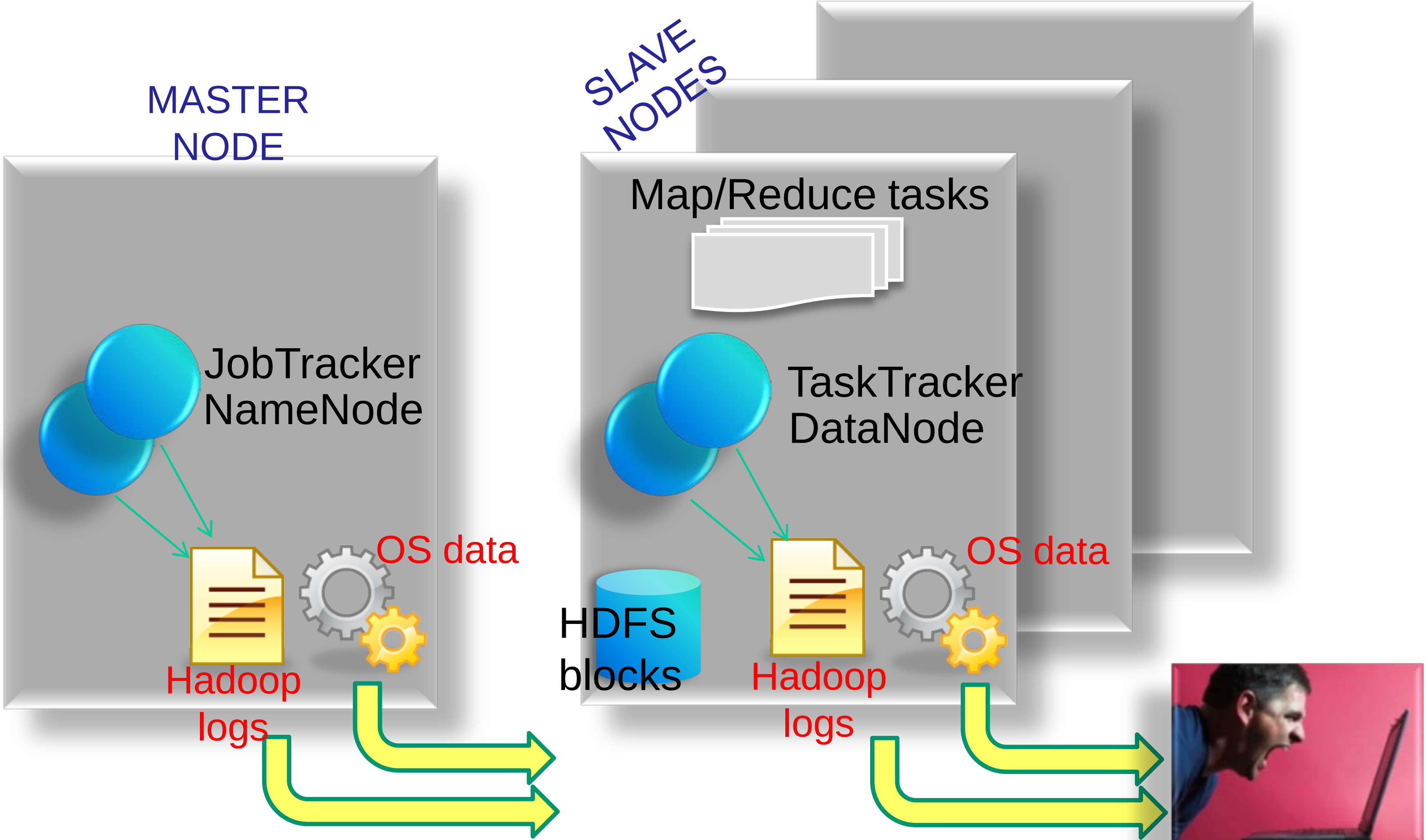
Target Hadoop Clusters

- Yahoo!'s M45 cluster
  - Production environment (managed by Yahoo!)
  - Offered to CMU as free cloud-computing resource
  - Diverse kinds of real workloads, problems in the wild
    - Massive machine-learning, language/machine-translation
  - Permission to harvest all logs and OS data each week
- Amazon's EC2 cluster
  - Production environment (managed by Amazon)
  - Commercial, pay-as-you-use cloud-computing resource
  - Workloads under our control, problems injected by us
    - gridmix, nutch, pig, sort, randwriter
  - Can harvest logs and OS data of only our workloads

