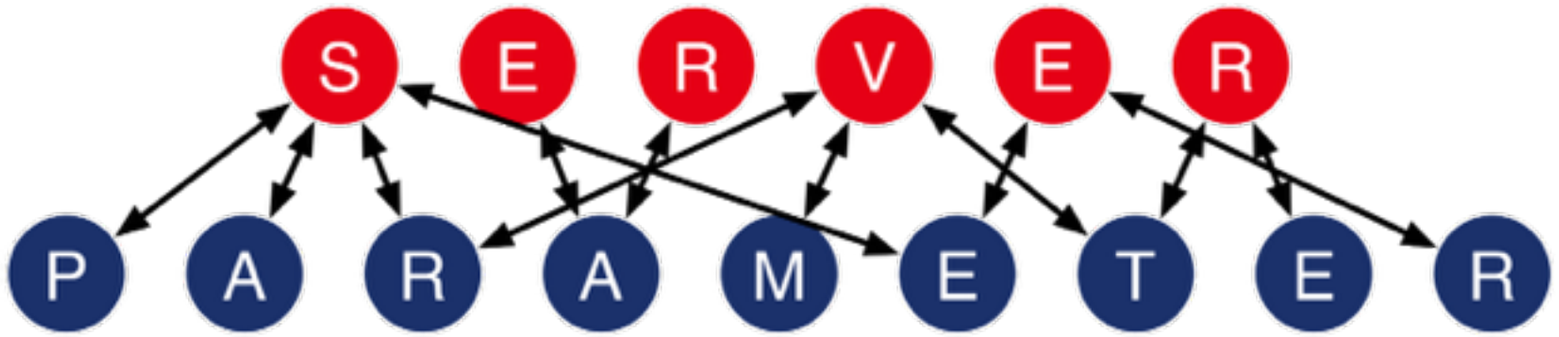
Scaling Distributed Machine Learning with the



Mu Li

muli@cs.cmu.edu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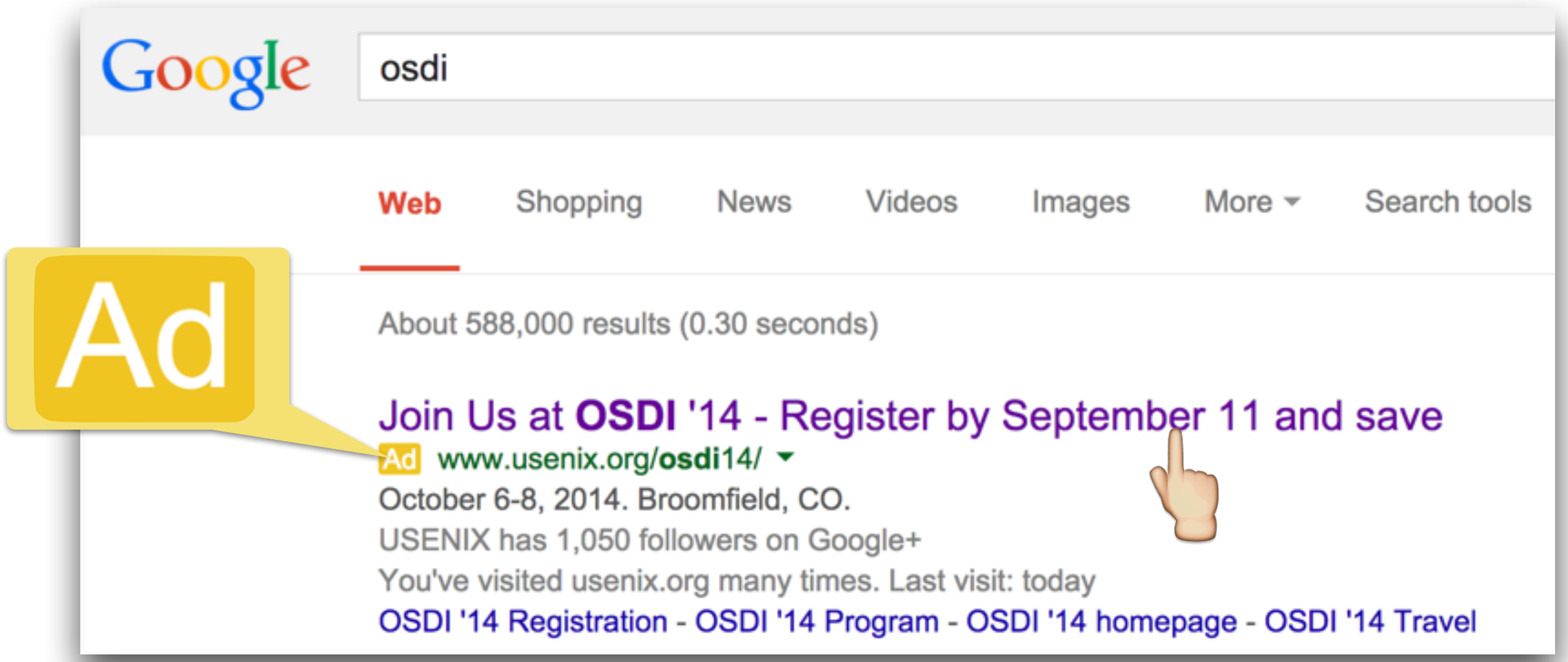
advertiser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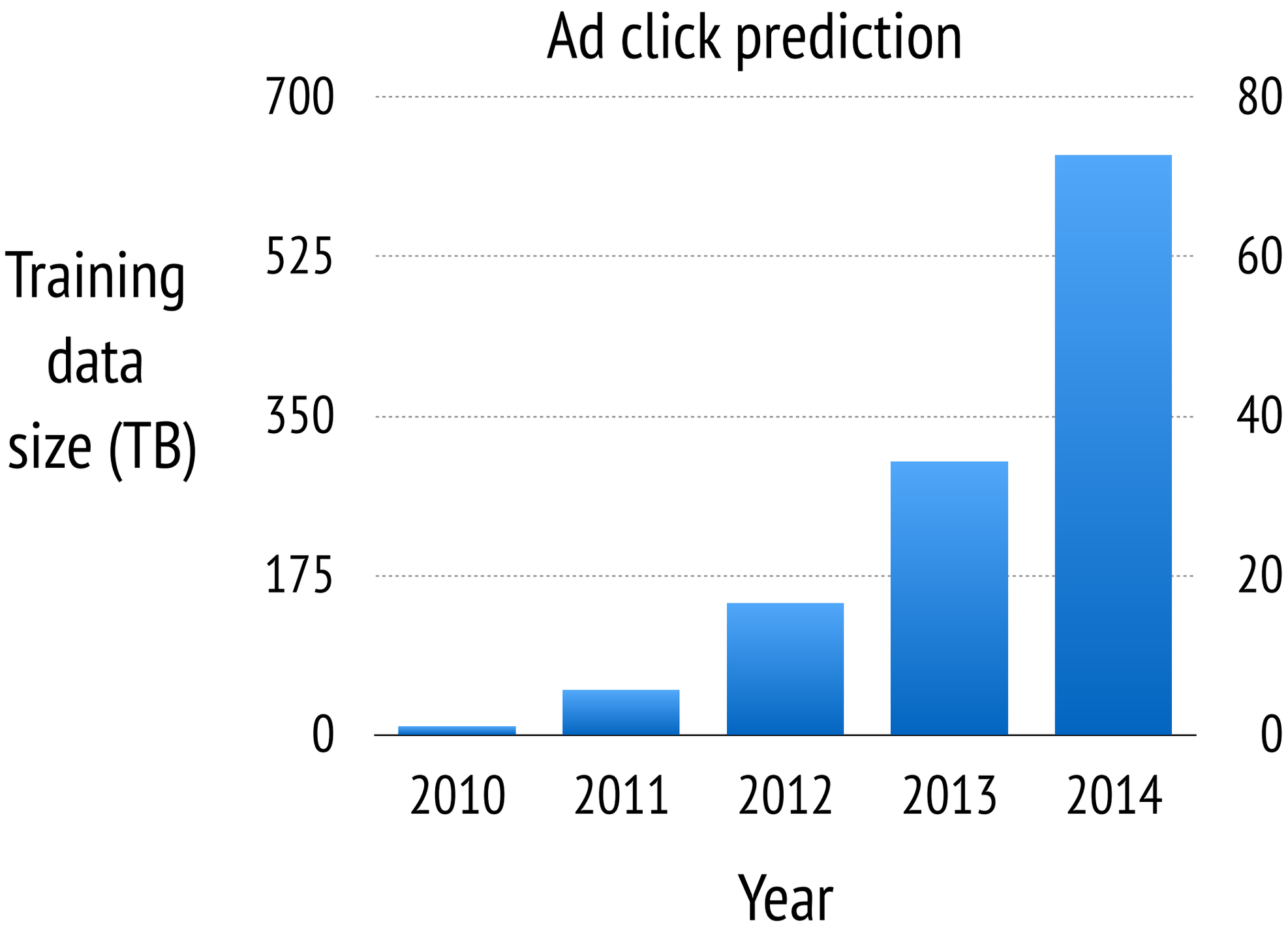
Machine learning is concerned with systems that can learn from data



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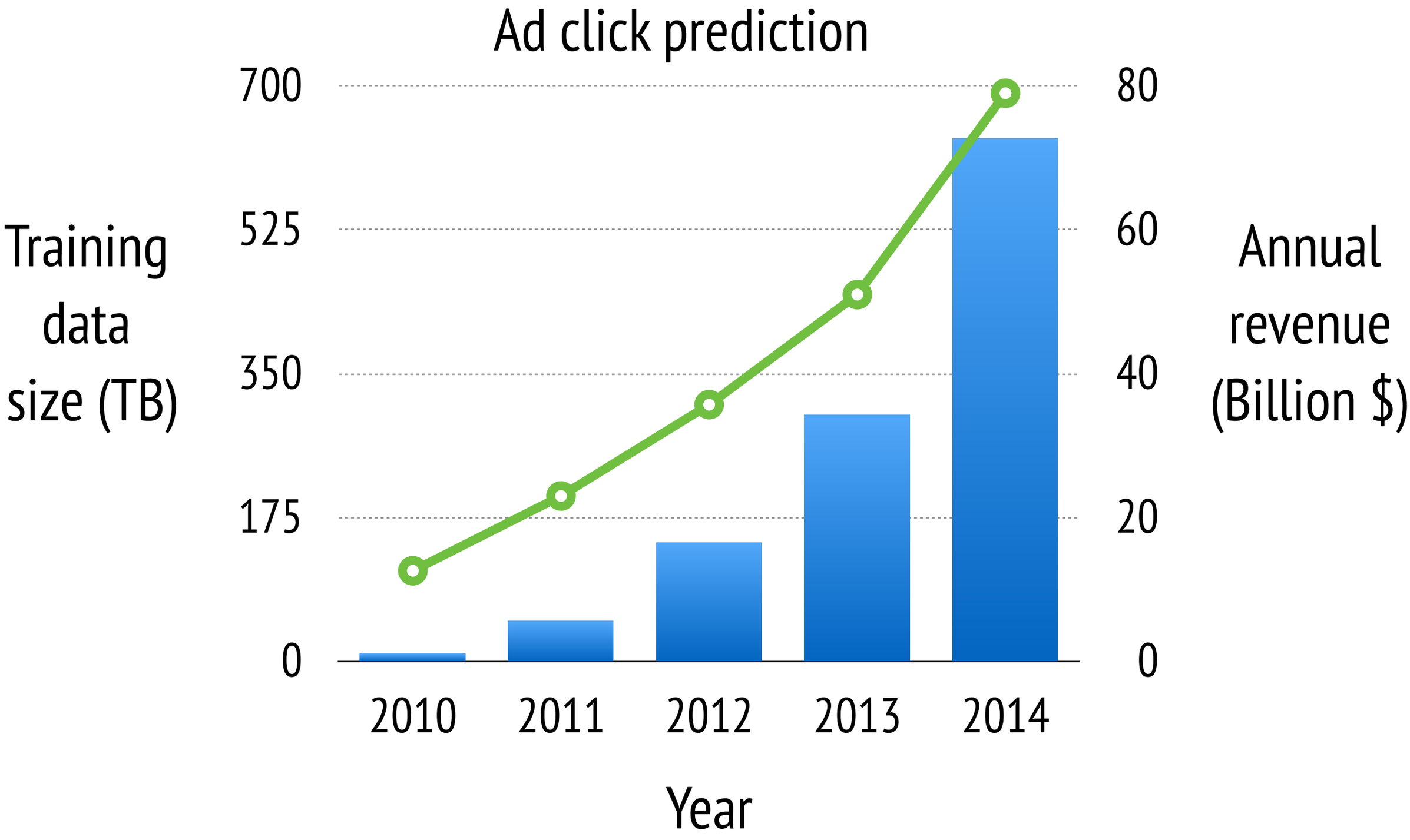
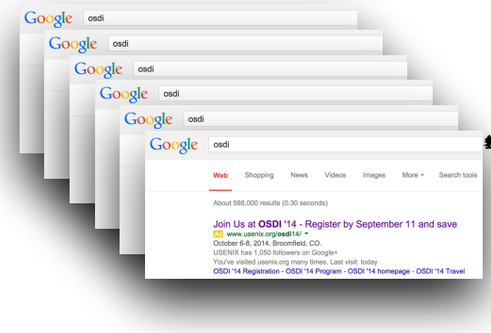


