Model-driven Autoscaling for Hadoop clusters

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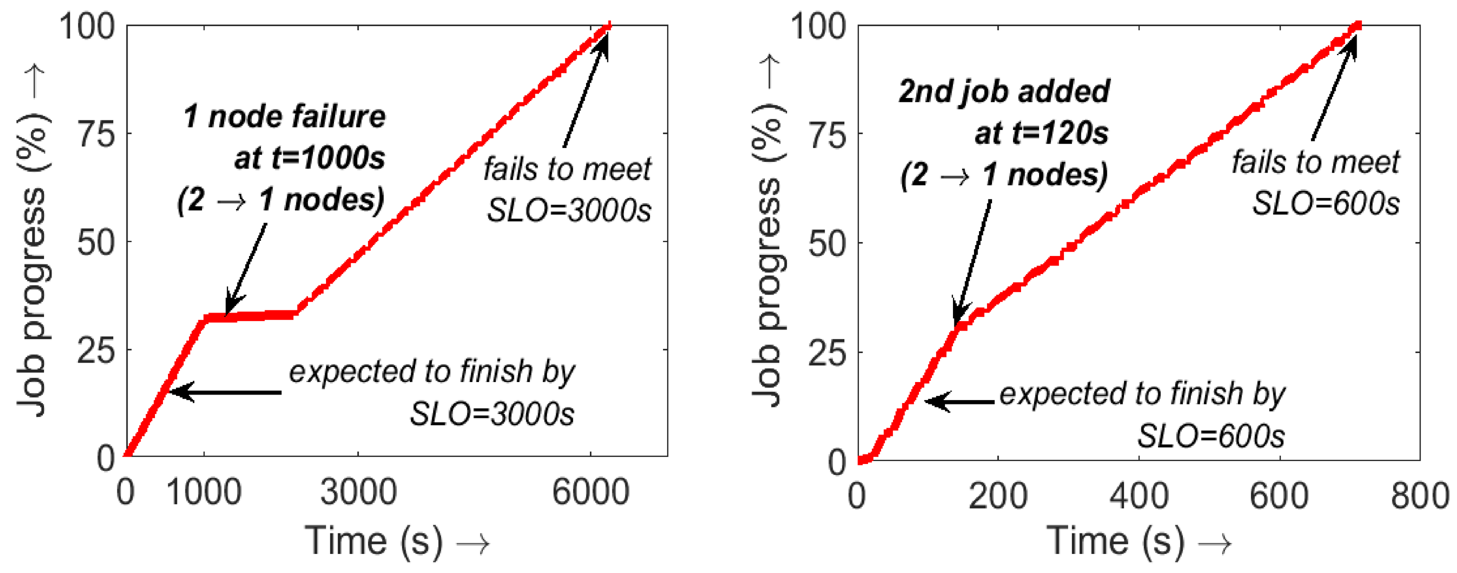
Problem

- **Hadoop performance vulnerable to variations in cloud**
  - Worker nodes can *fail* during job execution
  - Resource *contention* in the cloud can dynamically impact progress
  - Such variations lead to *SLO violations* if left unattended
- Prior work:
  - Mostly (*ARIA, CRESP, Starfish*) focuses on optimal *static* allocation
  - Others (*KOALA, Jockey*) rely on heuristics or complex simulations
- **How to *accurately* and *dynamically* resize Hadoop?**



(a) Node failure *(b) Resource contention*

Problem Statement: How to successfully autoscale Hadoop *while* job is in progress

Challenges

- **How to estimate Hadoop resource requirements?**
  - Complex system, several metrics (200+ via Ganglia)
  - Workload- and data-dependent behavior
  - *Need a practical model relating resource allocation and performance (execution time)*
- **Cloud environment is very dynamic**
  - Workload volume and mix are subject to change
  - Node failures, resource contention are common
  - *Need a dynamic solution*

Solution

- Model-driven approach to autoscaling

1. Develop workload-dependent performance models
  - Closed-form expressions relating performance to various parameters (resources, workload, Hadoop)
  - Focus on few important parameters

