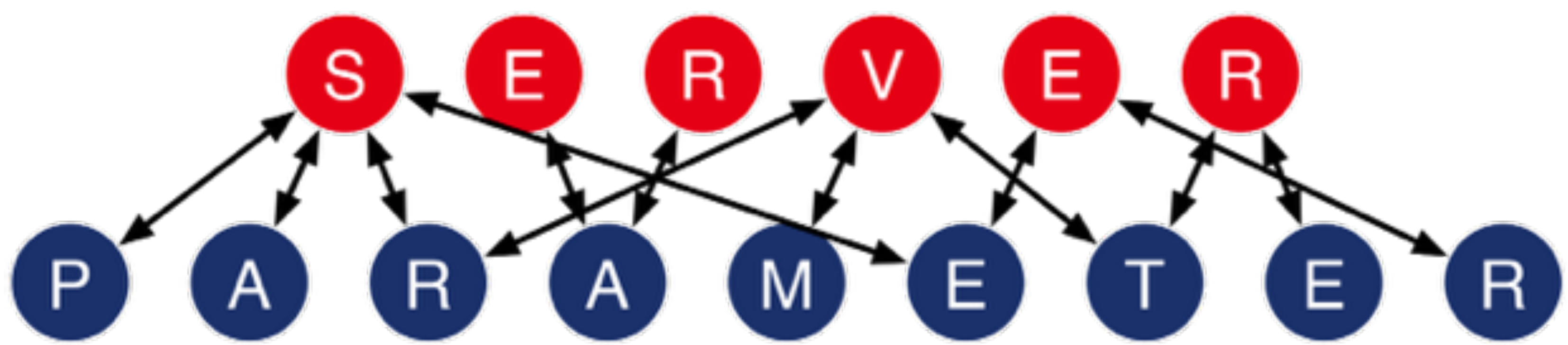
Scaling Distributed Machine Learning with the



Mu Li

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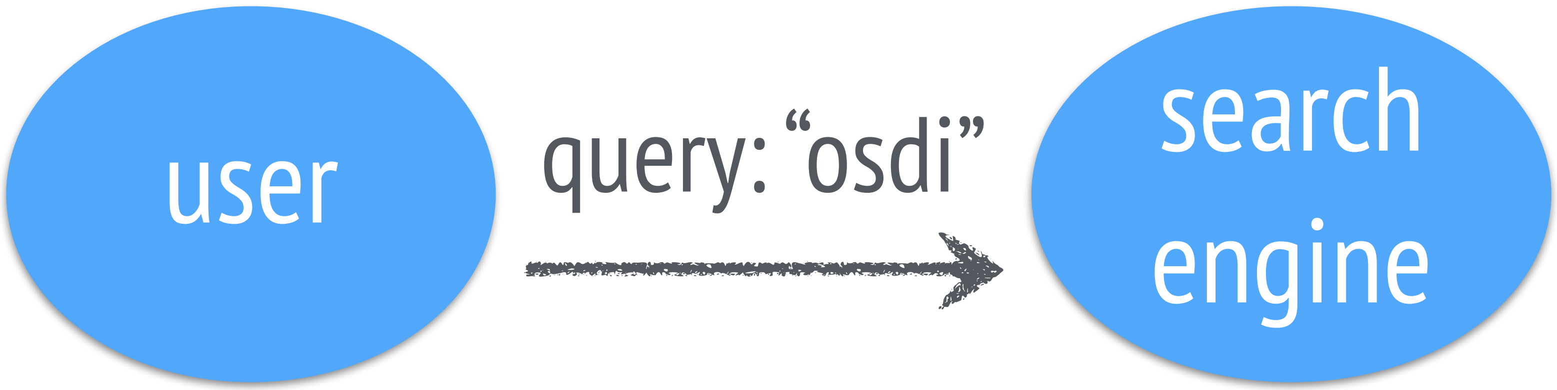
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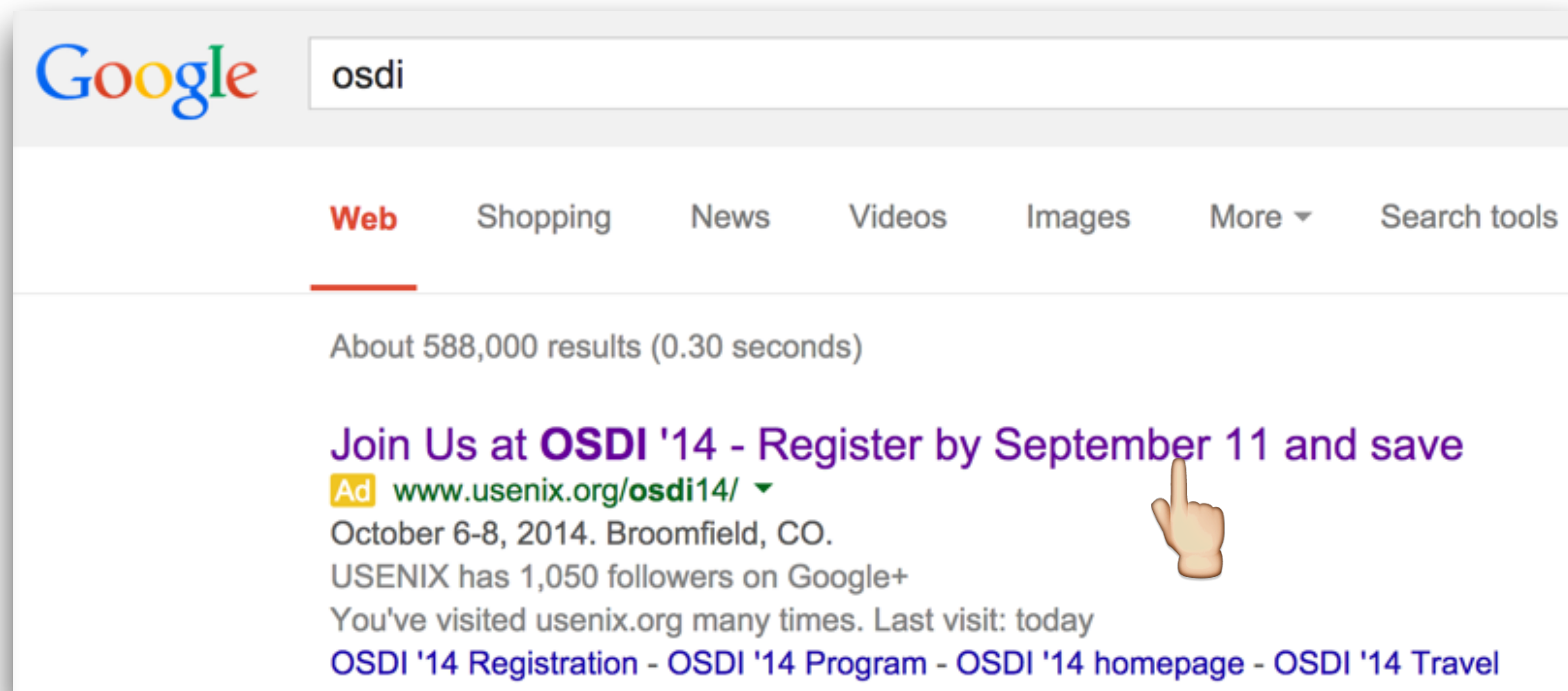
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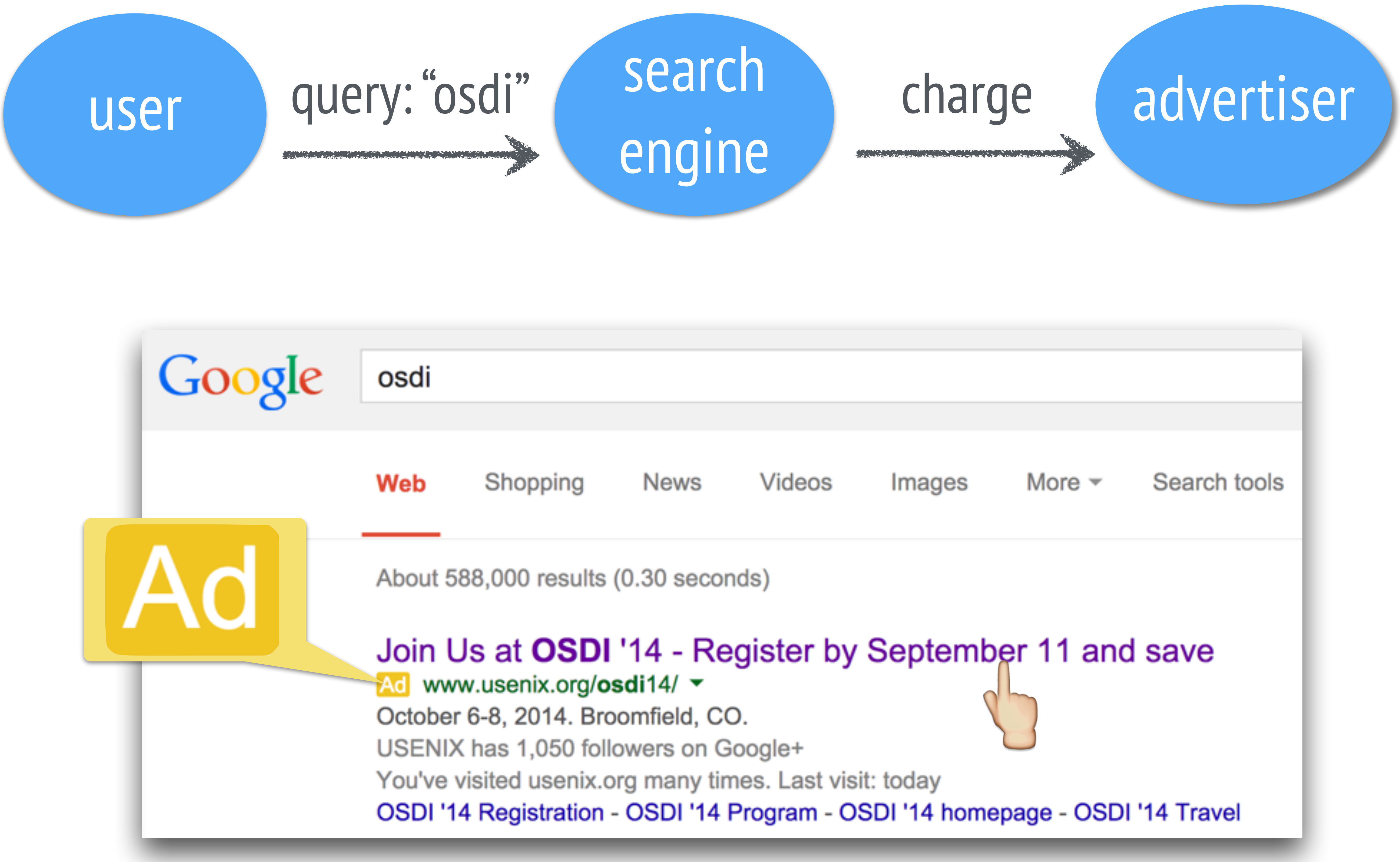
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Machine learning is concerned with systems that can learn from data

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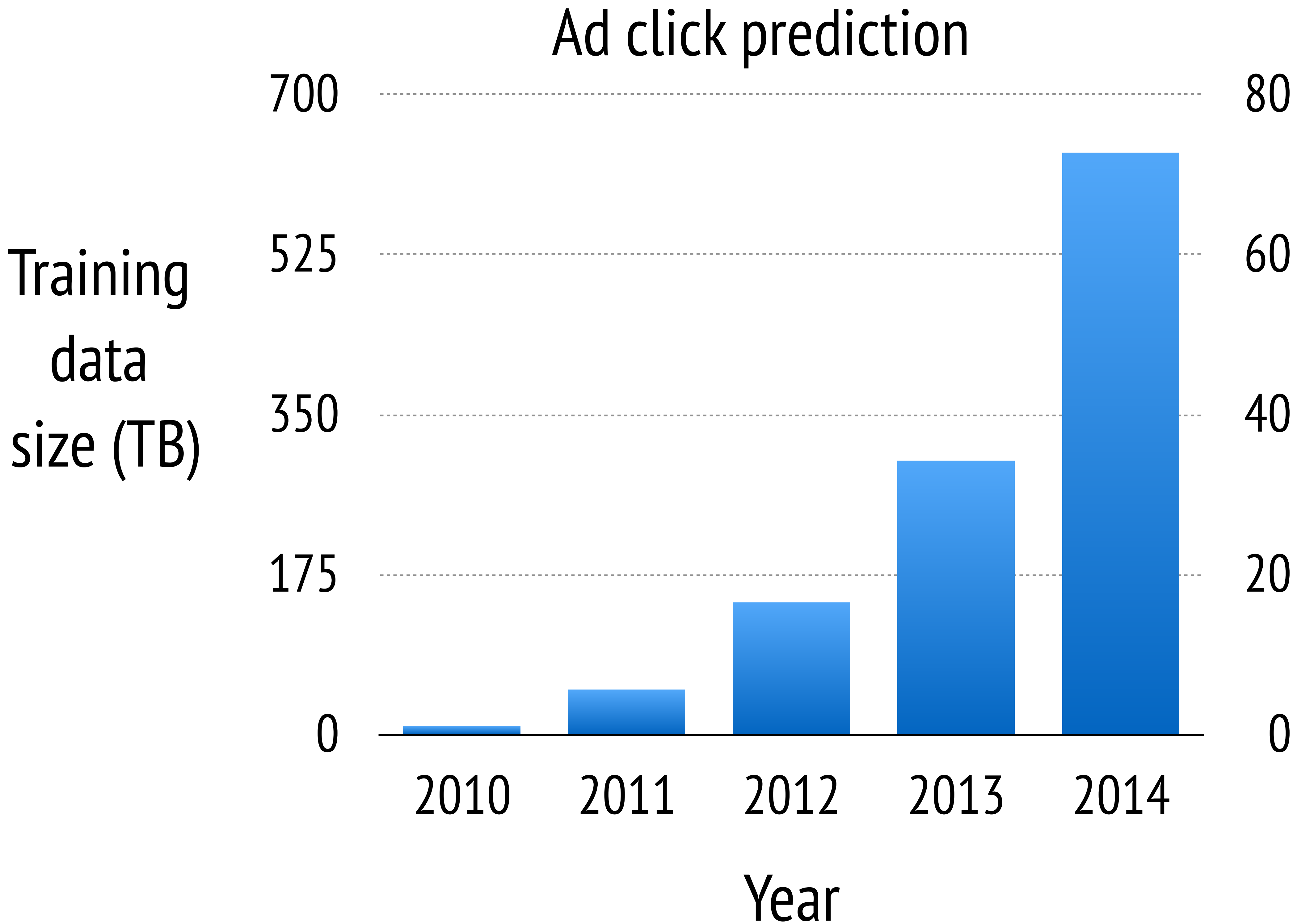

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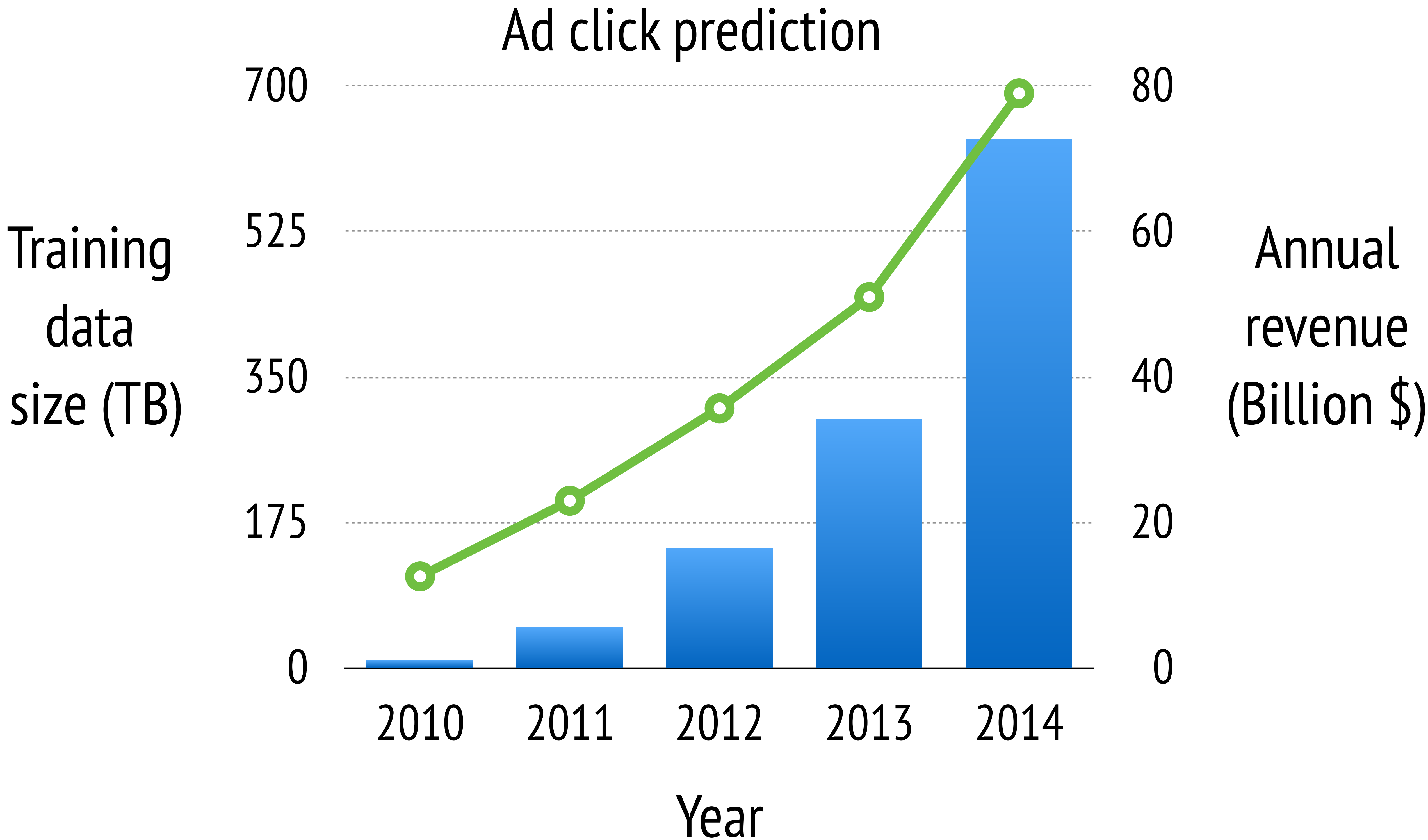

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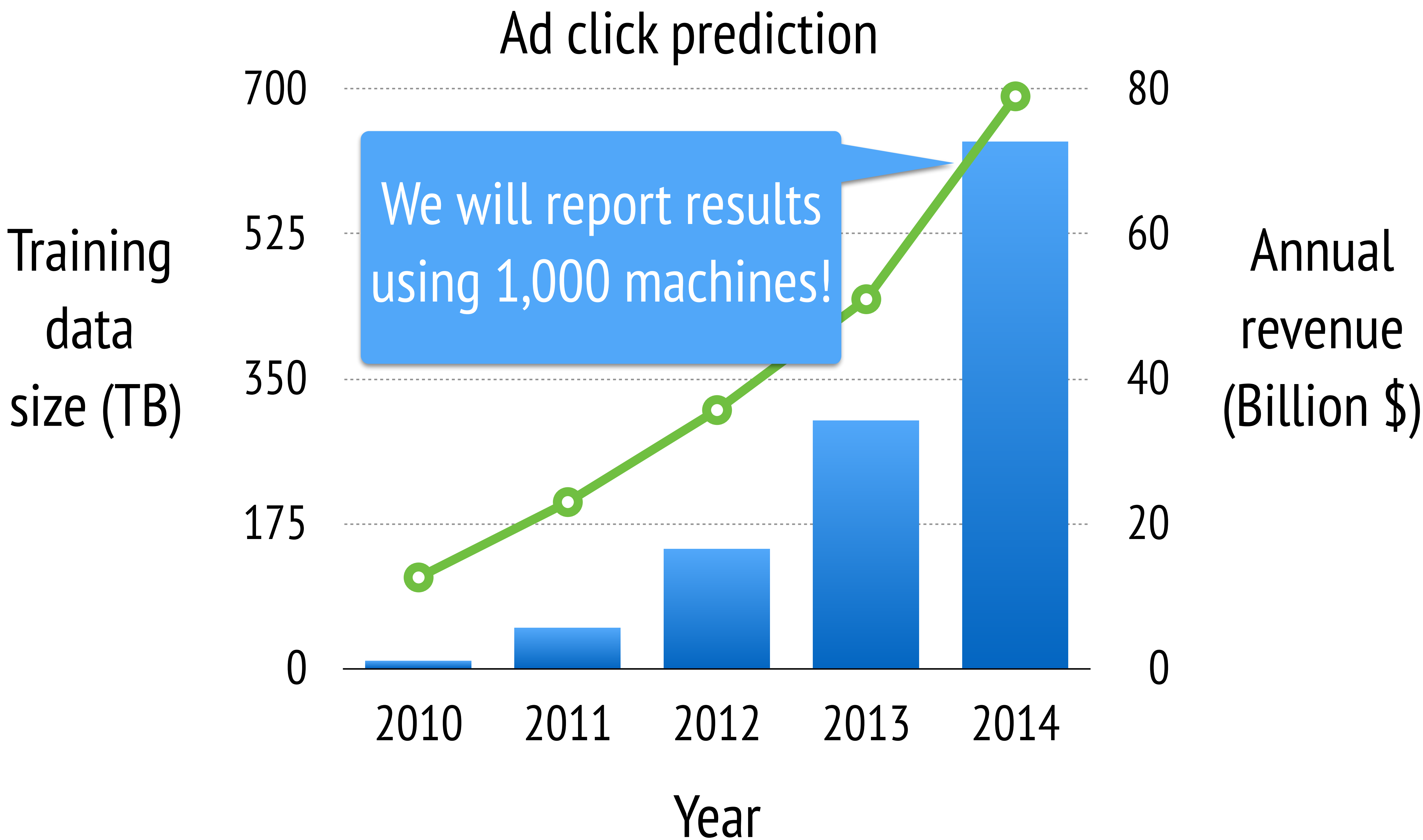
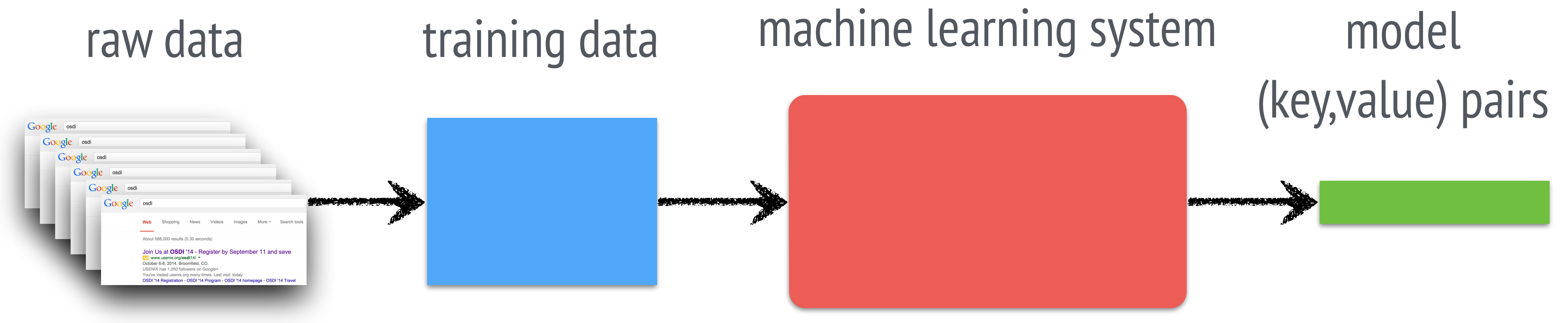


