

**ERNEST**

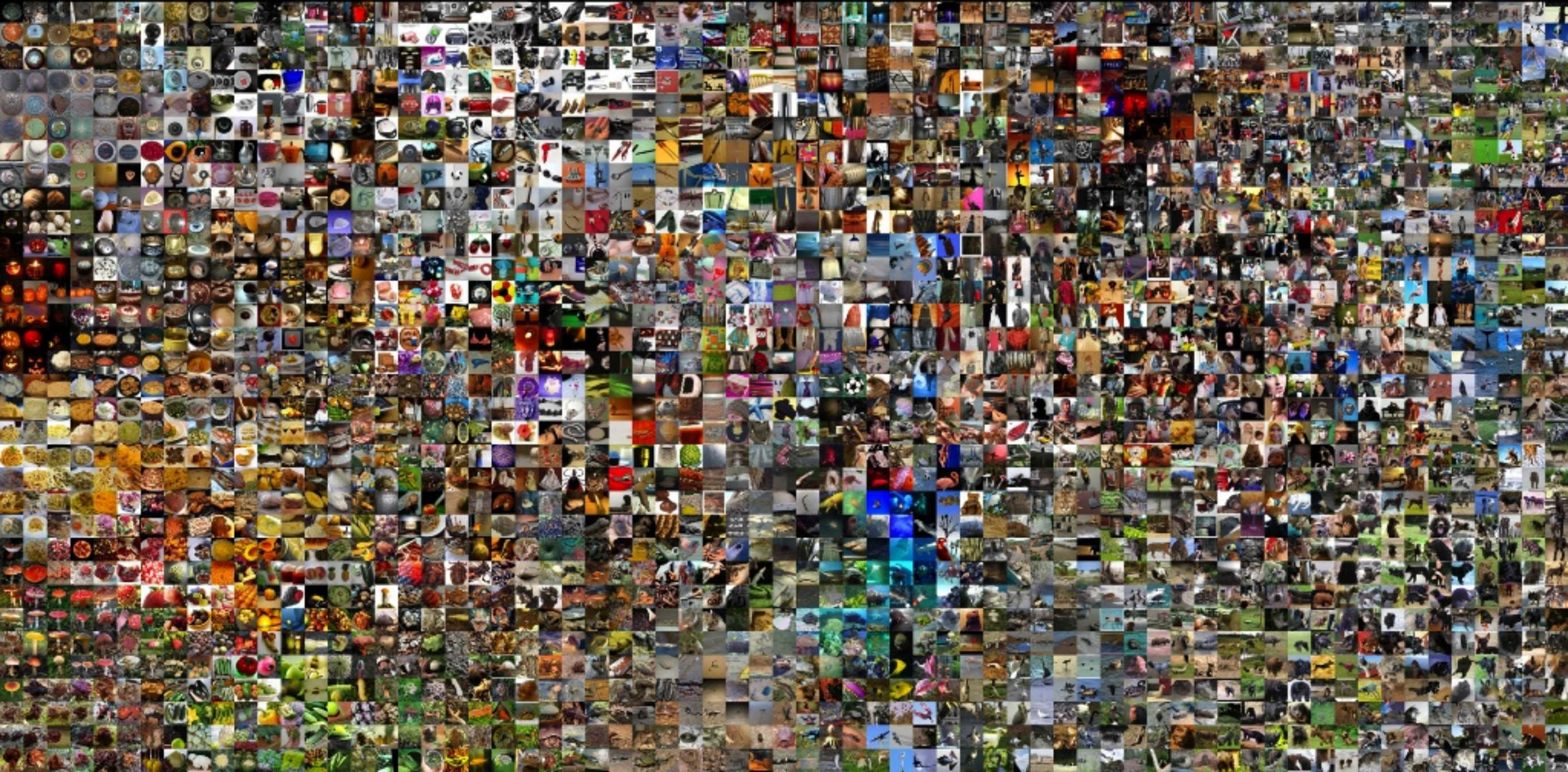
**EFFICIENT PERFORMANCE PREDICTION FOR  
ADVANCED ANALYTICS ON **APACHE SPARK****

**Shivaram Venkataraman, Zongheng Yang**  
**Michael Franklin, Benjamin Recht, Ion Stoica**





# WORKLOAD TRENDS: ADVANCED ANALYTICS





## WORKLOAD TRENDS: ADVANCED ANALYTICS



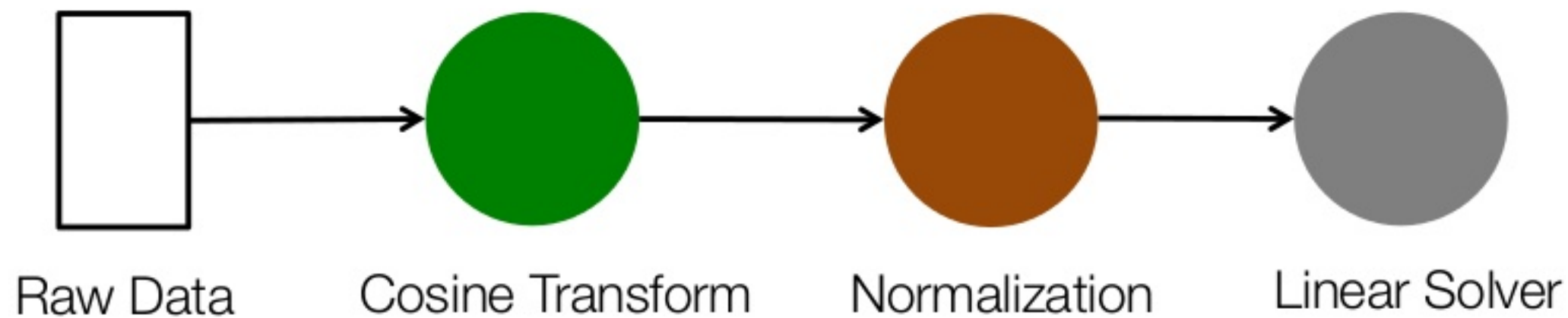
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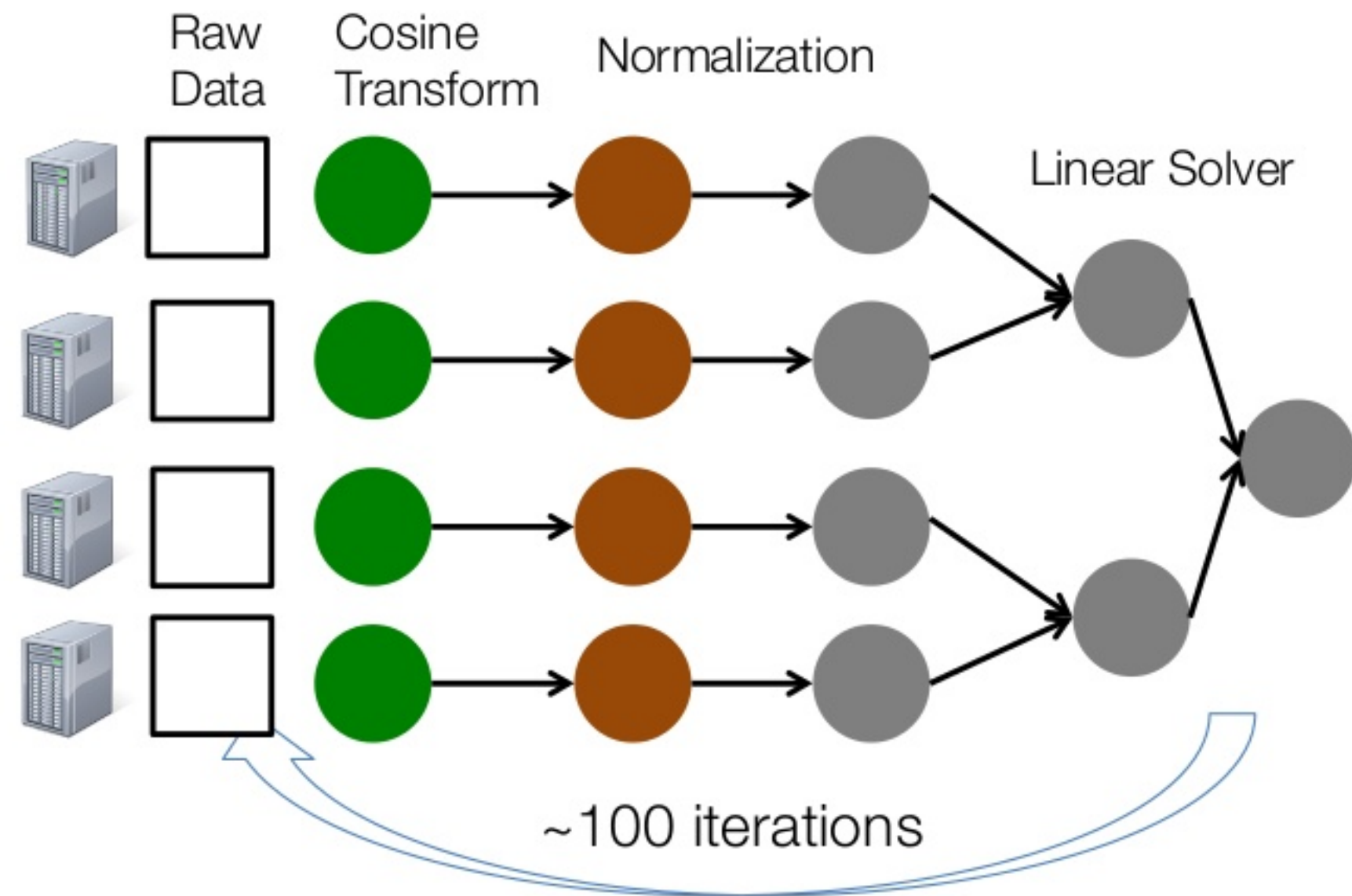


