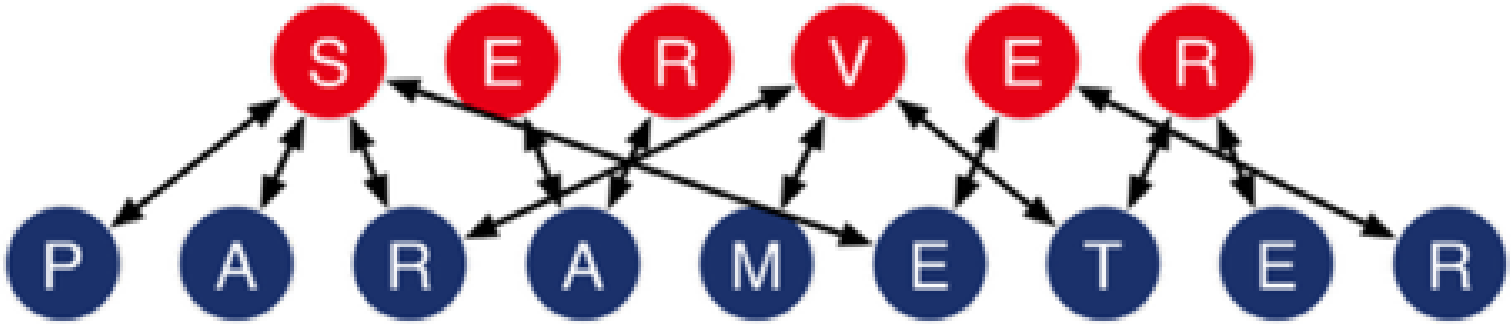
Scaling Distributed Machine Learning with the



BASED ON THE **PAPER** AND **PRESENTATION**:

SCALING DISTRIBUTED MACHINE LEARNING WITH THE PARAMETER SERVER – **GOOGLE**, **BAIDU**, **CARNEGIE MELLON UNIVERSITY**

INCLUDED IN THE PROCEEDINGS AT **OSDI 14**

PRESENTATION BY: SANCHIT GUPTA

Machine learning is concerned with systems that can learn from data

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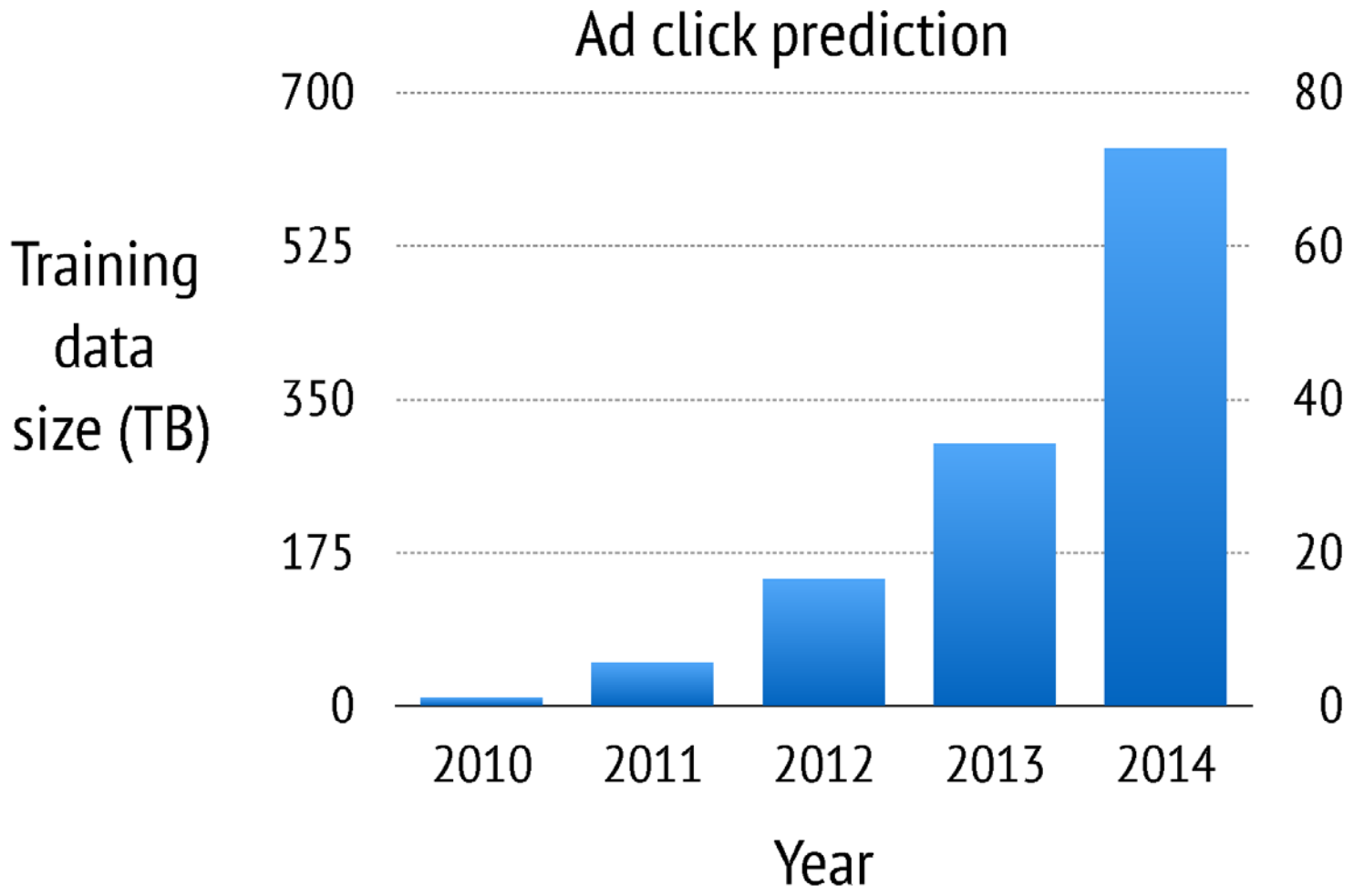

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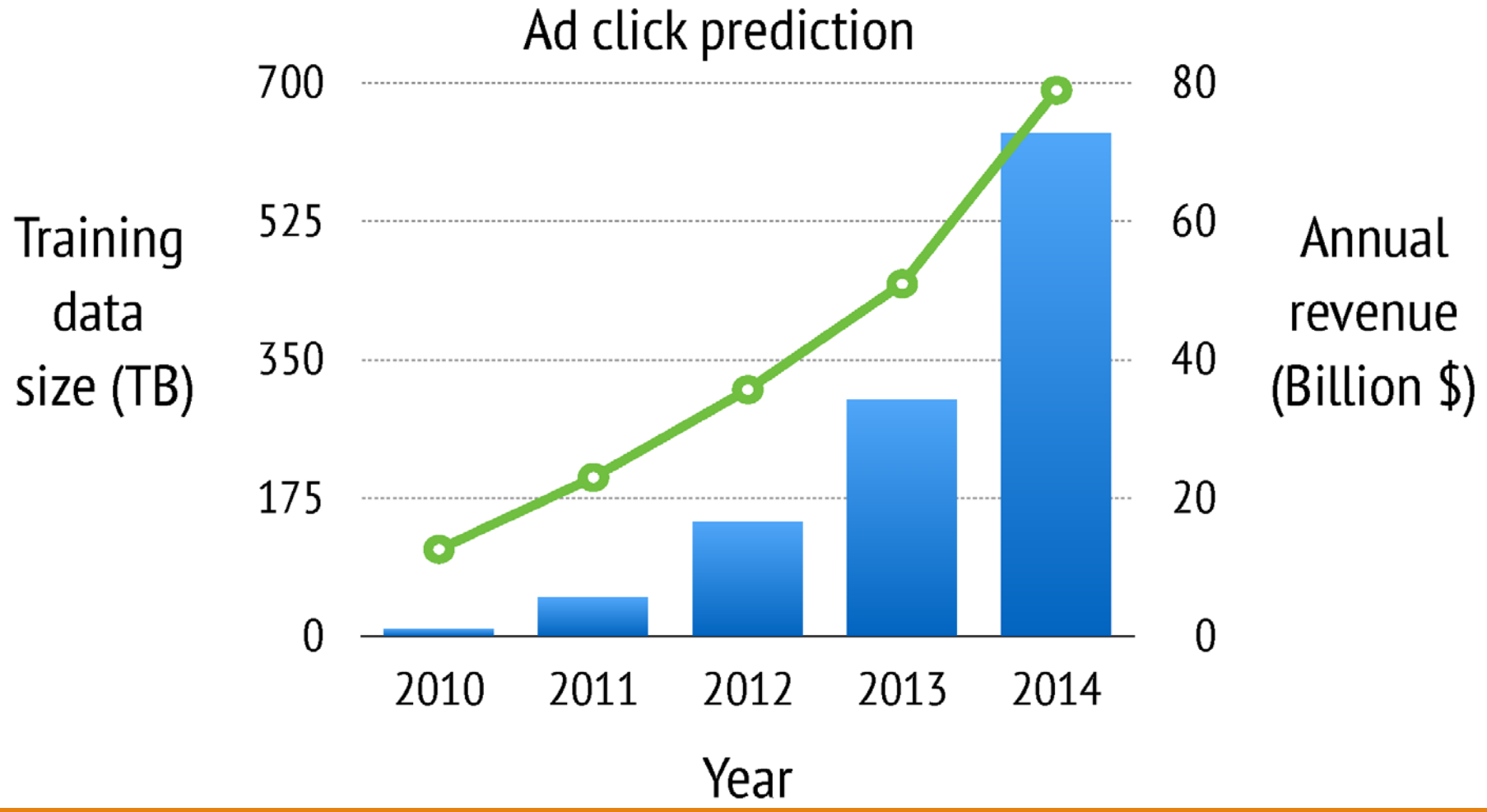

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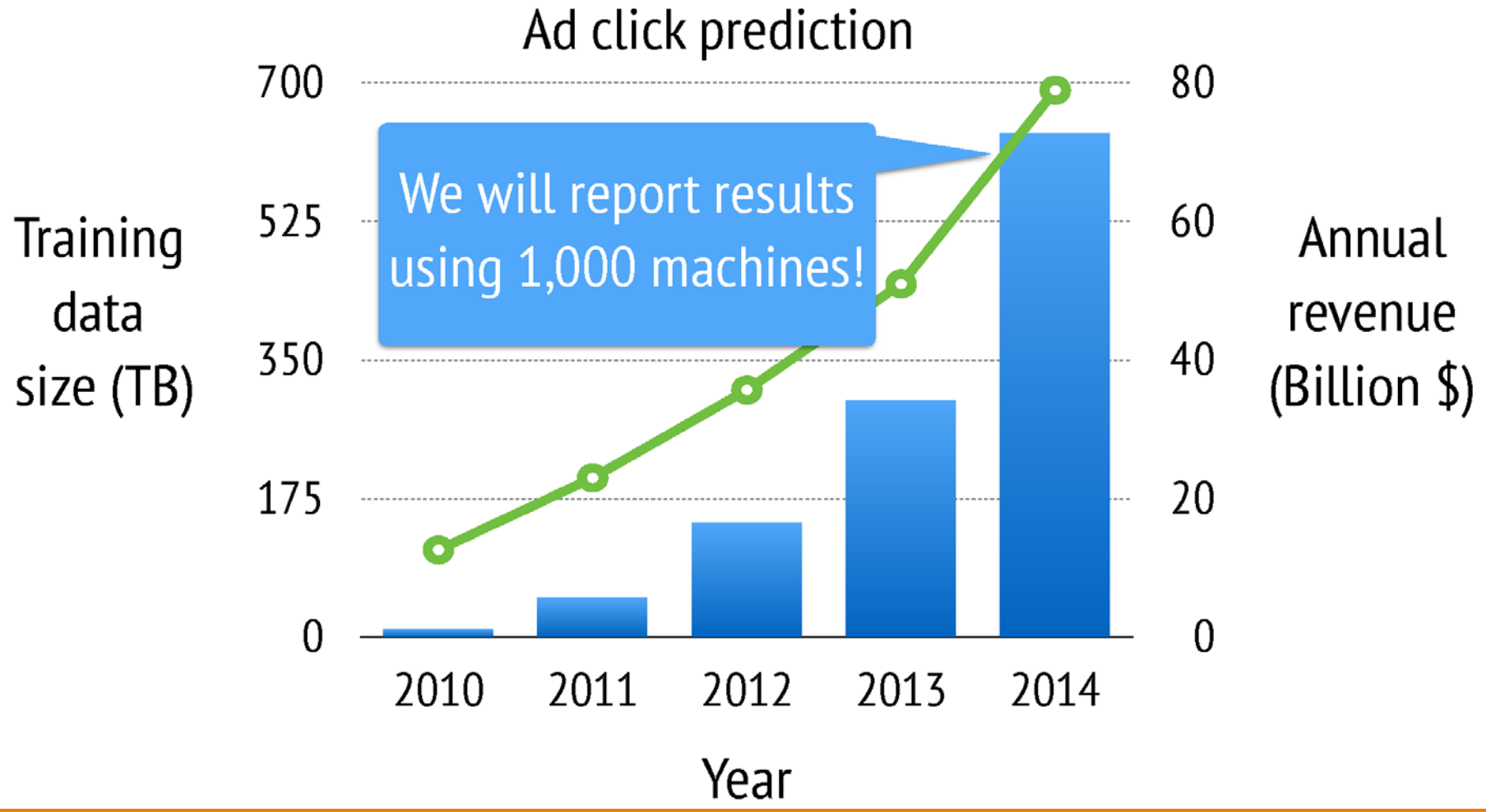
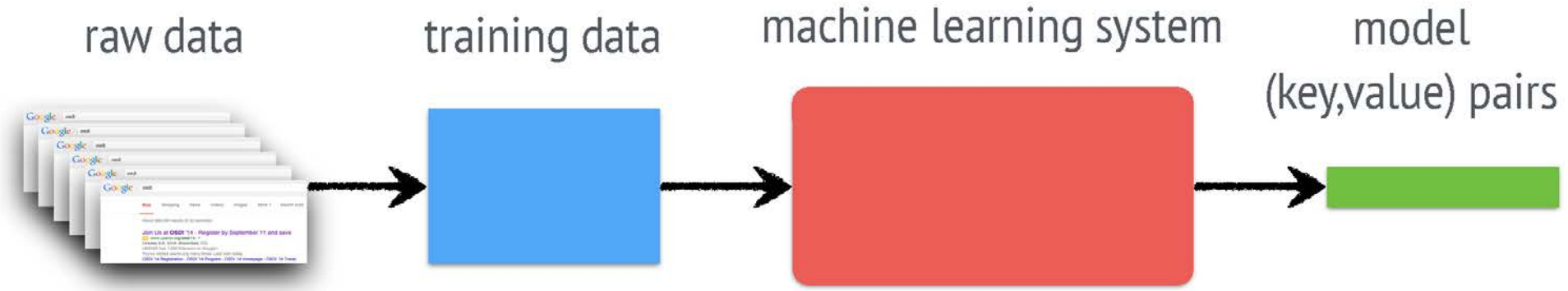


