“KAISA: An Adaptive Second-Order Optimizer Framework for Deep Neural Networks”

HPC 2021 # 61

Nikola Janjušević, Feb 6th 2023

Second-Order Optimization

Stochastic Kronecker-Factored Approximate Curvature (KFAC)

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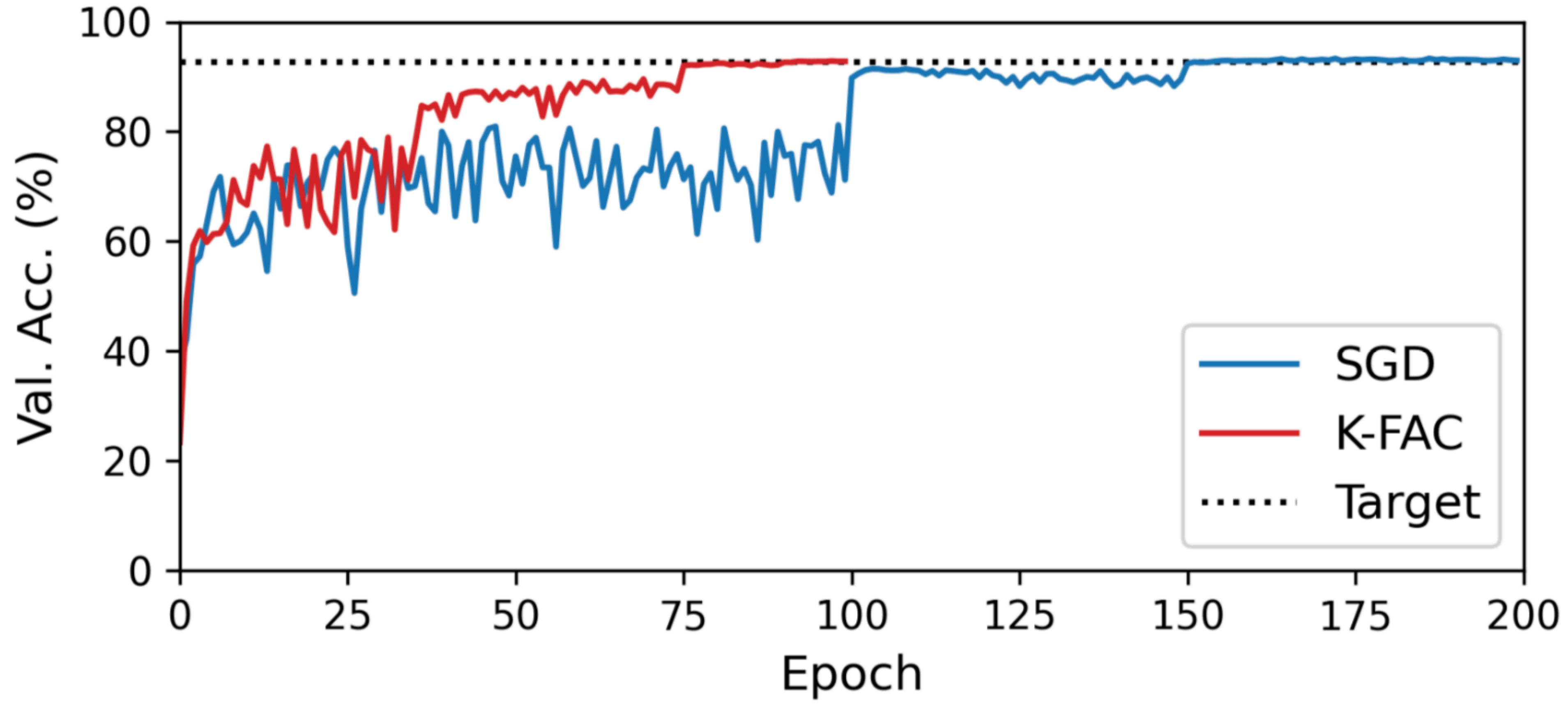

Figure 1: SGD vs. K-FAC training for ResNet-32 with the CIFAR-10 dataset. K-FAC reduces iterations needed for convergence.

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$$\text{SGD: } w^{(k+1)} = w^{(k)} - \frac{\alpha^{(k)}}{n} \sum_{i=1}^{n} \nabla L_i(w^{(k)}) \tag{1}$$

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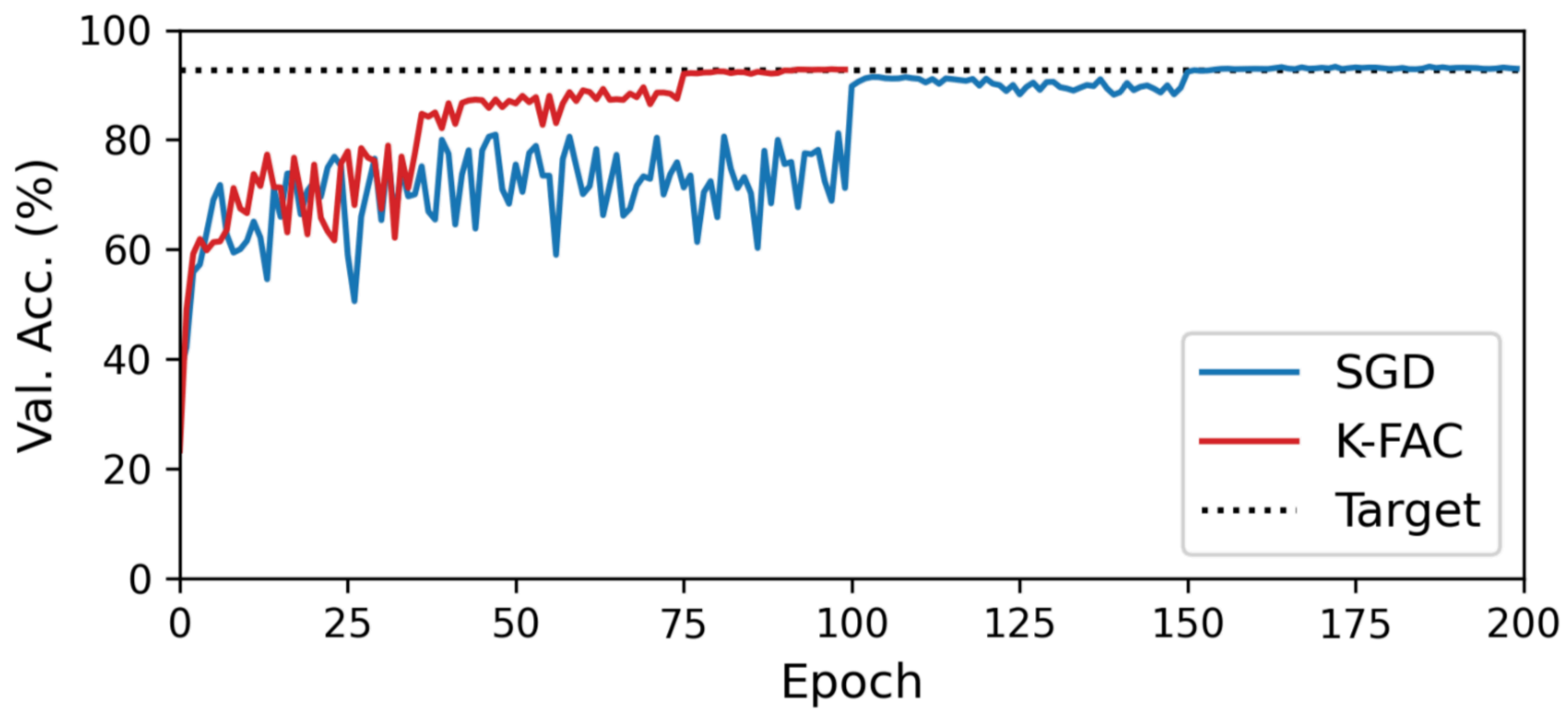

