FALQON: Accelerating LoRA Fine-tuning with Low-Bit Floating-Point Arithmetic

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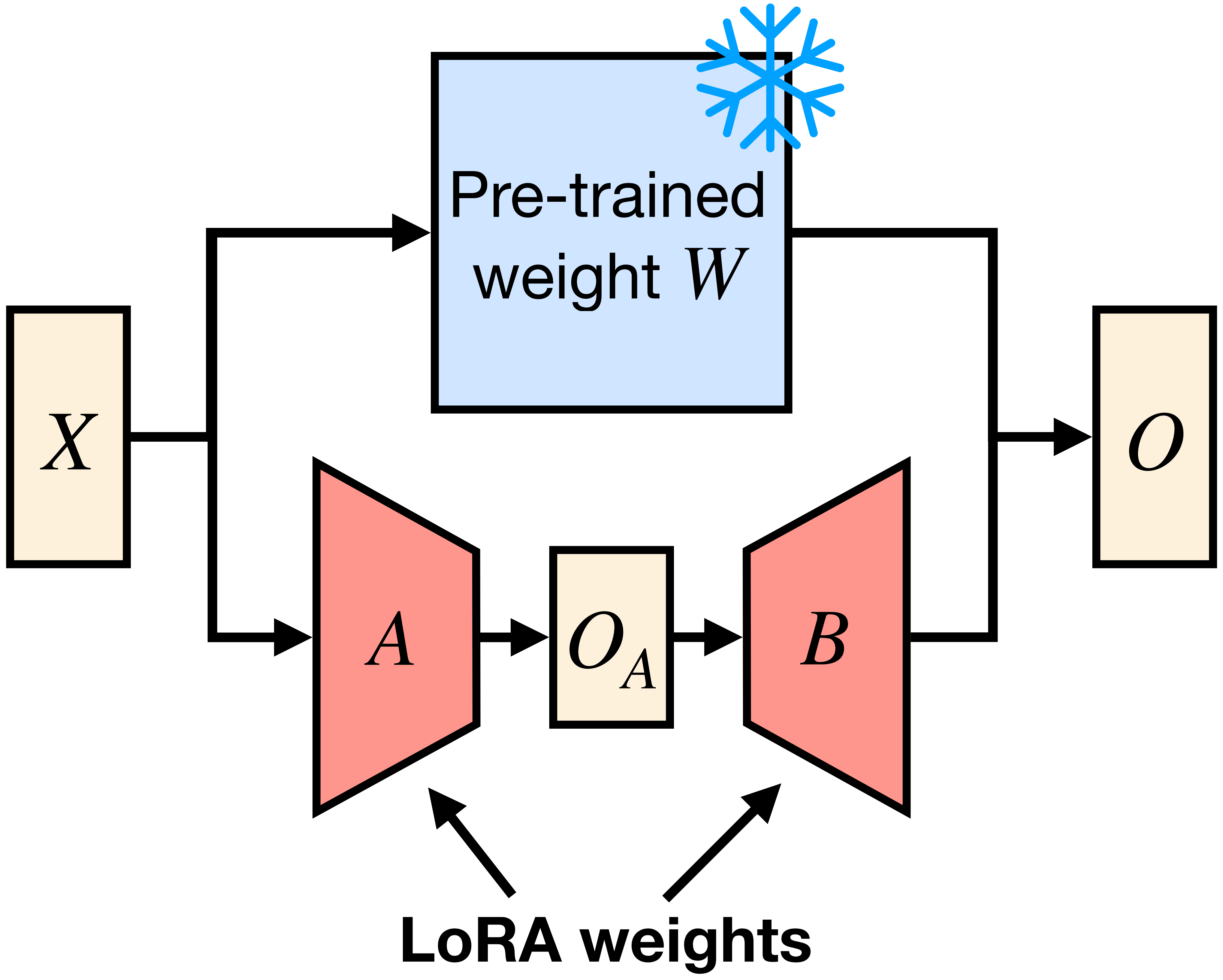
NEURAL INFORMATION PROCESSING SYSTEMS

Accelerated Intelligent Systems Lab.

Backgrounds

Low-Rank Adaptation (LoRA)

