CSCI 5541: Natural Language Processing

Lecture XX: LLM Compute efficiency and engineering

James Mooney

With slides borrowed from Song Han (MIT)

University of Minnesota
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What Is Efficiency and Why Does It Matter?

- Efficiency for NLP is concerned with delivering faster, cheaper, smaller, less energy intensive solutions to problems involving natural language
- Faster models means LLM model services (GPT3.5, Claude 2.0, etc.) can meet the demands of many clients more quickly
- Cheaper models reduce costs for LLM model service providers
- Smaller model sizes allow for service providers to use fewer resources and can allow for individuals to deploy LLMs to their own (smaller) devices
- Less energy intensive means lower cost and easier to deploy at the edge, where energy is harder to come by

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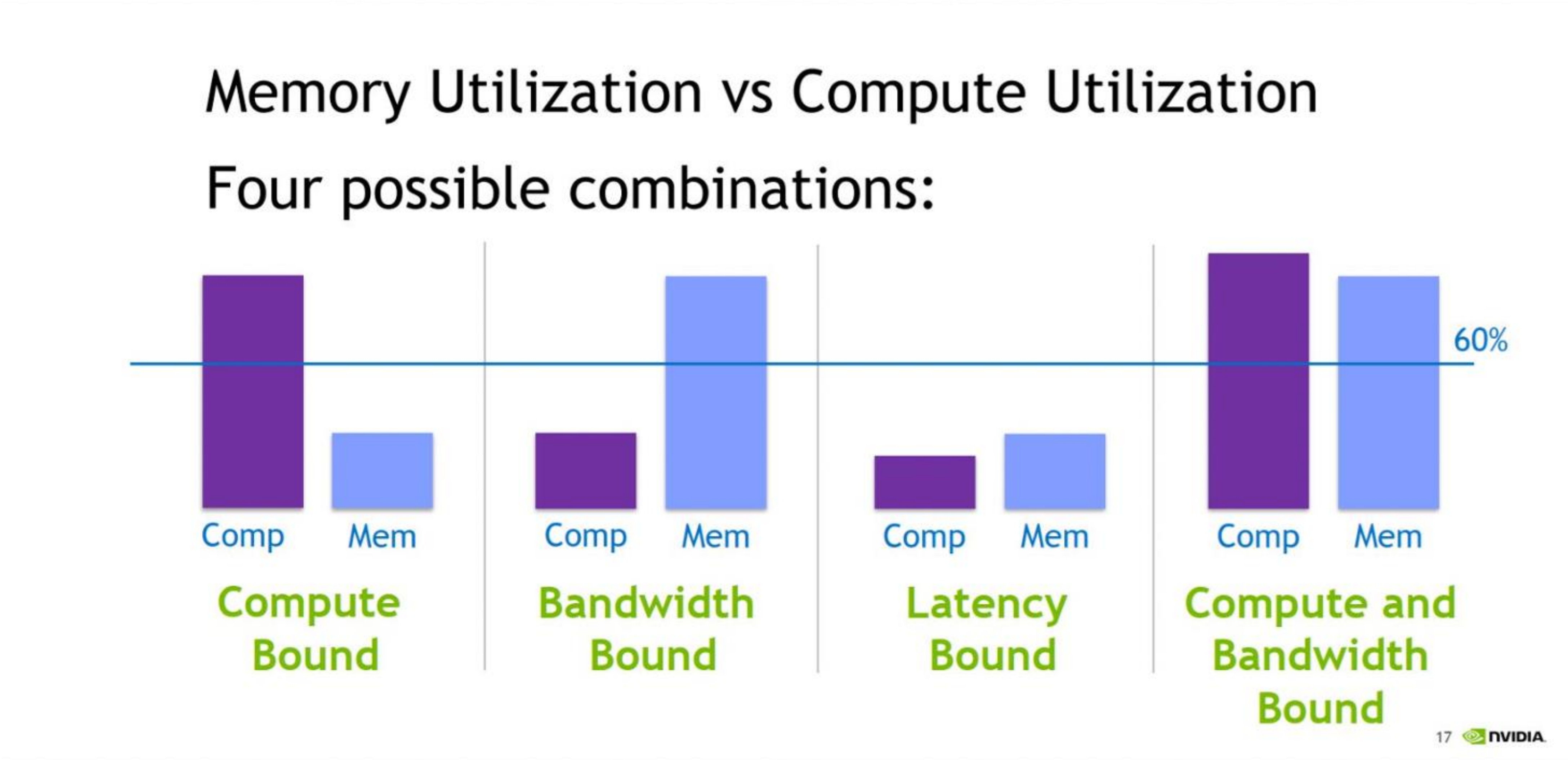
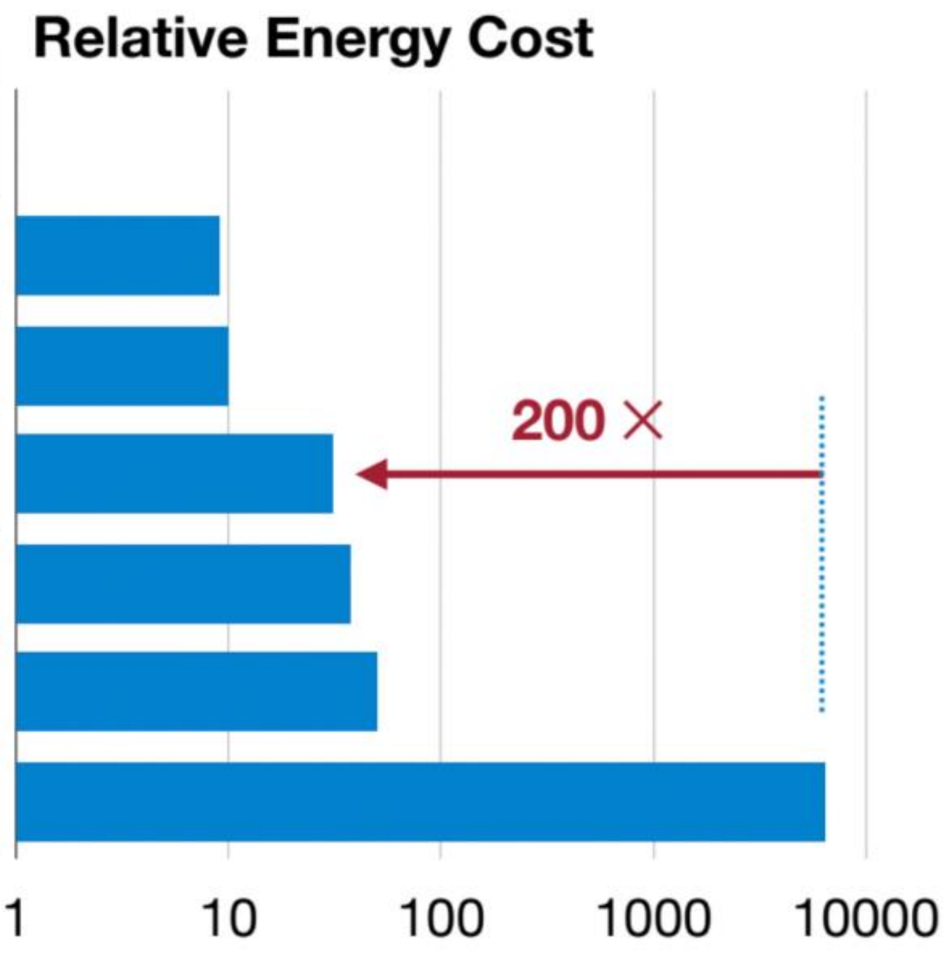
Model Speed


Memory Utilization vs Compute Utilization
Four possible combinations:
60%
Comp
Mem
Compute Bound
Comp
Mem
Bandwidth Bound
Comp
Mem
Latency Bound
Comp
Mem
Compute and Bandwidth Bound
17
NVIDIA

Model Energy Use

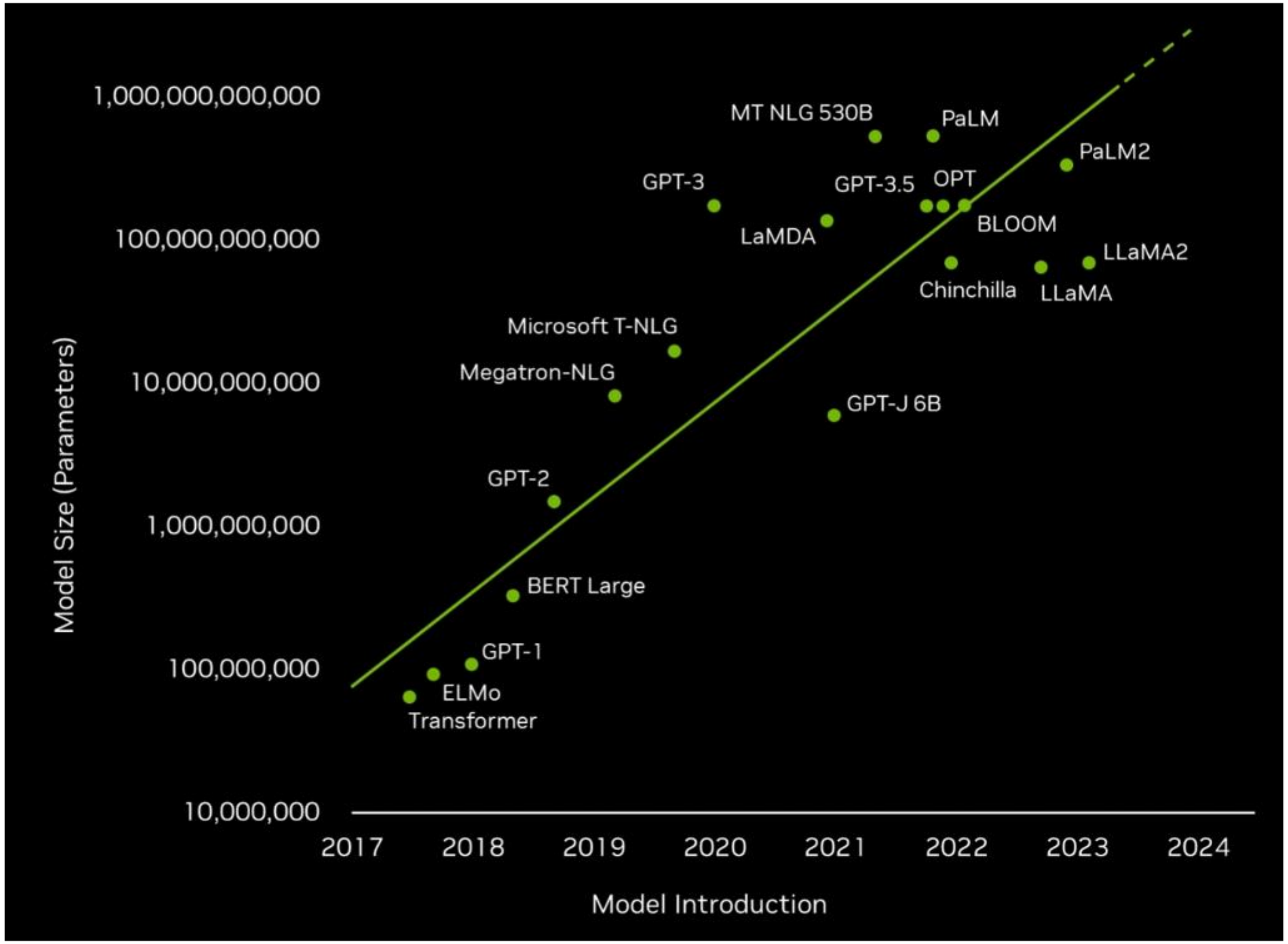
Operation	Energy [pJ]
32 bit int ADD	0.1
32 bit float ADD	0.9
32 bit Register File	1
32 bit int MULT	3.1
32 bit float MULT	3.7
32 bit SRAM Cache	5
32 bit DRAM Memory	640

Rough Energy Cost For Various Operations in 45nm 0.9V

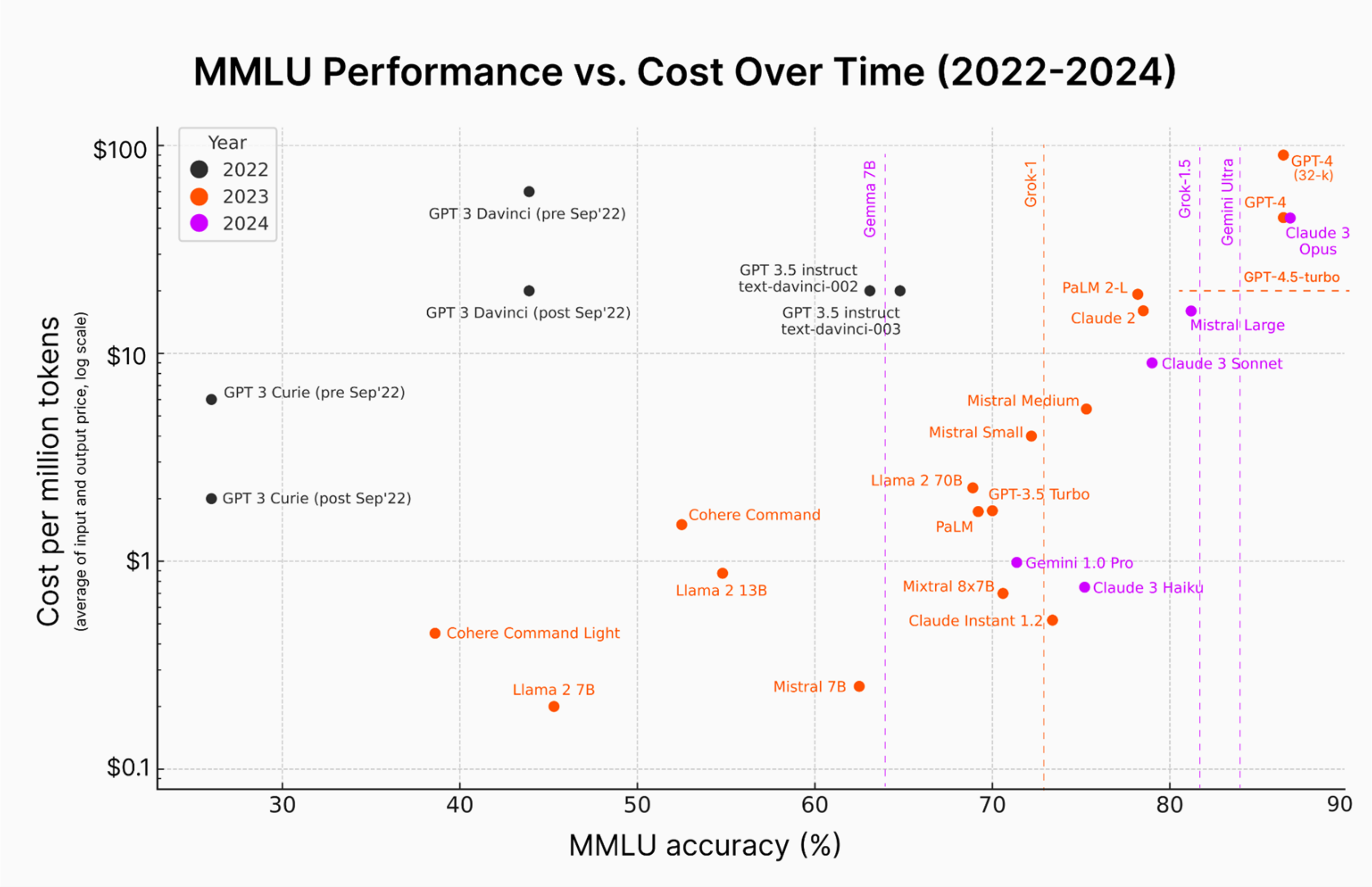


Computing's Energy Problem (and What We Can Do About it) [Horowitz, M., IEEE ISSCC 2014