Overview of machine learning

raw data



training data

machine learning system

model

(key,value) pairs

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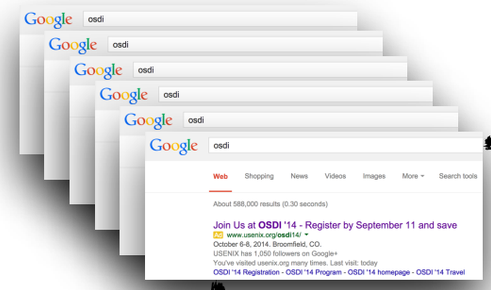

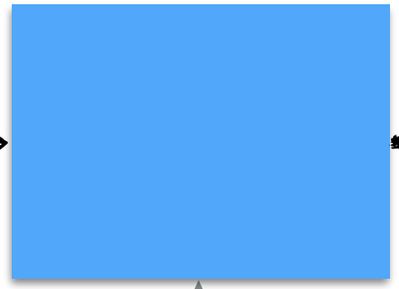

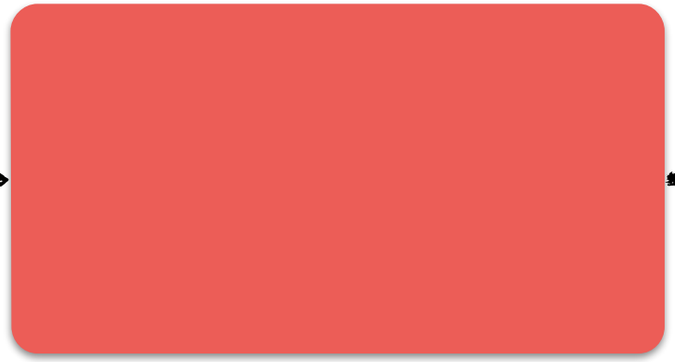

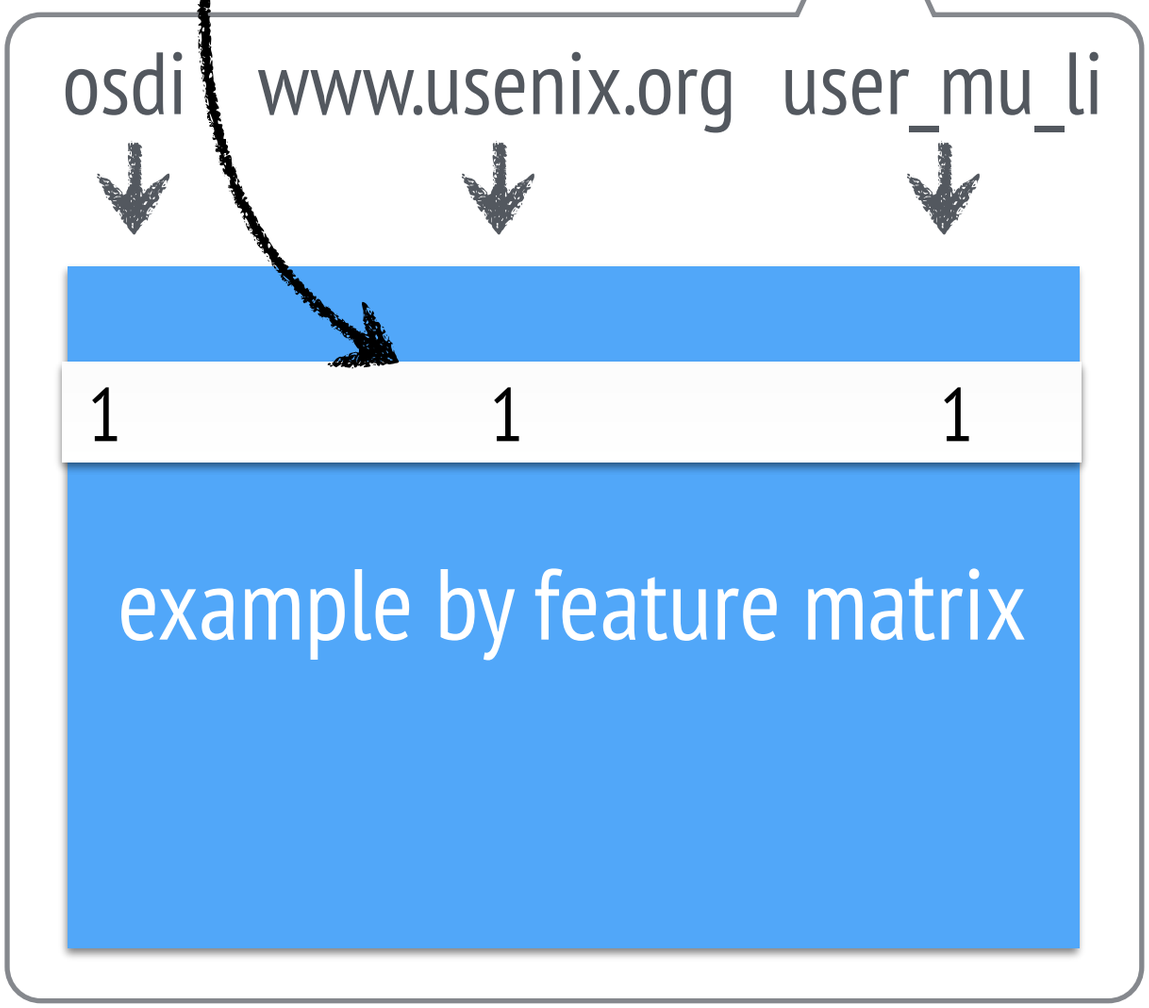

Overview of machine learning

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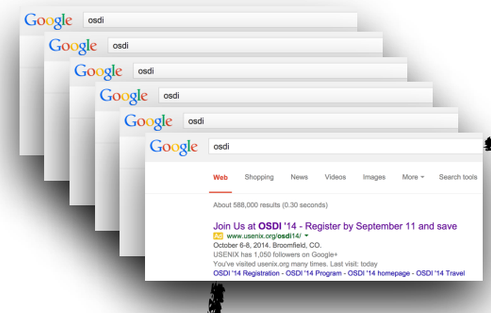
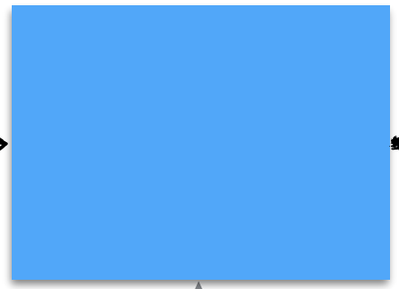
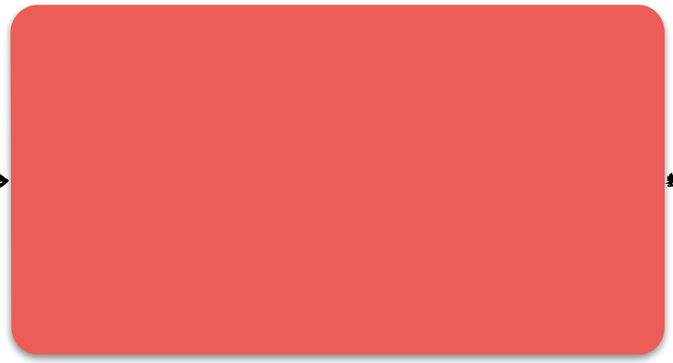






Scale of Industry problems

- 100 billion examples
- 10 billion features
- 1T – 1P training data
- 100 – 1000 machines