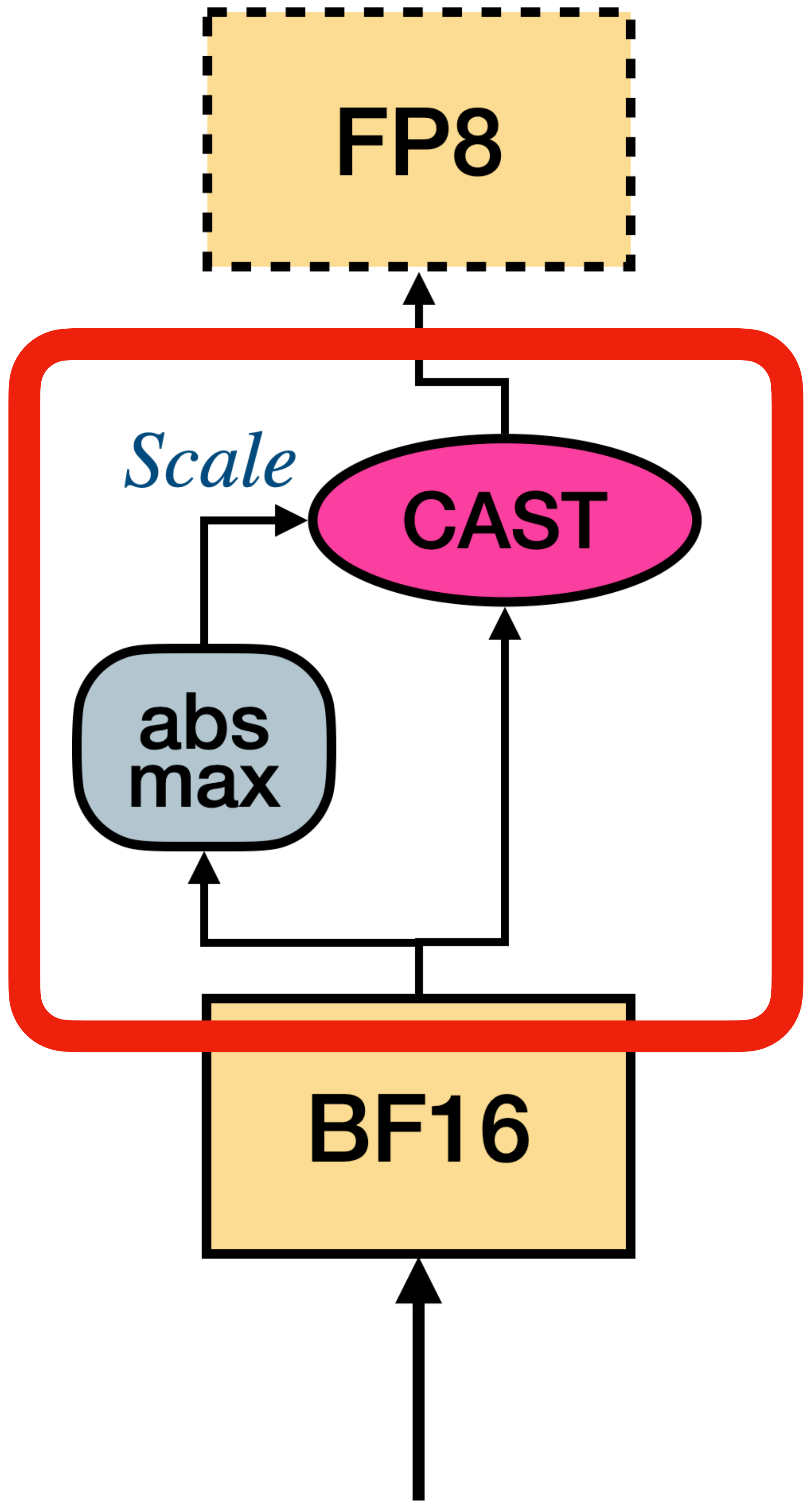


- Low-rank adaptation (LoRA)
  - Freeze pre-trained weights
  - Train LoRA weights only
  - Reduce memory consumption of gradient and optimizer state

$$W_{FT} = W_{orig} + \underbrace{\Delta W}_{\text{weight update}} \approx W_{orig} + \underbrace{BA}_{\text{low-rank projection (LoRA)}}$$

