In-situ MapReduce for Log Processing

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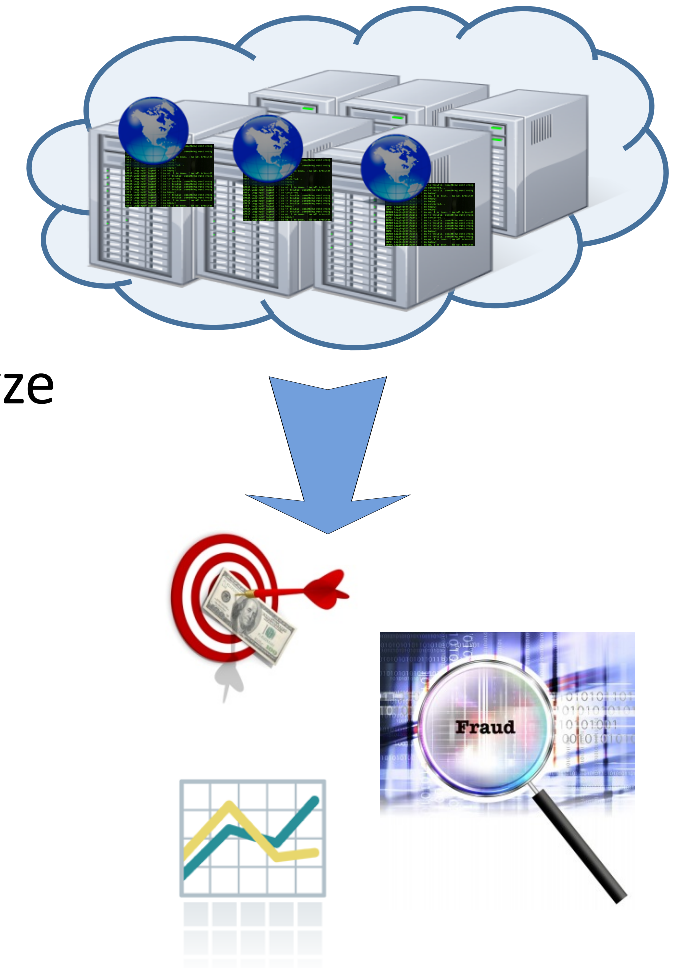
Log analytics

- Data centers with 1000s of servers
- Generating logs with valuable information



- Data-intensive computing: Store and analyze TBs of logs

Examples:

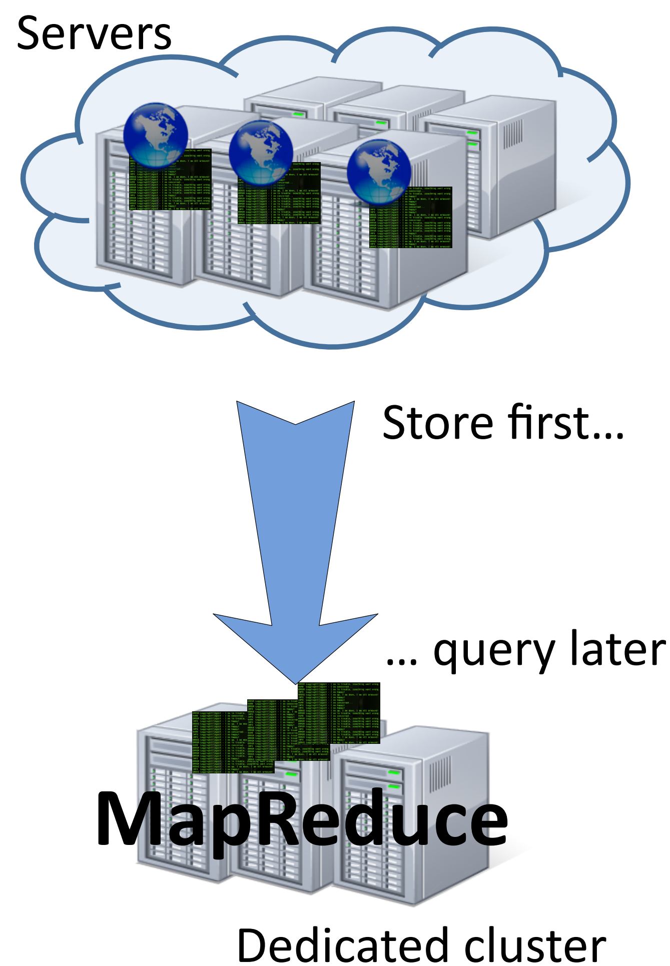
- Click logs: ad-targeting, personalization
- Social media feeds: brand monitoring
- Purchase logs: fraud detection
- System logs: anomaly detection, debugging