Performance Problems Studied

	Fault	Description
Resource contention	CPU hog	External process uses 70% of CPU
	Packet-loss	5% or 50% of incoming packets dropped
	Disk hog	20GB file repeatedly written to
	Disk full	Disk full
Application bugs Source: Hadoop JIRA	HADOOP-1036	Maps hang due to unhandled exception
	HADOOP-1152	Reduces fail while copying map output
	HADOOP-2080	Reduces fail due to incorrect checksum
	HADOOP-2051	Jobs hang due to unhandled exception
	HADOOP-1255	Infinite loop at Nameode

Hadoop: Instrumentation



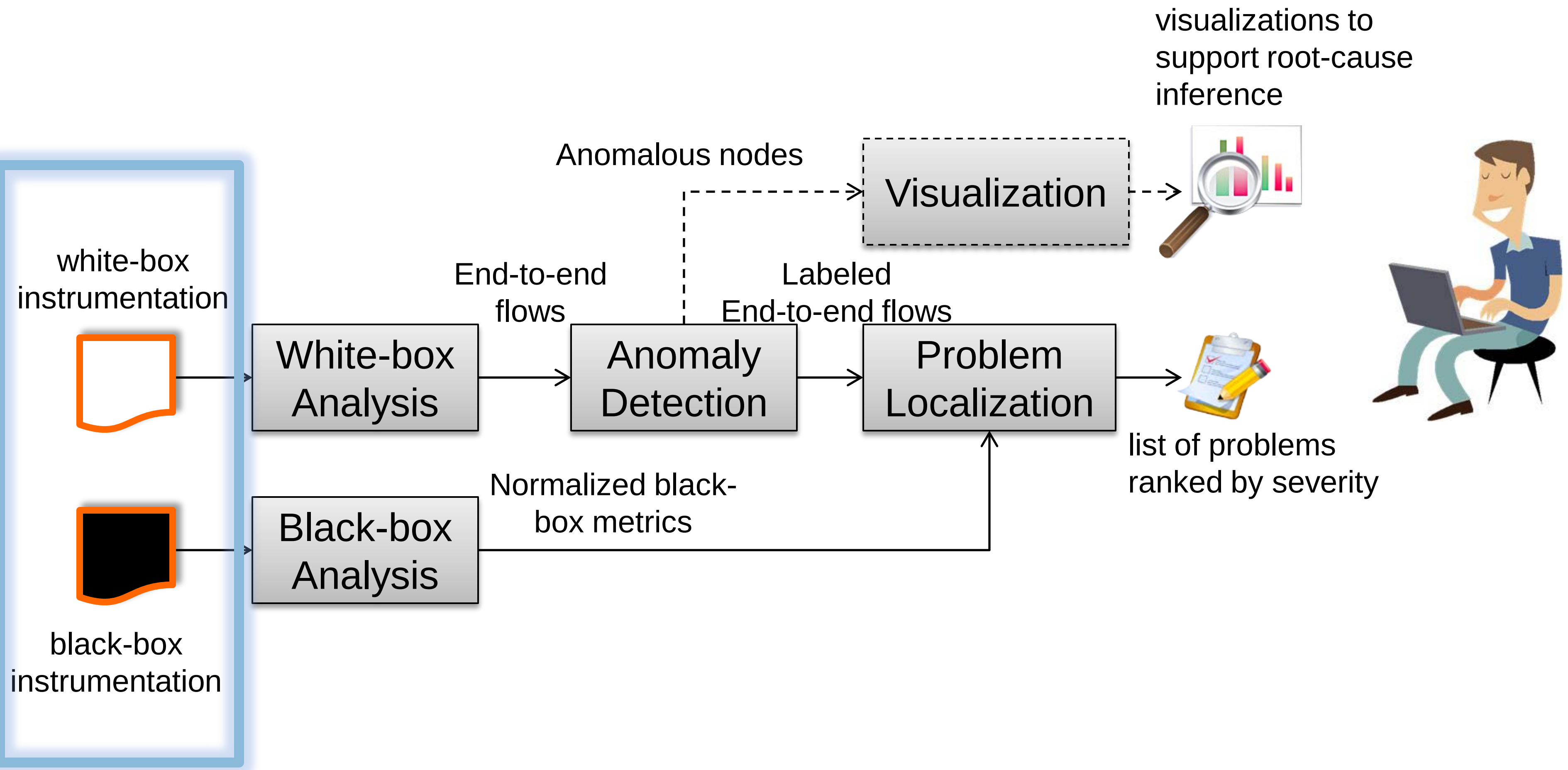
Intuition for Diagnosis

- One initial algorithm (now others underway)
- Slave nodes are doing *approximately similar* things for a given job
- Gather metrics and extract statistics
  - Determine metrics of relevance
  - For both black-box and white-box data
- Peer-compare histograms, means, etc. to determine "odd-man out"
- Extensions now to cover heterogeneity

