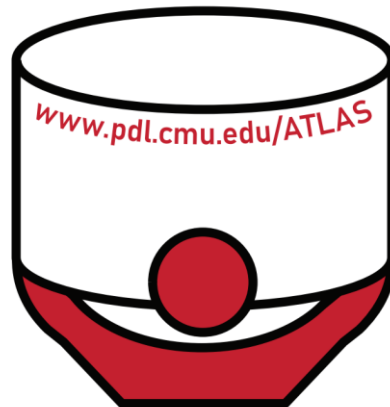


On the diversity of cluster workloads and its impact on research results

George Amvrosiadis, Jun Woo Park, Greg Ganger, Garth Gibson,
Elisabeth Baseman, Nathan DeBardeleben



Sources for cluster traces today

- Parallel Workload Archive (1993 – 2015)
 - 38 HPC cluster traces
(each: 1K+ cores, months long)
 - Publications: 250+
- Google cluster trace (2011)
 - 29 days of a 12,000-node cluster
 - Publications: 450+

26	LLNL Atlas		Nov 2006	Jun 2007
27	LLNL Thunder		Jan 2007	Jun 2007
28	ANL Intrepid		Jan 2009	Sep 2009
29	MetaCentrum		Dec 2008	Jun 2009
30	PIK IPLEX		Apr 2009	Jul 2012
31	RICC		May 2010	Sep 2010
32	CEA CURIE		Feb 2011	Oct 2012
33	Intel NetBatch pool A		Nov 2012	Dec 2012

Google cluster-usage traces: schema

*Charles Reiss, John Wilkes, Joseph Hellerstein
Version of 2013-05-06, for trace version 2. Revised 2014-11-17
Status: exported outside Google.
Copyright © 2011 Google Inc. All rights reserved.*

Google trace: exceedingly popular, but how representative of other clusters?

Project Atlas

- Mandate: use historical data to improve cluster efficiency
 - LANL: scheduler logs, sensor data, OS logs, ... → TBs / day
 - Recently: data from Two Sigma, Pittsburgh Supercomputing Center



Current goals:

- Investigate **overfitting** to existing traces in systems literature
- Produce **generalizable models** of cluster workloads
- Create **trace repository** and make data publicly available



Atlas repository: current traces

- **Two Sigma** business analytics clusters: 9 months (2016-2017)
 - 1300 nodes, 31500 cores, 328TB RAM
- **LANL Mustang** general-purpose cluster: 5 years (2011-2016)
 - 1600 nodes, 38400 cores, 100TB RAM
- **LANL OpenTrinity** capability cluster: 3 months (2017)
 - Trinity phase 1: 9400 nodes, 300000 cores, 1.15PB RAM

Entire
cluster lifetime

Repository accessible thru *project-atlas.org*
More traces coming soon! *You can contribute!*