Machine learning is concerned with systems that can learn from data

Overview of machine learning



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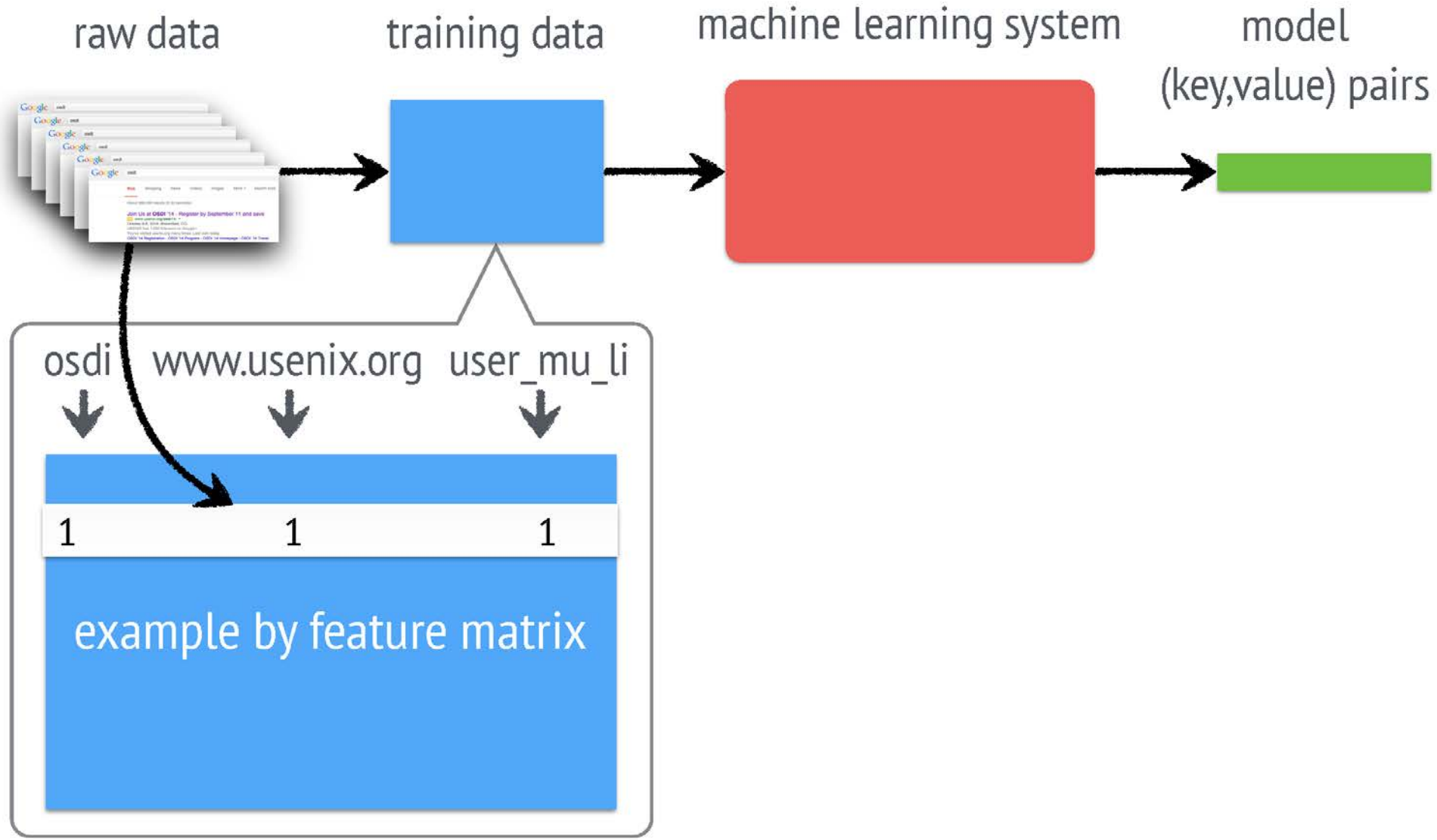

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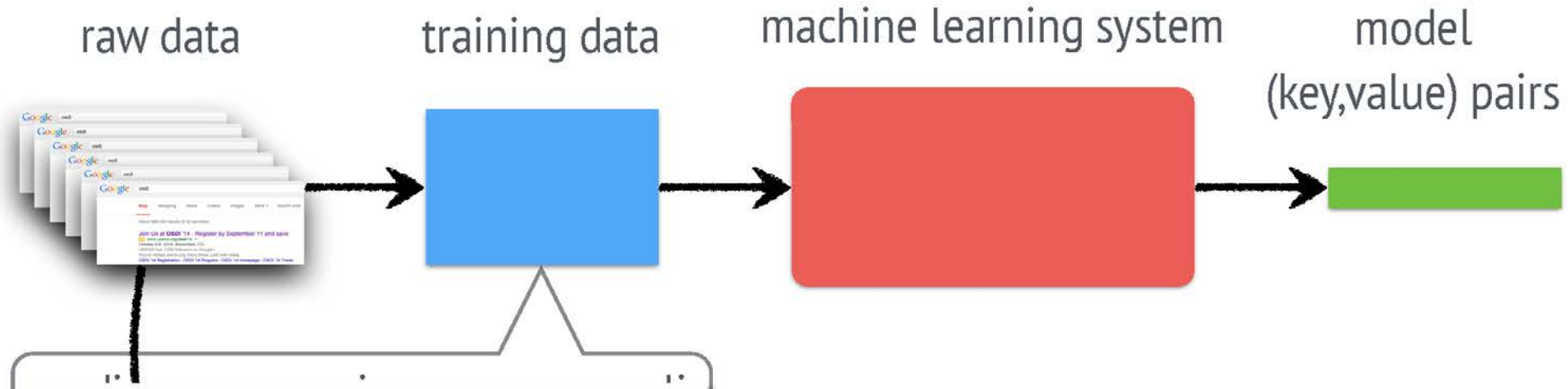
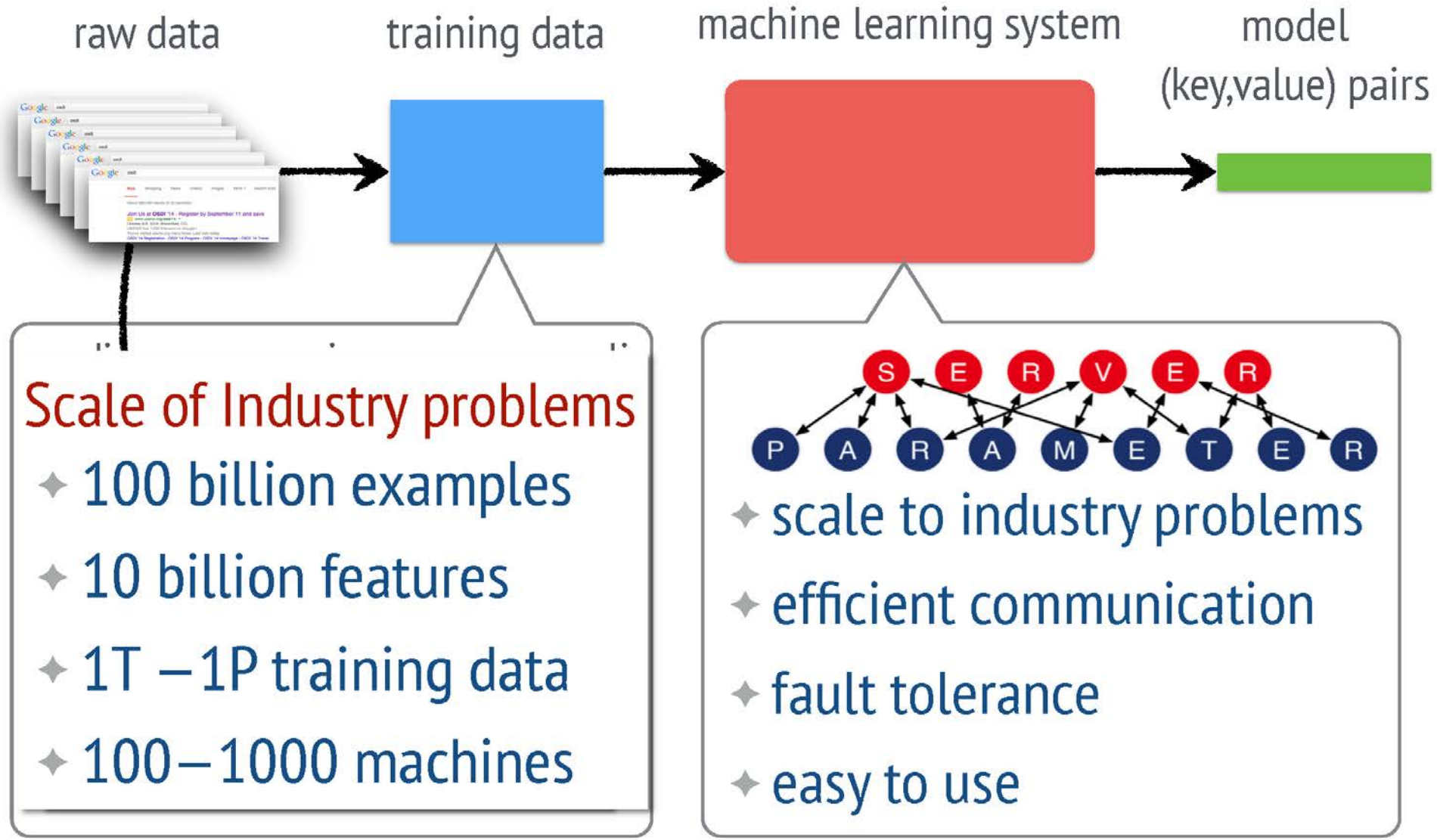


Scale of Industry problems

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

Overview of machine learning



Characteristics & Challenges of ML jobs

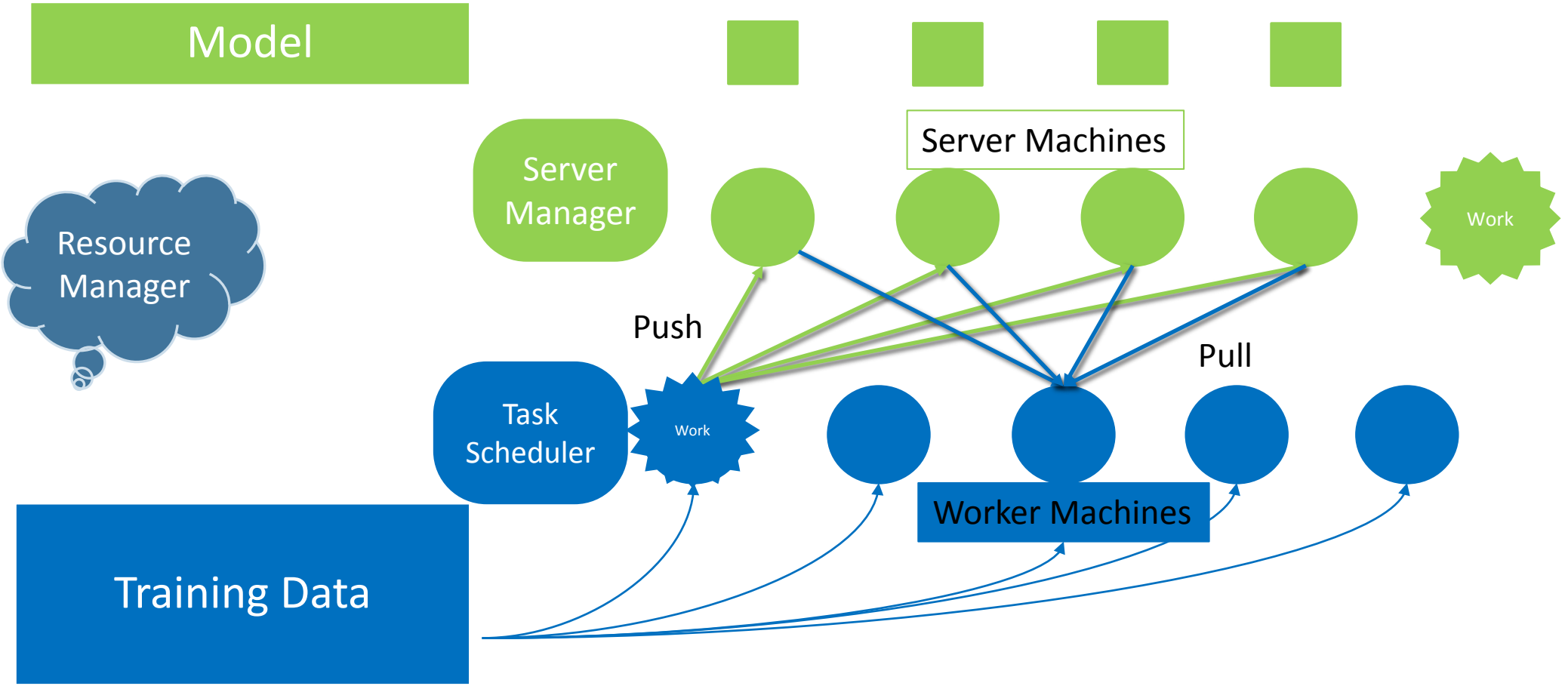
- Training Data is **Large** – 1TB to 1PB
- Complex Models with **Billions** and **Trillions** of Parameters
- Parameters are shared globally among worker nodes:
  - Accessing them incurs large **Network costs**
  - Sequential ML jobs require **barriers** and hurt performance by blocking
  - At scale, **Fault Tolerance** is required as these jobs run in a cloud environment where machines are unreliable and jobs can be preempted

