<u>SALSA: Analyzing Logs as</u> <u>StAte Machines</u>

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PARALLEL DATA LABORATORY

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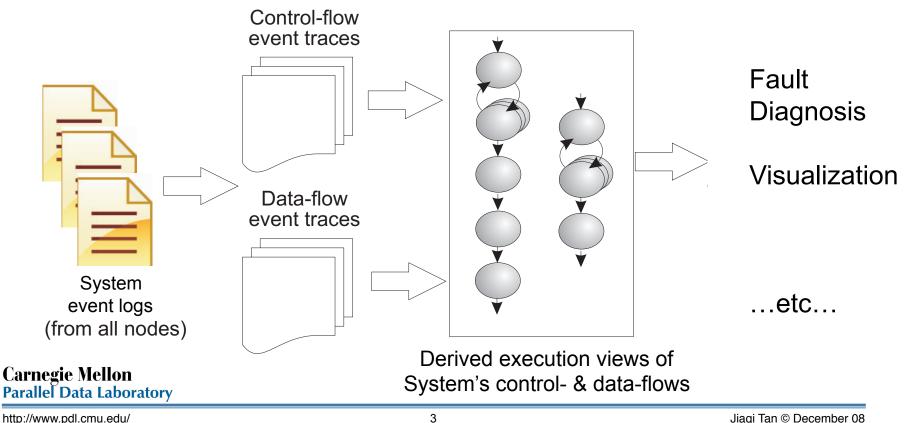
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Motivation

- Ubiquitous, rich logs
 - Many software systems generate logs
 - Semantically-rich data, but difficult to analyze: Typically unstructured text
- Current techniques
 - Study statistical properties of log events
 - Adds little application semantics to analysis
- Want to incorporate semantics in analysis

SALSA

- General technique to extract execution views from system event logs
- Execution structure: *a priori* knowledge



Outline

- SALSA: Log Analysis Technique
- Applying SALSA: Analyzing Hadoop Logs
- Use-case 1: Visualization
- Use-case 2: Diagnosis

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SALSA: State Extraction (1)

- Technique to extract state-machine views from logs
- Assumptions :
 - System has multiple concurrent, activities
 - Each activity emits log messages
 - Consider tasks as producers and consumers

- Extracts control-flow and data-flow views of execution
- Sample idealized log:

```
[ t1 ] Begin Task P1
[ t2 ] Begin Task C1
[ t3 ] Task P1 does some work
[ t4 ] Task C1 waits for data from
P1 and P2
[ t5 ] Task P1 produces data
[ t6 ] Task C1 consumes data from
P1 on host X
[ t7 ] Task P1 ends
[ t8 ] Task C1 consumes data from
P2 on host Y
[ t9 ] Task C1 ends
```

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SALSA: State Extraction (2)

- Model control-flow: states extracted from log messages
 - Interpret each log message as an event
 - Impose semantics: Interpret events as starts/ends of execution states

```
[ t1 ] Begin Task P1
[ t2 ] Begin Task C1
[ t3 ] Task P1 does some work
[ t4 ] Task C1 waits for data from
P1 and P2
[ t5 ] Task P1 produces data
[ t6 ] Task C1 consumes data from P1
on host X
[ t7 ] Task P1 ends
[ t8 ] Task C1 consumes data from P2
on host Y
[ t9 ] Task C1 ends
```

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SALSA: State Extraction (3)

- Model data-flow:
 - Extract producerconsumer interactions
 e.g. when log messages indicate source for consumer
- [t2] Begin Task C1 [t3] Task P1 does some work [t4] Task C1 waits for data from P1 and P2 [t5] Task P1 produces data [t6] Task C1 consumes data from P1 on host X [t7] Task P1 ends [t8] Task C1 consumes data from P2 on host Y [t9] Task C1 ends

t1 | Begin Task P1

 Can extract internode data-flows

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http://www.pdl.cmu.edu/

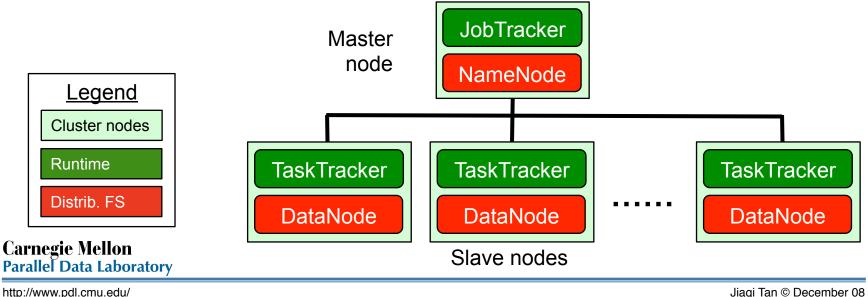
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Outline