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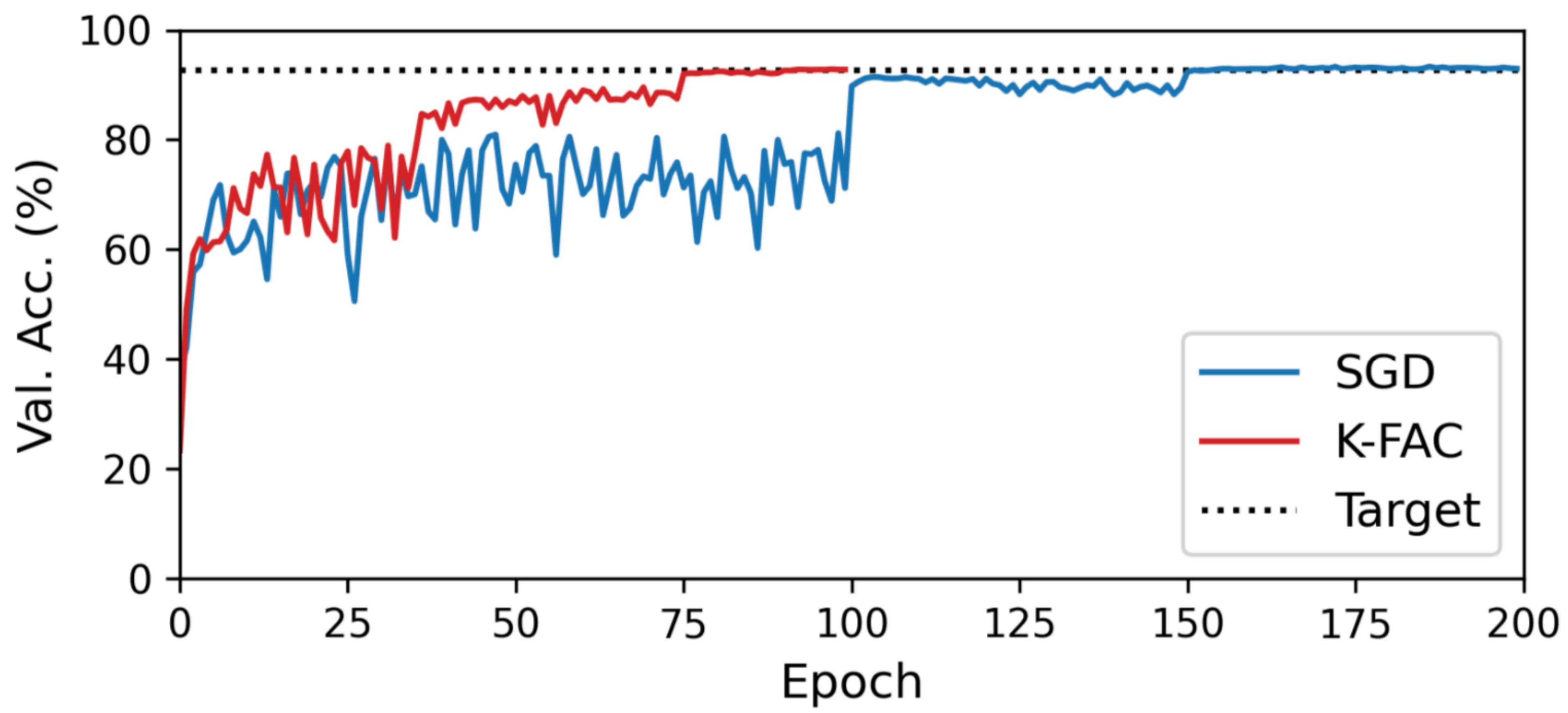

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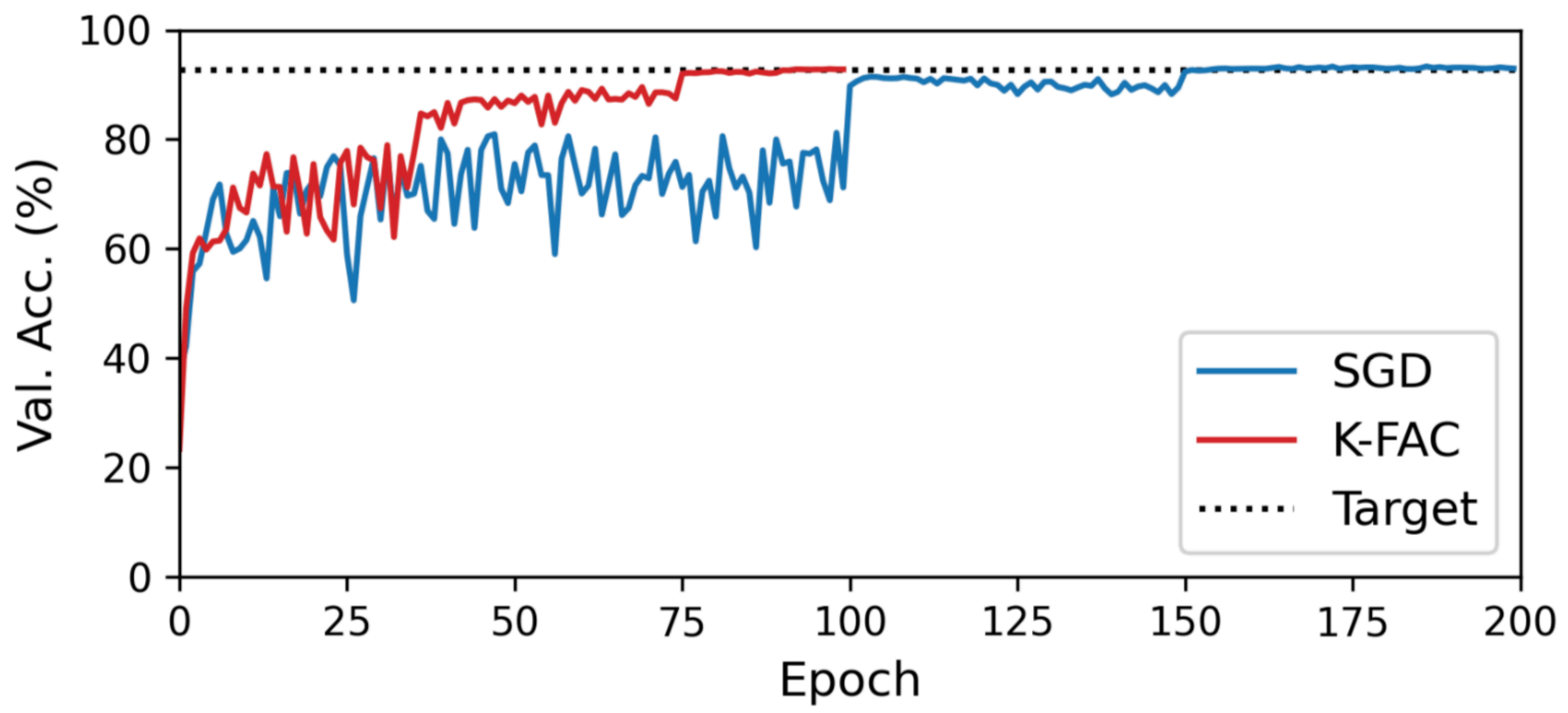