# KEYSTONE-ML TIMIT PIPELINE





# KEYSTONE-ML TIMIT PIPELINE



## PROPERTIES

Numerically Intensive

Iterative  
(each iteration many jobs)

Long Running → Expensive

# CLOUD COMPUTING CHOICES

t2.nano, t2.micro, t2.small  
m4.large, m4.xlarge, m4.2xlarge,  
m4.4xlarge, m3.medium,  
c4.large, c4.xlarge, c4.2xlarge,

Basic tier: A0, A1, A2, A3, A4  
Optimized Compute : D1, D2,  
D3, D4, D11, D12, D13  
D1v2, D2v2, D3v2, D11v2,...

n1-standard-1, ns1-standard-2,  
ns1-standard-4, ns1-standard-8,  
ns1-standard-16, ns1highmem-2,  
ns1-highmem-4, ns1-highmem-8,

## Instance Types and Number of Instances

i2.2xlarge, i2.4xlarge, d2.xlarge  
d2.2xlarge, d2.4xlarge,...

Compute Intensive: A10, A11,...

highcpu-32, f1-micro, g1-small...

AMAZON EC2

MICROSOFT AZURE

GOOGLE CLOUD ENGINE



# TYRANNY OF CHOICE





## USER CONCERNS

“What is the cheapest configuration to run my job in 2 hours?”

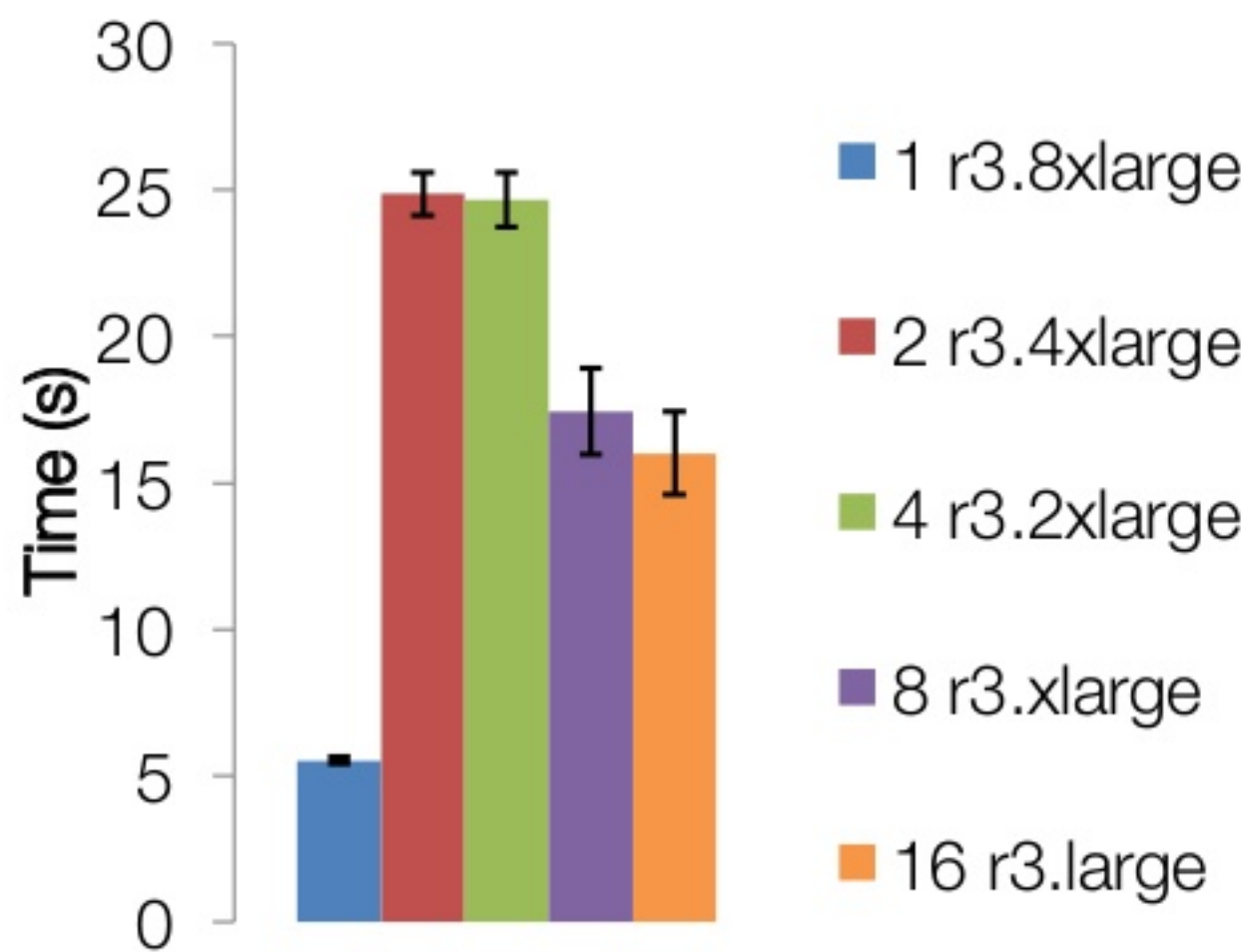
Given a budget, how fast can I run my job ?

“What kind of instances should I use on EC2 ?”