Log analytics today

- "Store-first-query-later"
  - Migrate logs to dedicated clusters

Problems:

- Scale
  - e.g. Facebook collects 100TB a day!
  - Data migration stresses network and disks
- Failures
  - e.g. server is unreachable
  - Delay analysis or process incomplete data
- Timeliness
  - e.g. long data migration times
  - Hinders real-time apps: ad-targeting, fraud detection



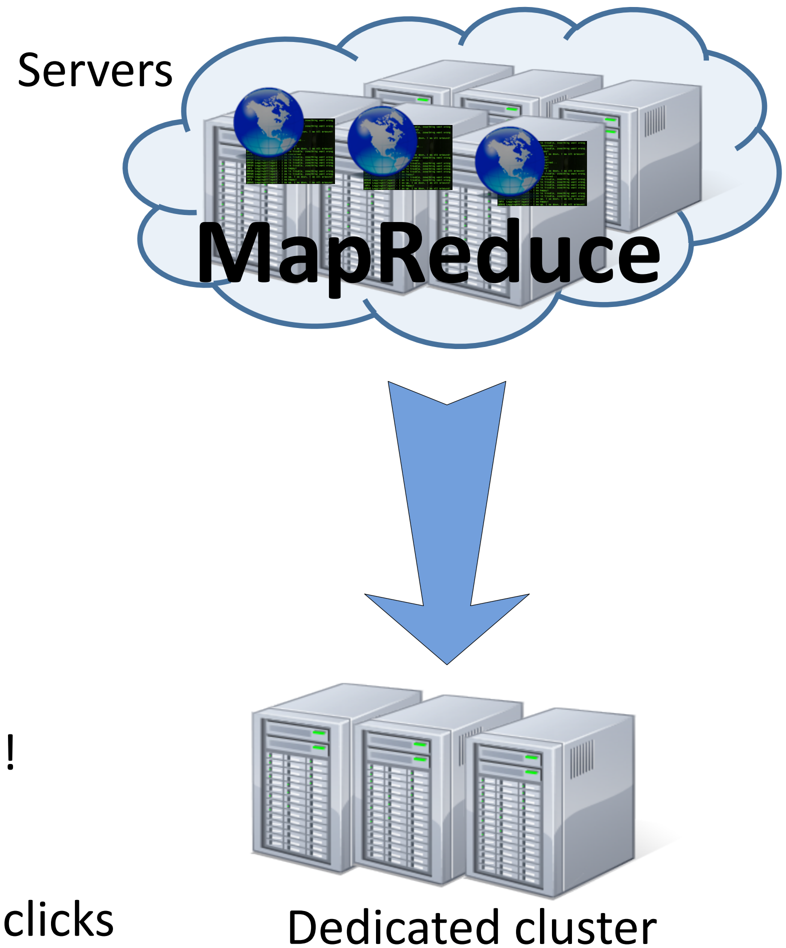
In-situ MapReduce (iMR)

Idea:

- Move analysis to the servers
- MapReduce for continuous data
- Ability to trade fidelity for latency

Optimized for:

- Highly selective workloads
  - e.g. up to 80% data filtered or summarized!
- Online analytics
  - e.g. Ad re-targeting based on most recent clicks



An iMR query

The same:

- MapReduce API
  - map(r) → {k,v} : extract/filter data
  - reduce({k, v[]}) → v’ : data aggregation
  - combine({k, v[]}) → v’ : early, partial aggregation