Overview of machine learning

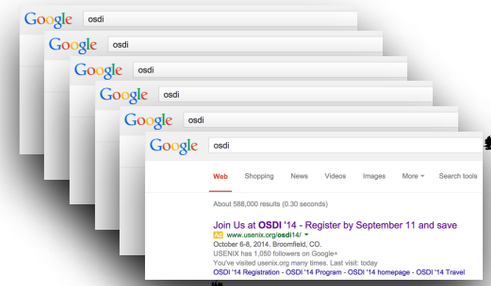
raw data

training data

machine learning system

model

(key,value) pairs



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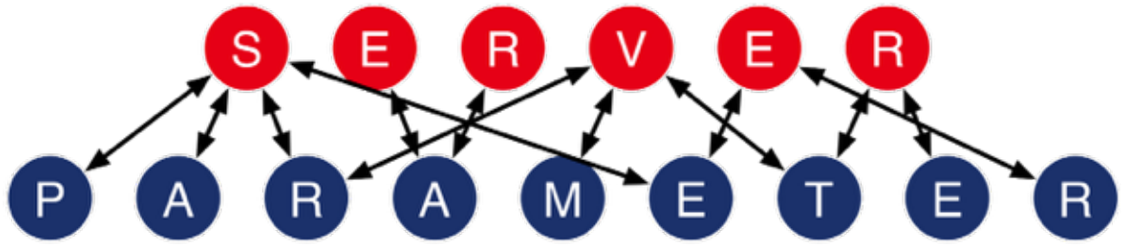
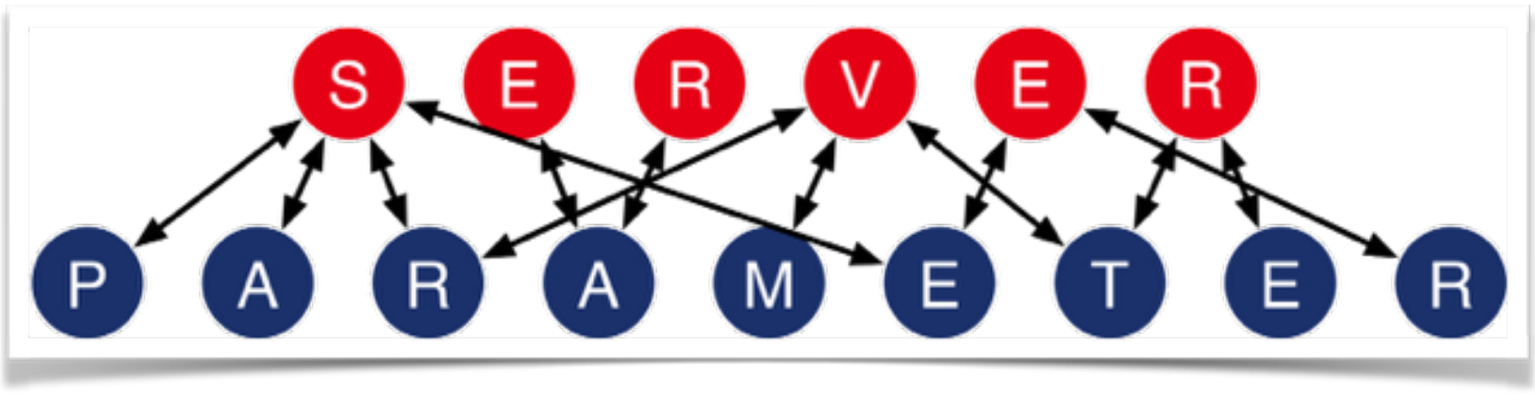
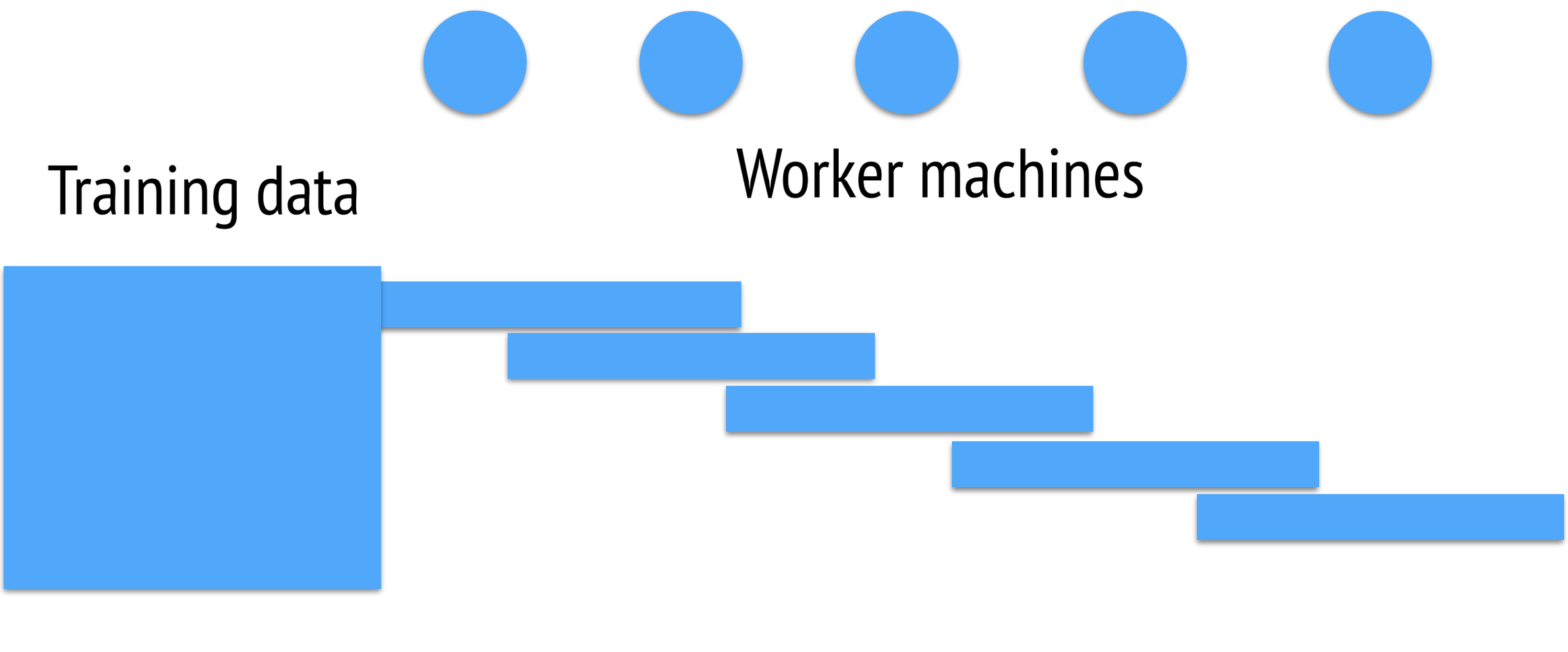


- scale to industry problems
- efficient communication
- fault tolerance
- easy to use

Industry size machine learning problems



Data and model partition



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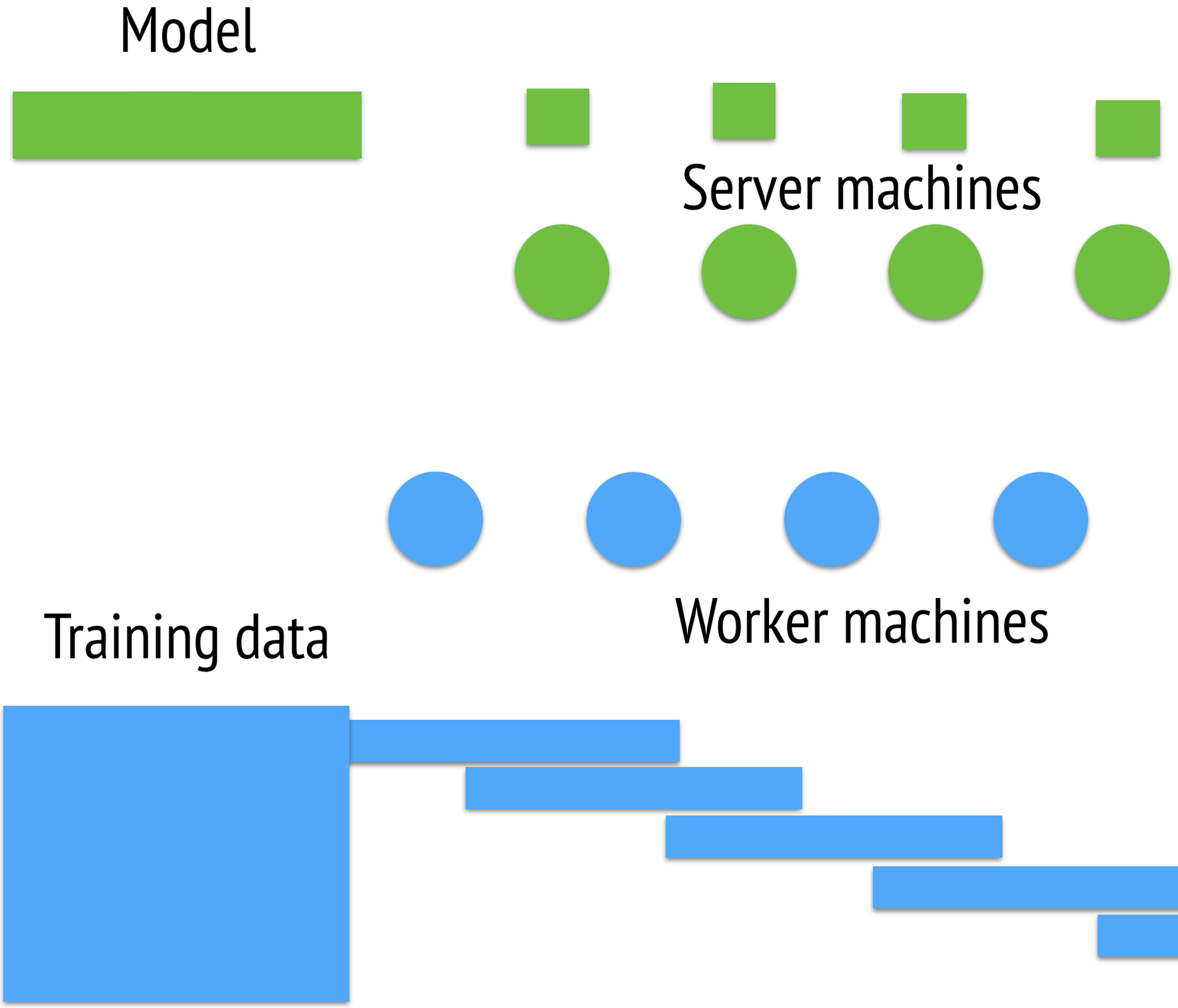

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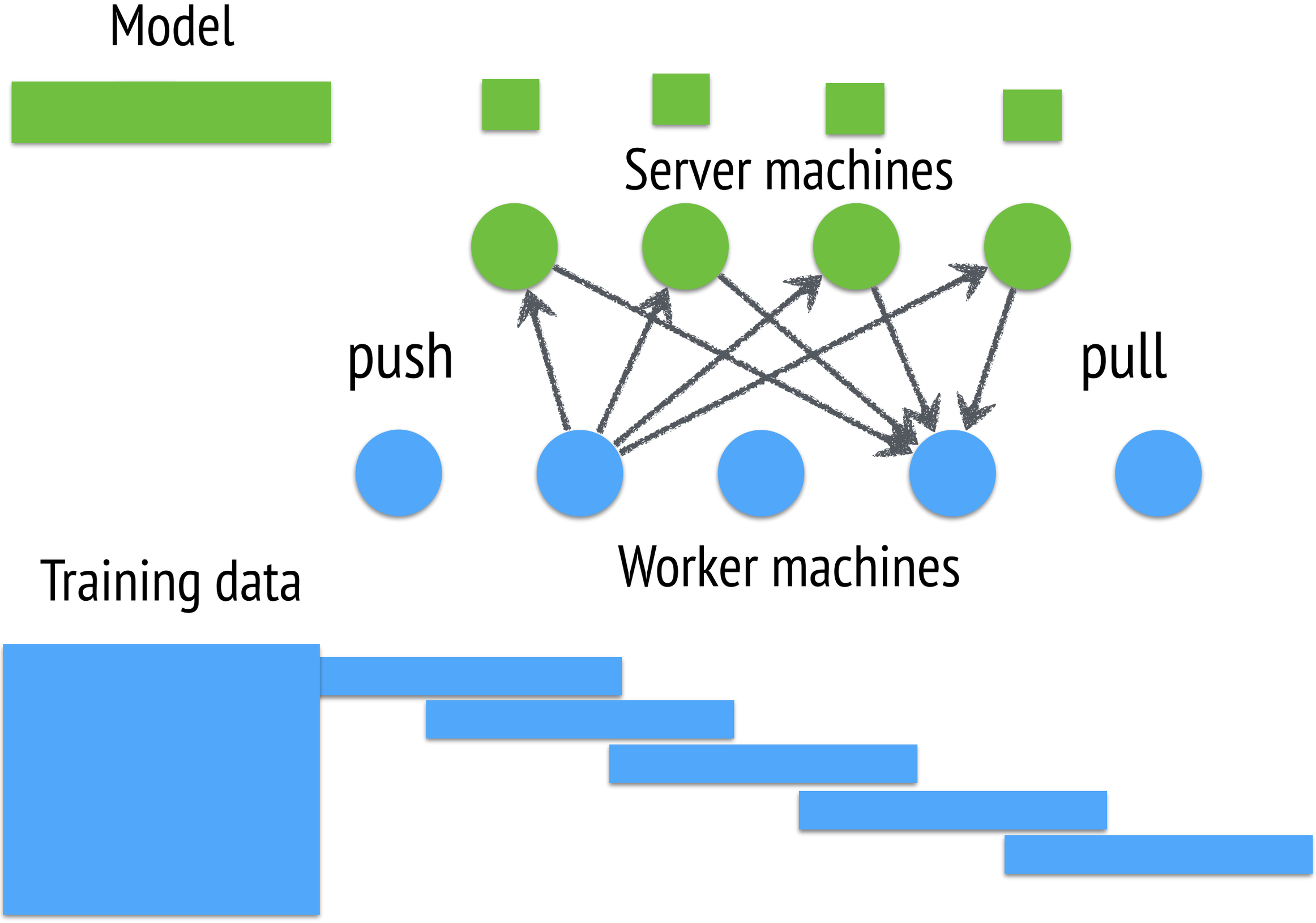
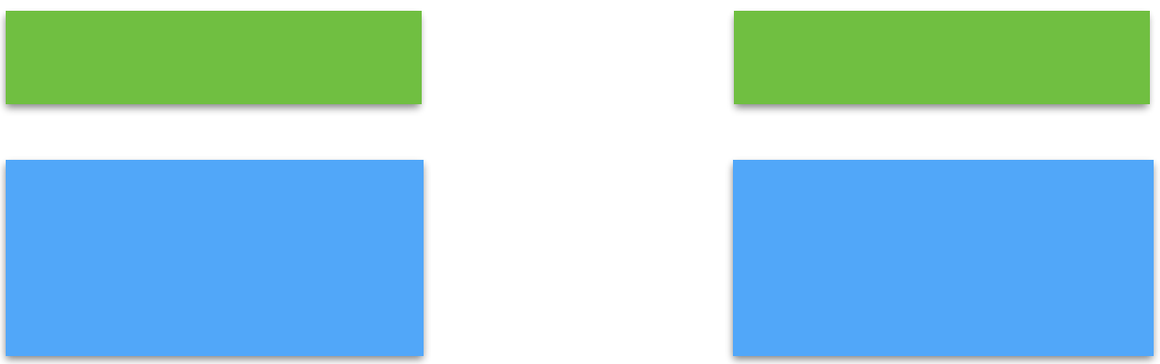