Model Size

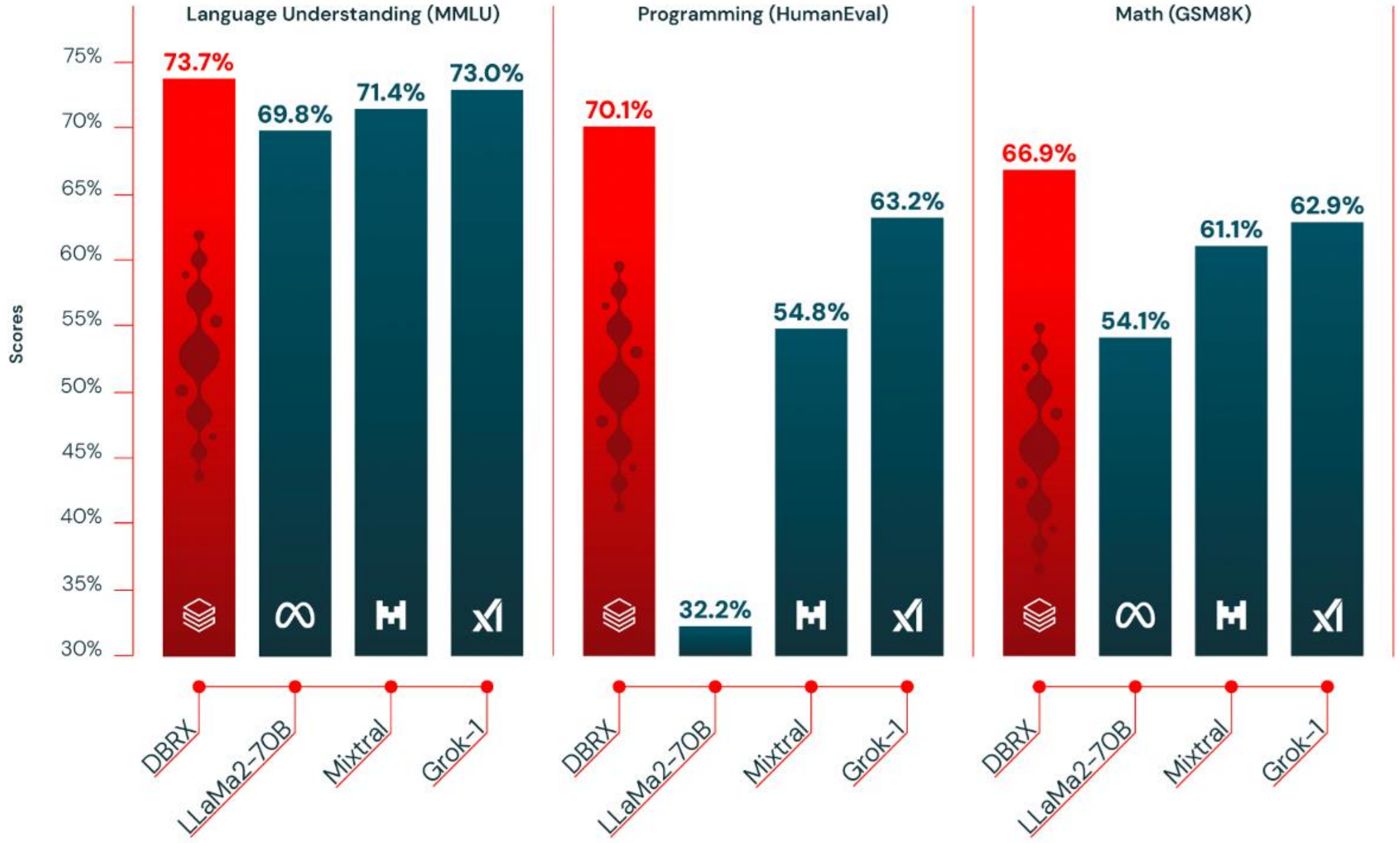

1,000,000,000,000
100,000,000,000
10,000,000,000
1,000,000,000
100,000,000
10,000,000
Model Size (Parameters)
2017
2018
2019
2020
2021
2022
2023
2024
Model Introduction
Transformer
ELMo
GPT-1
BERT Large
GPT-2
Megatron-NLG
Microsoft T-NLG
GPT-3
LaMDA
MT NLG 530B
GPT-3.5
OPT
PaLM
BLOOM
Chinchilla
PaLM2
LLaMA
LLaMA2
GPT-J 6B

Model Cost



MMLU Performance vs. Cost Over Time (2022-2024)
Year
2022
2023
2024
GPT 3 Davinci (pre Sep'22)
GPT 3 Davinci (post Sep'22)
GPT 3 Curie (pre Sep'22)
GPT 3 Curie (post Sep'22)
GPT 3.5 instruct
text-davinci-002
GPT 3.5 instruct
text-davinci-003
Gemma 7B
Grok-1
Grok-1.5
Gemini Ultra
GPT-4
(32-k)
GPT-4
Claude 3
Opus
GPT-4.5-turbo
PaLM 2-L
Claude 2
Mistral Large
Claude 3 Sonnet
Mistral Medium
Mistral Small
Llama 2 70B
GPT-3.5 Turbo
PaLM
Cohere Command
Gemini 1.0 Pro
Claude 3 Haiku
Mixtral 8x7B
Llama 2 13B
Claude Instant 1.2
Cohere Command Light
Llama 2 7B
Mistral 7B
$100
$10
$1
$0.1
Cost per million tokens
(average of input and output price, log scale)
30
40
50
60
70
80
90
MMLU accuracy (%)

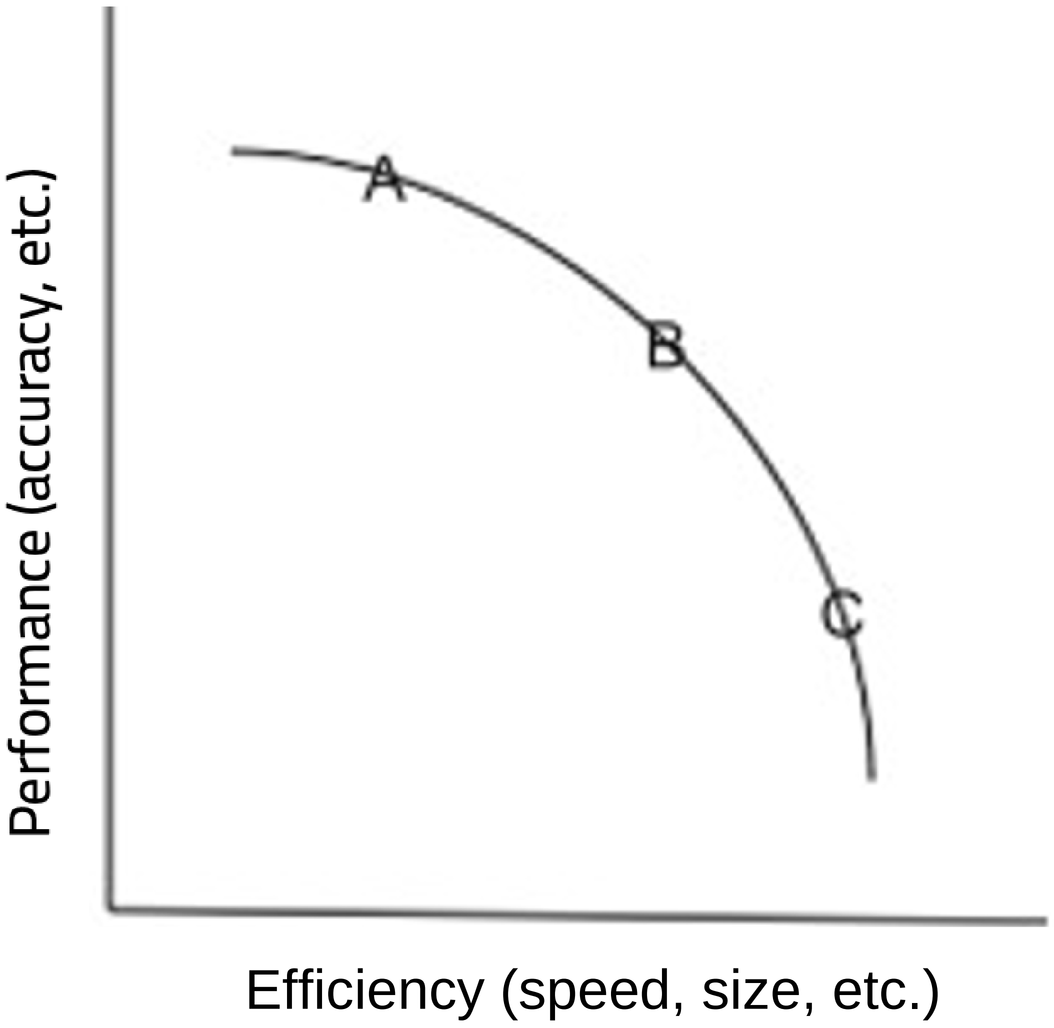
Development Speed



https://www.databricks.com/blog/introducing-dbrx-new-state-art-open-llm

Efficiency Tradeoff

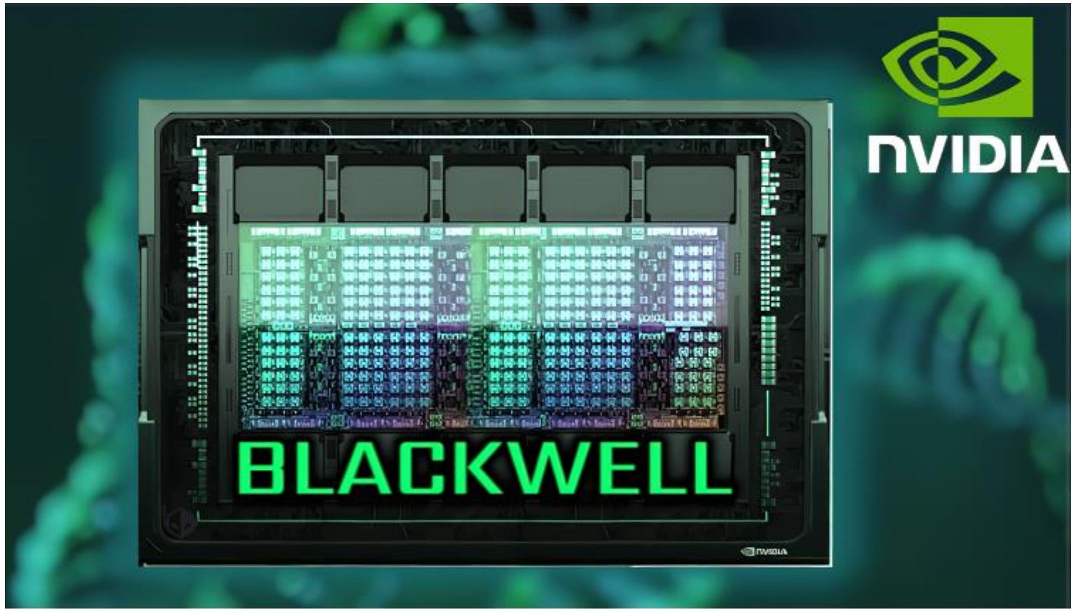
- ❑ More efficient models (smaller, faster) typically come at a cost of some performance of the model itself
- ❑ In the other direction, getting more performance from a model architecture likely means it will be larger, and require more computation

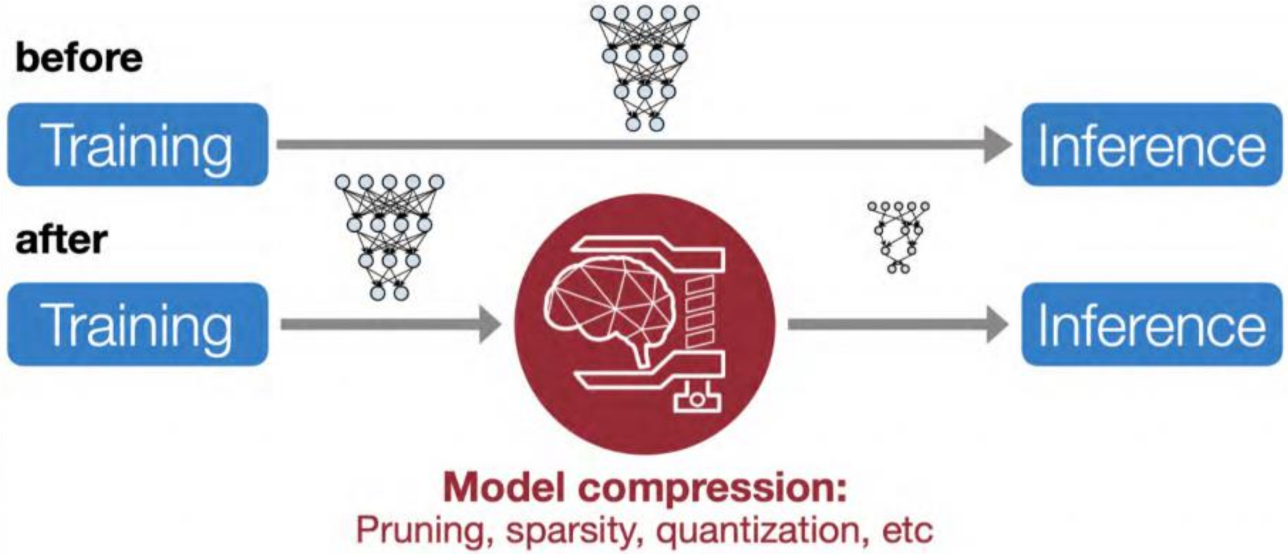


How to Improve Model Efficiency?