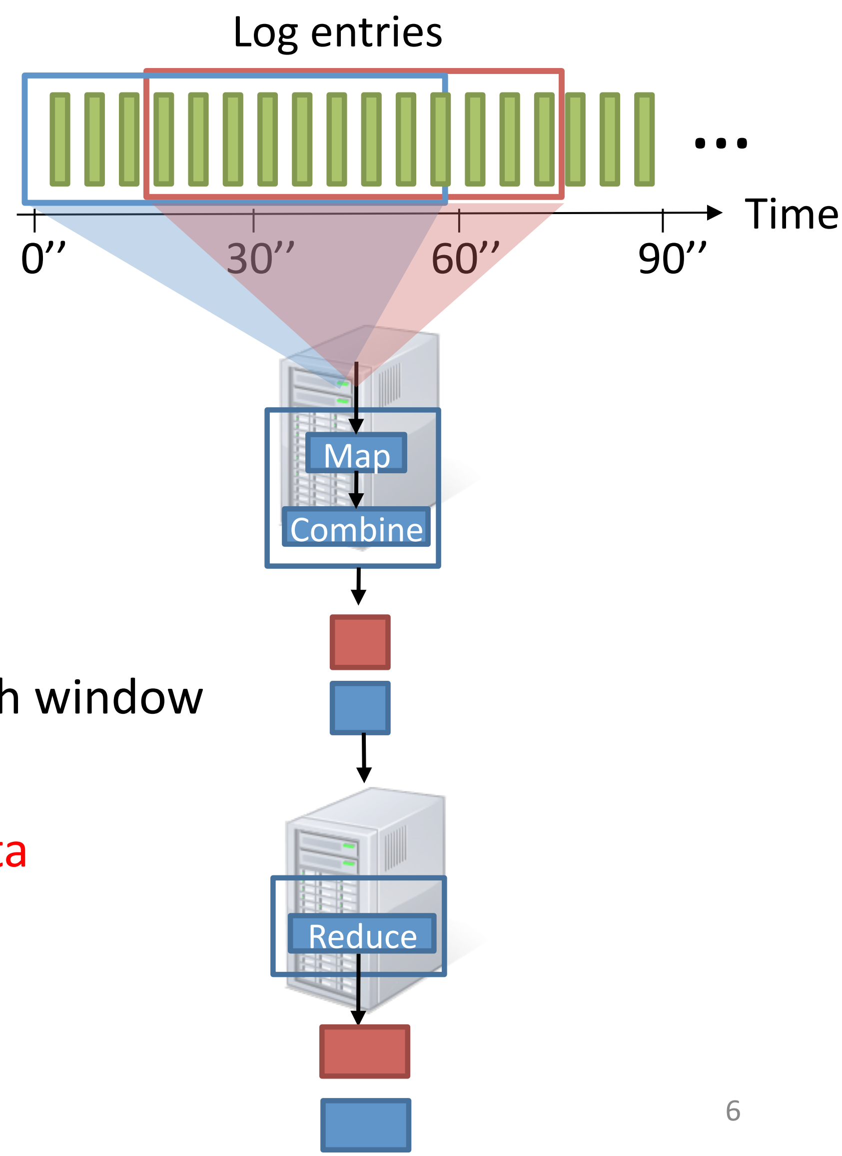
The new:

- Provides continuous results
- Because logs are continuous

Continuous MapReduce

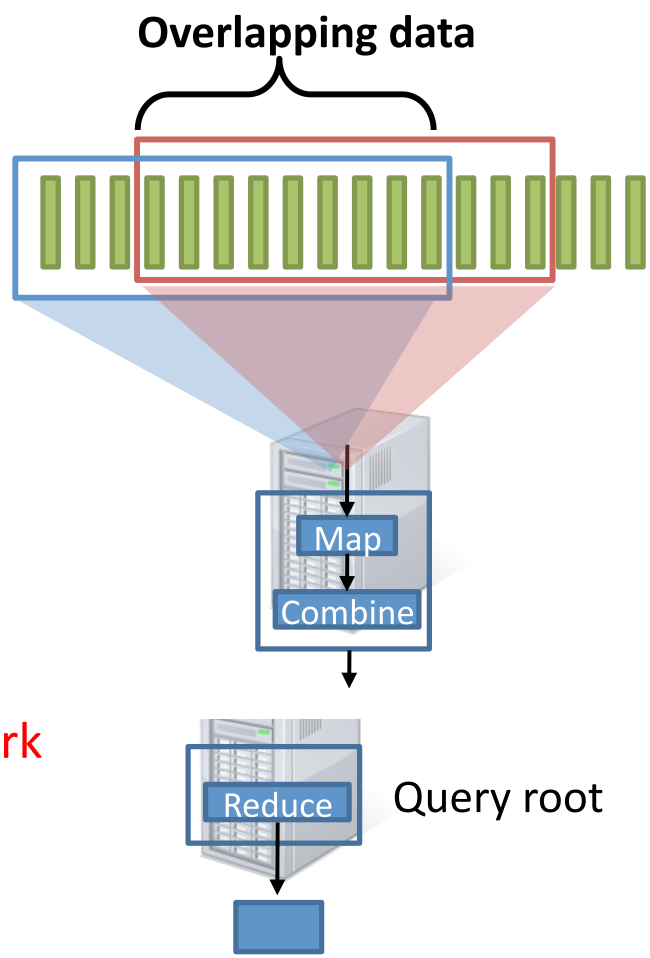
- iMR input is an infinite stream of logs
- Bound input with ***sliding windows***:
  - Range of data
  - Update frequency
  - e.g. Process user clicks over the last 60''…

    … and update analysis every 15''
- Nodes output stream of results, one for each window
- Analysis continuously updated with new data



Processing windows in-network

- Aggregation trees for efficiency
  - Distribute processing load
  - Reduce network traffic



Problem:

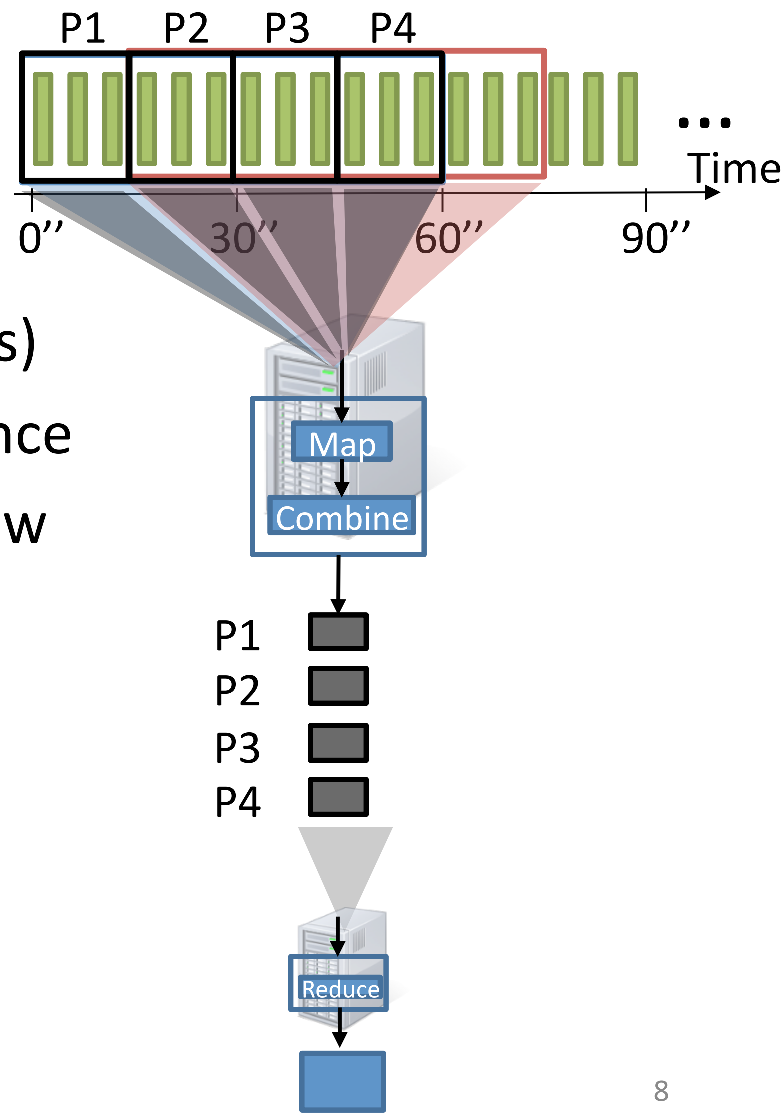
- Overlapping data
  - Processed multiple times: wastes CPU
  - Sent to the root multiple times: wastes network