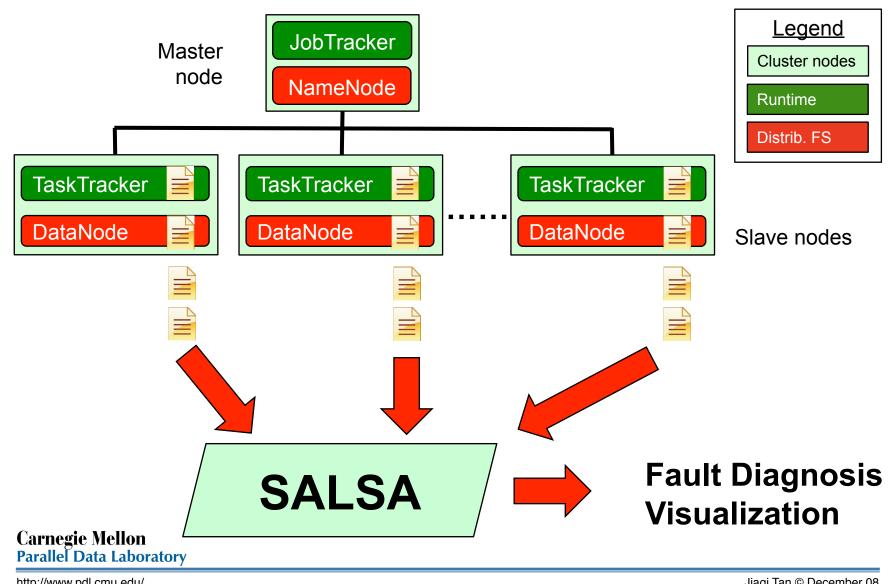
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Architecture of Hadoop

- MapReduce Runtime + Distributed Filesystem
- Master/Slave architecture
- Focus on slave node logs:
 - One log for each TaskTracker and DataNode
- Logs record processing activities



SALSA for Hadoop



Hadoop-specific Semantics

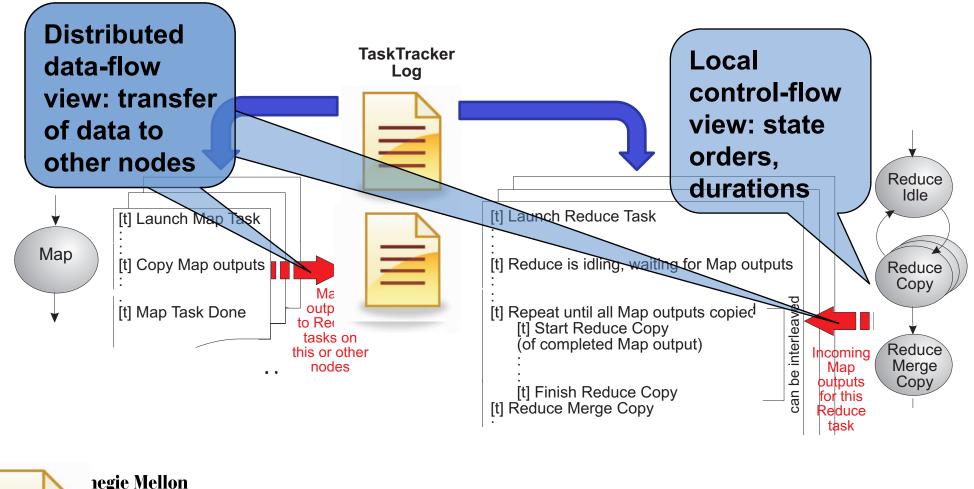
- Identify events from log messages
 - Match tokens in message
- Map events to starts/ends of execution states
 - Using mapping from *a priori* knowledge, e.g.:

Activity/State	Start Token	End Token
Мар	LaunchTaskAction [MapID]	Task [MapId] is done.
ReduceCopy	[ReduceID] Copying [MapID] output from [Hostname]	[ReduceID] done copying [MapID] output from [Hostname].