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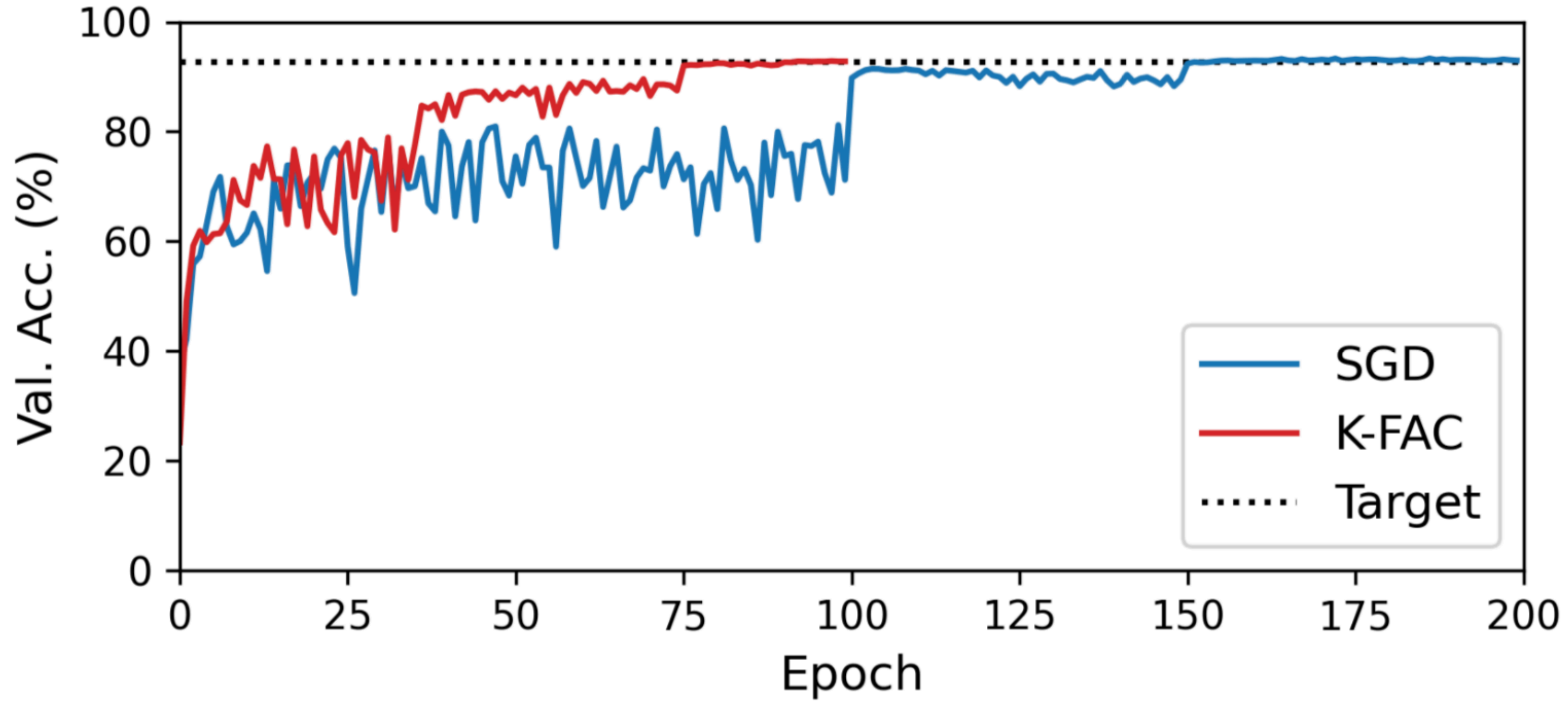

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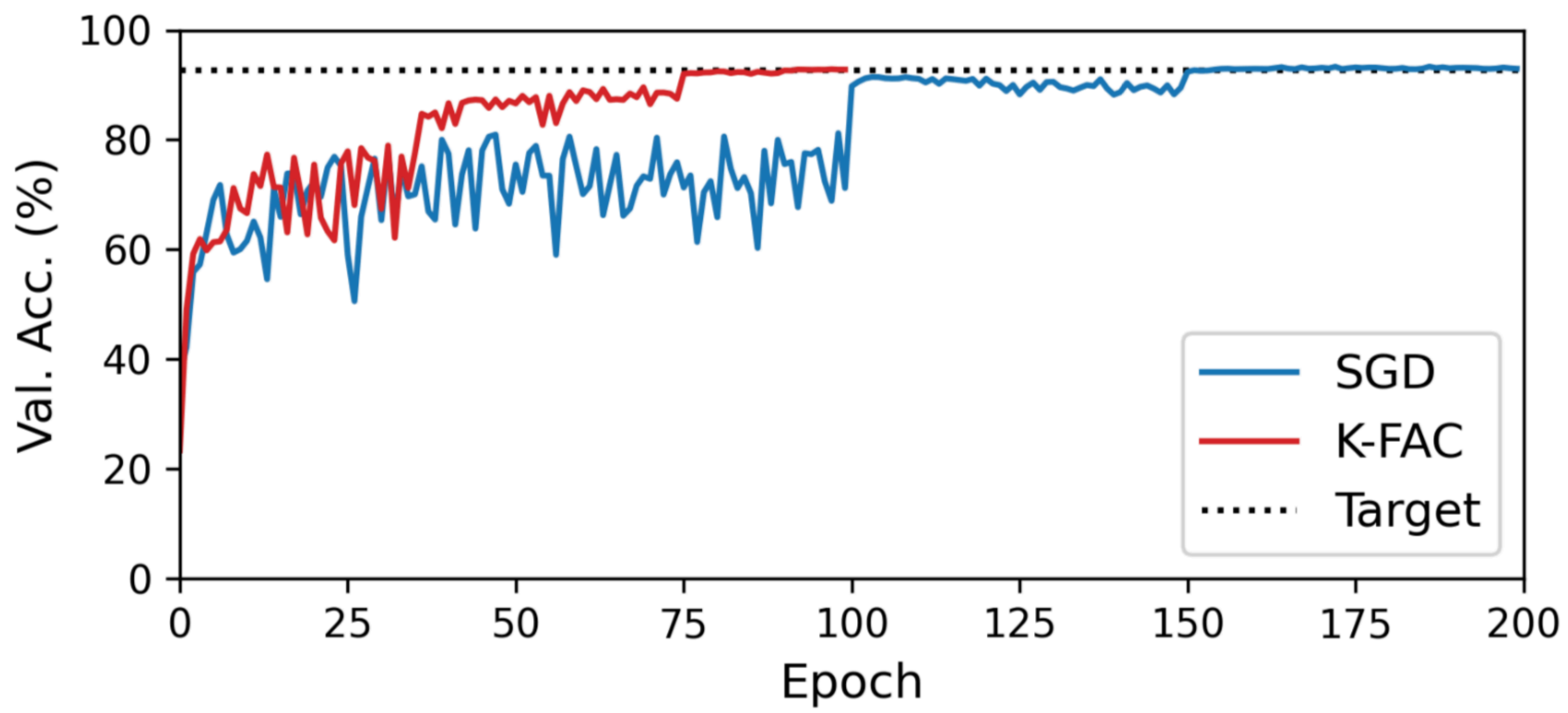