Efficient processing with *panes*

- Eliminate redundant work

- Divide window into *panes* (sub-windows)
- Each pane is processed and sent only once
- Root combines panes to produce window

- Saves CPU & network resources, faster analysis

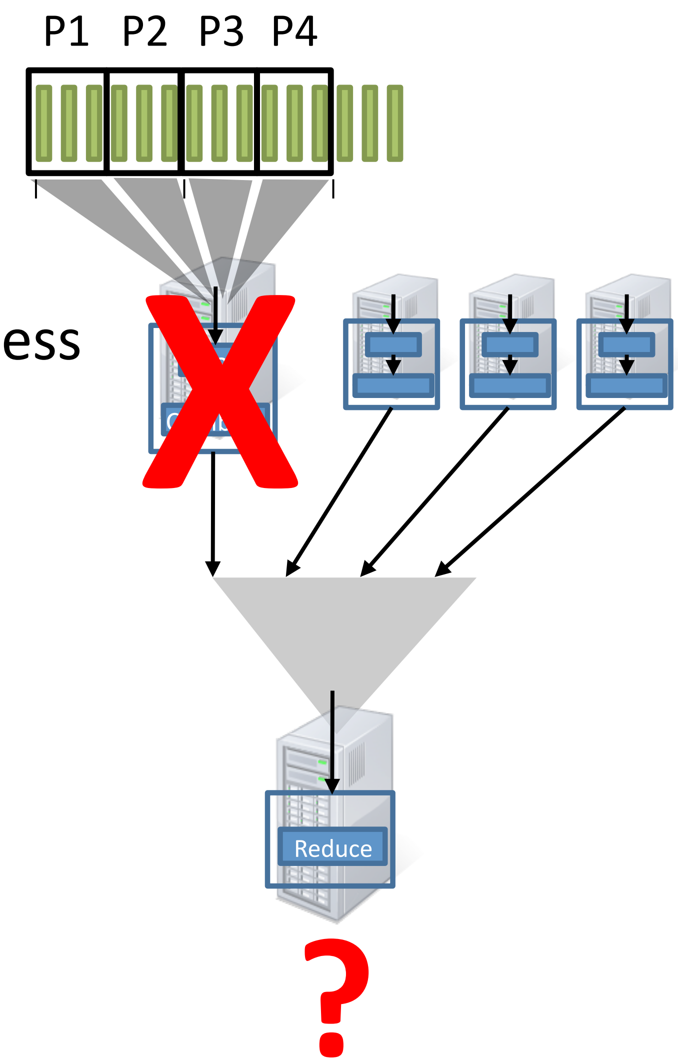


Impact of data loss on analysis

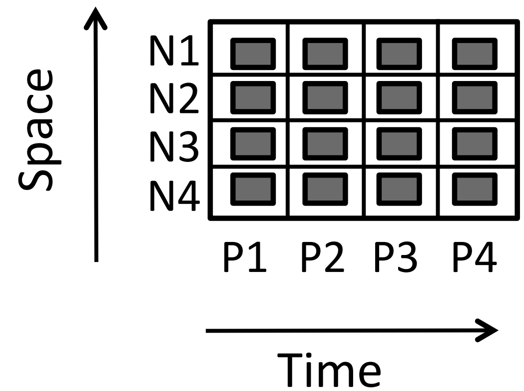
- Servers may get overloaded or fail
- Apps may have latency requirements
- Data loss is unavoidable to ensure timeliness