Example: distributed gradient descent

Workers **pull** the working set of model

Server machines



Worker machines

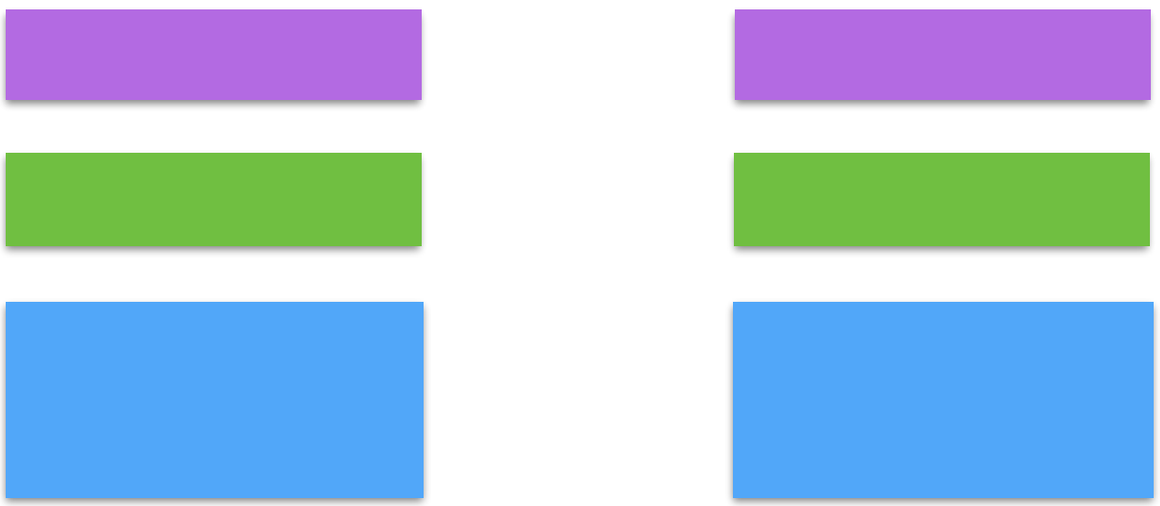
Example: distributed gradient descent

Workers **pull** the working set of model

Iterate until stop

Server machines

workers compute gradients



Worker machines

Example: distributed gradient descent

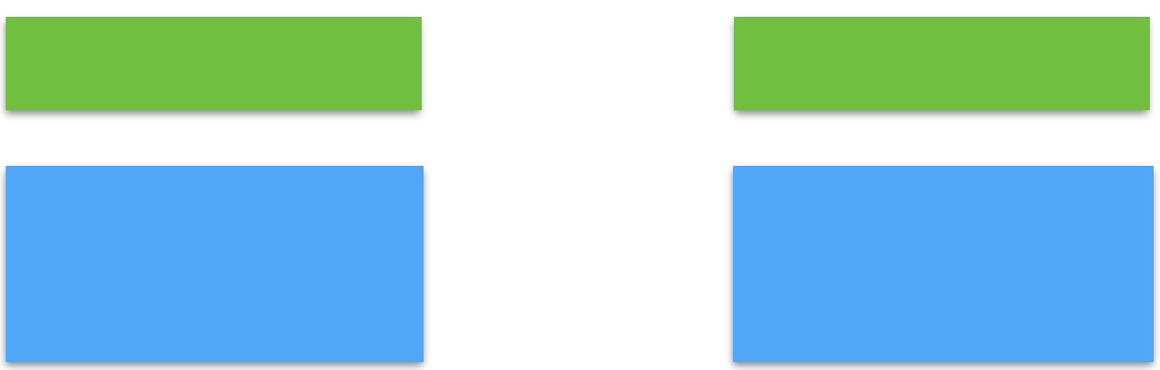
Server machines

Workers **pull** the working set of model

Iterate until stop

workers compute gradients

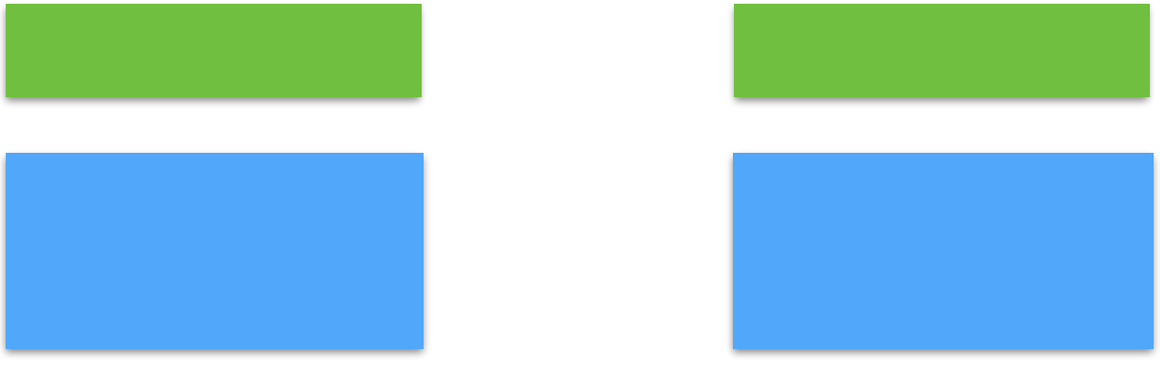
workers **push** gradients



Worker machines

Example: distributed gradient descent

Server machines



Worker machines

Workers **pull** the working set of model

Iterate until stop

workers compute gradients

workers **push** gradients

update model

Example: distributed gradient descent

Server machines

Workers **pull** the working set of model

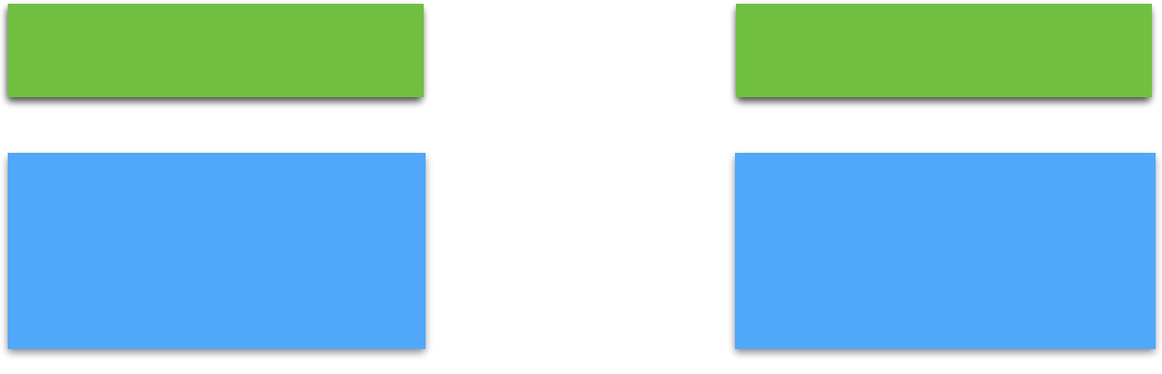
Iterate until stop

workers compute gradients

workers **push** gradients

update model