Backgrounds

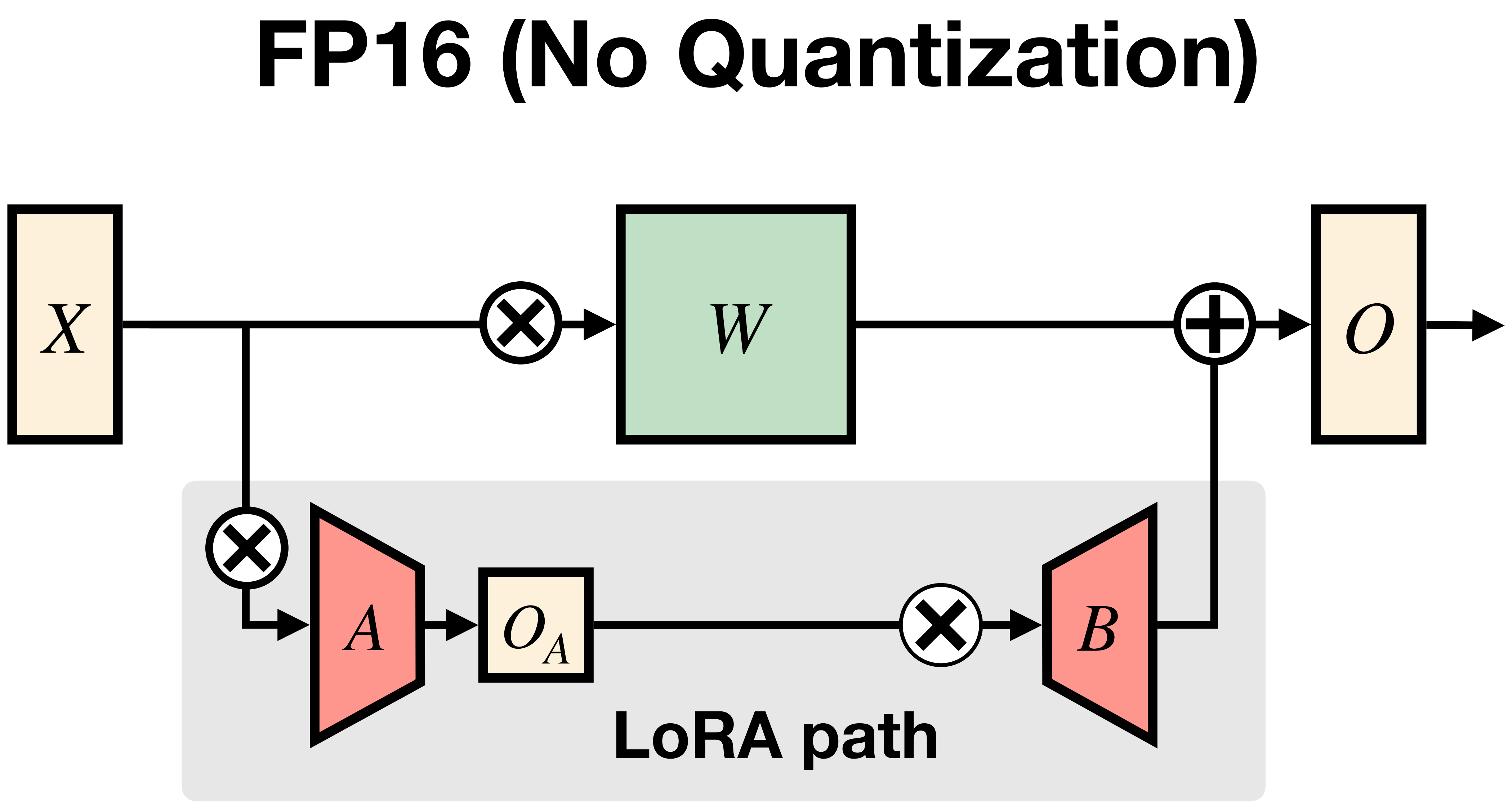
FP8 Quantization in Linear Layer

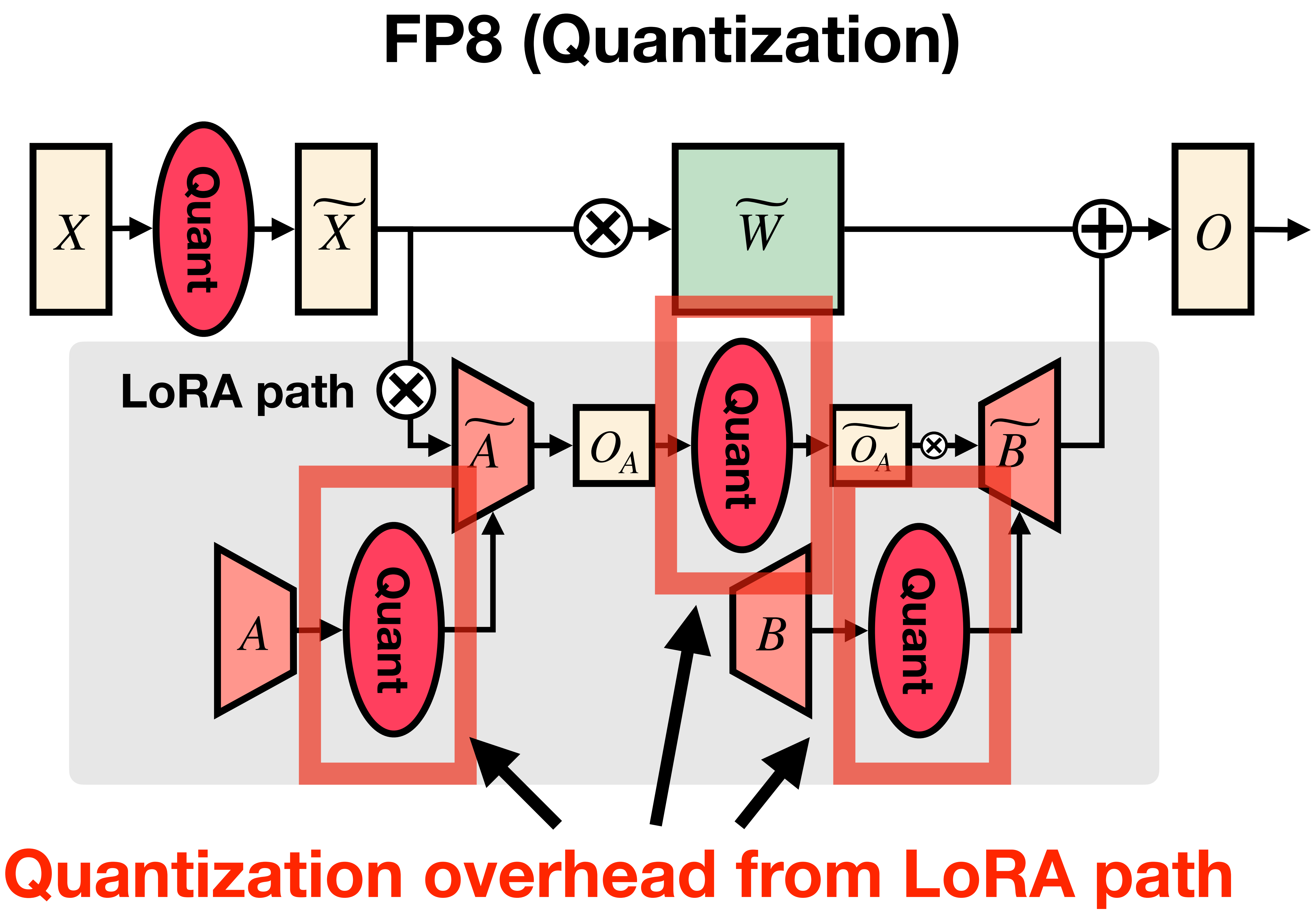


- FP8 quantization (conversion) requires scaling
  - Calculate absolute max (amax) for scaling
  - For quantization,
    we need a **reduction** for amax and **scaling**
  - For small-dimensional MatMul,
    the overhead exceeds the speed up