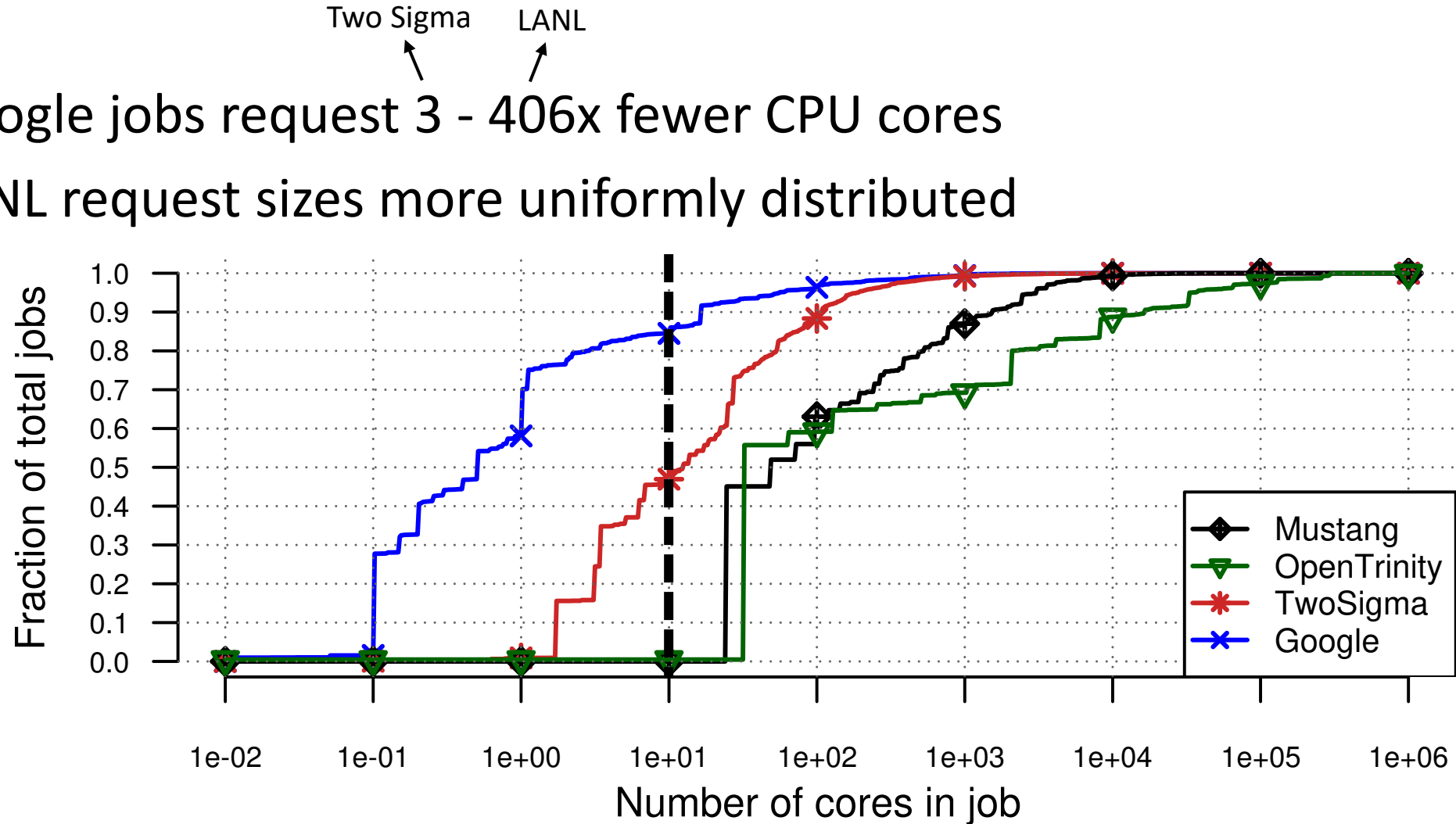
Overview

Characteristic	Google	Two Sigma	Mustang	OpenTrinity
Short jobs	Job characteristics			
Small jobs				
Diurnal patterns	Workload heterogeneity			
High job submission rate				
Resource over-commitment	Resource utilization			
Sub-second interarrival periods				
User request variability				
High failure rates	Failure analysis			
Costly failures (wasted CPU hours)				
Longer/larger jobs fail more often				