# DO CHOICES MATTER ? MATRIX MULTIPLY

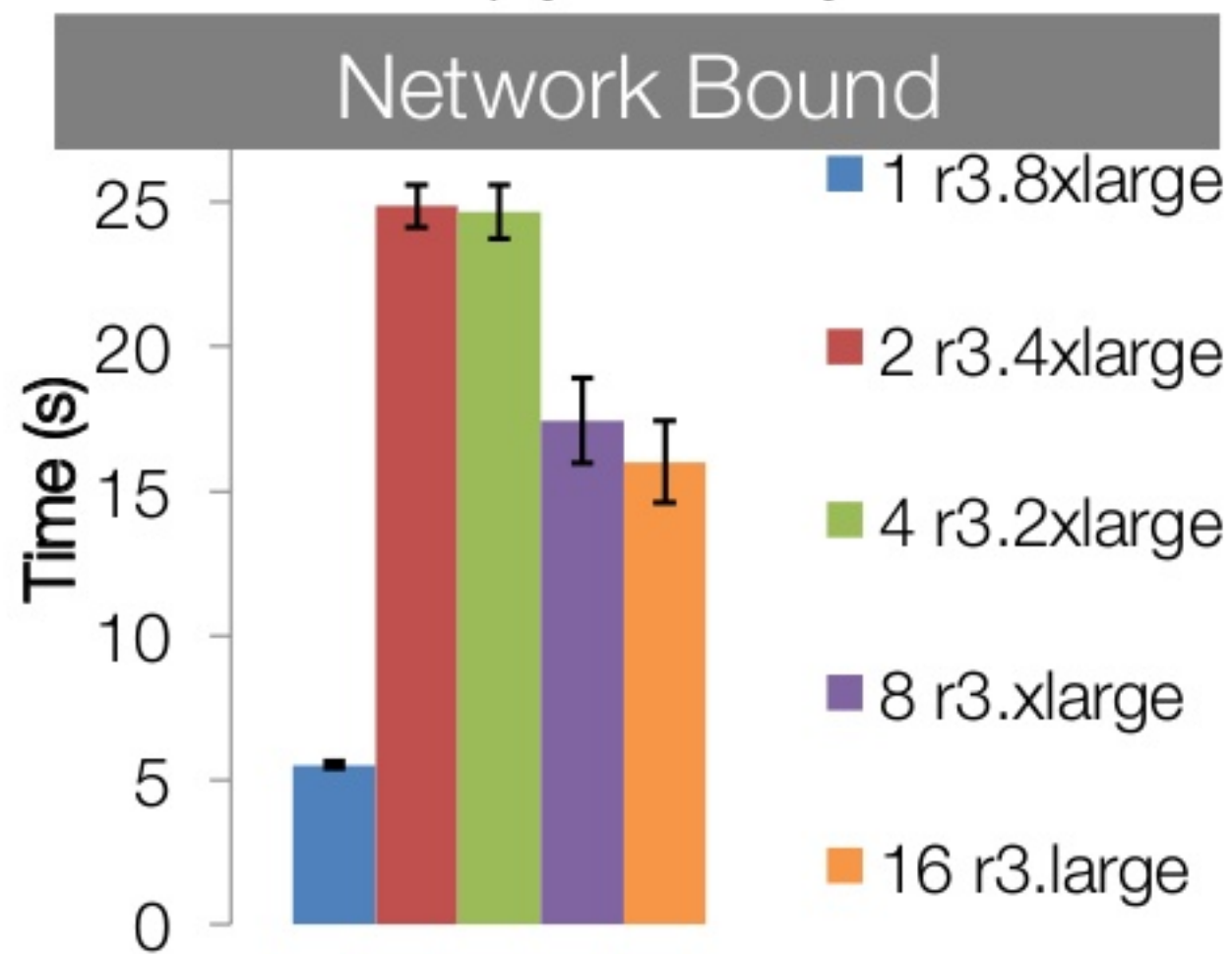
Matrix size: 400K by 1K



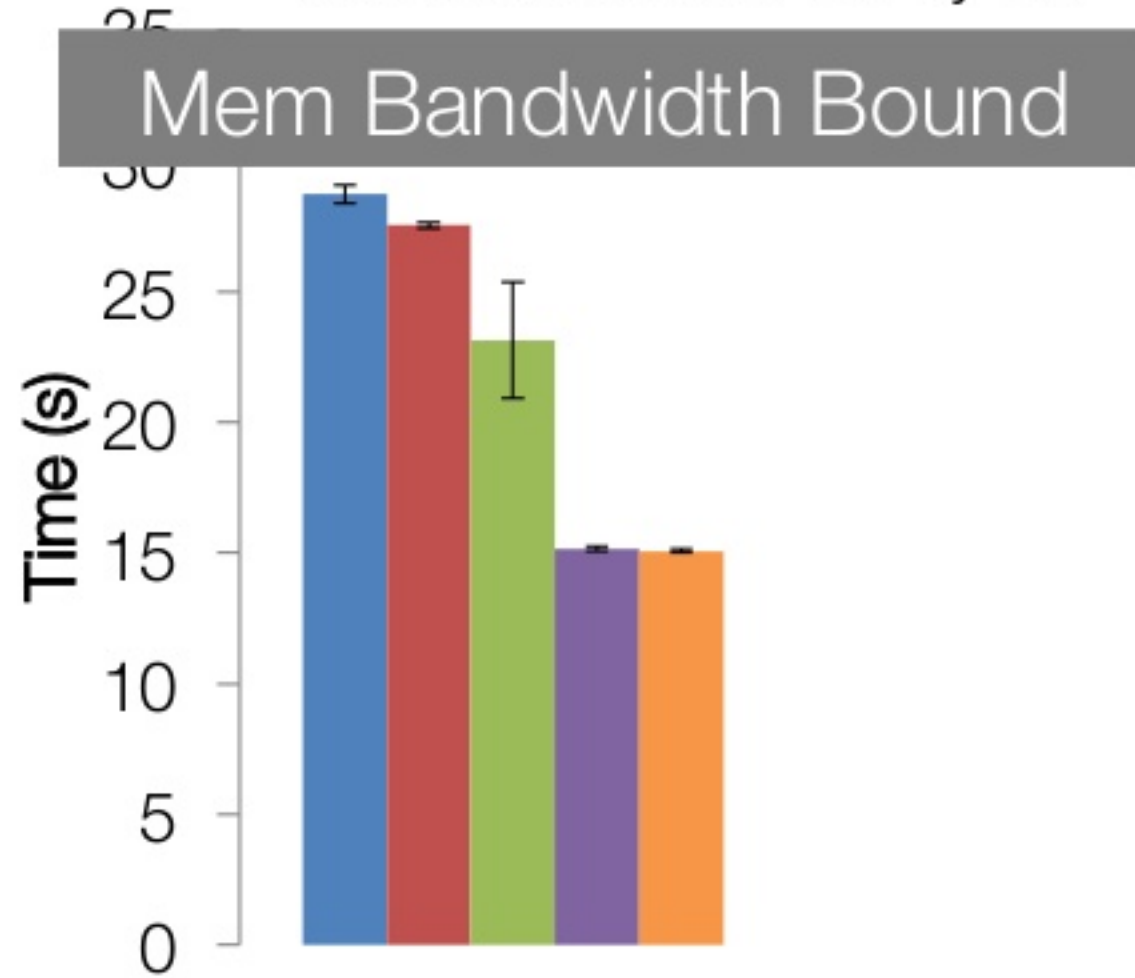
|        |             |
|--------|-------------|
| CORES  | = 16        |
| MEMORY | = 244 GB    |
| COST   | = \$2.66/HR |