Hardware

Software





Efficient LLMs

- Quantization
  - Background
  - K-Means vs. Linear Quantization
  - Quantization Granularity
  - Quantization Aware Training (QAT) vs Post-Training Quantization (PTQ)
  - LLM Quantization (LLM.int8(), SmoothQuant, AWQ, 1-bit LLMs)
- Sparsity (Mixture of Experts, Deja Vu: Contextual Sparsity)
- Efficient Inference Systems (vLLM, StreamingLLM, MHA/GQA/MQA)
- Parameter Efficient Fine-Tuning (BitFit, Adapter, Prompt Tuning, LoRA)

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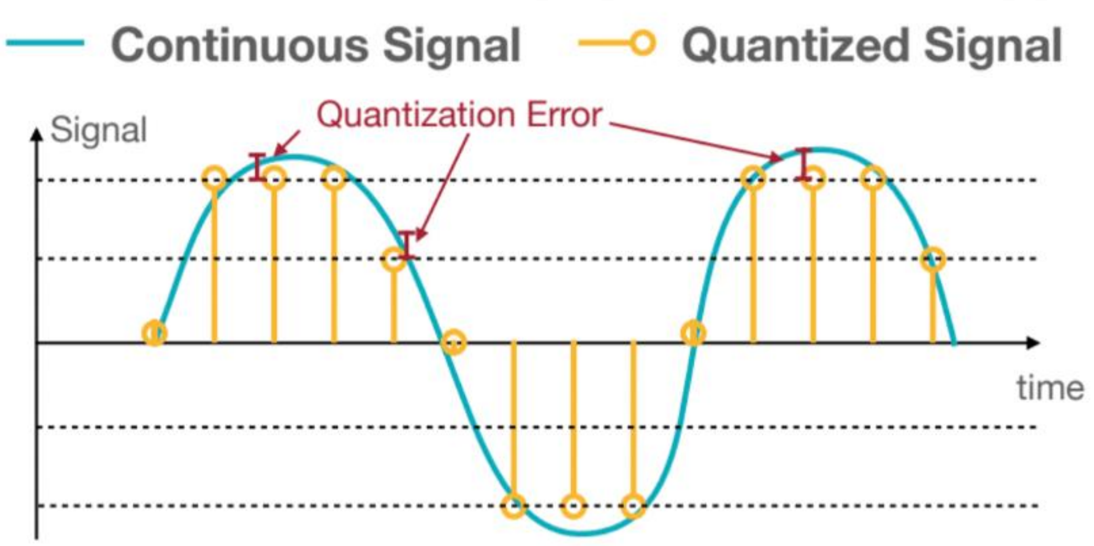
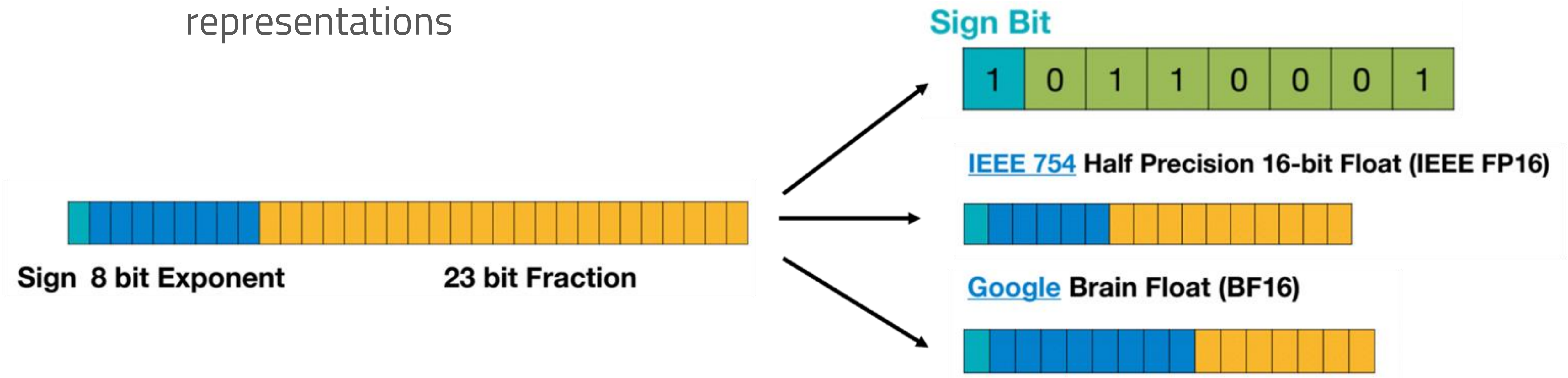
Quantization

Reduce model size by replacing high bit-width representations with low bit-width representations





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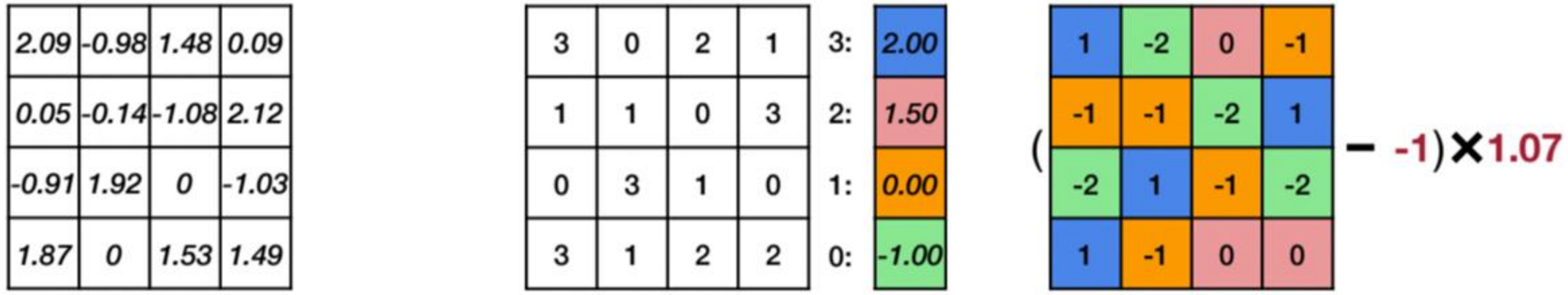
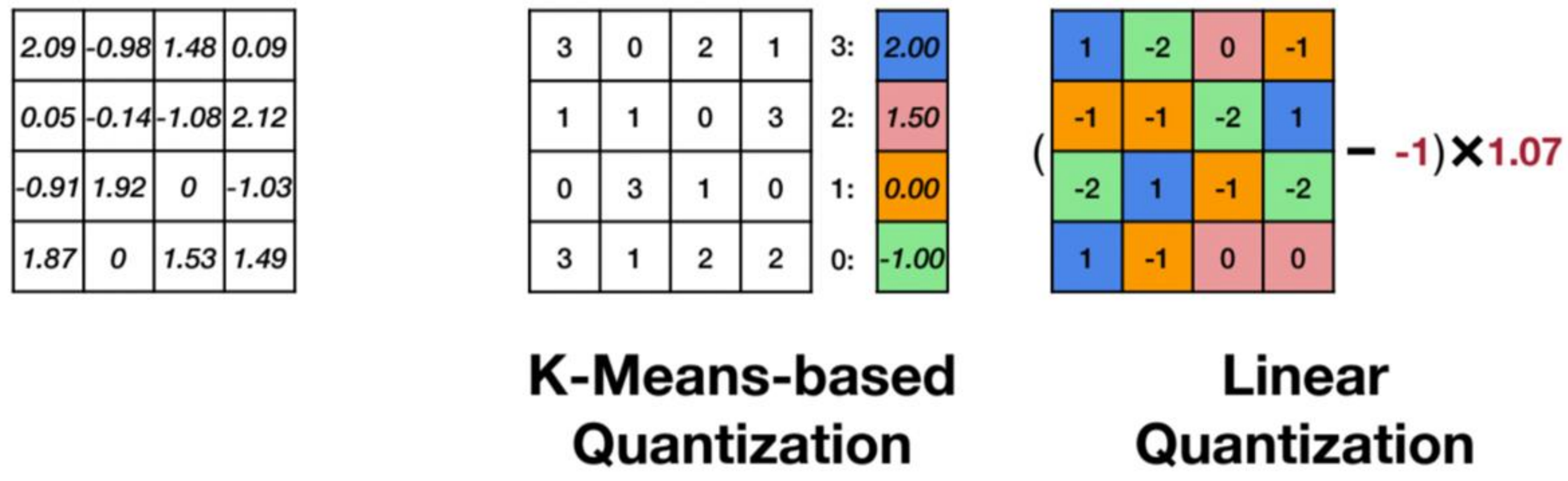
K-Means Quantization vs Linear Quantization



		K-Means-based Quantization	Linear Quantization
Storage	Floating-Point Weights	Integer Weights; Floating-Point Codebook	Integer Weights
Computation	Floating-Point Arithmetic	Floating-Point Arithmetic	Integer Arithmetic

K-Means Quantization vs Linear Quantization



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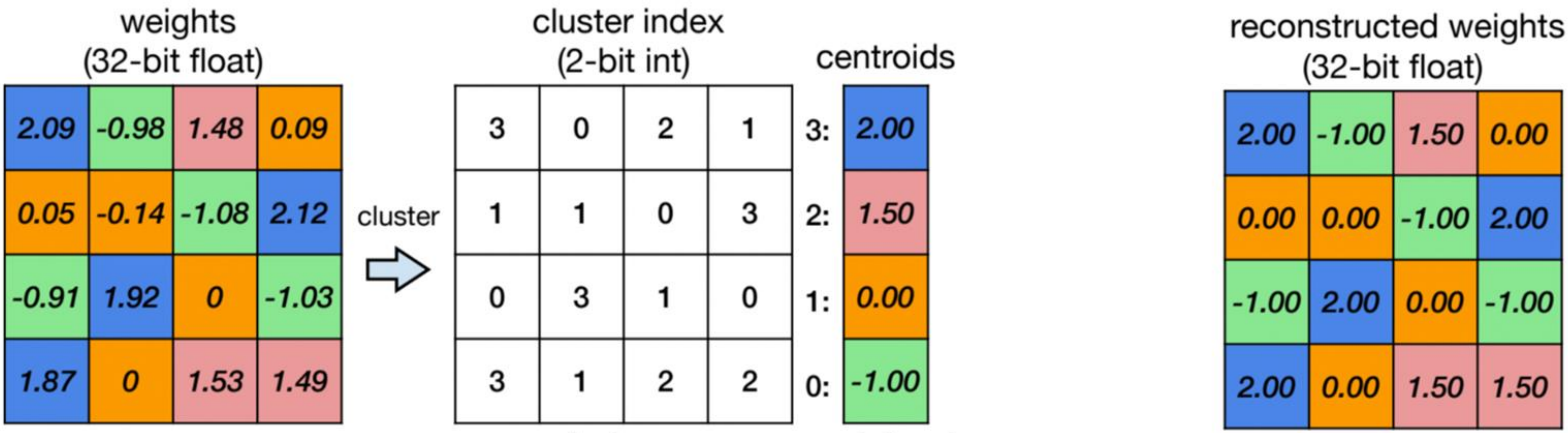
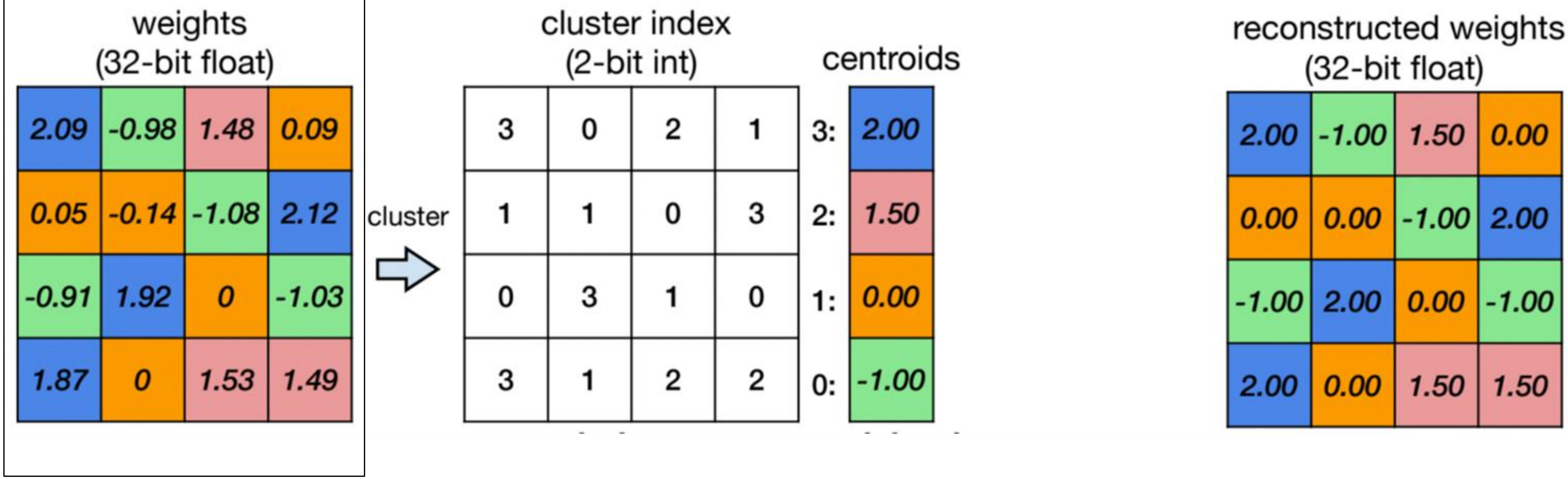
K-Means Quantization



Deep Compression [Han et al., ICLR 2016]

K-Means Quantization

Original weights



Deep Compression [Han et al., ICLR 2016]

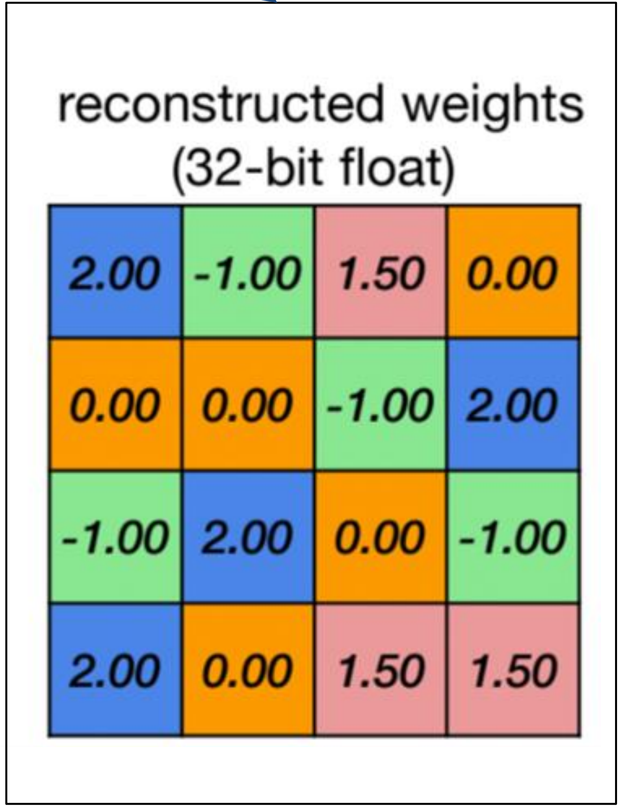
K-Means Quantization

Stored weights after clustering

Deep Compression [Han et al., ICLR 2016]

K-Means Quantization

Retrieved weights to be used at inference time



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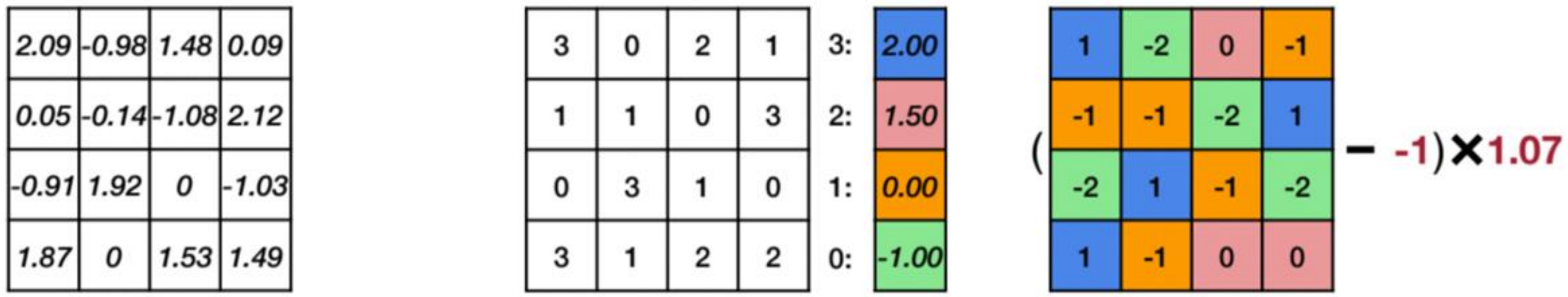
K-Means Quantization vs Linear Quantization