Motivational Study

Quantization Overhead of LoRA Layers



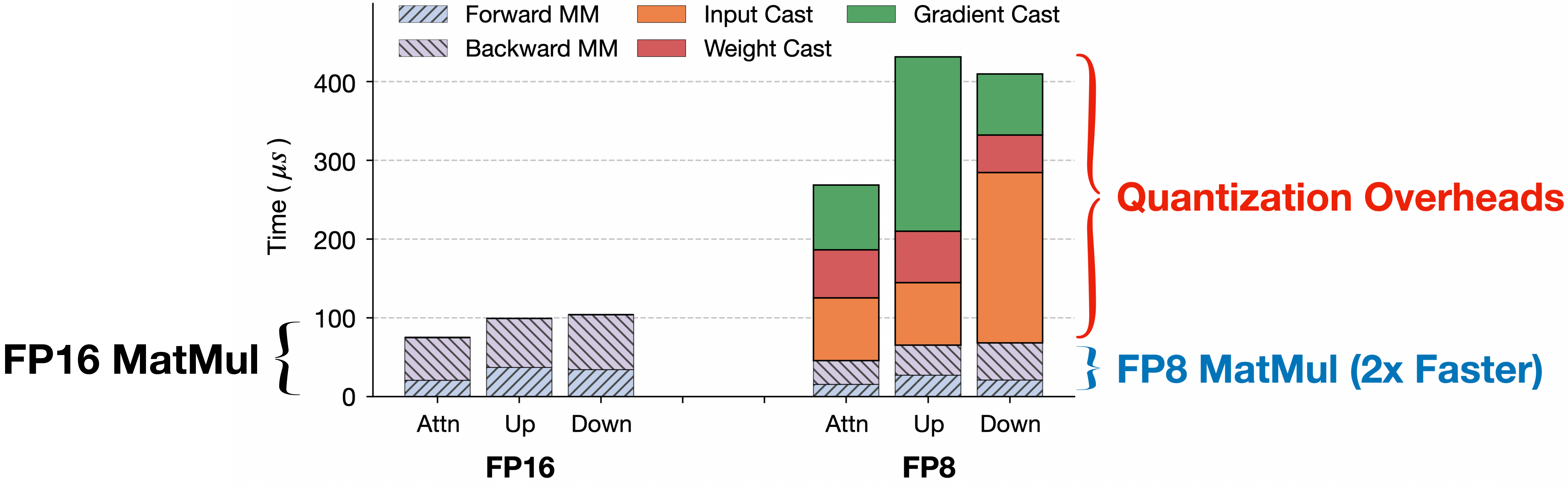


Motivational Study

FP8 Quantization Overhead of LoRA Layers

Problem: Current FP8 framework suffer from quantization overhead on LoRA

Research Goal: Design a low-overhead FP8 framework for LoRA



Proposed Method

1) Melded LoRA: Merging backbone and LoRA for Forward

Quantization Error

$\widetilde{W} = \text{Quantize}(W)$

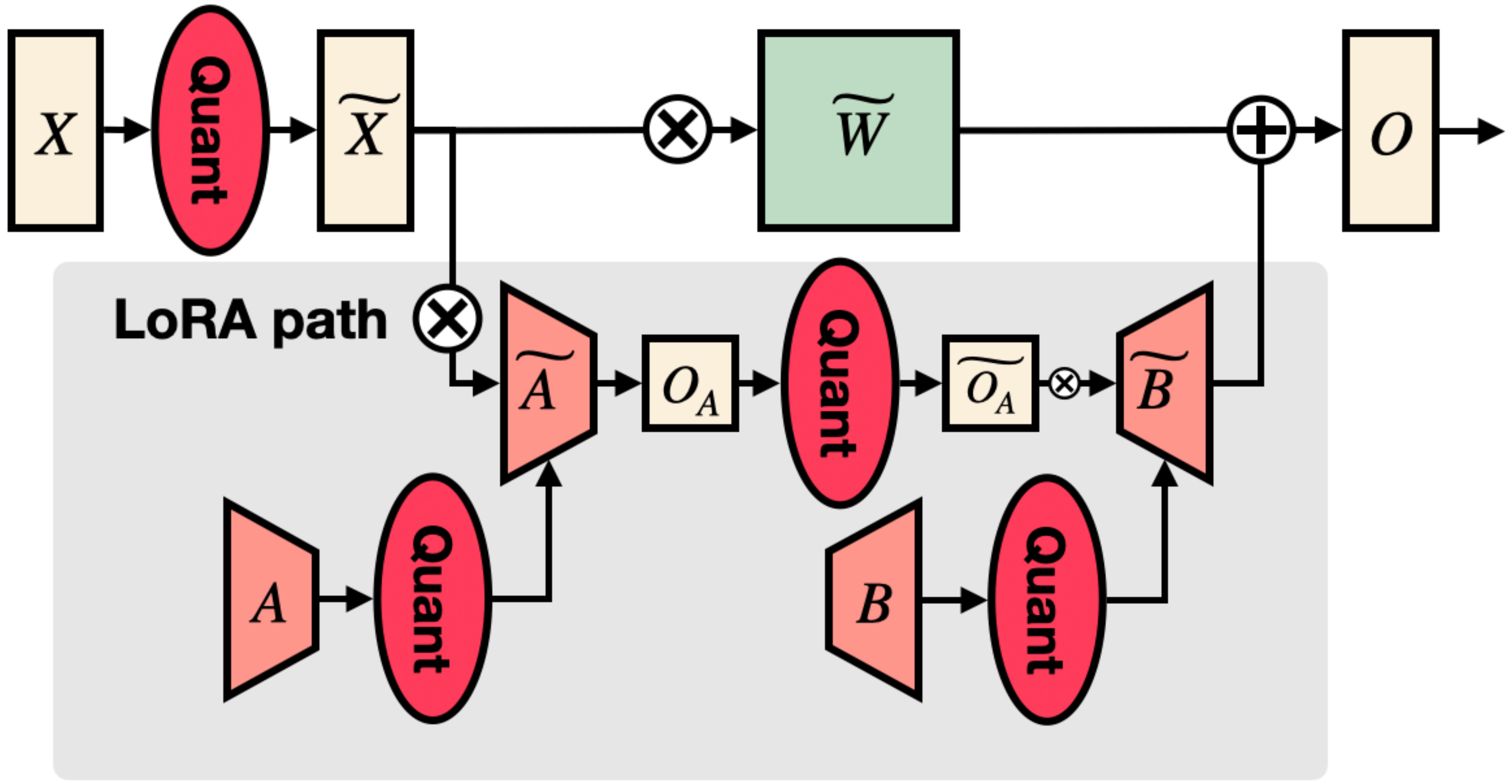
$$\widetilde{W} = W_{orig} + \underbrace{\Delta W_Q}_{\text{Quantization Error}}$$