- Inputs: Hadoop application semantics
 - Message token \rightarrow event mapping
 - Event \rightarrow State start/end mapping

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Applying SALSA to Hadoop



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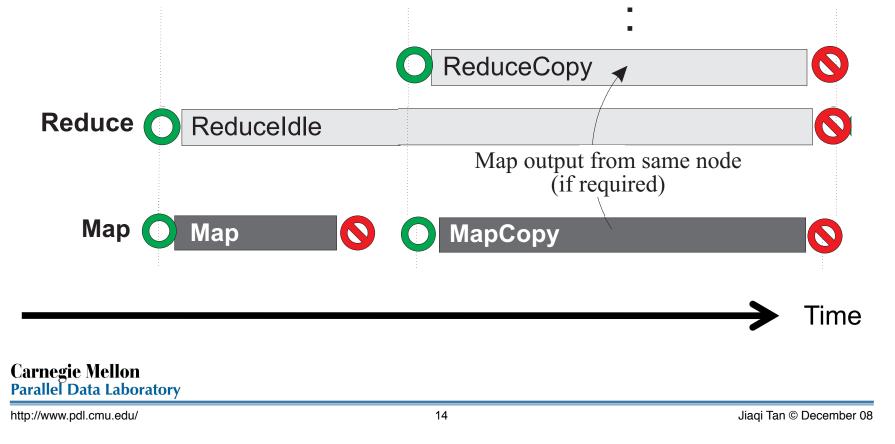
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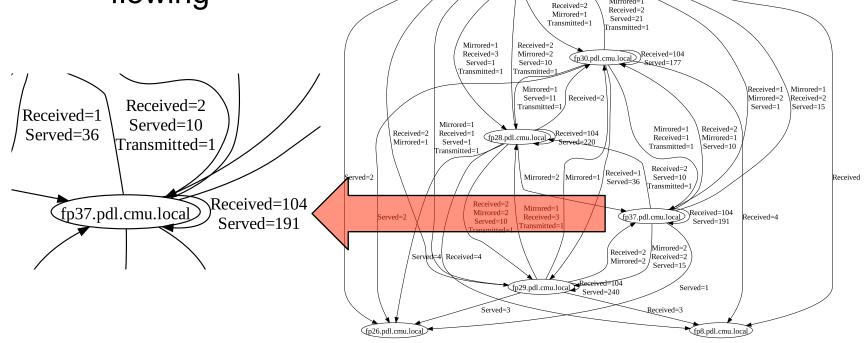
Control-flow Visualization

- Modeled execution of Hadoop TaskTracker: state machine view of logs
- · Can be augmented to show data-flows



Data-flow Visualization

- Aggregate DataNode data-flows
 - Each node: one DataNode
 - Each edge: annotated with number of blocks
 flowing



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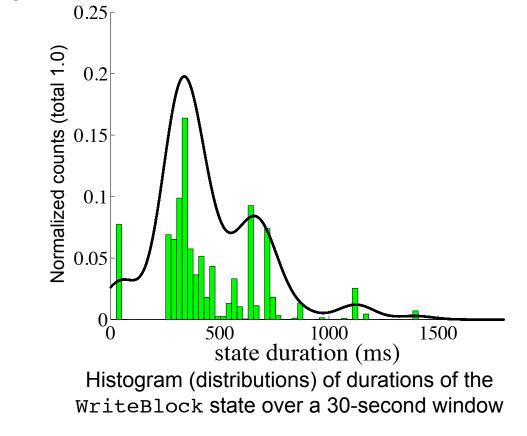
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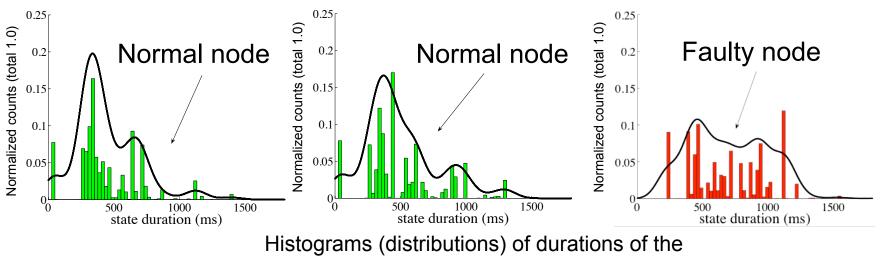
Durations of States

• Expressing aggregate control-flow: Build a histogram of state-durations for each node



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Intuition: Peer Comparison



WriteBlock state over a 30-second window

- In fault-free conditions, durations of a state are similar across nodes
- Faulty nodes: durations of the state are different than non-faulty nodes

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Diagnosis Algorithm

- Diagnosis metrics: State durations of:
 - TaskTracker: Map, ReduceMergeCopy
 - DataNode: ReadBlock, WriteBlock
- Build a histogram of durations per node
 - One histogram in every window
- Compare histograms across nodes
 - Compute statistical measure of distance (Jensen-Shannon Divergence) between histograms
 - Indict nodes whose histograms have distances greater than threshold to more than half the other nodes