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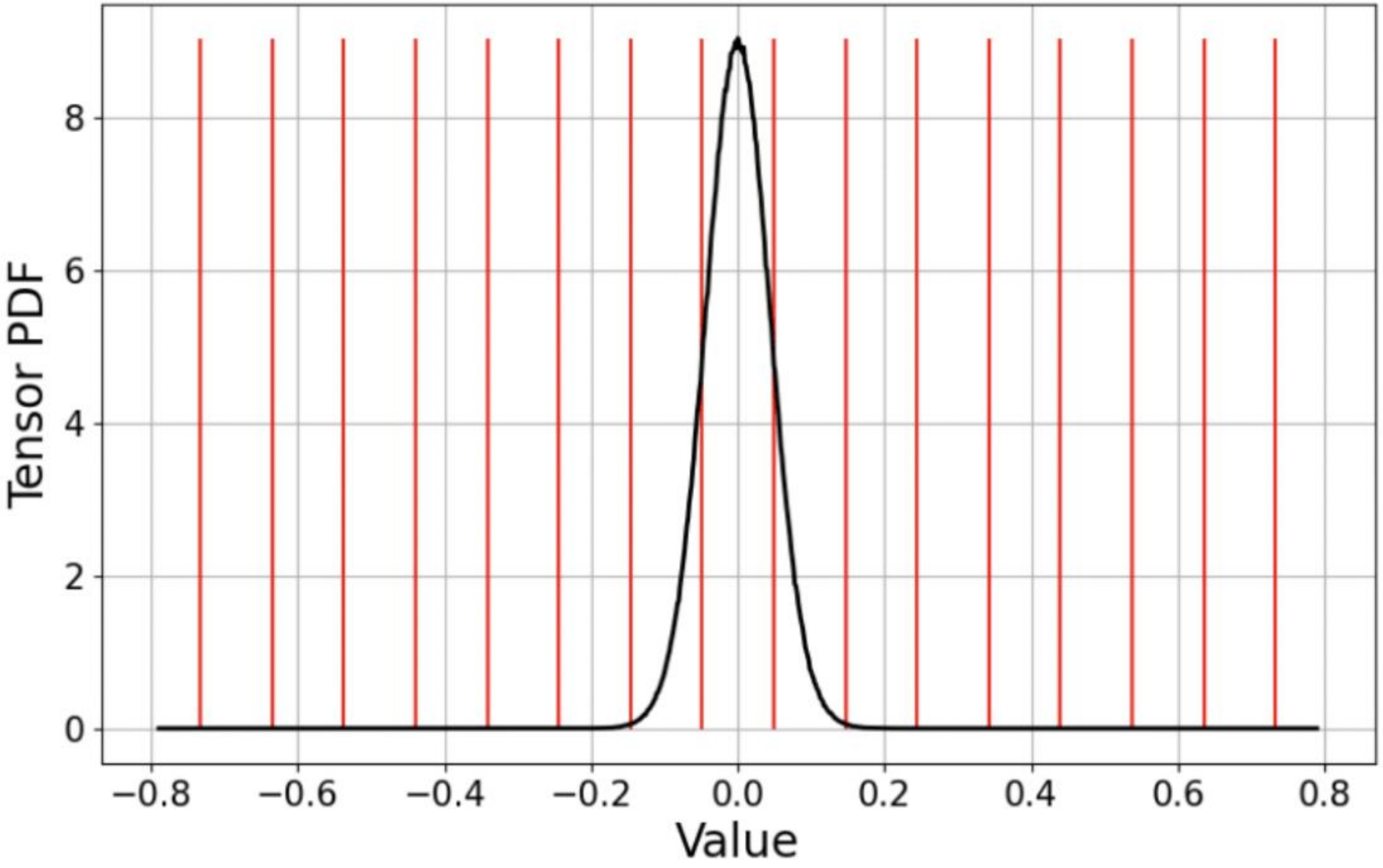
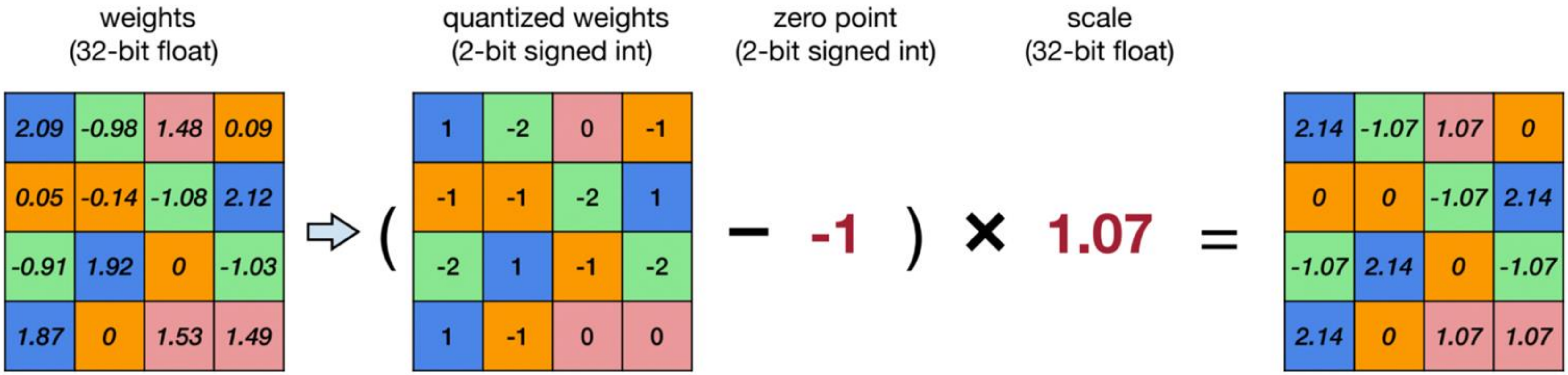
Linear Quantization

- ❑ Apply linear function on weights and hidden state activations from floating point values (r) to integer values (q)
- ❑ Original weights (black), Quantized bins (red)



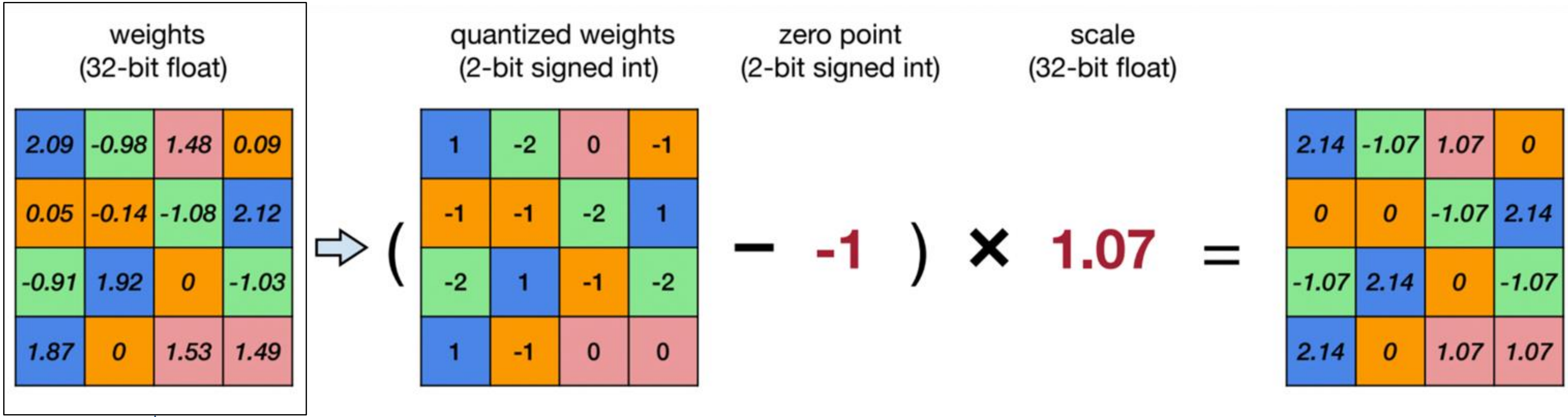
Linear Quantization



Binary	Decimal
01	1
00	0
11	-1
10	-2

Quantization and Training of Neural Networks for Efficient Integer-Arithmetic-Only Inference [Jacobet al., CVPR 2018]

Linear Quantization



Original Weights

Binary	Decimal
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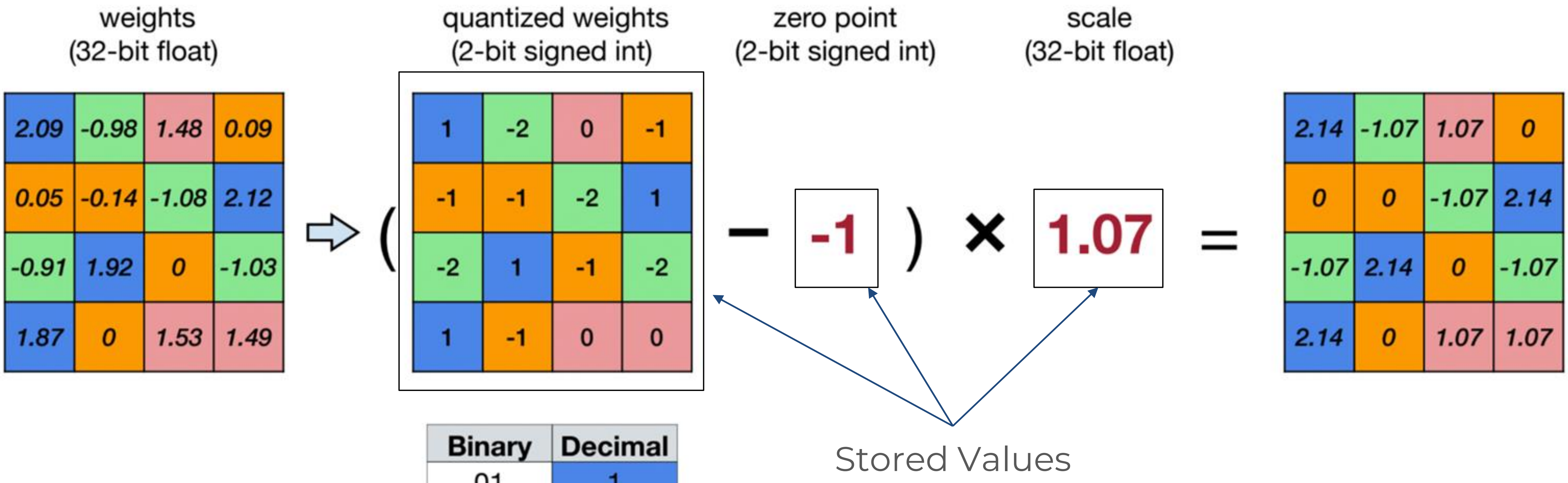
Quantization and Training of Neural Networks for Efficient Integer-Arithmetic-Only Inference [Jacobet al., CVPR 2018]

Linear Quantization



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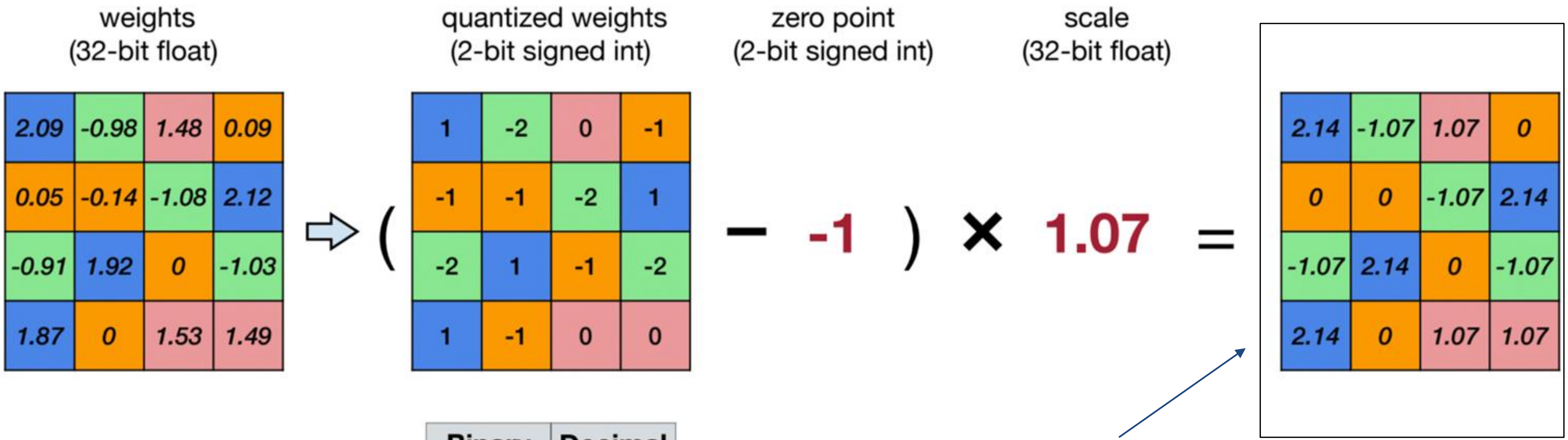

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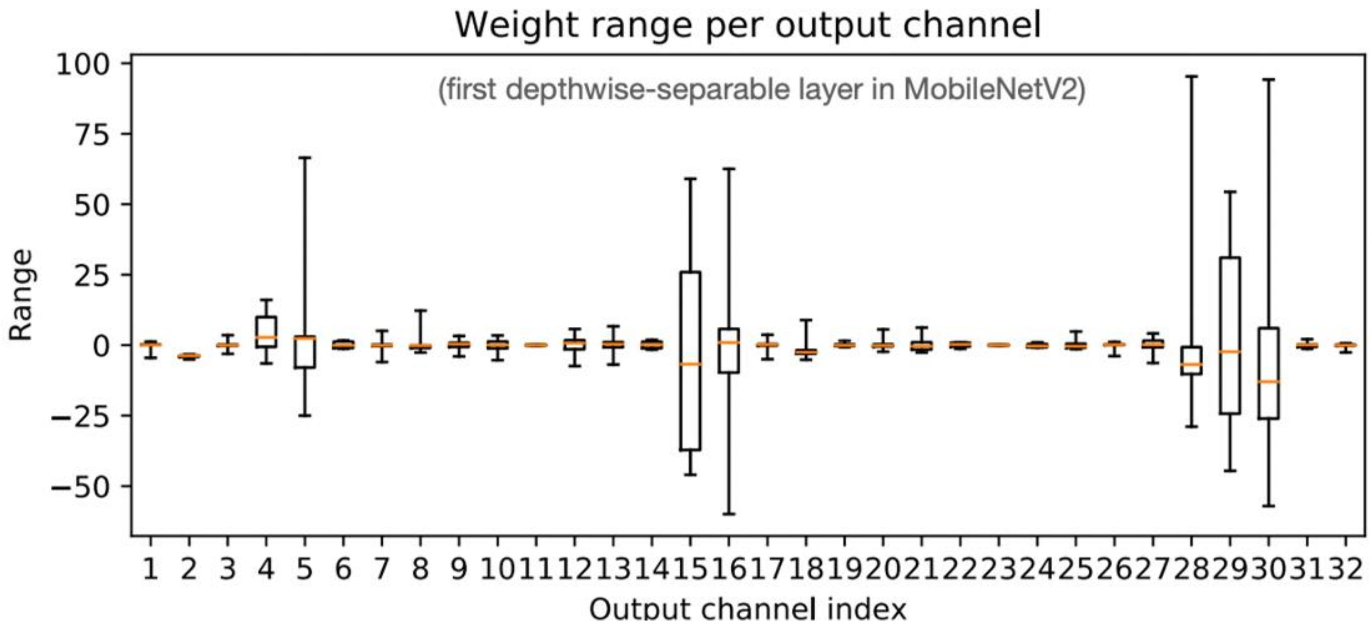
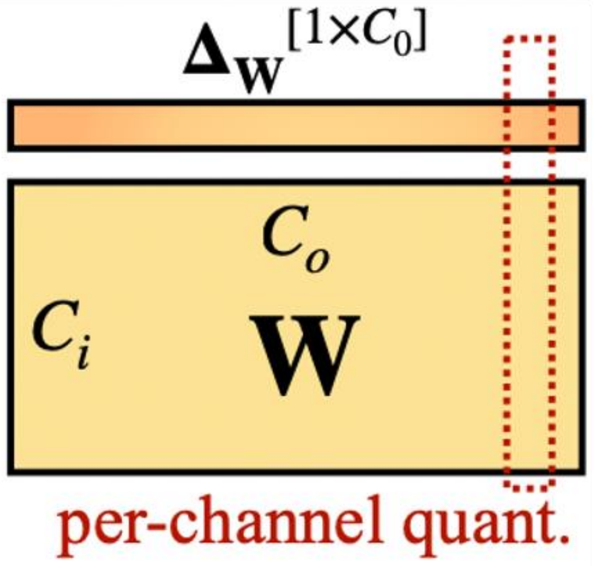
Weight Granularity