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

Overview of Approach

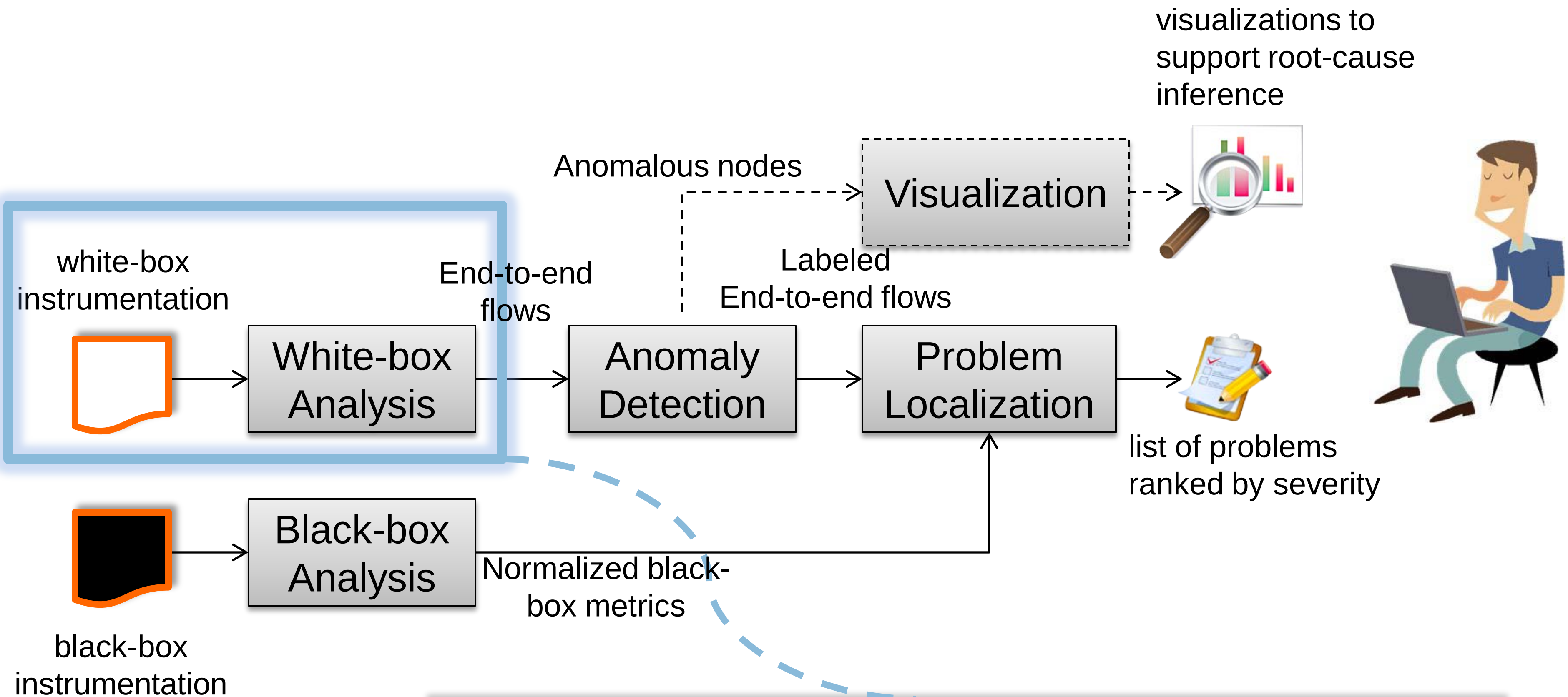


How About Those Metrics?

- White-box metrics (from Hadoop logs)
  - Event-driven (based on Hadoop's activities)
  - *Durations*
    - Map-task durations, Reduce-task durations, ReduceCopy-durations, etc.
  - System-wide dependencies between tasks and data blocks
  - Heartbeat information: Heartbeat rates, Heartbeat-timestamp skew between the Master and Slave nodes

- Black-box metrics (from OS /proc & Ganglia)
  - 64 different time-driven metrics (sampled every second)
  - Memory used, context-switch rate, User-CPU usage, System-CPU usage, I/O wait time, run-queue size, number of bytes transmitted, number of bytes received, pages in, pages out, page faults