$$W_{orig} + \widehat{B}\,\widehat{A}$$

where, $\widehat{B}\,\widehat{A} \approx \Delta W_Q$

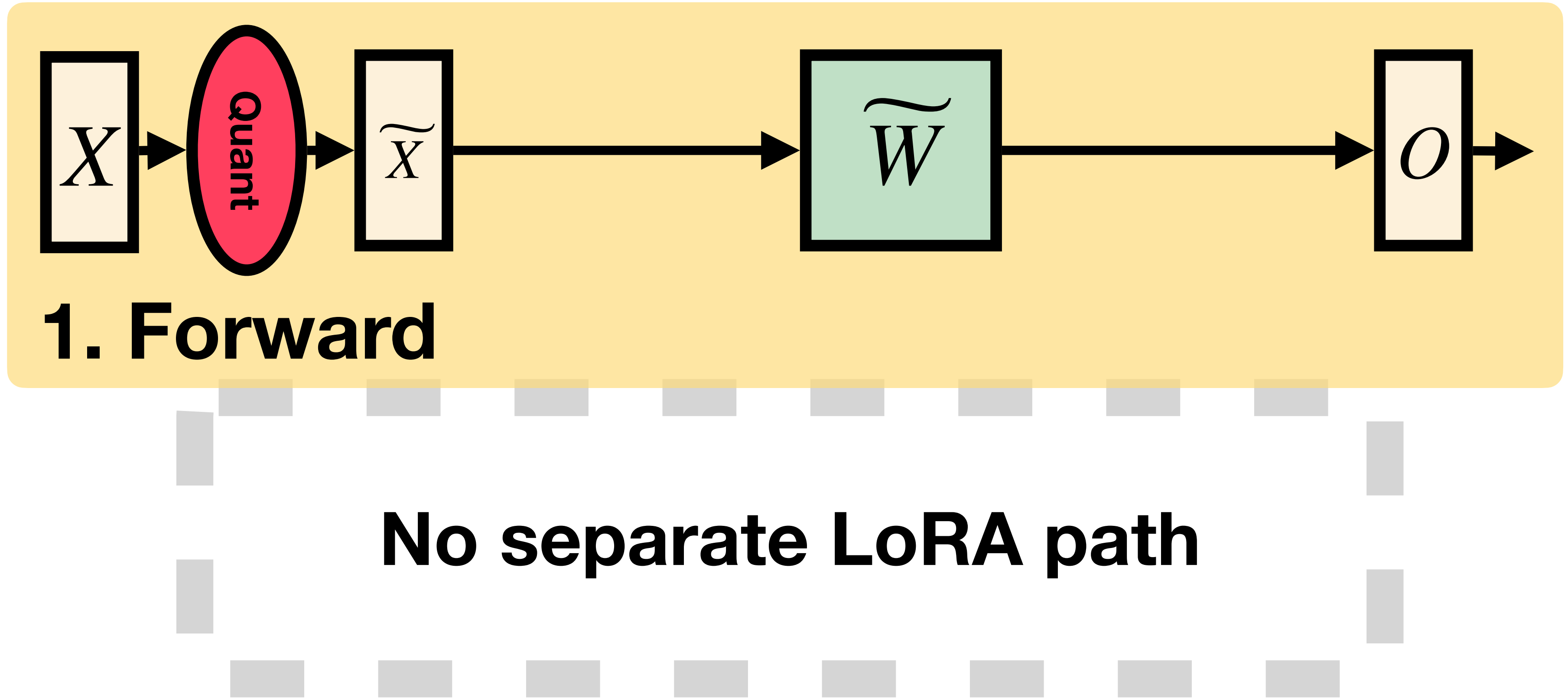
Quantization Error as LoRA

FP8 (Baseline)



FP8 (Ours)

Melded LoRA



Proposed Method

2) Efficient Gradient Computation for Melded LoRA

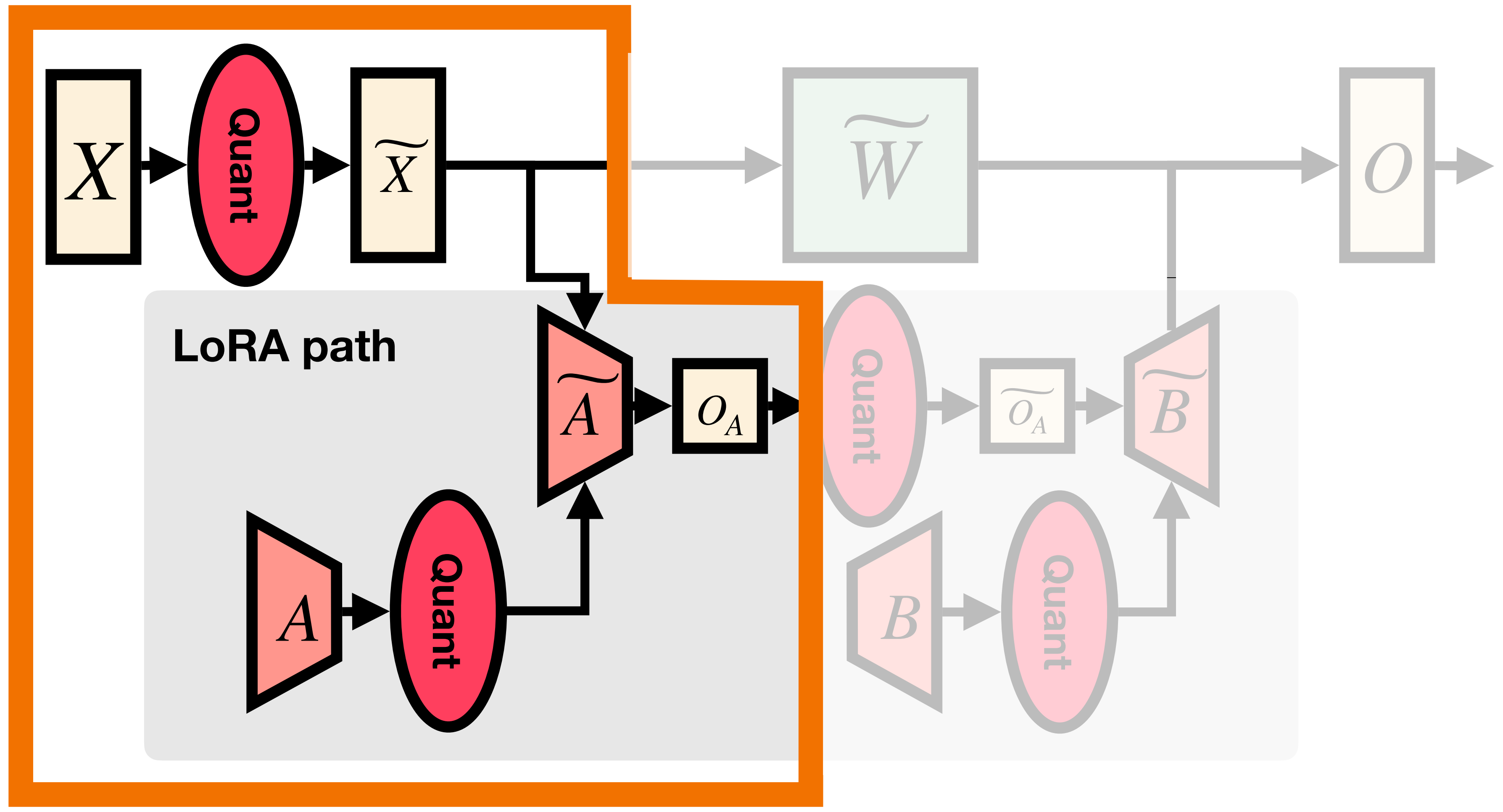
For backward:

(1) We freeze the A matrix

(2) Compute gradient of B matrix

$$\frac{\partial \mathcal{L}}{\partial B} = \frac{\partial \mathcal{L}}{\partial O} x^\top A^\top = \frac{\partial \mathcal{L}}{\partial O} (Ax)^\top$$

Naive Ax computation yields further overhead



Proposed Method

2) Efficient Gradient Computation for Melded LoRA

For backward:

(1) We freeze the A matrix

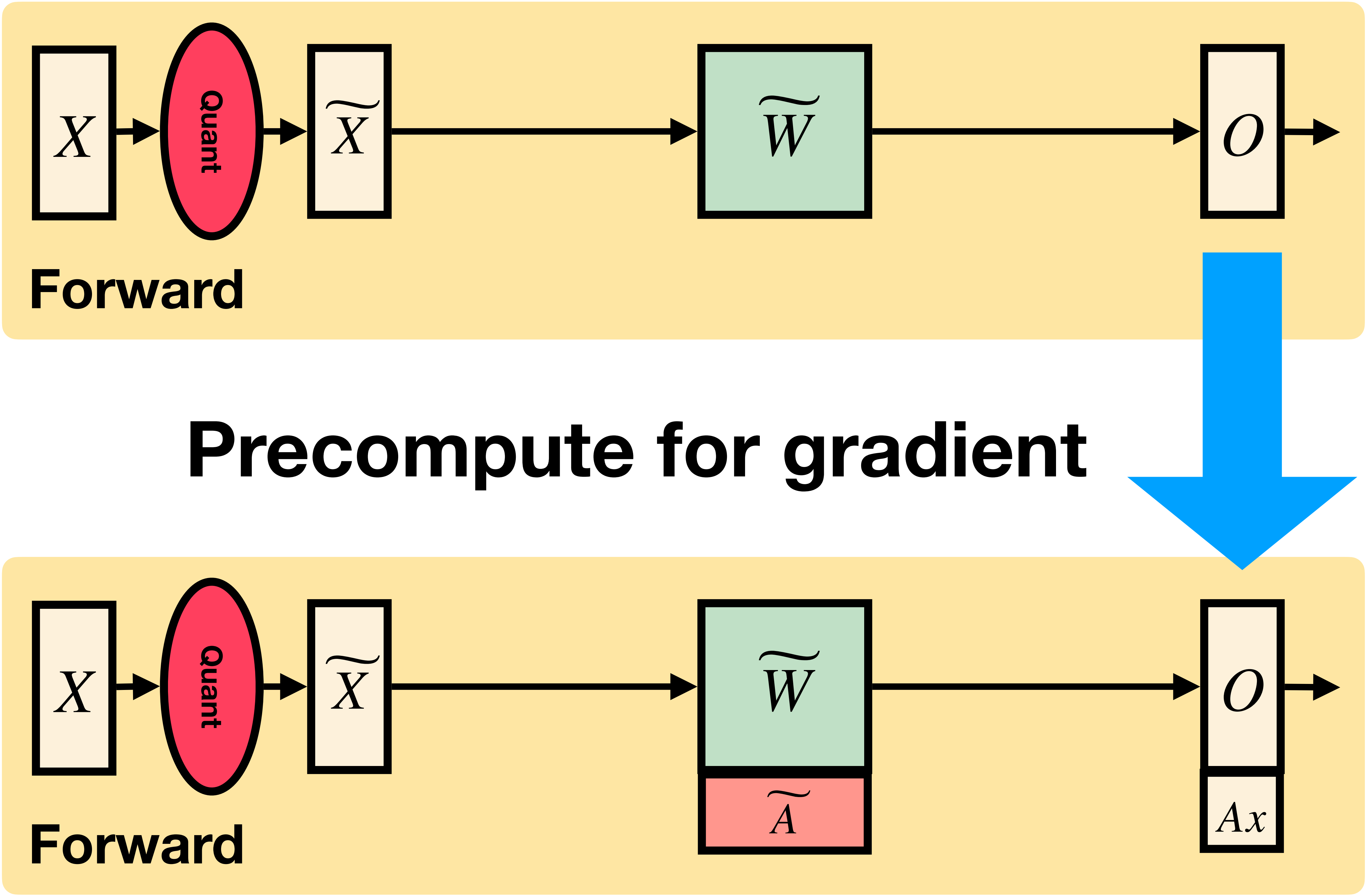
(2) Compute gradient of B matrix

$$\frac{\partial \mathscr{L}}{\partial B} = \frac{\partial \mathscr{L}}{\partial O} x^\top A^\top = \frac{\partial \mathscr{L}}{\partial O}(Ax)^\top$$

(2)-1 Merge A matrix to W:

$$\widetilde{W}' = \begin{bmatrix} \widetilde{W} \\ \widetilde{A} \end{bmatrix} \in \mathbb{R}^{(m+r)\times n}$$

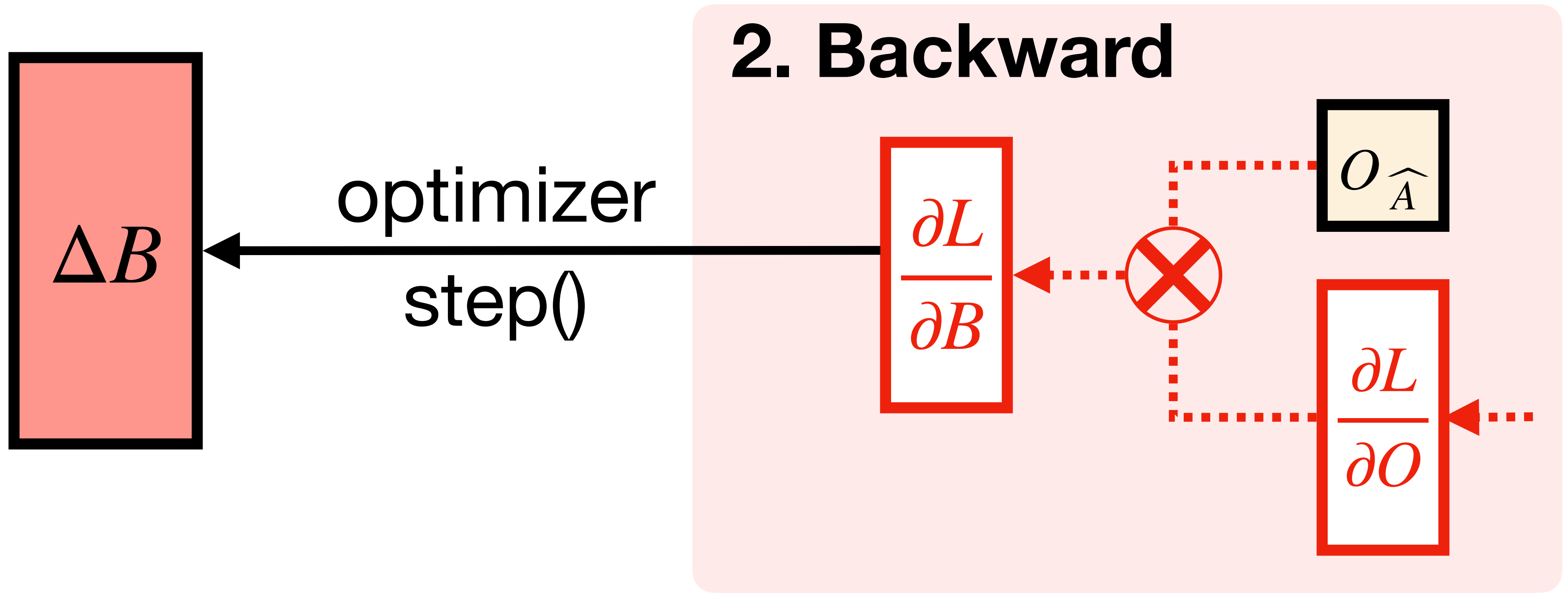
(2)-2 Precompute Ax in forward: $\widetilde{W}'\widetilde{x} = \begin{bmatrix} O \\ Ax \end{bmatrix} \in \mathbb{R}^{(m+r)\times d}$