- Weight matrices will often have different variances along each output channel
- High variance in weights means that applying linear quantization will result in large performance degradation
- To fix this, we can perform linear quantization along each channel of the weight tensor separately

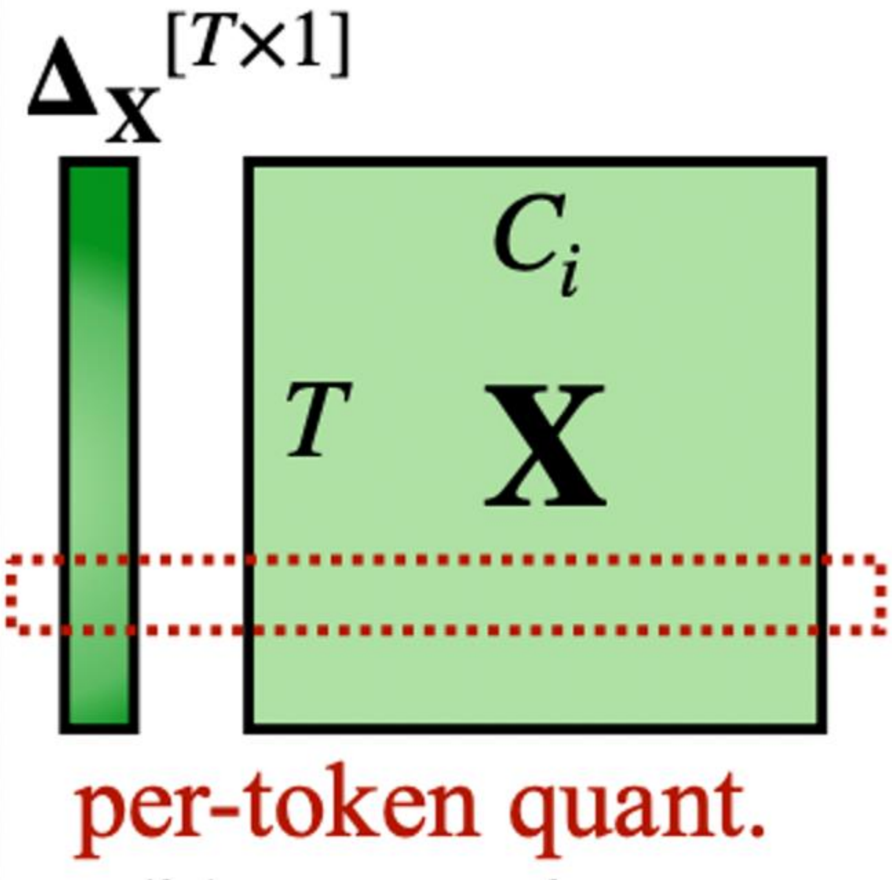




SmoothQuant: Accurate and Efficient Post-Training Quantization for Large Language Models[Xiao et. al., ICML 2023]

Activation Granularity

- Activations can have a similar problem whereby the variance by channel can be quite different
- The variance by token can also differ dramatically
- When applying quantization, we should split up channels, tokens to take this into account



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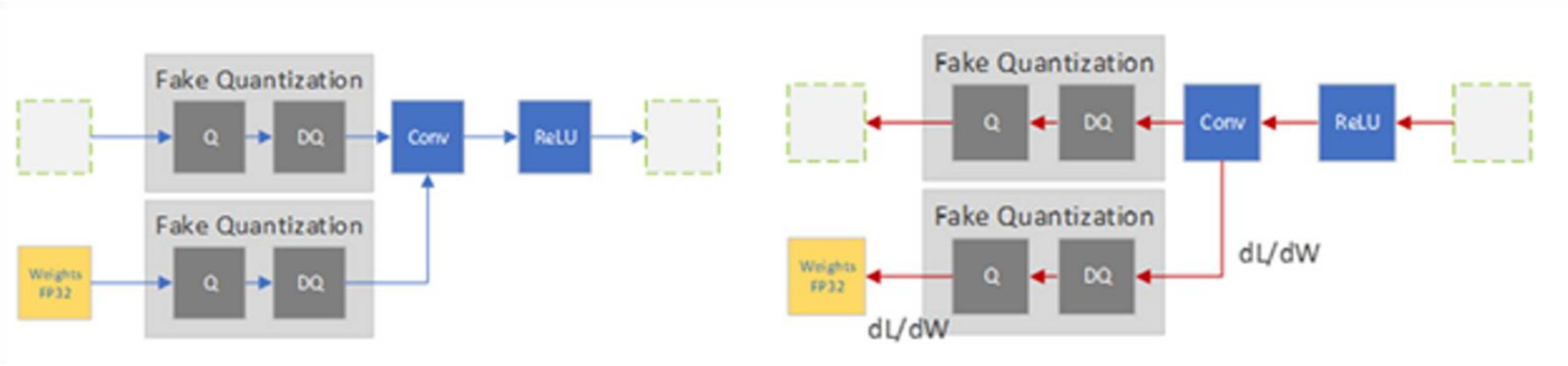
Quantization Aware Training (QAT)

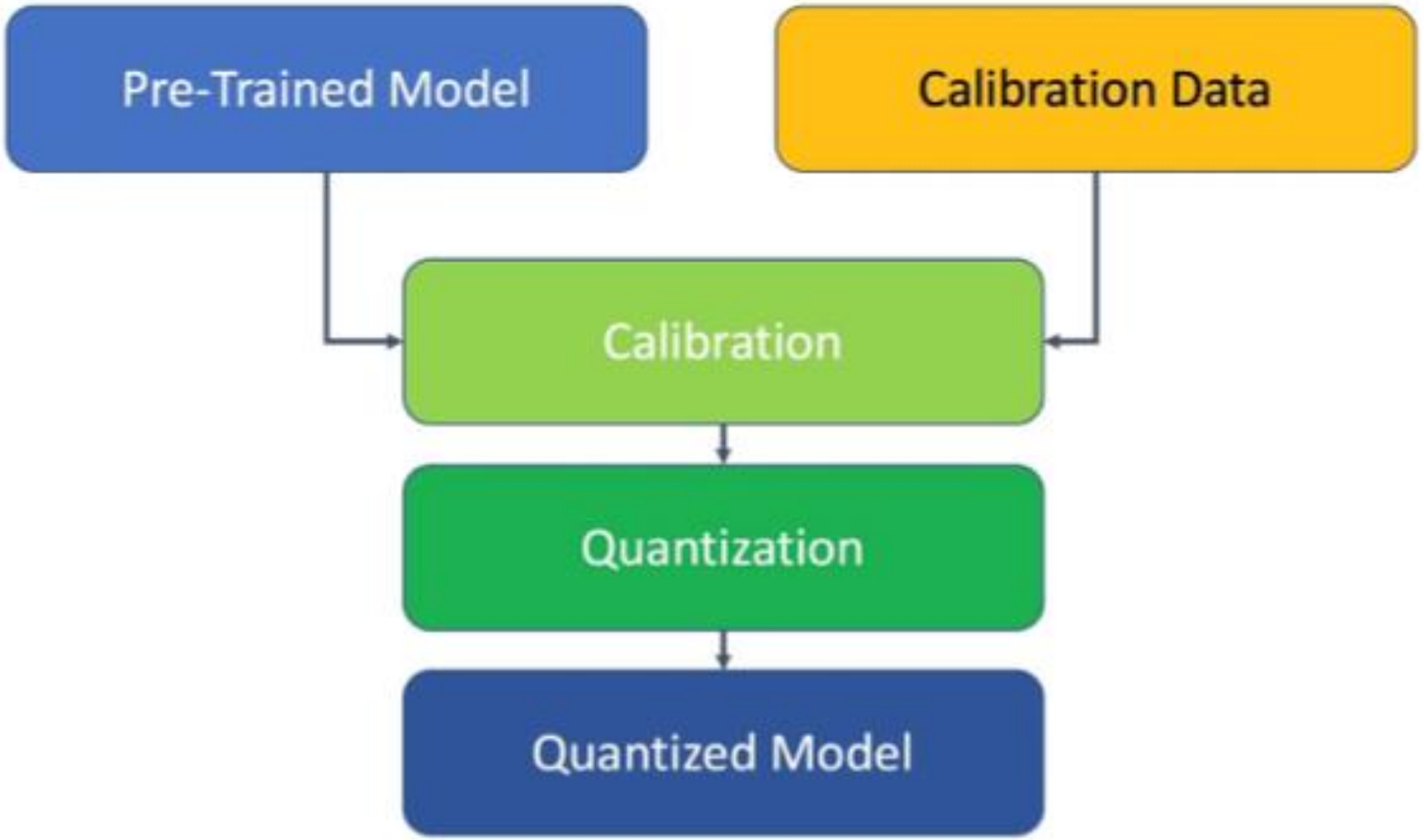
Quantize while training



https://pytorch.org/blog/quantization-in-practice/

Post Training Quantization (PTQ)

Quantize after training



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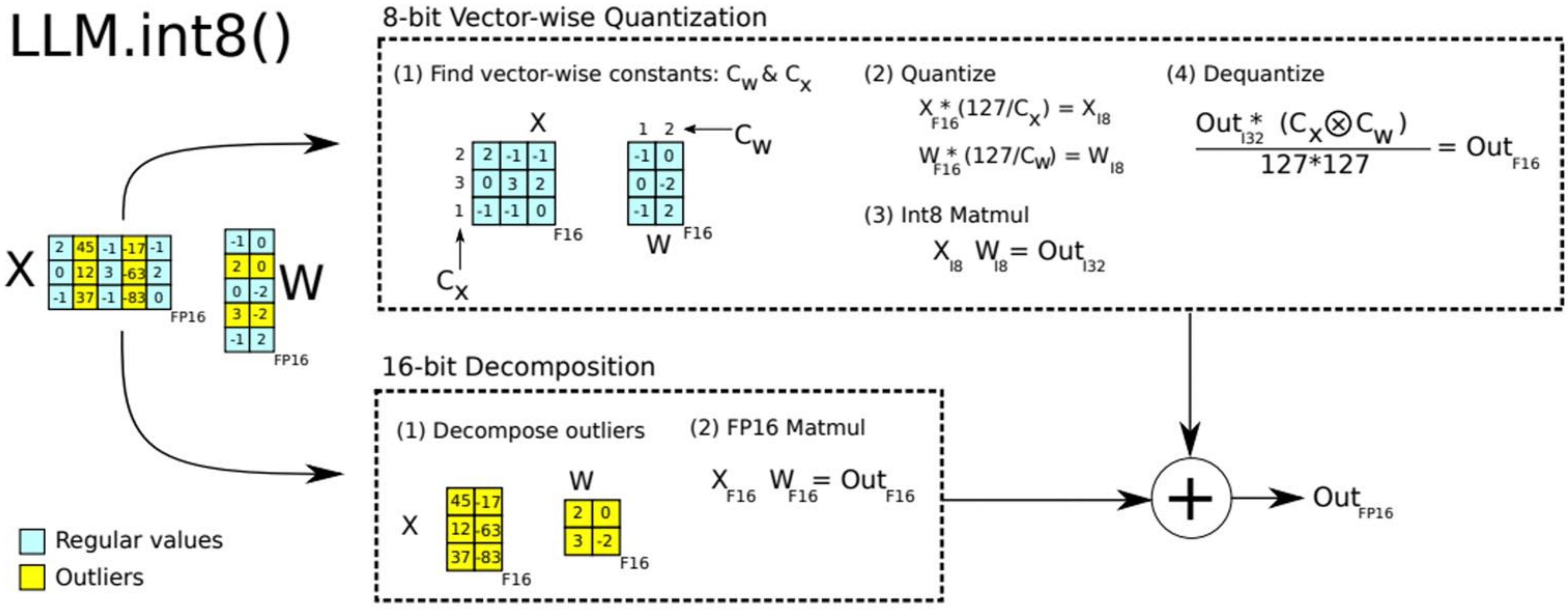
LLM.int8() (W8A8)

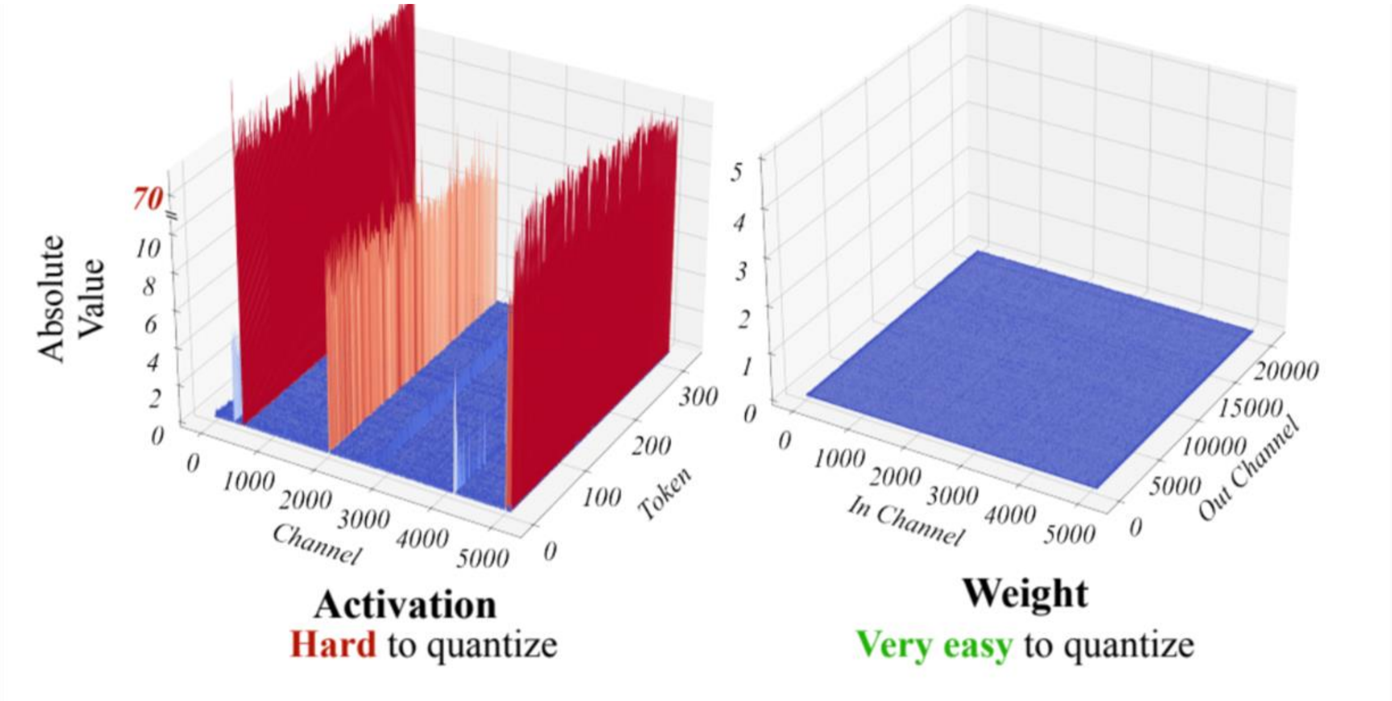
Stored 8-bit weights



LLM.int8(): 8-bit Matrix Multiplication for Transformers at Scale [Dettmers et. al., NeurIPS 2022]

