DiFacto — Distributed Factorization Machines

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Joint work with Ziqi Liu, Alex Smola, and Yu-Xiang Wang

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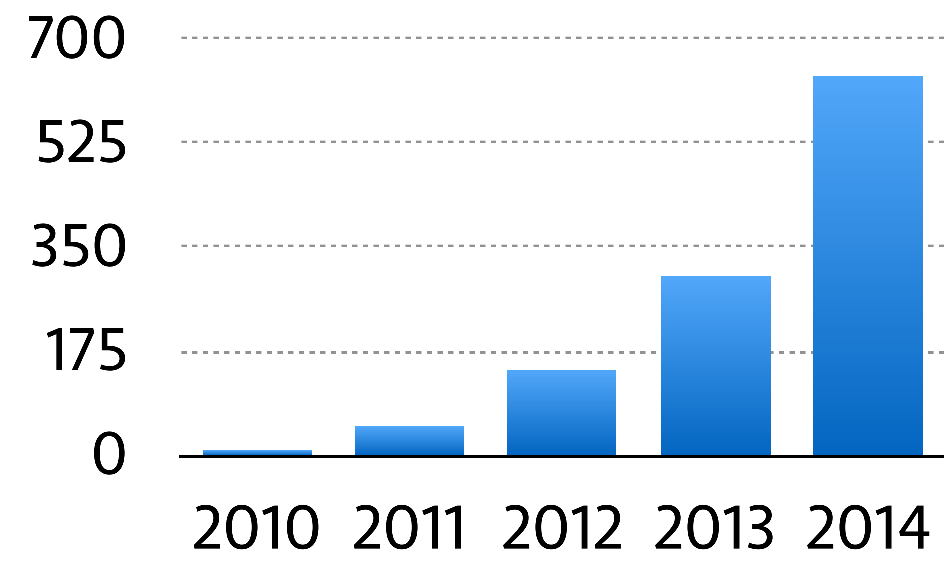
Linear model is widely used for large-scale datasets

Training data size (TB) of linear model
for Ads CTR estimation
in an Internet company



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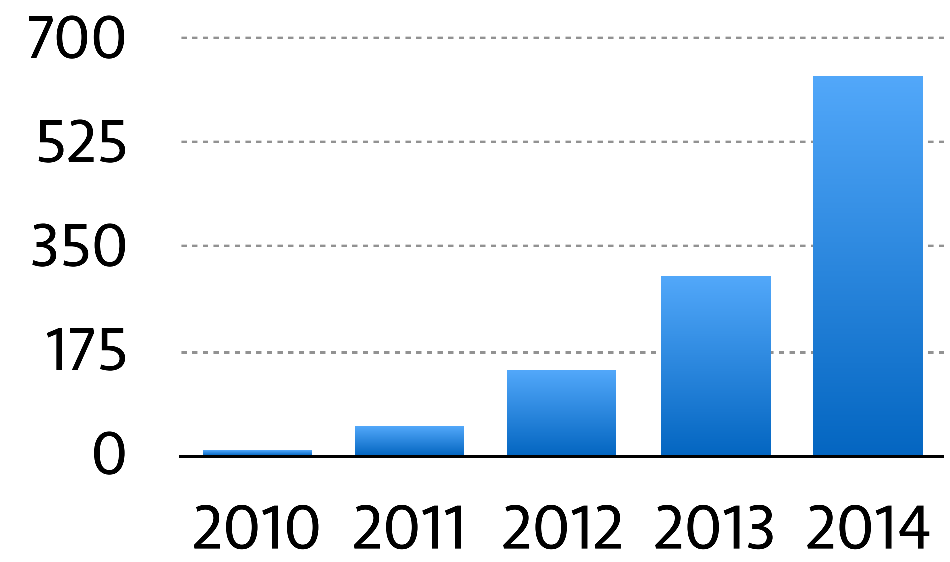
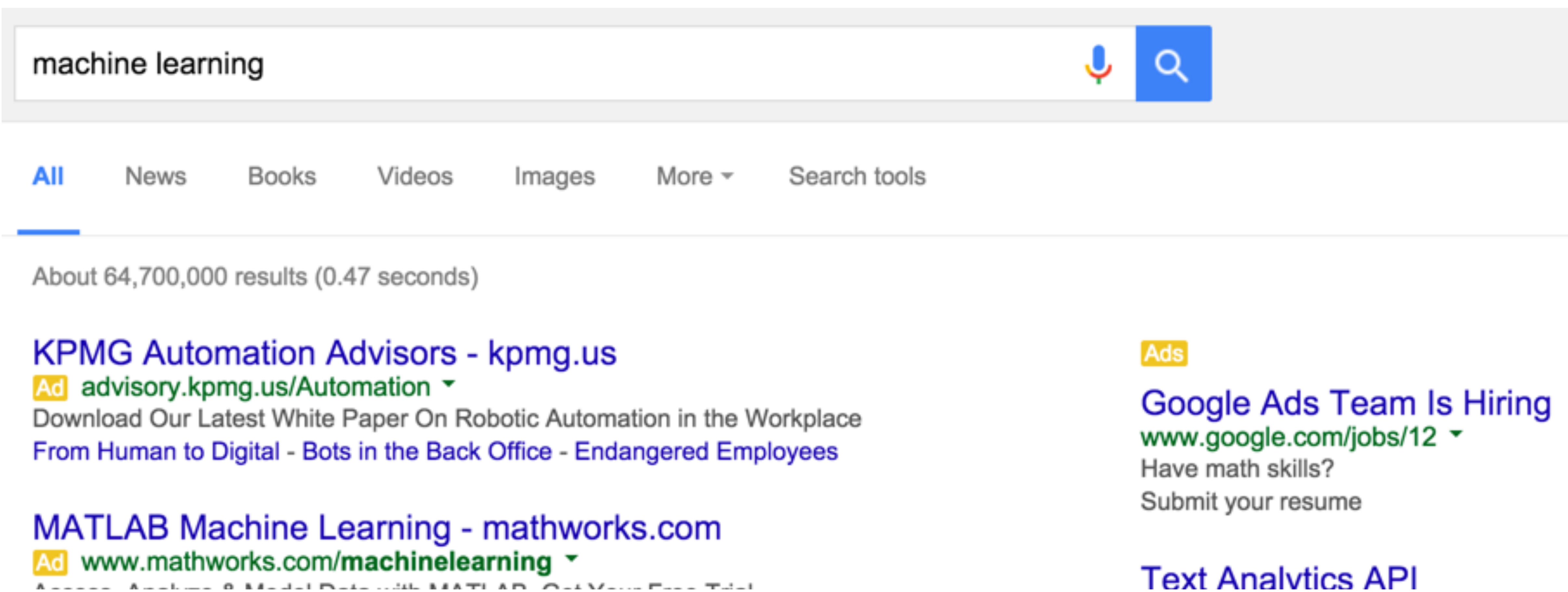
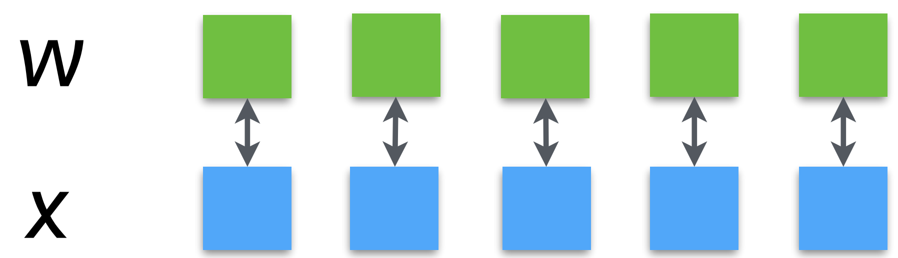


Reach model capacity limit when the data go very large



Factorization Machine

- Linear model predicts by $f(x) = \sum_i x_i w_i$



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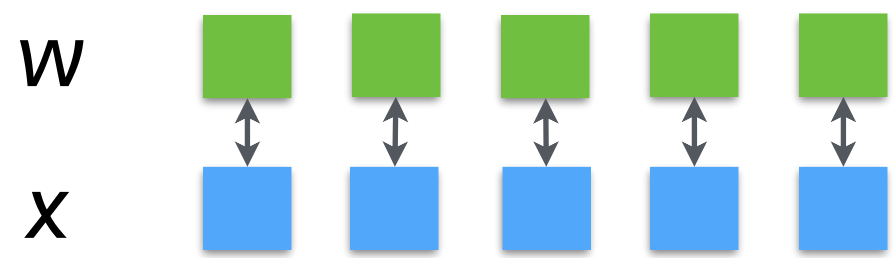

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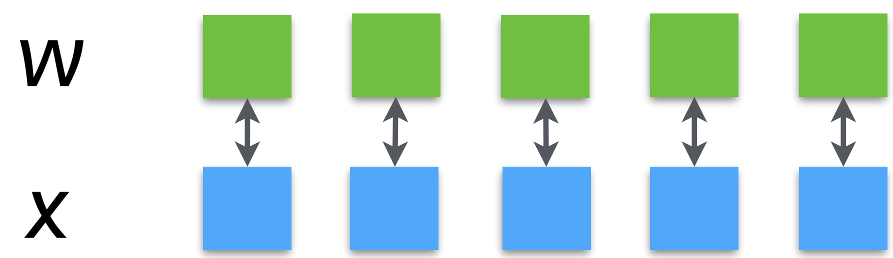

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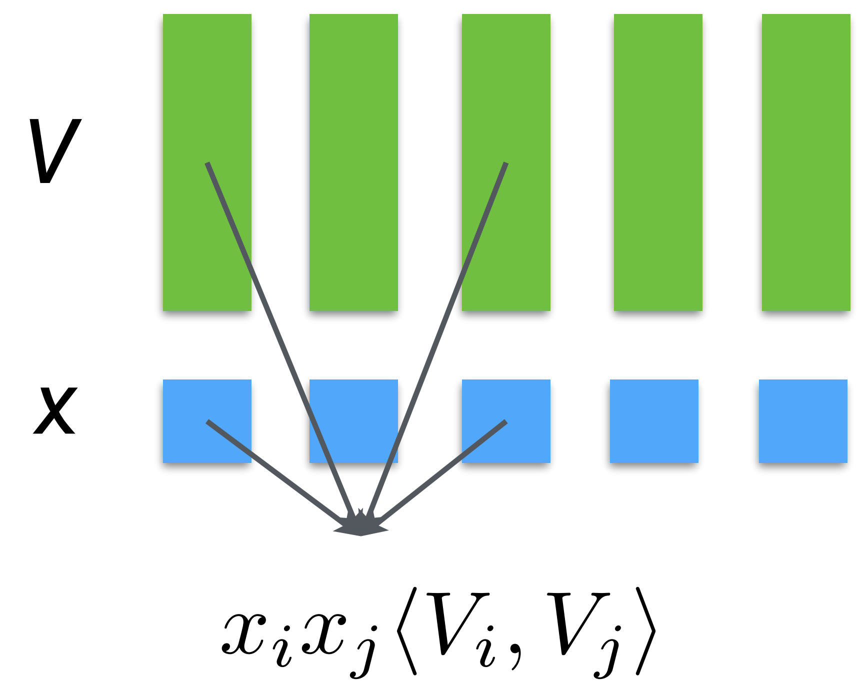

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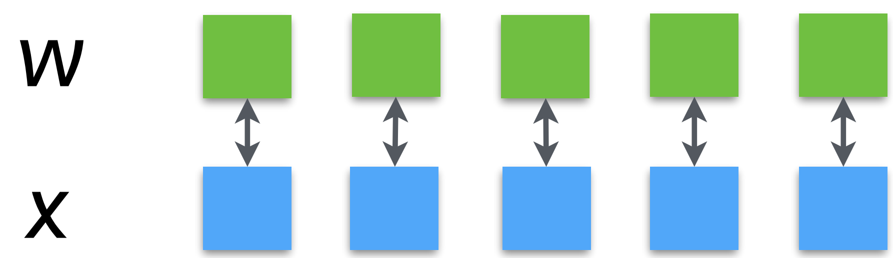

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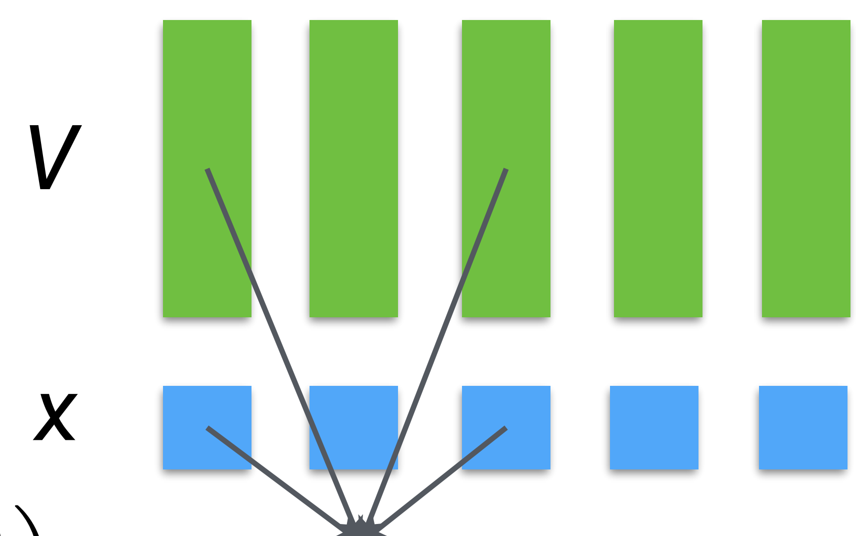
(can go beyond second-order)

$$+ \sum_{i<j<k} x_i x_j x_k \operatorname{tr}\left(V_i^{(3)} \otimes V_j^{(3)} \otimes V_k^{(3)} \right)$$



$x_i x_j \langle V_i, V_j \rangle$

The Challenge

Both computation and storage costs of k-dimension FM are k times larger than linear model

- On Criteo CTR dataset with 1.5B examples and 0.36B features

k	model size	FLOP per data pass	time for a single CPU (in theory)
100	288GB	10 P	5 hours
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Key Take Away