White-Box Analysis



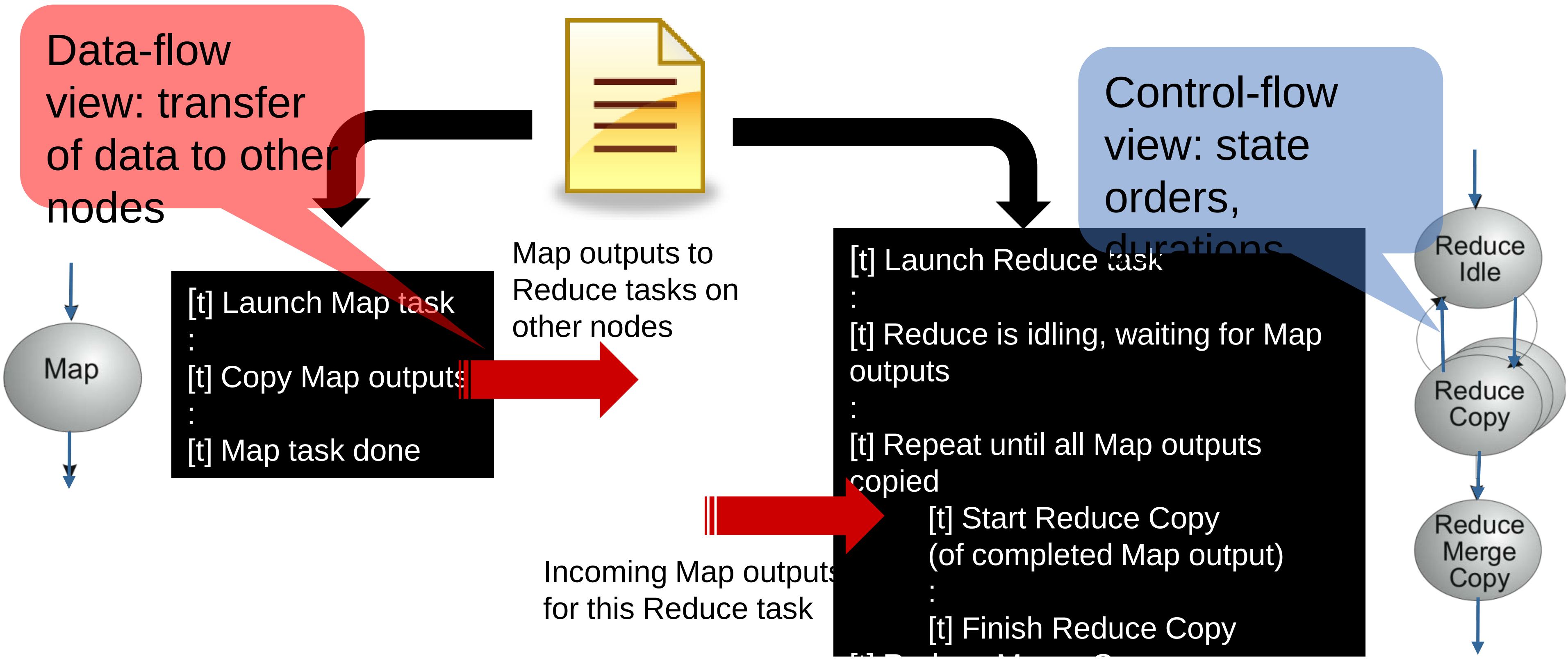
Questions

- 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 Analysis

- SALSA: Analyzing Logs as StAte Machines [*USENIX WASL 2008*]
- Extract state-machine views of execution from Hadoop logs
  - Distributed control-flow view of logs
  - Distributed data-flow view of logs
- Diagnose failures based on statistics of these extracted views
  - Control-flow based diagnosis
  - Control-flow + data-flow based diagnosis
- Perform analysis incrementally so that we can support it online a