Challenges:

- Characterize incomplete results
- Allow users to trade fidelity for latency



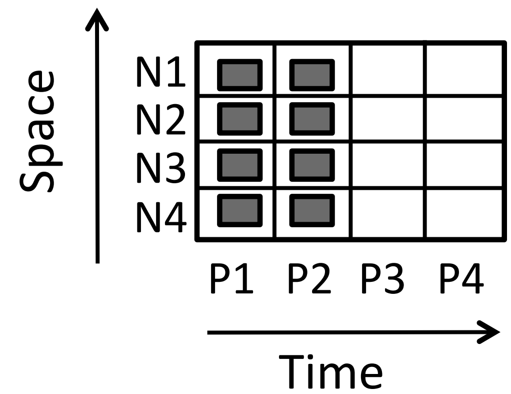
Quantifying data fidelity



- Data are naturally distributed across:
  - Space (server nodes)
  - Time (processing window)
- Panes describe temporal and spatial nature of data
- ***C*²** metric: annotates result windows with a "scoreboard"
  - Marks successfully received panes

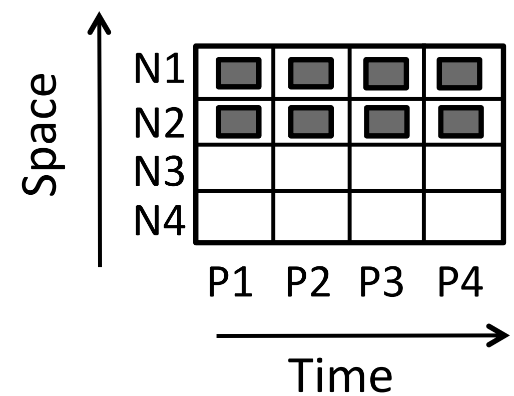
Trading fidelity for latency

- Use C^2 spec to trade fidelity for latency



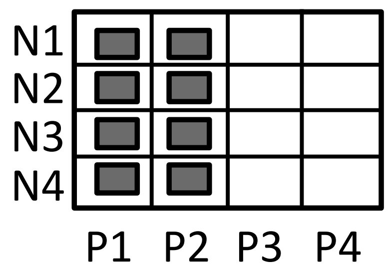
Users may specify:

- Maximum latency requirement
  - e.g. process window within 60sec
- Minimum fidelity
  - e.g. at least 50% of the total data



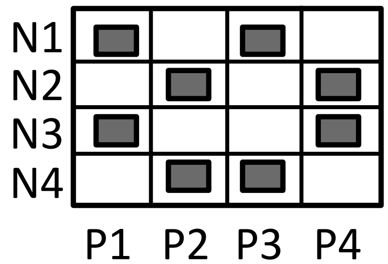
- Different ways to meet minimum fidelity
  - Impact latency and accuracy of analysis
- We identified 4 useful classes of C^2 specifications

Minimizing result latency



- Minimum fidelity with earlier results
  - e.g. 50% of the data
- Gives freedom to decrease latency
  - Returns the earliest data available
  - e.g. data from the fastest servers
- Appropriate for uniformly distributed events
  - Accurately summarizes relative event frequencies

Sampling non-uniform events



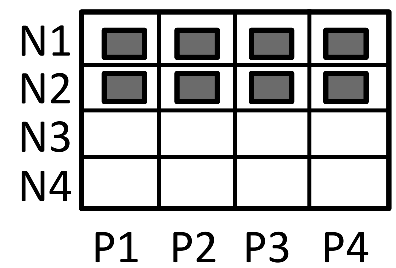
- Minimum fidelity with random sampling
  - e.g. random 50% of the data
- Less freedom to decrease latency
  - Included data may not be the first available
- Appropriate even for non-uniform data
  - Reproduces relative occurrence of events