Make large-scale FM as cheap as linear model

Statistic Model

Distributed Optimization

Evaluation

Key Observation

- High-dimensional datasets are often extremely sparse
  - The count of feature occurrence often obeys a pow law distribution. e.g the Criteo dataset

occurrence >	1	10	100
# features (%)	53%	5.8%	0.49%

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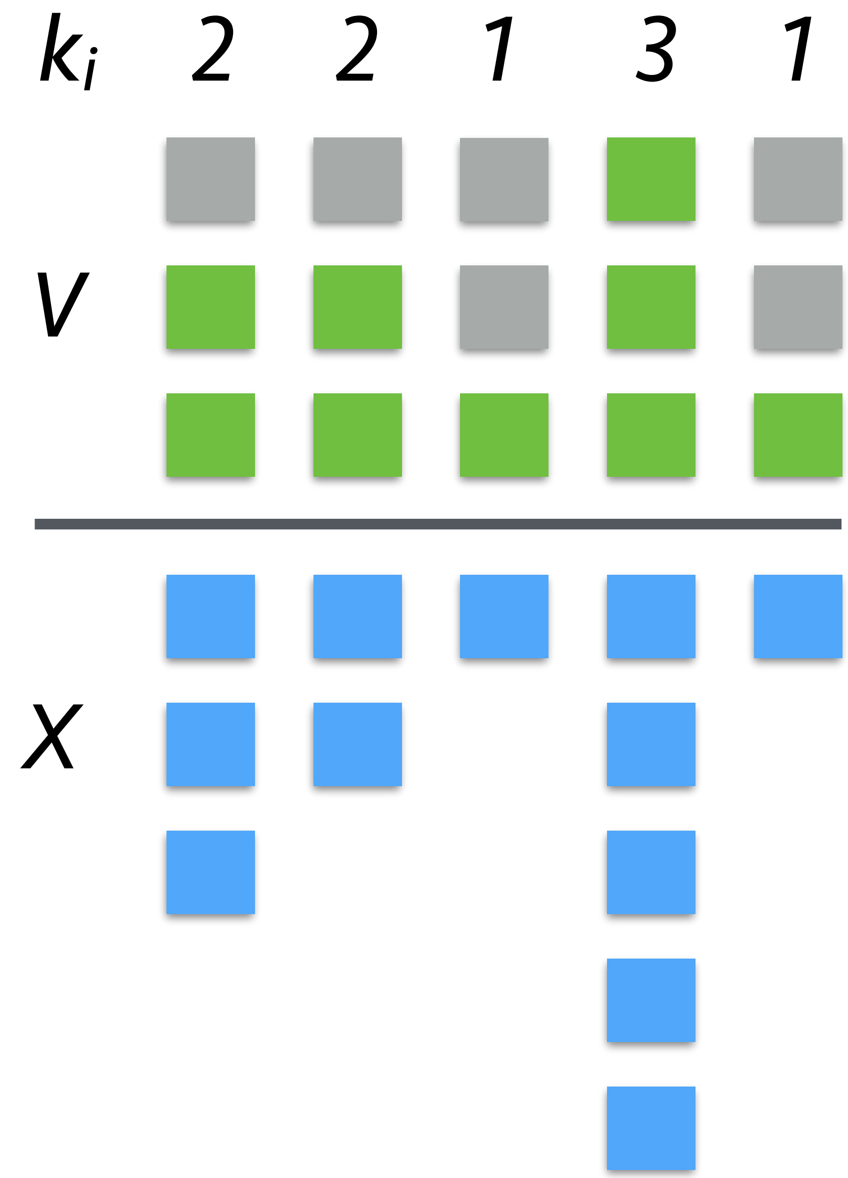
Our solution

Data and model adaptive regulazations to reduce model capacity on unimportant features

Memory Adaptive Constraints

- Limit the effective embedding dimension k_i for "tail" feature i

$$V_{ij} = 0 \text{ for all } j > k_i$$



Memory Adaptive Constraints

- Limit the effective embedding dimension k_i for "tail" feature i

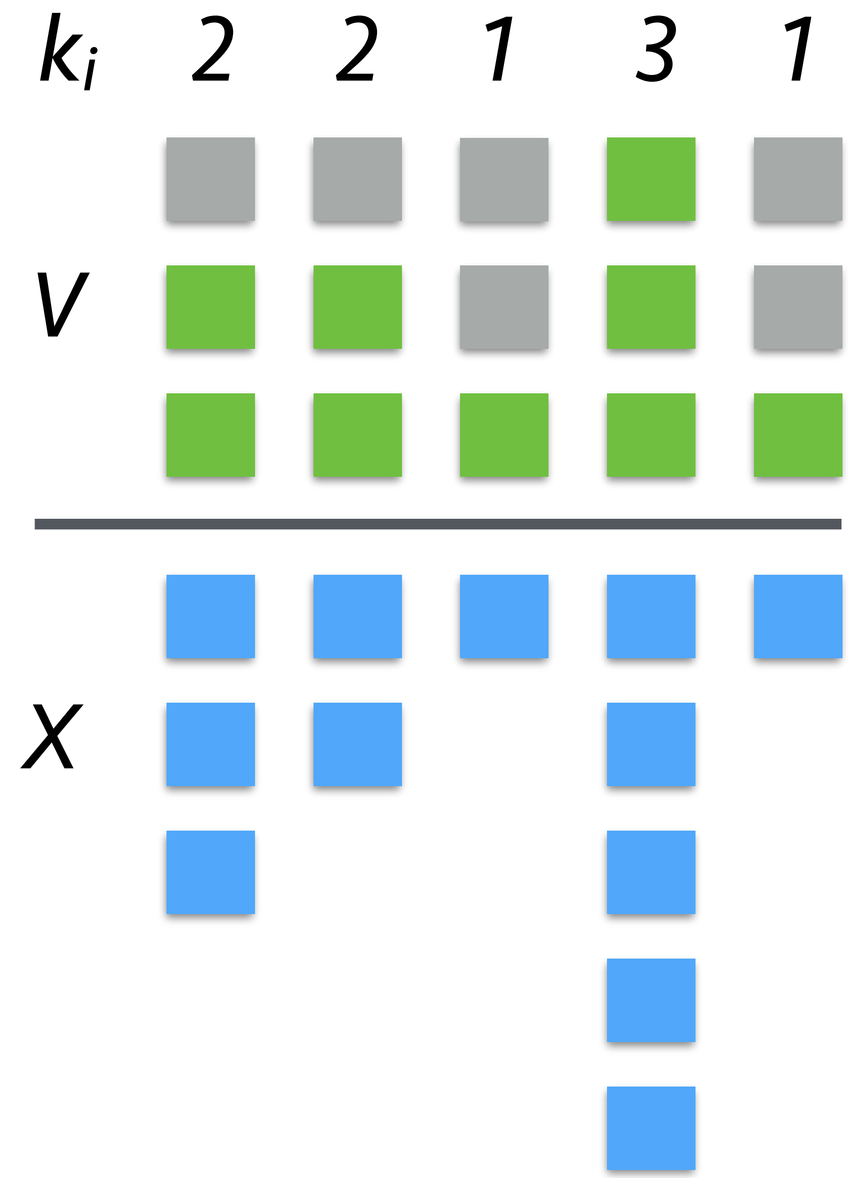
$$V_{ij} = 0 \text{ for all } j > k_i$$

- Choose k_i according to the number of occurrence of feature i, n_i
  - simple choice:

$$k_i = \begin{cases} k & \text{if } n_i \geq k \\ 0 & \text{otherwise} \end{cases}$$

  - three levels:

$$k_i = \begin{cases} 10k & \text{if } n_i \geq 10k \\ k & \text{if } 10k > n_i \geq k \\ \min(n_i, k) & \text{otherwise} \end{cases}$$

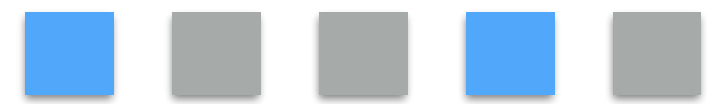


Sparse Regularization

- Model adaptive capacity control by sparse regularization
- Encourage a sparse linear term

$$\lambda_1 \left\| w \right\|_1$$

w



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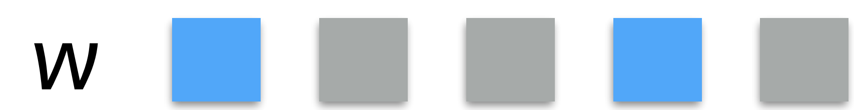

- Need sparse V too:
  - Structured sparsity on V

$$\sum_i \left[w_i^2 + \|V_i\|_2^2\right]^{\frac{1}{2}} + \|V_i\|_2$$

  - A simpler solution

$$V_i = 0 \text{ if } w_i = 0$$

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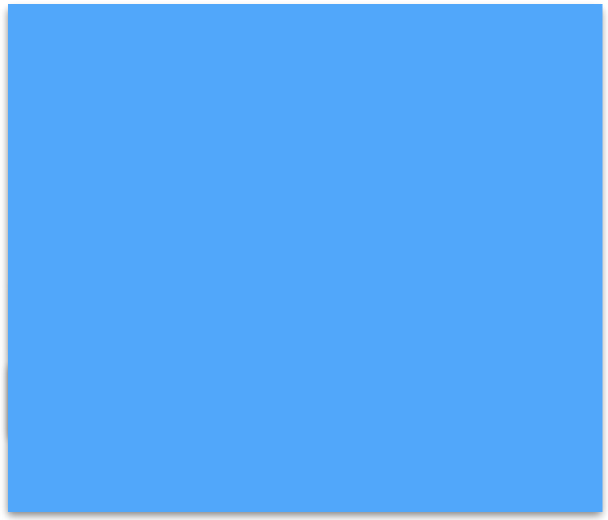
Evaluation

Distributed by Parameter Server (Li et al, '14)

Training data



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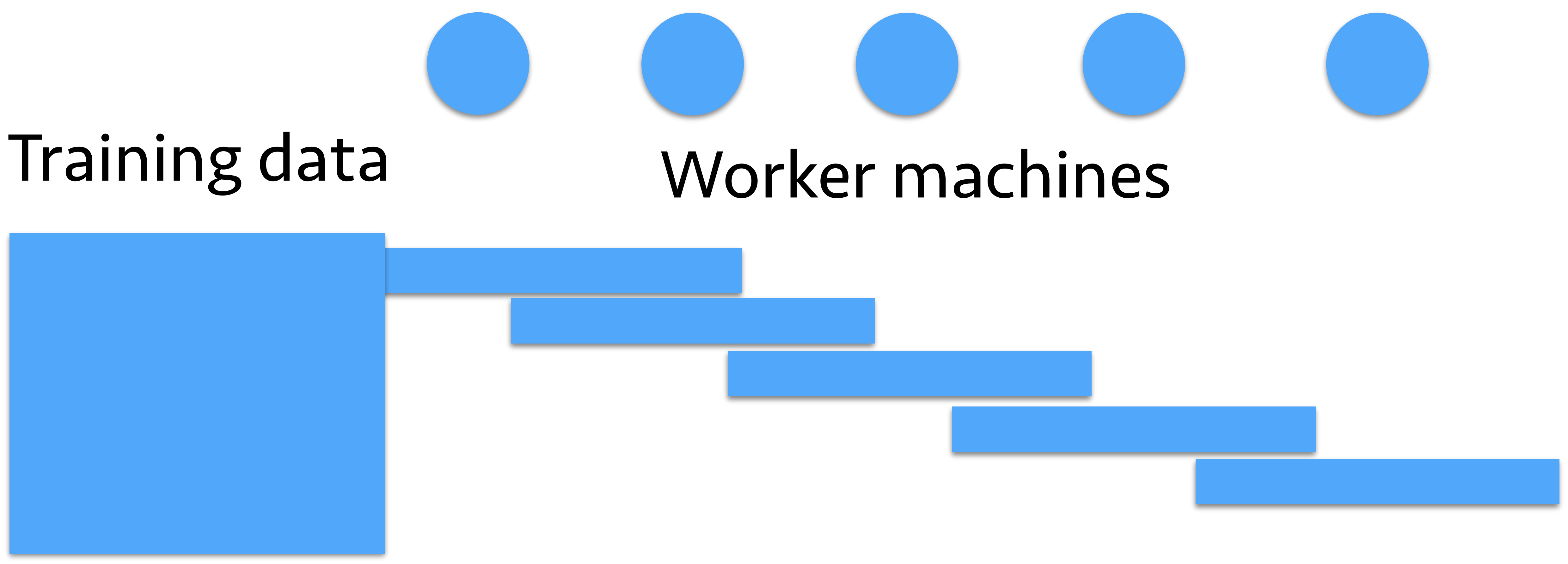

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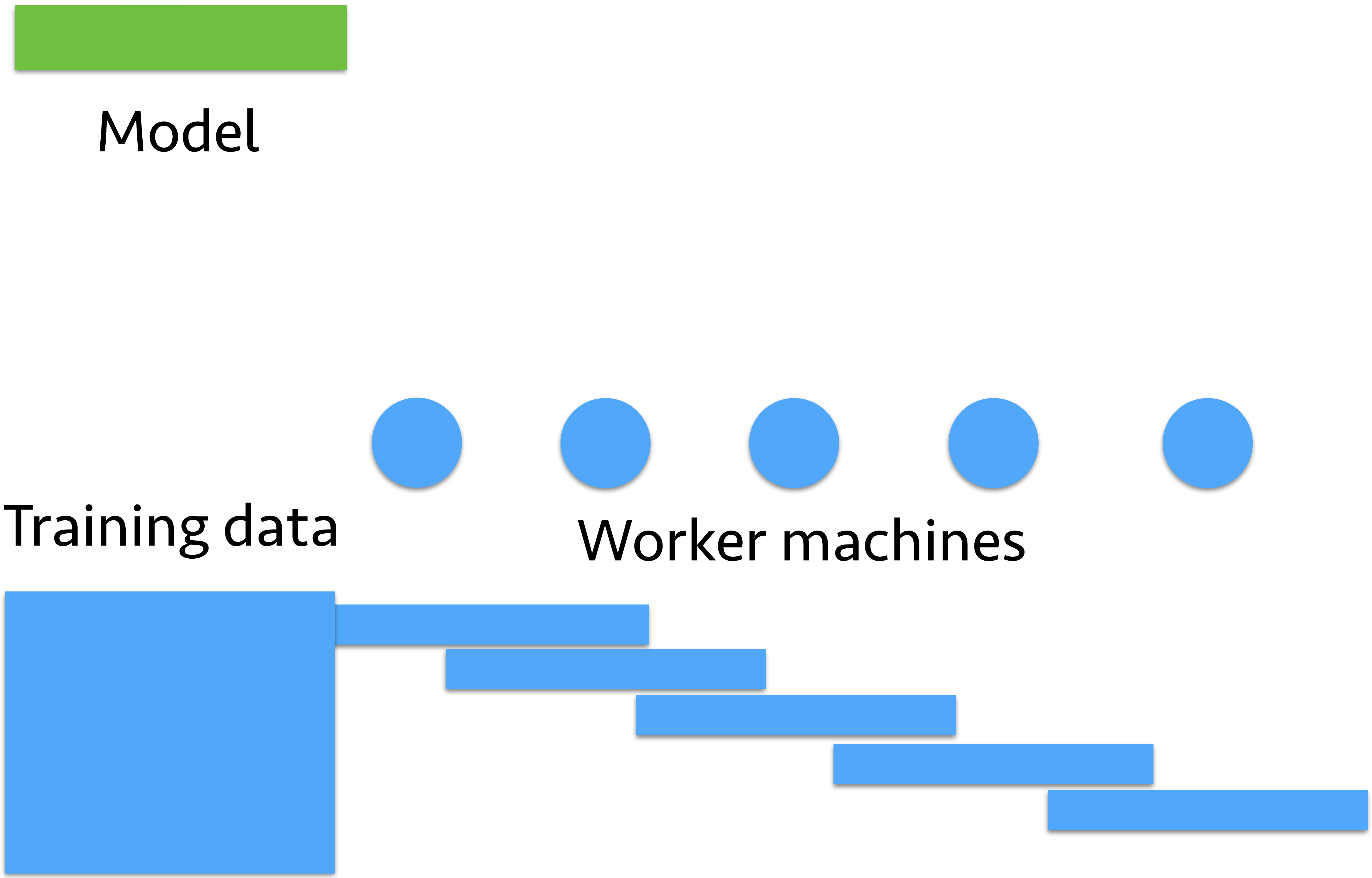