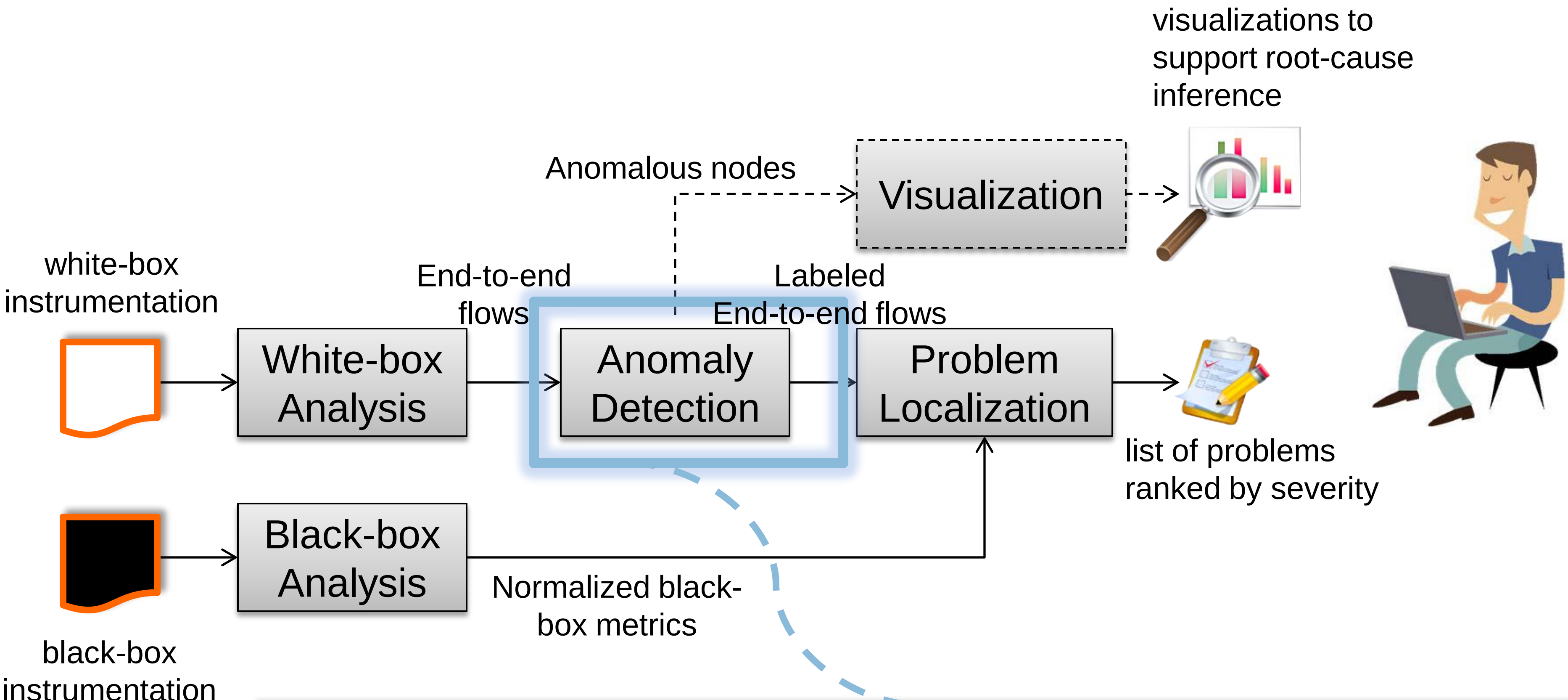
White-Box Analysis for Hadoop



Distributed Control+Data Flow

- Distributed control-flow
  - Causal flow of task execution across cluster nodes, i.e., Reduces waiting on Maps via Shuffles
- Distributed data-flow
  - Data paths of Map outputs shuffled to Reduces
  - HDFS data blocks read into and written out of jobs
- Job-centric causal flow: Fused Control+Data Flows
  - Correlate paths of data and execution
  - Create conjoined causal paths from data source before, to data destination after, processing