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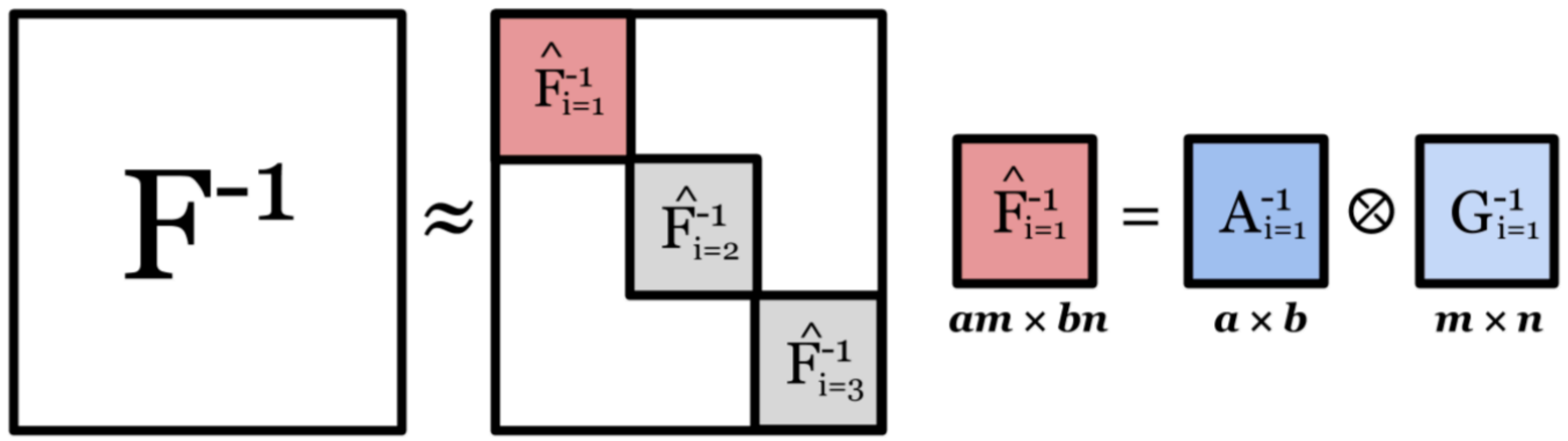

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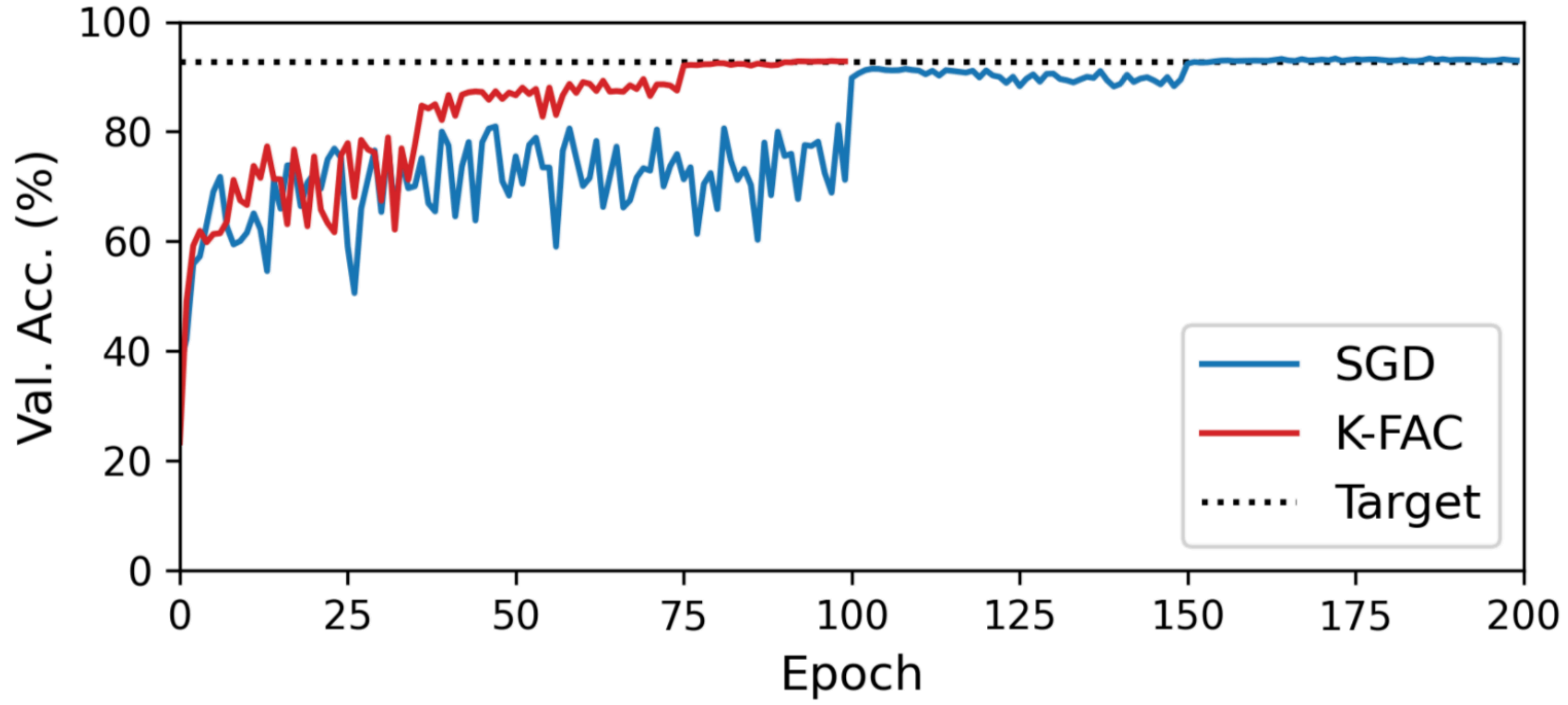

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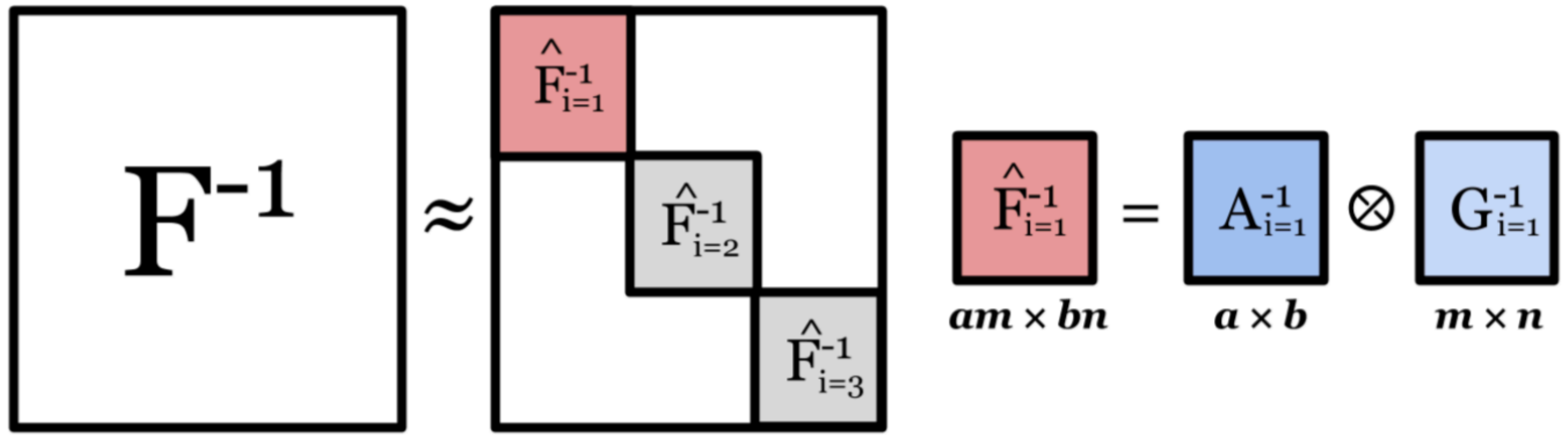