Overview of machine learning



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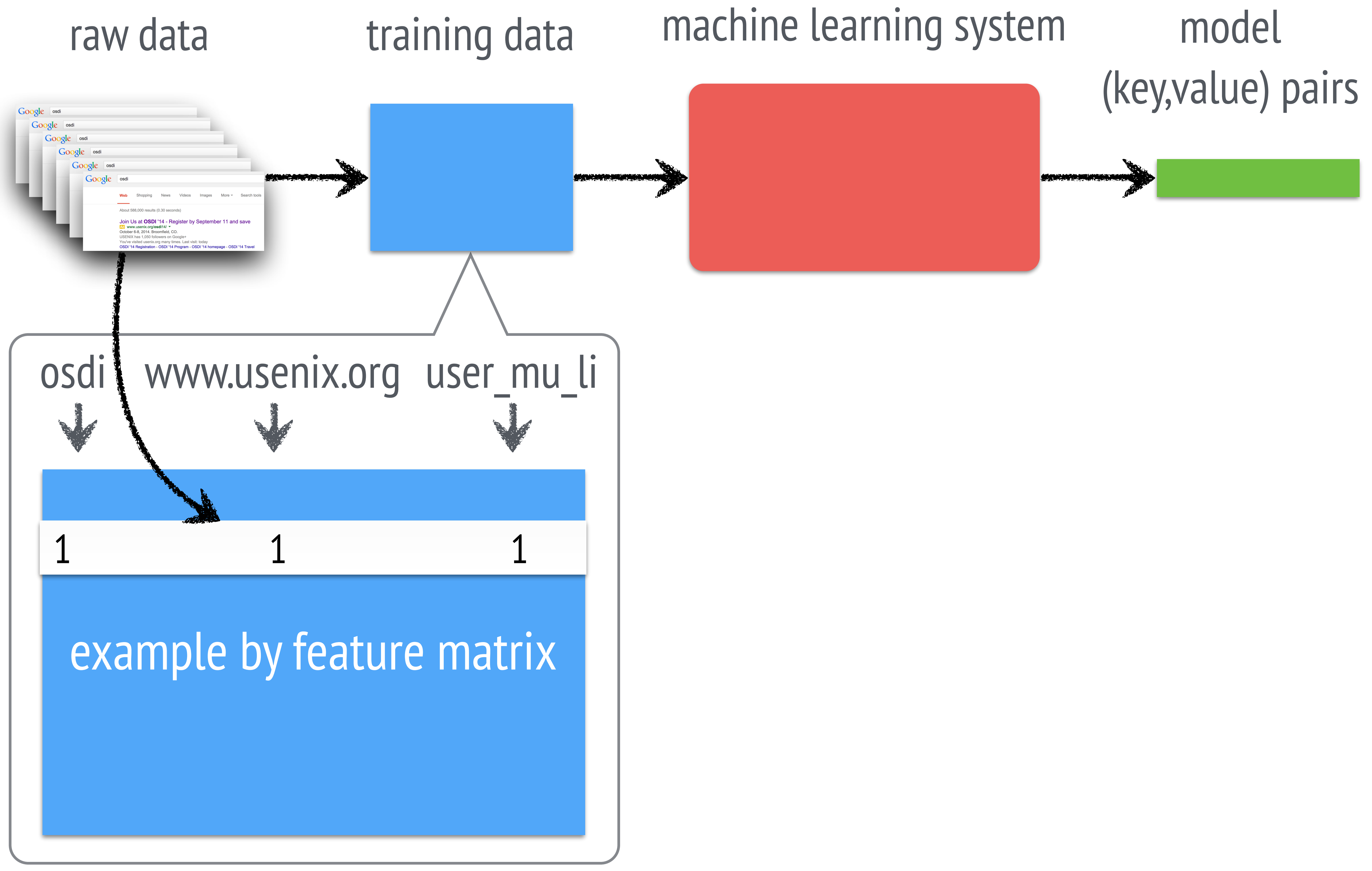

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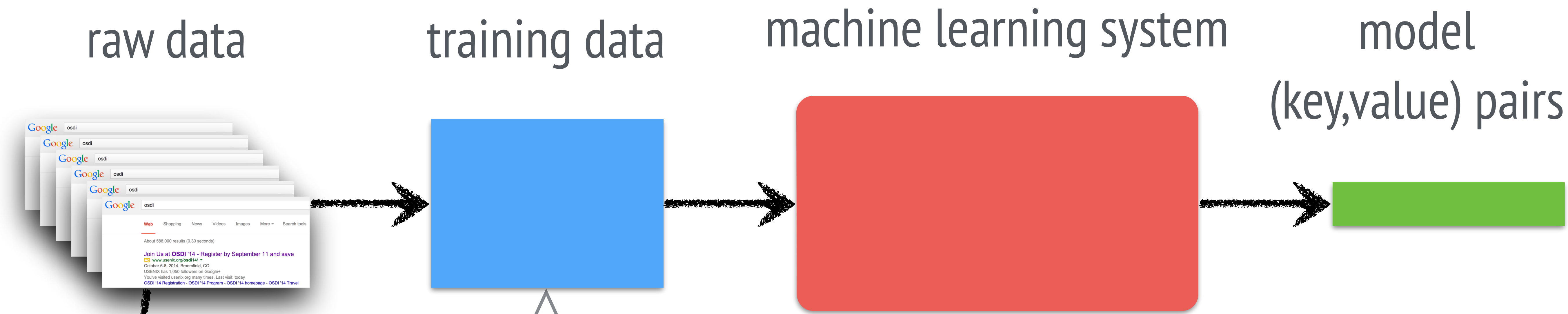

Scale of Industry problems

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

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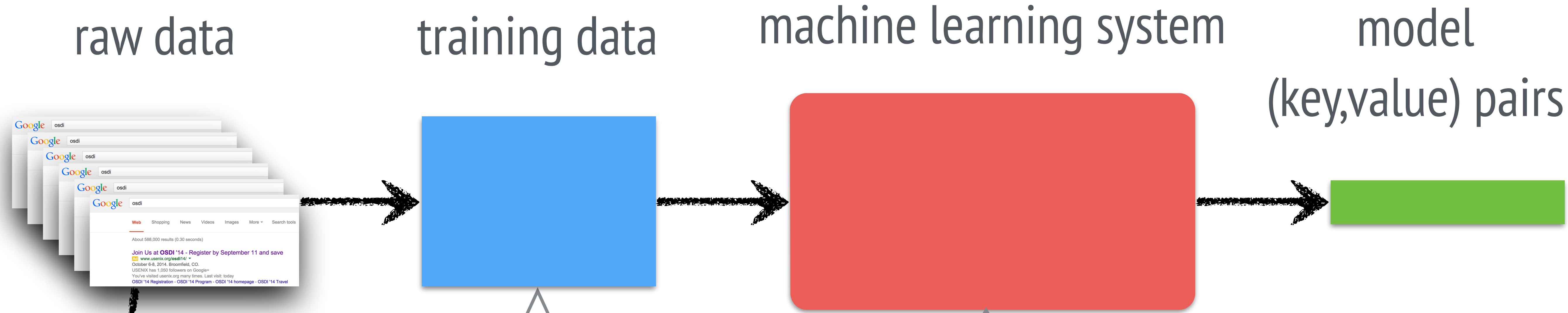

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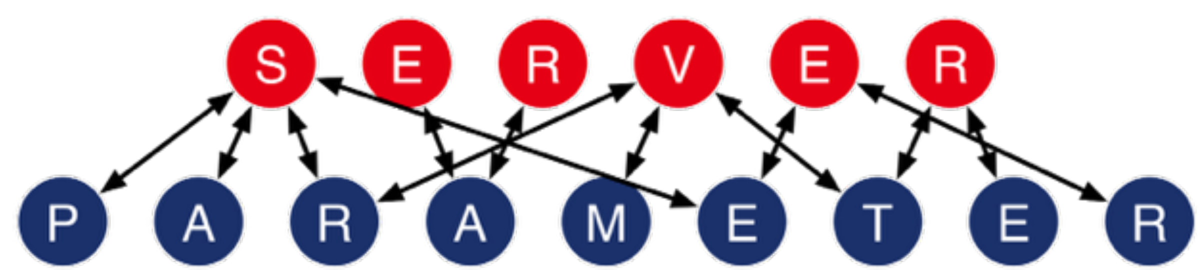
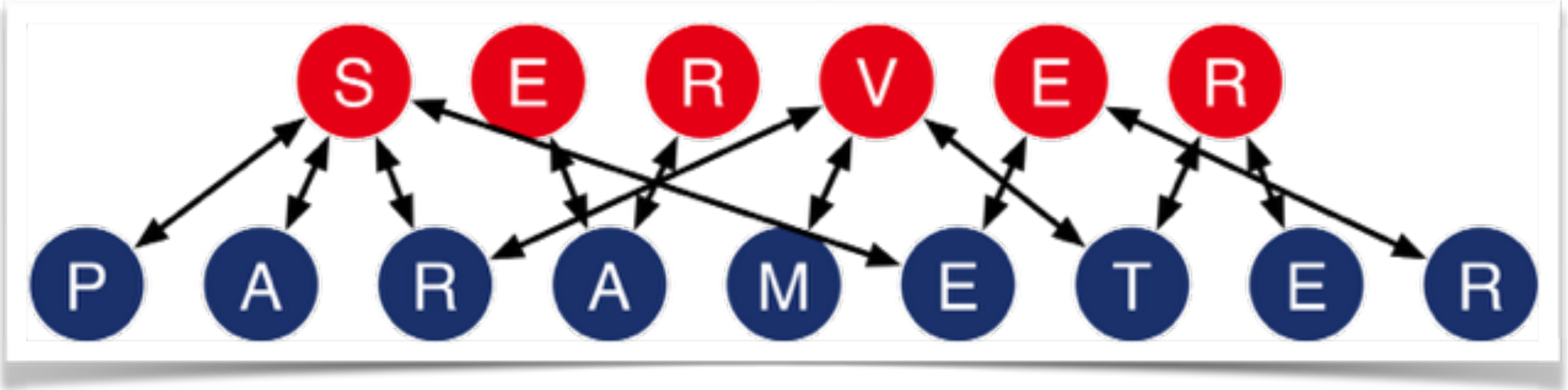


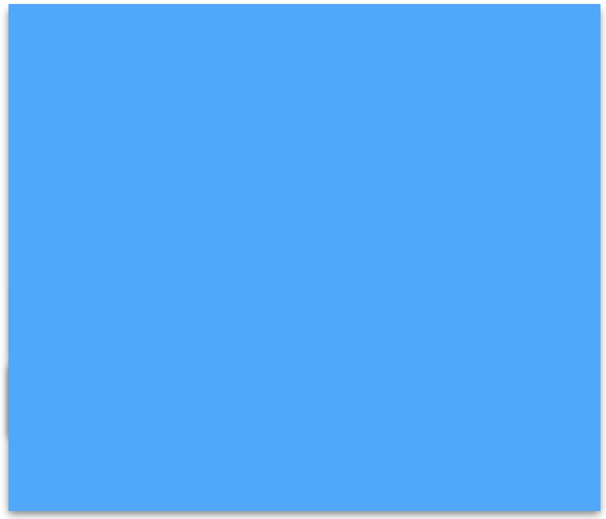
- scale to industry problems
- efficient communication
- fault tolerance
- easy to use

Industry size machine learning problems



Data and model partition

Training data



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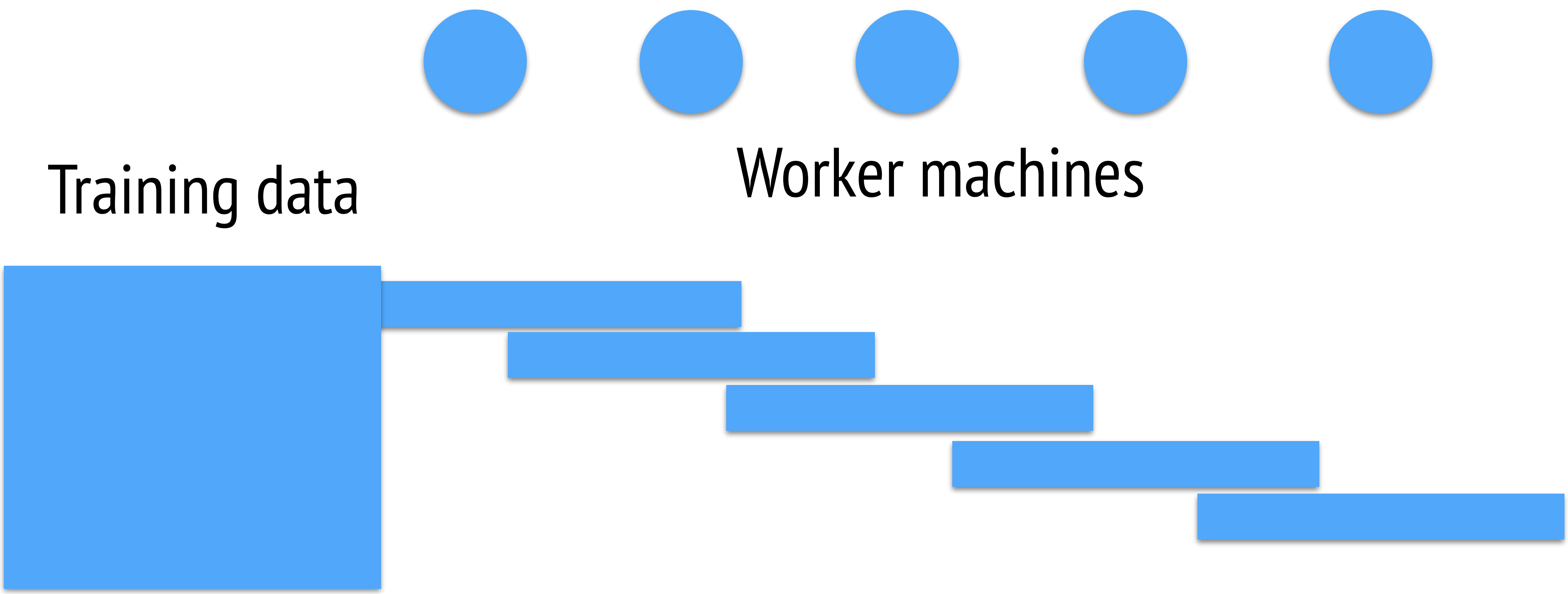

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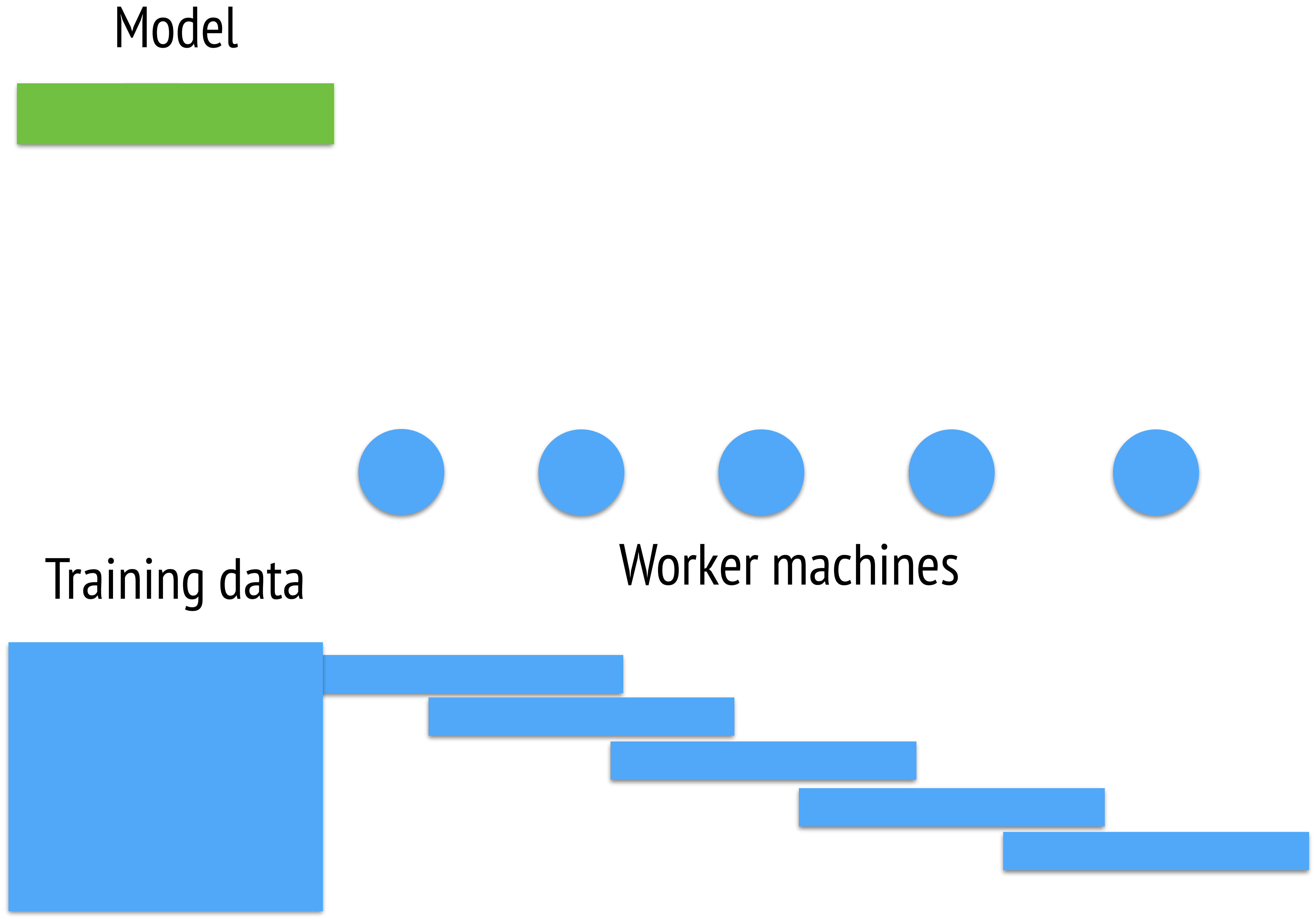

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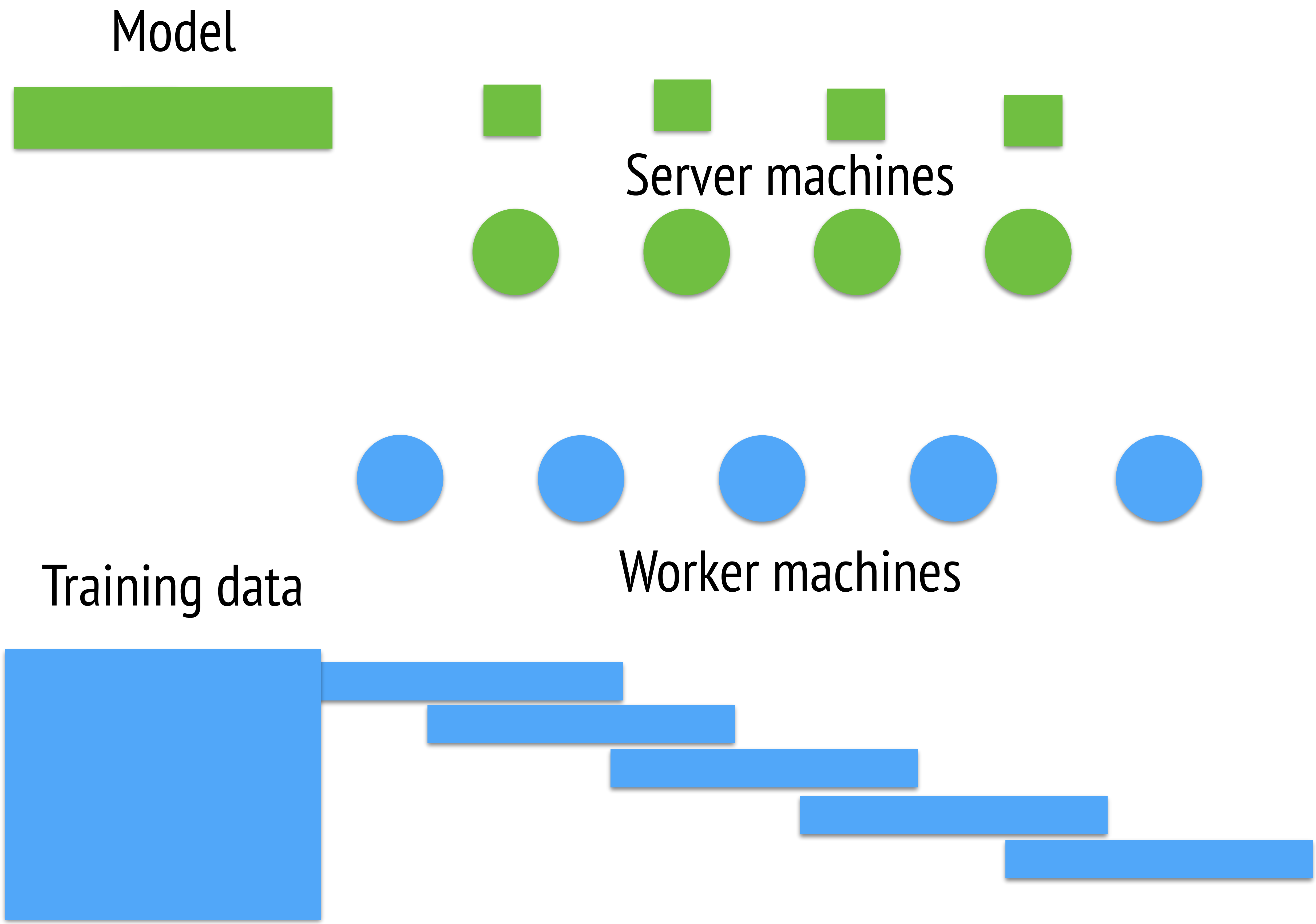

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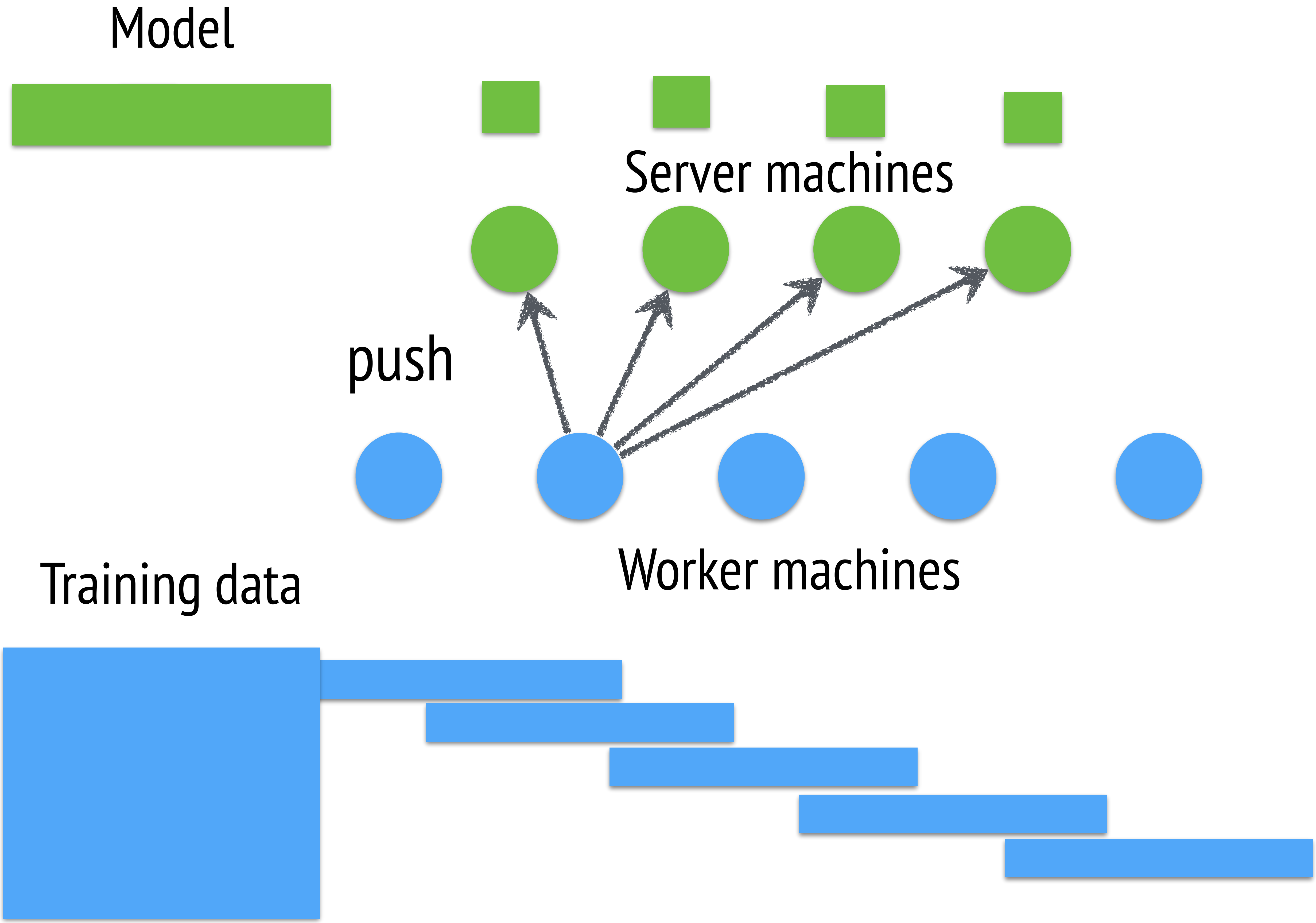