Correlating events across time and space

- Leverage knowledge about data distribution

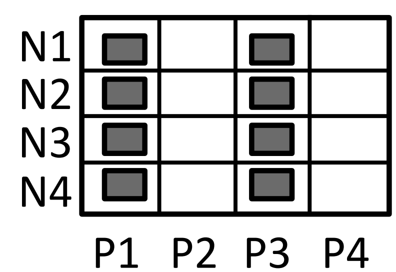
Temporal completeness:

- Include all data from a node or no data at all
  - e.g. all data from 50% of the nodes
- Useful when events are local to a node
  - e.g. counting events on a per node basis



Spatial completeness:

- Each pane contains data from all nodes
- Useful for correlating events across servers
  - e.g click sessionization



Prototype

- Builds upon Mortar distributed stream processor [Logothetis et al., USENIX'08]
  - Sliding windows
  - In-network aggregation trees

- Extended to support:
  - MapReduce API
  - Paned-based processing
  - Fault tolerance mechanisms: operator restart, adaptive data routing

Processing data in-situ

- Analysis co-located with client-facing services
- Limited CPU resources for log analysis

- Goal: use available resources intelligently

- Load shedding mechanism
  - Nodes monitor local processing rate
  - Shed panes that cannot be processed on time

- Increases result fidelity under time and resource constraints

Evaluation

- System scalability
- Usefulness of C^2 metric
  - Understanding incomplete results
  - Trading fidelity for latency
  - Applications:
    - Click-stream sessionization
    - HDFS failure detection
- Processing data in-situ
  - Improving fidelity under load with load shedding
  - Minimize impact on services

Exploring fidelity-latency tradeoffs

- Hadoop DFS anomaly detection algorithm [Tan et al. WASL'08]
- Query: compute distribution of service times for every HDFS server, to detect outliers
- Data: HDFS log trace from 30-node cluster

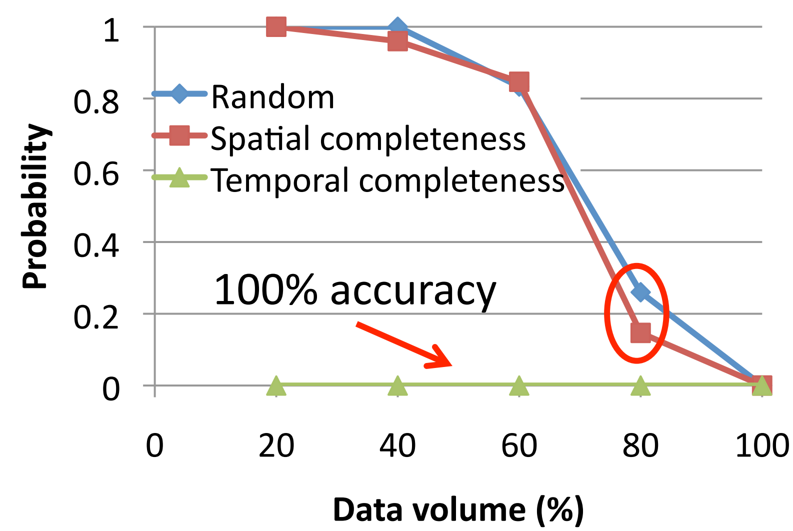
Exploring fidelity-latency tradeoffs

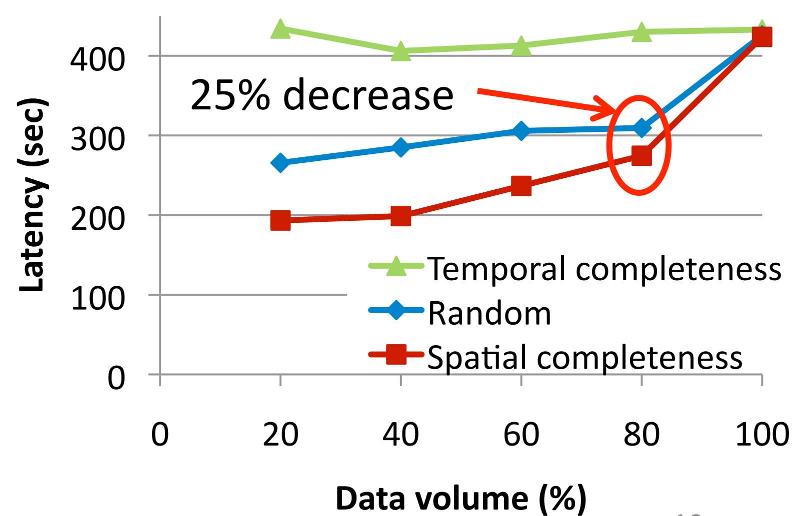
- Data loss affects accuracy of distribution
- Report: probability observed distribution is incorrect