# DO CHOICES MATTER ?

Matrix Multiply: 400K by 1K



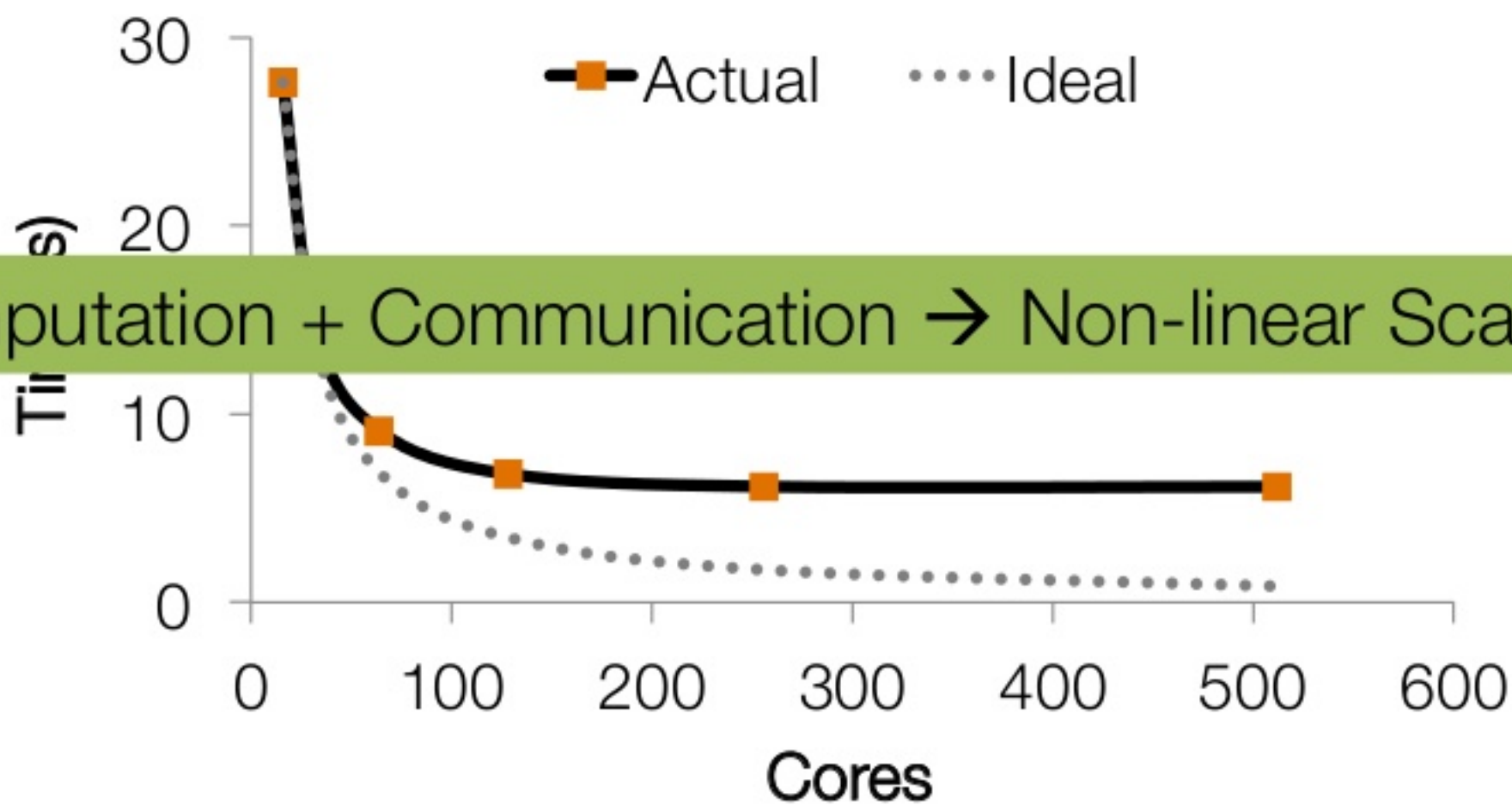
QR Factorization 1M by 1K





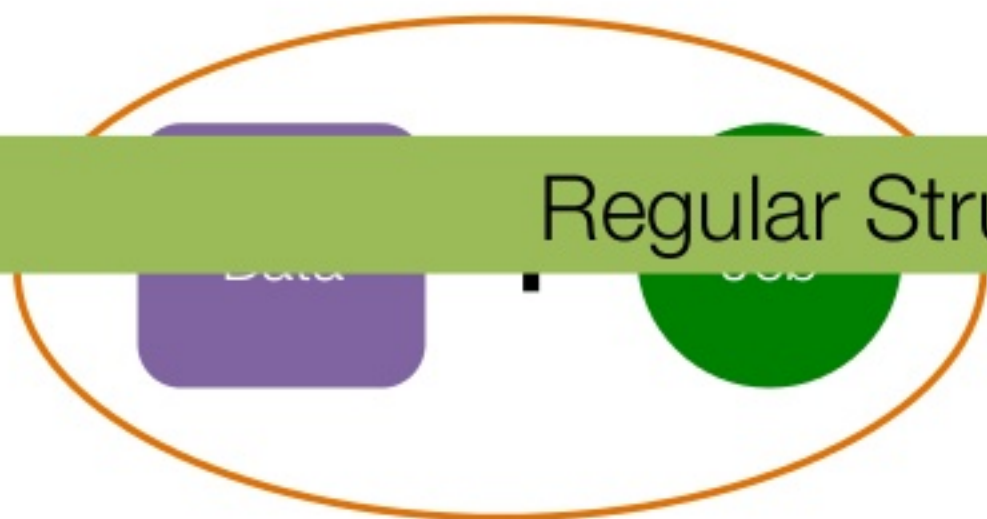
# DO CHOICES MATTER ?

r3.4xlarge instances, QR Factorization: 1M by 1K



# APPROACH

## Performance Model



Regular Structure + Few Iterations

# CHALLENGES

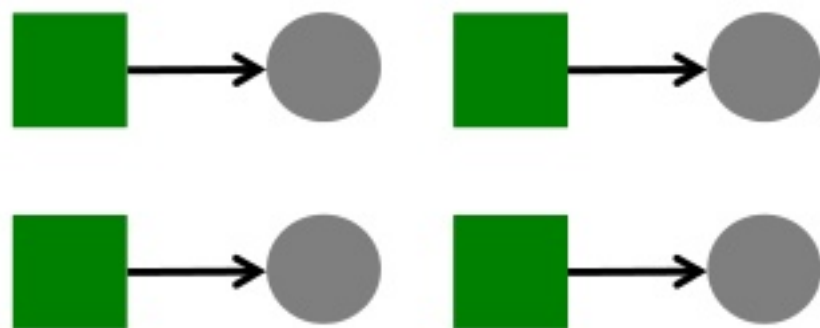
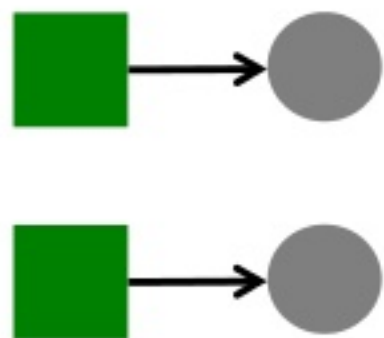
Black Box Jobs

Model Building Overhead

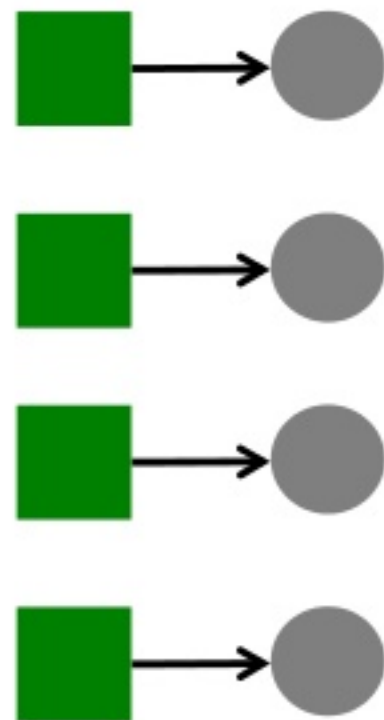


# MODELING JOBS

# COMPUTATION PATTERNS



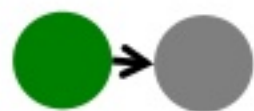
**TIME**  $\propto$  **INPUT**



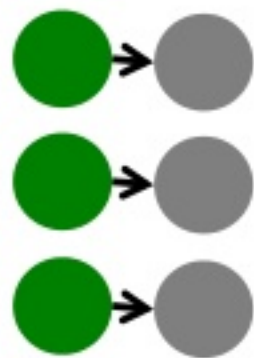
**TIME**  $\propto \frac{1}{\text{MACHINES}}$