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$$w_i^{(k+1)} = w_i^{(k)} - \alpha^{(k)}(\hat{F}_i + \gamma I)^{-1}\nabla L_i(w_i^{(k)}) \tag{13}$$

$$= w_i^{(k)} - \alpha^{(k)}(G_i + \gamma I)^{-1}\nabla L_i(w_i^{(k)})(A_{i-1} + \gamma I)^{-1}. \tag{14}$$

Distributed Implementation

MEM, COMM, HYBRID - OPT

- Workers n=1,2,...,N
  - *each have copy of entire DNN*
- DNN layers i=1,2,...,M
- Gradient-Reduce:

$$\nabla L_n \rightarrow \nabla L = \frac{1}{N}\sum_{n=1}^{N} \nabla L_n$$

- Factor-Reduce:

$$A^n_{(i-1)}, G^n_i \rightarrow A_{(i-1)} = \sum_{n=1}^{N} A^n_{(i-1)}, G_i = \sum_{i=1}^{N} G^n_i$$

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- **COMM-OPT**: $A_{(i-1)}$, G_i *i=1,…,M split across all workers, decomps stored on all workers.*
  A. *Grad all-reduce*
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  C. *Eigen-decomp broadcast*
  D. *Precondition Gradient*

HYBRID-OPT & results

tunable memory-comm tradeoff

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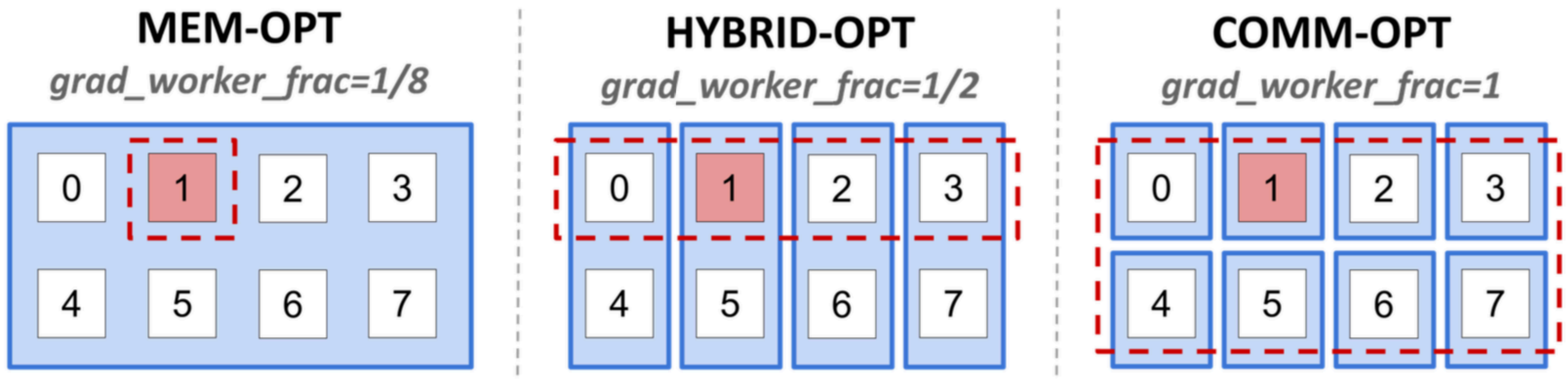

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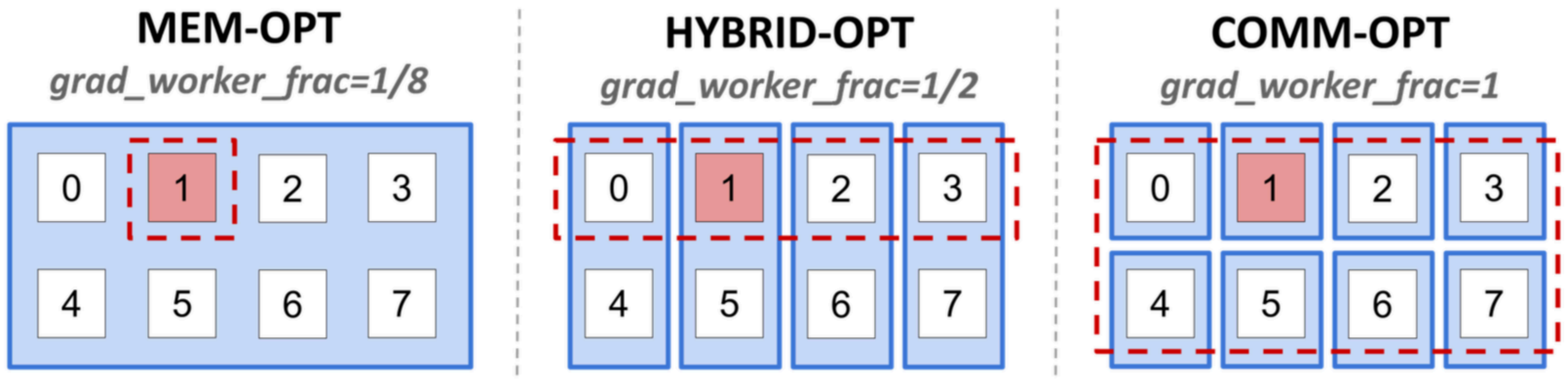

"I'll precondition the gradient for you"

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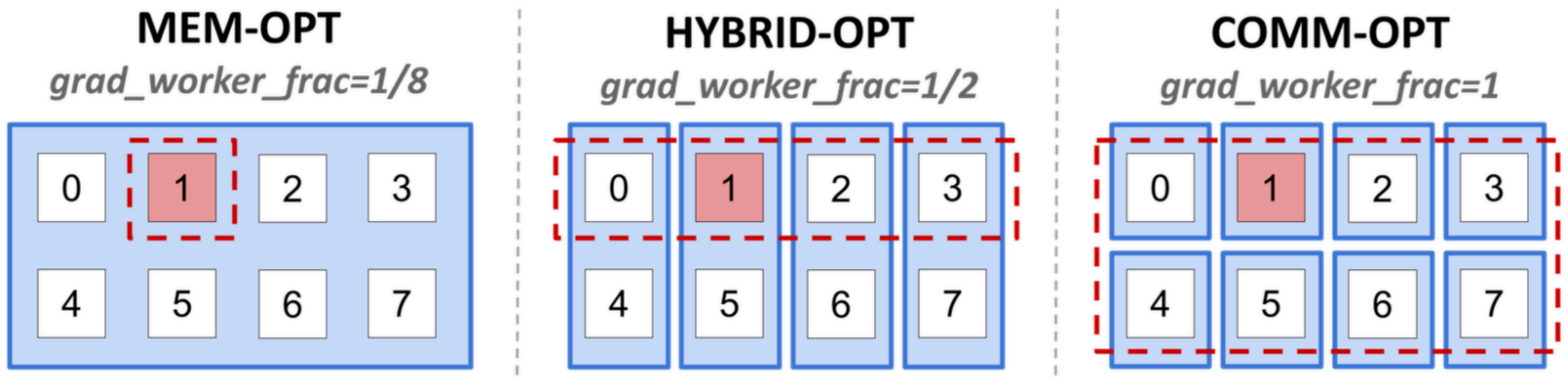