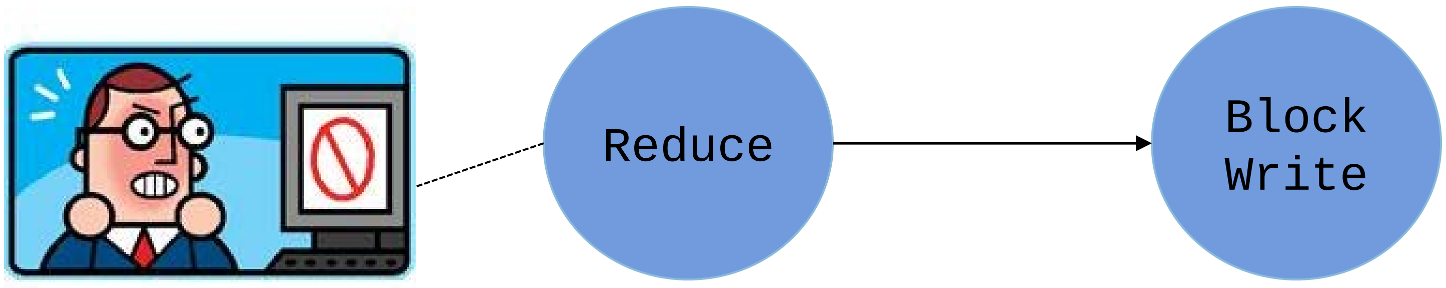
Anomaly Detection



Questions

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

Anomaly Detection



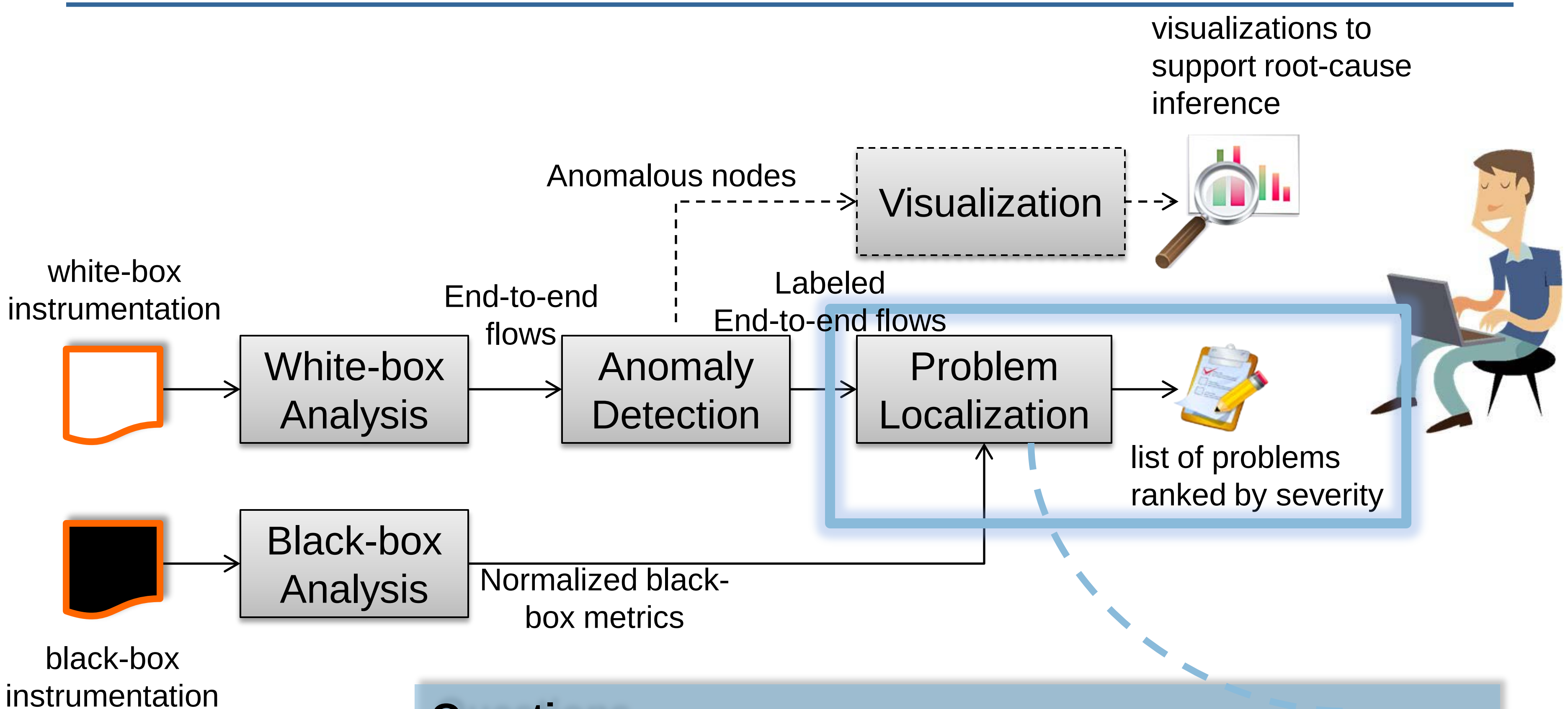
- Some user-visible problems manifest as errors
  - Detected by extracting error codes from failed flows, or
  - Apply domain-specific heuristics
- Performance problems can be harder to detect
  - Exploit the notions of “peers” to detect performance problems
  - Determine what system behaviors can be 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 (1)