Key Goals and Features of Design

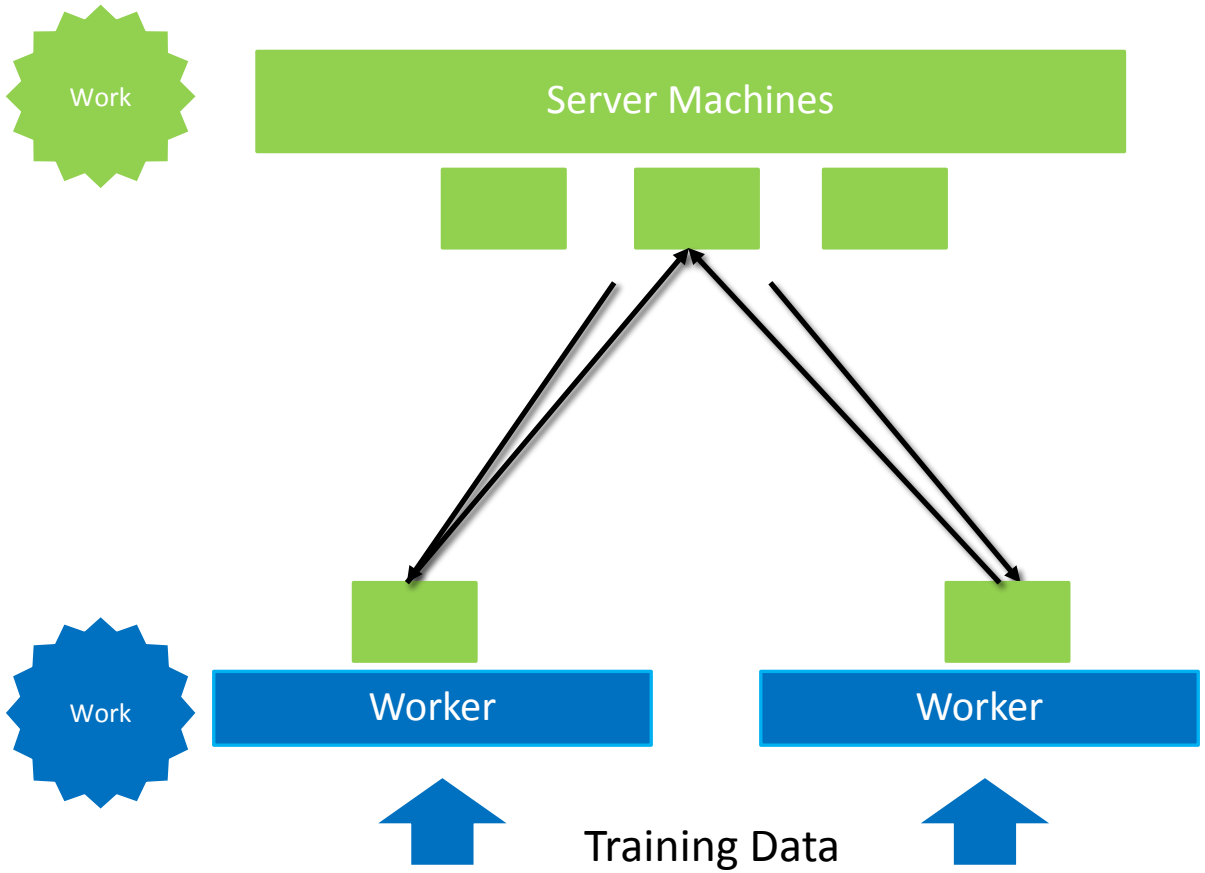
- **Efficient Communication**: asynchronous communication model (does not block computation)
- **Flexible Consistency Models**: Algorithm designer can balance algorithmic convergence and system efficiency
- **Elastic Scalability** : New nodes can be added without restarting framework
- **Fault Tolerance and Durability**: Recovery from and repair in 1 sec.
- **Ease of Use**: easy for users to write programs

Architecture & Design Details

Architecture: Data and Model



Example: Distributed gradient Descent



- Workers get the Assigned training data
- Workers **Pull** the Working set of Model
- Iterate until Stop:
  - Workers **Compute** Gradients
  - Workers **Push** Gradients
  - Servers **Aggregate** into current model
  - Workers **Pull** updated model

Architecture: Parameter Key-Value

- Model Parameters are represented as Key – Value pairs
- Parameter Server approach models the Key-Value pairs as sparse Linear Algebra Objects.
- **Batch** several key-value pairs required to compute a vector/matrix instead of sending them one by one
- **Easy to Program**! – Lets us treat the parameters as key-values while endowing them with matrix semantics

(Key, value) vectors for the shared parameters

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- Good for programmers: Matches mental model
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Example: computing gradient

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

Architecture: Range Push and Pull

- Data is sent between Workers and Servers using *PUSH* and *PUSH* operations.

- Parameter Server optimizes updates **communication** by using RANGE based *PUSH* and *PULL.*

- Example: Let ***w*** denote parameters of some model
  - *w.push(**Range,** dest)*
  - *w.pull**(Range**, dest**)***
  - These methods will send/receive all existing entries of ***w*** with ***keys*** in ***Range***

Architecture: Asynchronous tasks and Dependency

- Challenges for Data Synchronization:
  - There is a MASSIVE communication traffic due to frequent access of Shared Model
  - Global barriers between iterations – leads to:
    - idle workers waiting for other computation to finish
    - High total finish time

Task

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

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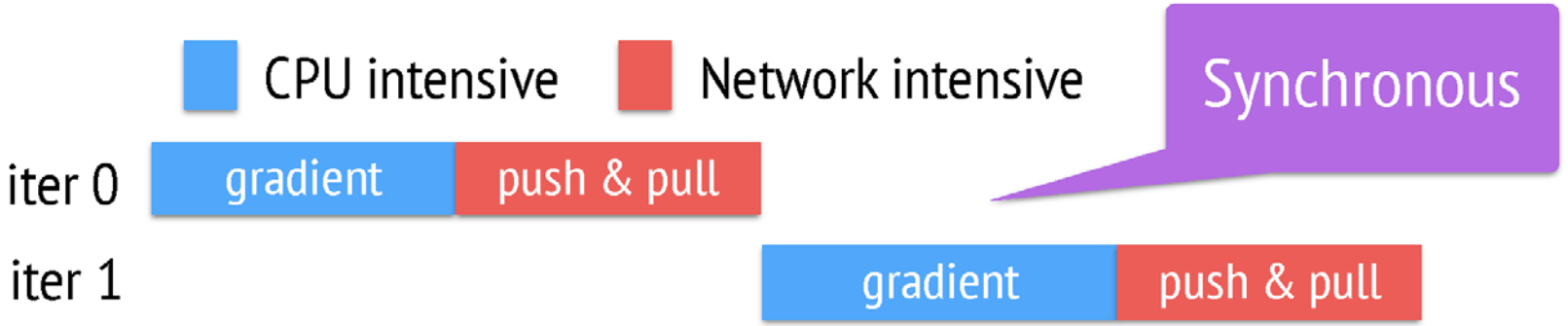

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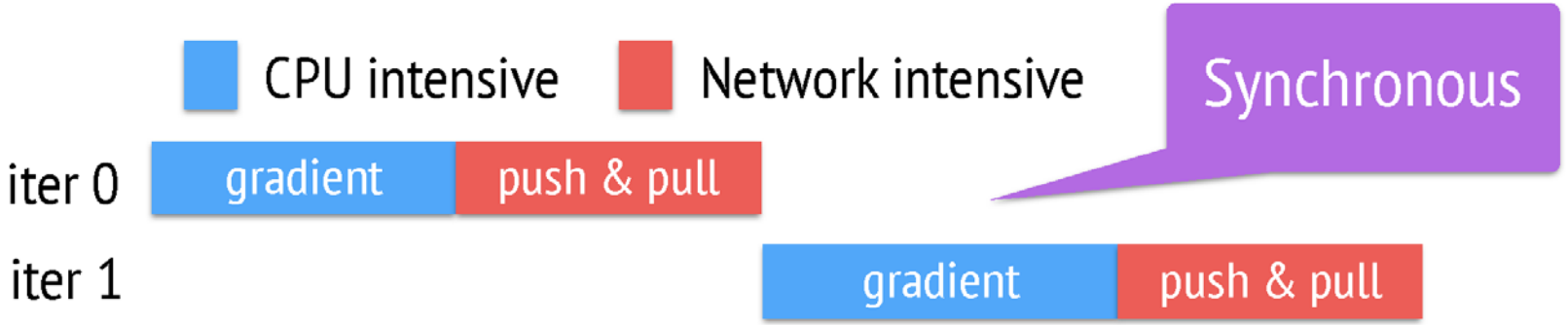

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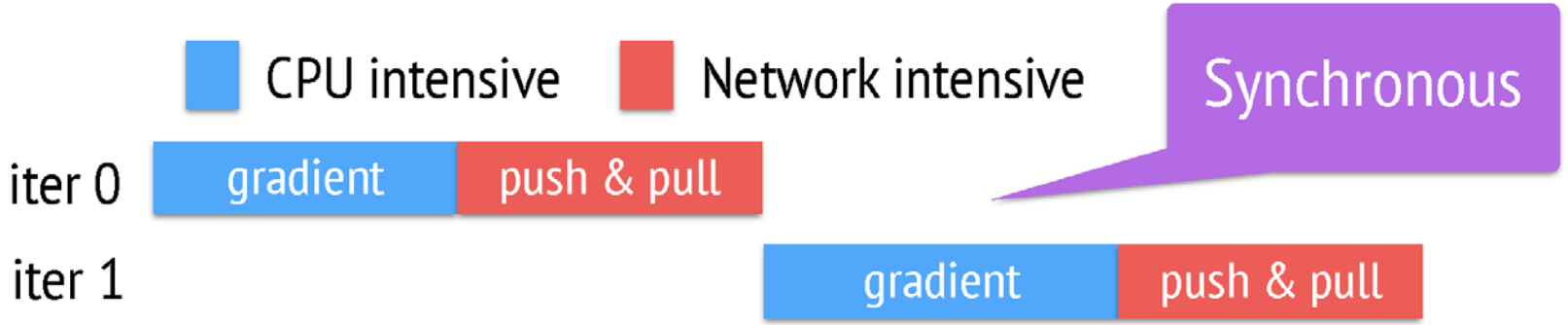