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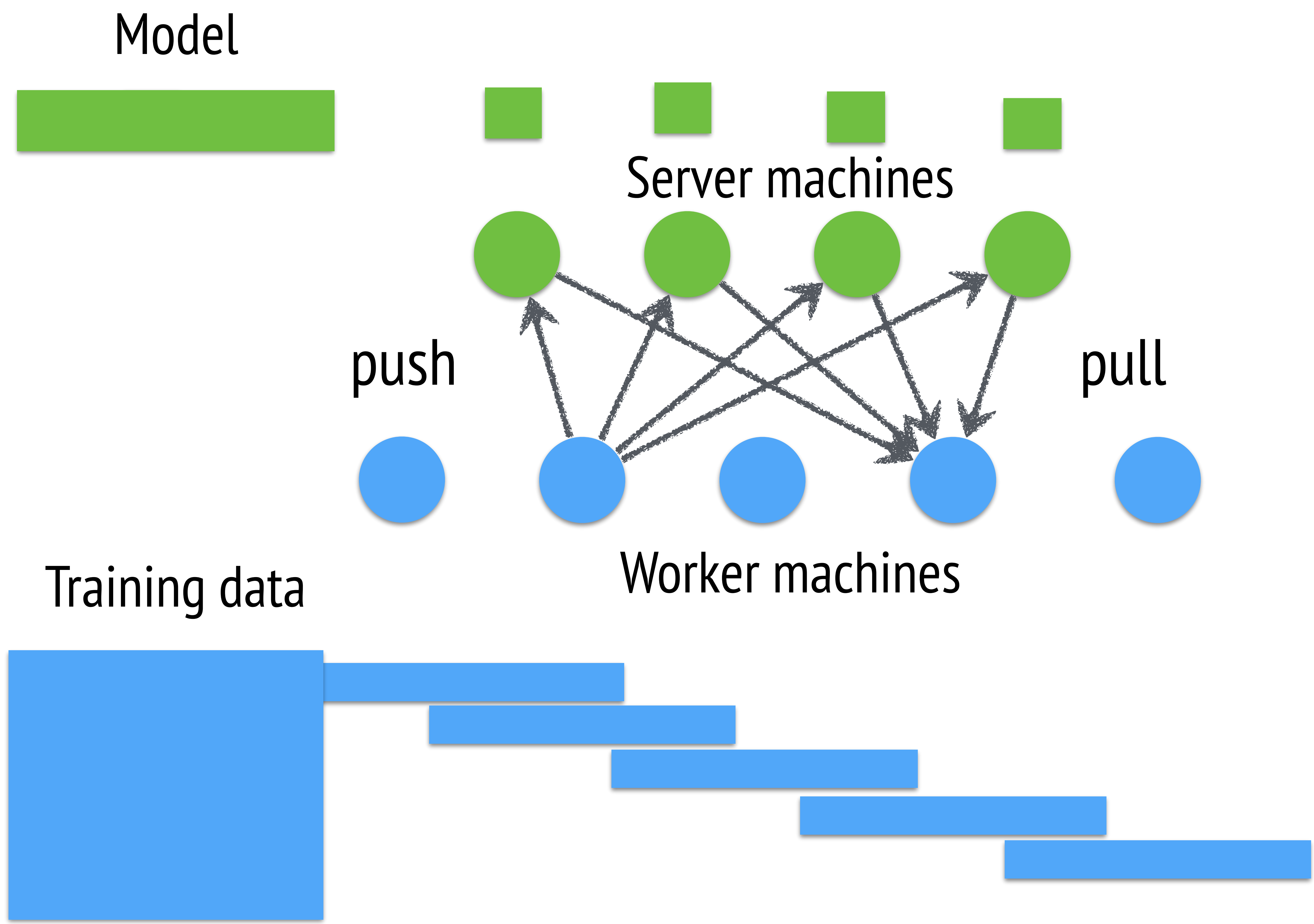
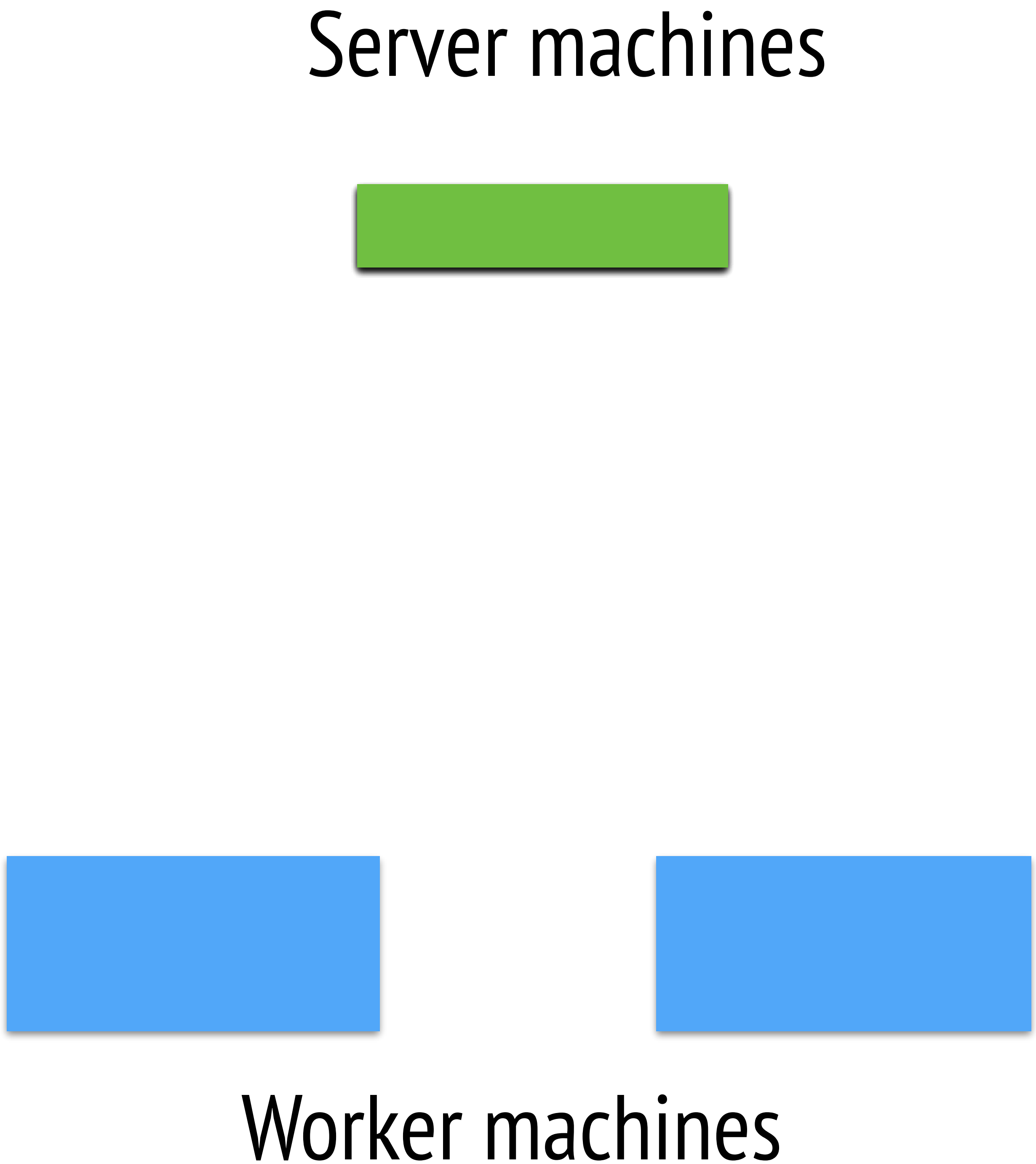
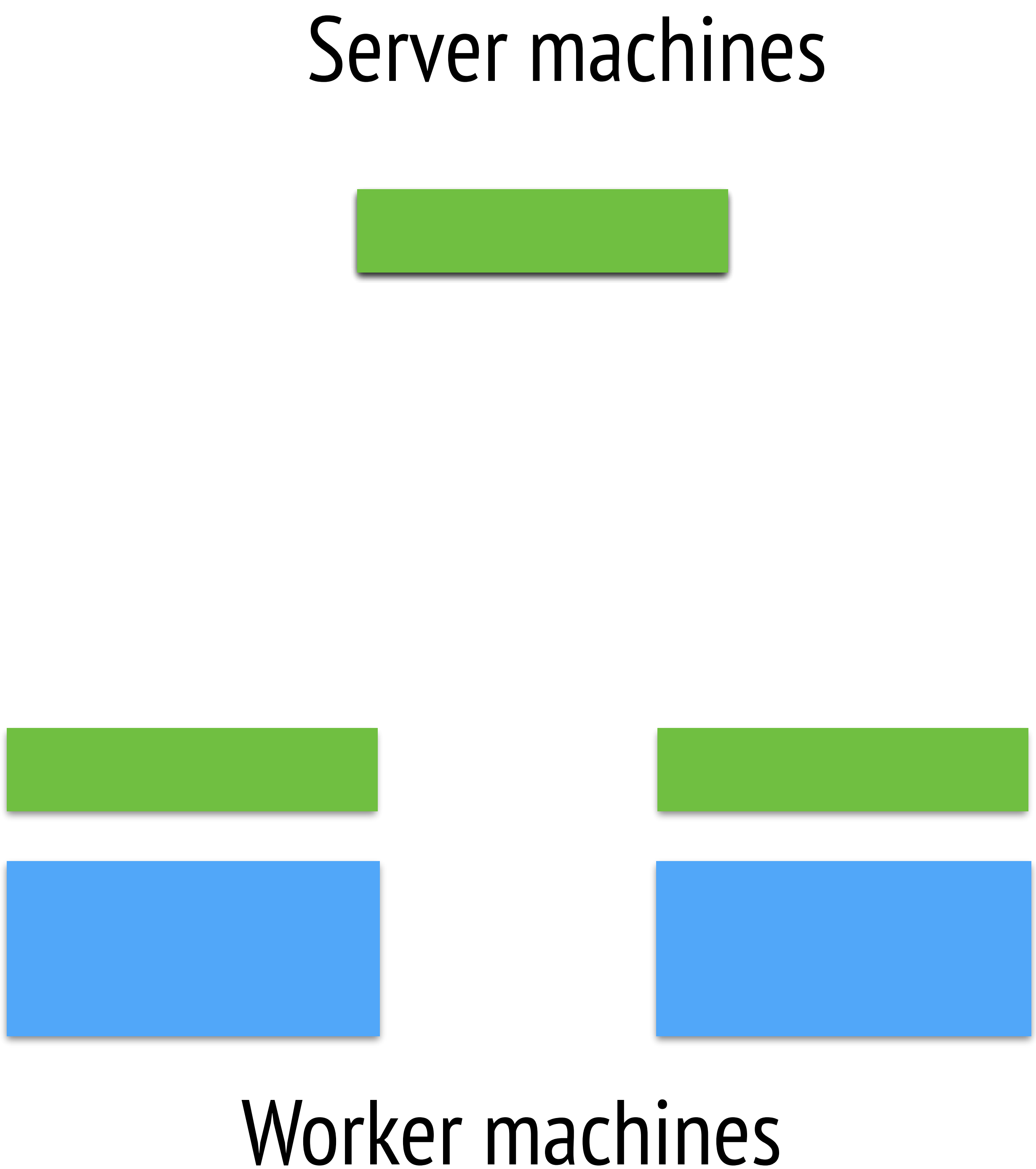


Example: distributed gradient descent



Example: distributed gradient descent

Workers **pull** the working set of model



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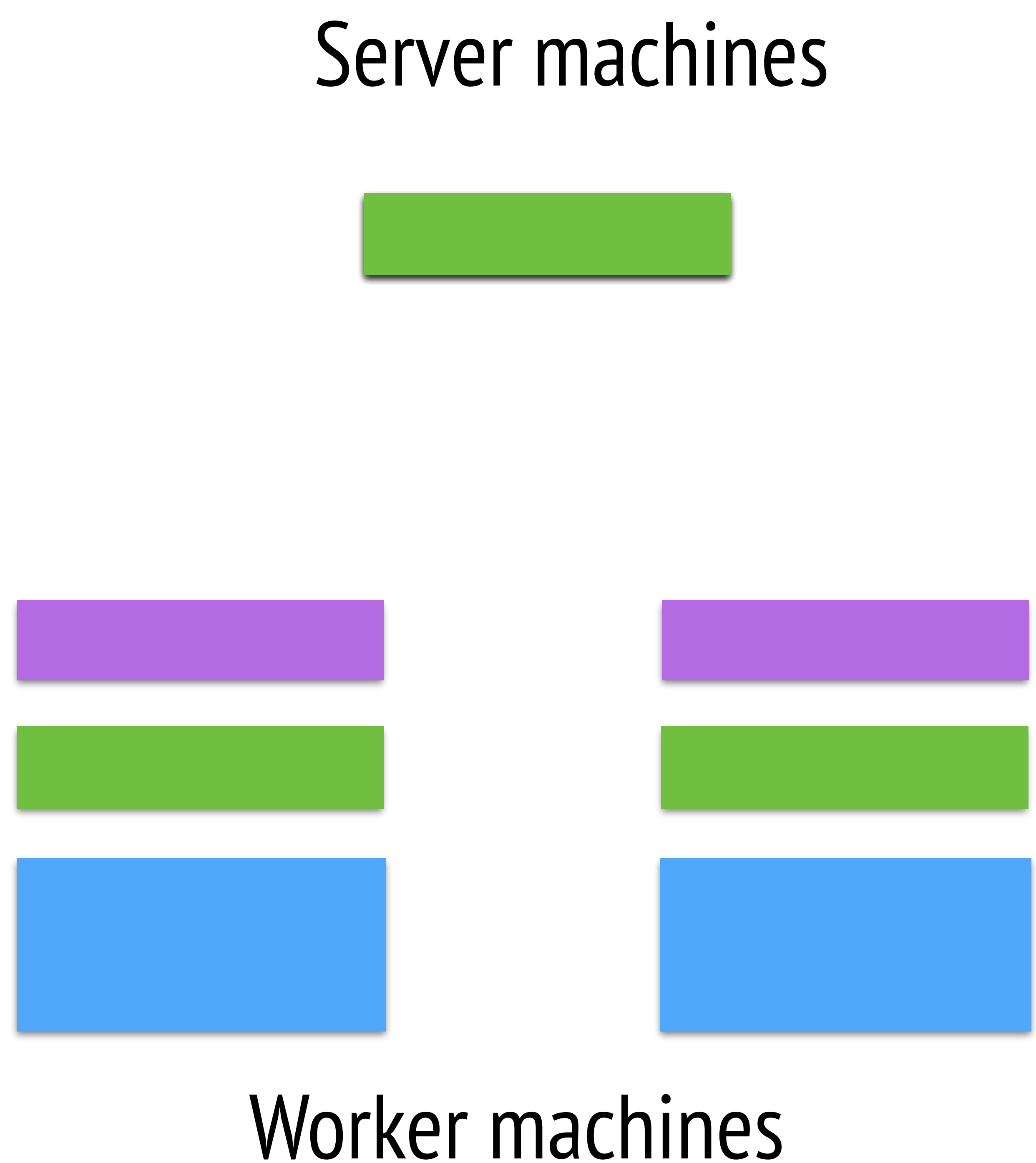
Iterate until stop

workers compute gradients



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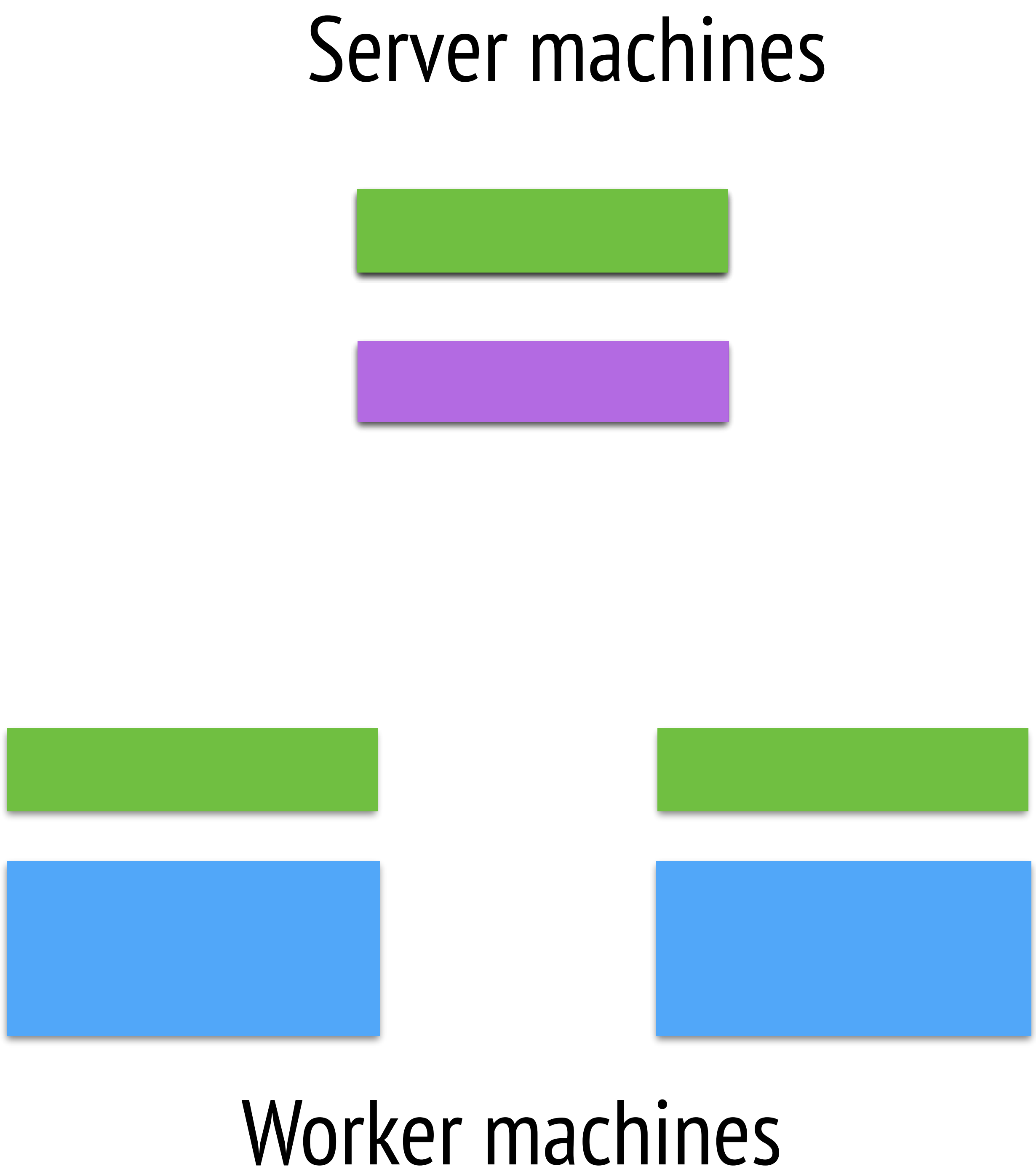

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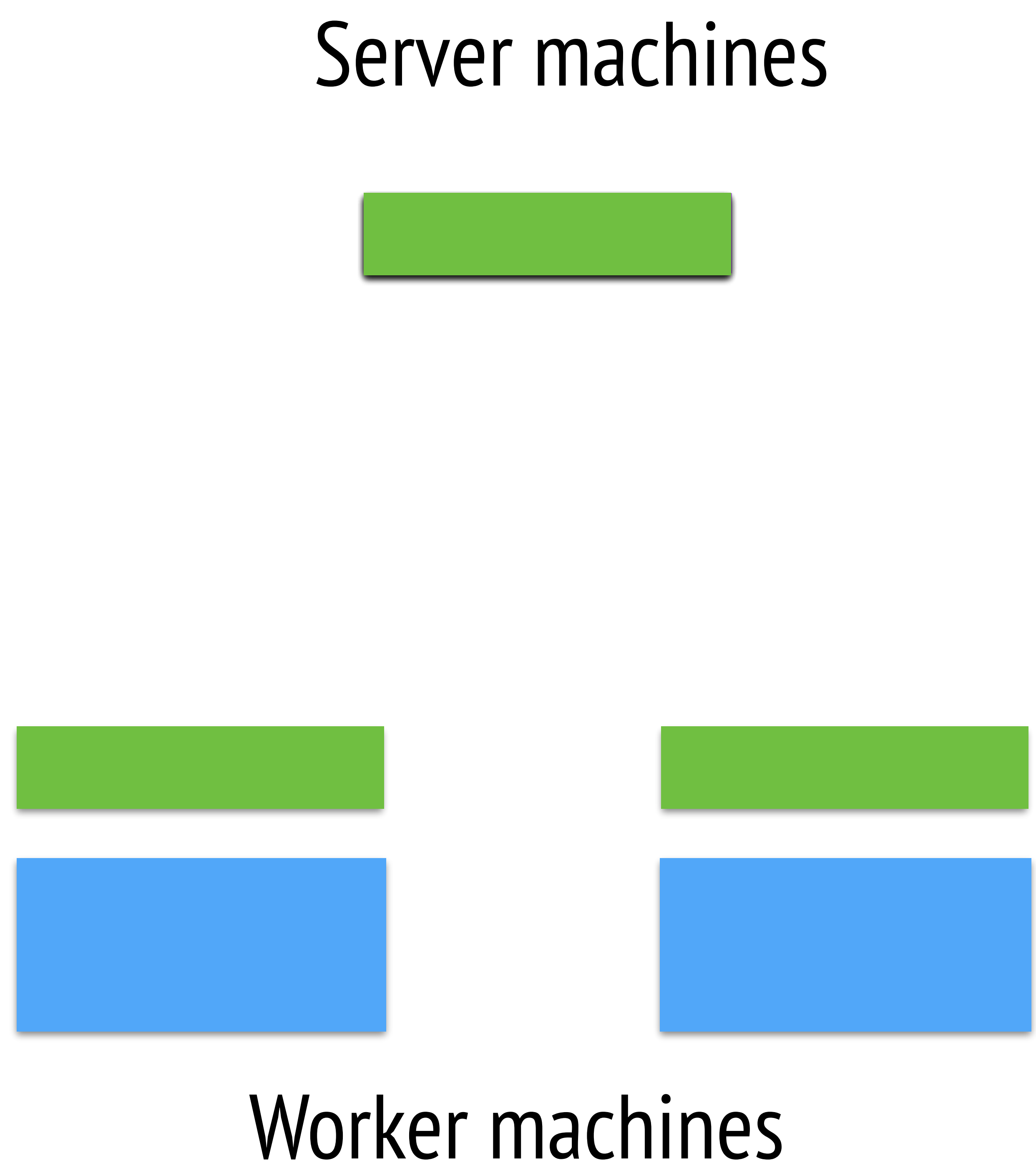

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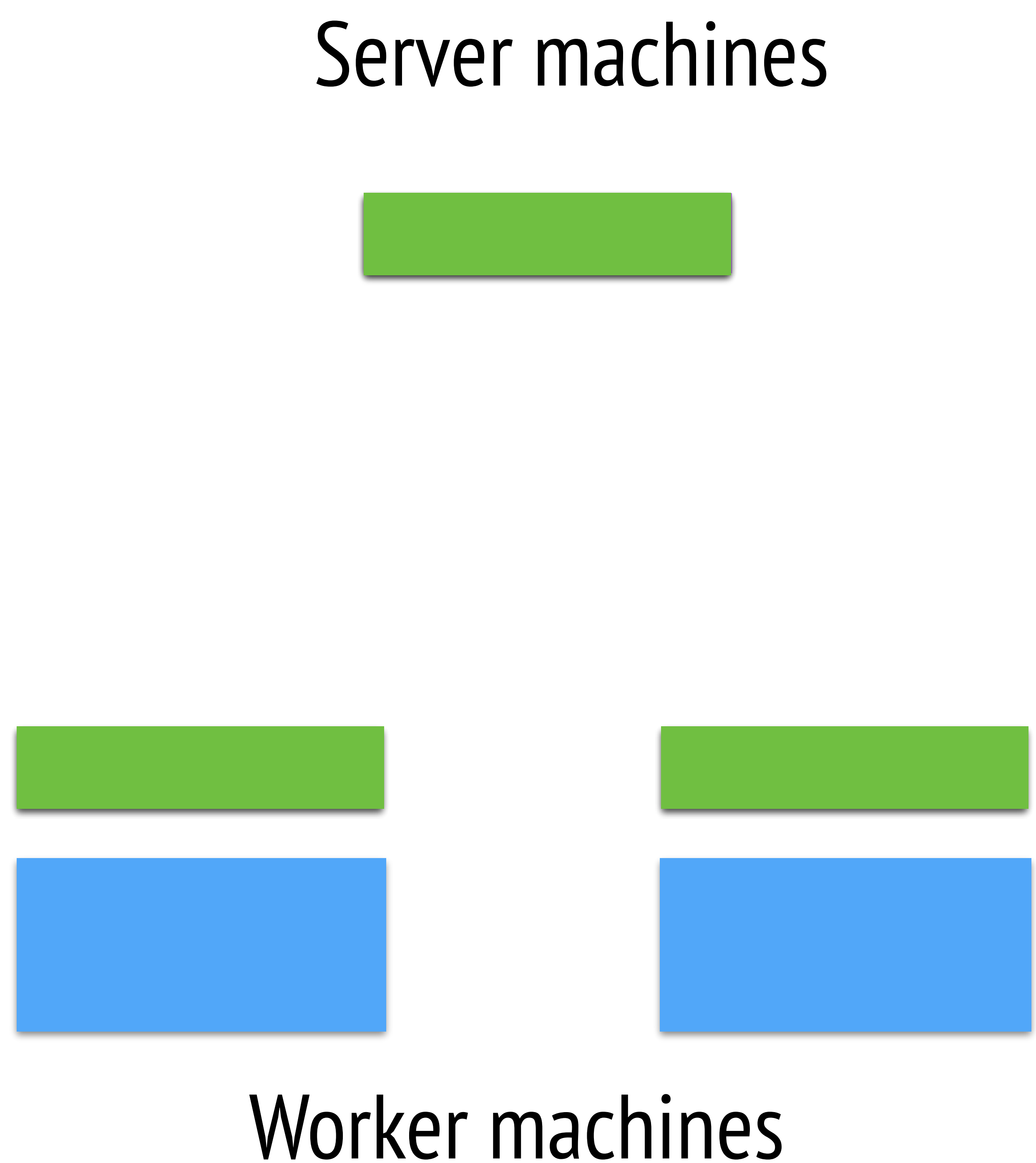
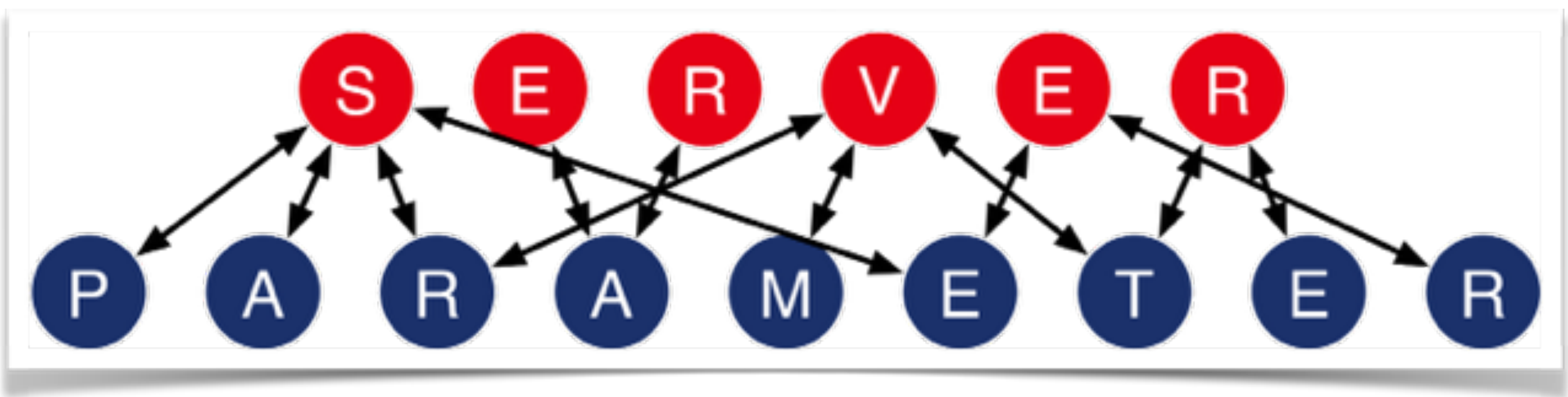