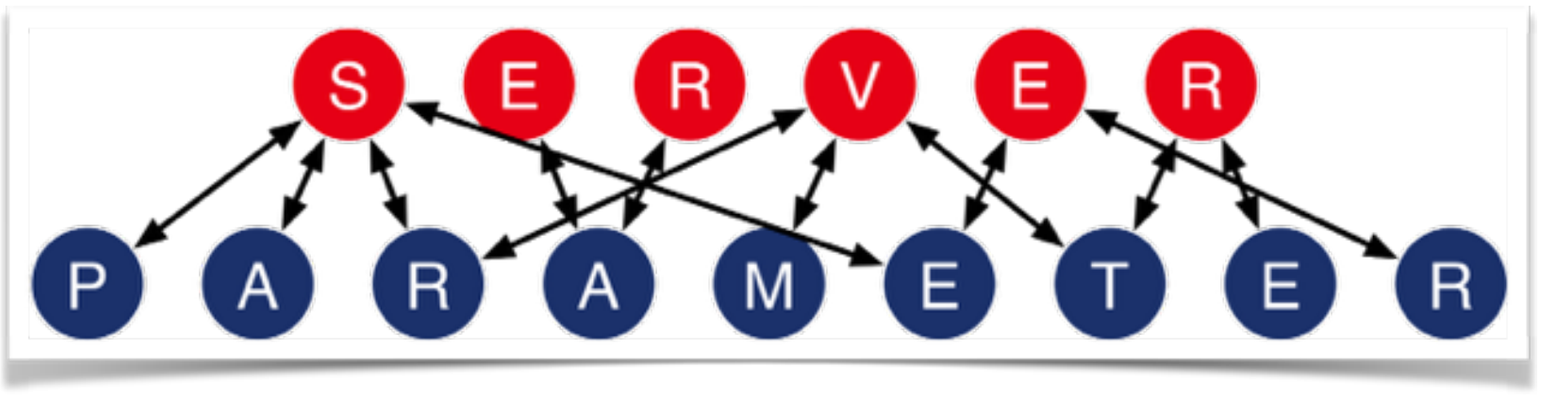
workers **pull** updated model



Worker machines

Industry size machine learning problems

Efficient communication

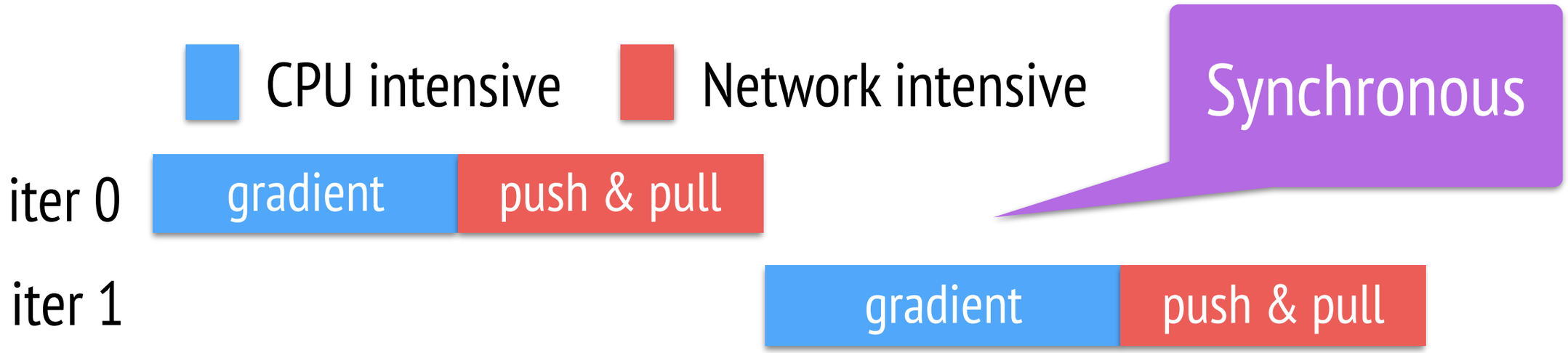


Challenges for data synchronization

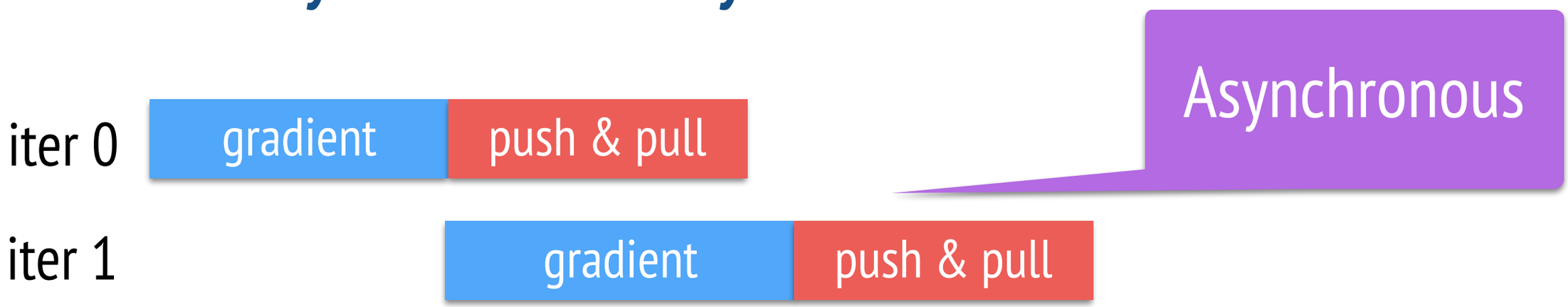
- Massive communication traffic
  - frequent access to the shared model
- Expensive global barriers
  - between iterations

Task

- a push / pull / user defined function (an iteration)
- "execute-after-finished" dependency



- executed asynchronously

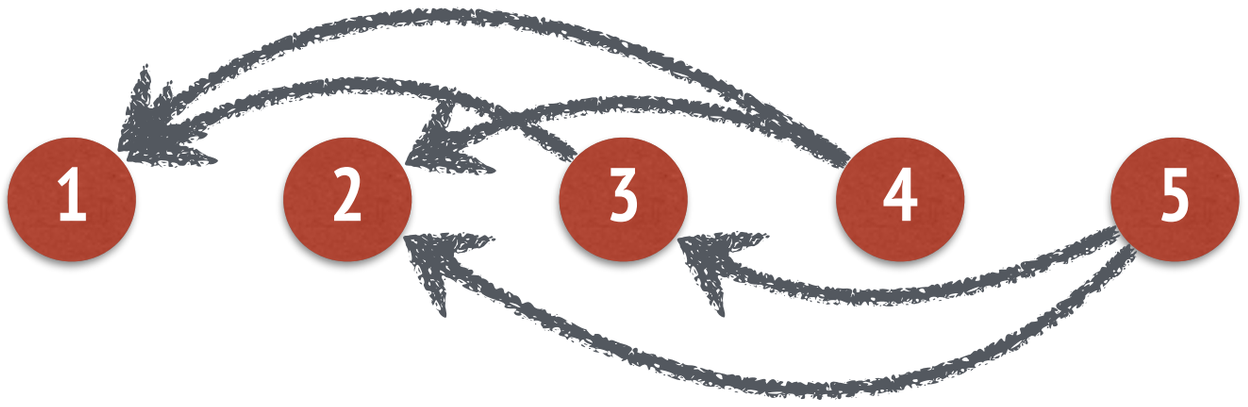


Flexible consistency

- Trade-off between algorithm efficiency and system performance

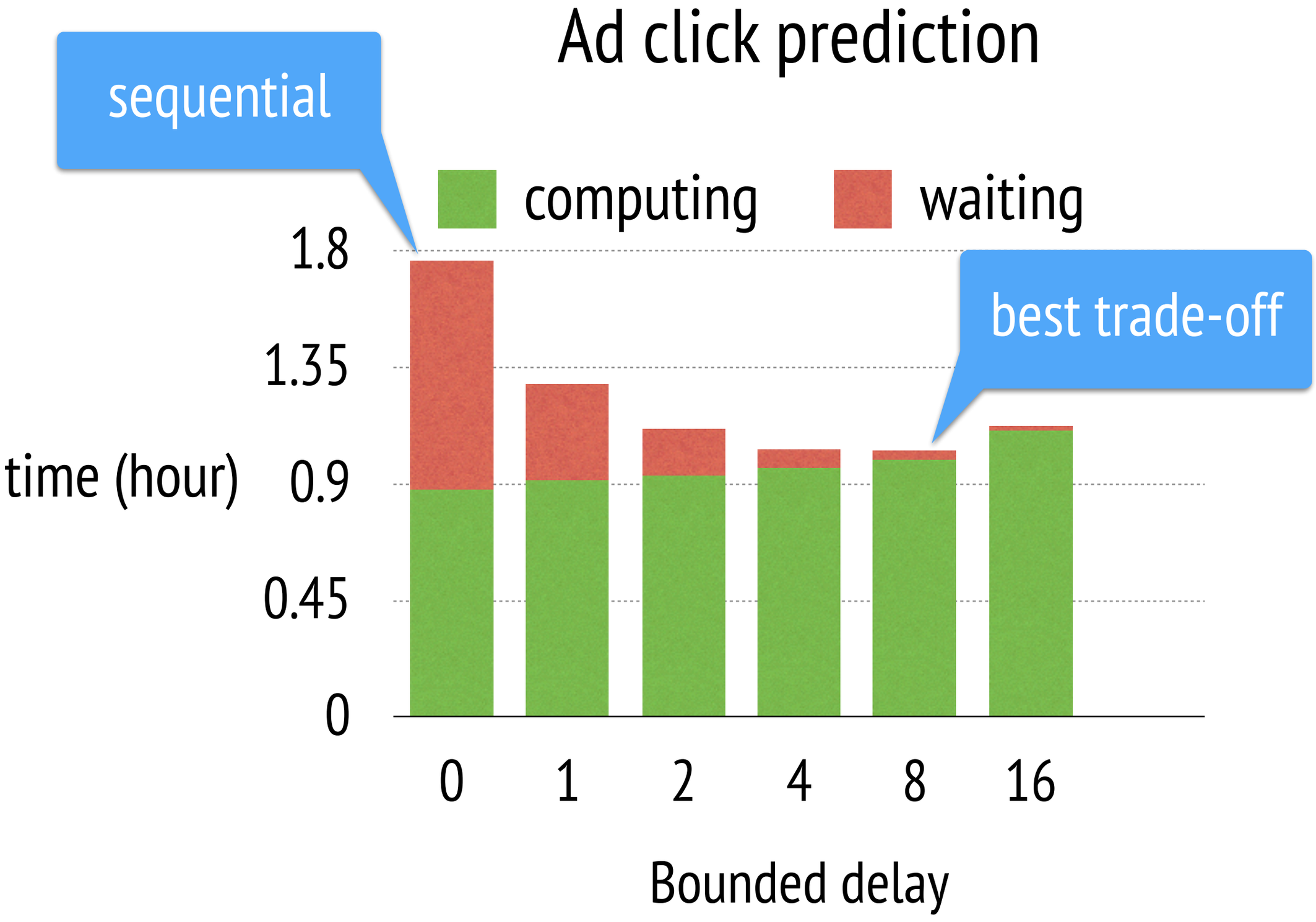
Sequential

1-bounded delay



Eventual

Results for bounded delay

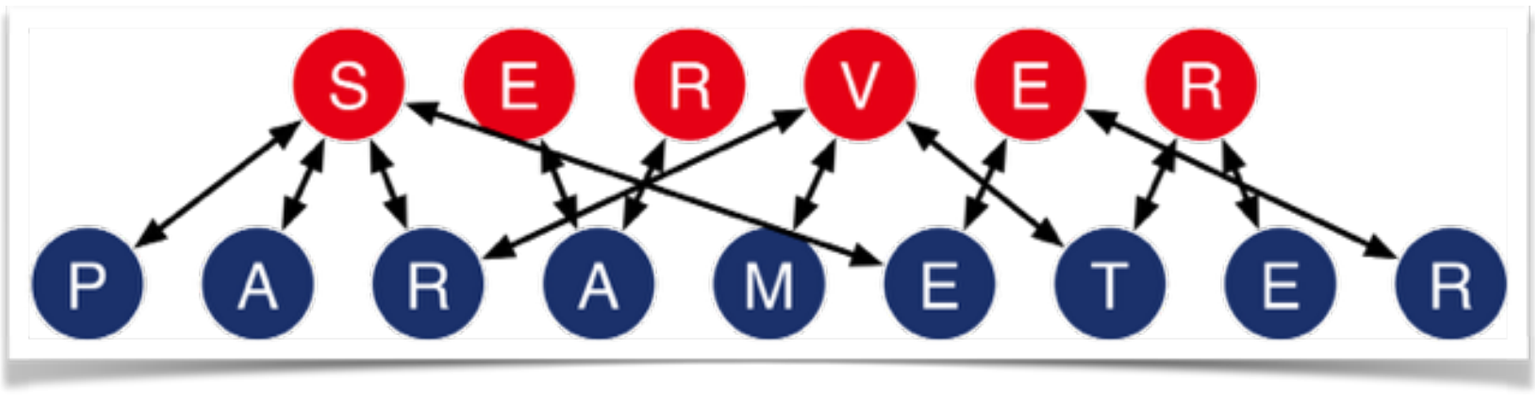


User-defined filters

- Selectively communicate (key, value) pairs
- E.g., the KKT filter
  - ★ send pairs if they are likely to affect the model
  - ★ >95% keys are filtered in the ad click prediction task