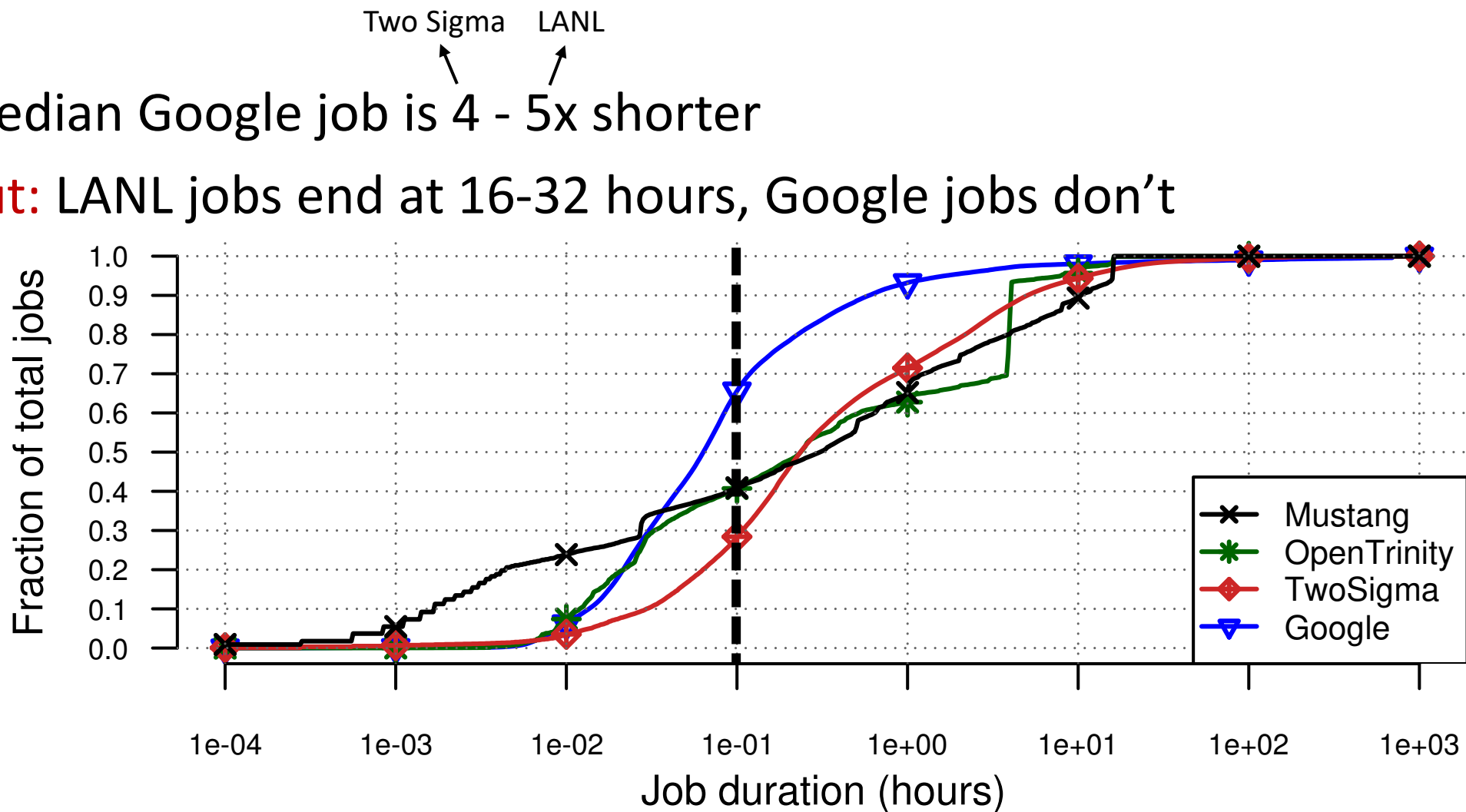
Job Sizes

- Google jobs request 3 - 406x fewer CPU cores
- LANL request sizes more uniformly distributed



Job Duration

- Median Google job is 4 - 5x shorter
- **But:** LANL jobs end at 16-32 hours, Google jobs don't