Industry size machine learning problems

Efficient communication



Challenges for data synchronization

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- Massive communication traffic
  - frequent access to the shared model

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

Task

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- a push / pull / user defined function (an iteration)

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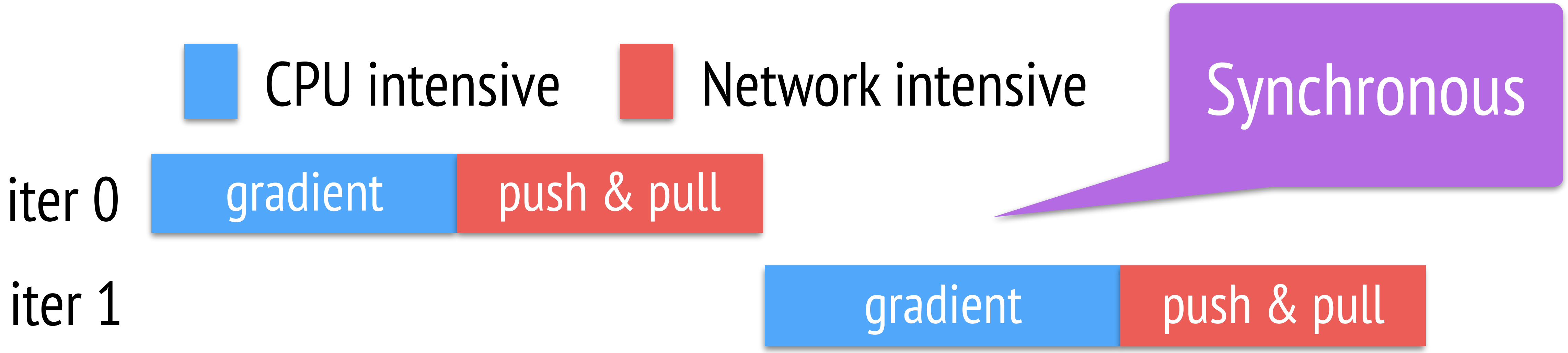

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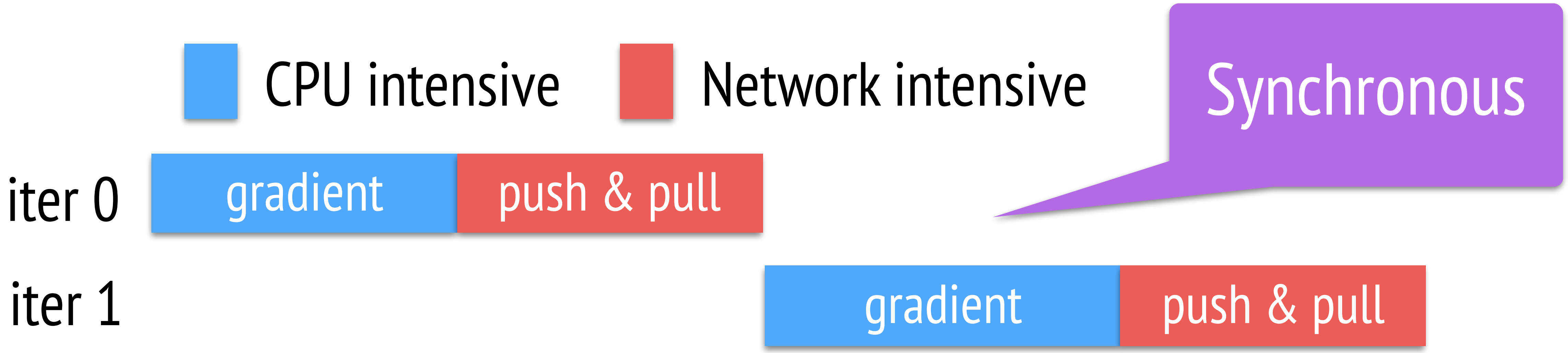

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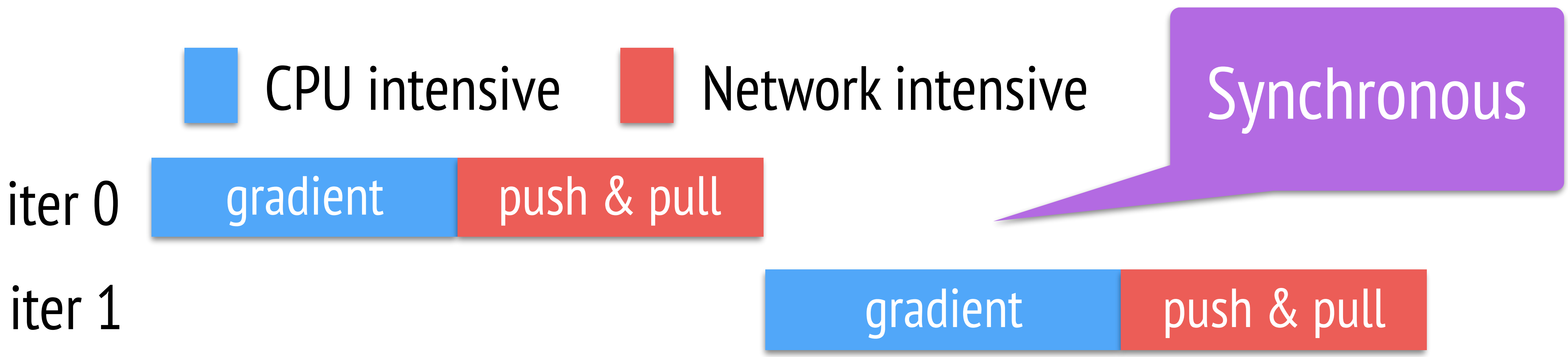

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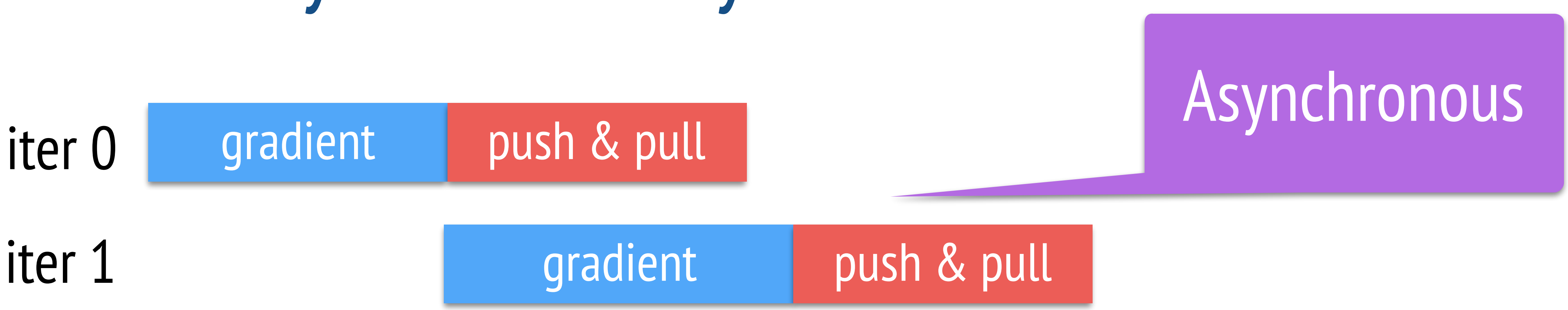

Flexible consistency

- Trade-off between algorithm efficiency and system performance

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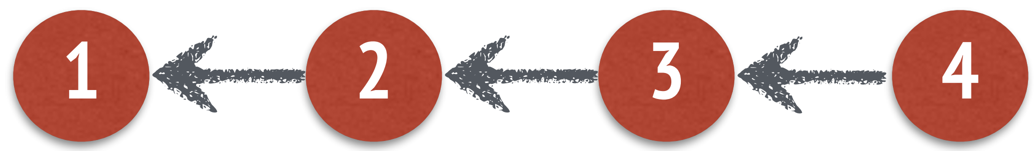
Sequential



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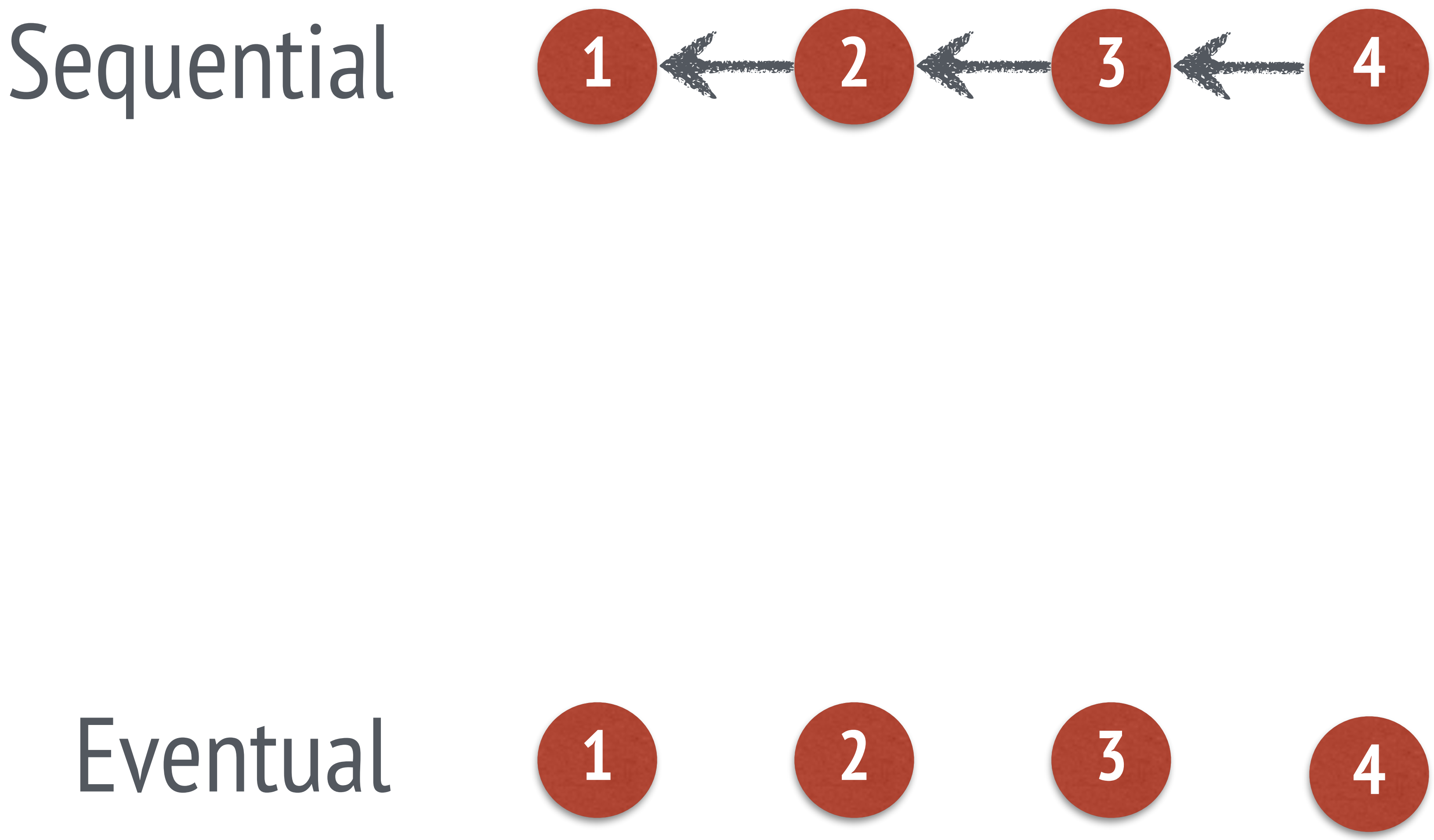

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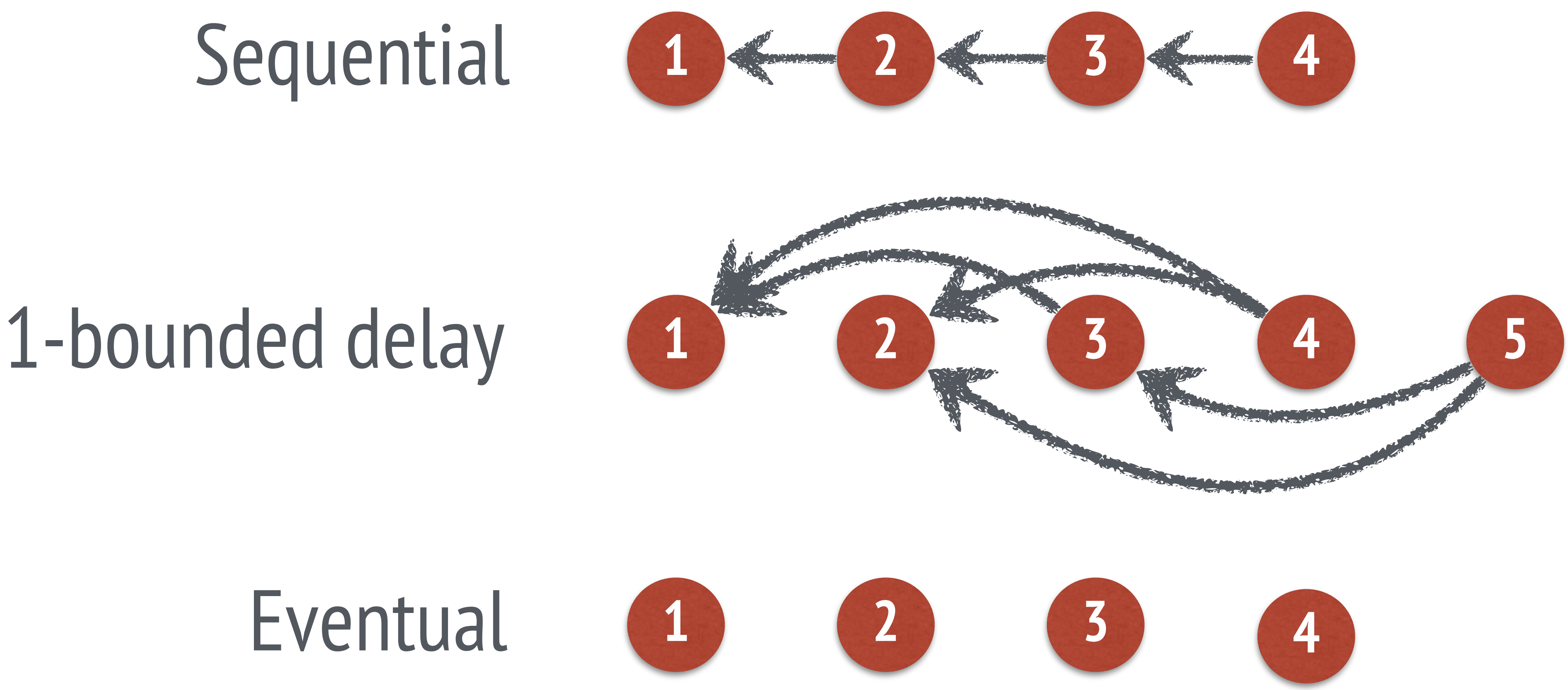

Results for bounded delay

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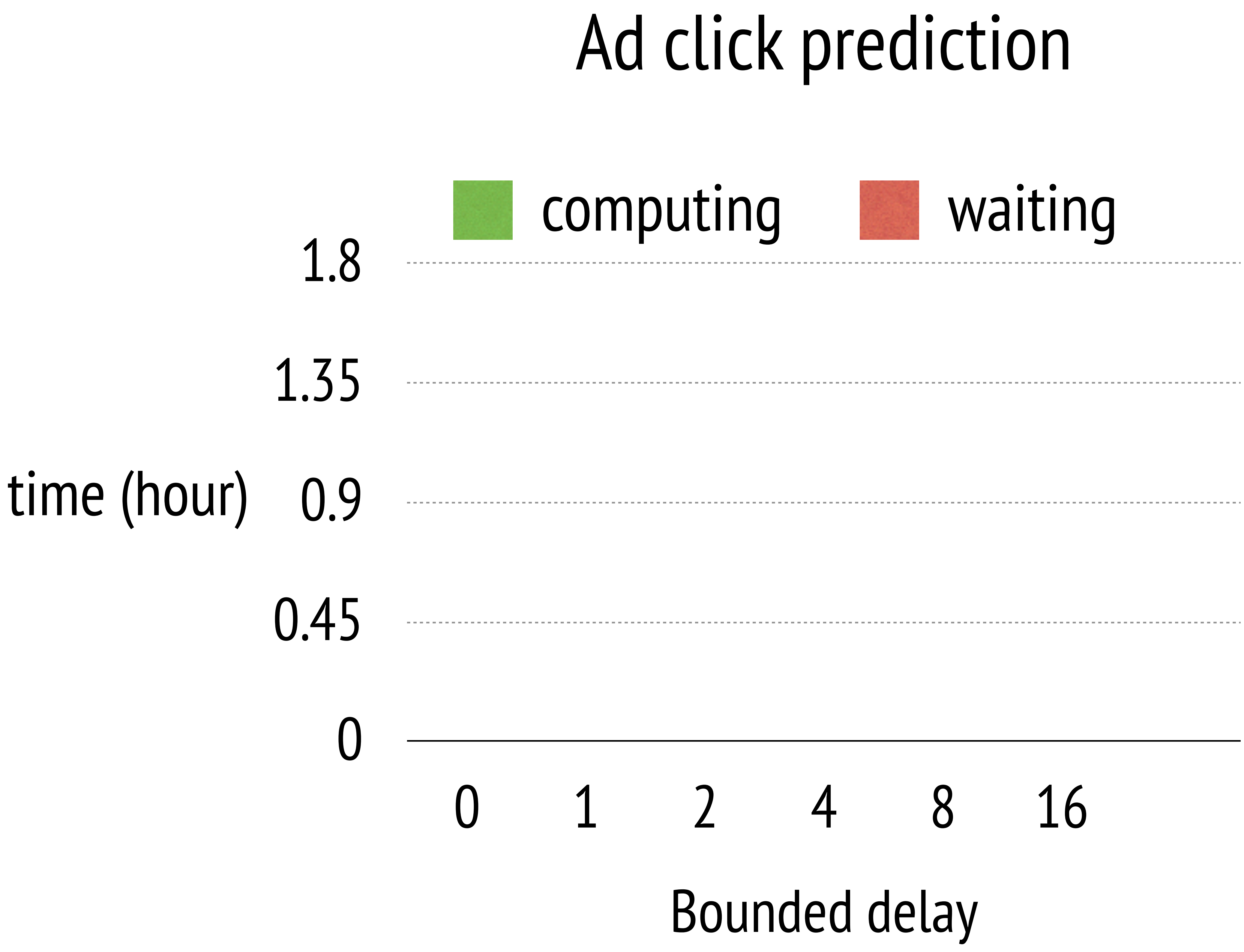

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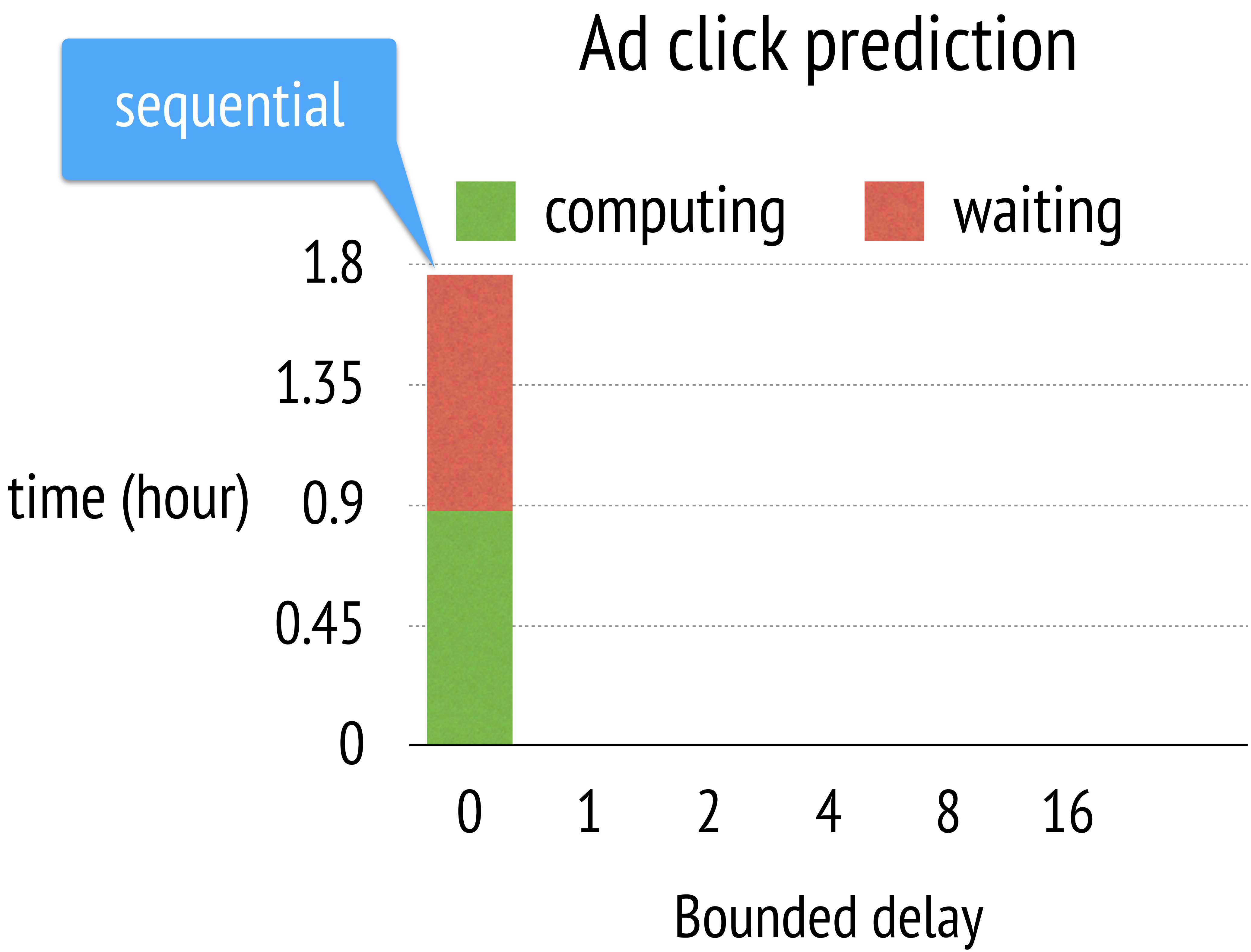