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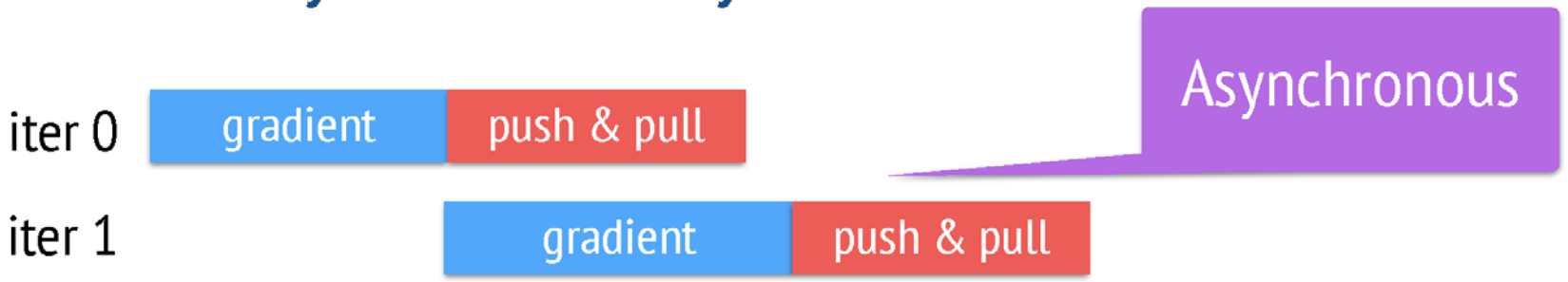
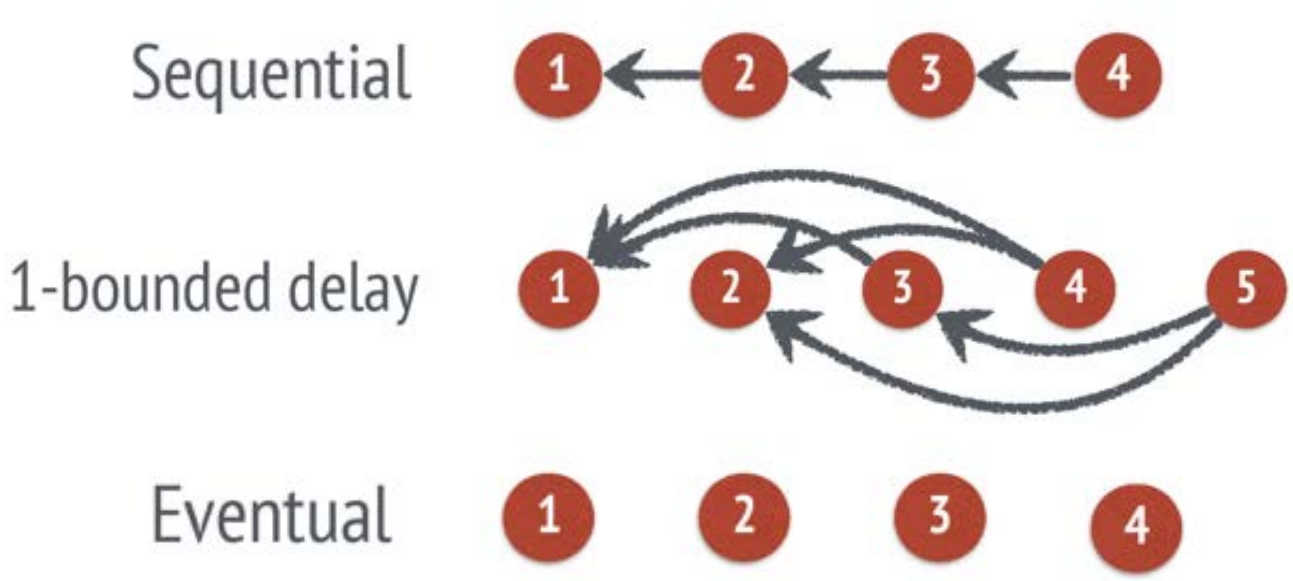


Architecture: Flexible Consistency

- Can change the consistency model for the system, as per the requirements of the job
- Up to the algorithm designer to choose the flexible consistency model
- Trade-off between **Algorithm Efficiency** and **System** Performance



Results for bounded delay

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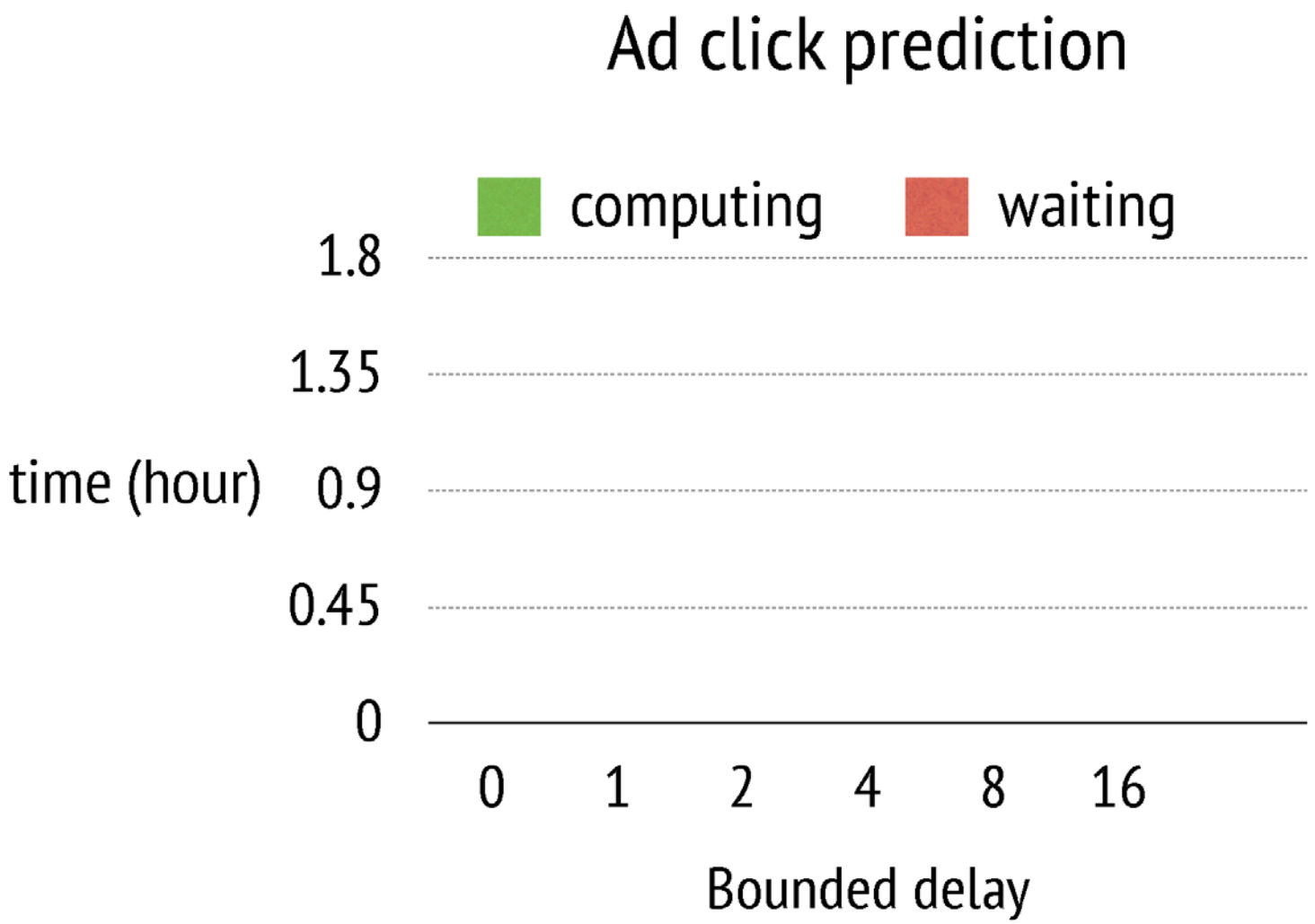

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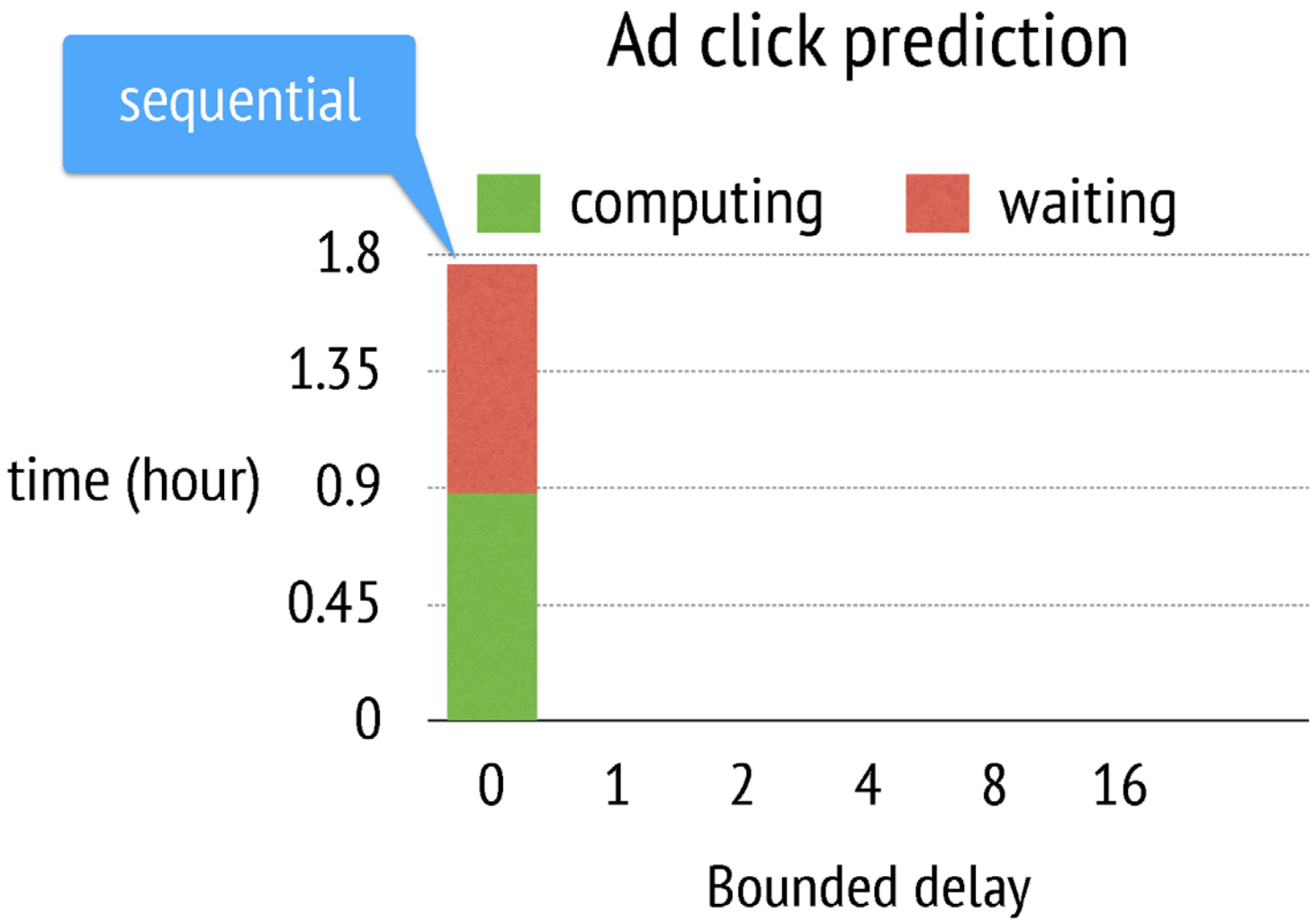

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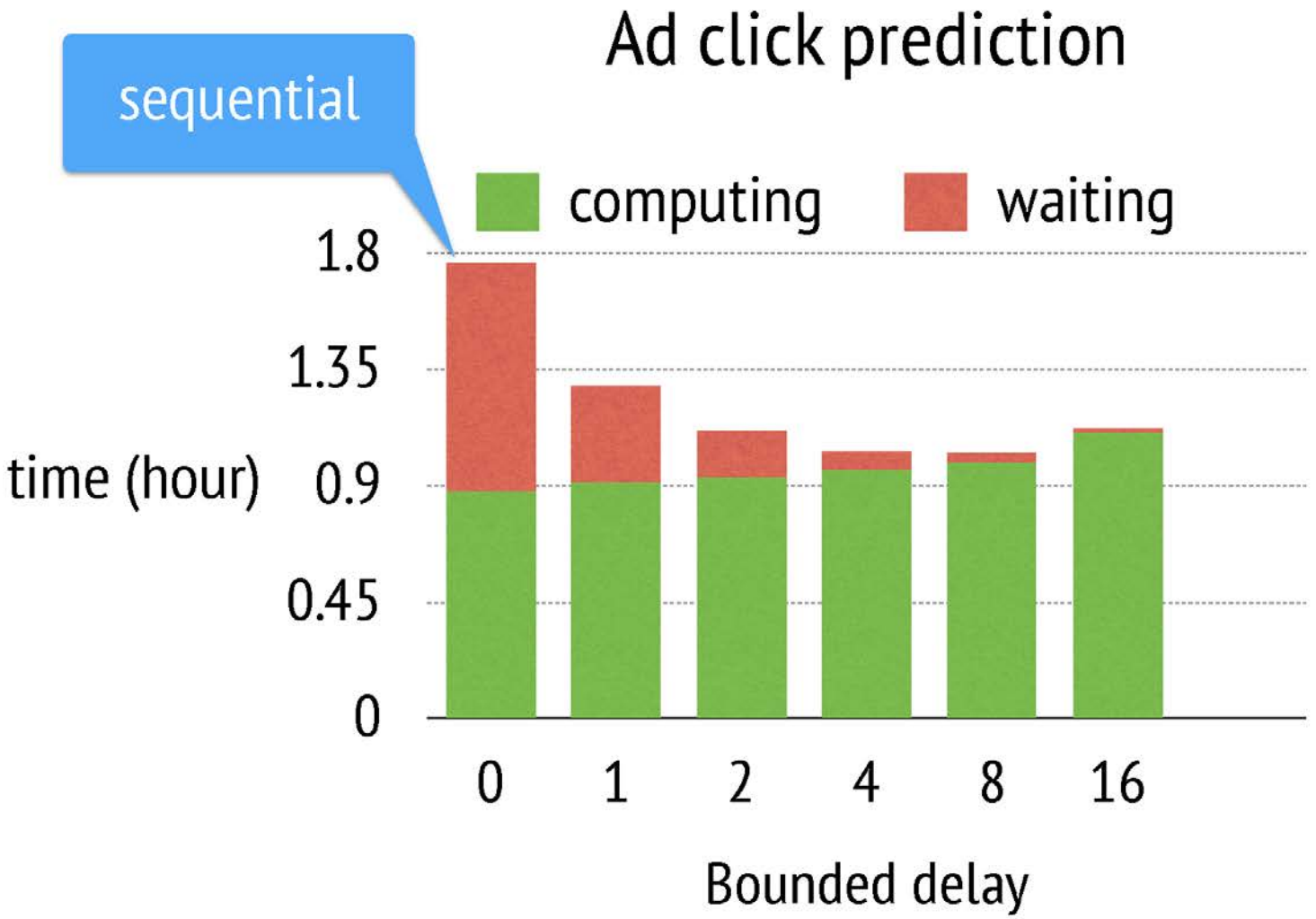