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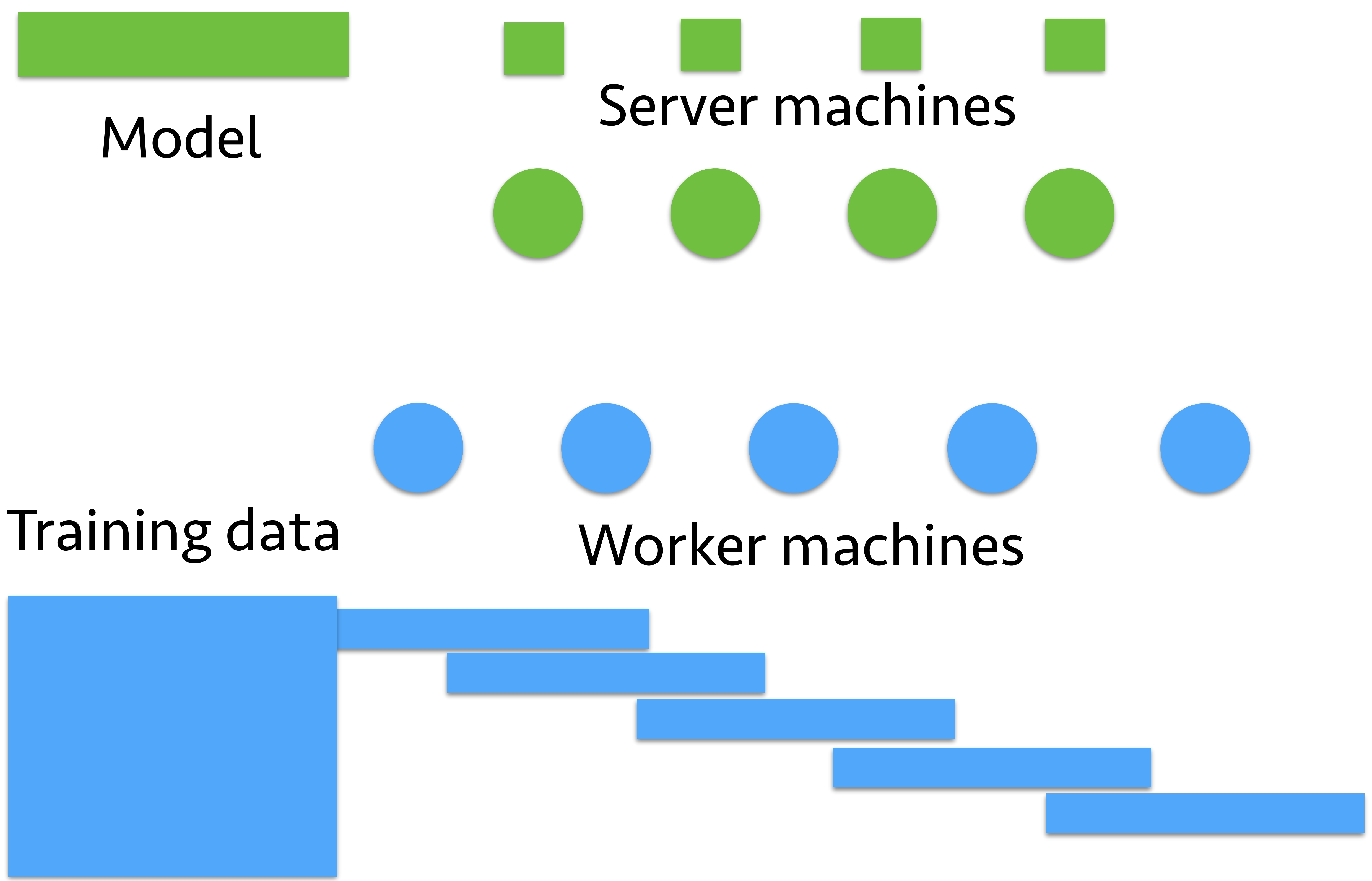

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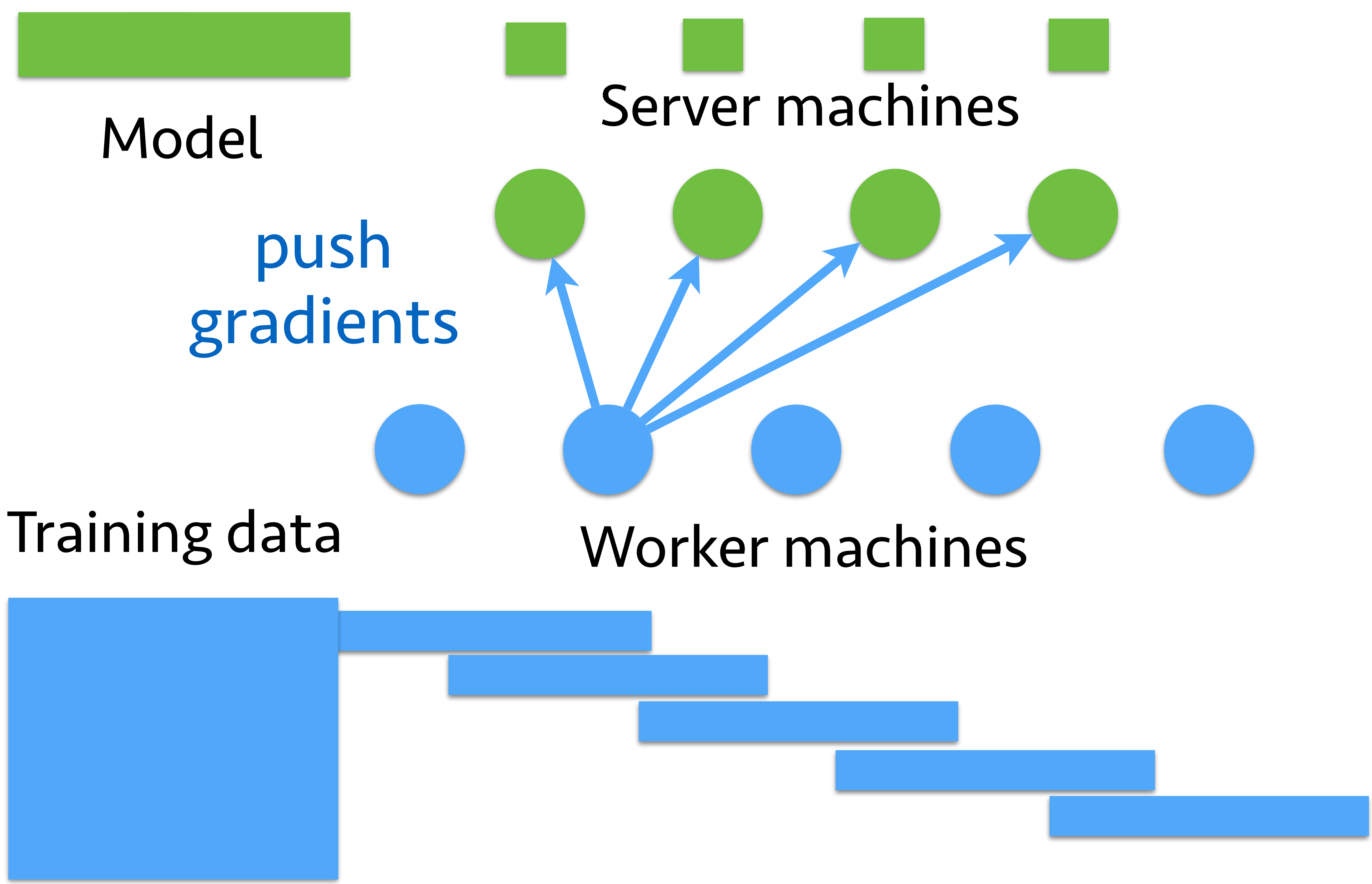

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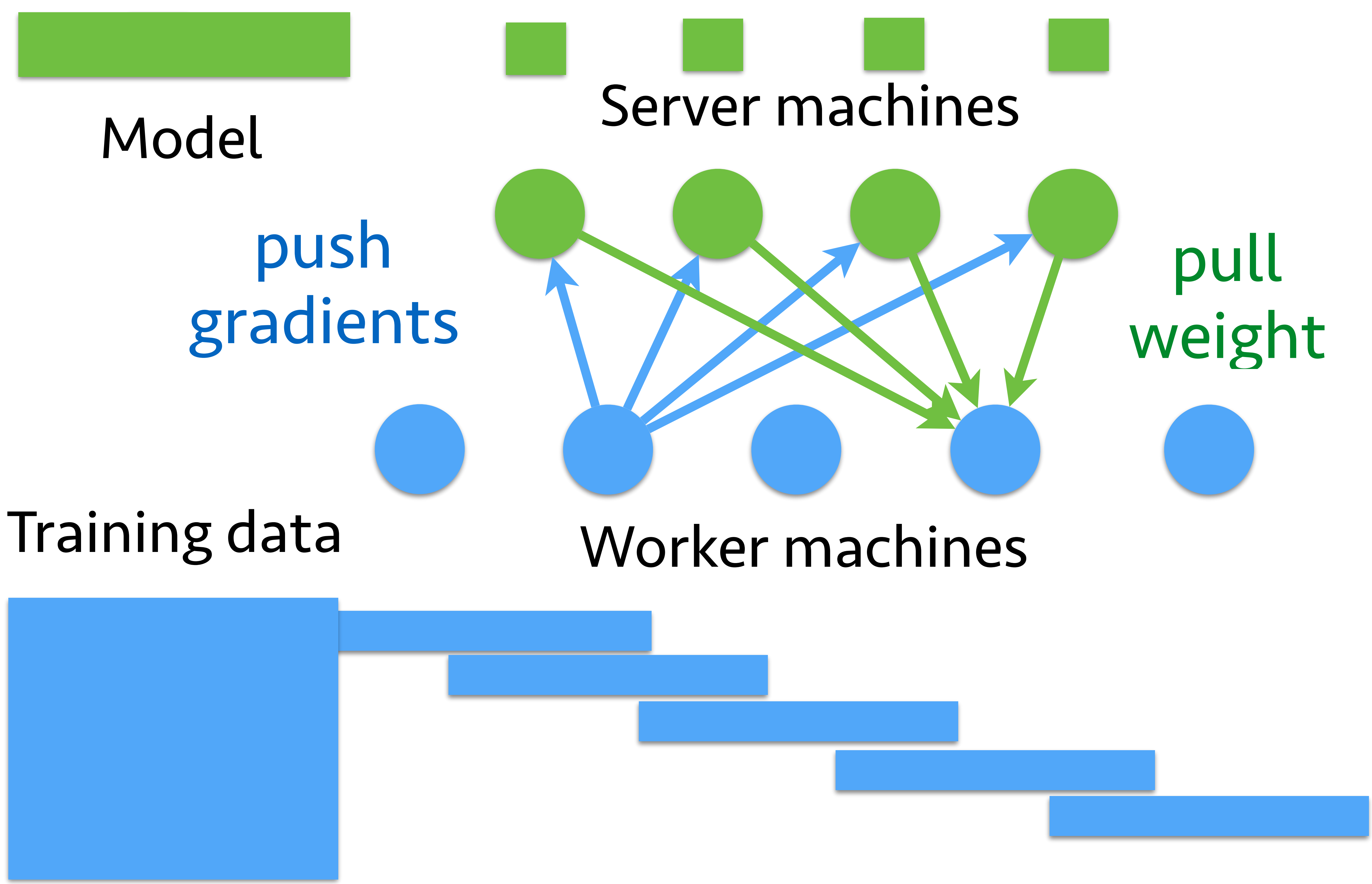
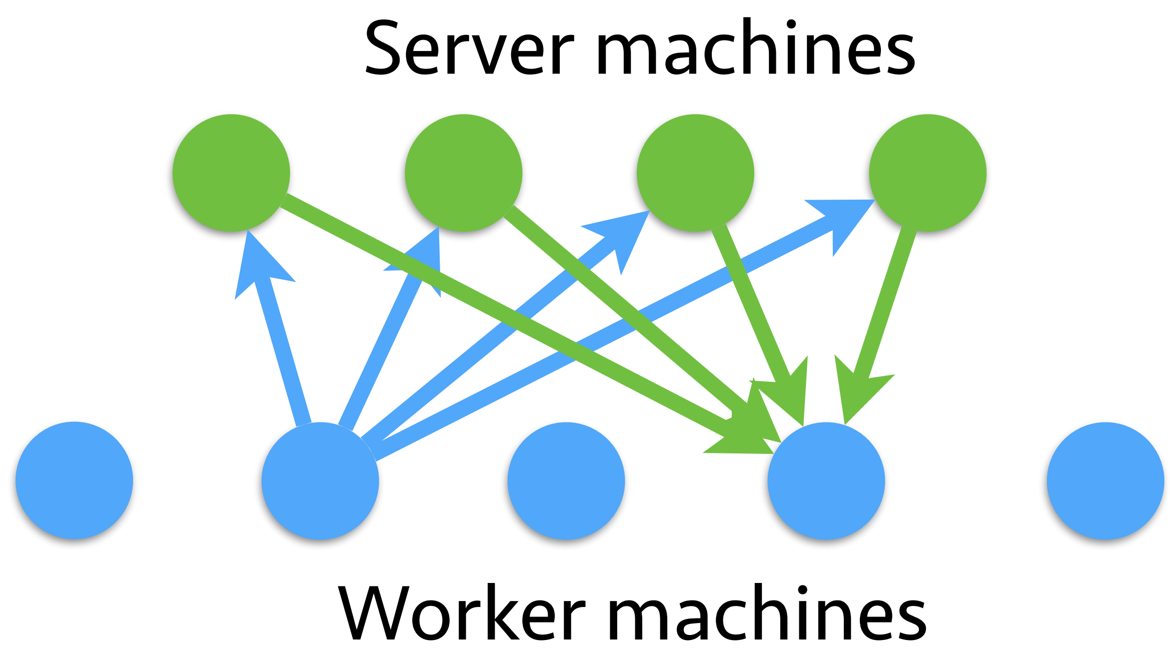


Distributed Asynchronous SGD



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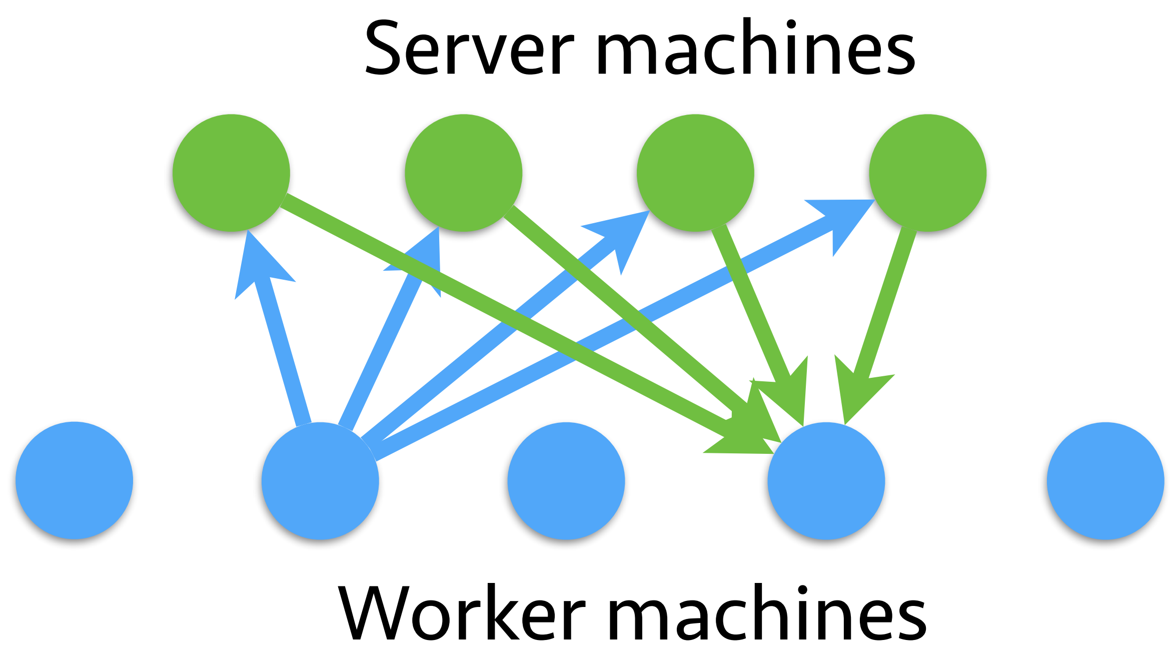