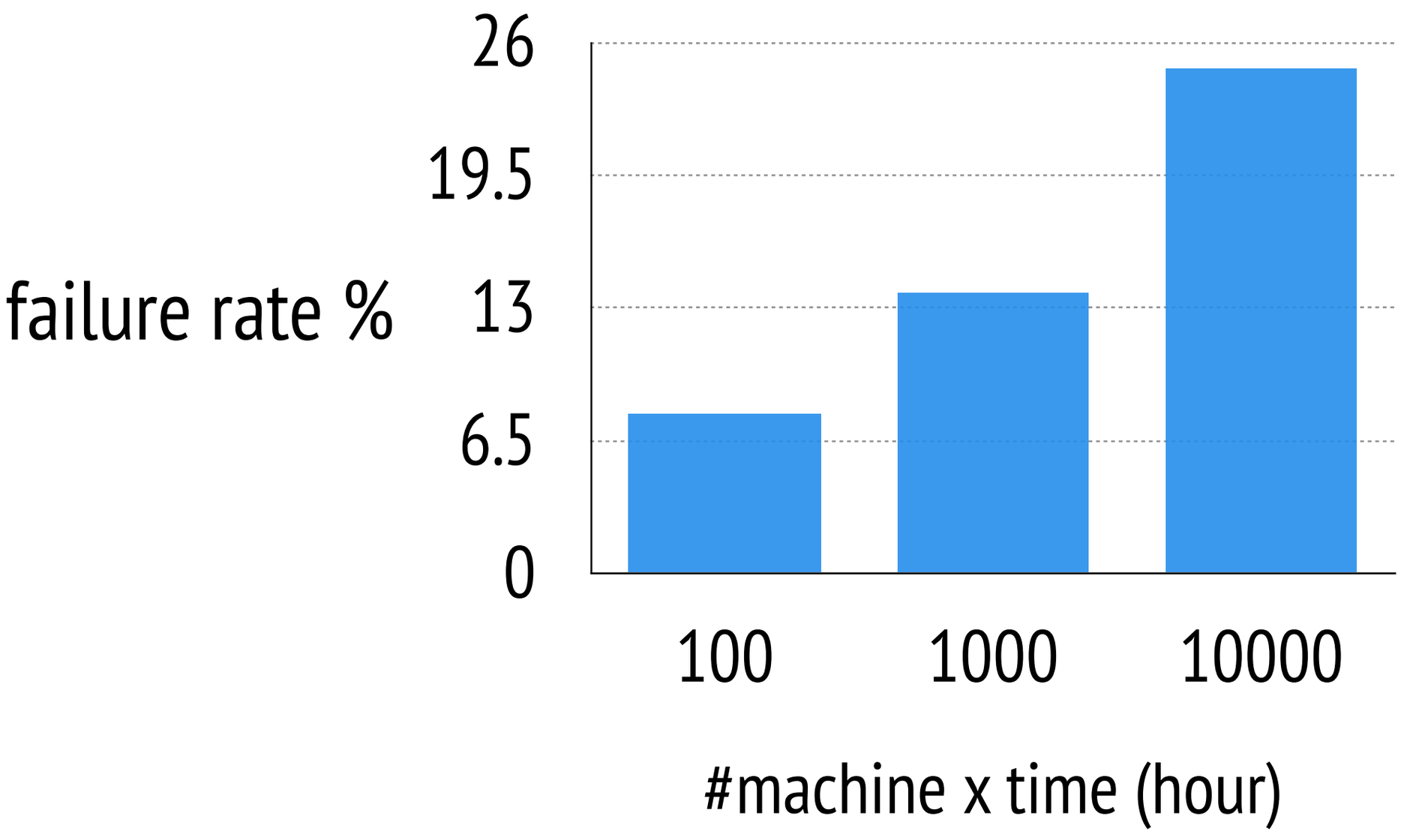
Industry size machine learning problems ✓

Efficient communication ✓



Fault tolerance

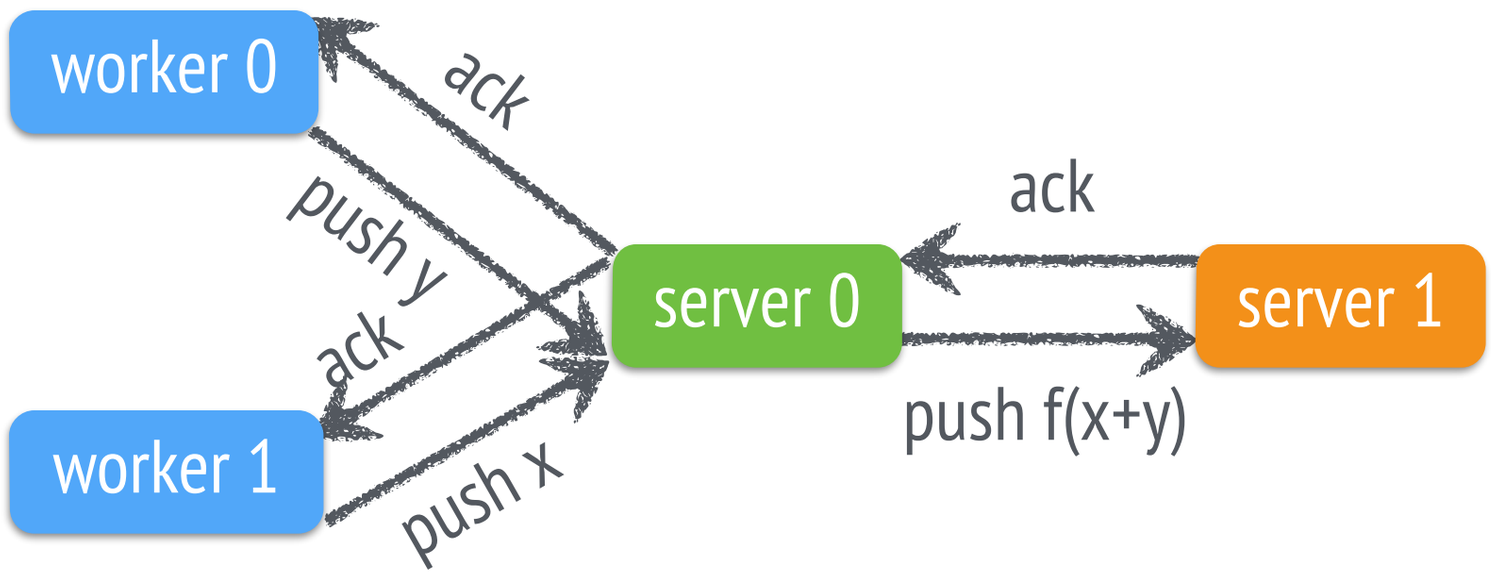
Machine learning job logs in a three-month period:



Fault tolerance

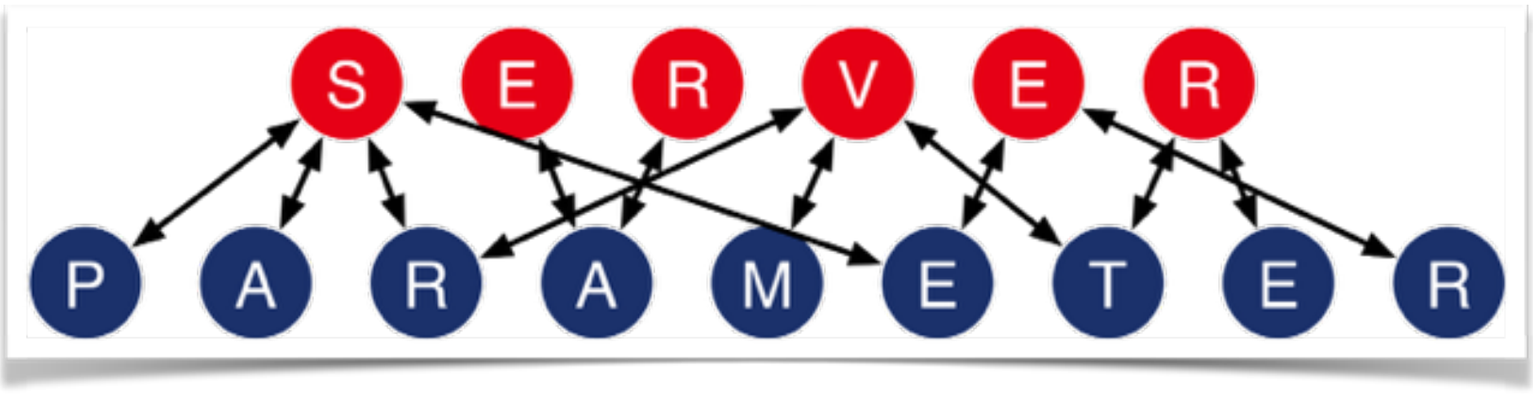
- Model is partitioned by consistent hashing
- Default replication: Chain replication (consistent, safe)

- Option: Aggregation reduces backup traffic (algo specific)



Industry size machine learning problems ✓

Efficient communication ✓



Fault tolerance ✓

Easy to use

(Key, value) vectors for the shared parameters

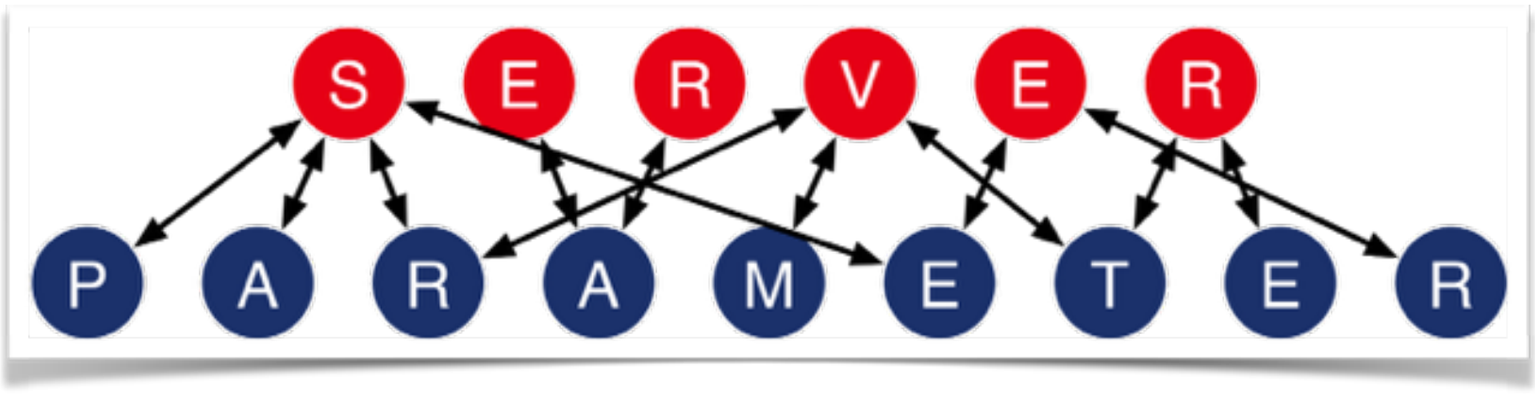
- Good for programmers: Matches mental model
- Good for system: Expose optimizations based upon structure of data

Example: computing gradient

$$\text{gradient} = \text{data}^T \times (- \text{label} \times 1 / (1 + \exp (\text{label} \times \text{data} \times \text{model}))$$