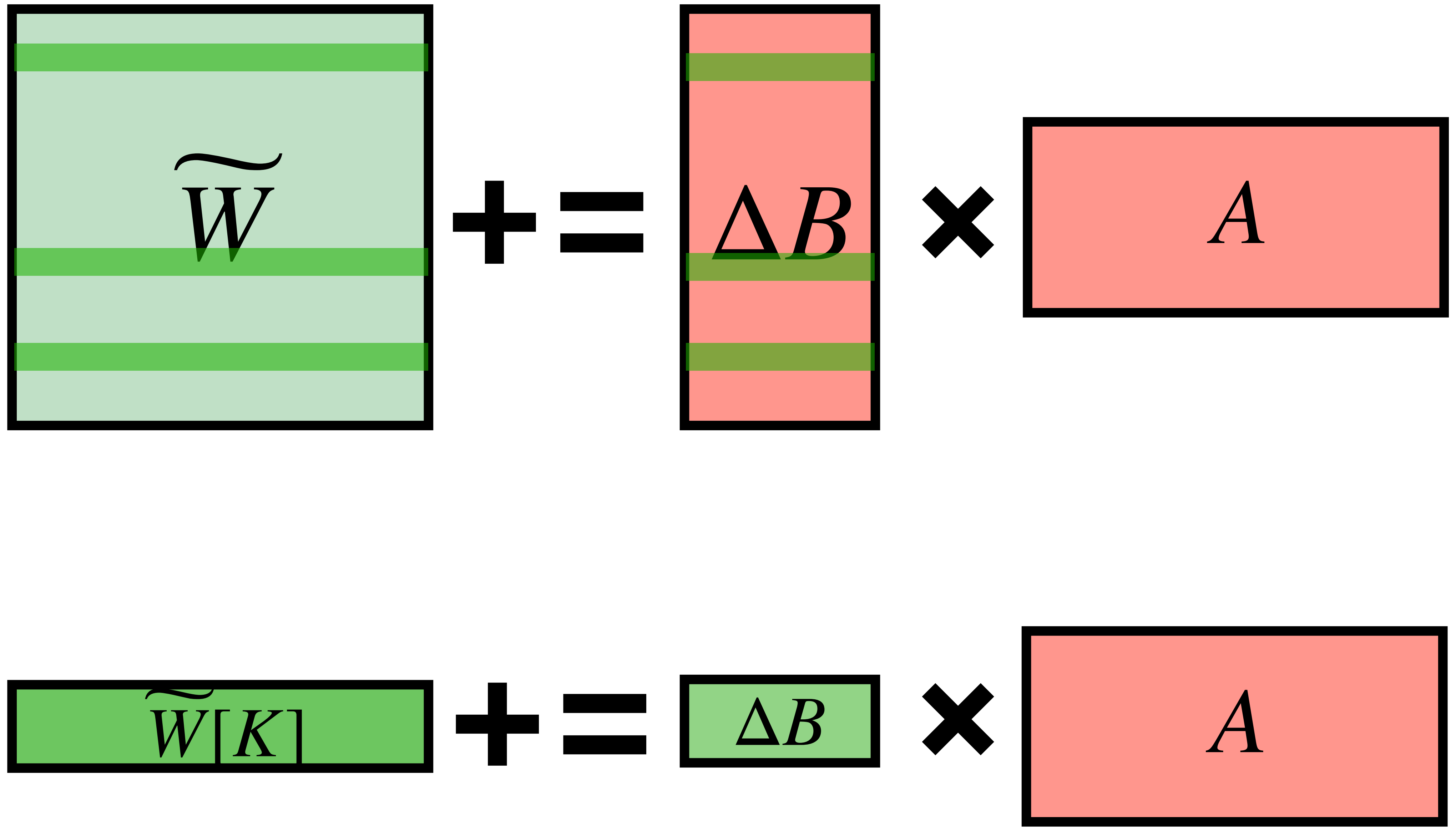
Proposed Method

3) Row-wise **Update** of Quantized Weights

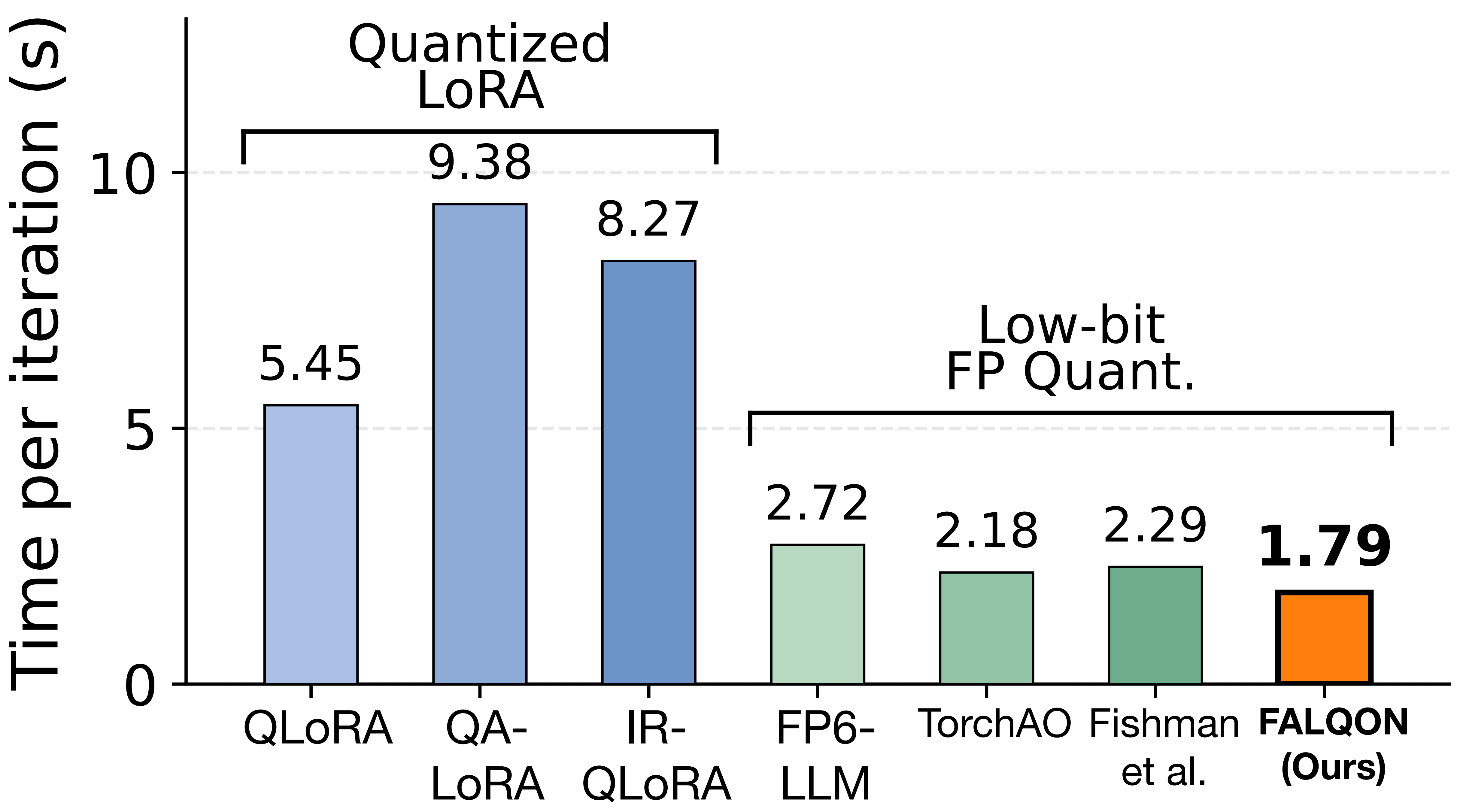
- ΔBuffer: store updates of B
    - Initialized to a zero-matrix