Workers run independently

- For each iteration
  - read a new minibatch
  - pull weights from the servers
  - compute gradients
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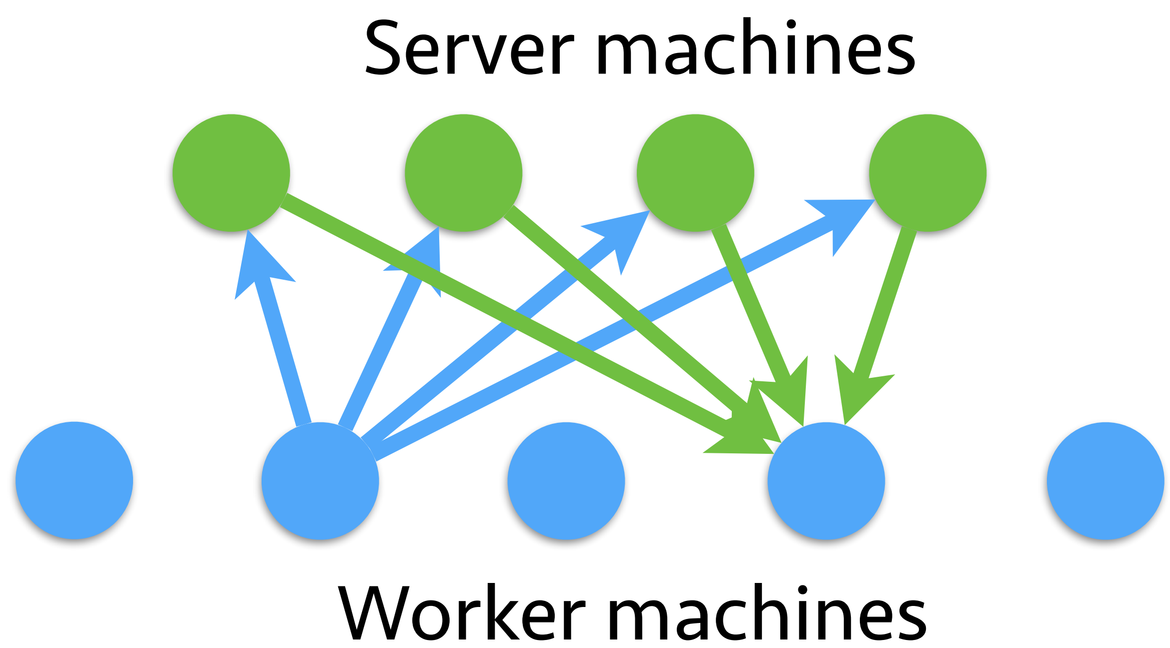

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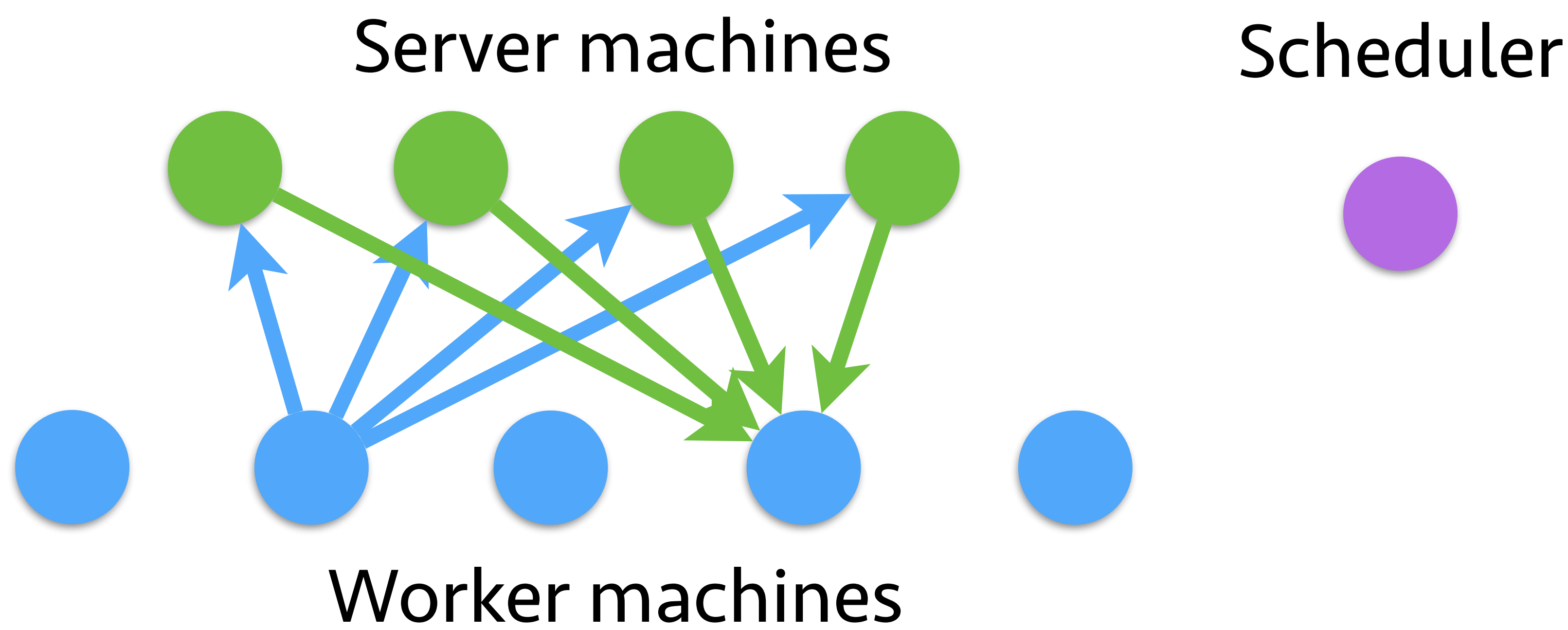

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Scheduler node:

- manages load balanced
- achieves fault tolerance

Data consistency

- Async SGD trade-off data consistency for system performance

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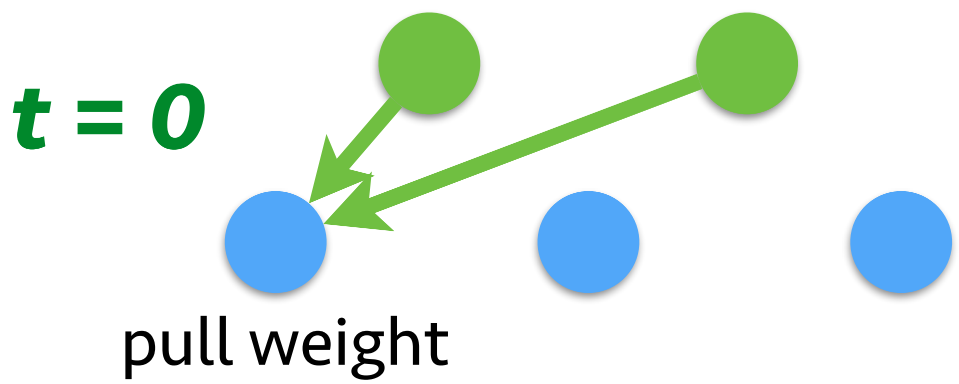

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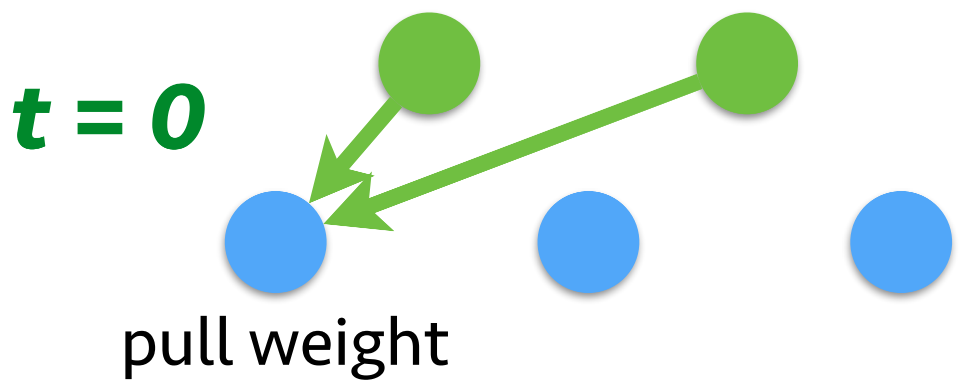

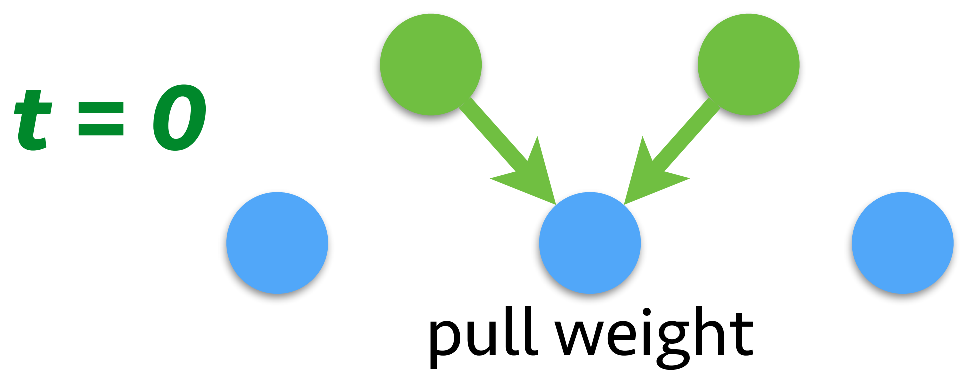

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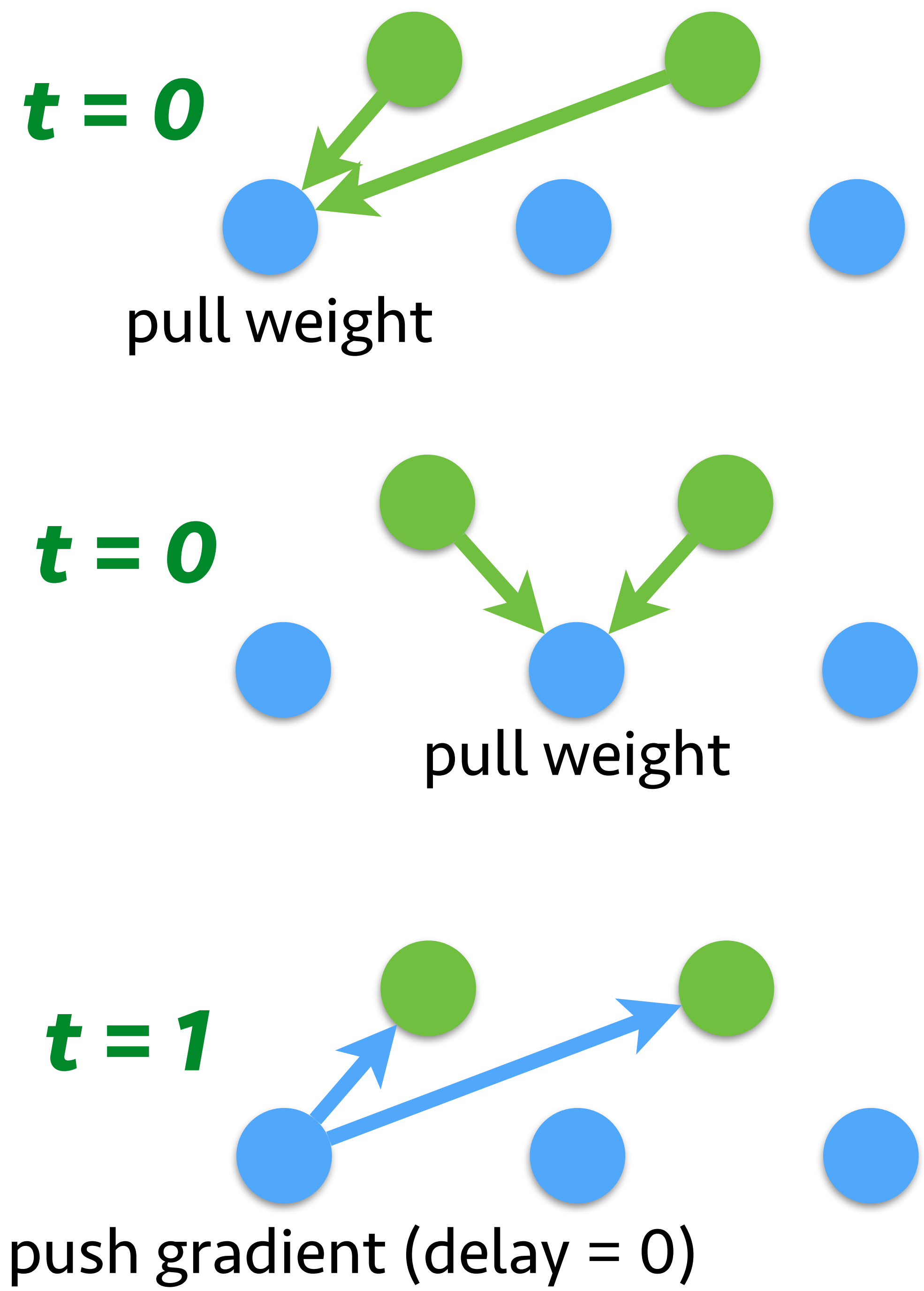