# COMMUNICATION PATTERNS

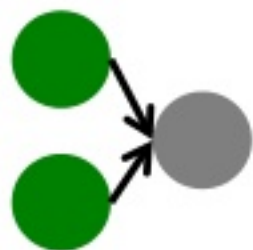
## ONE-TO-ONE



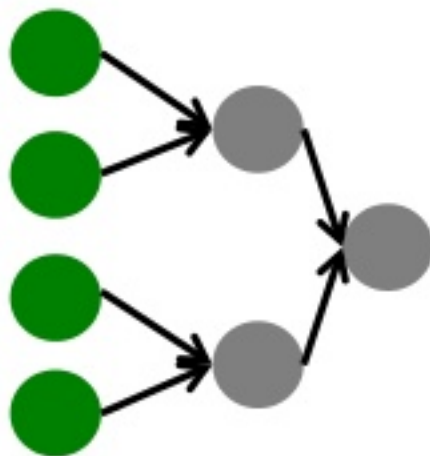
## CONSTANT



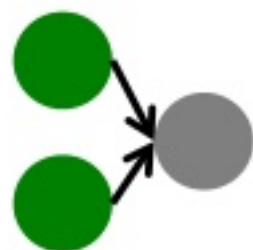
## TREE DAG



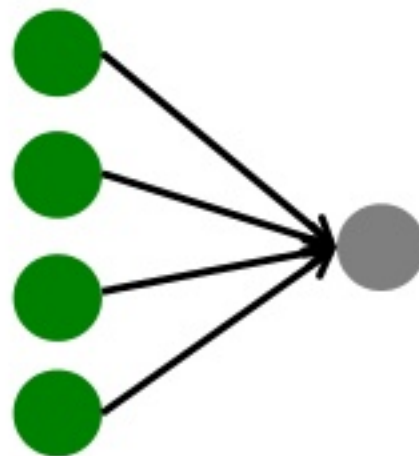
## LOG



## ALL-TO-ONE



## LINEAR





# BASIC MODEL

Computation (linear)

↑

Serial Execution ↗

$$time = x_1 + x_2 * \frac{input}{machines} + x_3 * \log(machines) + x_4 * (machines)$$

Tree DAG ↑

All-to-One DAG ↓

Collect Training Data

Fit Linear Regression

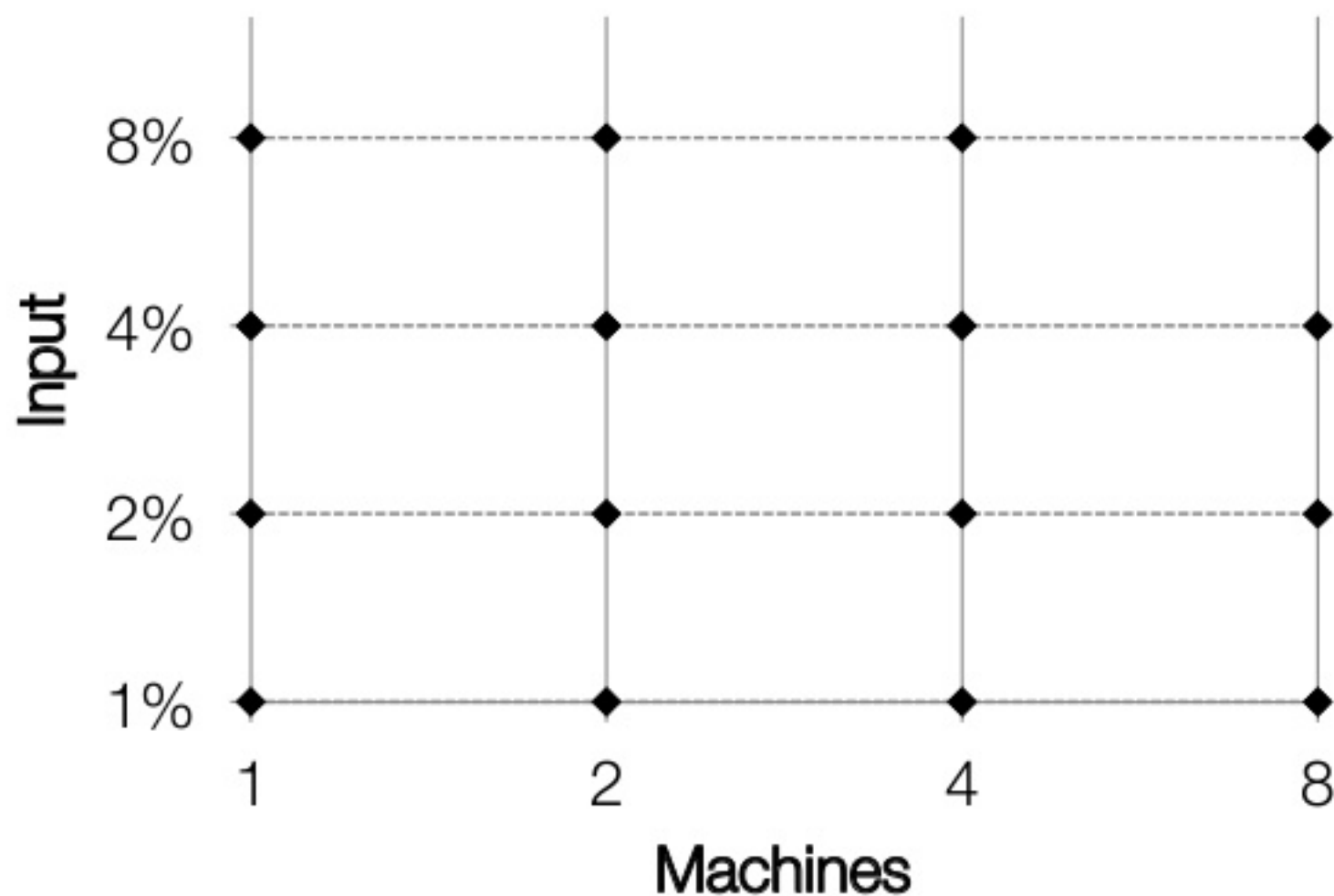
# DOES THE **MODEL** MATCH REAL APPLICATIONS ?

Number of data items:  $n$ , Number of processors:  $p$ , Constant number of features

| Algorithm           | Compute  |            |
|---------------------|----------|------------|
|                     | $O(n/p)$ | $O(n^2/p)$ |
| GLM Regression      | ✓        |            |
| KMeans              | ✓        |            |
| Naïve Bayes         | ✓        |            |
| Pearson Correlation | ✓        |            |
| PCA                 | ✓        |            |
| QR (TSQR)           | ✓        |            |

| Communication |        |              |                    |
|---------------|--------|--------------|--------------------|
| $O(1)$        | $O(p)$ | $O(\log(p))$ | Other              |
|               | ✓      | ✓            |                    |
| ✓             | ✓      |              | $O(\text{center})$ |
|               | ✓      |              |                    |
|               |        | ✓            |                    |
|               | ✓      | ✓            |                    |
|               |        | ✓            |                    |

# COLLECTING TRAINING DATA



Grid of  
input, machines

Associate cost with  
each experiment

Baseline: Cheapest  
configurations first



# OPTIMAL DESIGN OF EXPERIMENTS

## Given a Linear Model

$$y_i = a_i^T x + w_i, \quad i = 1, \dots, m,$$

$\lambda_i$  – Fraction of times each experiment is run

$$\text{Minimize} \quad \text{tr}\left(\left(\sum_{i=1}^m \lambda_i a_i a_i^T\right)^{-1}\right)$$