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Experimentation

- Hadoop 0.12.3 cluster
 - 5-slaves, 1-master, identically configured nodes
- Workloads:
 - RandWriter: writes 32GB random data to disk
 - Sort: sorts 3GB of records of random data
 - Nutch: distributed web crawler for Hadoop
- Data Collection
 - Hadoop logs harvested and processed offline
- Faults Injected: External resource hogs
 - Disk Hog, CPU Hog

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Selected Diagnosis Results

- Different states effective at diagnosing different classes of faults
 - Dependent on type of activity of state
- Map state: effective for CPU and Disk Hogs
 - (TP > 0.8, FP < 0.25)
- ReduceMergeCopy: primarily disk activity
 - Disk Hog: TP = 1.0, FP < 0.05

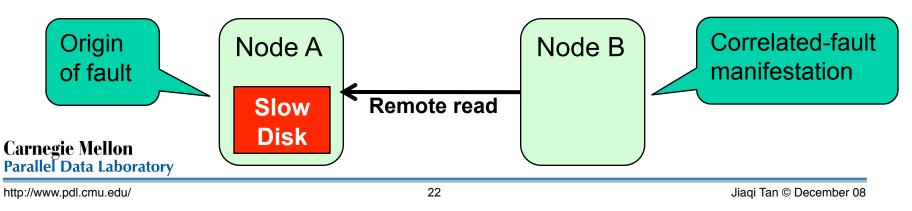
- Less effective on CPU-related issues

• CPU Hog: TP > 0.3, FP < 0.15

Carnegie Mellon Parallel Data Laboratory TP = True-positive rate [0.0,1.0] FP = False-positive rate [0.0,1.0] Perfect diagnosis: TP=1.0, FP=0.0

Correlated Fault-Manifestations

- Correlated fault-manifestations
 - Fault originates on one node
 - Other non-faulty nodes exhibit manifestations
 - Symmetric behavioral change: need technique other than peer-comparison
- Example: Disk Hog injected on one node
 - Reads from affected node slowed down
 - Show up as slower reads on other nodes

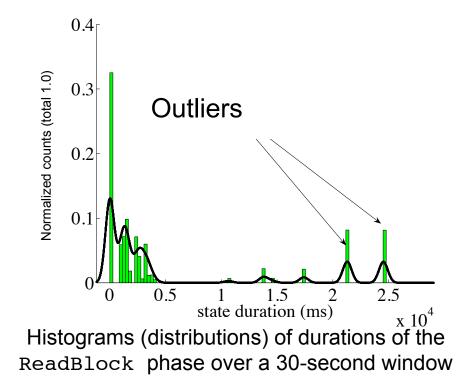


Data-flow Augmented Diagnosis

- Key idea:
 - Non-faulty nodes must somehow interact with faulty node for fault-manifestation to spread
- SALSA extracts data-flow from logs
- Localizing correlated fault-manifestations
 - Compare node's histogram of phase durations with its own past histograms
 - Identify outliers in current histogram
 - If majority of outlier phases associated with single node, indict that node

Historical Comparison

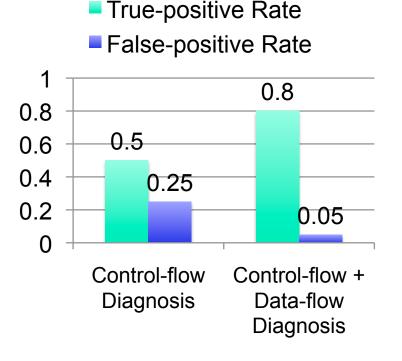
- Detect outlier phases as compared to past
- Indict node associated with many outliers



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Correlated Fault-Manifestation: Results

 Improved Disk Hog diagnosis using ReadBlock on Sort workload



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Summary

- SALSA: Log Analysis Technique
 - Extract state-machine views of execution
 - Augment analysis with application semantics
 - Provides control-flow and data-flow views
- Applying SALSA: Analyzing Hadoop Logs
- Use-case 1: Visualization
- Use-case 2: Diagnosis
 - Peer comparison of state durations for Hadoop
 - Detected resource hogs
 - Detected source of correlated-fault manifestation

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Reaching us

- Our Hadoop diagnosis efforts:
 - ASDF: Automated, Online Fingerpointing for Hadoop: CMU-PDL-08-104
 - Ganesha: Black-box Fault Diagnosis for MapReduce Environments: CMU-PDL-08-112, Also a poster at SysML '08: Come talk to us!
 - SALSA: Analyzing Logs as State Machines: Longer version as CMU-PDL-08-111
- My email: jiaqit at andrew dot cmu dot edu
- Our website: http://www.ece.cmu.edu/~fingerpointing

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