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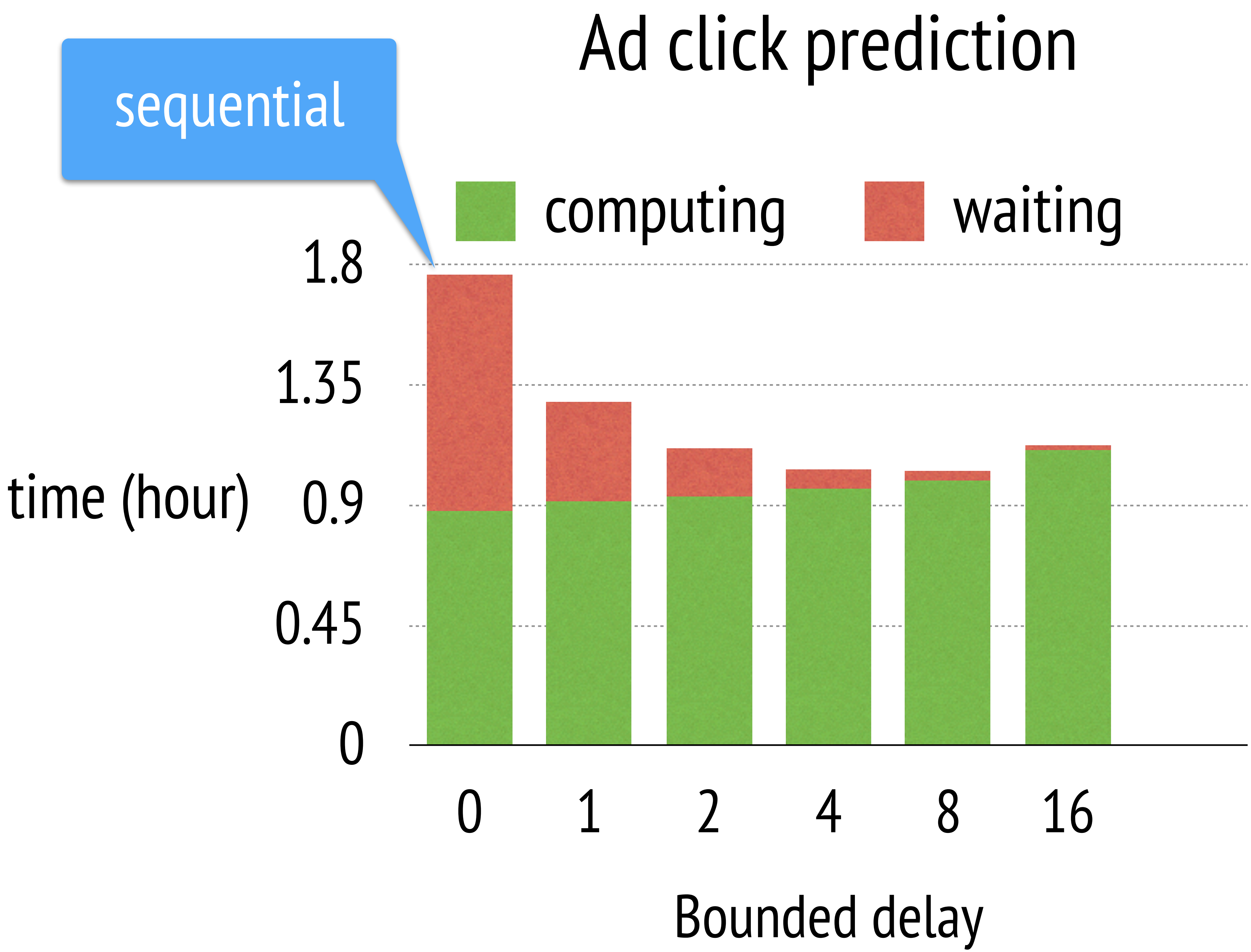

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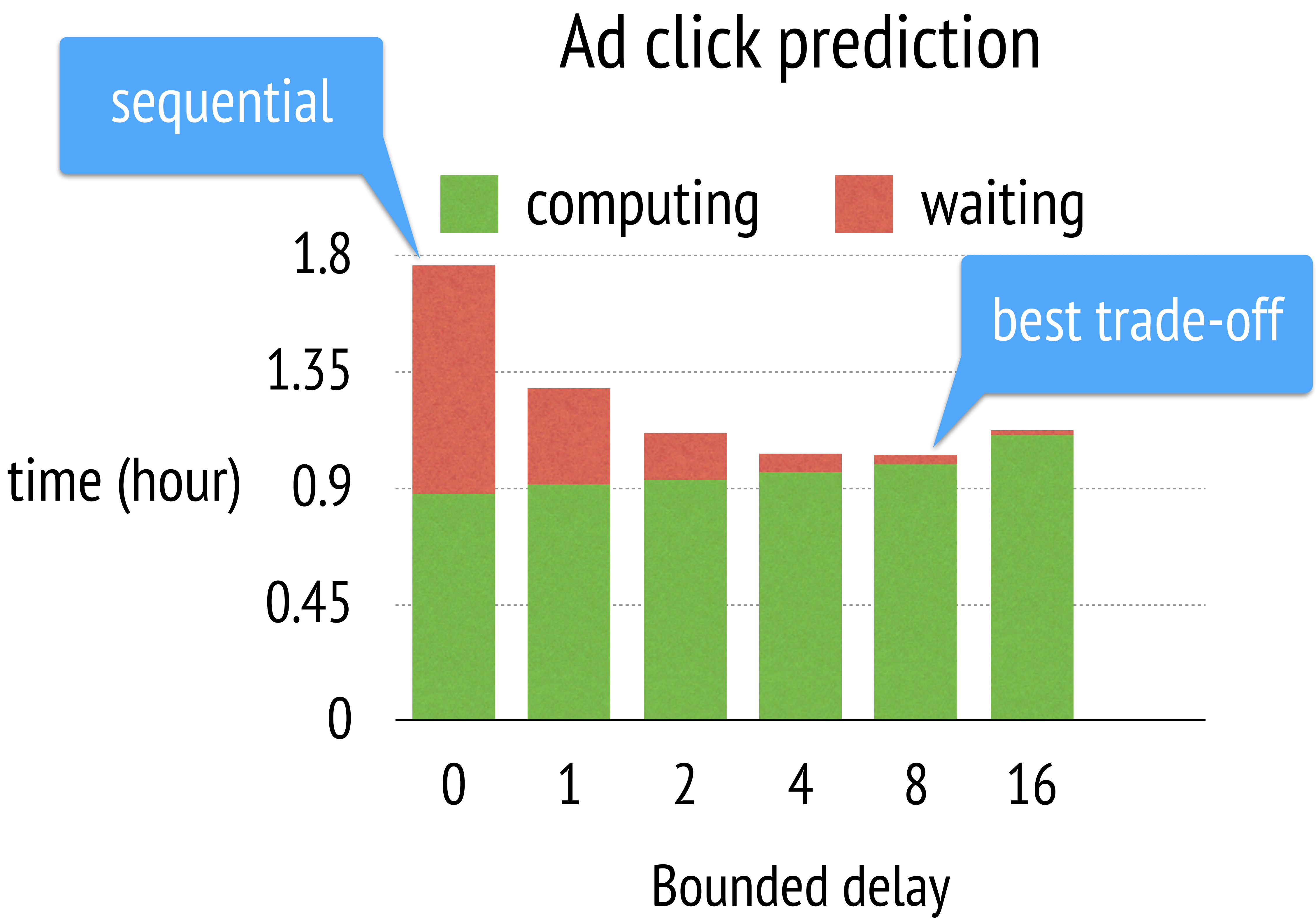

User-defined filters

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- Selectively communicate (key, value) pairs

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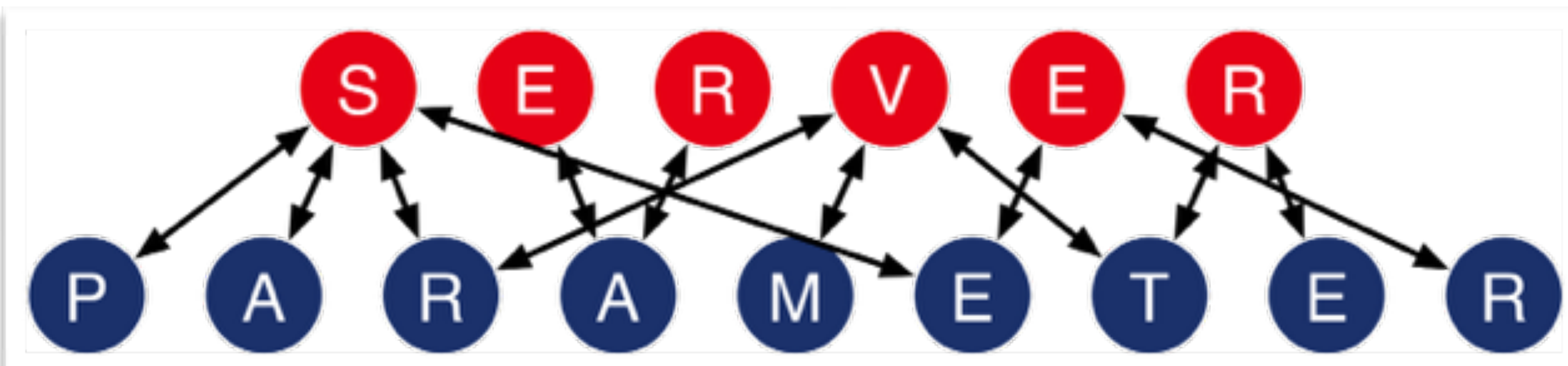
- Selectively communicate (key, value) pairs
- E.g., the KKT filter
  - send pairs if they are likely to affect the model
  - >95% keys are filtered in the ad click prediction task

Industry size machine learning problems

Efficient communication



Fault tolerance

Machine learning job logs in a three-month period:

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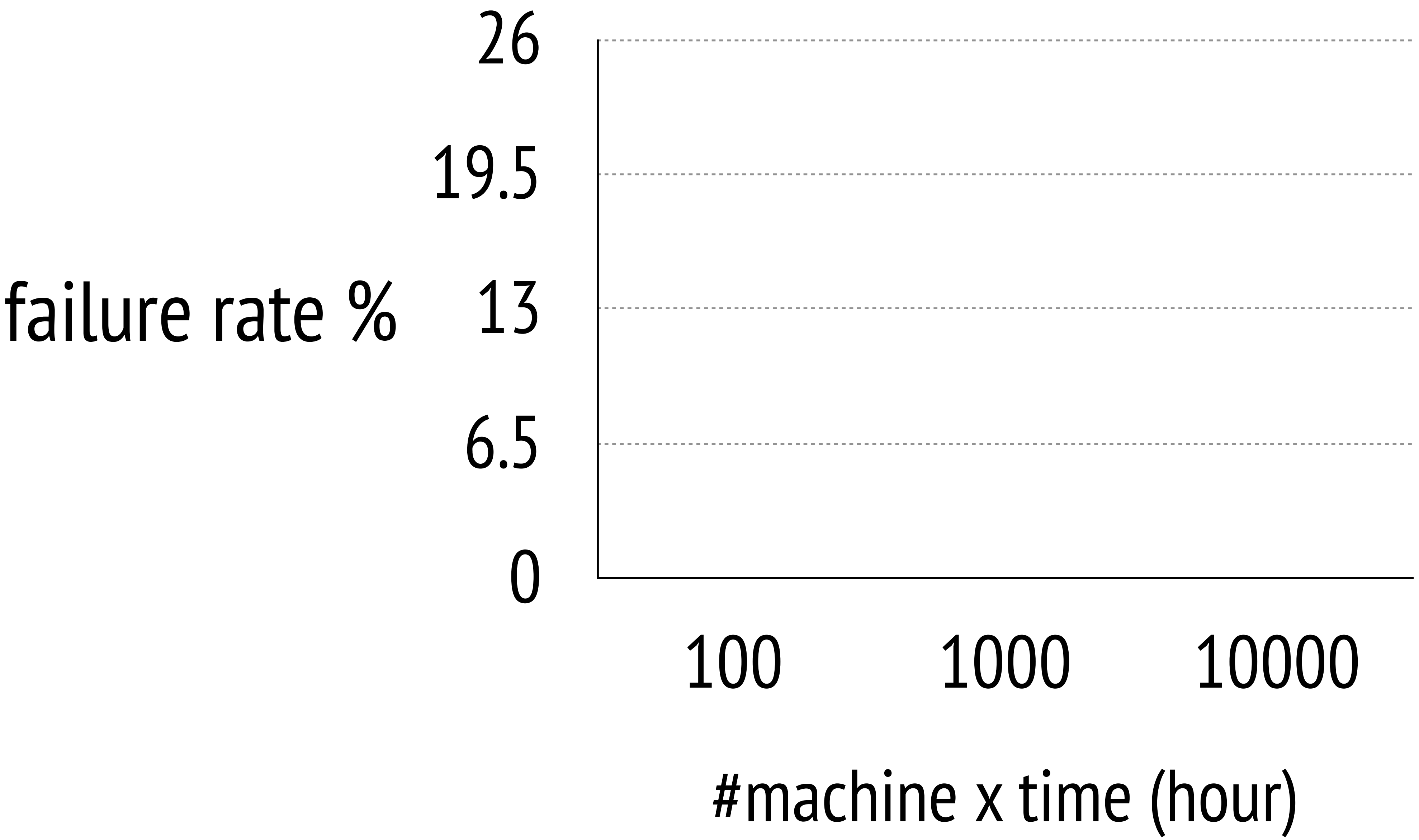

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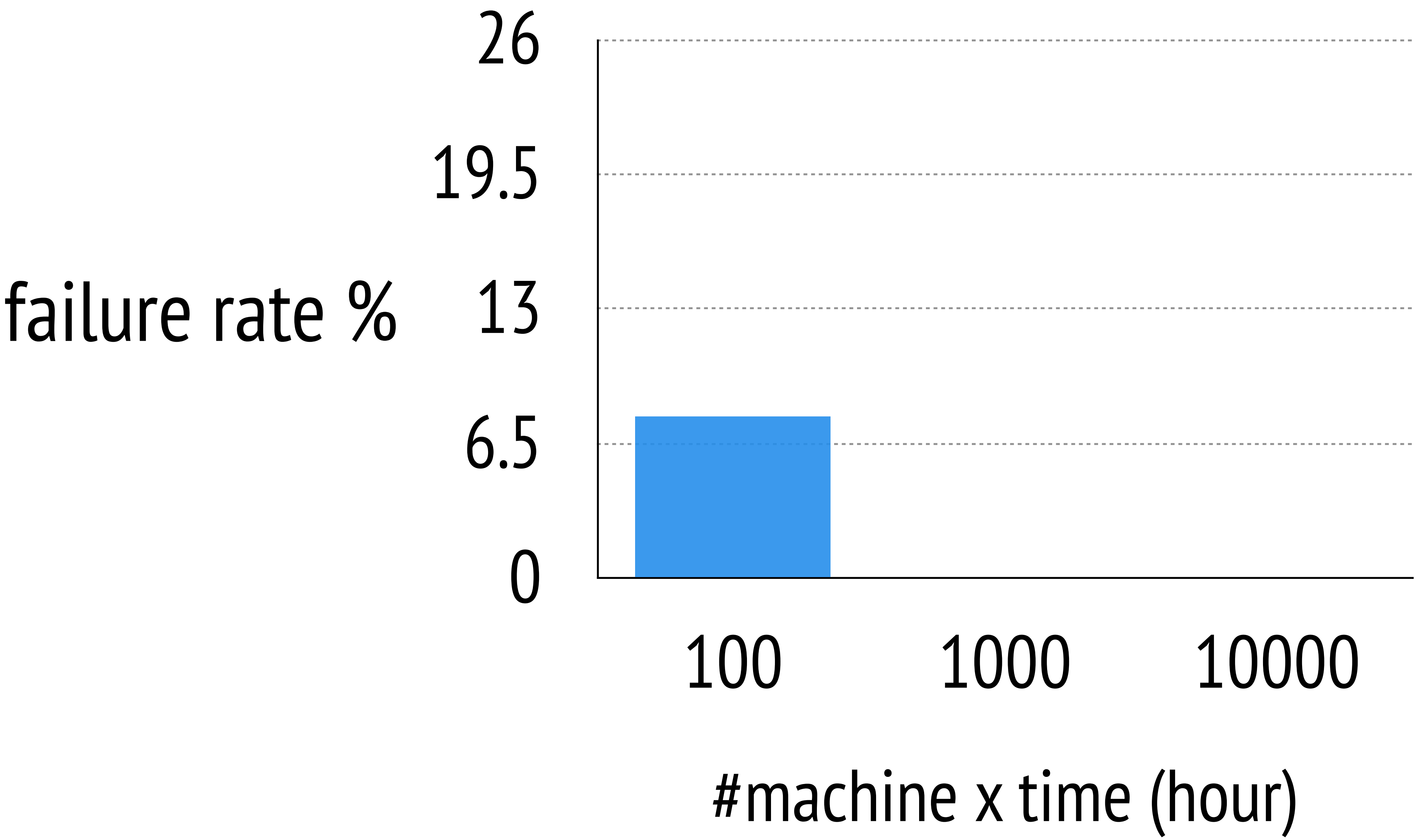

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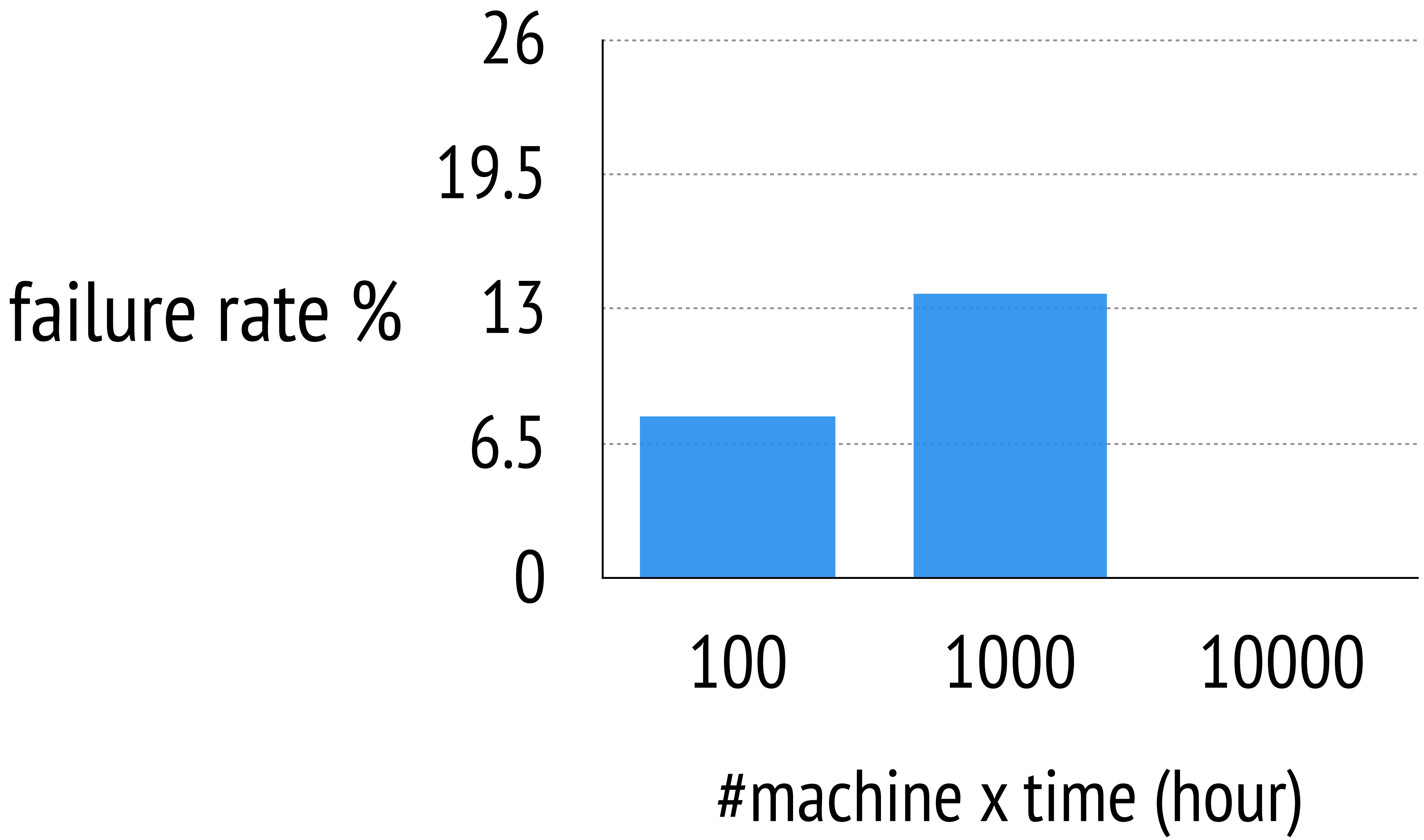

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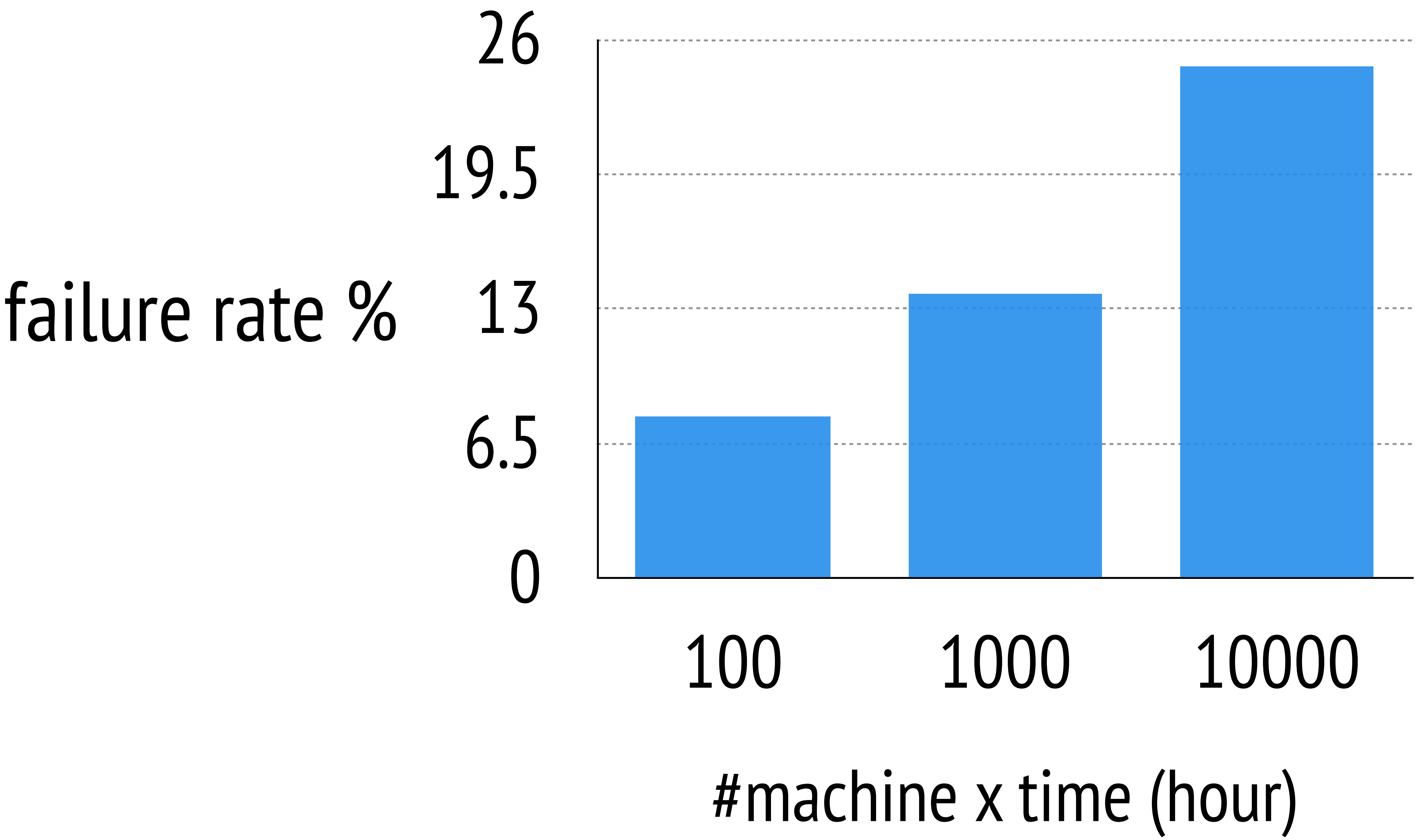