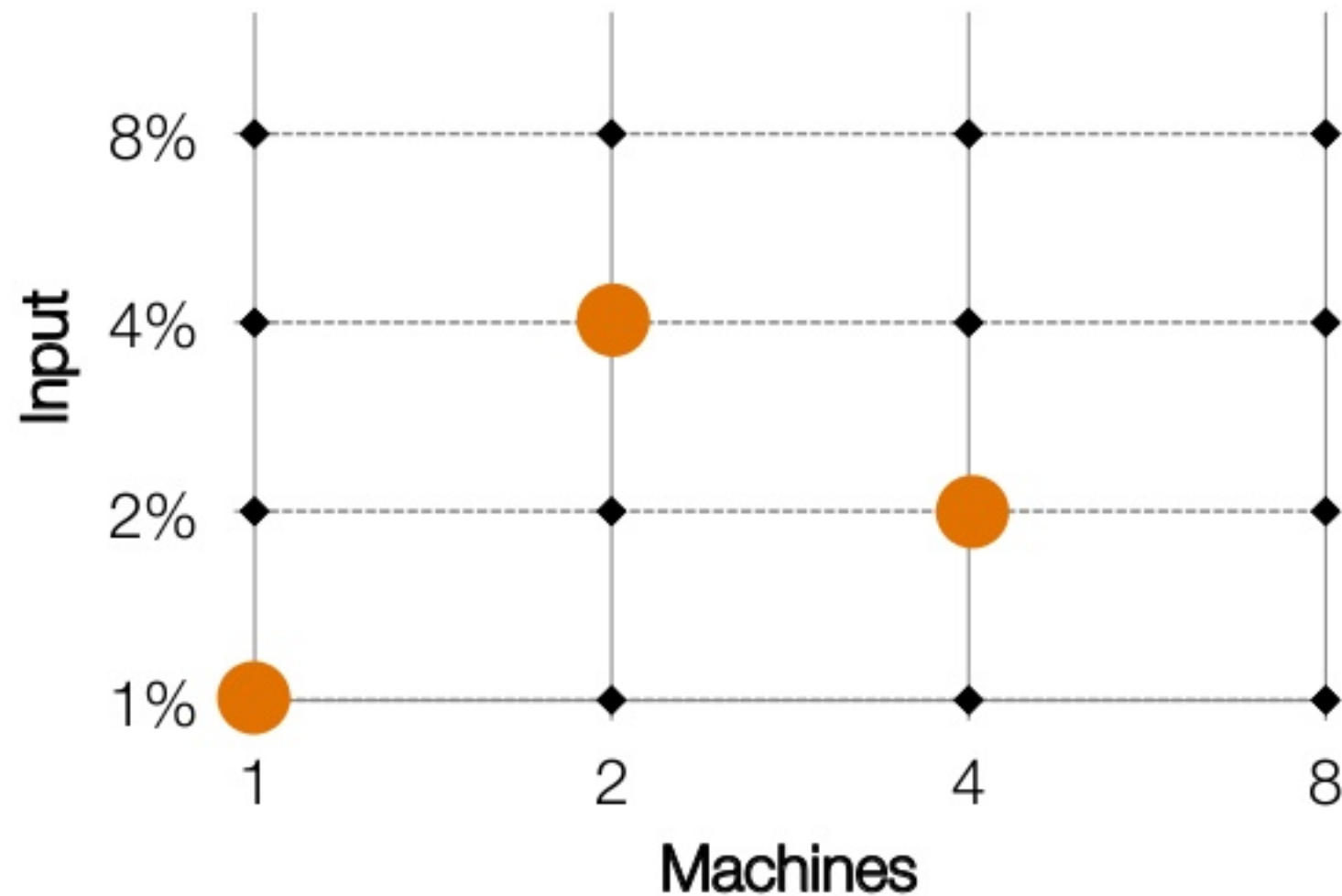
$$\text{subject to} \quad \lambda_i \geq 0, \lambda_i \leq 1$$

$$\sum_{i=1}^m c_i \lambda_i \leq B$$

Lower variance →  
Better model

Bound total cost

# OPTIMAL DESIGN OF EXPERIMENTS



Use off-the-shelf solver  
(CVX)

# USING ERNEST

## ERNEST

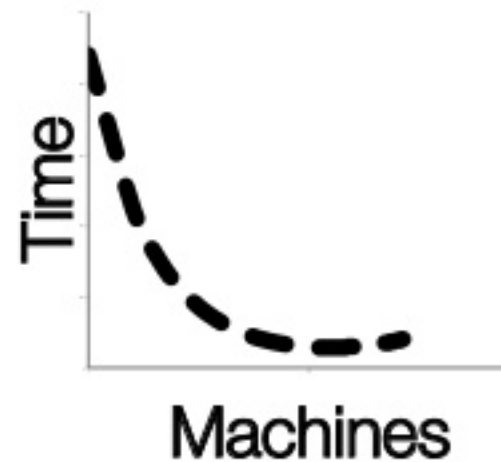


Experiment Design

Training Jobs

Use few iterations for training

Linear Model



Machines,  
Input Size



# EVALUATION

## OBJECTIVES

Optimal number of machines  
Prediction accuracy  
Model training overhead  
Importance of experiment design  
Choosing EC2 instance types  
Model extensions

## WORKLOADS

Keystone-ML  
Spark MLlib  
ADAM  
GenBase  
Sparse GLMs  
Random Projections

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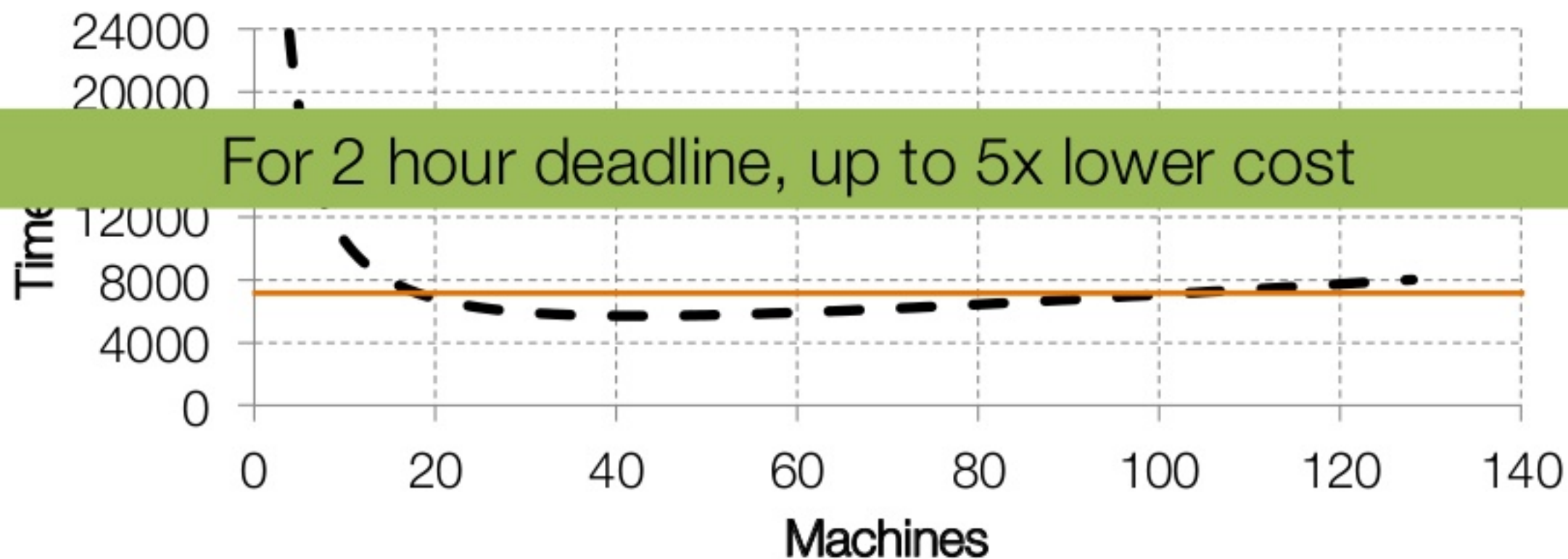
Sparse GLMs