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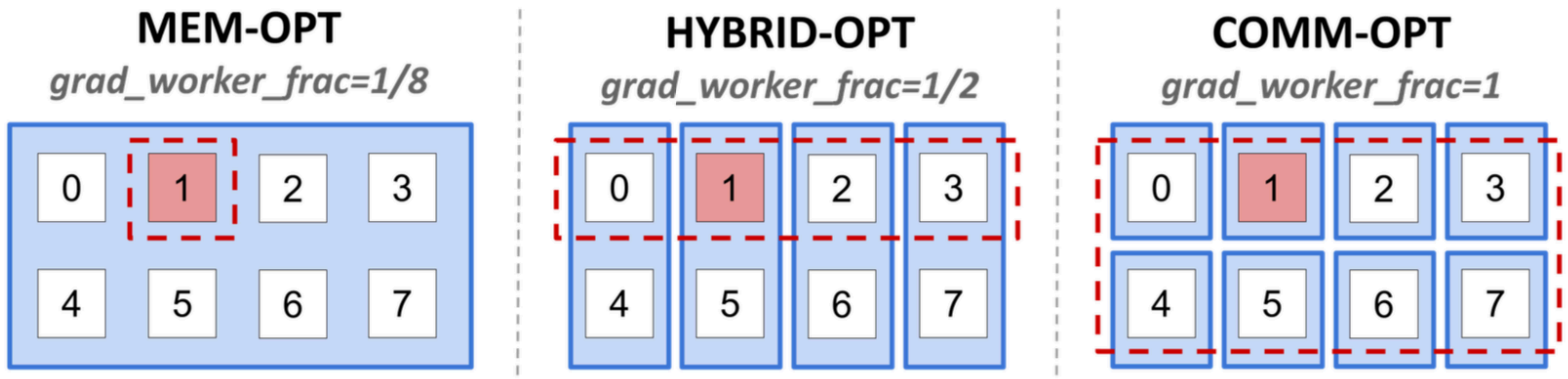

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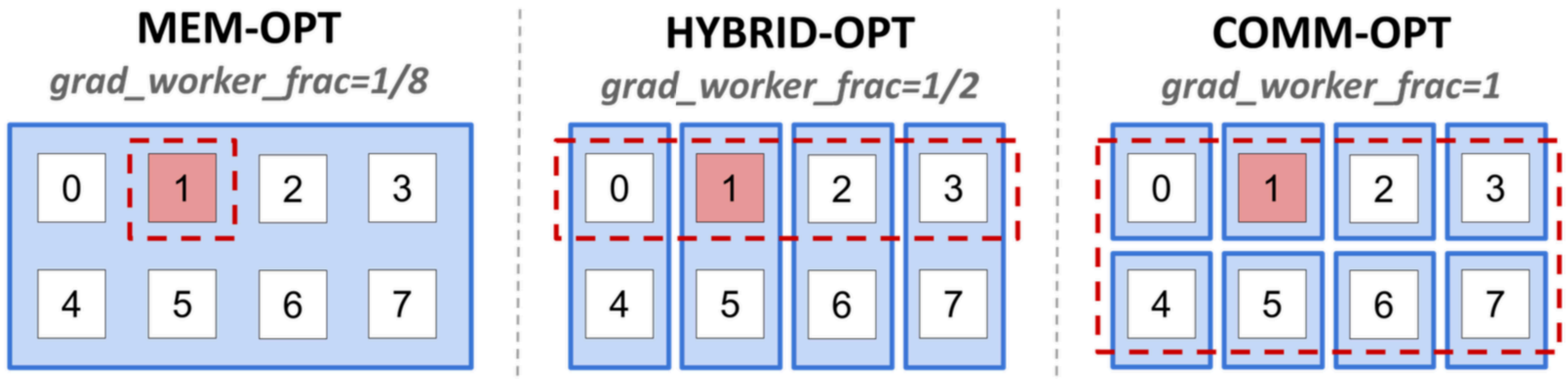

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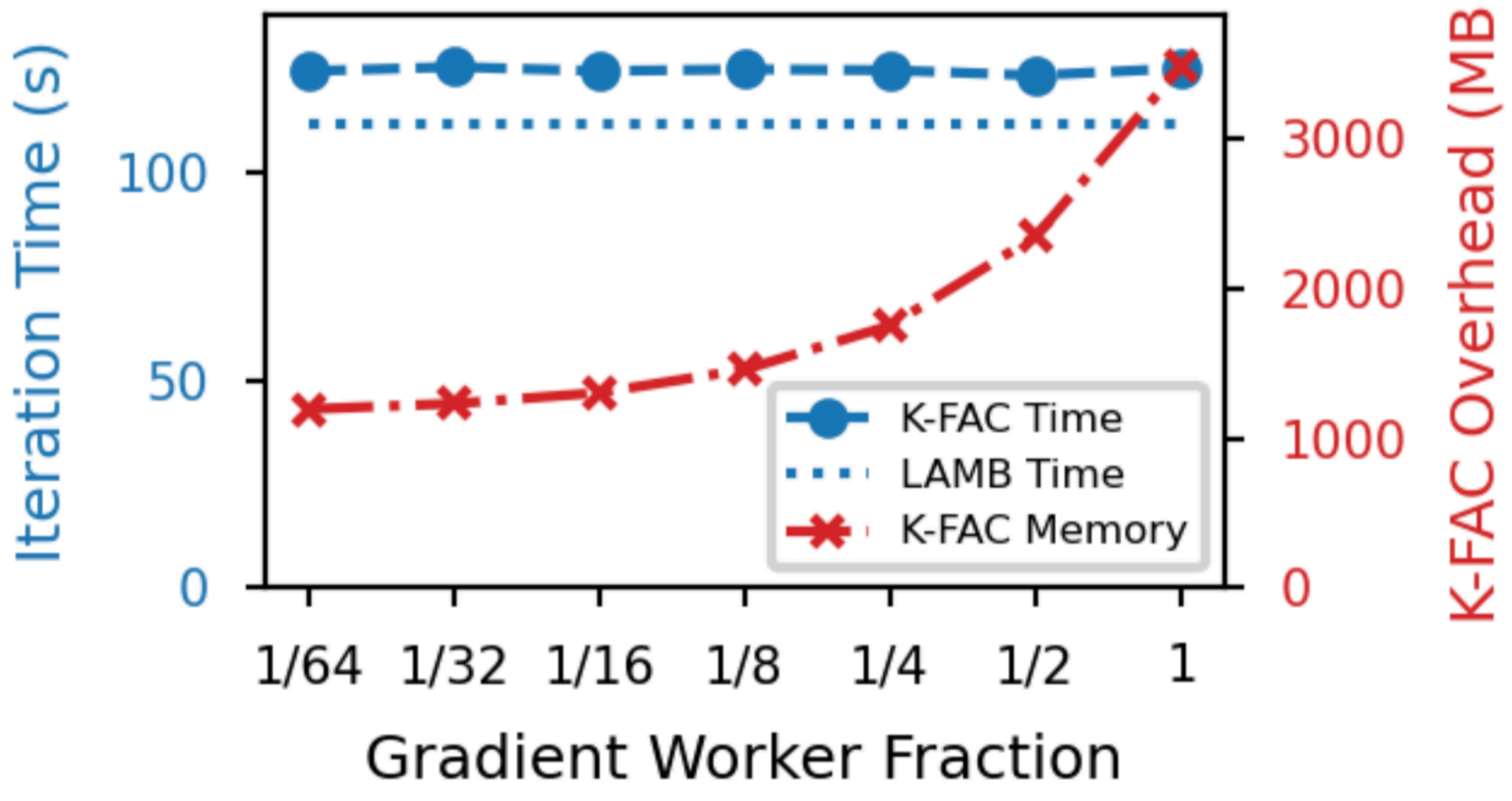

(f) BERT-Large Phase 2 (FP16)