- Top-K Row-wise Update
    - Small updates cannot exceed quantization-grid
    - Apply large update rows only

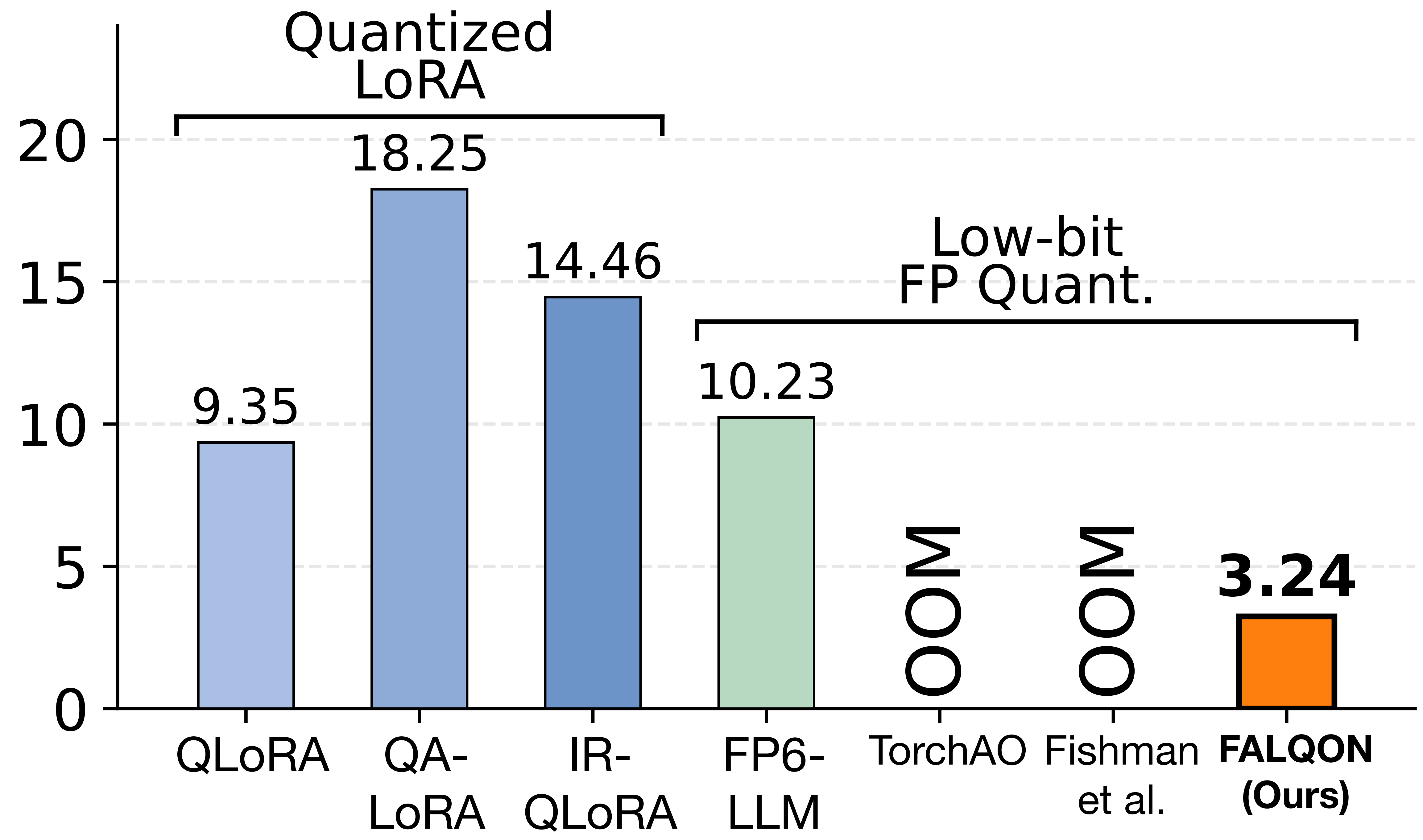


Evaluation



5-shot MMLU	0.3272	0.3548	0.3388	0.2295	0.3393	0.3537	0.3491

LLaMA-7B



5-shot MMLU	0.4443	0.4729	0.4349	0.2298	OOM	OOM	0.4644

LLaMA-13B

Conclusion

- We show that existing FP8 quantization methods incur substantial overhead with small-dimensional LoRA adapters.
- We propose FALQON, which merges the LoRA adapter in the quantized backbone and significantly reduces quantization overhead.
- FALQON achieves up to three times speedup over existing quantized LoRA methods.