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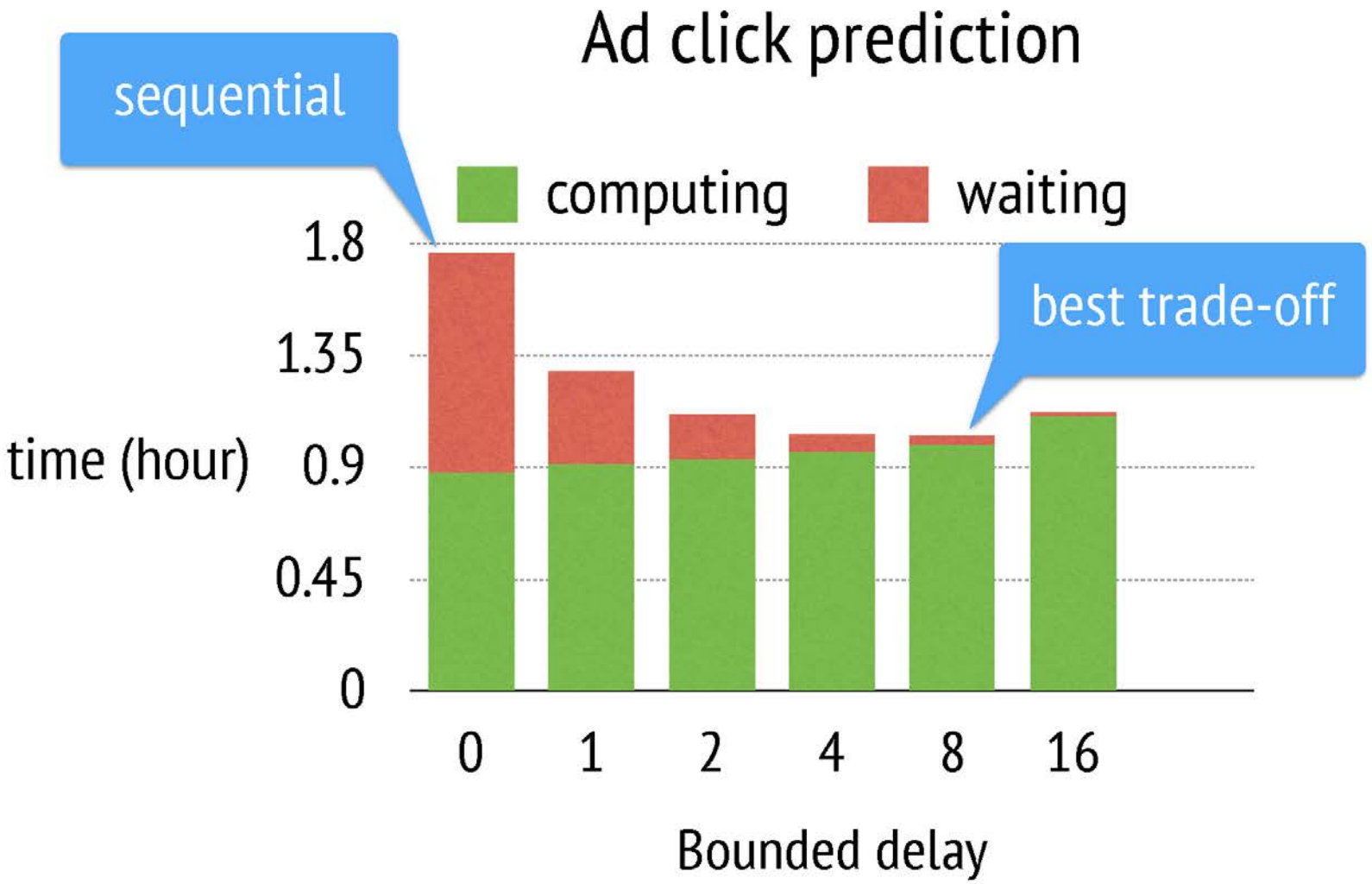


Architecture: User Defined Filters

- Selectively Synchronize (key, value) pairs.
- Filters can be placed at either or both the *Server* machines and *Worker* machines.
- Allows for fine-grained consistency control within a task
- Example: *Significantly modified filter*: Only pushes entries that have changed for more than an amount.

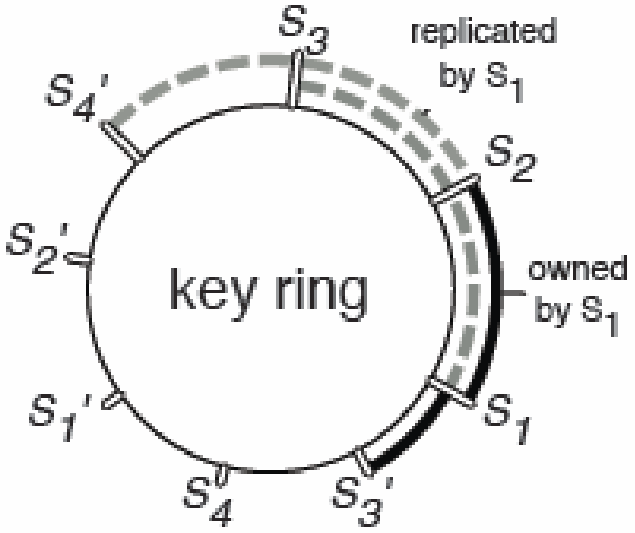
Implementation: Vector Clocks & Messaging

- Vector Clocks are attached for each (Key, value) pairs for several purposes:
  - Tracking Aggregation Status
  - Rejecting doubly sent data
  - Recovery from Failure
- As many (key, value) pairs get updated at the same time during one iteration, they can share the same clock stamps. This reduces the space requirements.
- Messages are sent in *Ranges* for efficient lookup and transfers.
- Messages are compressed using Google's Snappy compression library.

Implementation: Consistent Hashing & Replication

- The parameter server partitions the keys on to the Servers using *Ranged Partitioning*.

- The *Servers* are themselves hashed to a virtual ring similar to Chord.
- Server nodes store a replica of (Key, value) pairs in *k* nodes counter clockwise to it.



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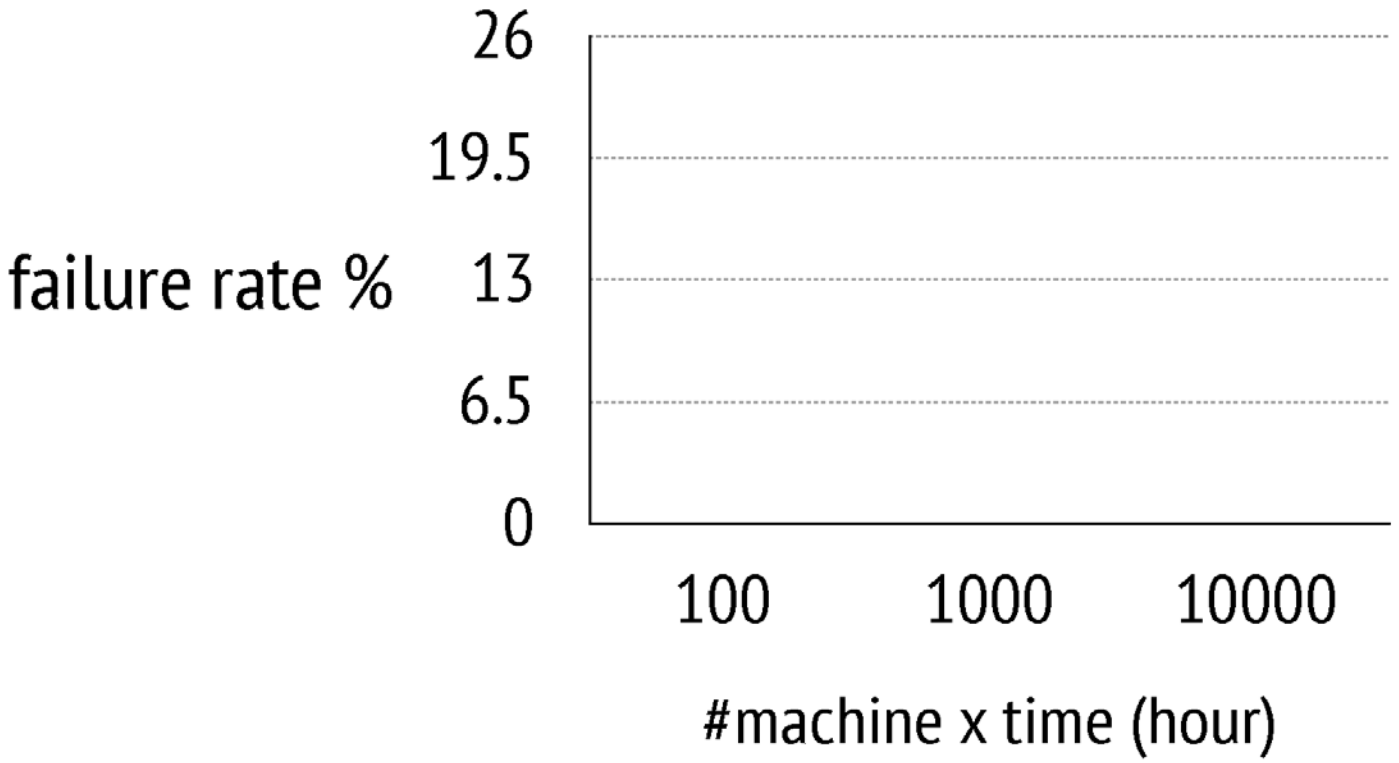

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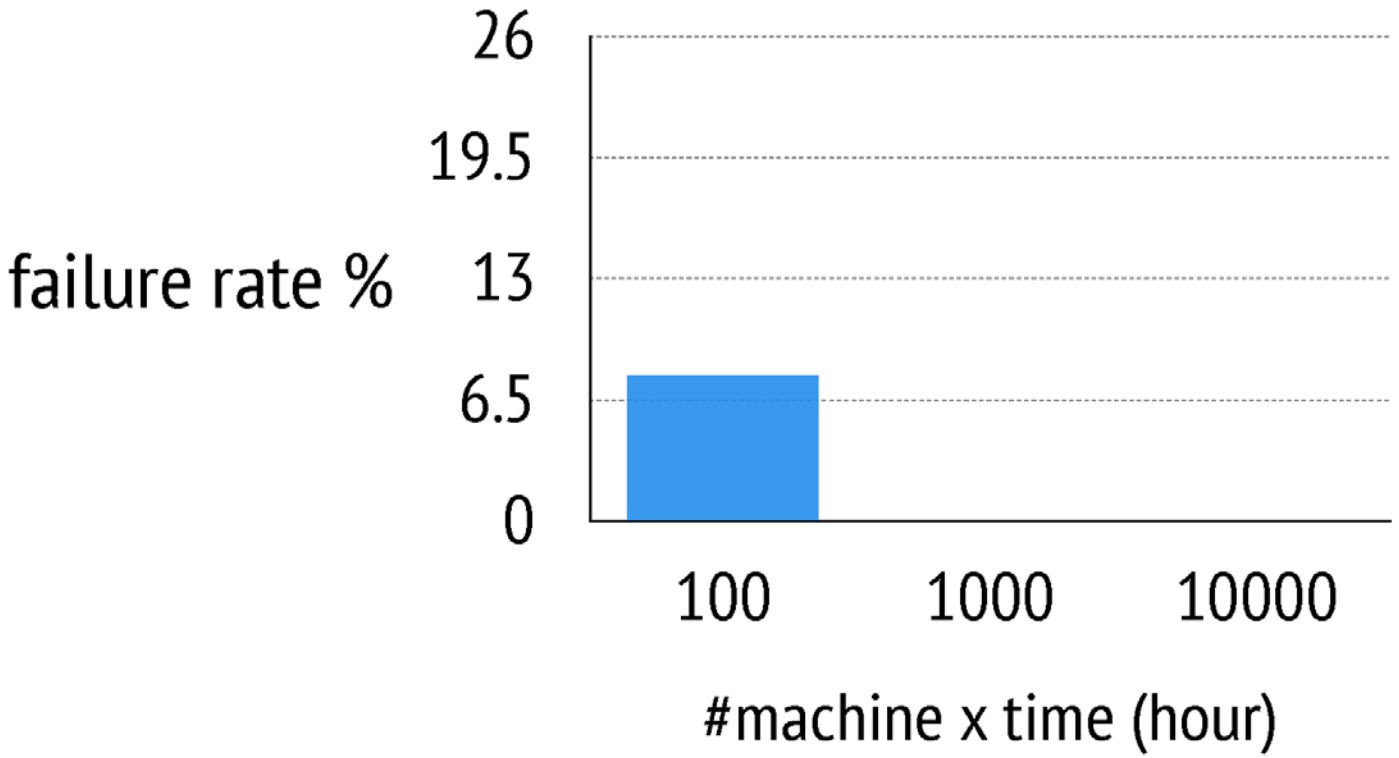