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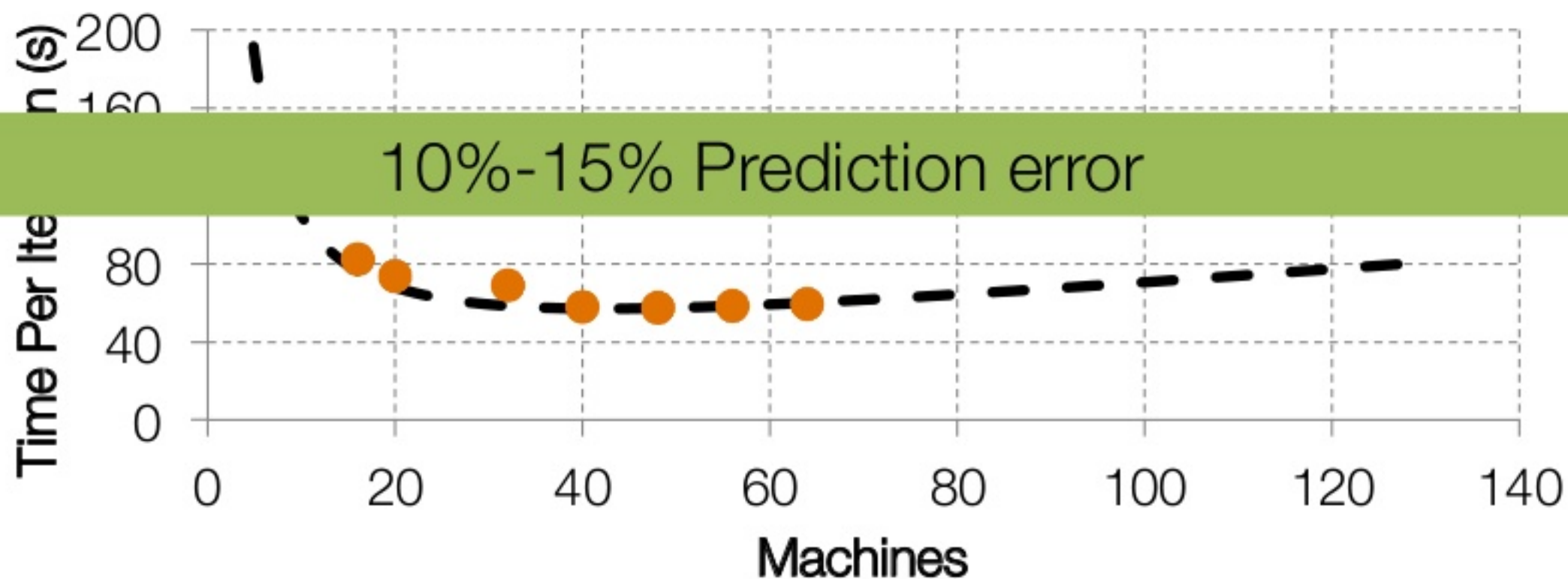
# NUMBER OF INSTANCES: KEYSTONE-ML