Overview

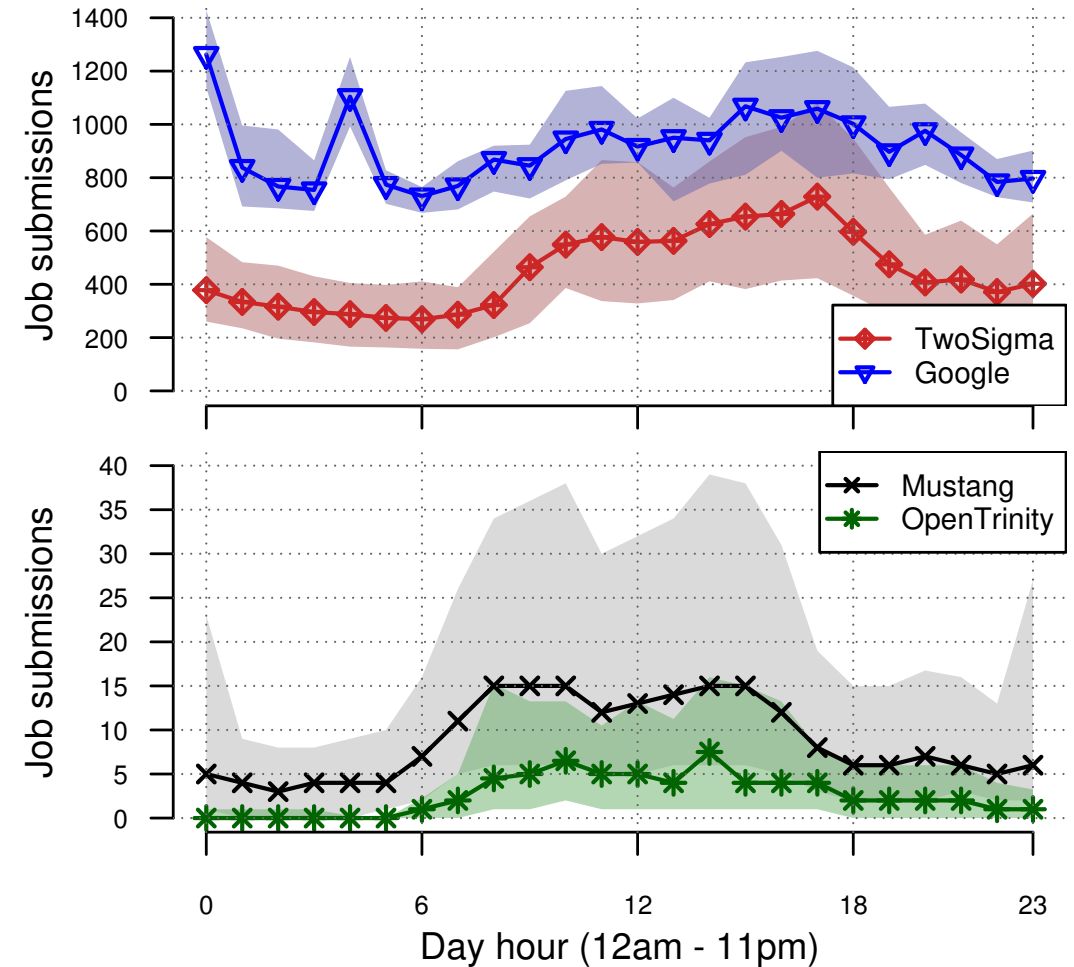
Characteristic	Google	Two Sigma	Mustang	OpenTrinity
Short jobs	✓	✗	✗	✗
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Longer/larger jobs fail more often				



Workload Heterogeneity

- Reversed diurnal patterns
 - More/smaller Google jobs between midnight and 4AM
- Job submission rate
 - 10-1000x more scheduling requests in Two Sigma, Google

1K jobs/hour → 3.6 sec/job
70K tasks/hour → 51 msec/task



Task placement algorithms achieve subsecond latency today [Quincy, Firmament]
but we should aim for msec latencies