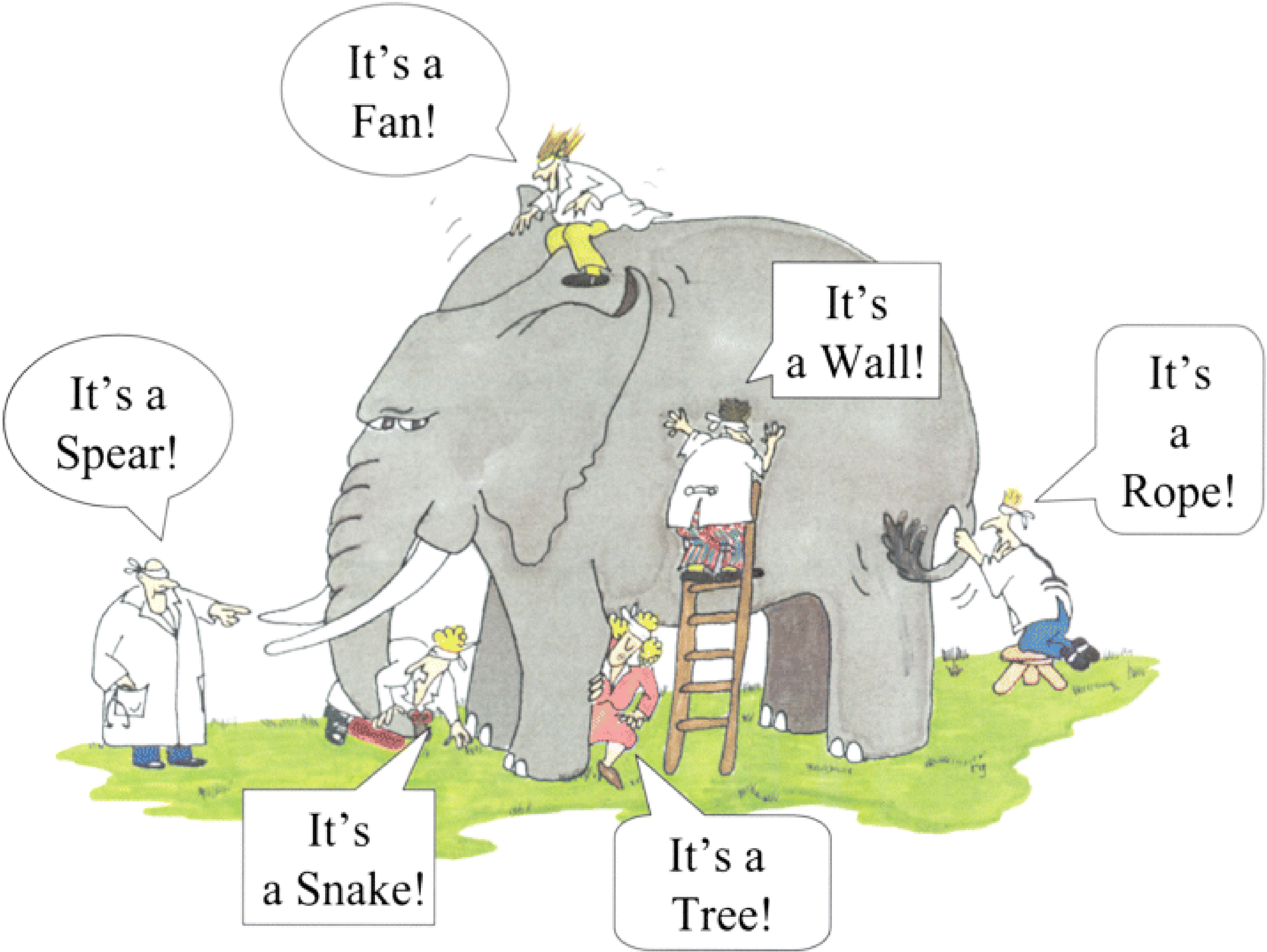
- Detect performance problems using “peers”
  - Empirical analysis of production data to identify peers
    - 219,961 successful jobs (Yahoo! M45 and OpenCloud)
    - 89% of jobs had low variance in their Map durations
    - 65% of jobs had low variance in their Reduce durations
  - Designate tasks belonging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

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?


It's a Fan!
It's a Spear!
It's a Wall!
It's a Rope!
It's a Snake!
It's a Tree!

Fusing the Metrics

JobTracker Durations views

TaskTracker Durations views

Job-centric data flows

TaskTracker heartbeat timestamps

JobTracker heartbeat timestamps

Black-box resource usage

Fusing Black-box Metrics

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

Experimental Evaluation

		HADOOP
FAULT INJECTION	Workload	Gridmix cluster benchmark
	Injected faults	Resource hogs/Task hangs 10 iterations per fault
	Experimental setup	10-node EC2 cluster 2 1.2GHz cores, 7GB RAM
CASE STUDIES	Production Sytem	OpenCloud
	Status	Post-mortem offline analysis of real incidents

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

Case: 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.

Lessons Learned (1)

- Synthesis of end-to-end causal traces possible
  - Local logs capture local control- and data-flow info
  - Inferring implicit dependencies
- In absence of labeled data, peer-comparison is feasible approach for anomaly detection
  - Peers can be tasks (Hadoop), end-to-end flows
- 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