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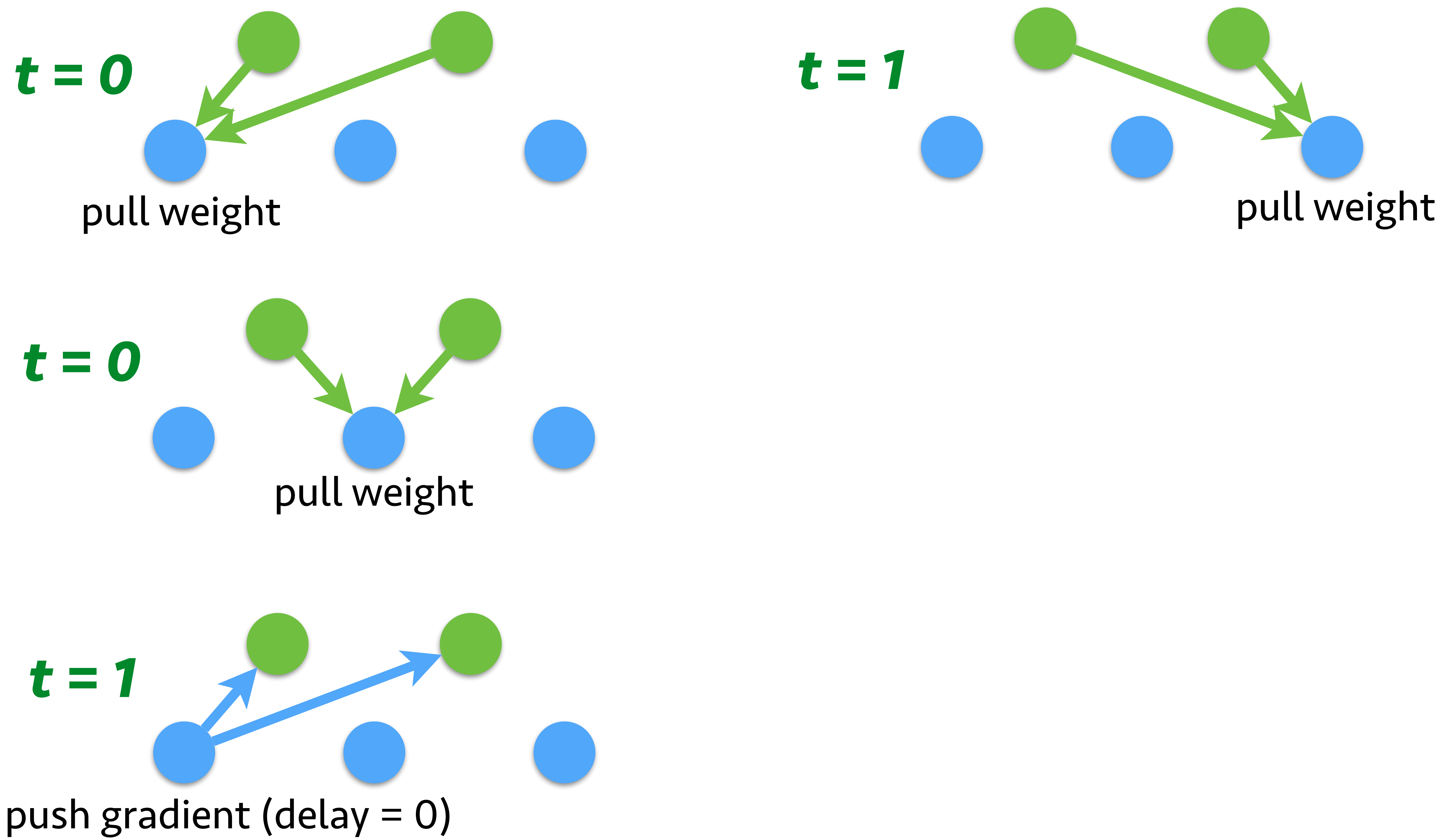

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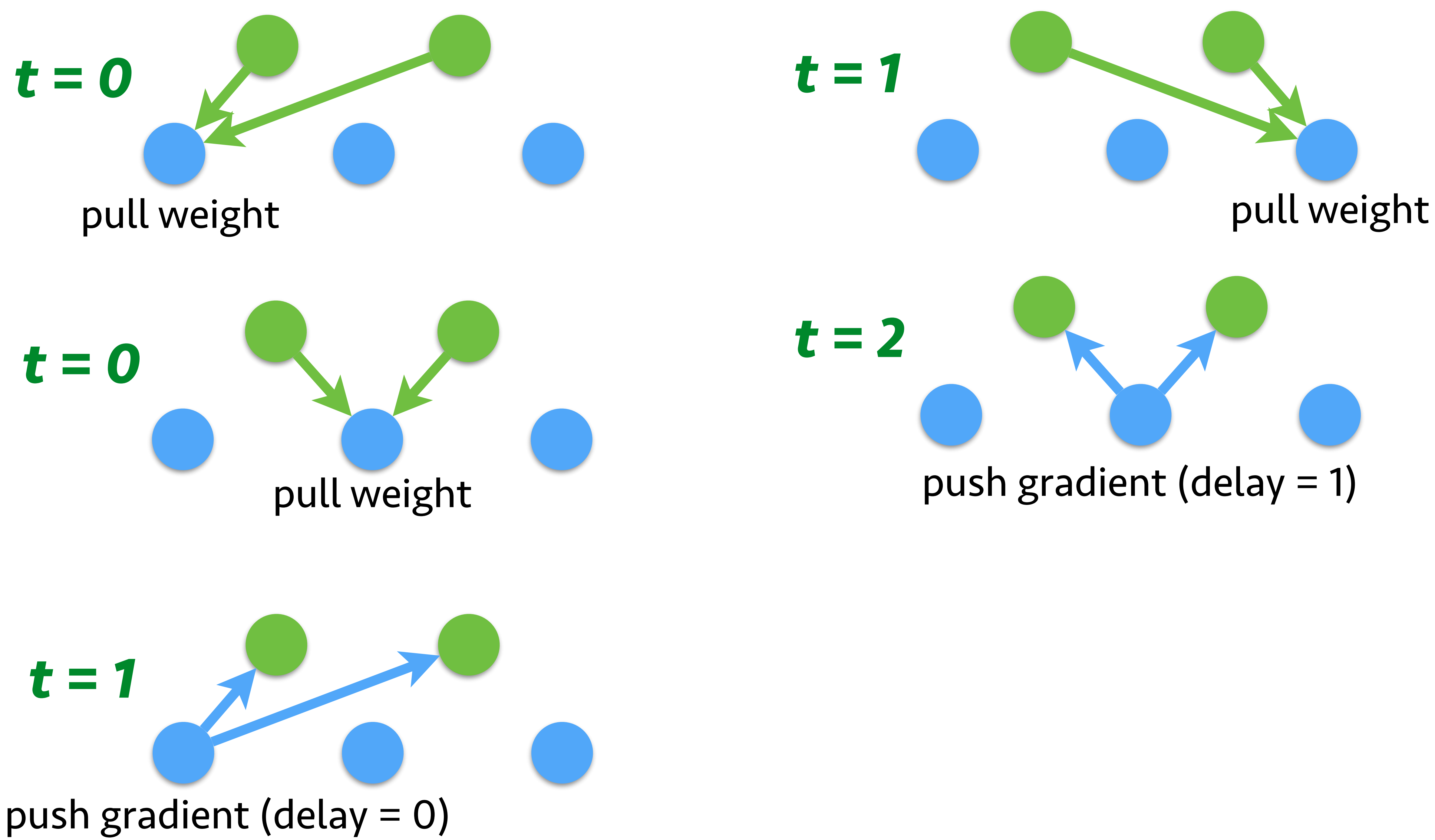

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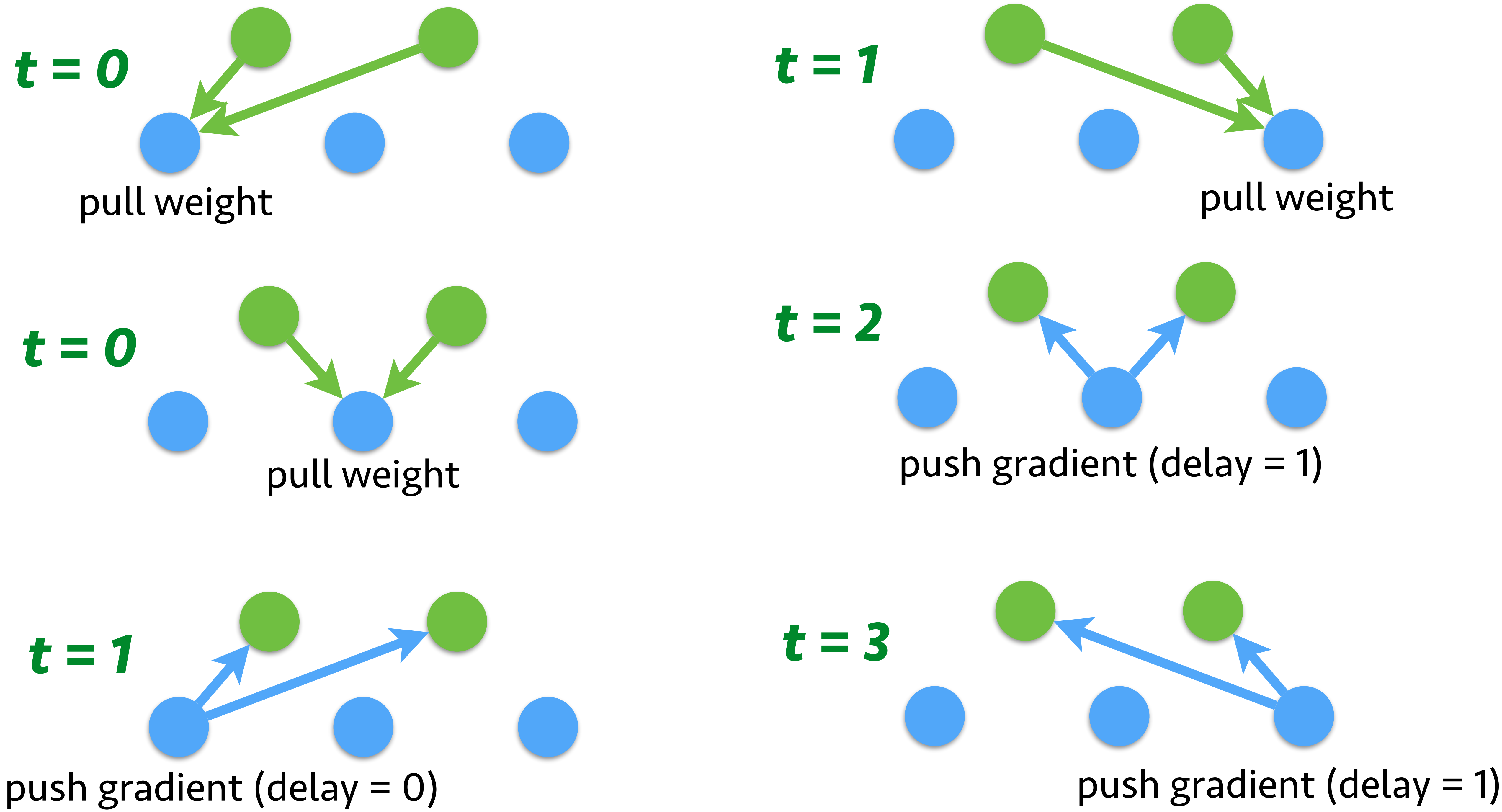

Theoretical Analysis

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  - maximal delay is upper-bonded by τ
  - stochastic gradient is L-Lipschitz, and variance is bounded by σ^2
- If choose a constant step-size $\eta = \sqrt{\frac{C}{L\tau\sigma^2}}$ then for every $T \geq 4LC(\tau+1)^2/\sigma$

$$\frac{1}{T}\sum_{t=1}^{T}\mathbb{E}\|\nabla f(x_t)\|^2 \leq 4\sqrt{\frac{CL}{T}}\sigma$$

  - LHS is an intuitive measure of distance from stationary point
  - Delay may slow convergence
  - We can use a large learning rate for large minibatch size or sparse dataset