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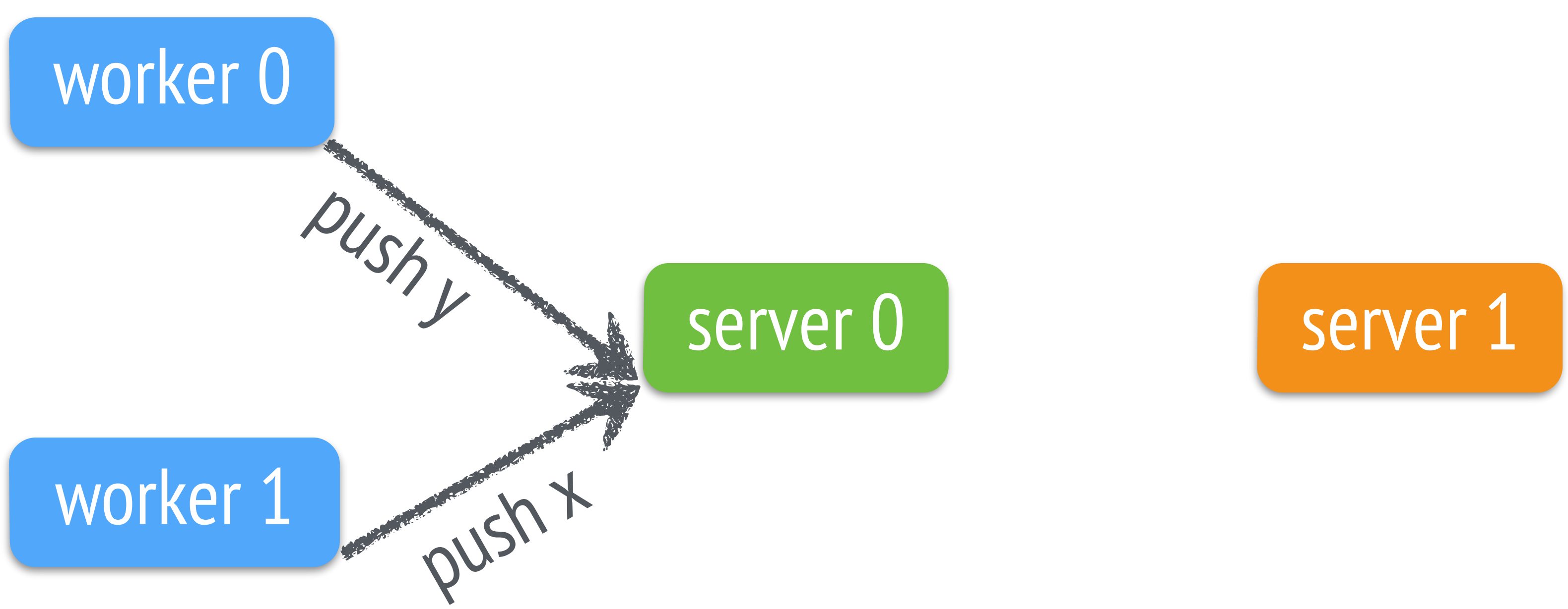

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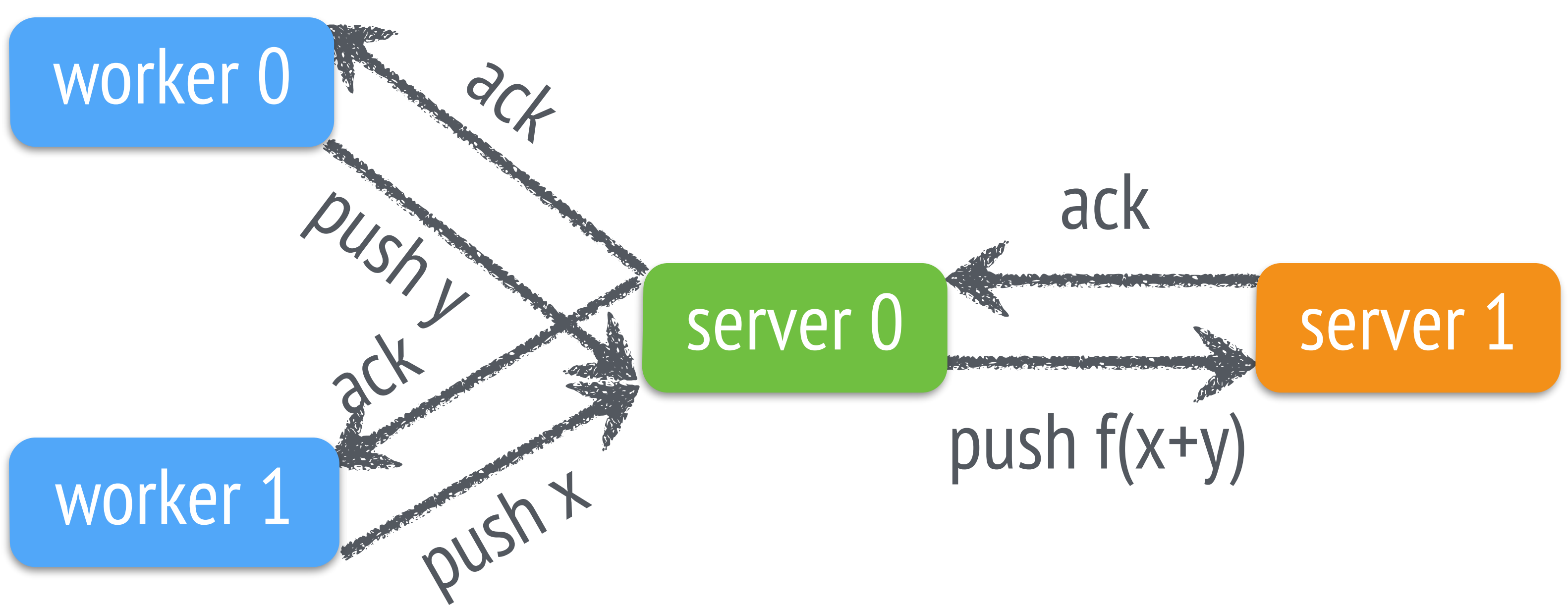

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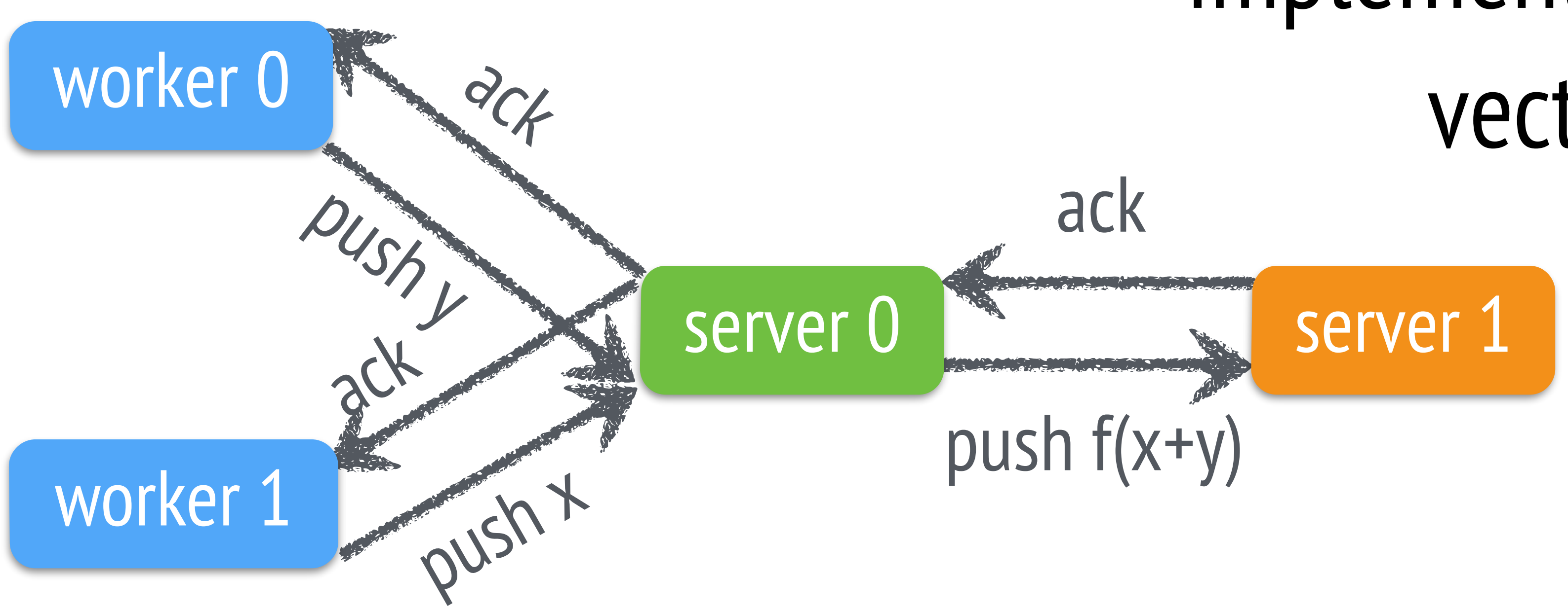

implemented by efficient vector clock

Industry size machine learning problems

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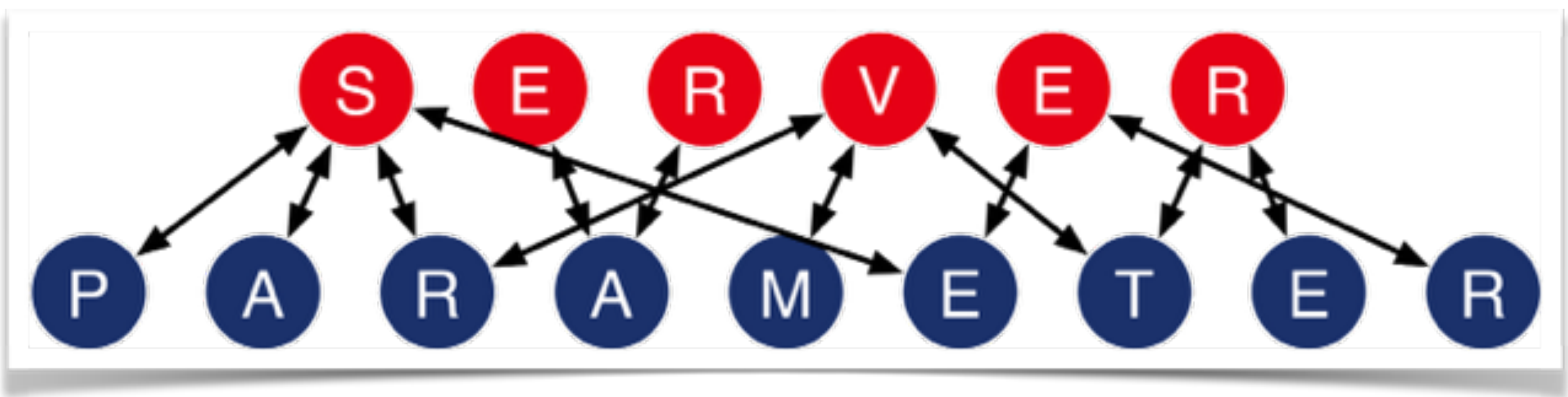
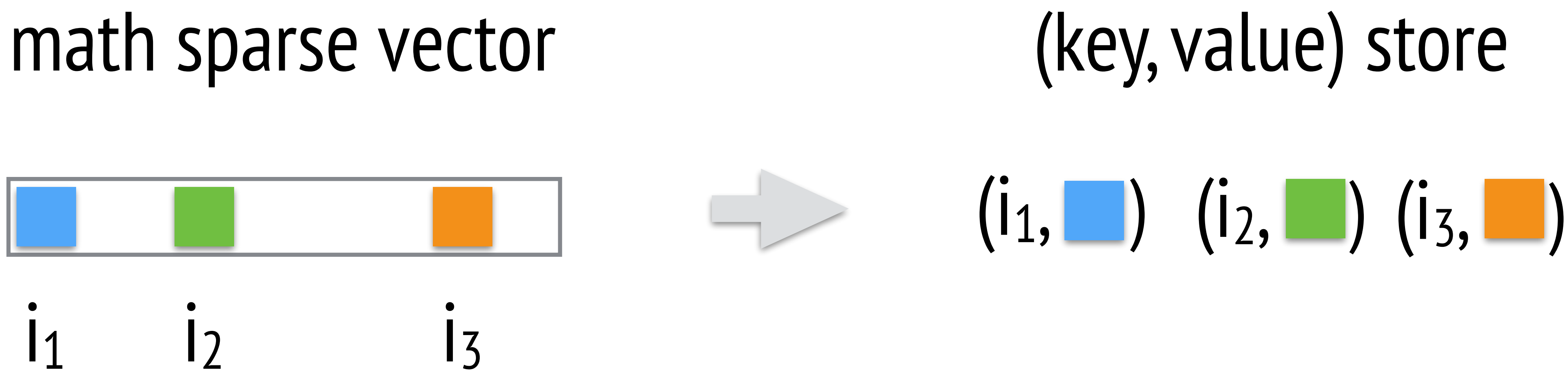


Fault tolerance

Easy to use

(Key, value) vectors for the shared parameters



(Key, value) vectors for the shared parameters

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

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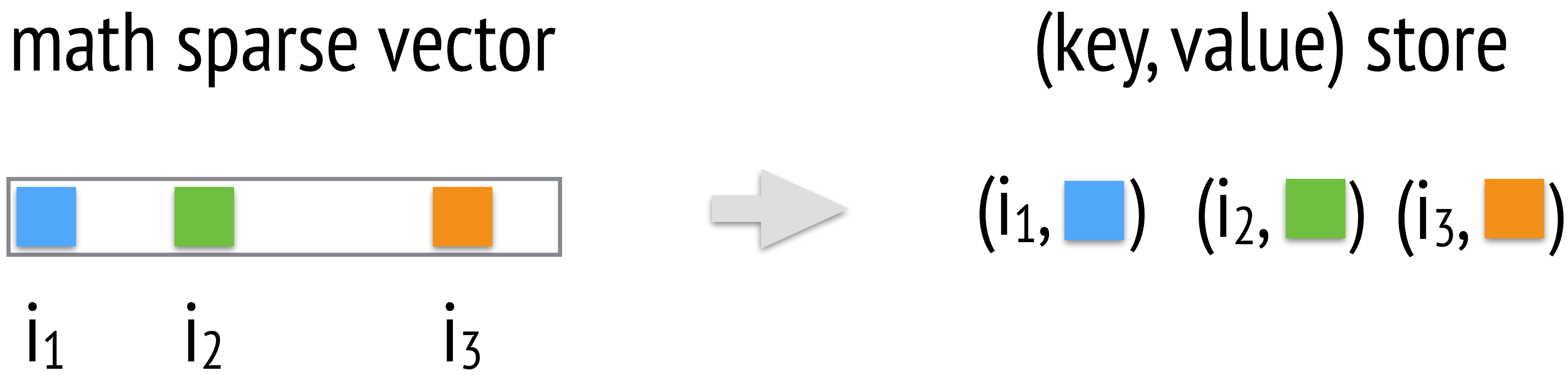

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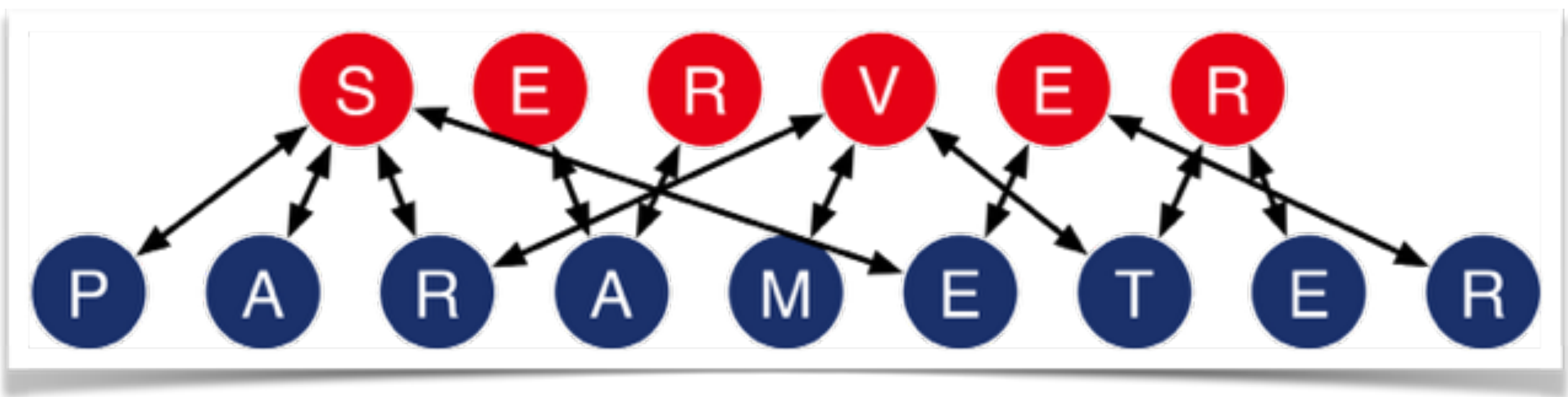
Example: computing gradient

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

Industry size machine learning problems

Efficient communication



Fault tolerance

Easy to use

Evaluation

Sparse Logistic Regression

- Predict ads will be clicked or not

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- 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

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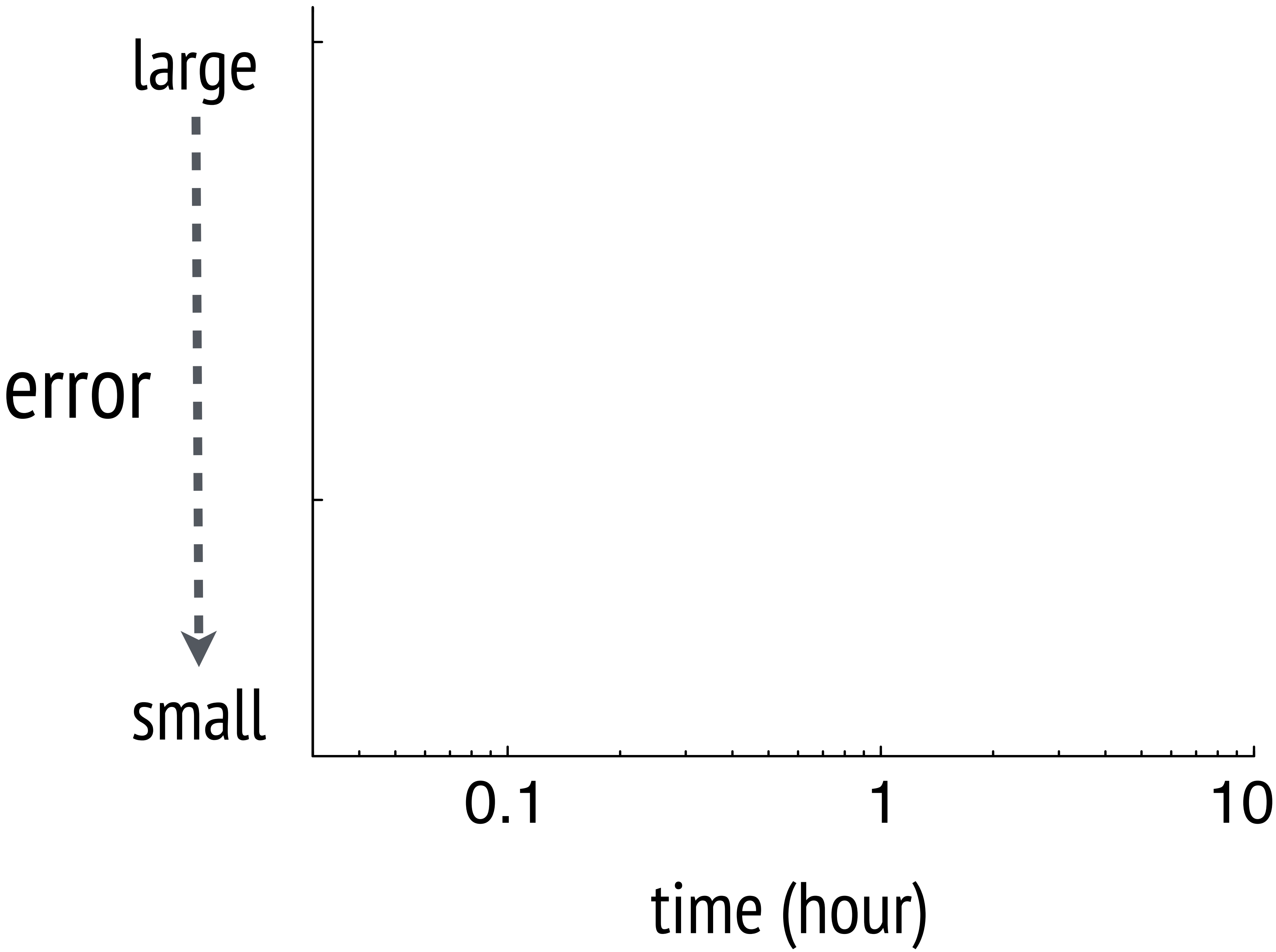
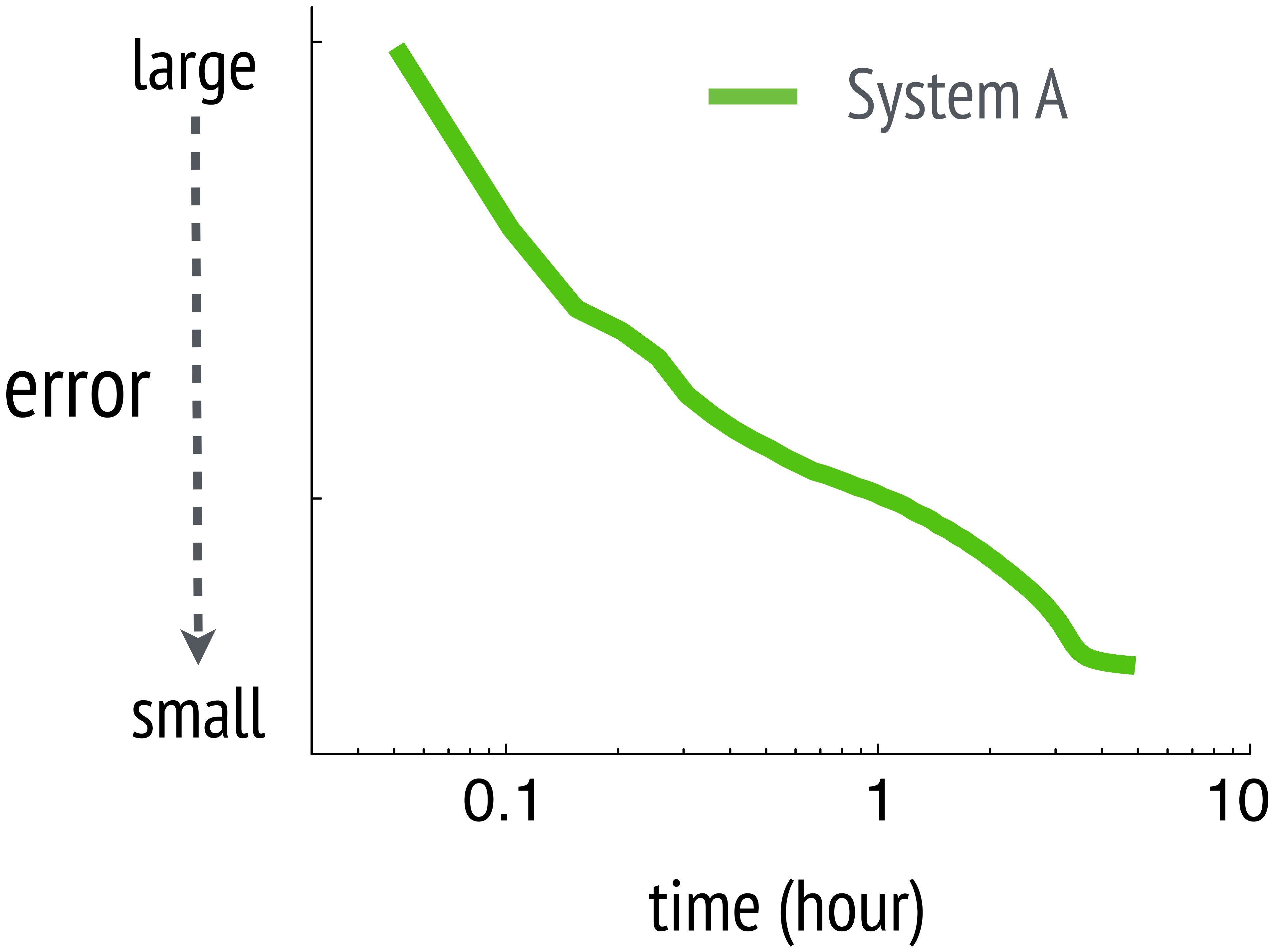
- 636T real ads data
  - 170 billions of examples, 65 billions of features
- 1,000 machines with 16,000 cores