- Temporal completeness
  - Distributions are 100% accurate
  - Computed on per server basis

- Spatial completeness & random sampling
  - Poor results if more than 20% data lost
  - Reduce latency by >25%

- C² allows to trade fidelity for lower latency





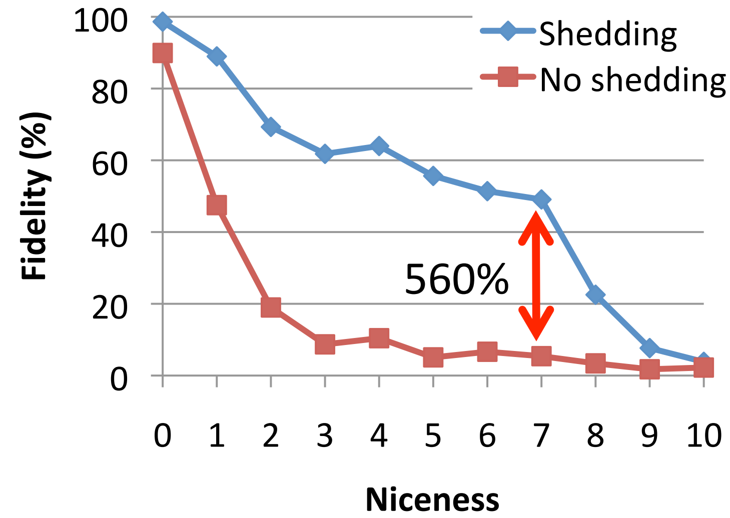
In-situ performance

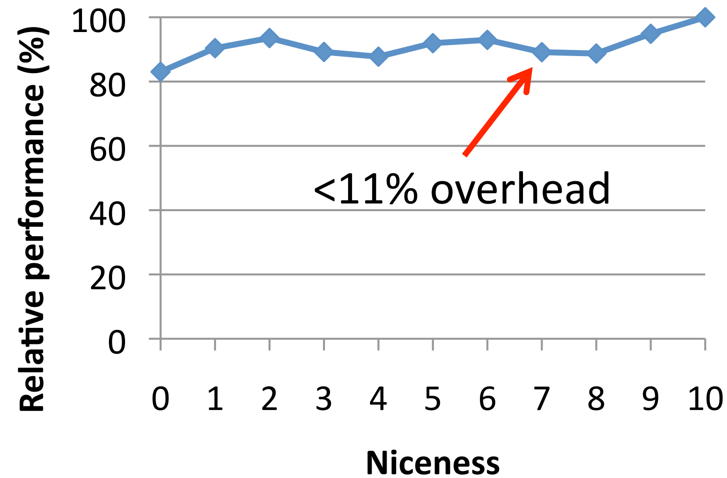
- iMR side-by-side with a real service (Hadoop) on a 10-node cluster
- iMR executes a word count query
- Latency requirement set to 60sec.

- Vary CPU allocated to iMR (*niceness*)
- Report:
  - Result fidelity
  - Hadoop performance (job throughput)

- Shedding improves fidelity by 560% !
- Hadoop performance drops by <11%

- Little impact on Hadoop, while still delivering useful results





Conclusion

- In-situ architecture processes logs at the sources, avoids bulk data transfers, reduces analysis time
- Model allows incomplete data under failures or server load, provides timely analysis
- C^2 metric helps understand incomplete data and trade fidelity for latency
- Pro-actively sheds load, improves data fidelity under resource and time constraints