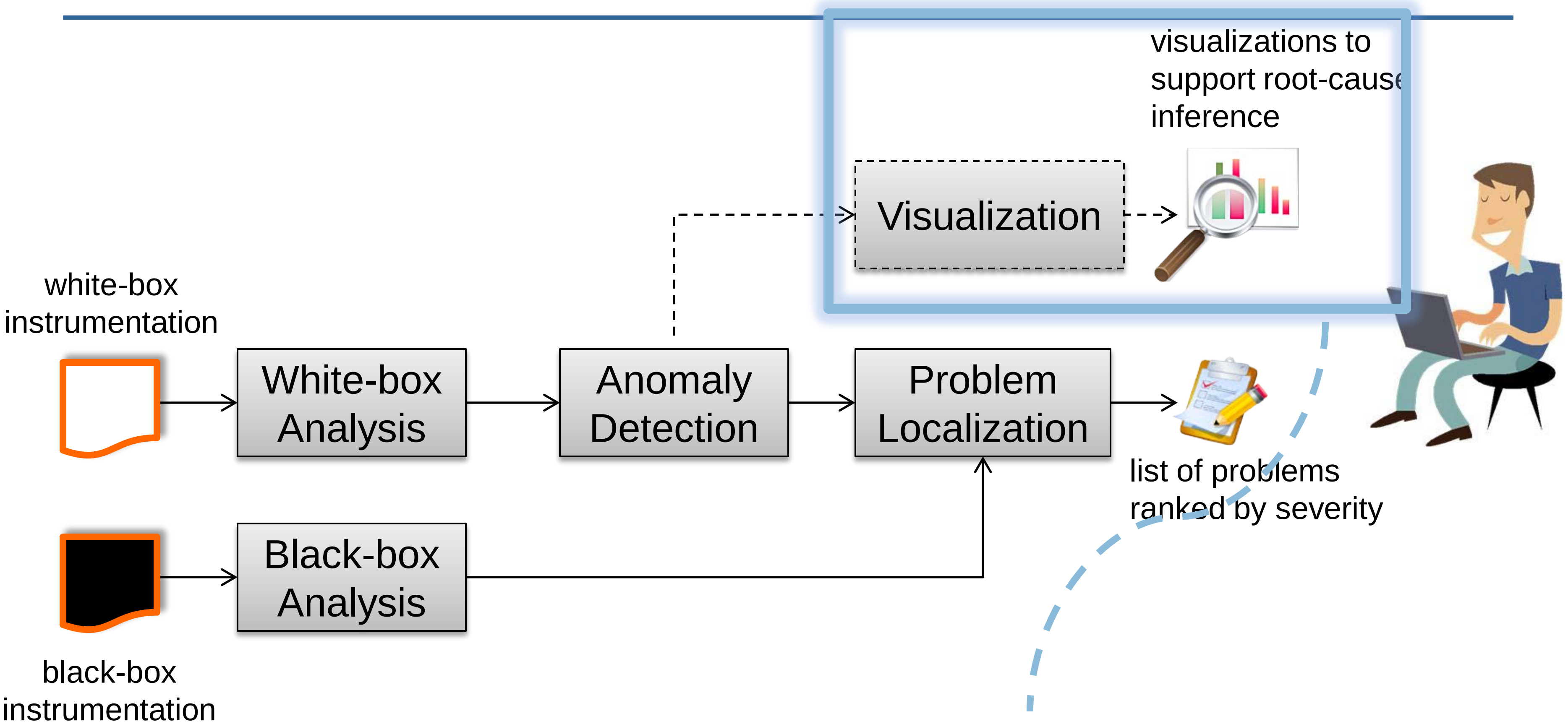
Extensions (Future Work)

- 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

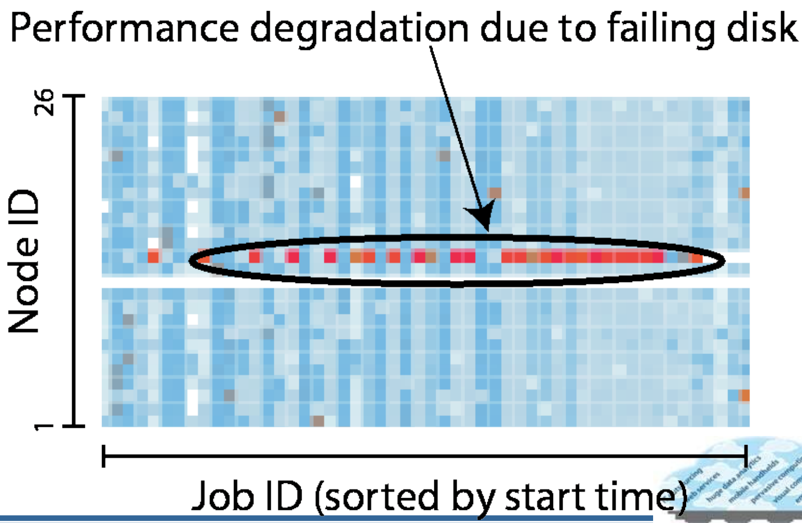
Visualization



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 performance 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)

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Publications (2)

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Students

- Soila Kavulya – now at Intel Labs
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- Nathan Mickulicz
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- Mike Kasick – graduating early 2014
- Rolando Martins – post-doctoral researcher