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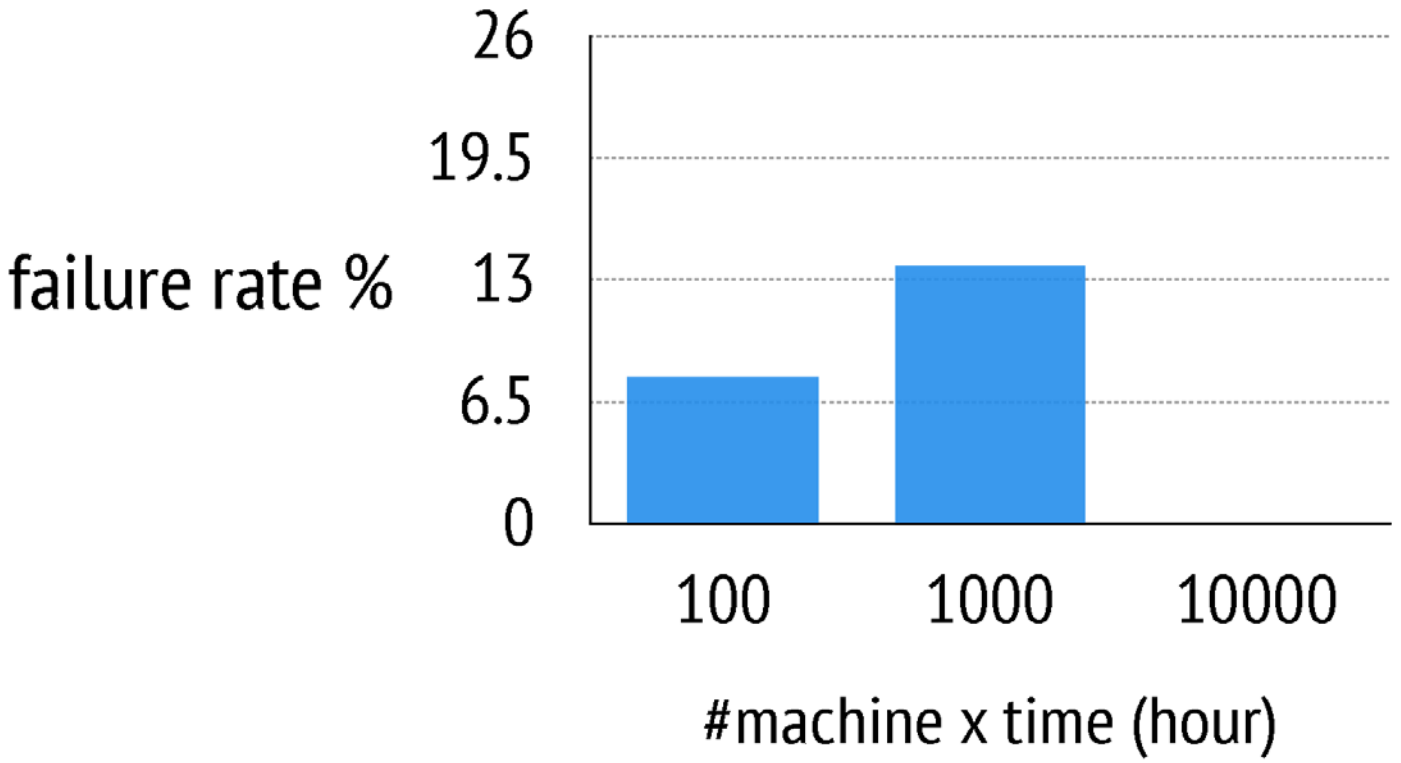

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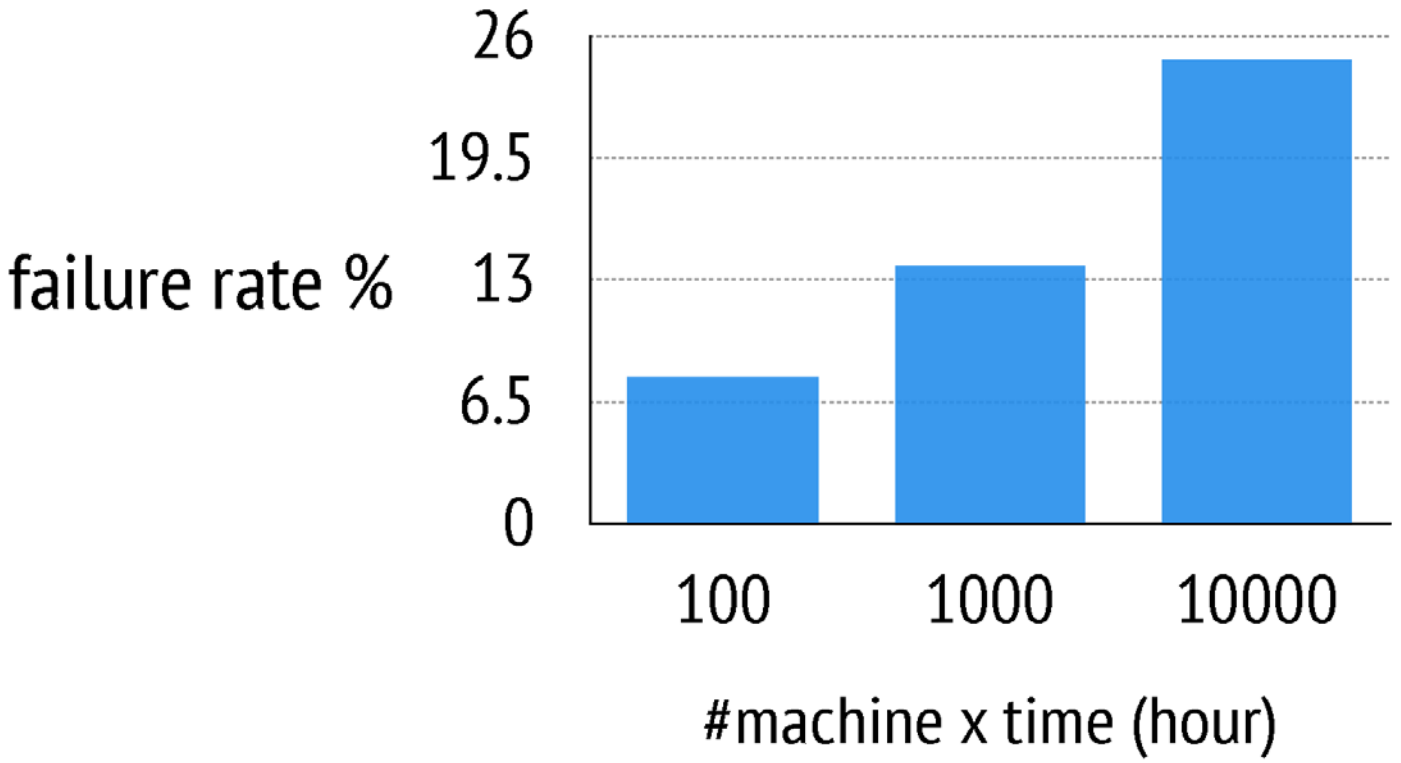

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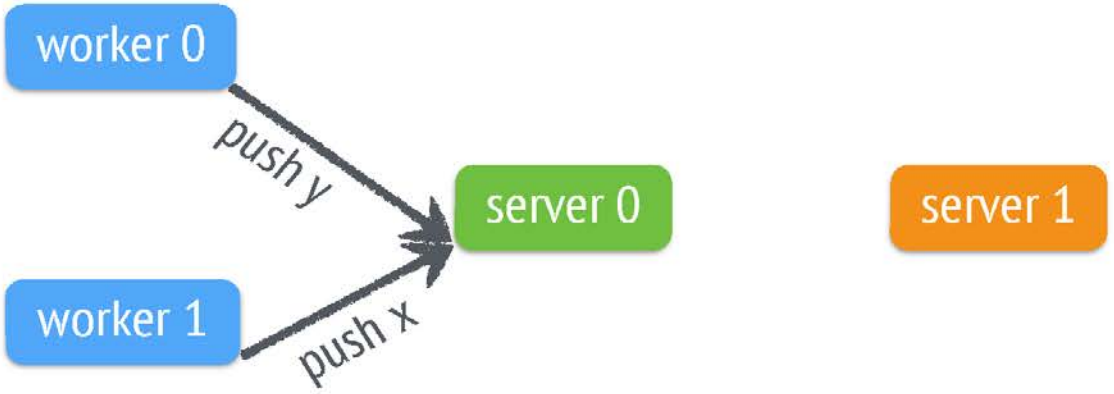

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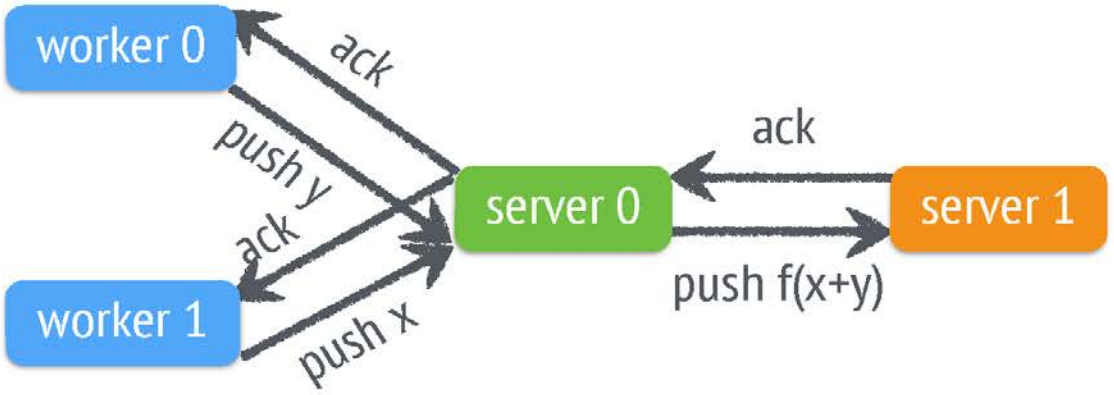

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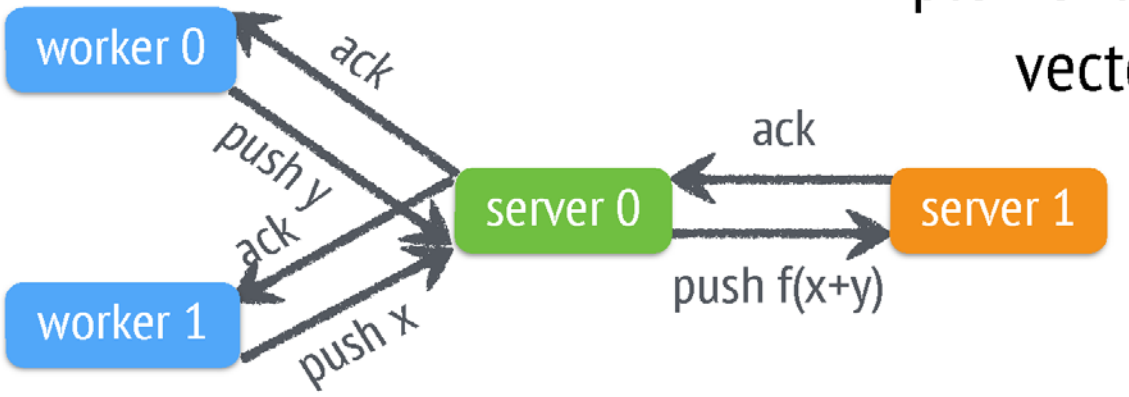
implemented by efficient vector clock