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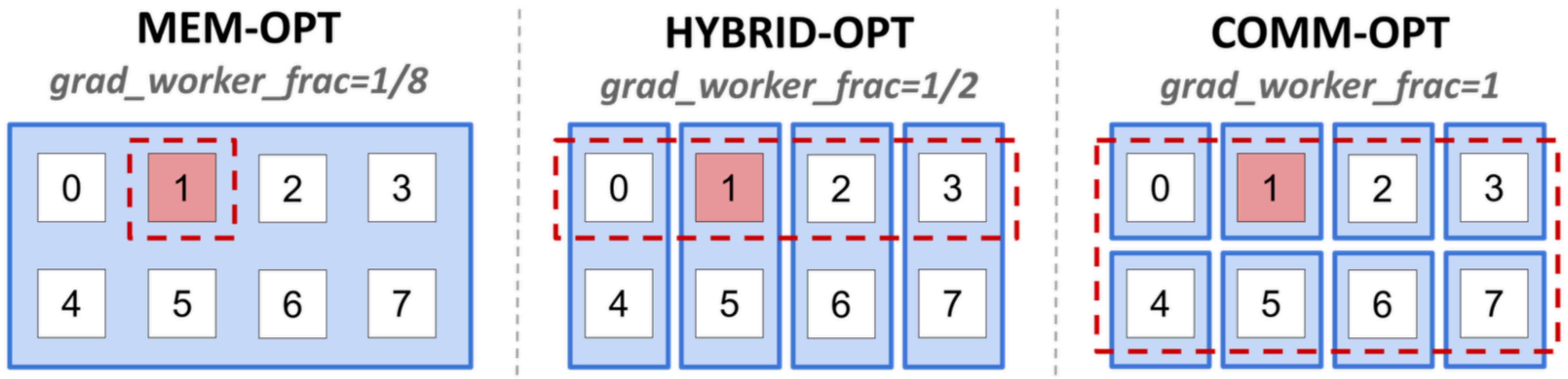

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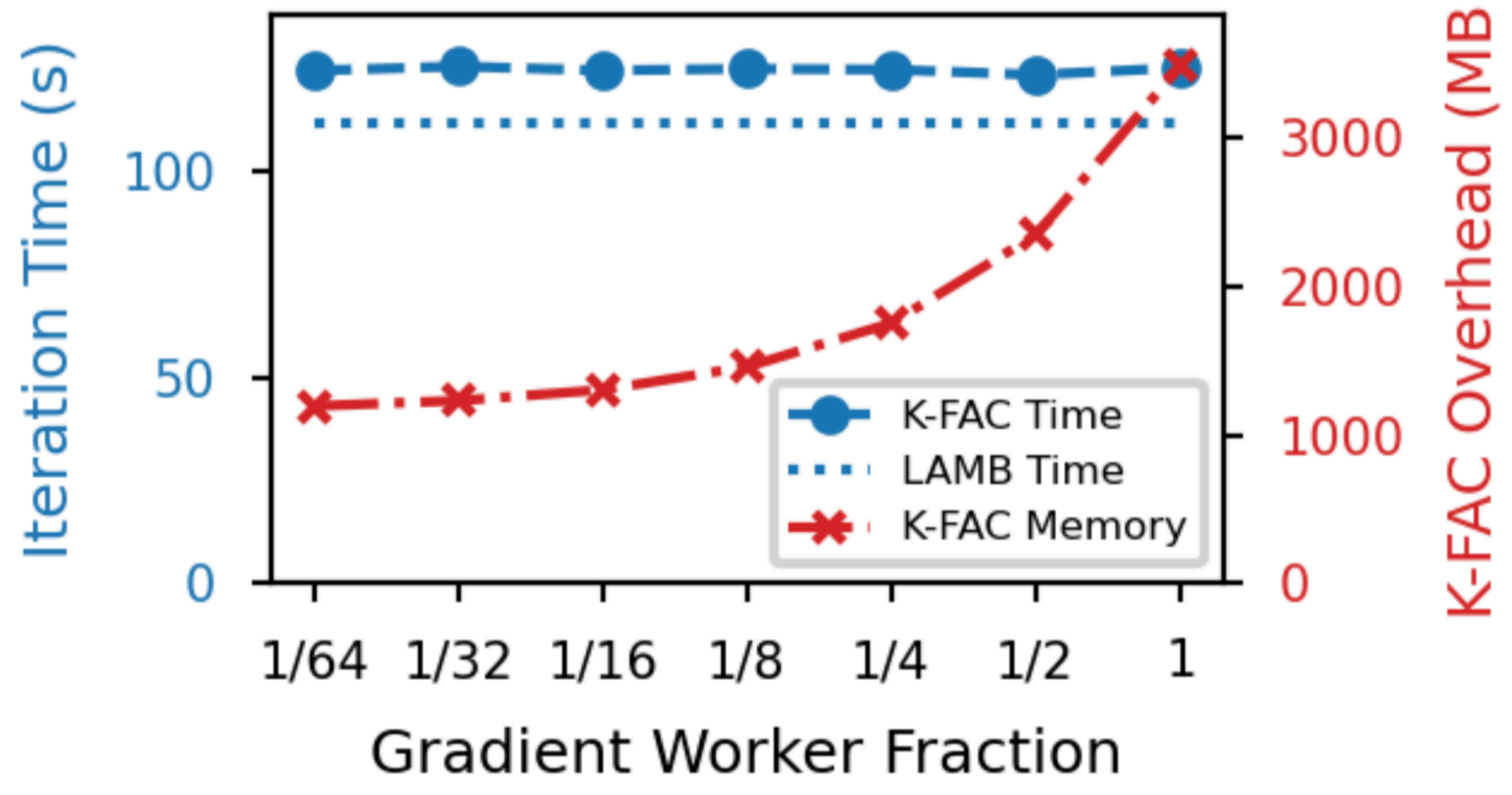