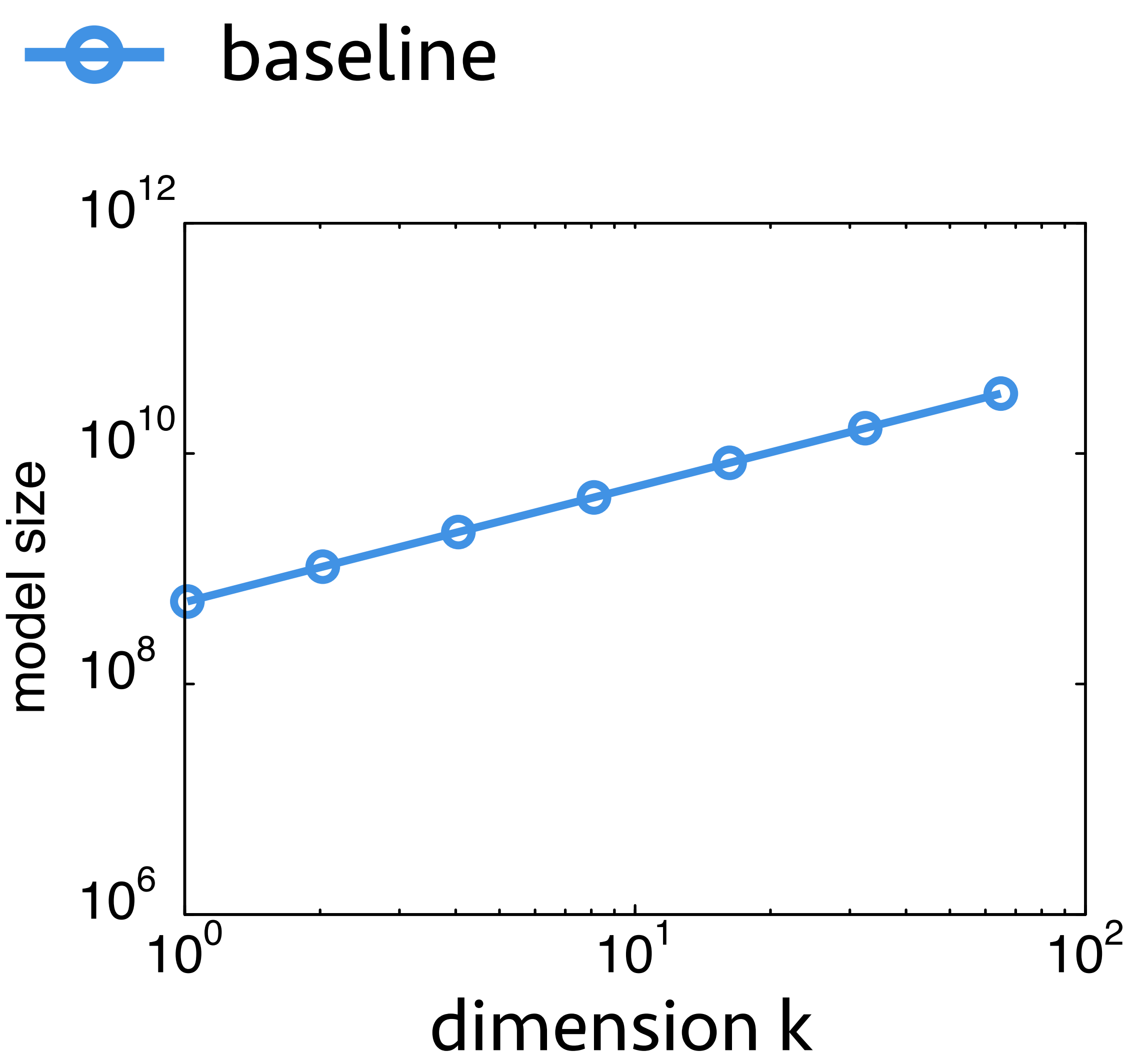
Statistic Model

Distributed Optimization

Evaluation

Adaptive Memory

- Criteo dataset: 1.5B examples, 360M features
- Run on 10 AWS EC2 machines



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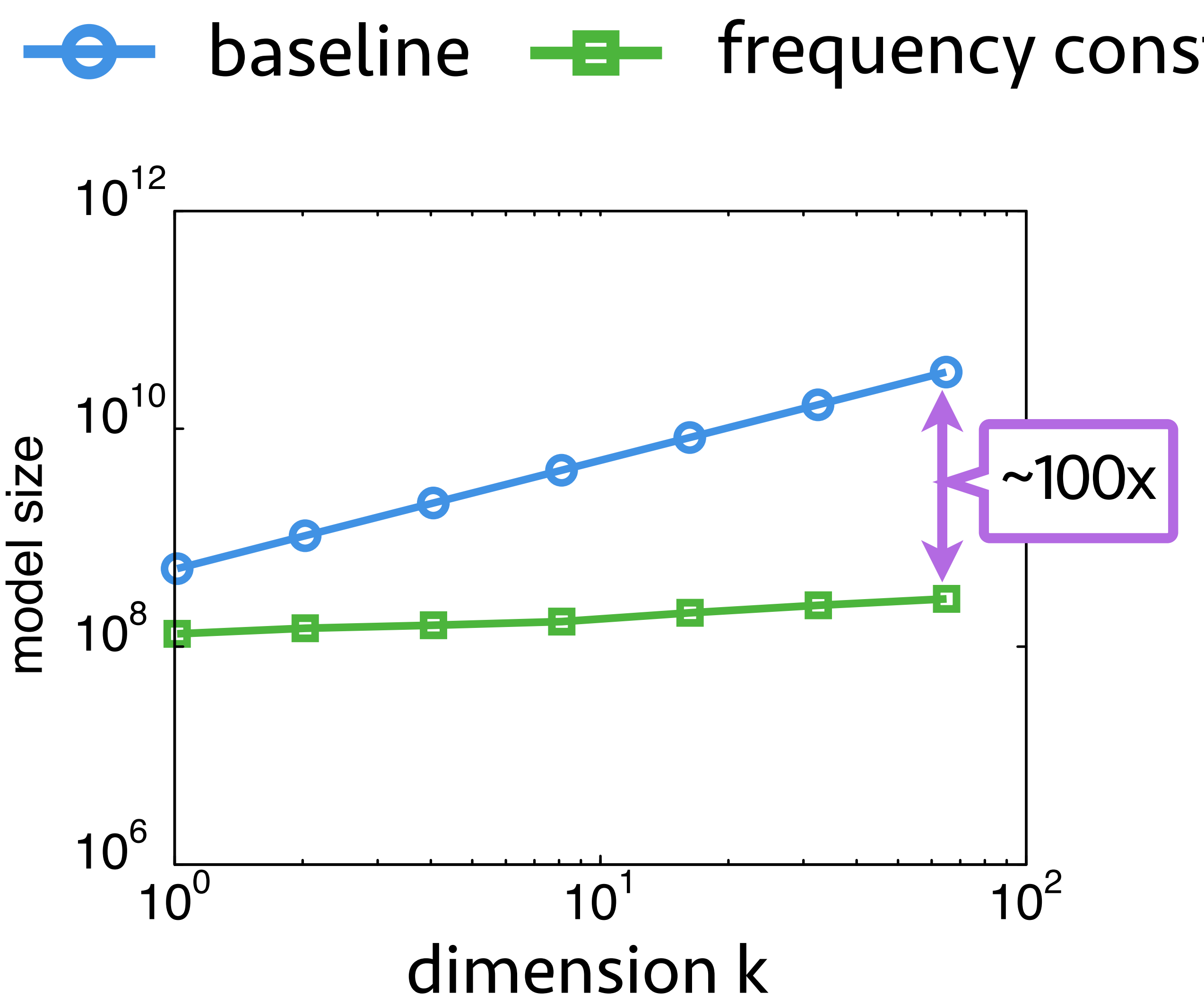

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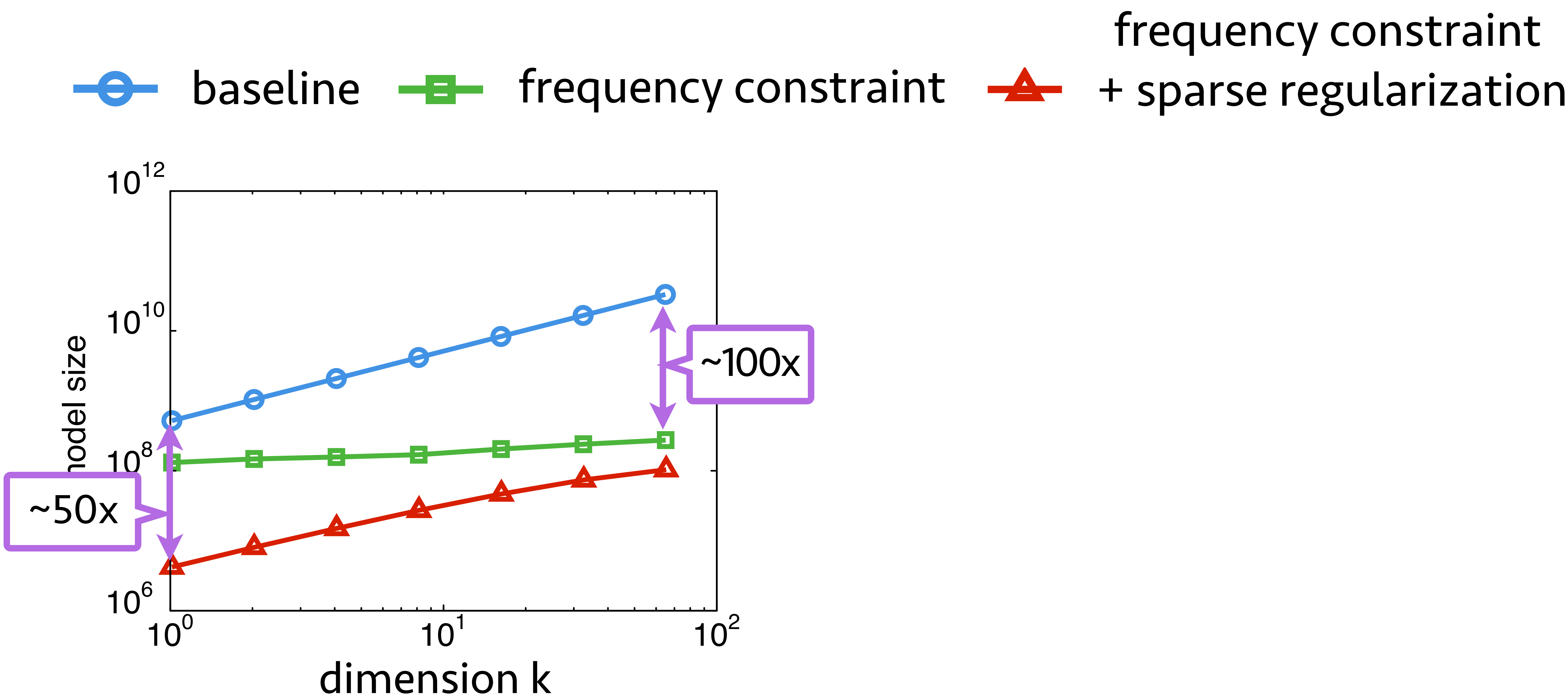

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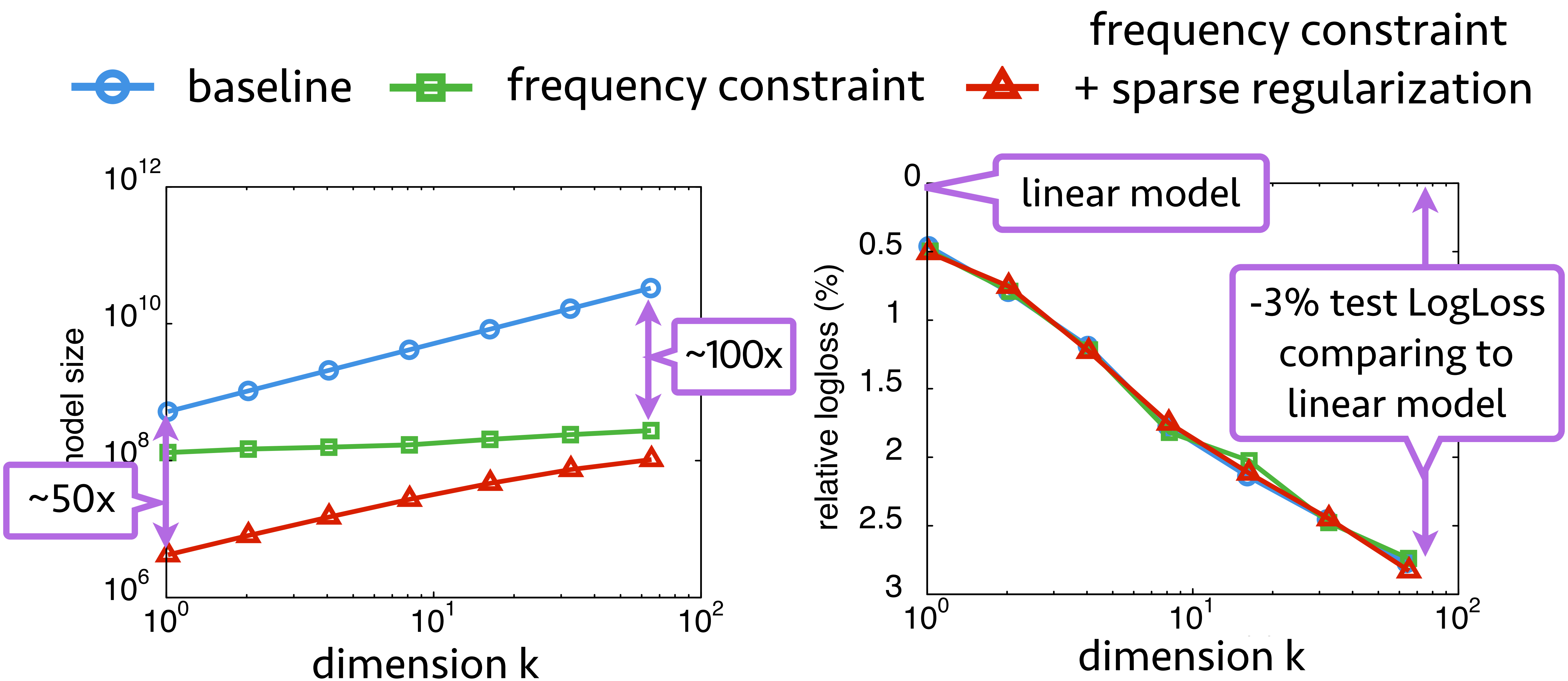

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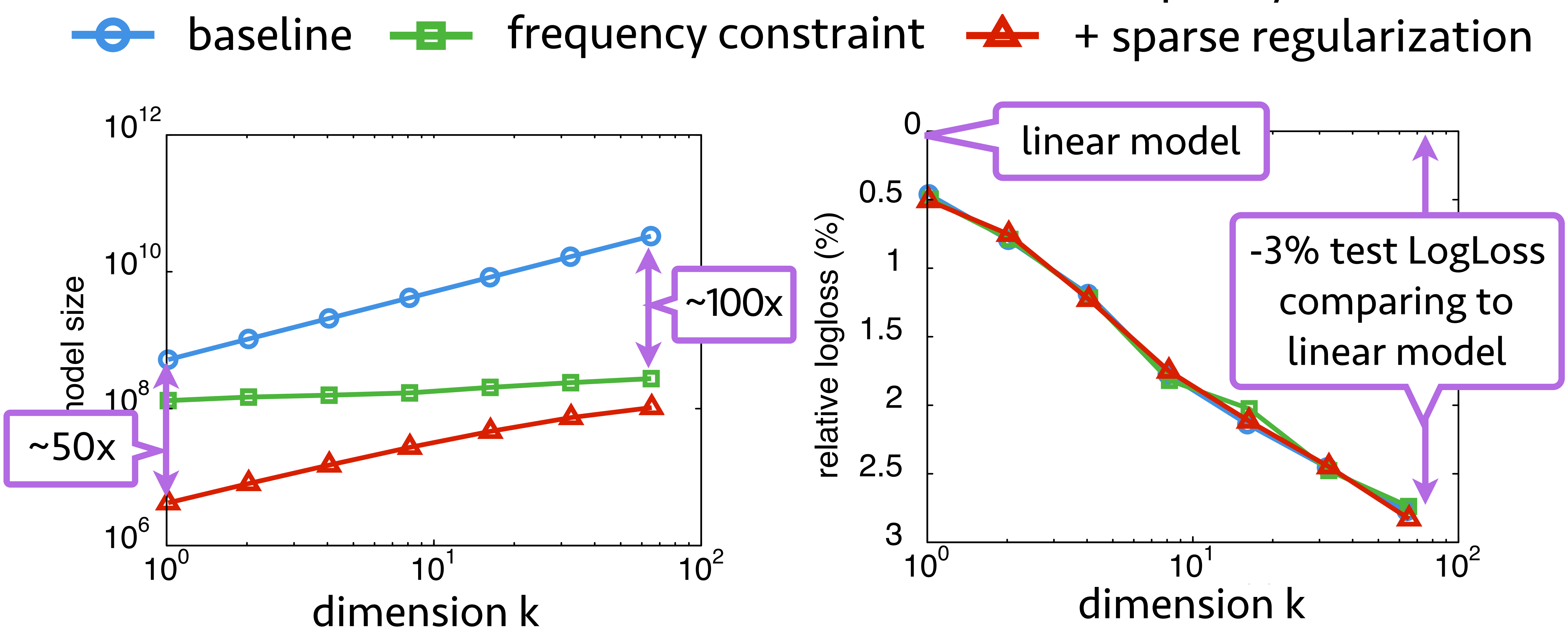


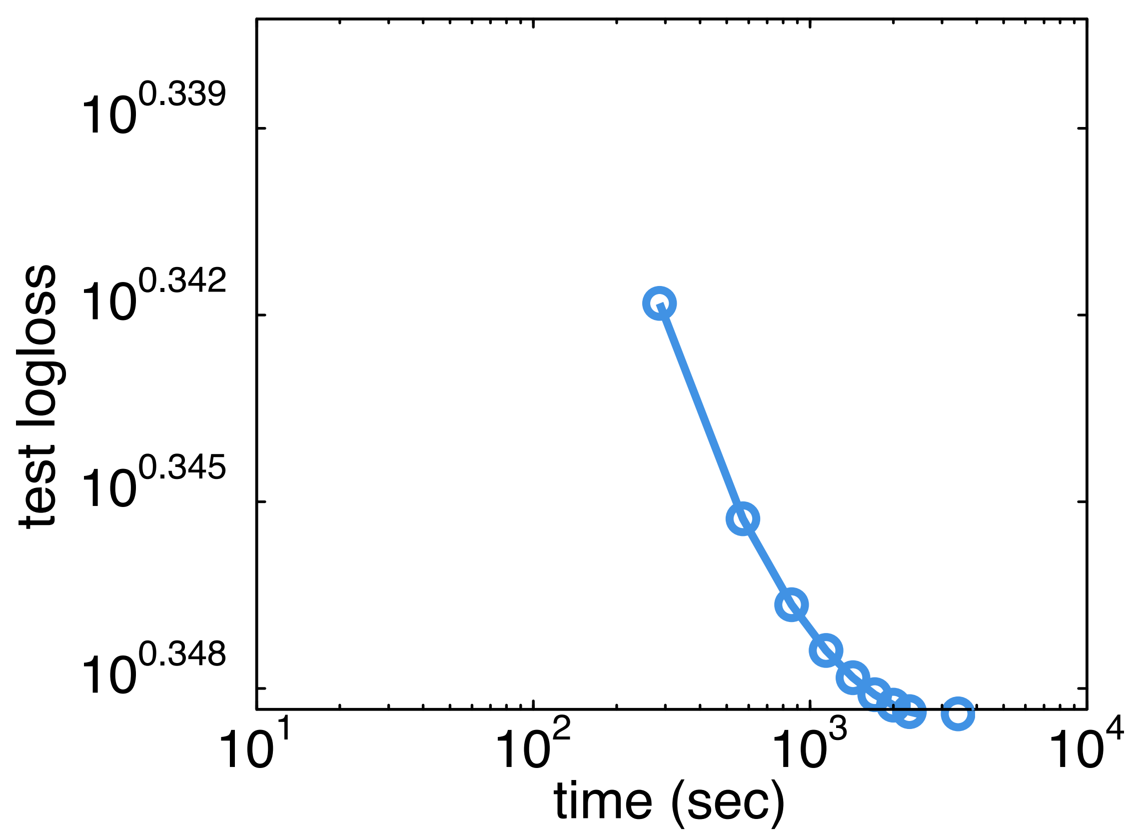
only 2x more computation cost
for FM with *k=100* comparing to linear model