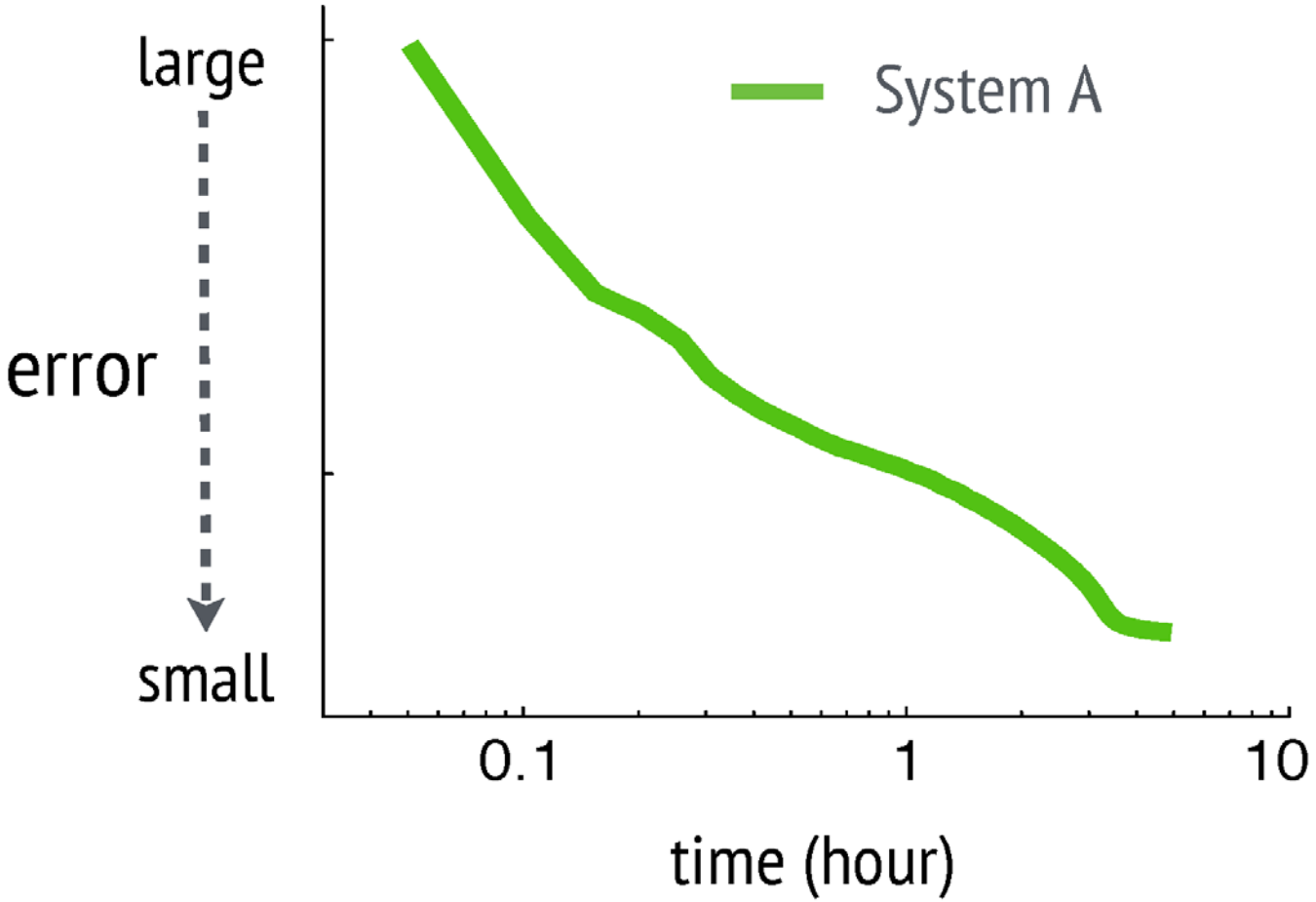
Evaluation

Evaluation: Sparse Logistic Regression

- One of the most popular large scale Risk Minimization algorithm.
- For example in the case of ads prediction, we want to predict the revenue an ad will generate.
- It can be done by running a logistic regression on the available data for ads which are 'close to' the ad we want to post.
- The experiment was run with:
  - 170 billion examples
  - 65 billion unique features
  - 636 TB of data in total
  - 1000 machines: 800 workers & 200 servers
  - Machines: 16 cores, 192 GB DRAM, and 10 Gb Ethernet links

	Method	Consistency	LOC
System A	L-BFGS	Sequential	10,000
System B	Block PG	Sequential	30,000
Parameter Server	Block PG	Bounded Delay KKT Filter	300

Progress



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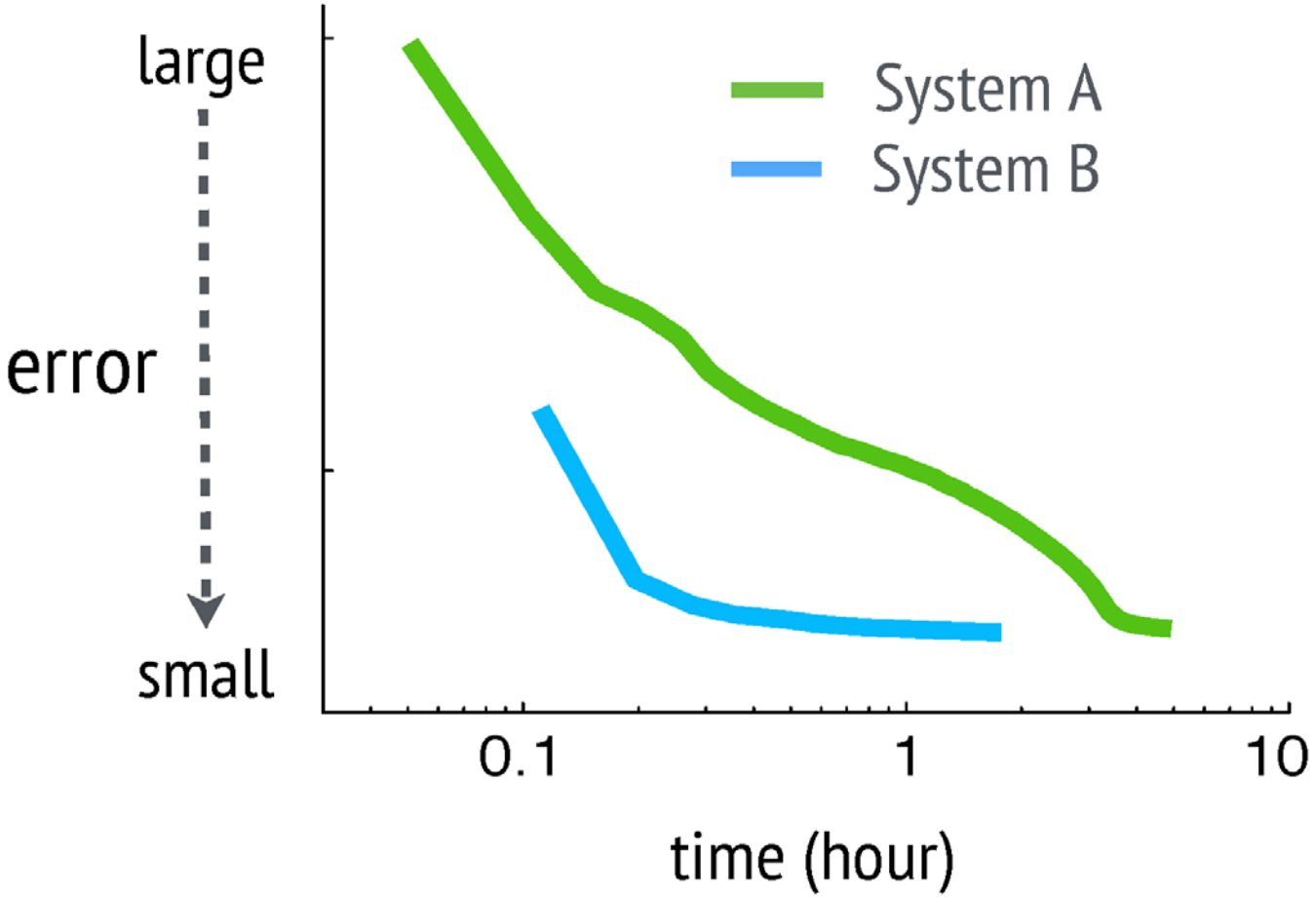

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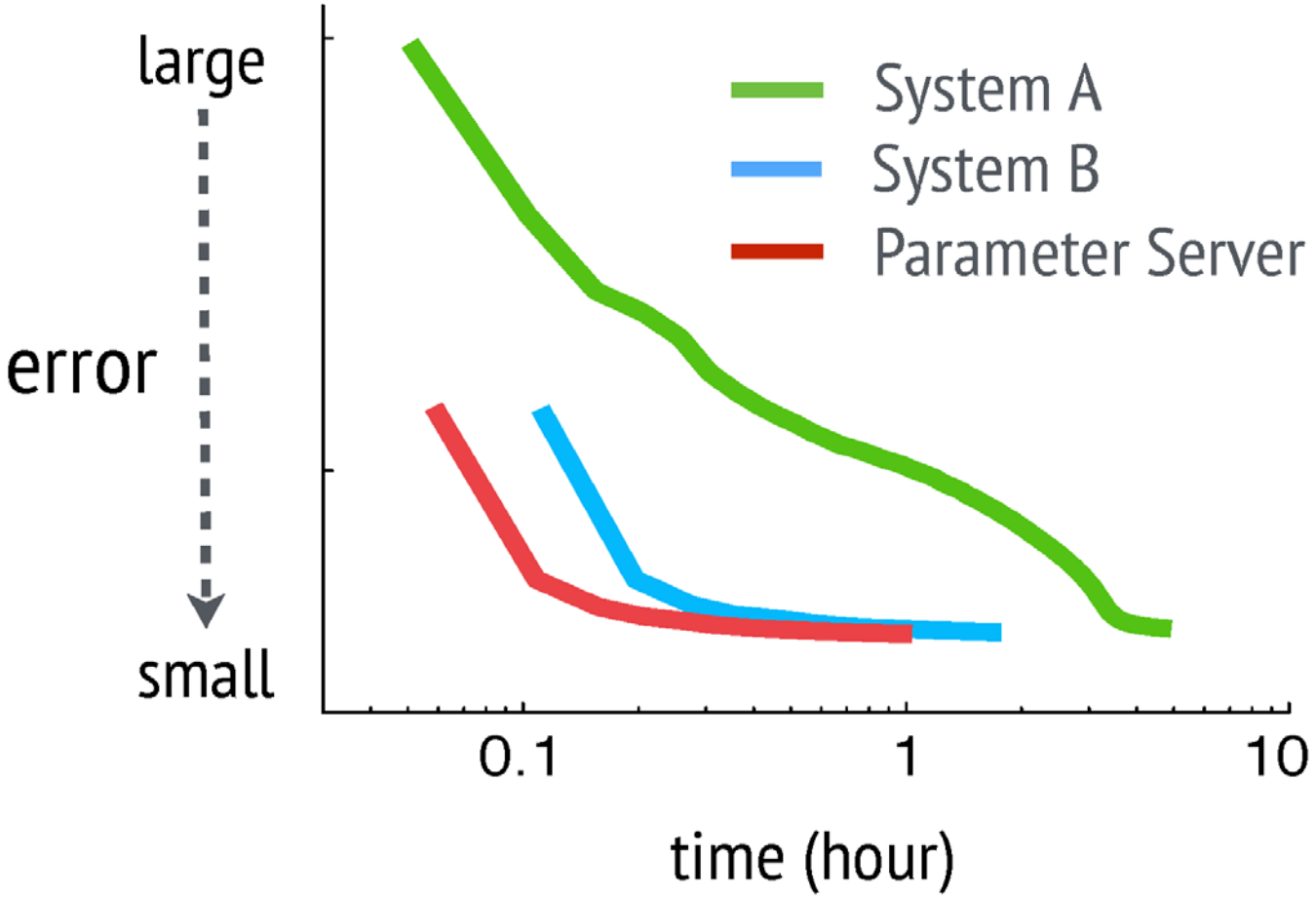
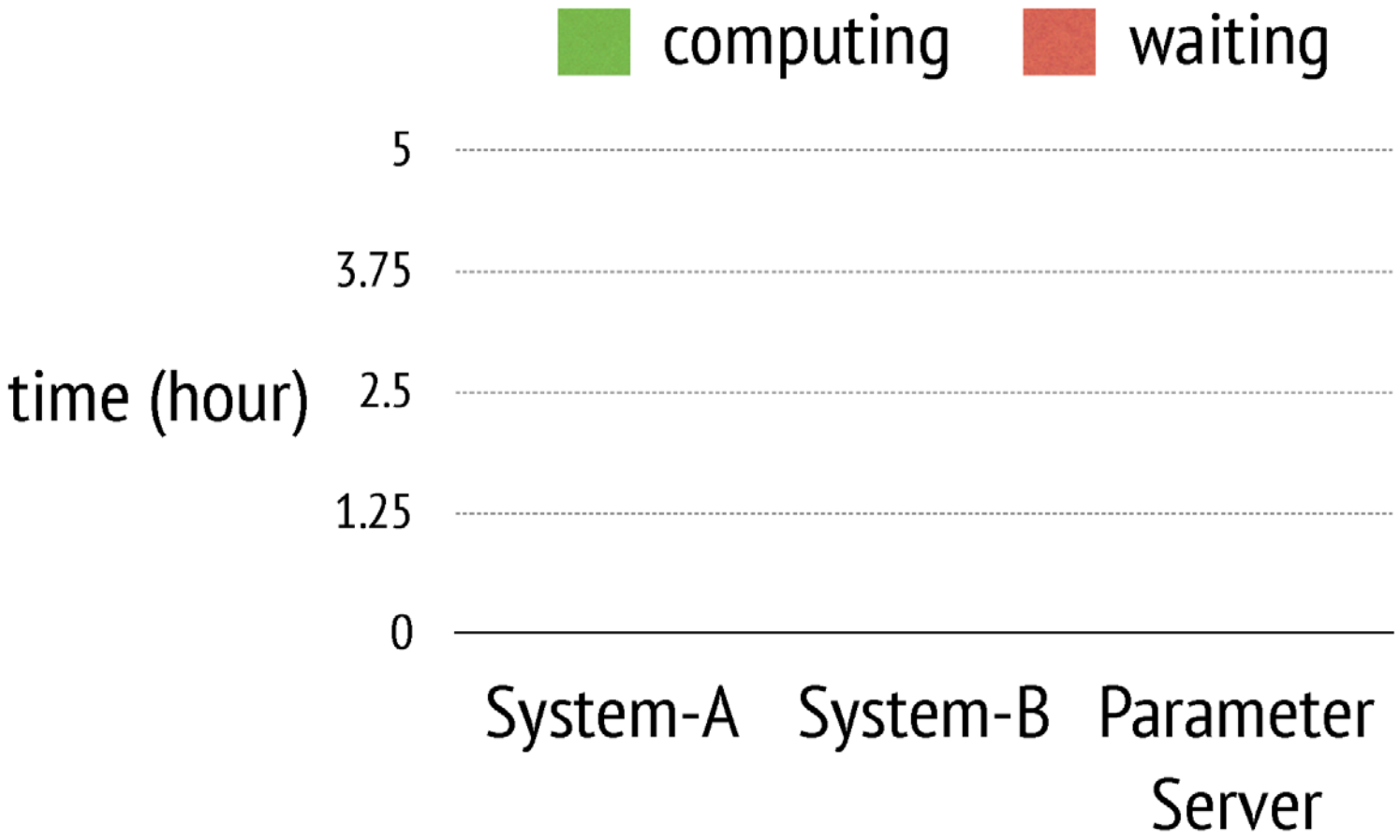

large
error
small
System A
System B
Parameter Server
0.1
1
10
time (hour)