SmoothQuant (W8A8)

Observation: High variance channels are fixed in activations in LLM FFN layers-weights have relatively little difference in variance



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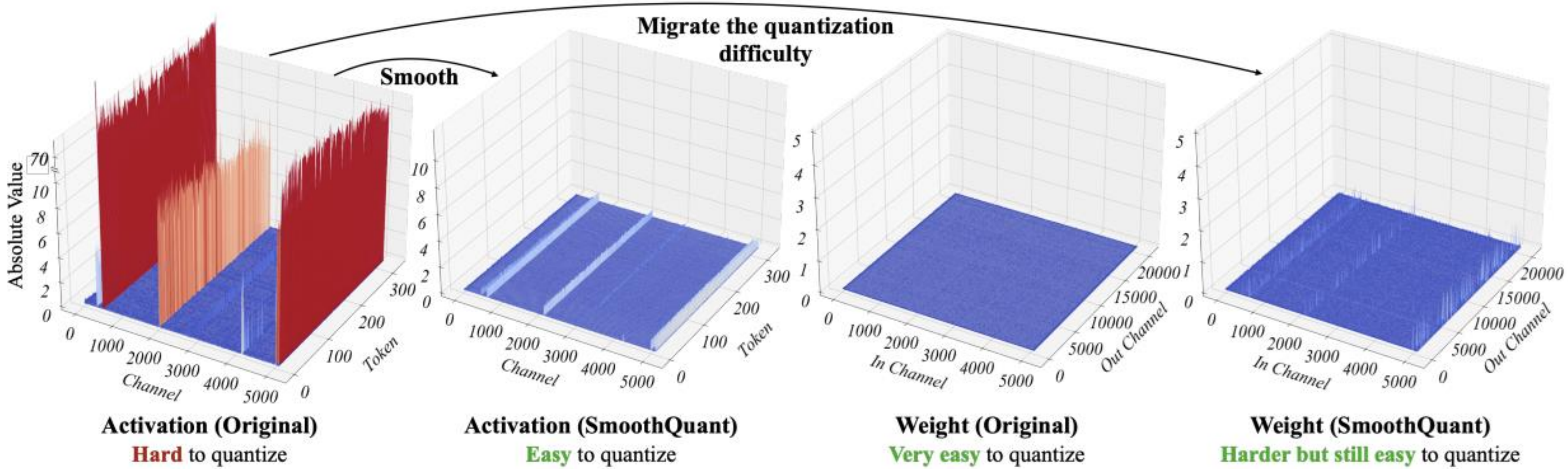
SmoothQuant (W8A8)



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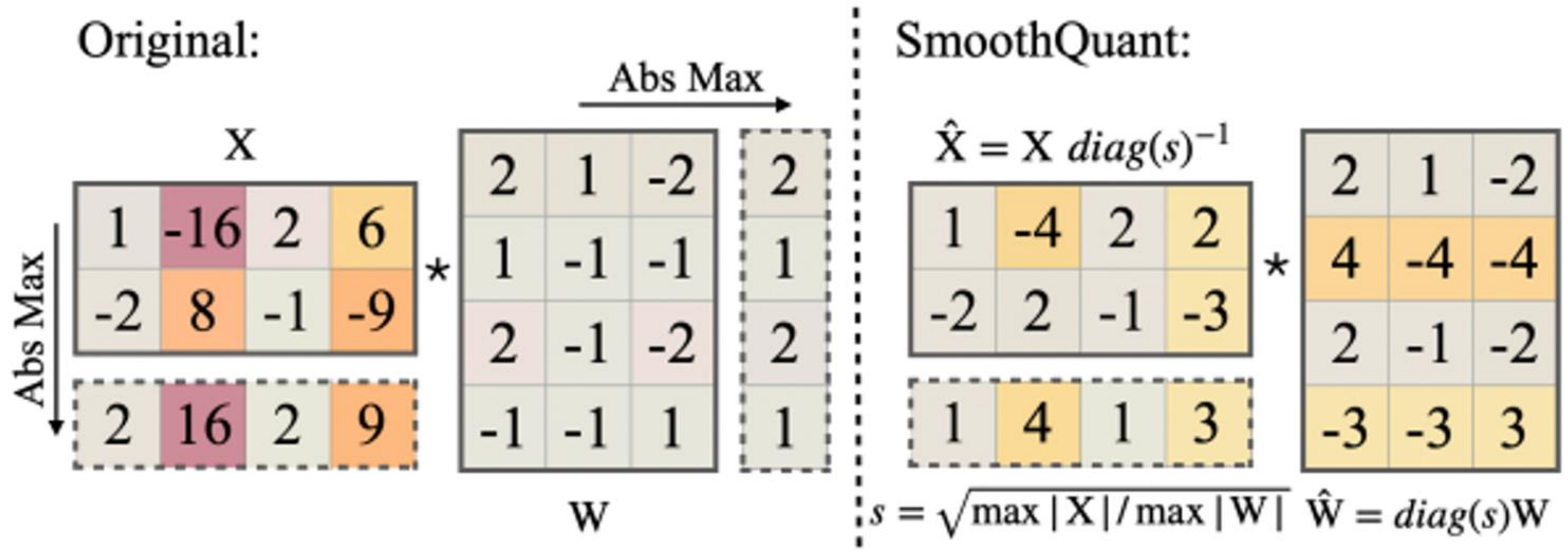
SmoothQuant (W8A8)



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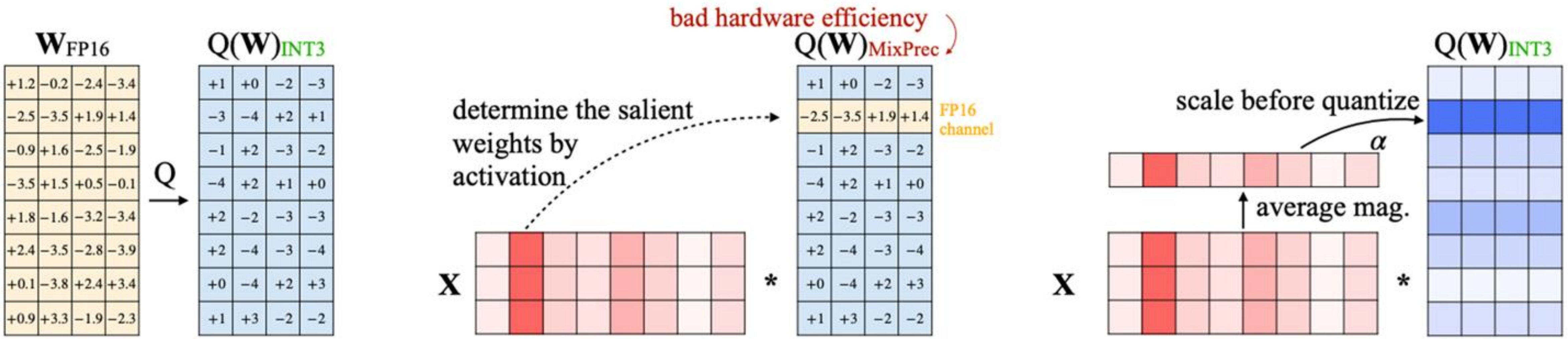
AWQ (W4A16)

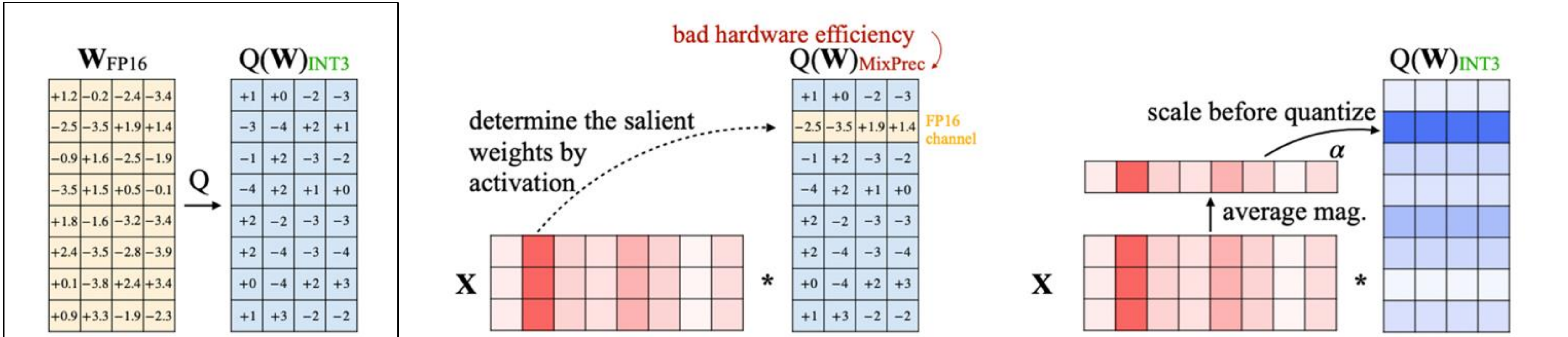


(a) RTN quantization (**PPL** 43.2) (b) Keep 1% salient weights in FP16 (**PPL** 13.0) (c) Scale the weights before quantization (**PPL** 13.0)

AWQ: Activation-aware Weight Quantization for LLM Compression and Acceleration [Lin et. al., arxiv 2023]

AWQ (W4A16)

Normal quantization on LLMs performs poorly due to outliers in the model's hidden state



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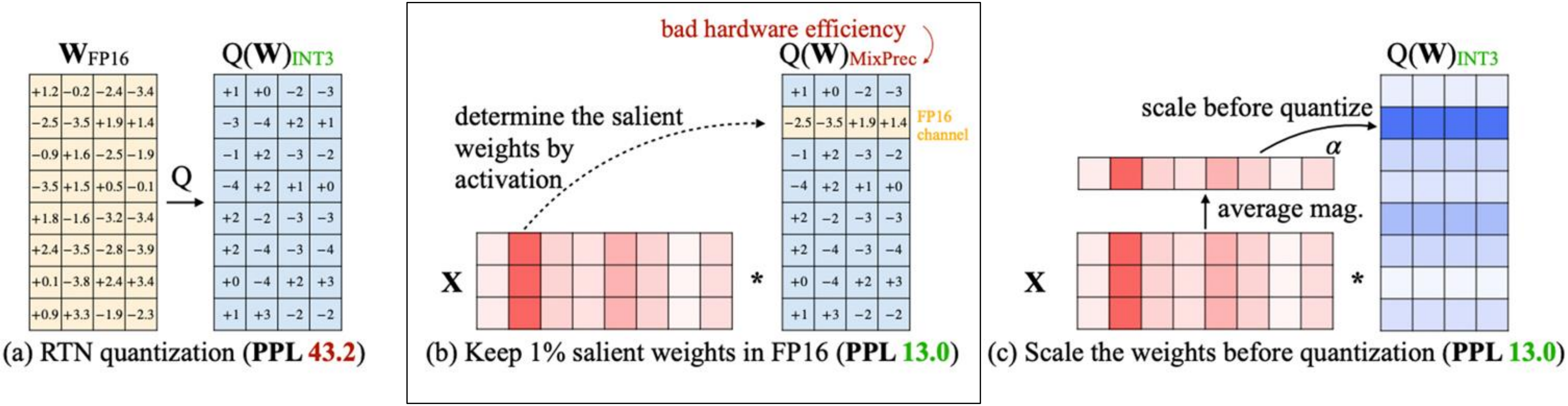
AWQ (W4A16)

LLM.int8() can resolve these issues, but mixed precision matrix multiplication is hardware inefficient



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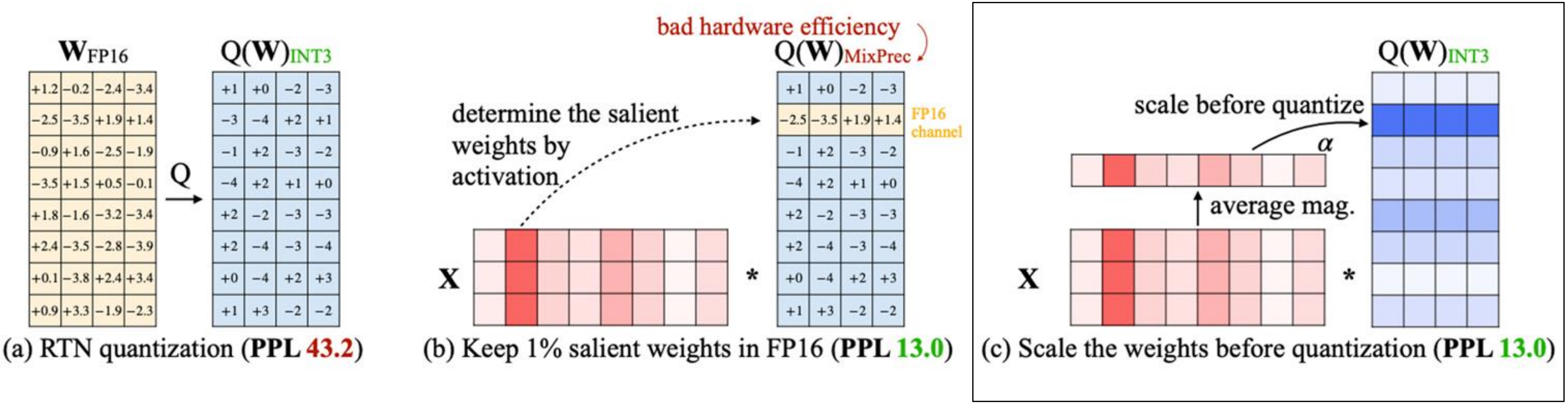
AWQ (W4A16)

As in SmoothQuant, we can resolve this issue by shifting the difficulty to the weights using a scaling factor.