TIMIT Pipeline on r3.xlarge instances, 100 iterations

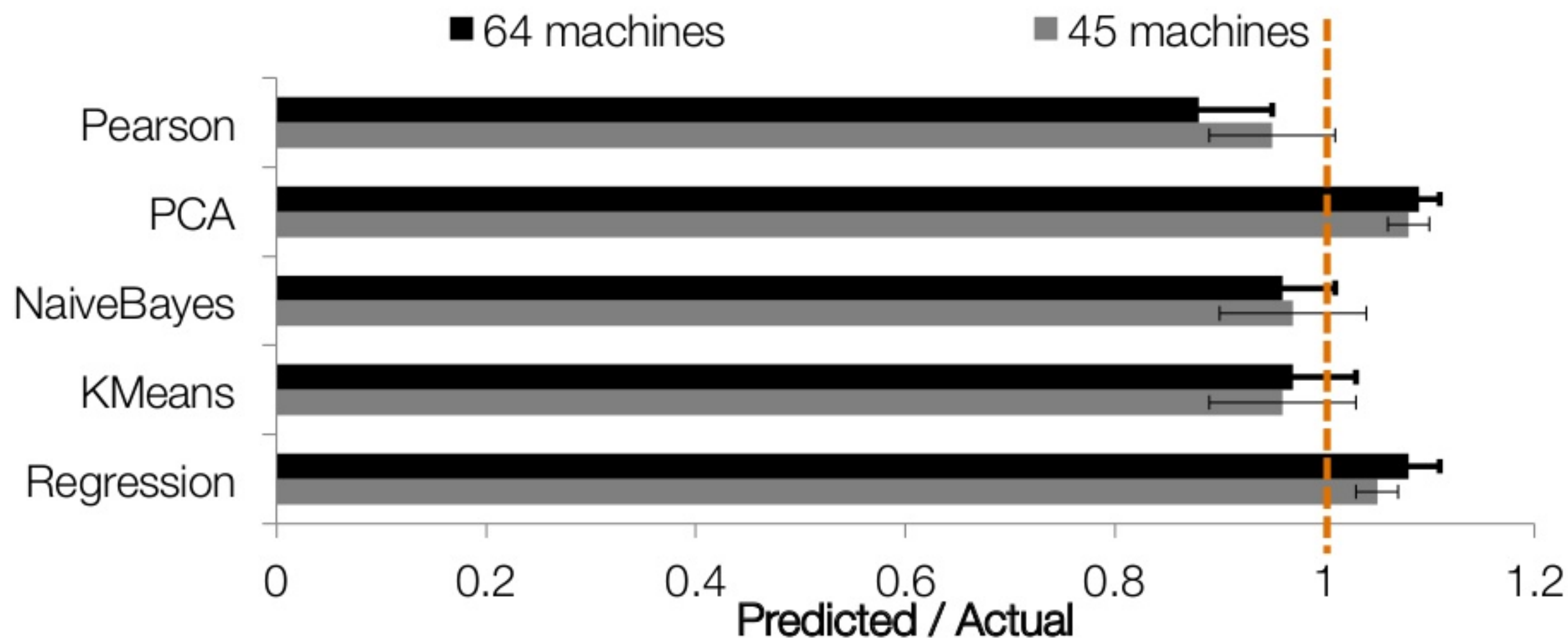


# ACCURACY: KEYSTONE-ML

TIMIT Pipeline on r3.xlarge instances, Time Per Iteration



# ACCURACY: SPARK MLLIB





# TRAINING TIME: KEYSTONE-ML

TIMIT Pipeline on r3.xlarge instances, 100 iterations

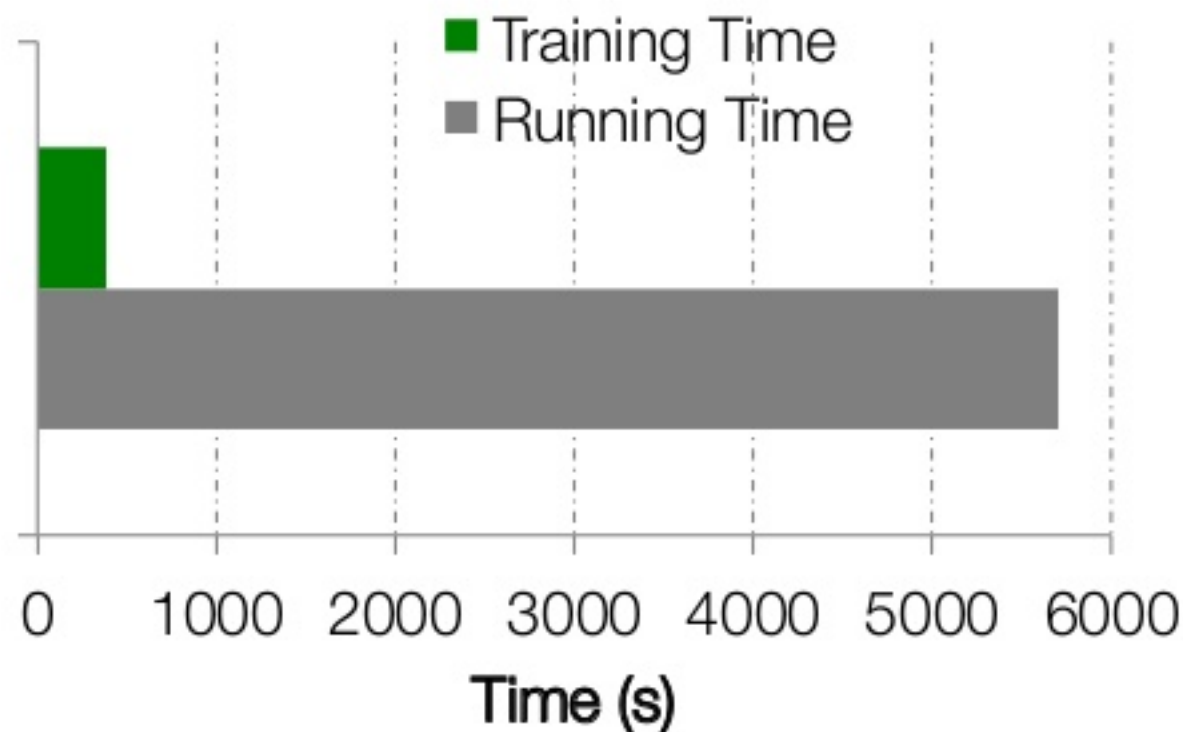
## EXPERIMENT DESIGN

7 data points

Up to 16 machines

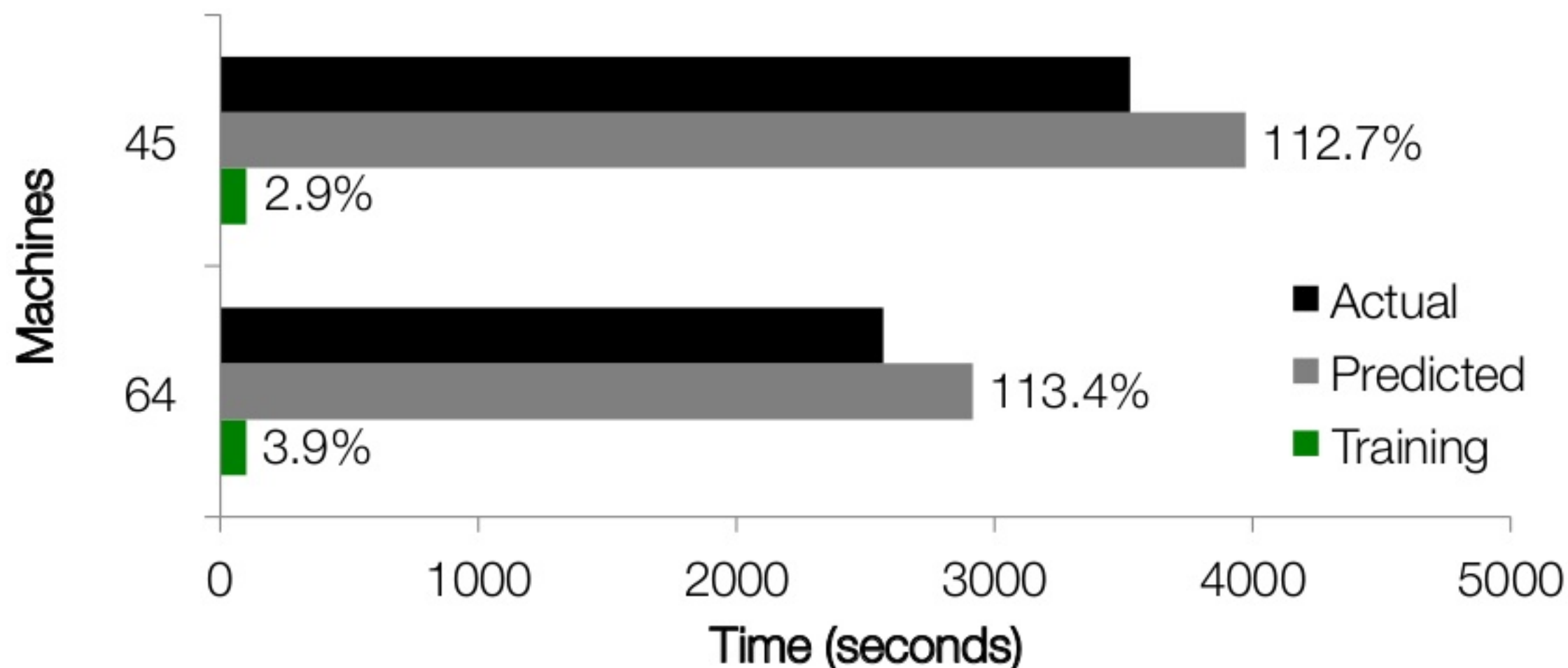
Up to 10% data

42 machines

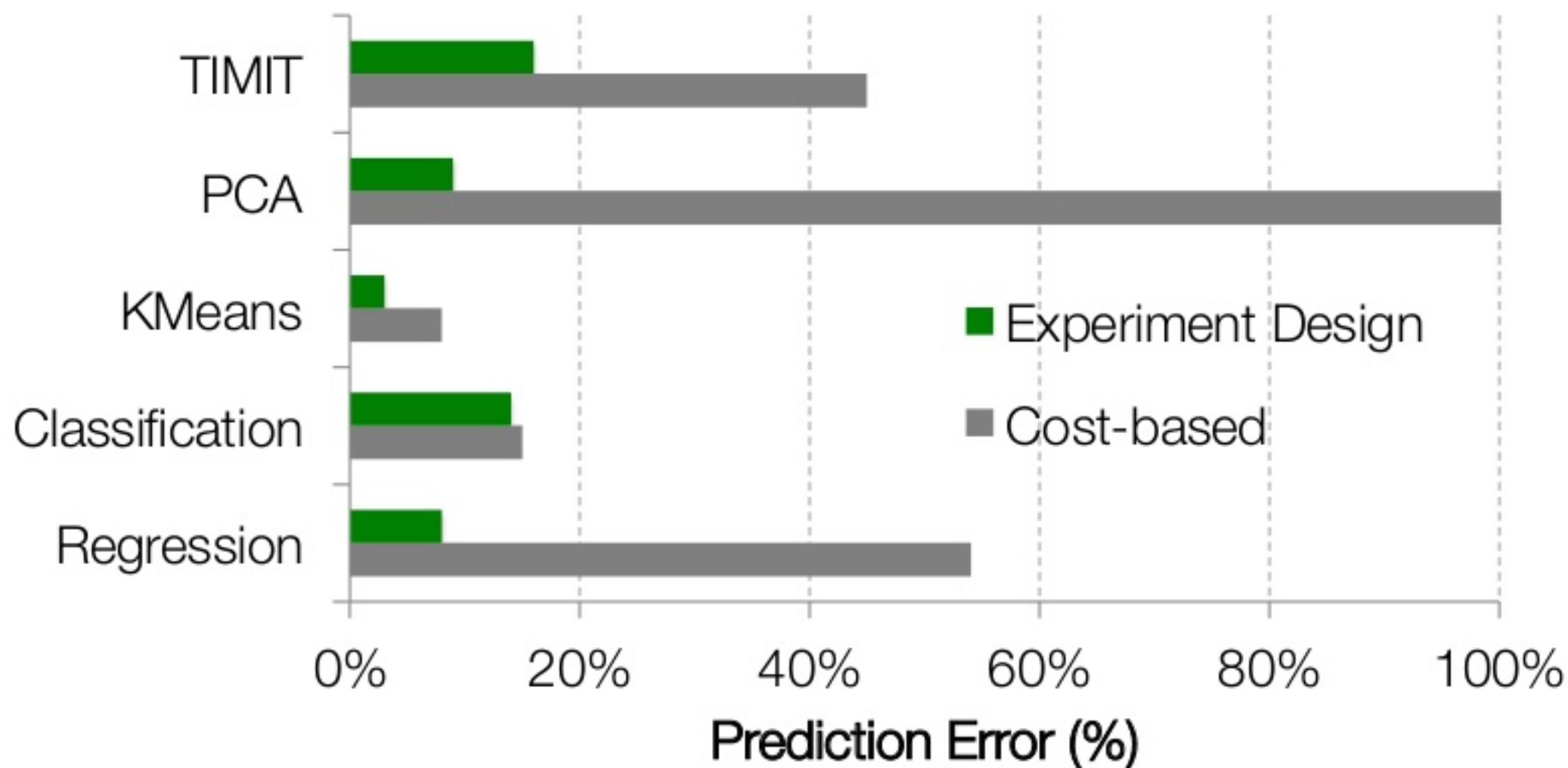


# ACCURACY, OVERHEAD: GLM REGRESSION

MLlib Regression: < 15% error



# IS EXPERIMENT DESIGN **USEFUL** ?





## MORE DETAILS

Detecting when the model is wrong

Model extensions

Amazon EC2 variations over time

Straggler mitigation strategies

<http://shivaram.org/publications/ernest-nsdi.pdf>

Python-based implementation

Experiment Design, Predictor Modules

Example using SparkML + RCV1

**OPEN** SOURCE

<https://github.com/amplab/ernest>

# IN CONCLUSION

Workload Trends: Advanced Analytics in the Cloud  
Computation, Communication patterns affect scalability

Ernest: Performance predictions with low overhead

- End-to-end linear model

- Optimal experimental design

Workloads / Traces ?

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