Industry size machine learning problems ✓

Efficient communication ✓



Fault tolerance ✓

Easy to use ✓

Evaluation

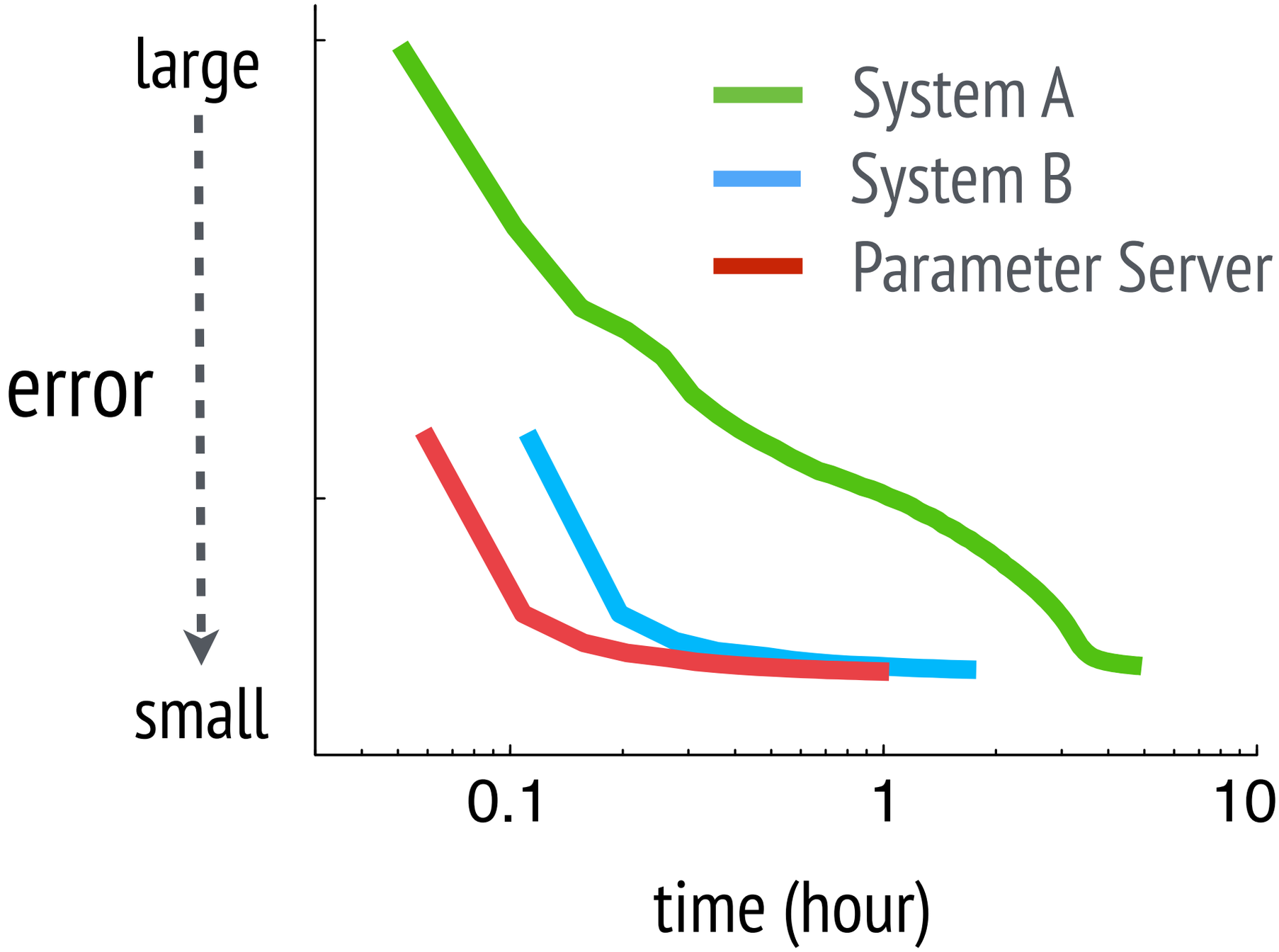
Sparse Logistic Regression

- Predict ads will be clicked or not
- Baseline: two systems in production

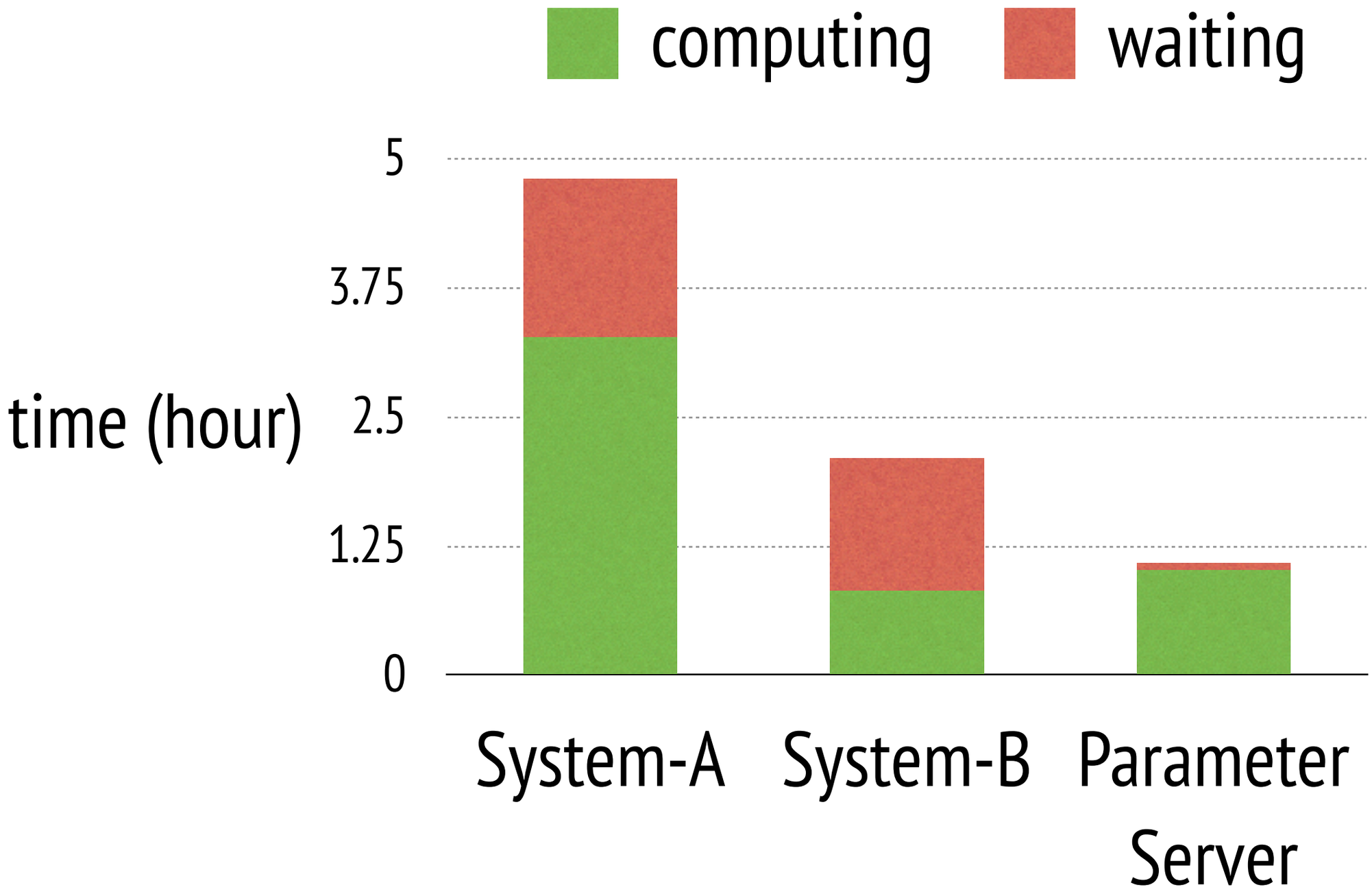
	Method	Consistency	LOC
System-A	L-BFGS	Sequential	10K
System-B	Block PG	Sequential	30K
Parameter Server	Block PG	Bounded Delay + KKT	300

- 636T real ads data
  - 170 billions of examples, 65 billions of features
- 1,000 machines with 16,000 cores

Progress

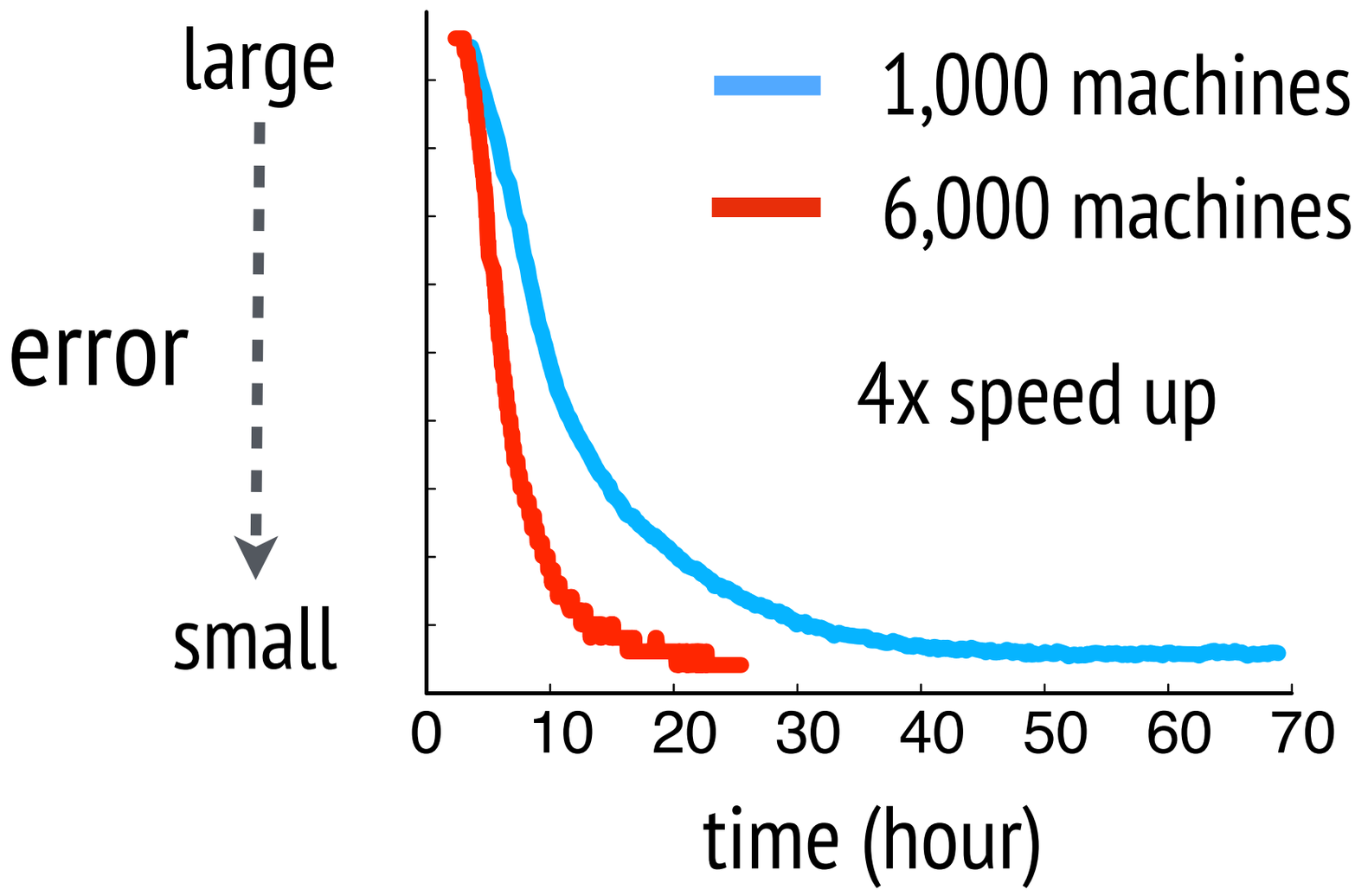

large
error
small
System A
System B
Parameter Server
0.1
1
10
time (hour)