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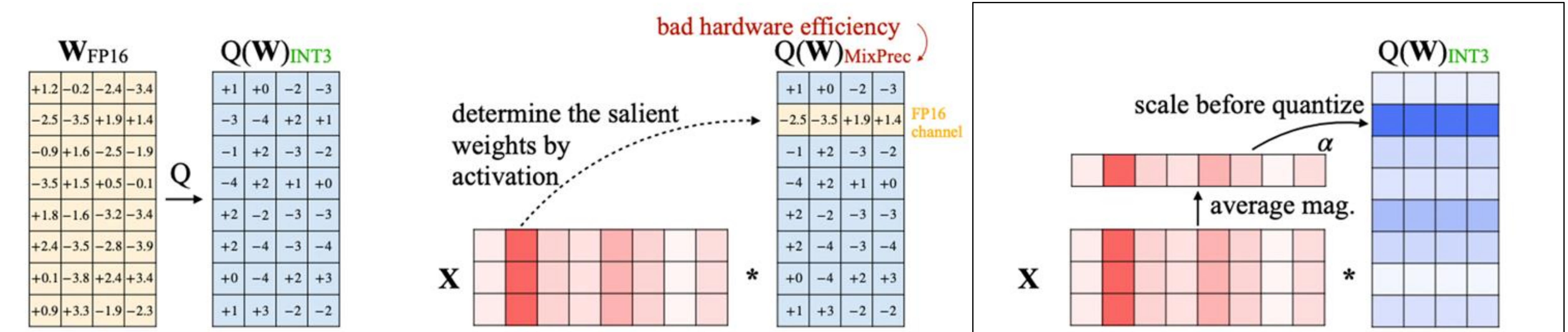
AWQ (W4A16)

Where Smoothquant quantizes both activations and weights, AWQ only quantizes the weights



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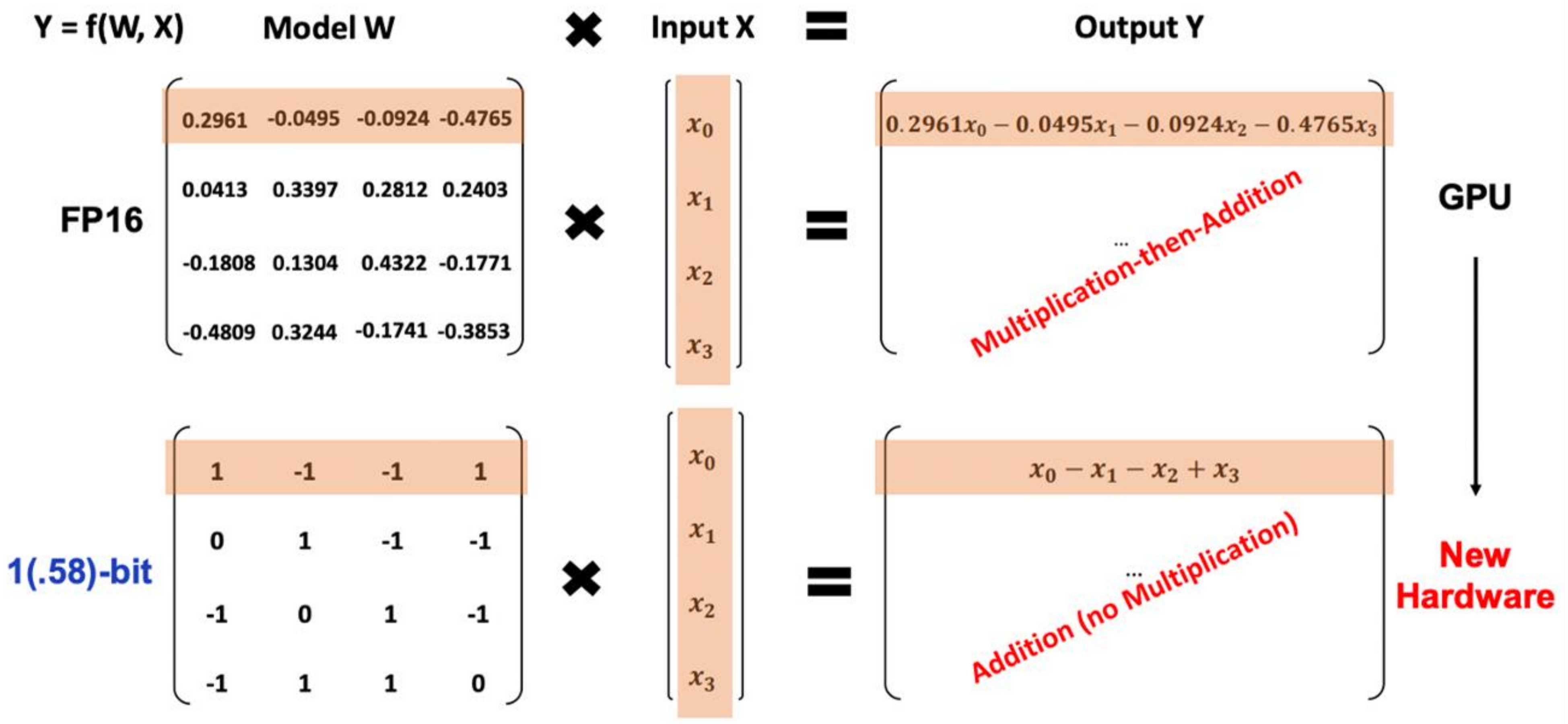
Era of 1-bit LLMs (W1.58A8)

Weight-only QAT algorithm that uses only weights in {-1, 0, 1}



The Era of 1-bit LLMs: All Large Language Models are in 1.58 Bits [Ma et al., 2024]

Era of 1-bit LLMs (W1.58A8)

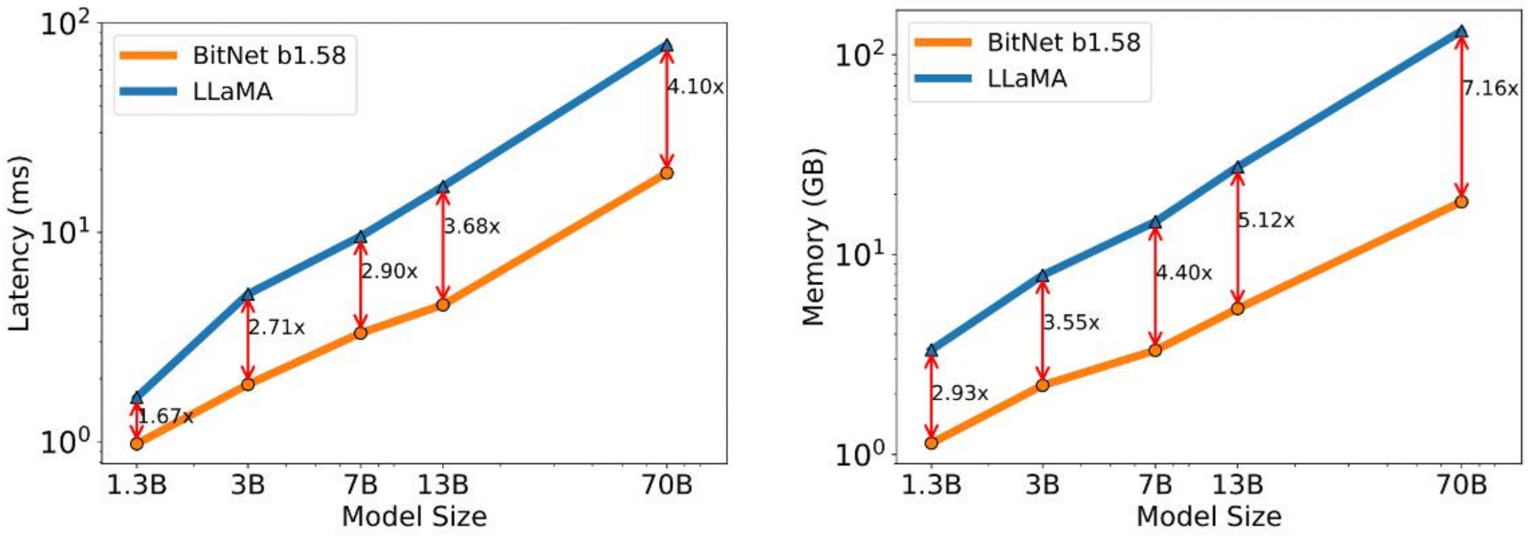


Figure 2: Decoding latency (Left) and memory consumption (Right) of BitNet b1.58 varying the model size.

Models	Size	Max Batch Size	Throughput (tokens/s)
LLaMA LLM	70B	16 (1.0x)	333 (1.0x)
BitNet b1.58	70B	**176 (11.0x)**	**2977 (8.9x)**

Table 3: Comparison of the throughput between BitNet b1.58 70B and LLaMA LLM 70B.

The Era of 1-bit LLMs: All Large Language Models are in 1.58 Bits [Ma et al., 2024]

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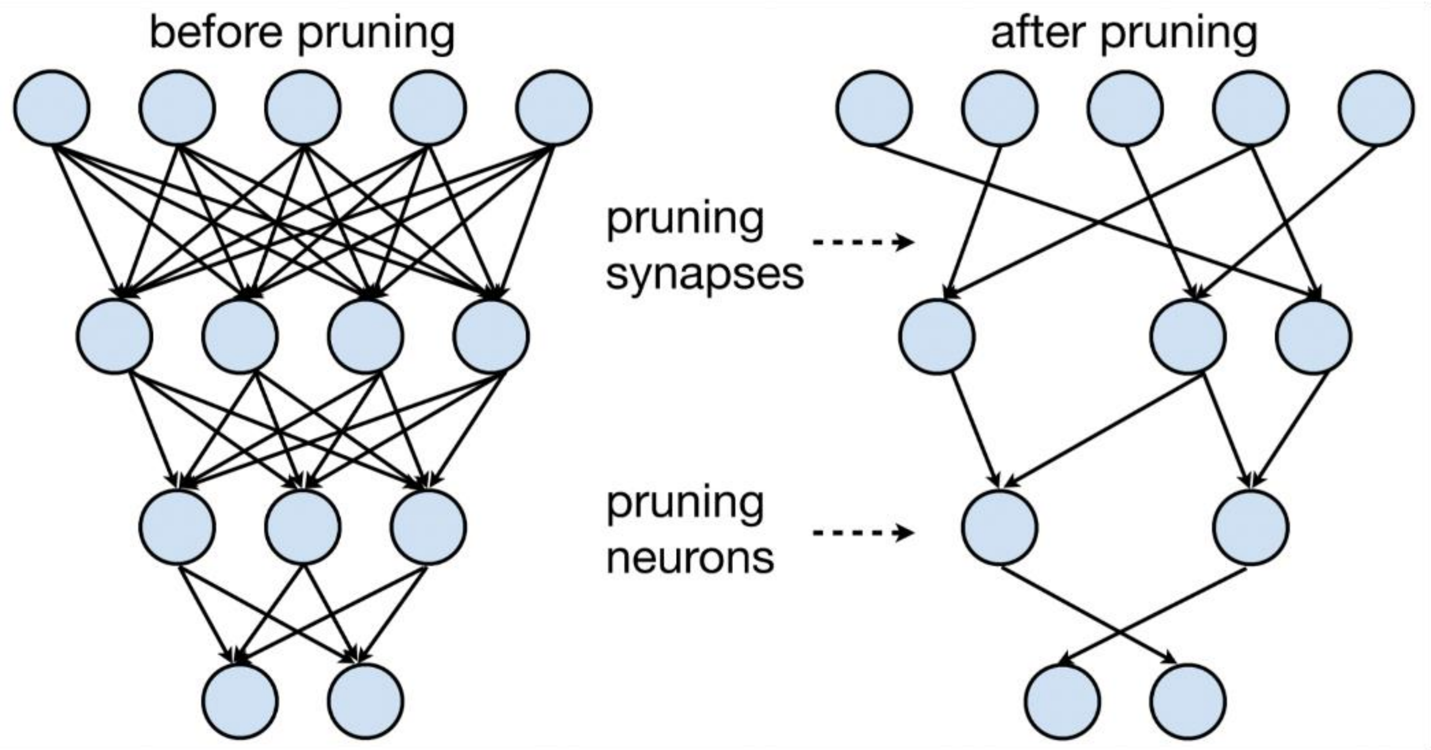
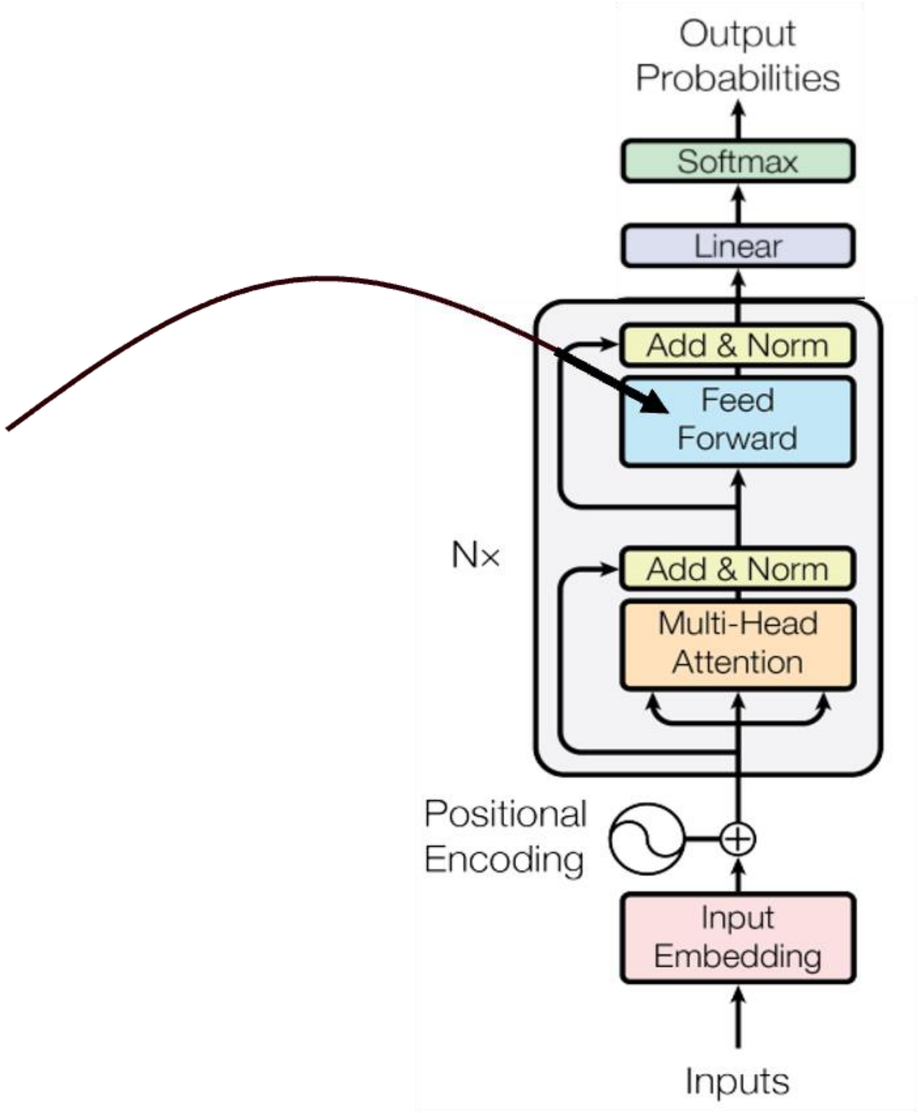
Sparsity

Even though our model may have many parameters, we can get speedups by only using a much smaller number of those parameters for a given instance