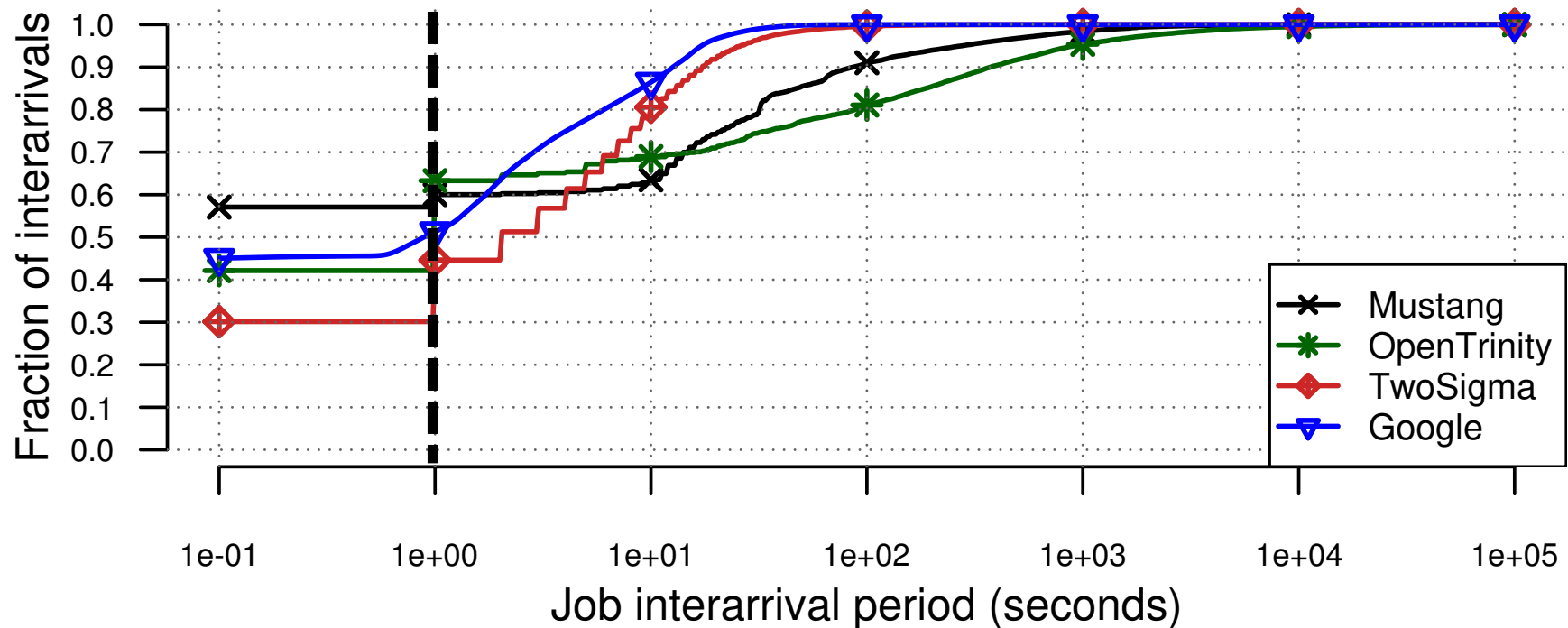
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Diurnal patterns	✗	✓	✓	✓
High job submission rate	✓	✓	✗	✗
Resource over-commitment	Resource utilization			
Sub-second interarrival periods				
User request variability				
High failure rates	Failure analysis			
Costly failures (wasted CPU hours)				
Longer/larger jobs fail more often				



Resource utilization: intensity

- Only Google overcommits resources (others at 65-90%)
- 43-64% of inter-arrivals <1sec long
 - 20% of inter-arrivals >100sec at LANL → Maintenance



Systems should be tested with subsecond job interarrivals [Firmament, Quasar]