Time decomposition



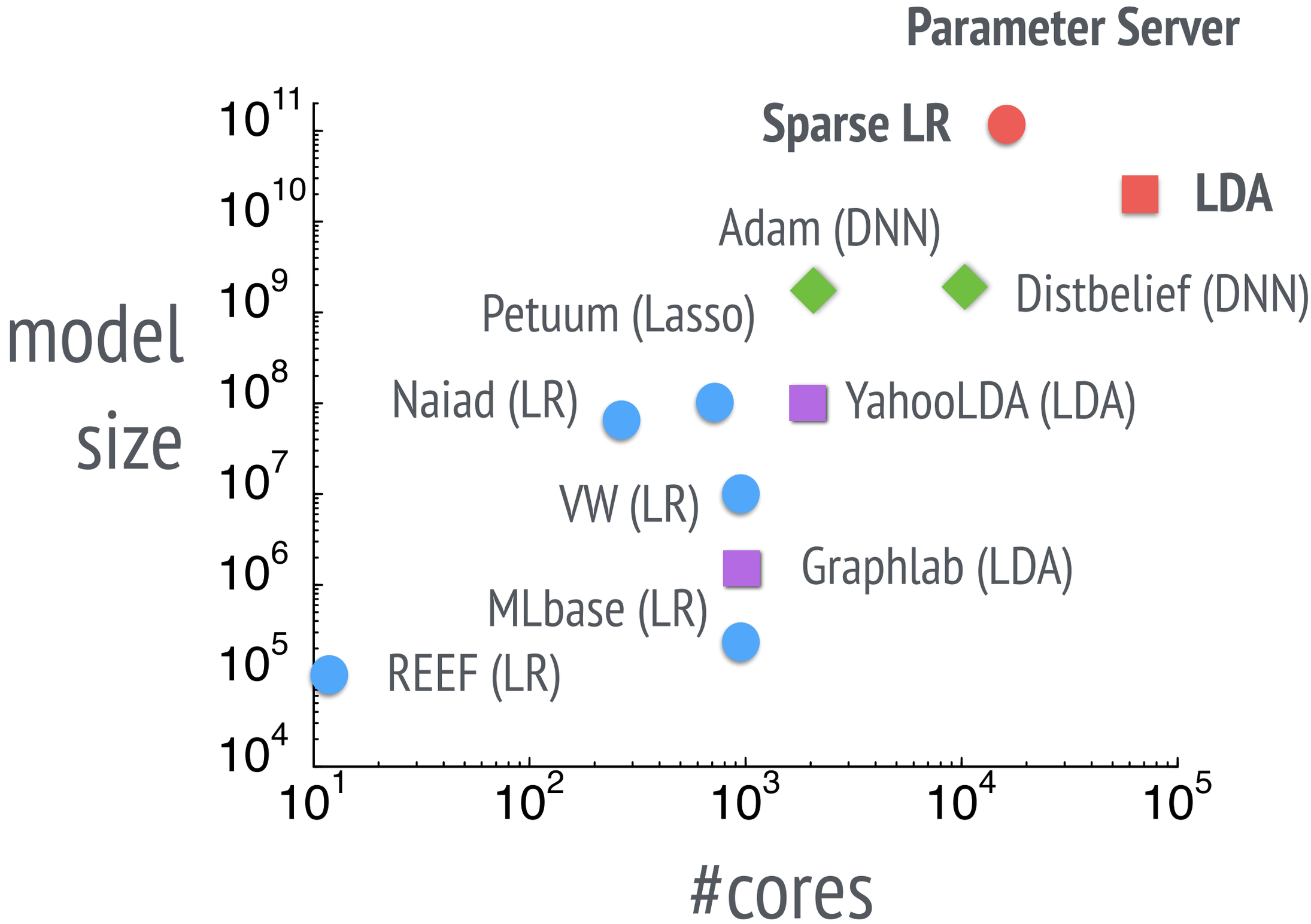
Topic Modeling ("LDA")

- Gradient descent with eventual consistency
- 5B users' click logs, Group users into 1,000 groups based on URLs they clicked



Largest experiments of related systems

Data were collected on April'14



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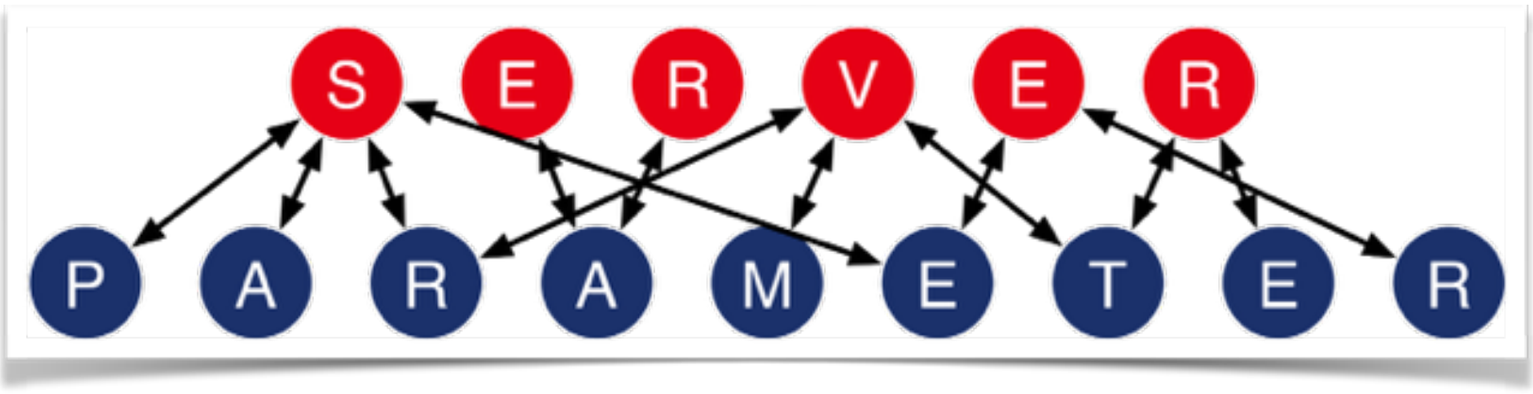
Efficient communication ✓



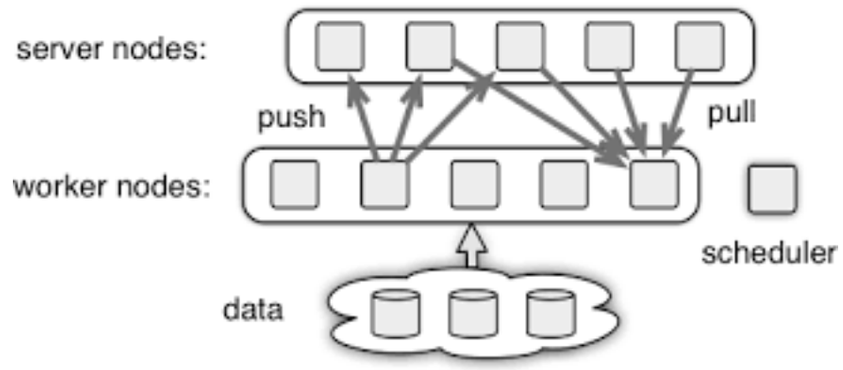
Fault tolerance ✓

Easy to use ✓

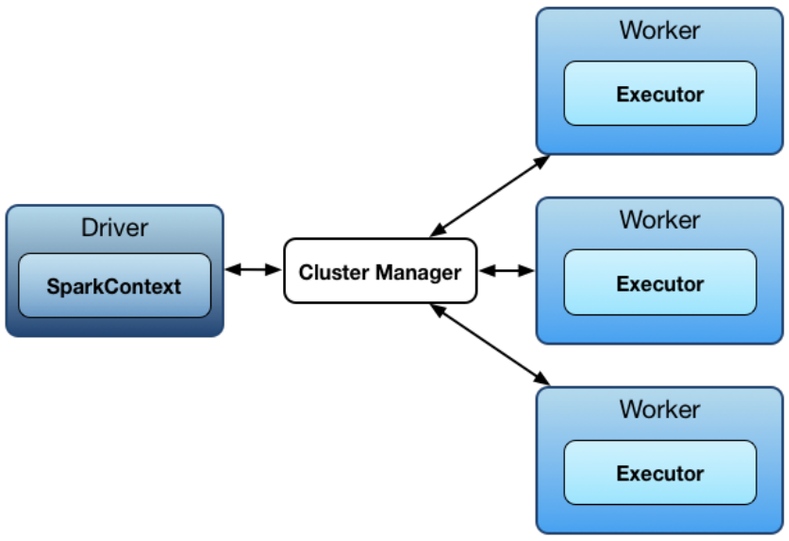
Evaluation ✓

Insights

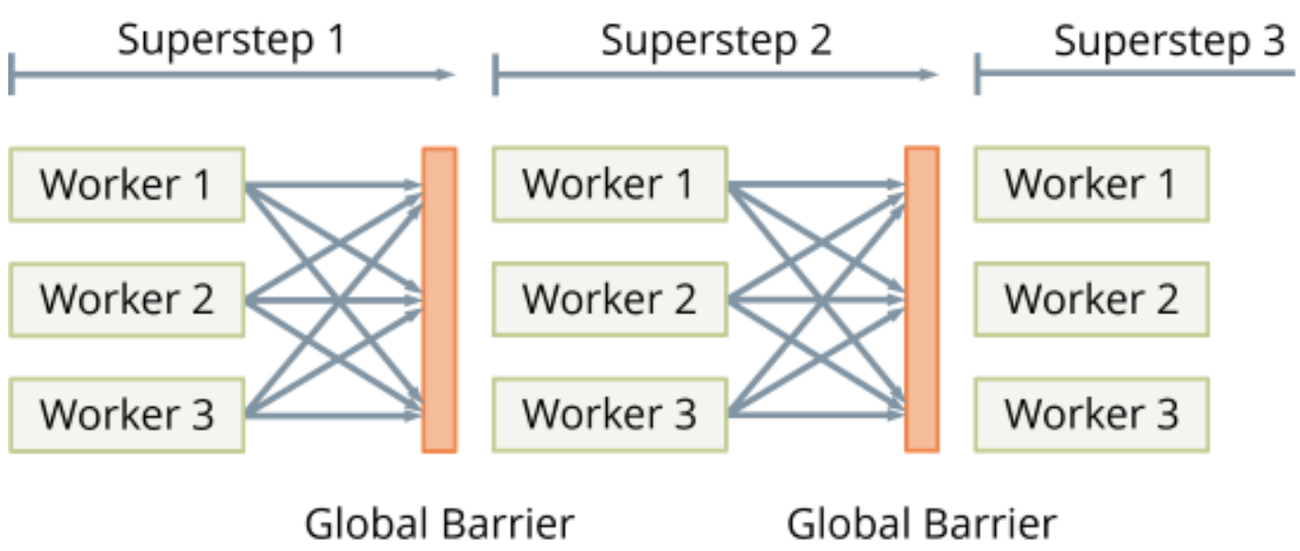
- The whole system is customized for machine learning, except the scheduler.



- Fault tolerance: checkpoint
- Spark, graph processing and parameter server



Spark



Graph processing