Progress



Progress



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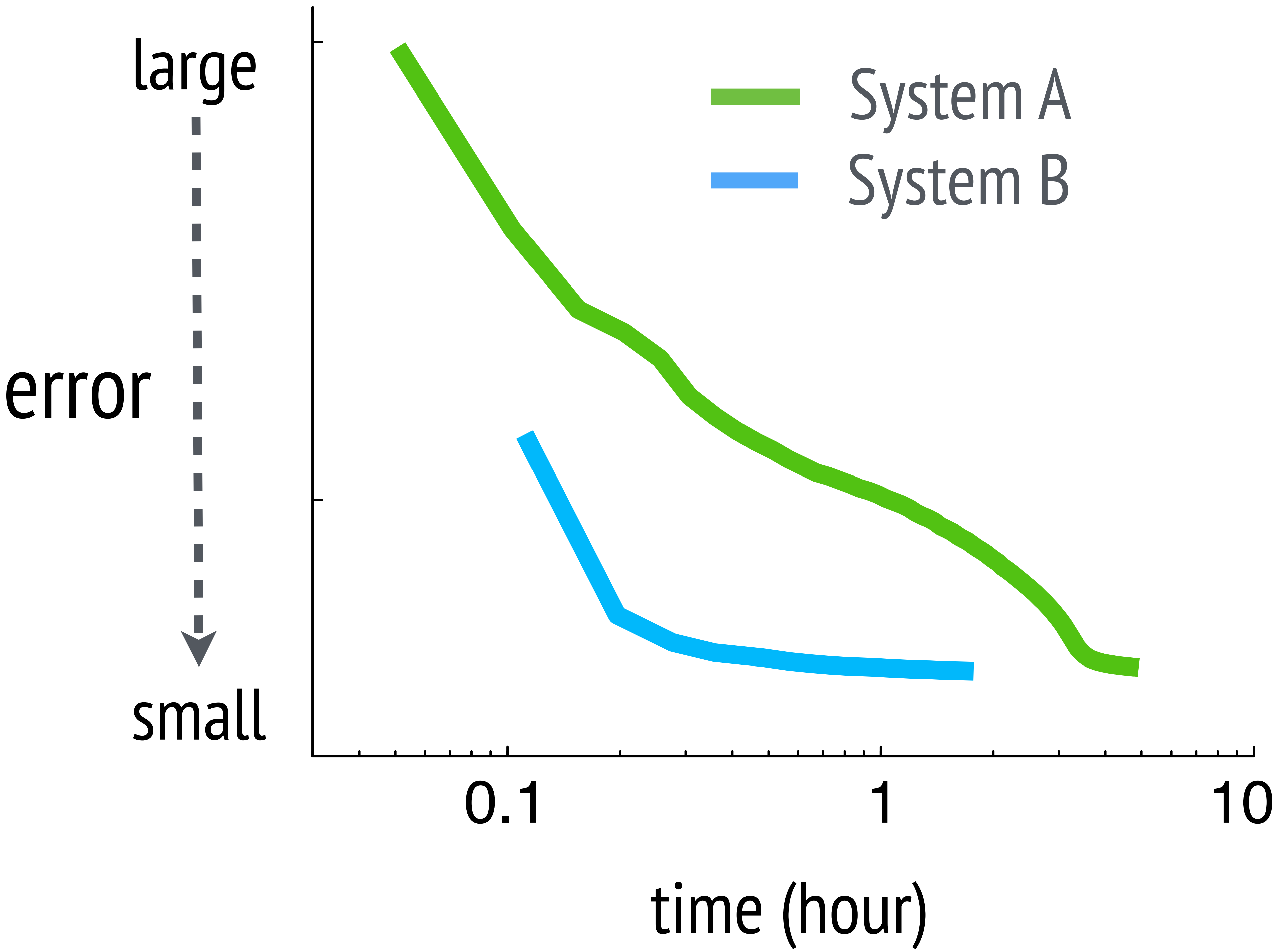

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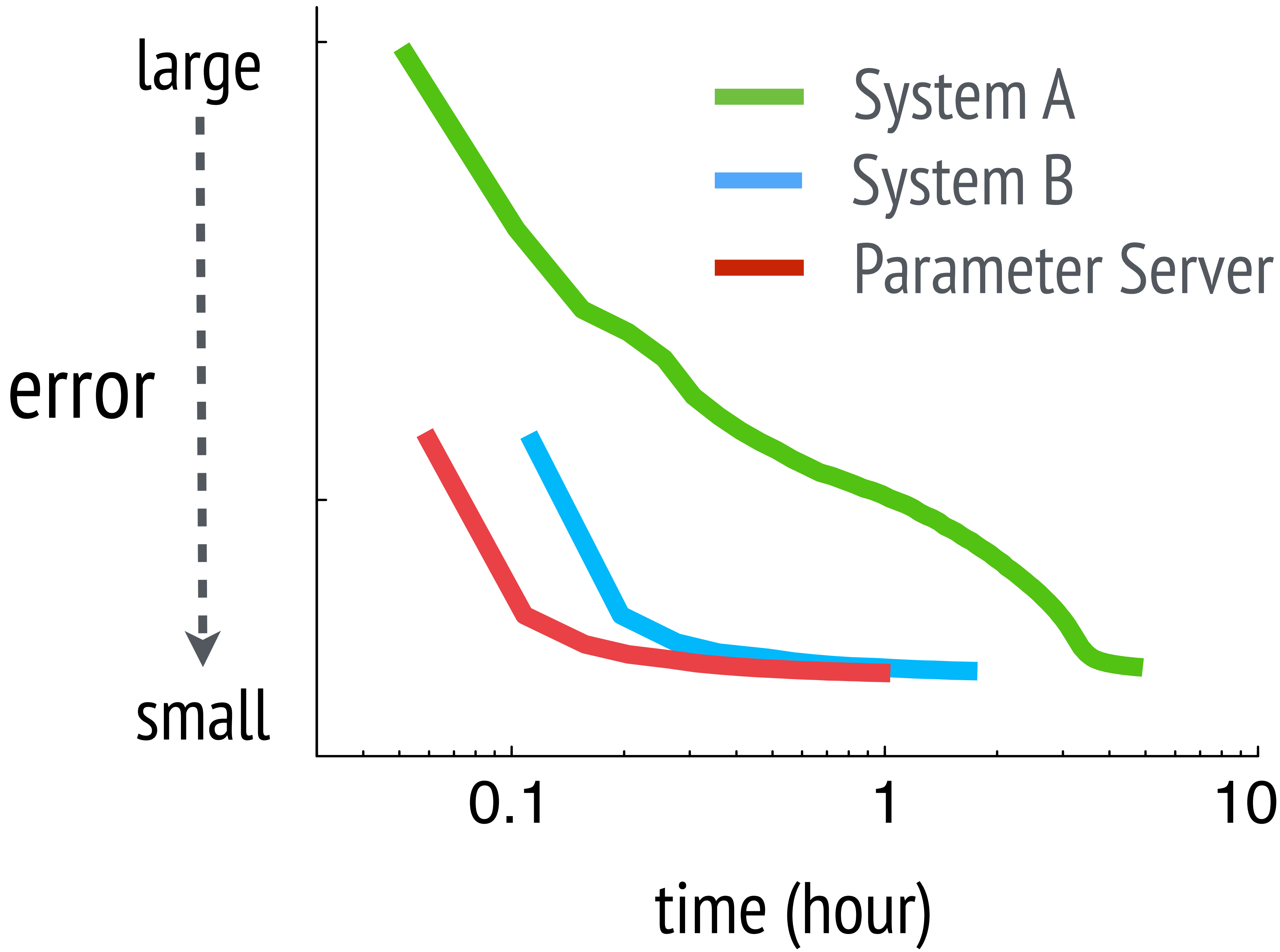
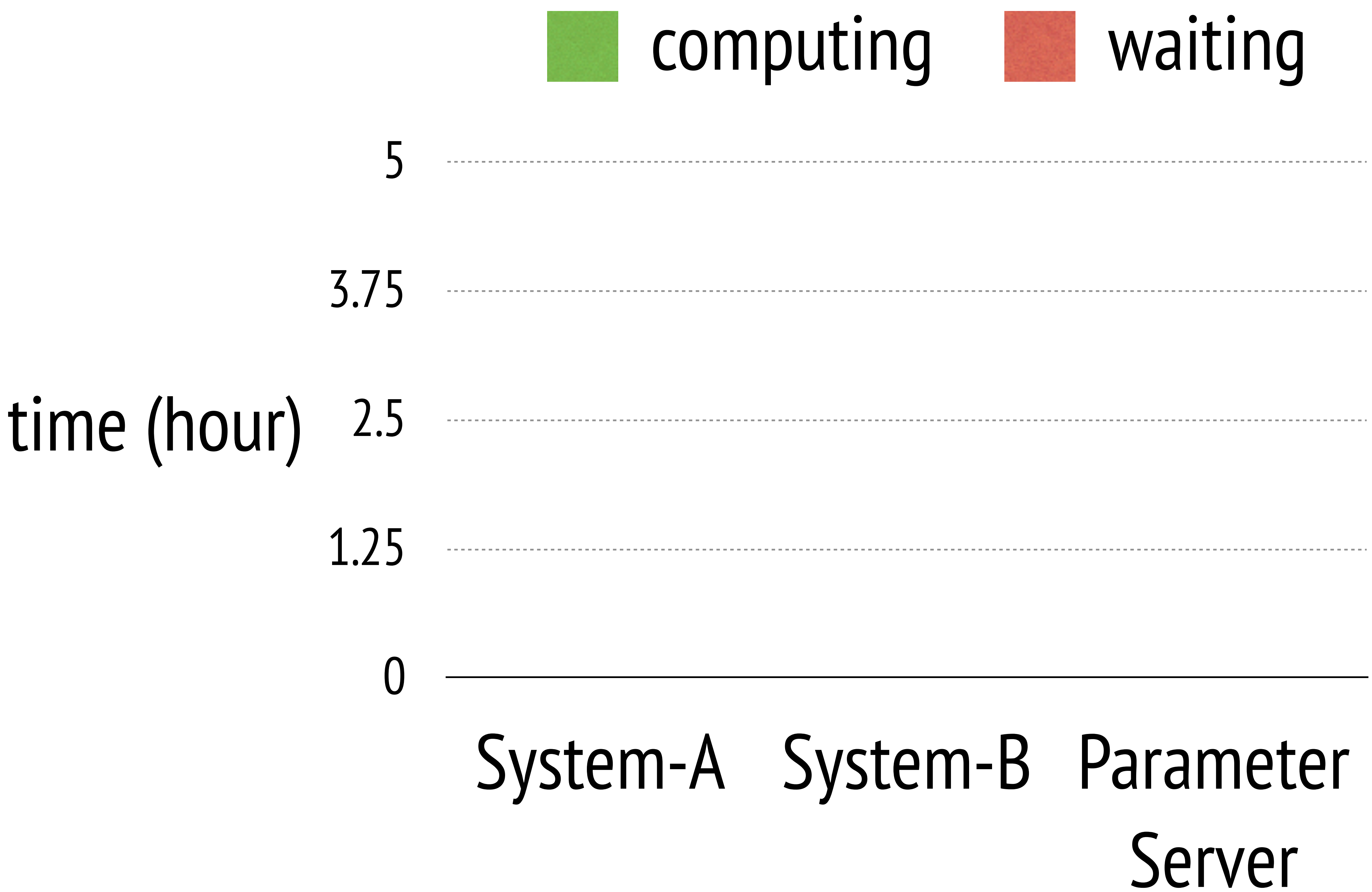


large
error
small
System A
System B
Parameter Server
0.1
1
10
time (hour)

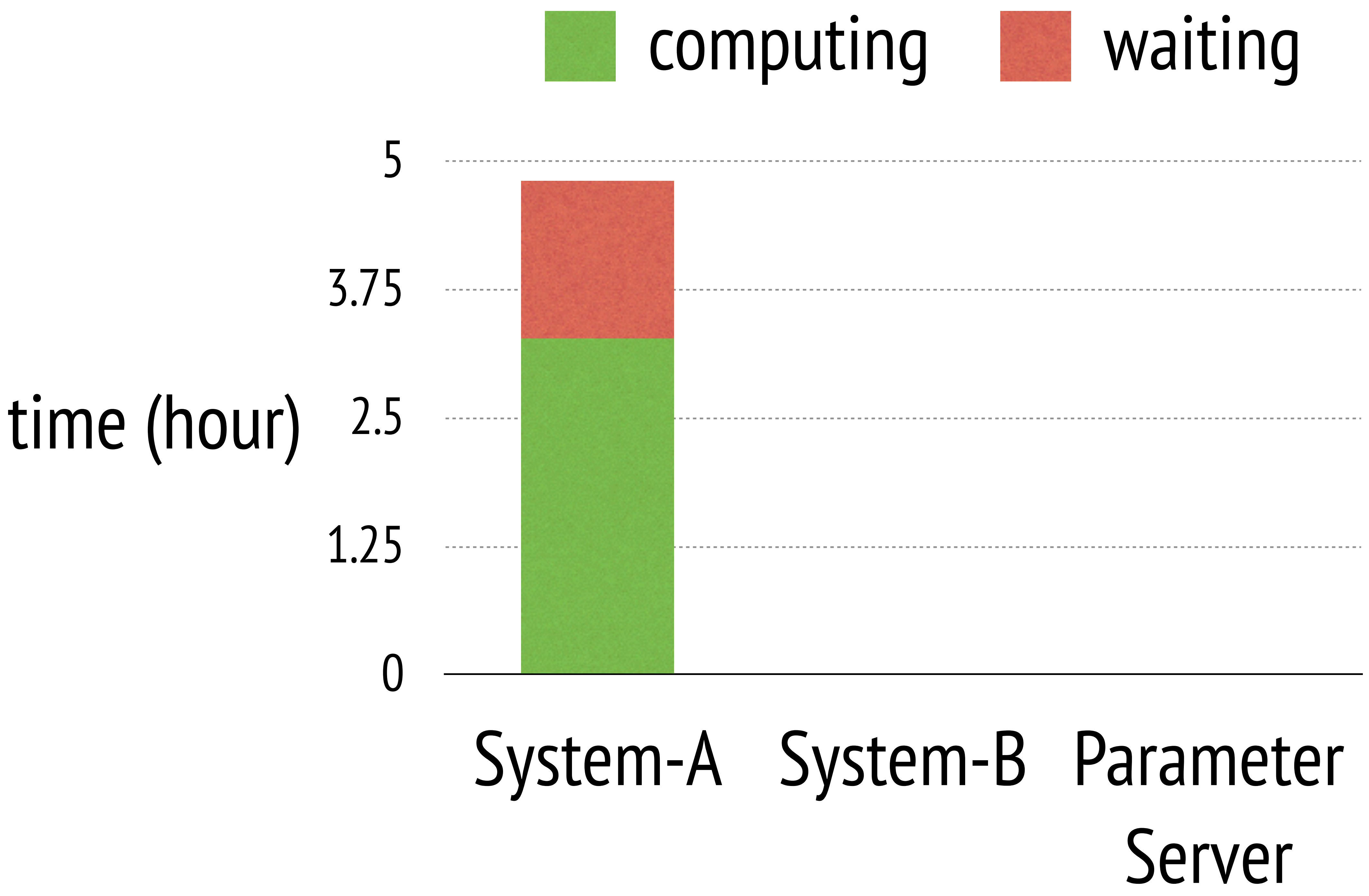
Time decomposition

time (hour)

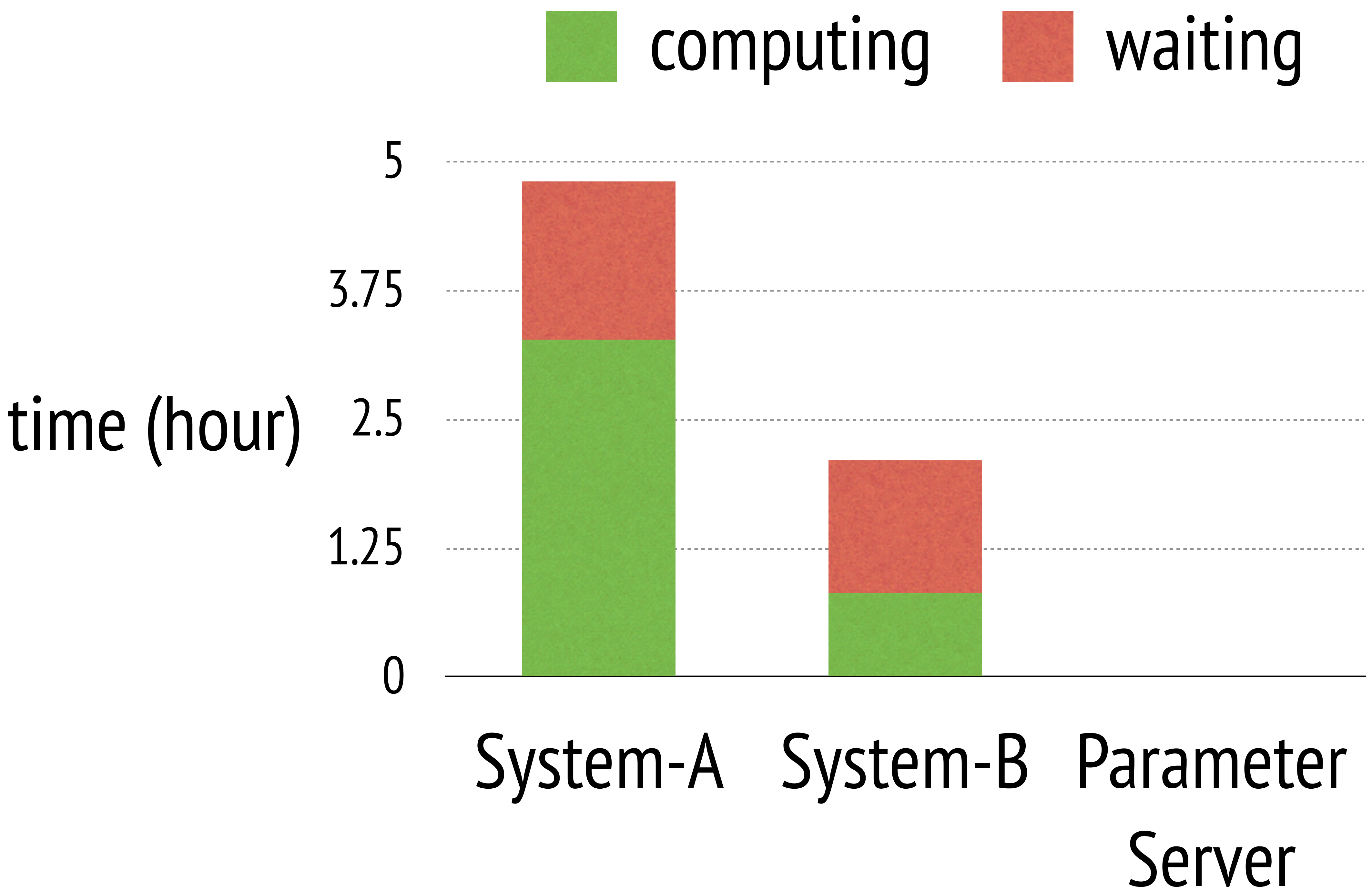
Time decomposition



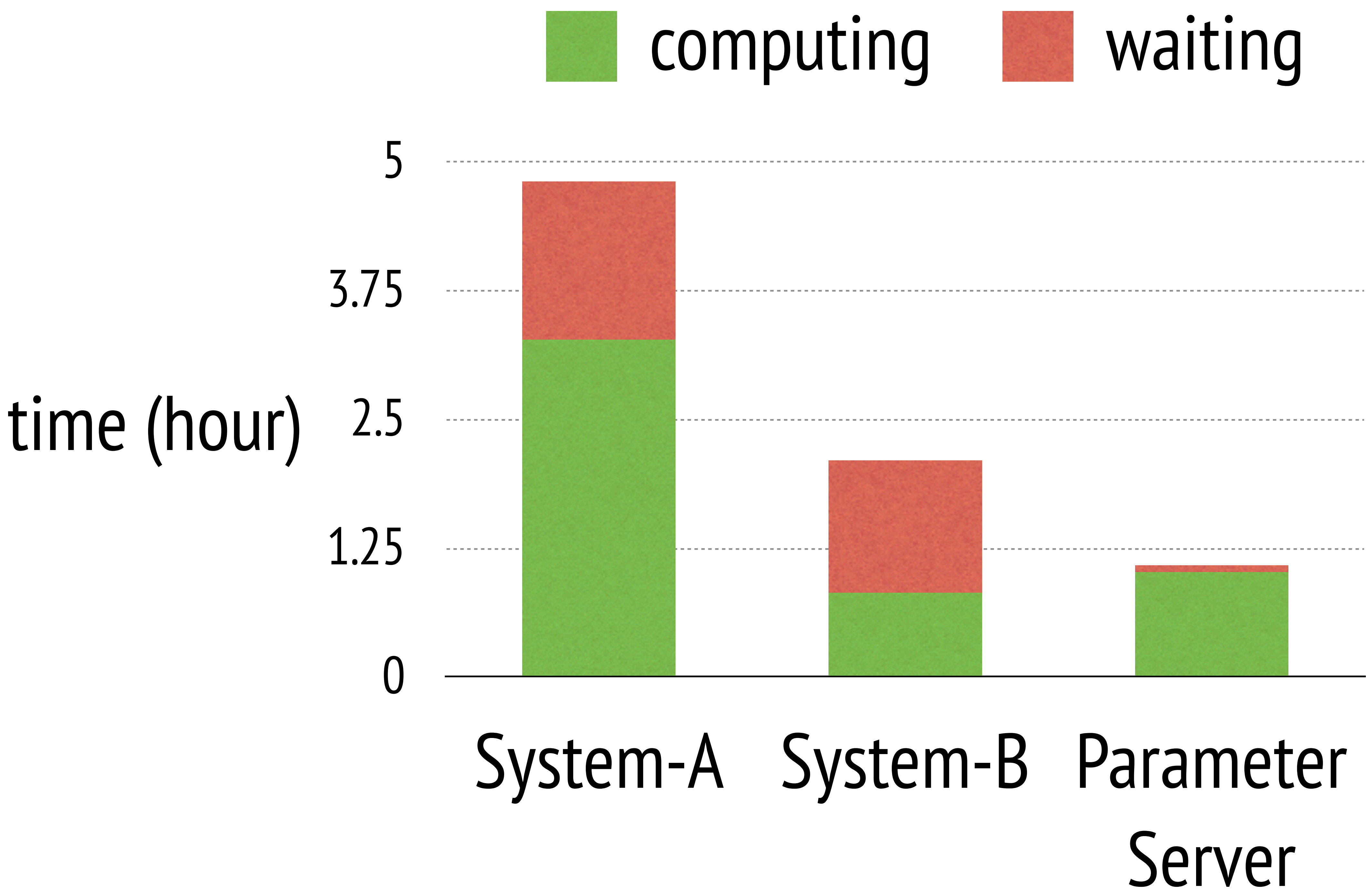
Time decomposition



Time decomposition



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

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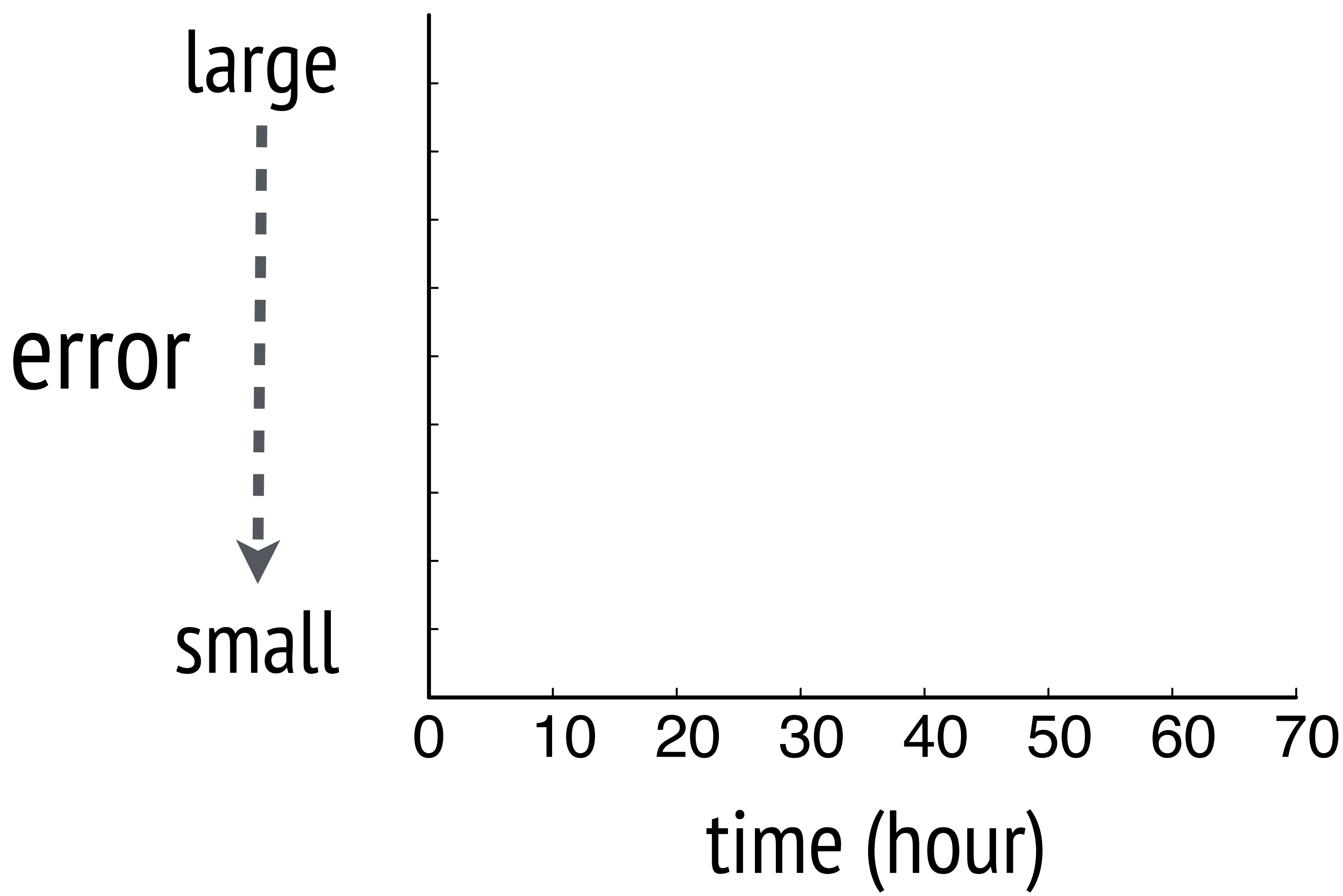