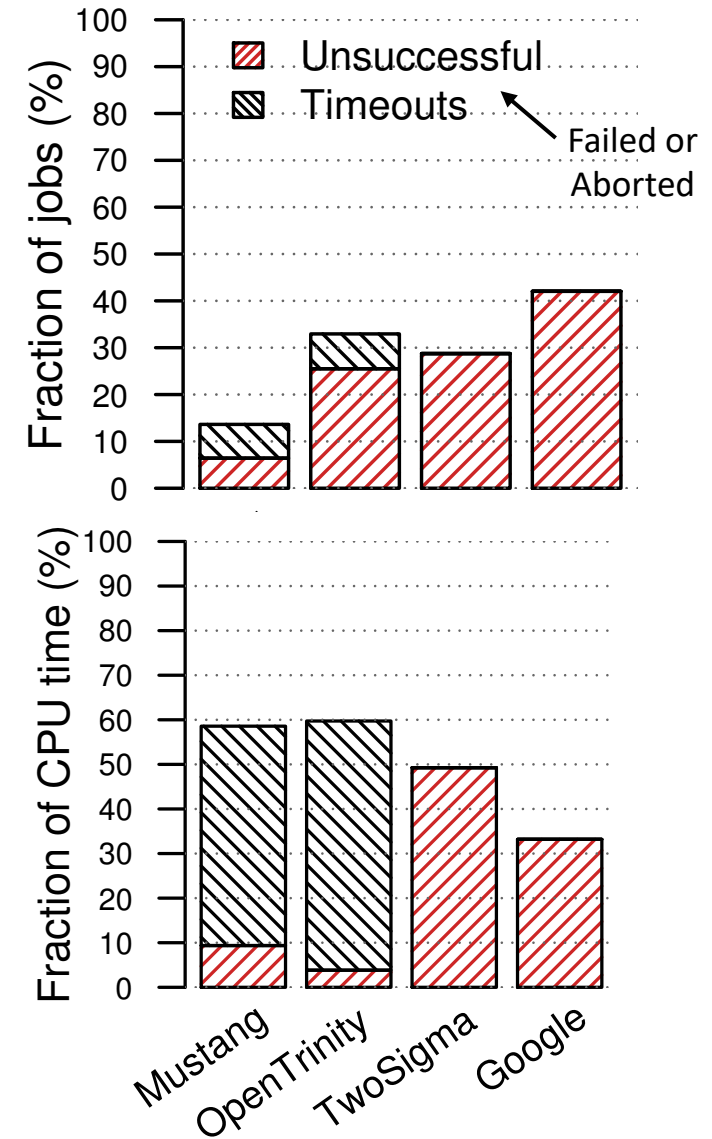
Overview

Characteristic	Google	Two Sigma	Mustang	OpenTrinity
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High job submission rate	✓	✓	✗	✗
Resource over-commitment	✓	✗	✗	✗
Sub-second interarrival periods	✓	✓	✓	✓
User request variability	✗	✓	✓	✓
High failure rates	Failure analysis			
Costly failures (wasted CPU hours)				
Longer/larger jobs fail more often				



Unsuccessful jobs

- Unsuccessful job rates at Google are significant
 - 1.4-6.8x higher than other traces
 - ↙ Two Sigma
 - ↘ LANL
- Highest efficiency: HPC clusters
 - 34-80% fewer CPU hours wasted* at LANL
 - Time wasted decreases with job runtime