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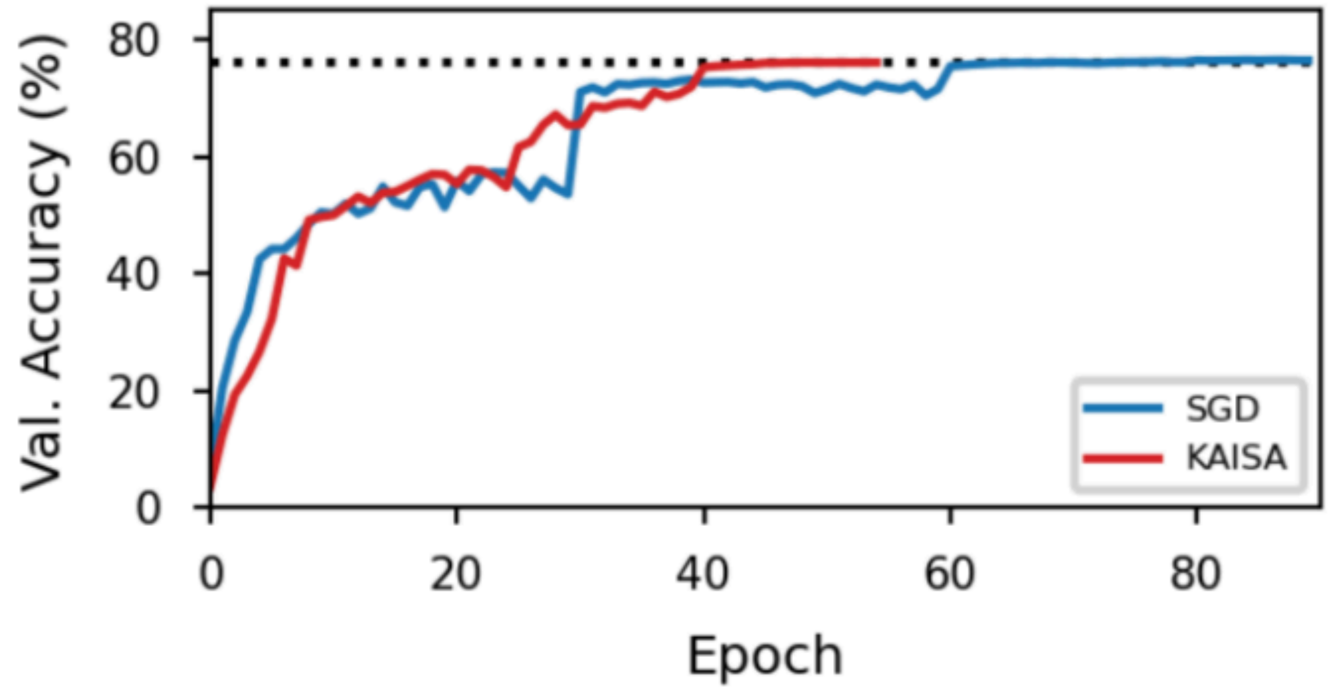
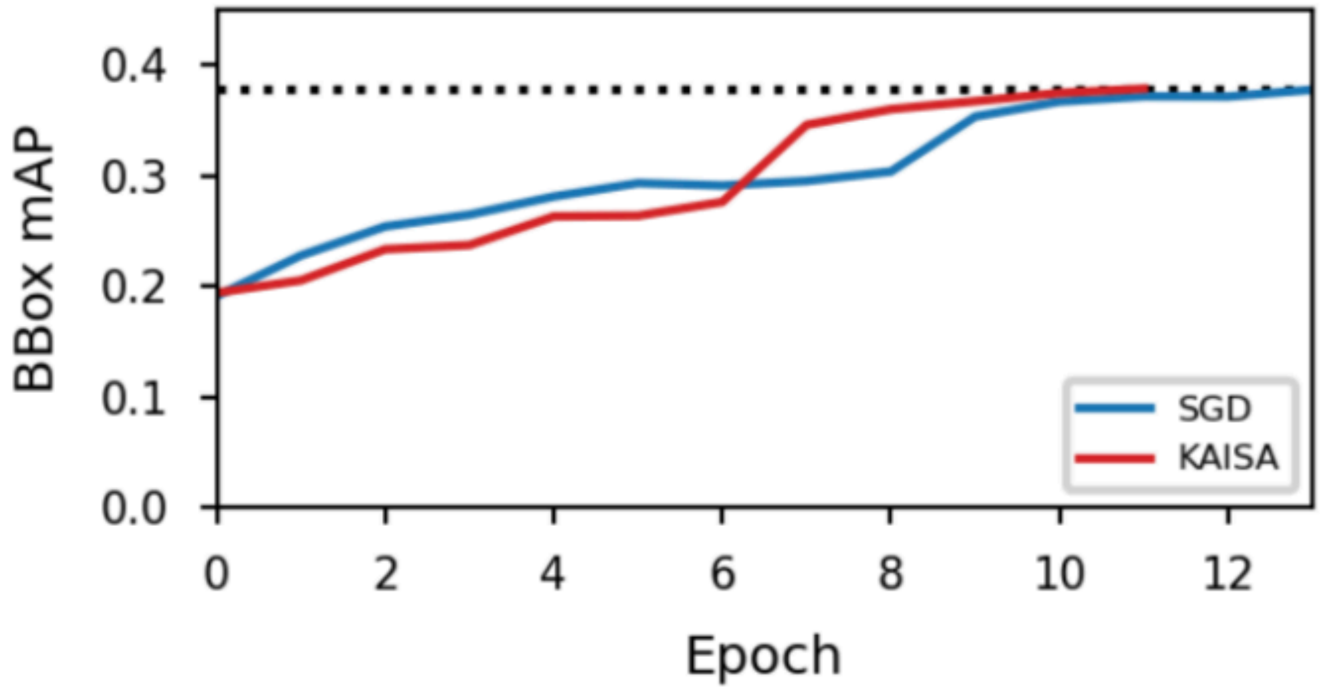
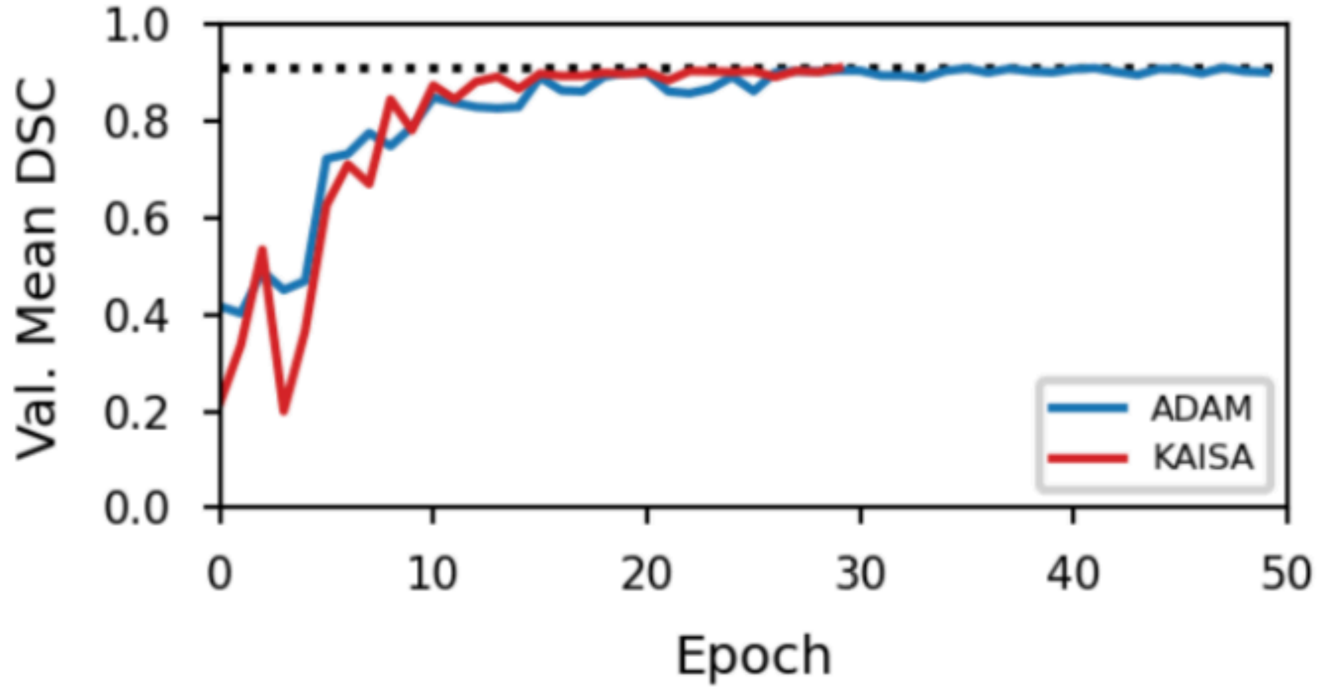


(a) ResNet-50. The time-to-convergence is 268.1 mins for K-FAC and 354.0 mins for momentum SGD.



(b) Mask R-CNN. The time-to-convergence is 115.8 mins for K-FAC and 136.1 for SGD.



(c) U-Net. The time-to-convergence is 10.9 mins for K-FAC and 14.6 for ADAM.