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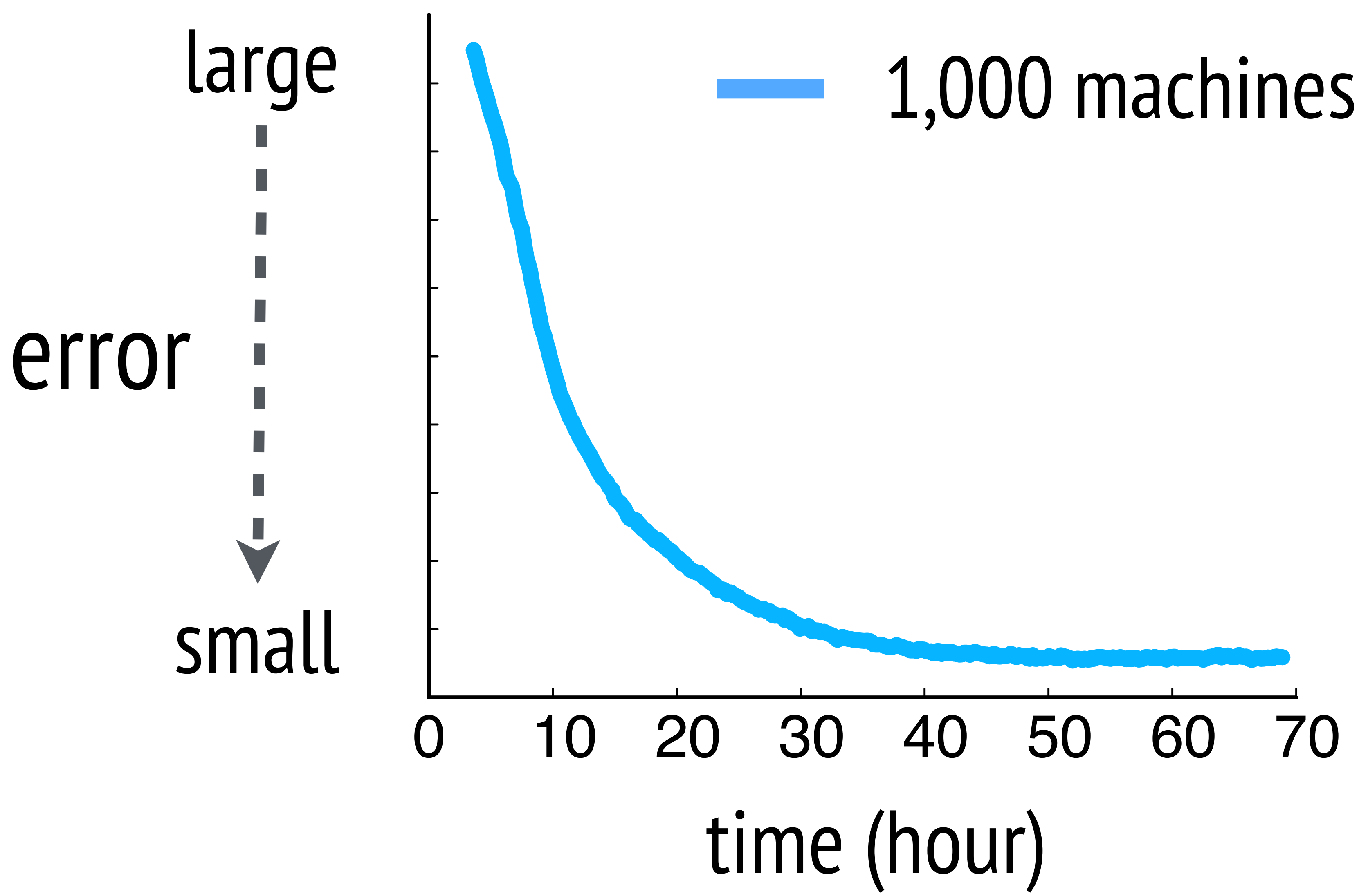

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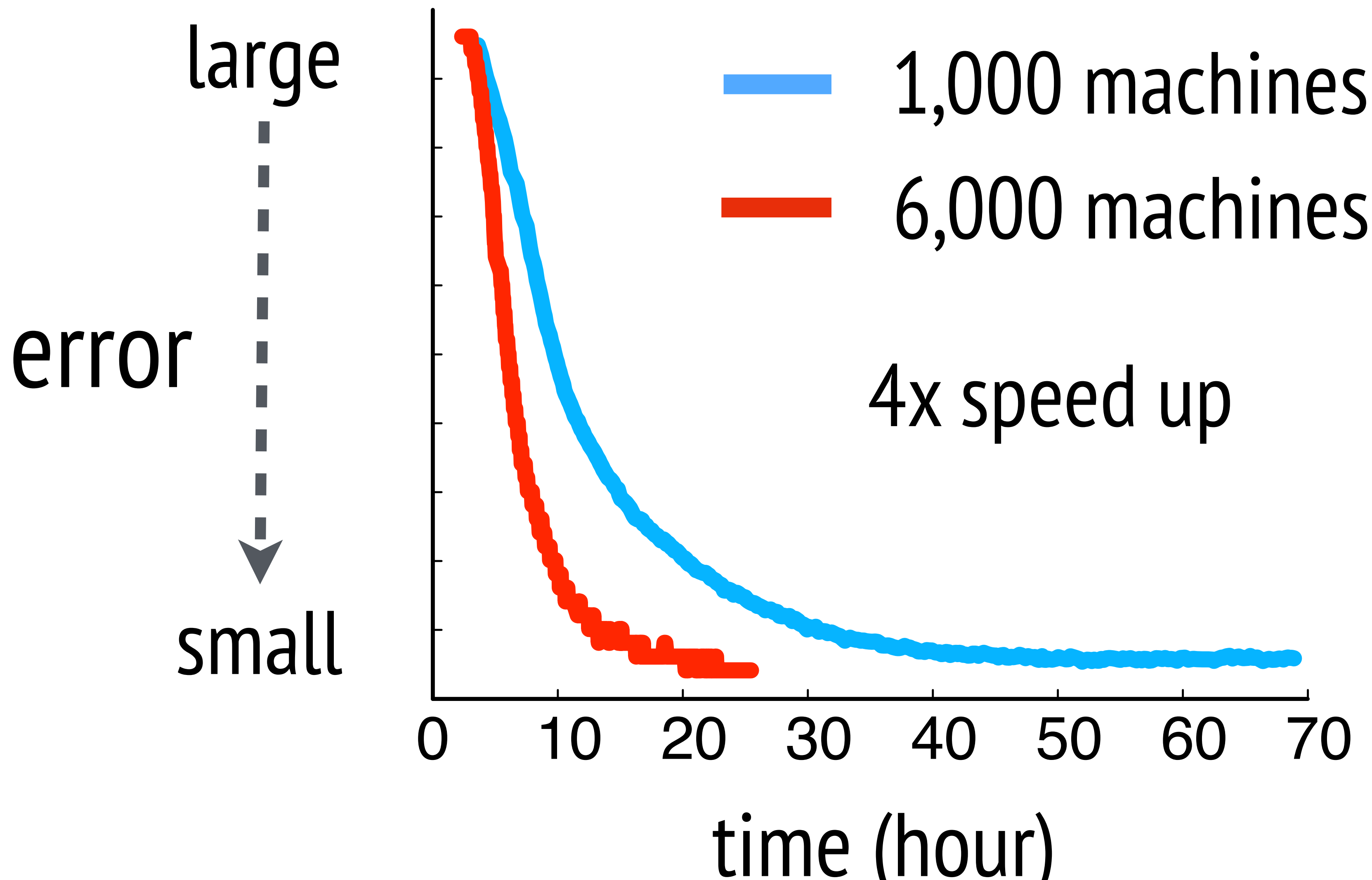
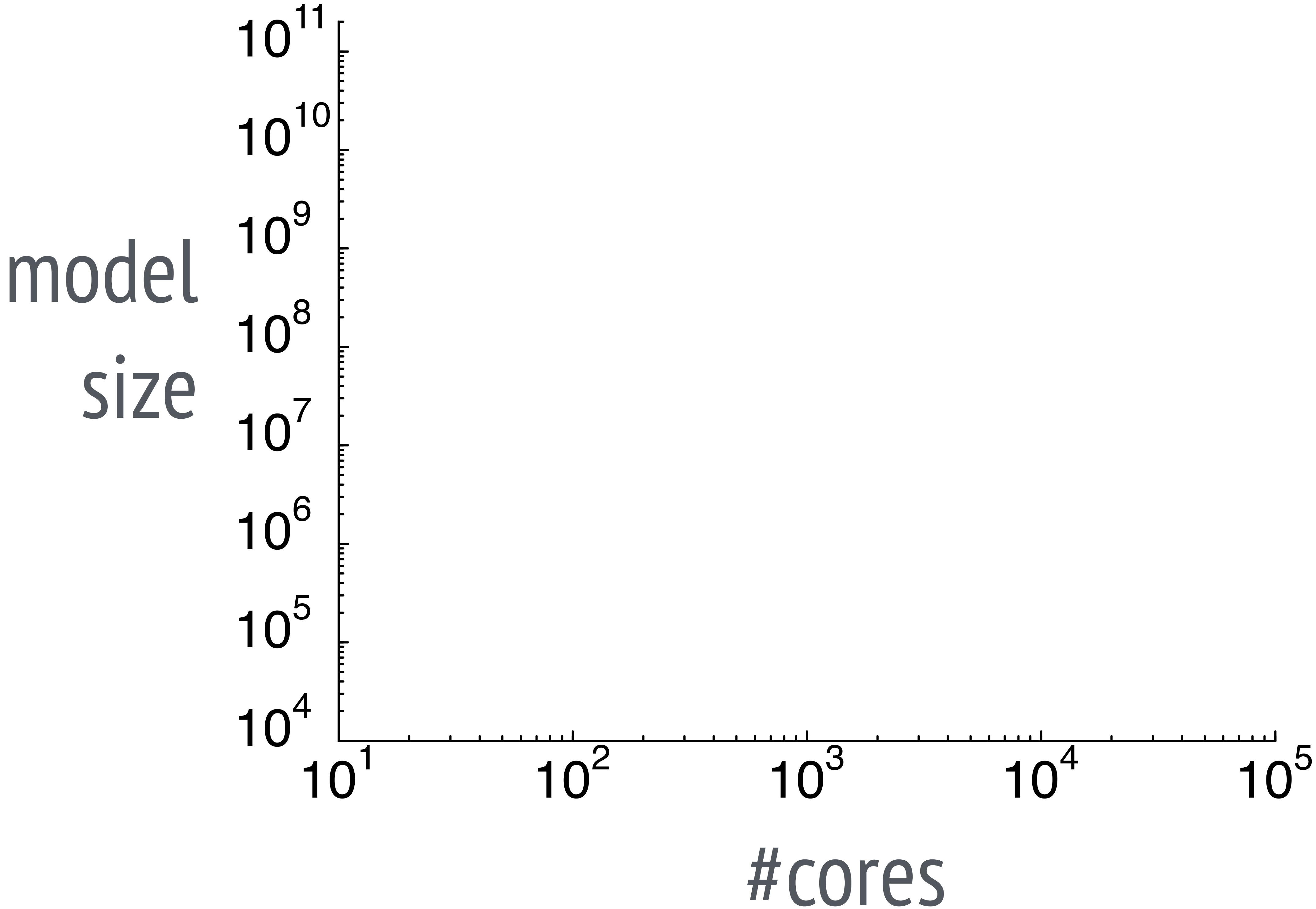


Largest experiments of related systems

Data were collected on April'14



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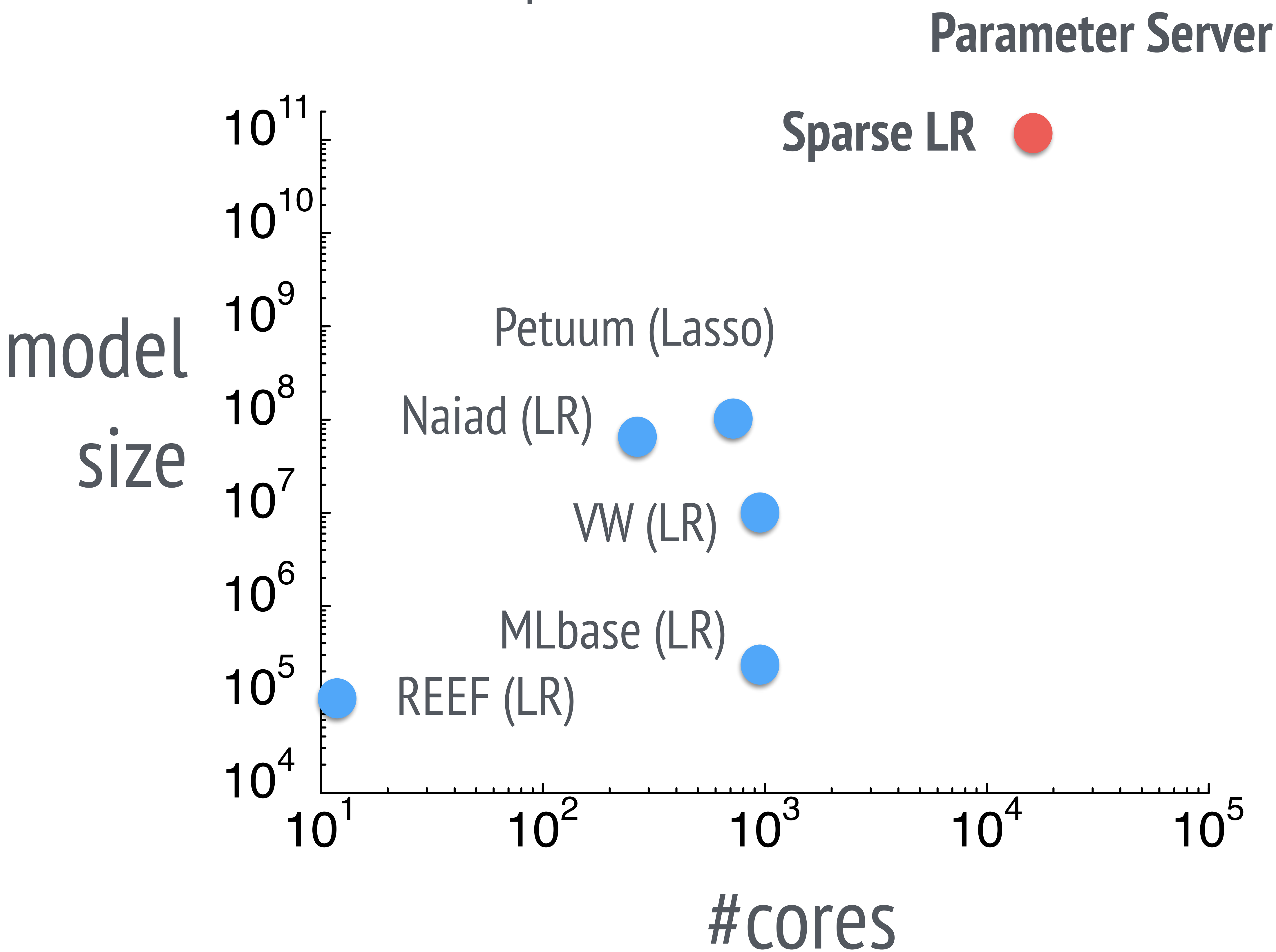

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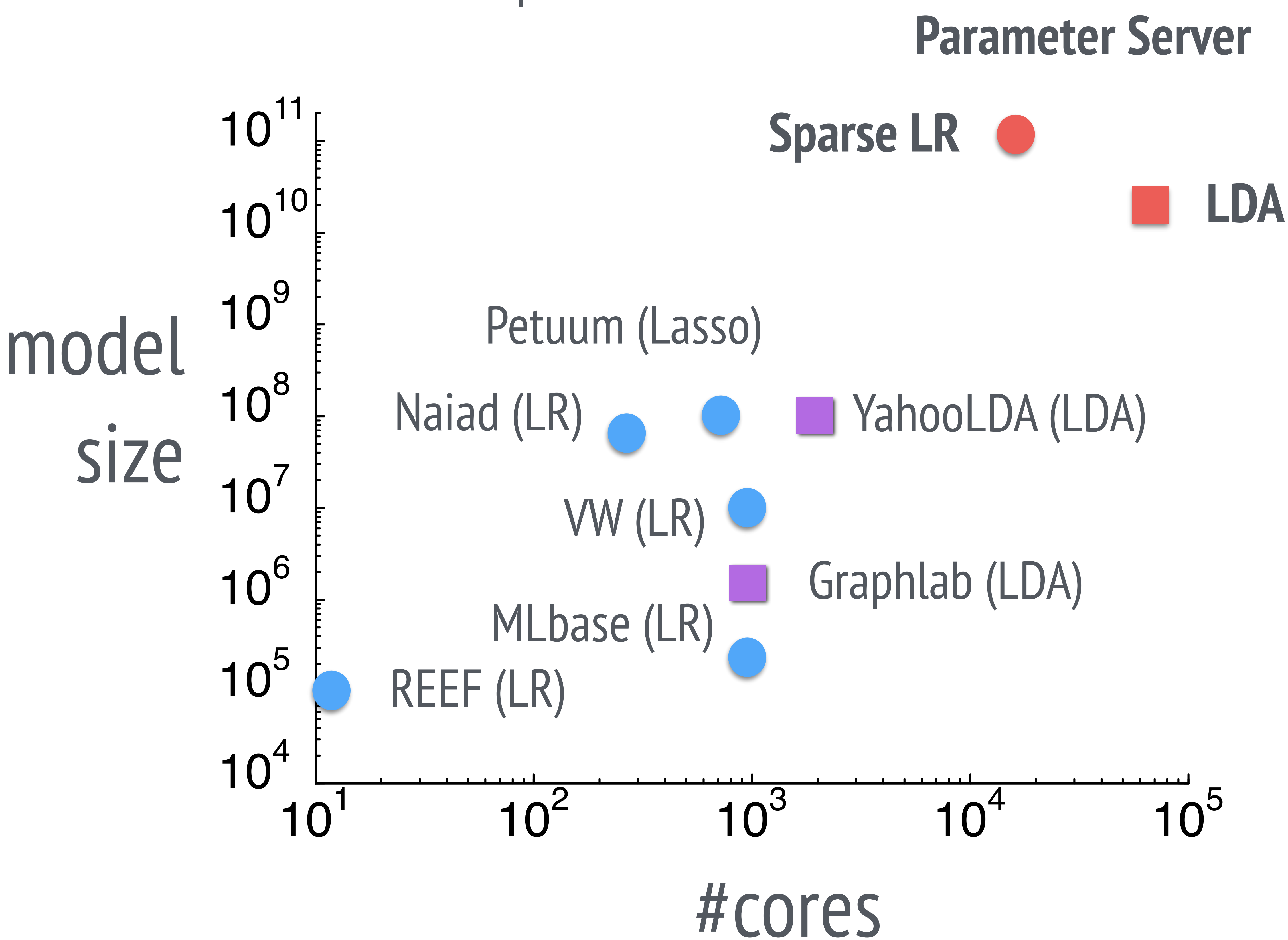

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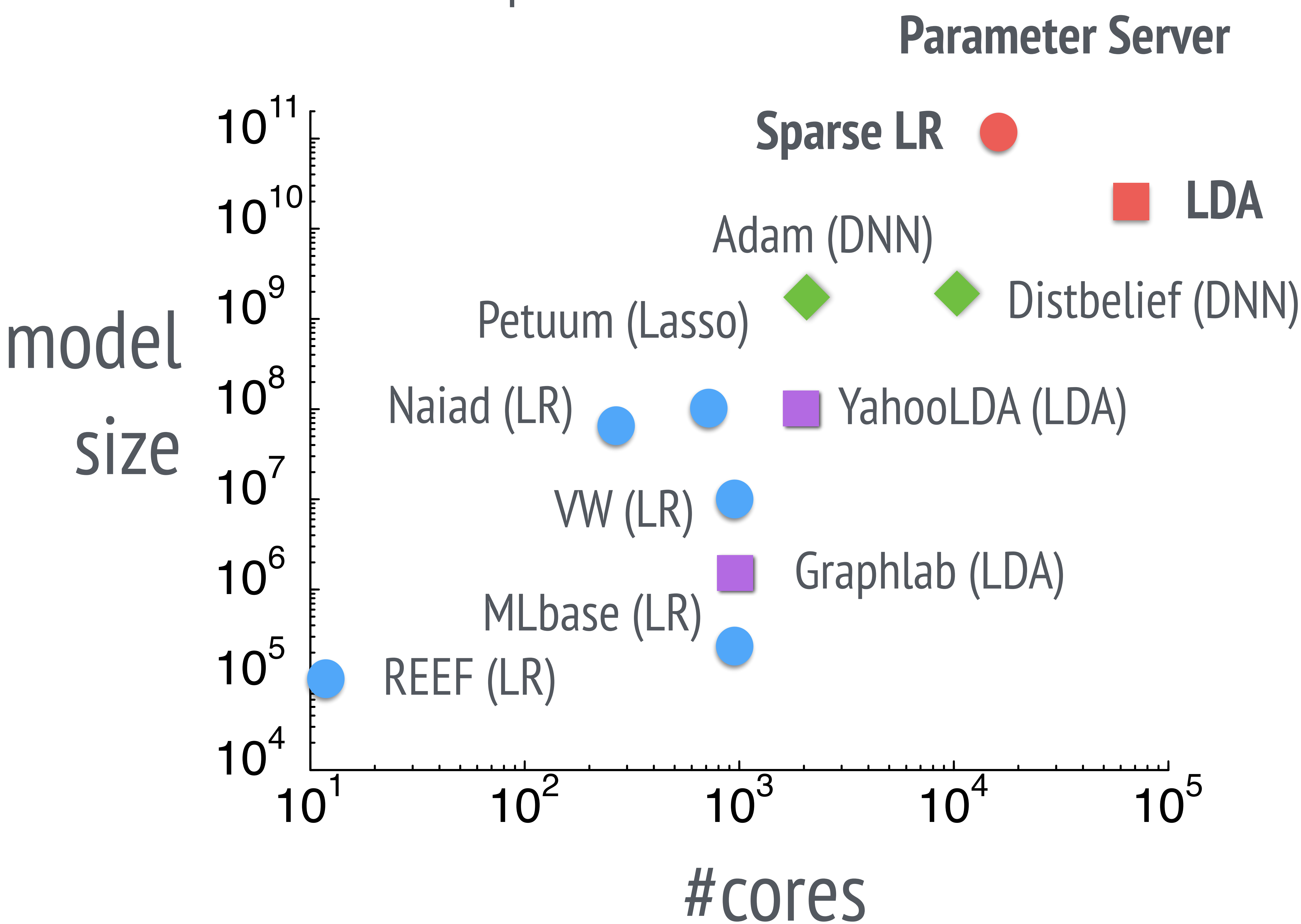
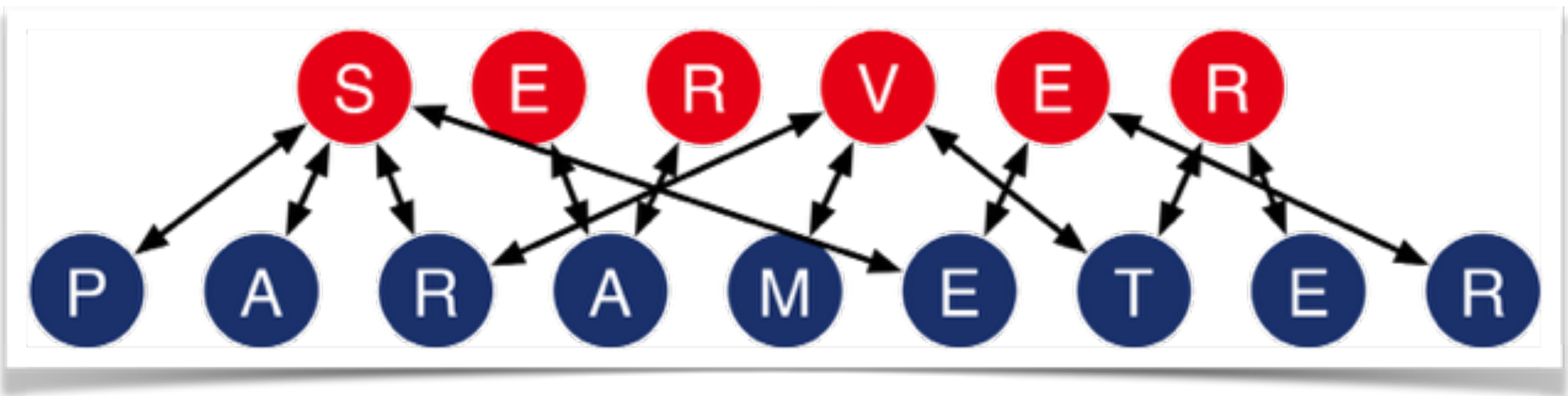


Industry size machine learning problems

Efficient communication



Fault tolerance

Easy to use

Evaluation

Industry size machine learning problems

Efficient communication

Code available at
parameterserver.org

Fault tolerance

Easy to use

Evaluation

Q&A