Defining *failure* is crucial: software errors may be benign

A case for dataset pluralism

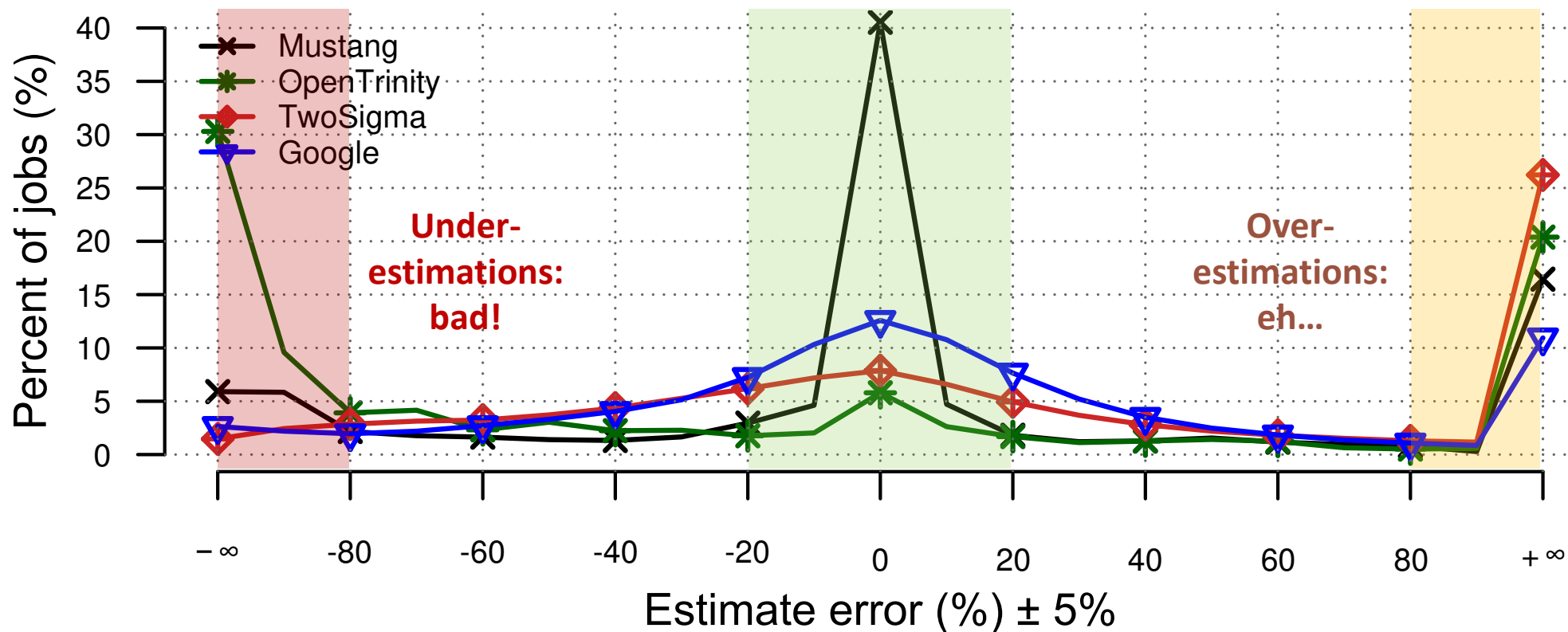


Estimating job runtimes

- Runtime estimates: improve cluster efficiency
 - Adjust to heterogeneous hardware → lower response times
 - Job packing → increased utilization
- How do we come up with runtime estimates?
 - User-provided (Moab, Slurm @ LANL) → **mostly inaccurate**
 - Leverage job repeats (Rayon in Hadoop) → **effectiveness depends on workload**
- JVuPredict/3Sigma: generate estimates automatically ^[EuroSys 2018]
 - **Step 1:** Use past runtimes of jobs with similar *feature(s)*
 - **Step 2:** Select predictor with highest accuracy



JVuPredict: Accuracy across traces



- Reliance on: user ID, number of cores, job name (if present)
 - Logical job names matter!
 - Need busy (100K+ jobs) or long (3+ months) traces for training



Summary

Private more similar to HPC, except:
Failure rates, Job submission rate

Characteristic	Google	Two Sigma	Mustang	OpenTrinity
Short jobs	✓	✗	✗	✗
Small jobs	✓	✗	✗	✗
Diurnal patterns	✗	✓	✓	✓
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Sub-second interarrival periods	✓	✓	✓	✓
User request variability	✗	✓	✓	✓
High failure rates	✓	✓	✗	✓
Costly failures (wasted CPU hours)	✓	✓	✗	✗
Longer/larger jobs fail more often	✓	✗	✗	✗