2. Leverage performance models for autoscaling
  - Keep track of %age input data processed
  - Scale-out: Launch new VMs and start Hadoop services
  - Scale-in: Stop Hadoop services and remove VMs

Modeling Results

- WordCount: ($T_{map/red}$: map/red stage time)

$$T_{map} = \left(430\frac{D}{M}+6\right)\cdot\left\lceil\frac{M}{N_{mc}\cdot n_{ms}}\right\rceil\cdot n_{ms}$$

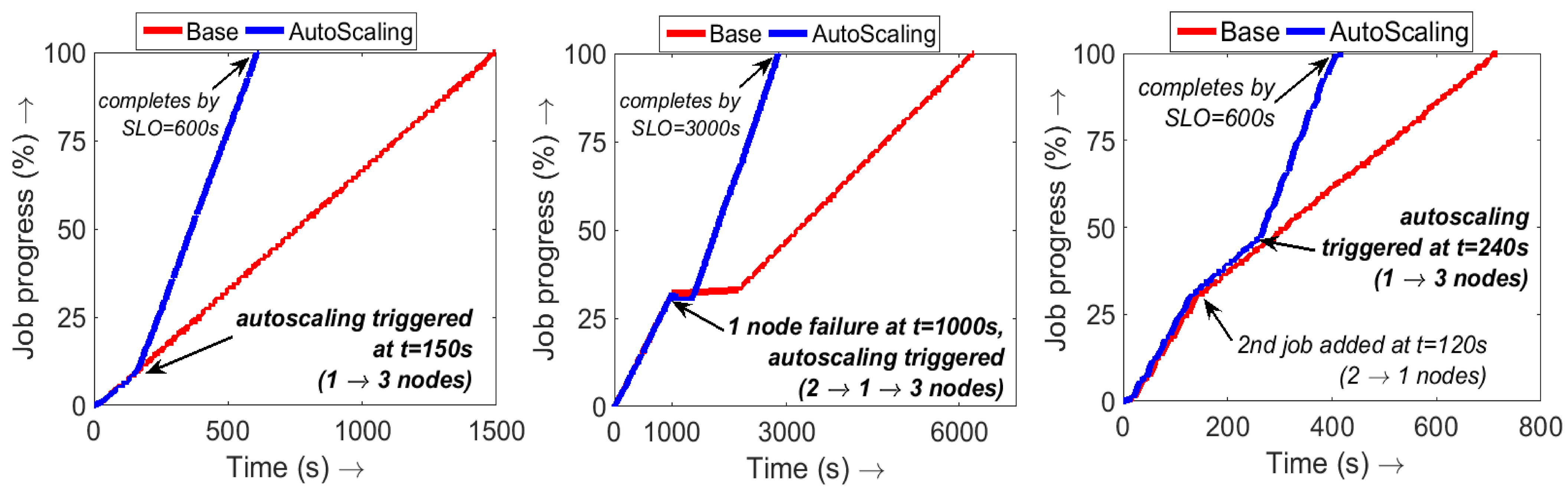
$$T_{red} = \left(5+0.5\frac{D}{R}+\left(6+0.7\frac{D}{R}\right)\cdot\left(\left\lceil\frac{R}{N_{rc}\cdot n_{rs}}\right\rceil-1\right)\right)\cdot n_{rs}+0.1\frac{M}{R}$$

M (R)	Number of Map (Reduce) tasks
N_{mc} (N_{rc})	Number of Map (Reduce) configured cores
n_{ms} (n_{rs})	Number of Map (Reduce) slots per core
D	Size of input data, in GB

- *(M/R)* term for data movement in Shuffle
- Obtained via regression on training data
- Similar results for TeraSort and Kmeans
- Modeling error is about 4% (max 10%)

Autoscaling Evaluation

- WordCount results on various Hadoop clusters
- Autoscaling managed by simple reactive controller



(a) EC2 cluster **(simple scale-out)** *(b) OpenStack Havana* **(failure recovery)** *(c) OpenStack Icehouse* **(resource contention)**

Lessons:
- Simple analytical models can suffice for resource estimation
- Hadoop jobs can be *dynamically* autoscaled to meet SLOs

Limitations:
- Preliminary results based on simple use-cases
- Need to address HDFS data movement