Time decomposition



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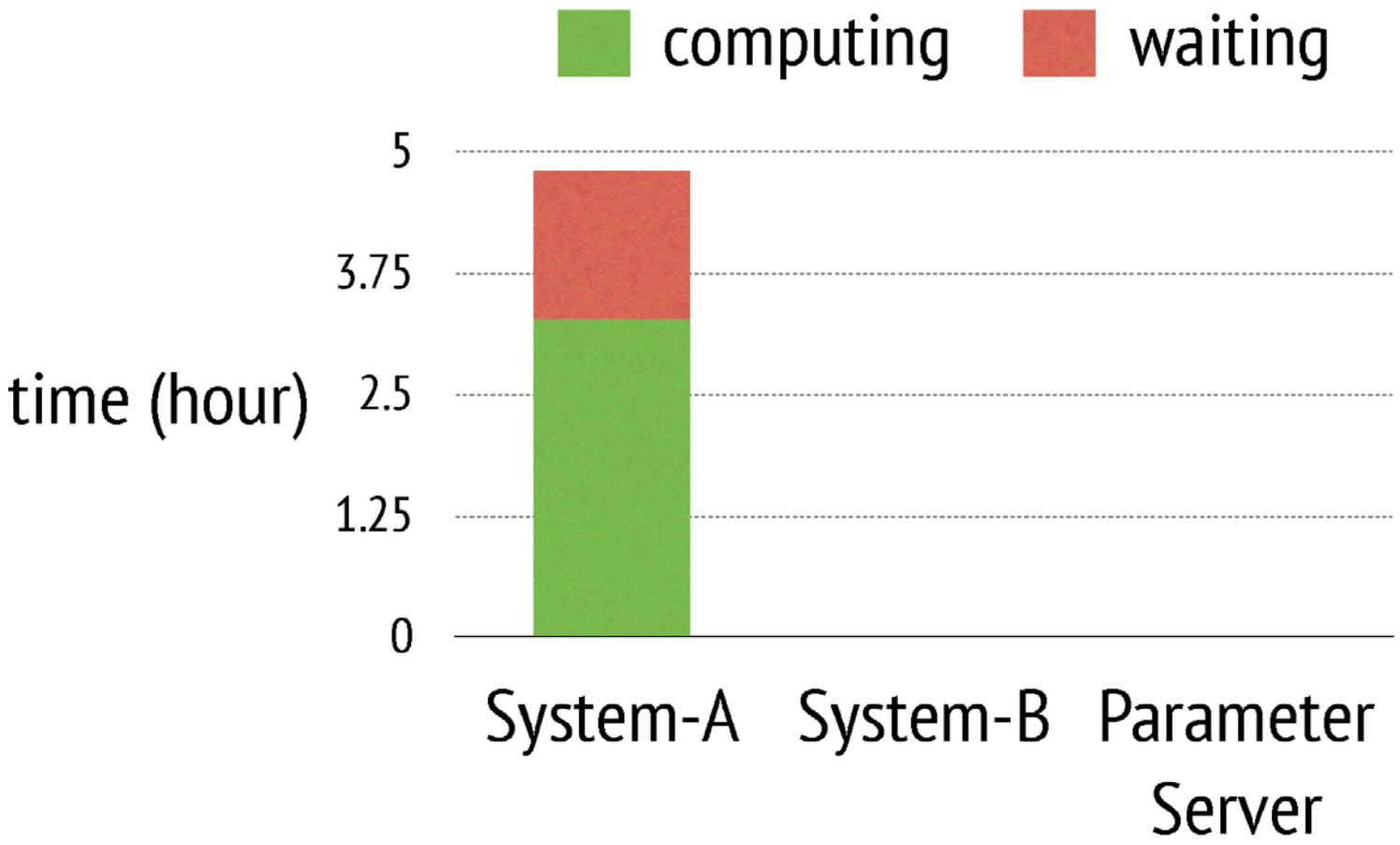

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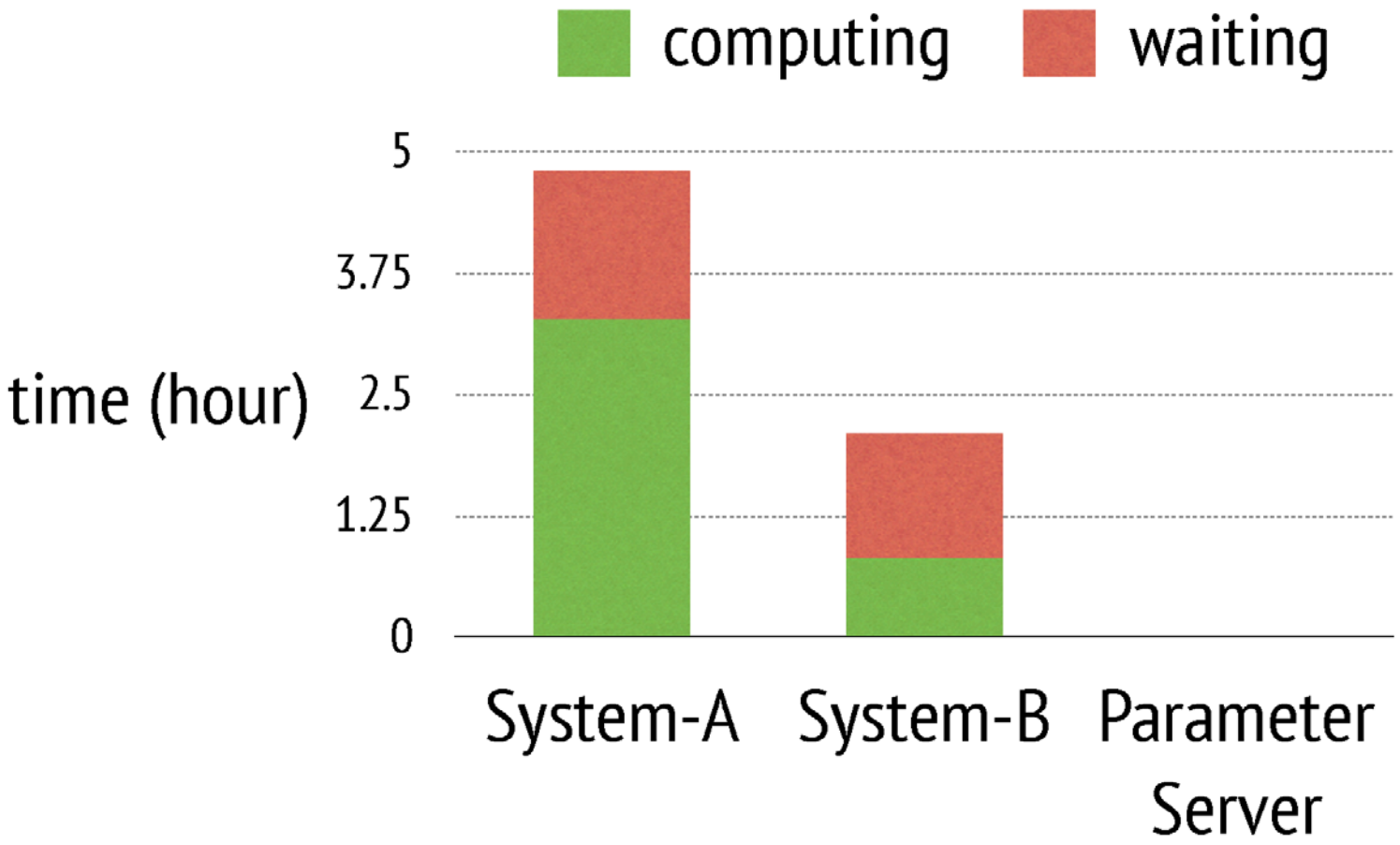

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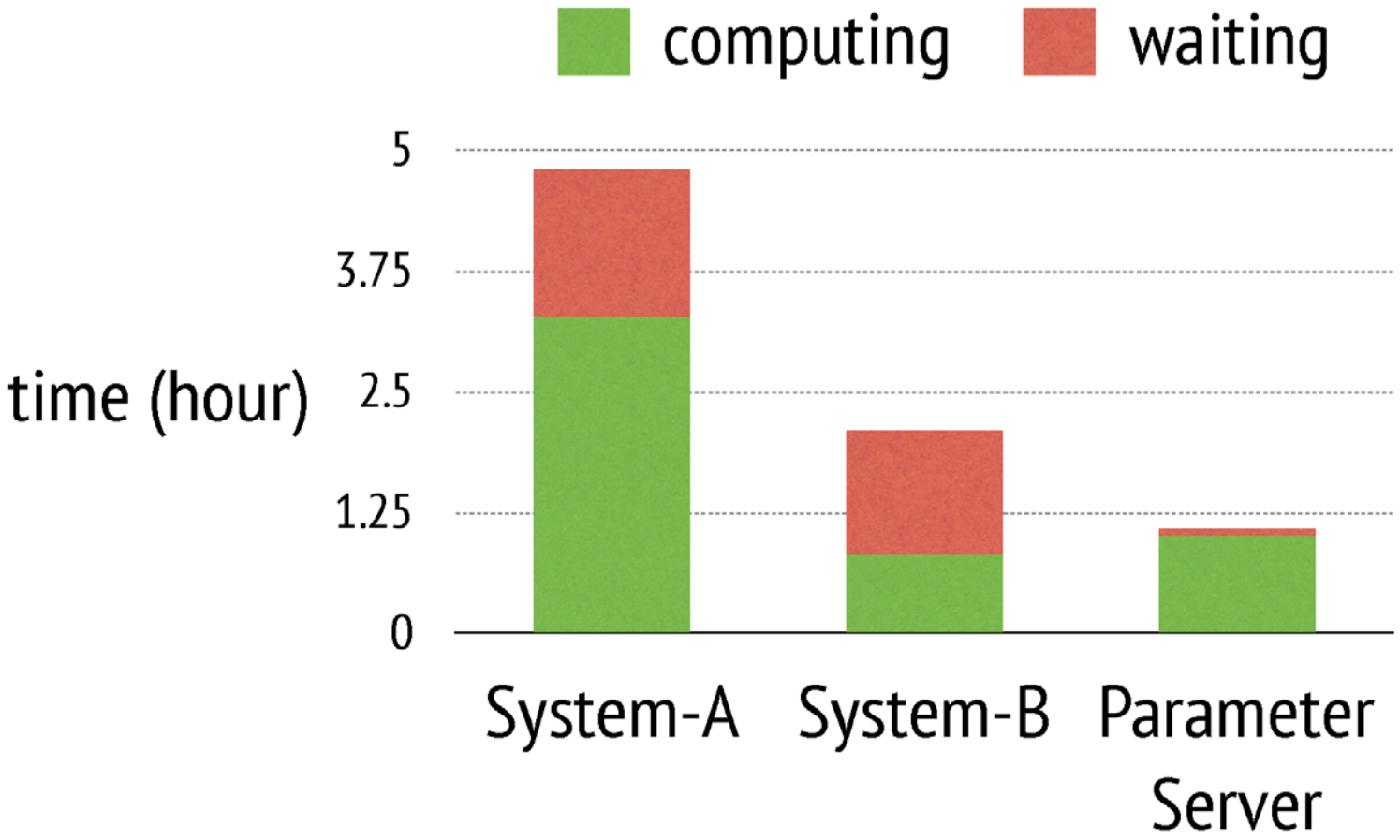

Summary and Discussion

Summary: Pros

- **Efficient Communication**:
  - Batching (key,value) pairs in Linear Algebra objects
  - Filters to reduce unnecessary communication & message compression
  - Caching keys at worker and server nodes for local access
- **Flexible Consistency Models**:
  - Can choose between Sequential, Eventual, and Bounded delay consistency models
  - Allows for tradeoffs between System Performance and Algorithmic Convergence
- **Fault Tolerance and Durability**:
  - Replication of data in Servers
  - Failed workers can restart at the point of failure by using vector clocks
- **Ease of Use**:
  - Linear Algebra objects allow for intuitive implementation of tasks

Summary: Cons & Further Discussion

- What are System A and System B? No insight into design differences.
- *Server Manager Failures* and *Task Scheduler* failures are not discussed.
- No experiments on the other two systems with *Bounded delay* model. System B's waiting time may reduce if implemented with a Bounded Delay model.