Compare to LibFM

- LibFM is a widely used library for FM (Rendle et al)

LibFM

Sampled Criteo



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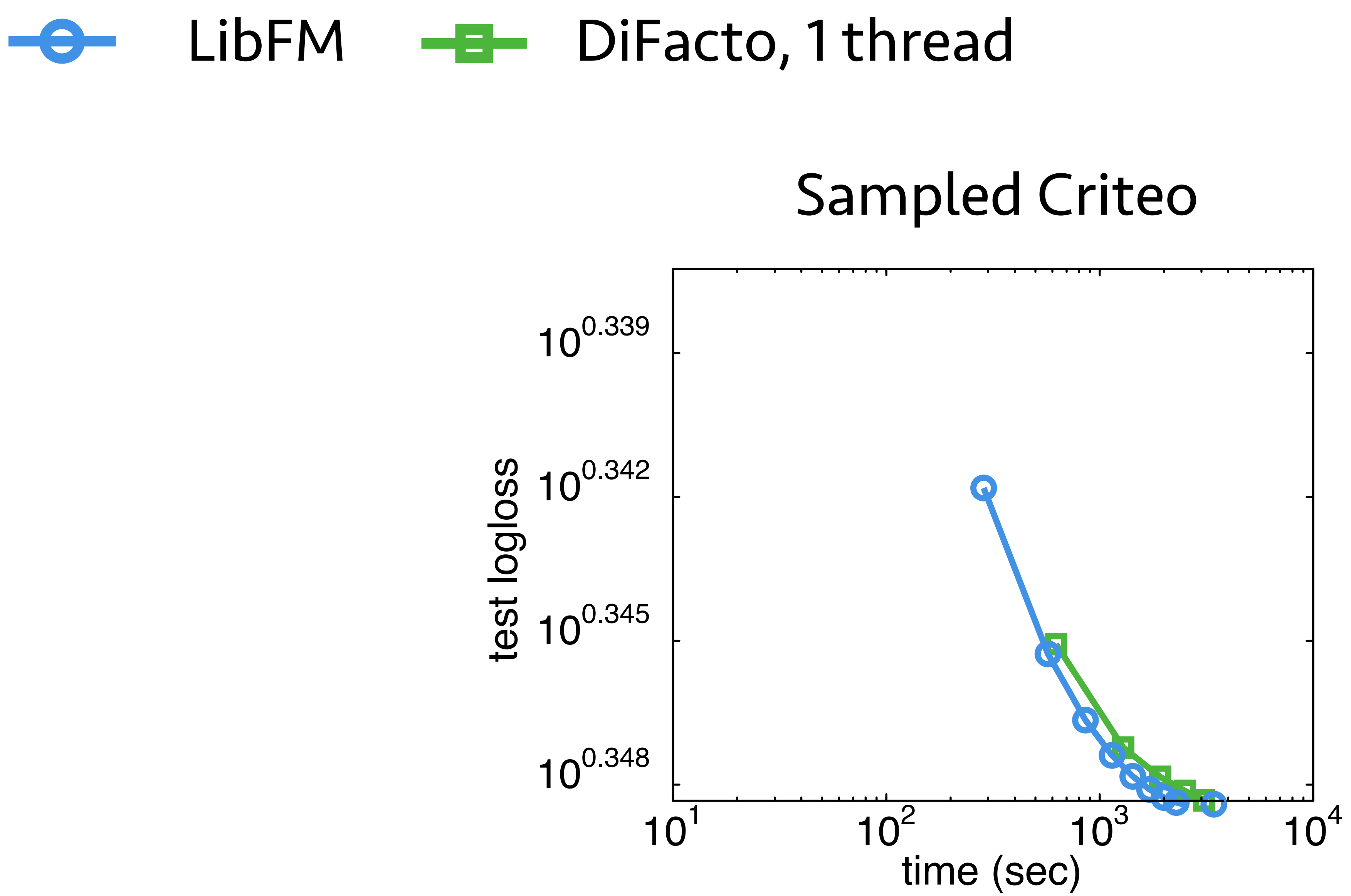

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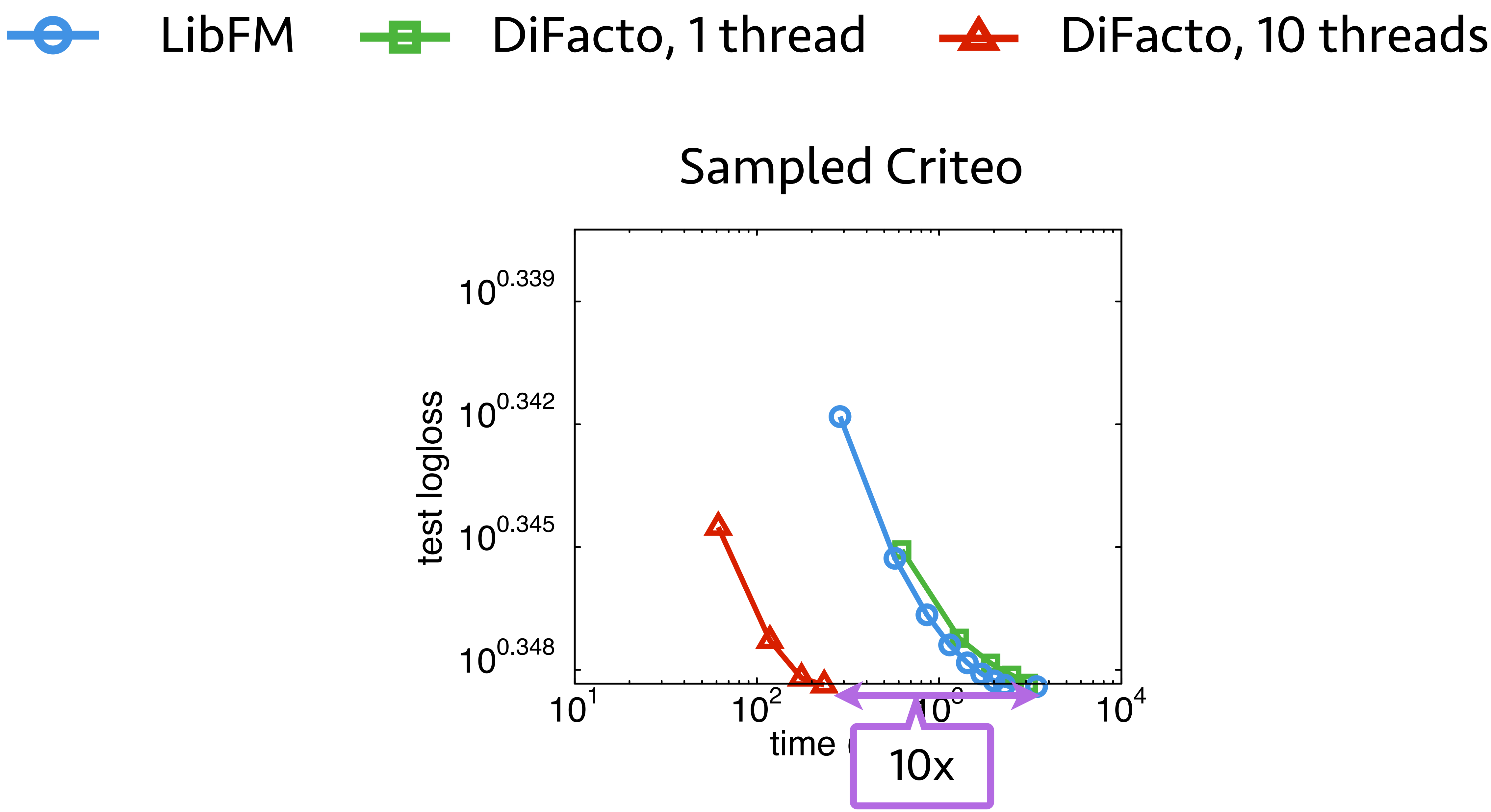

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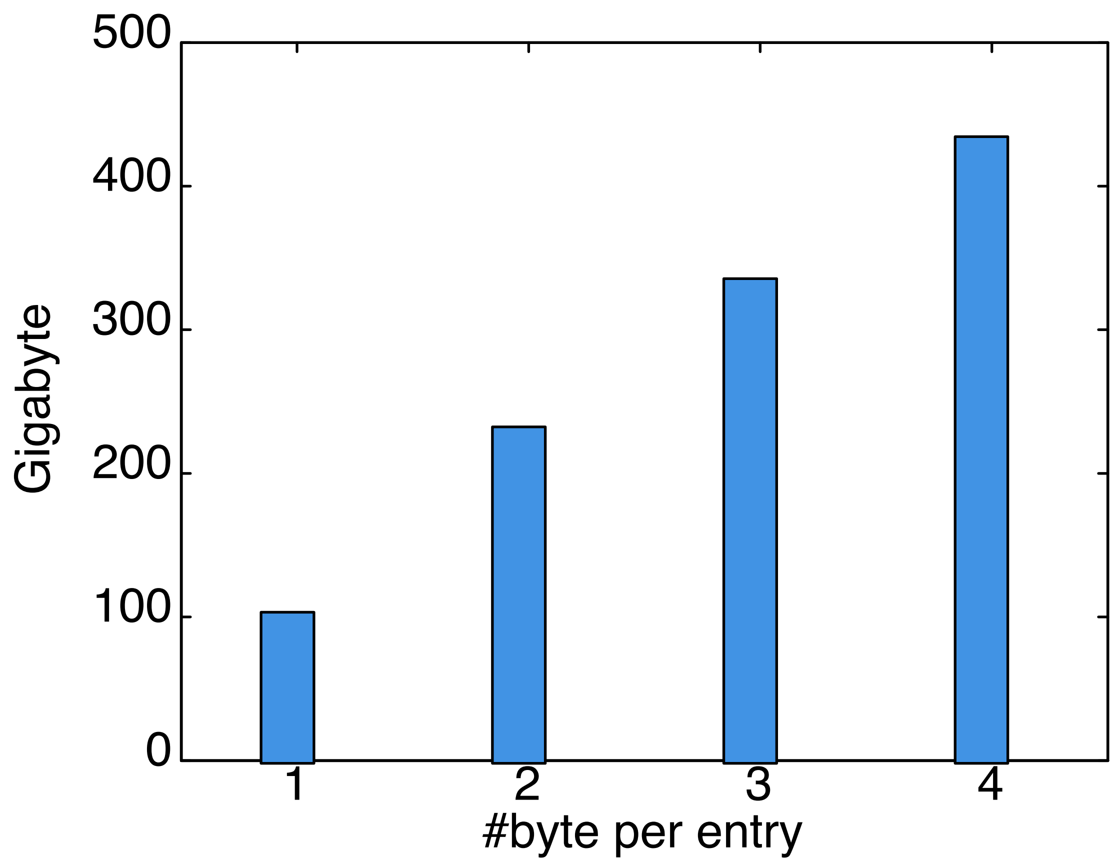

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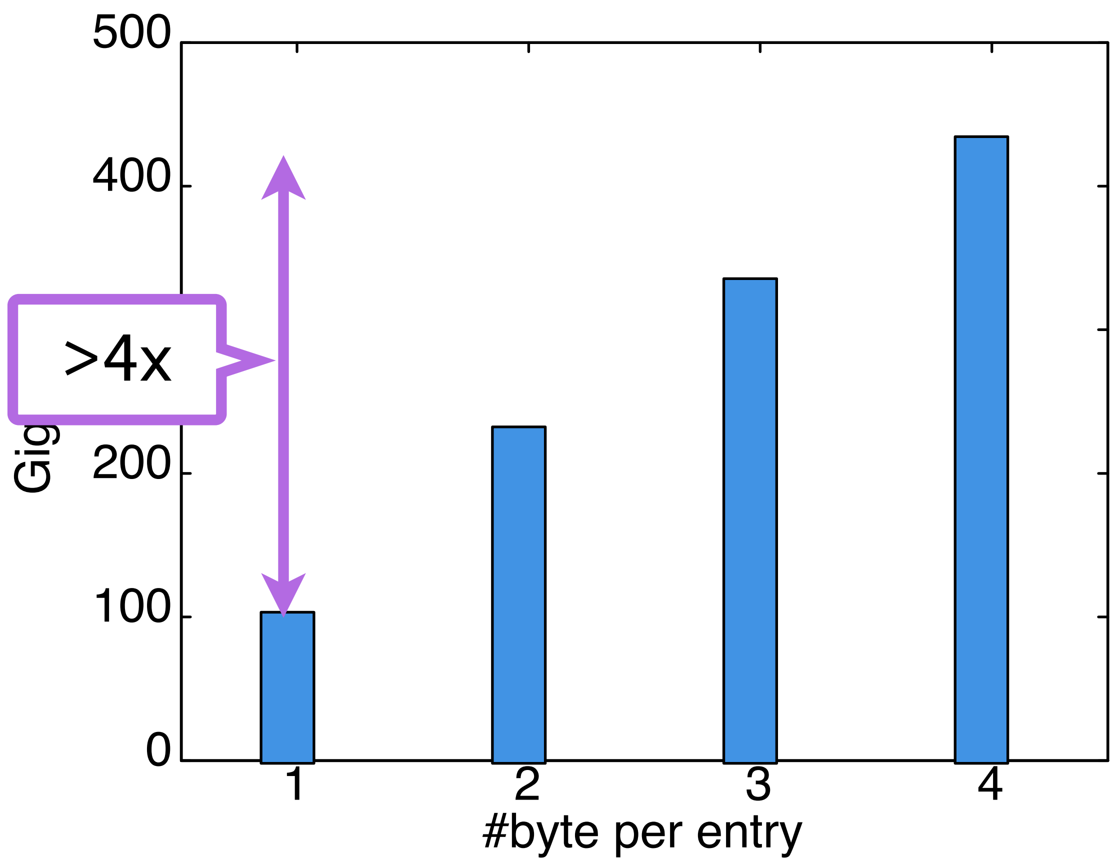

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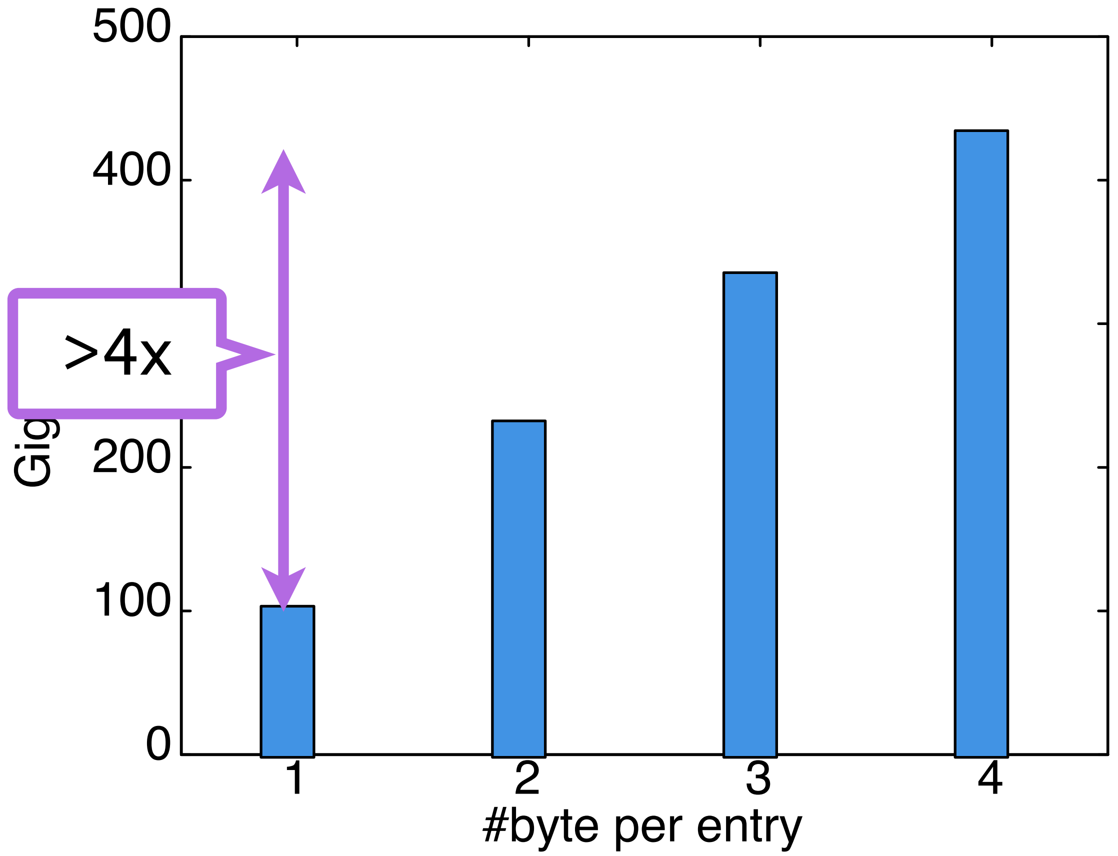

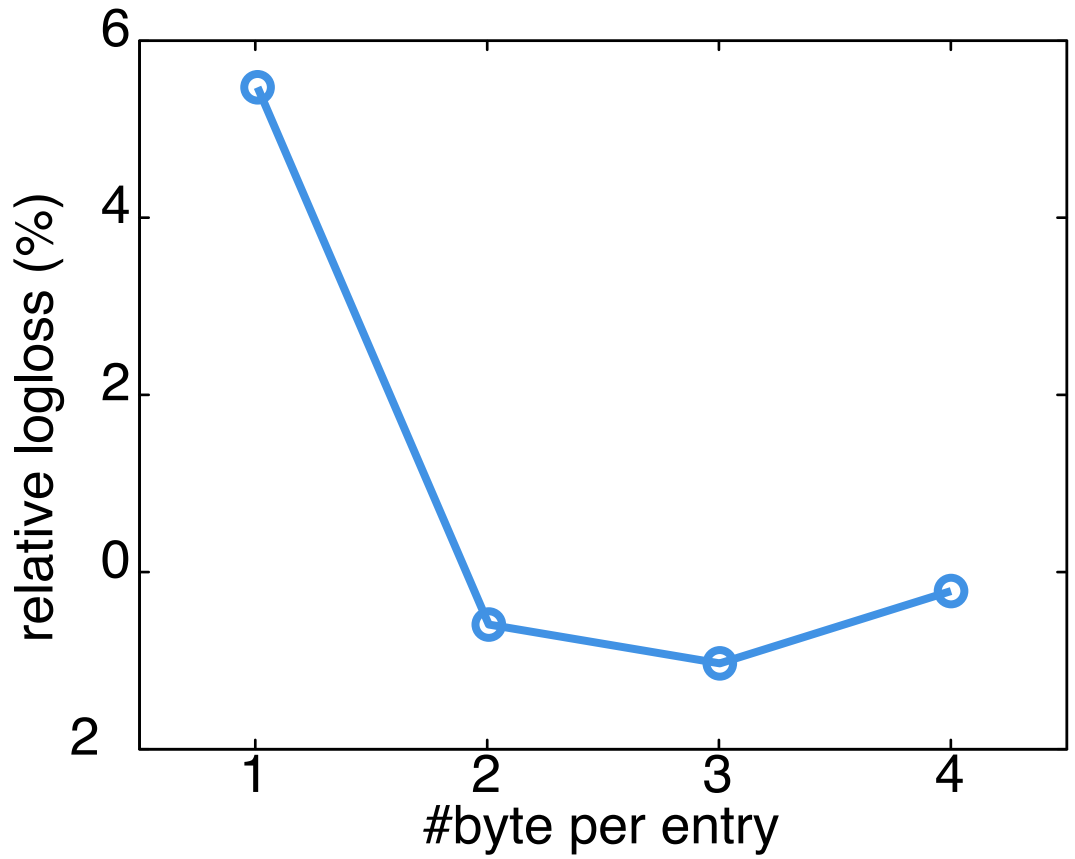

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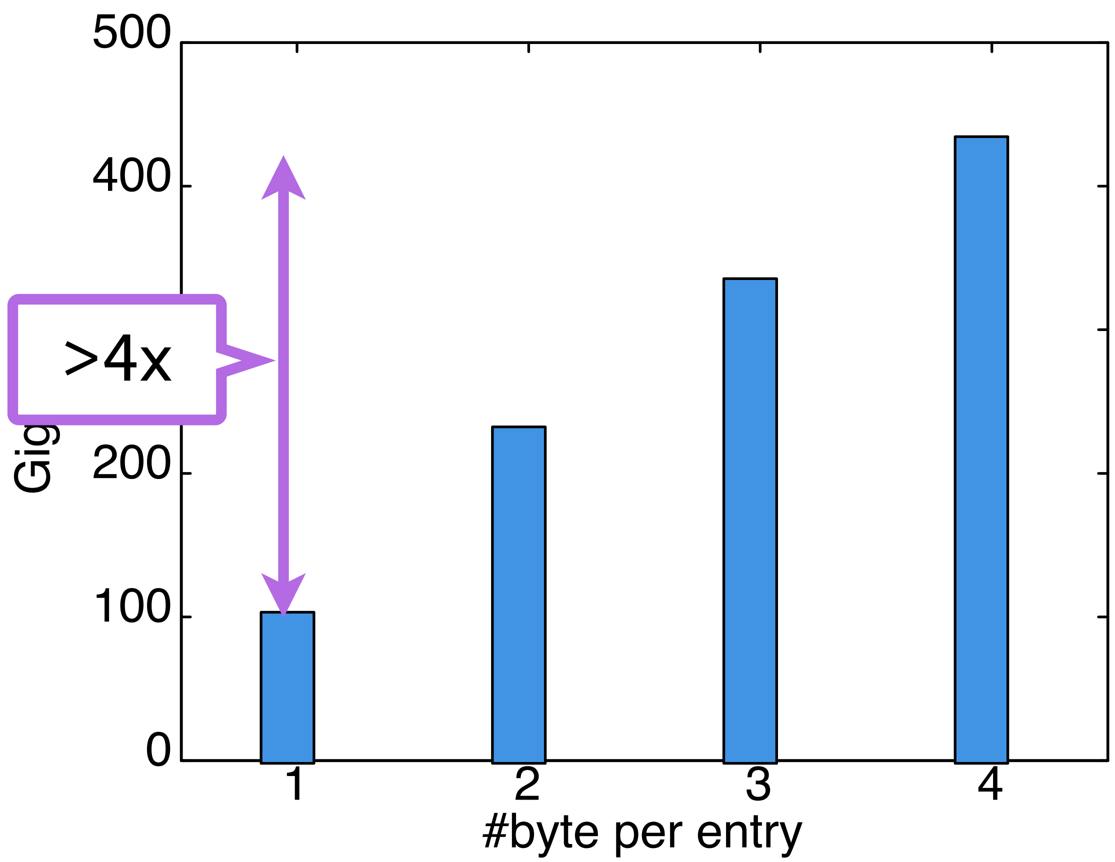
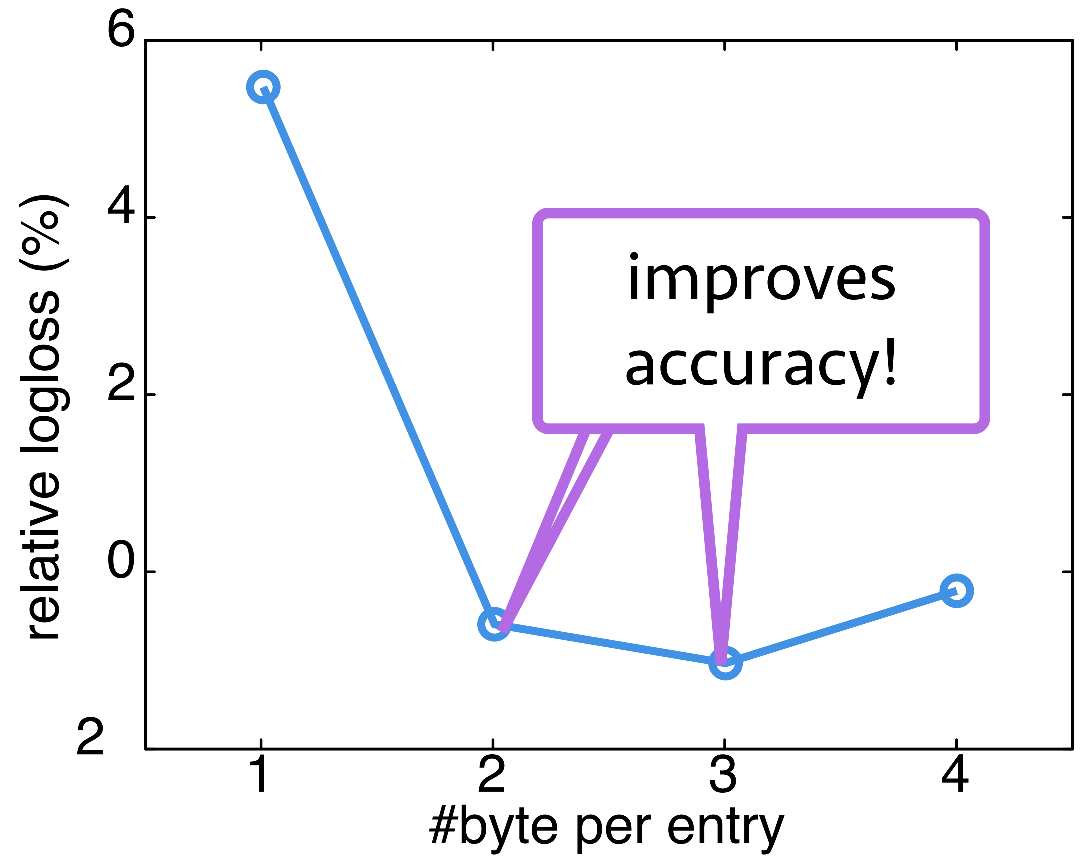
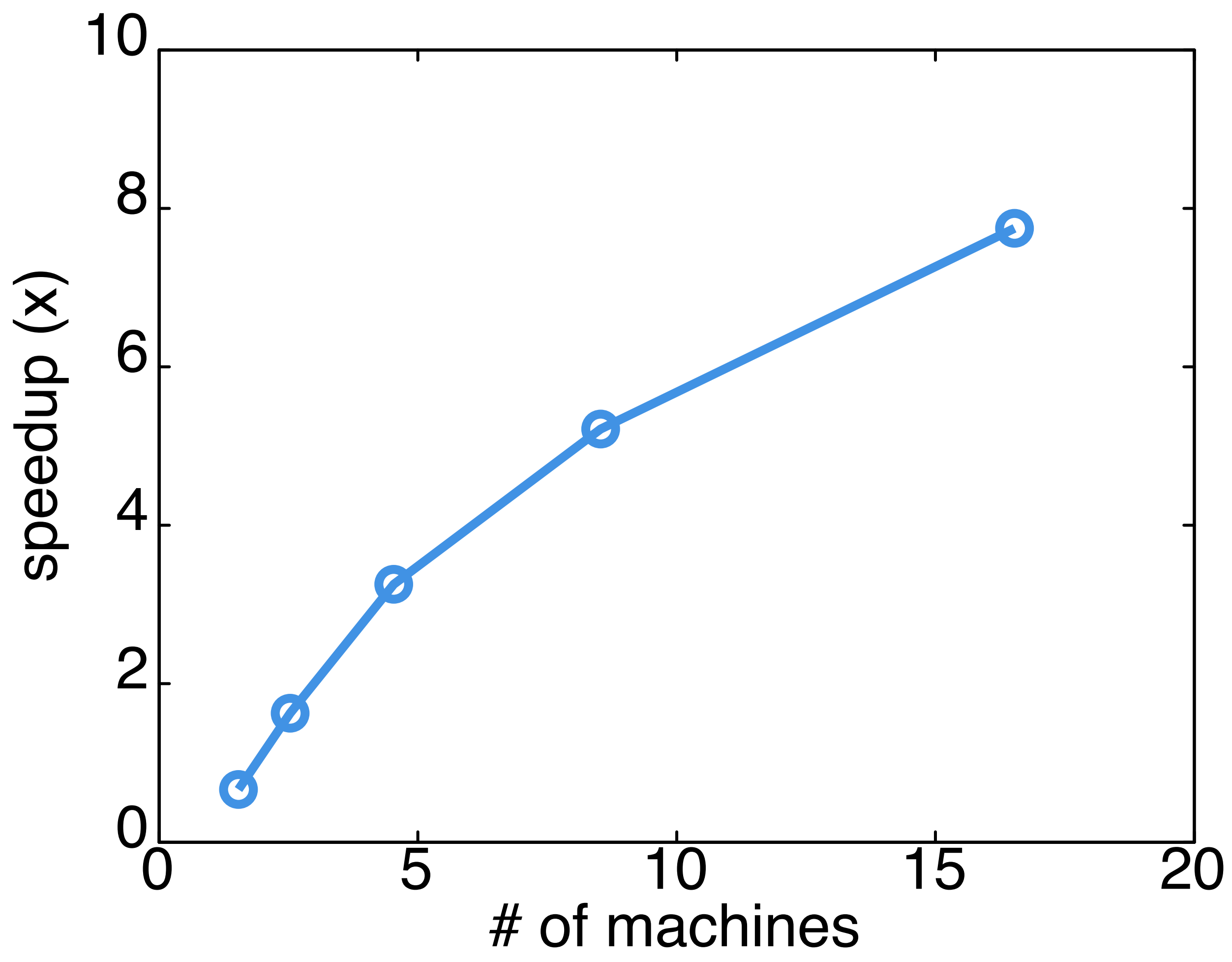




Scalability

- Scaling from 1 machine to 16 machines



Conclusion

- **Goal:** scale factorization machine into large-scale datasets
- **Solution 1:** Data and model adaptive **regularizations** to reduce model capacity on unimportant features
- **Solution 2:** Efficient **distributed training** by asynchronous SGD using the parameter server framework
- **Results:** FM with a 100-dimension embedding provides significant accuracy improvement over linear model, with only ~2x more computation and storage cost
- **Codes** are publicly available at the DMLC project

dmlc DiFacto https://github.com/dmlc/difacto