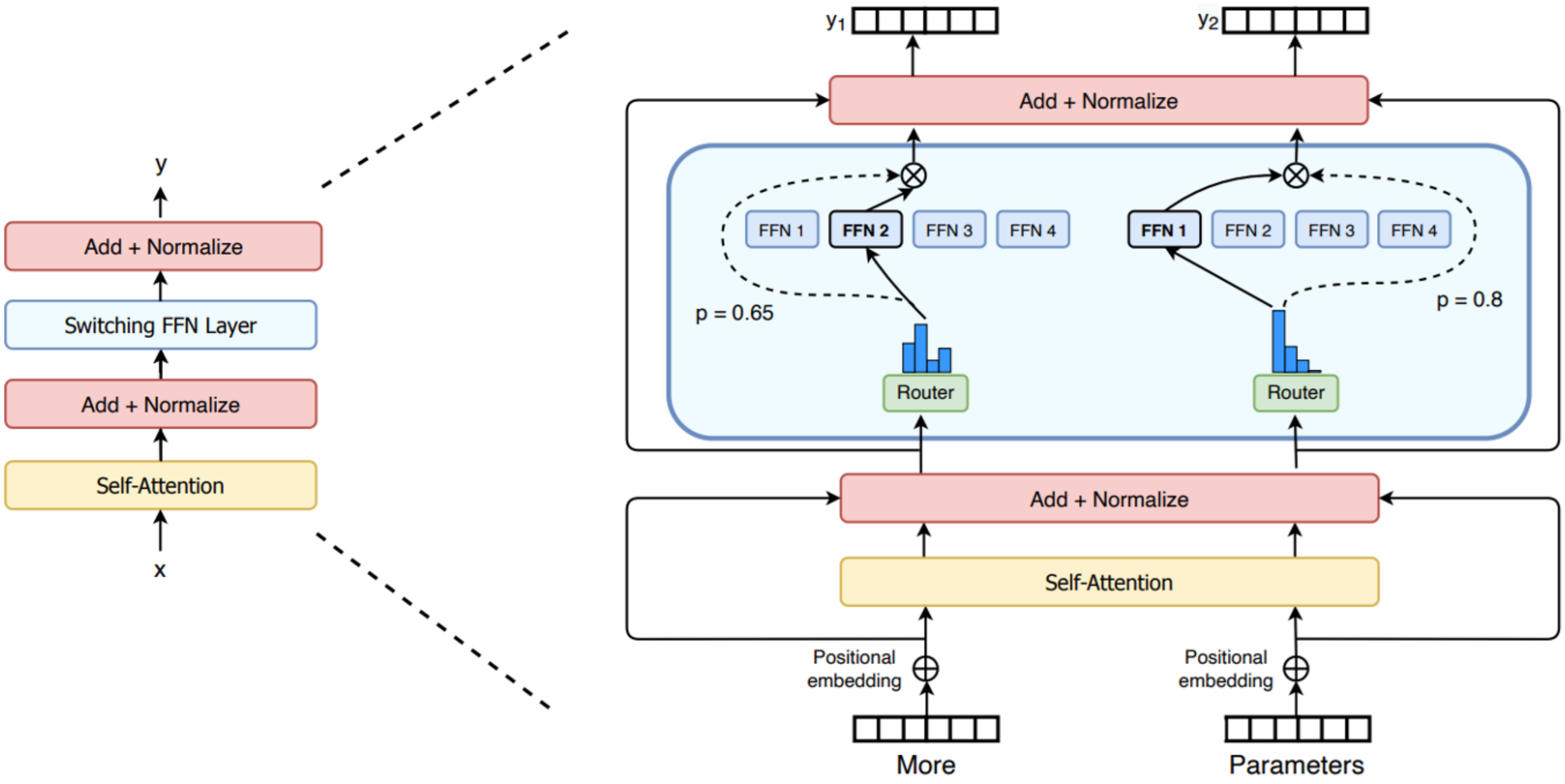


Mixture of Experts (MoE)

Replace FFN layers in traditional transformers with a switching FFN layer (more generally called an MoE layer)



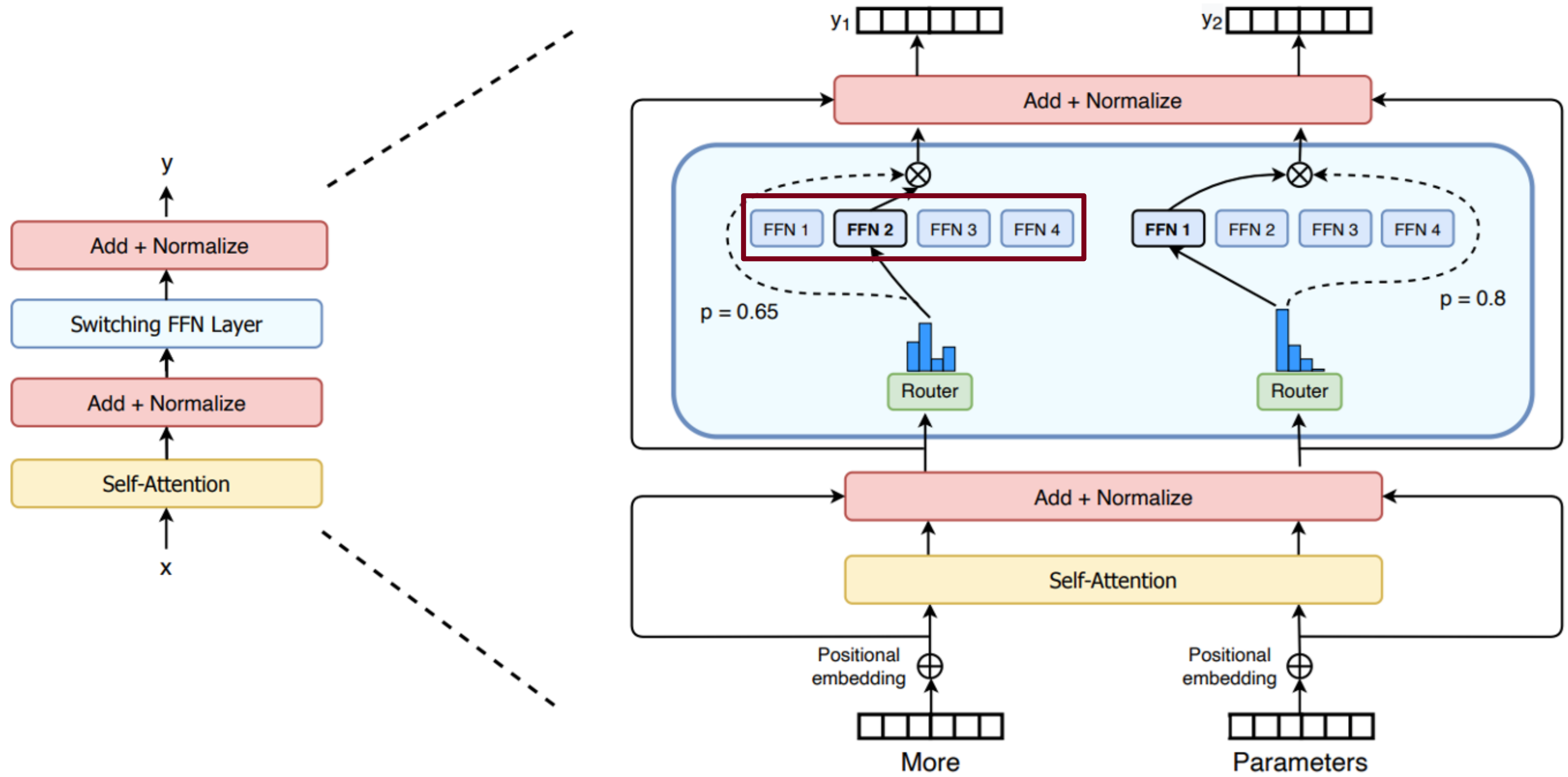
Mixture of Experts (MoE)



Switch Transformers: Scaling to Trillion Parameter Models with Simple and Efficient Sparsity [Fedus et al., CoRR 2021]

Mixture of Experts (MoE)

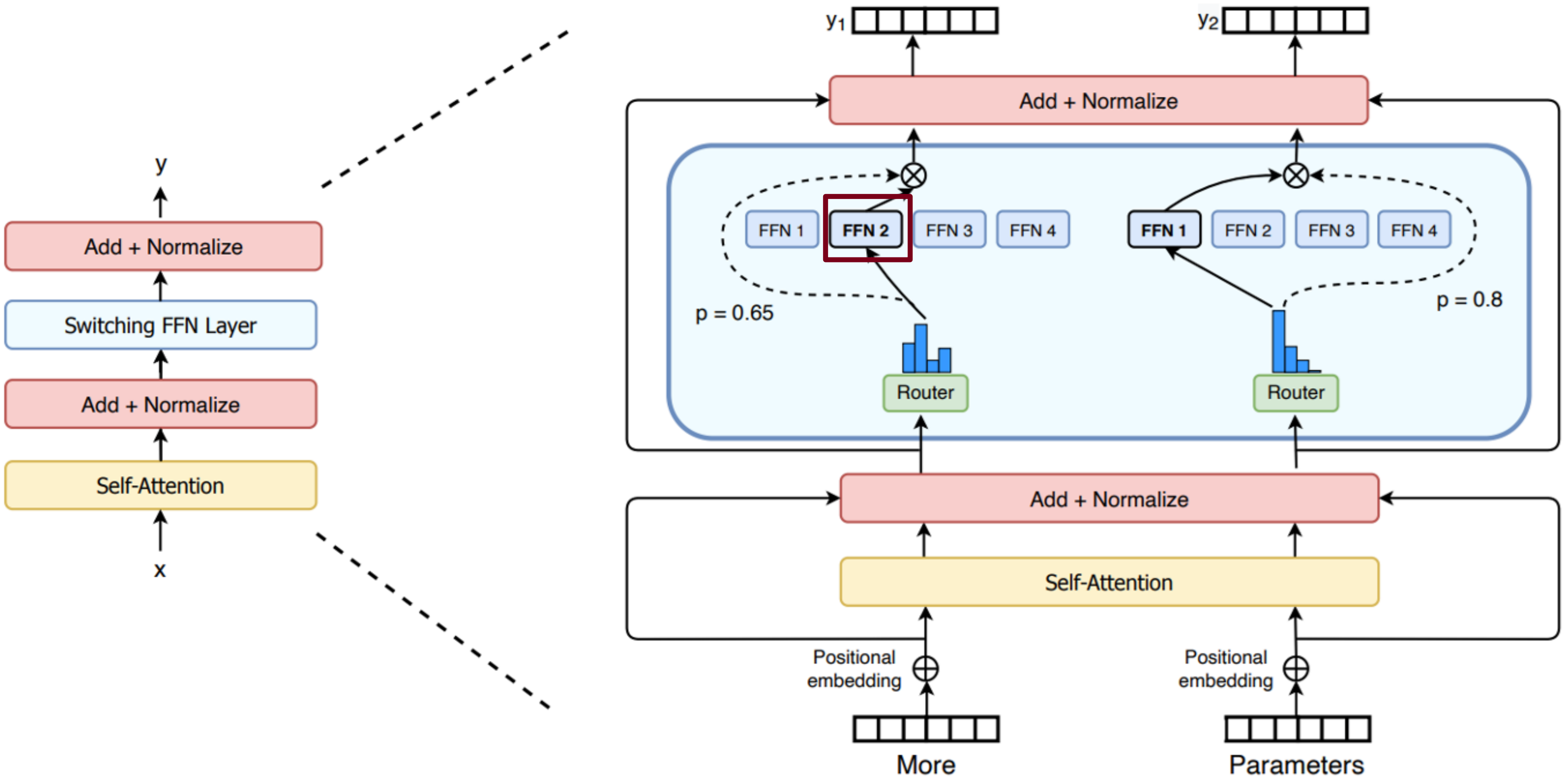
Four FFN layers



Switch Transformers: Scaling to Trillion Parameter Models with Simple and Efficient Sparsity [Fedus et al., CoRR 2021]

Mixture of Experts (MoE)

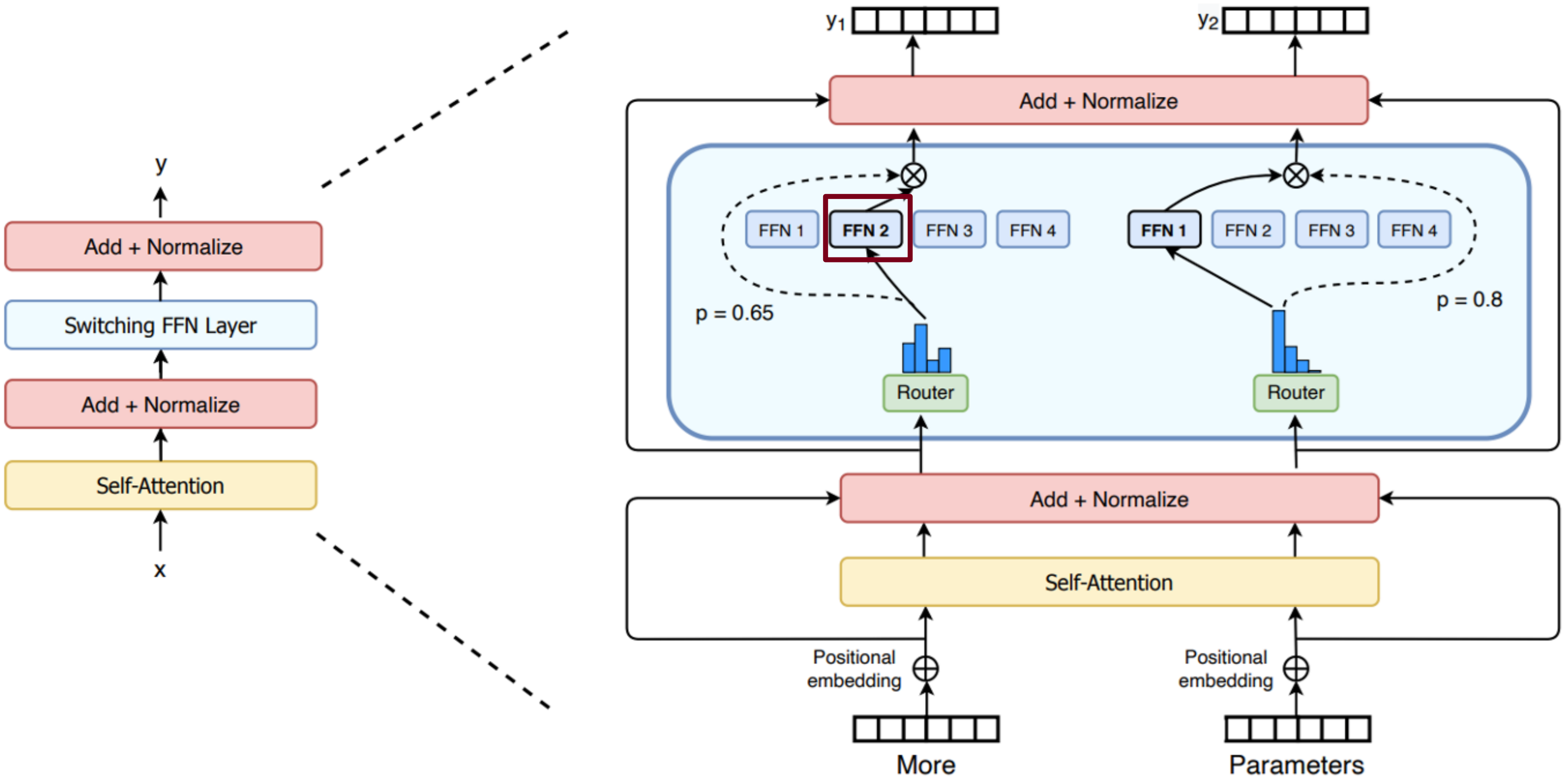
Only one is used per token



Switch Transformers: Scaling to Trillion Parameter Models with Simple and Efficient Sparsity [Fedus et al., CoRR 2021]

Mixture of Experts (MoE)

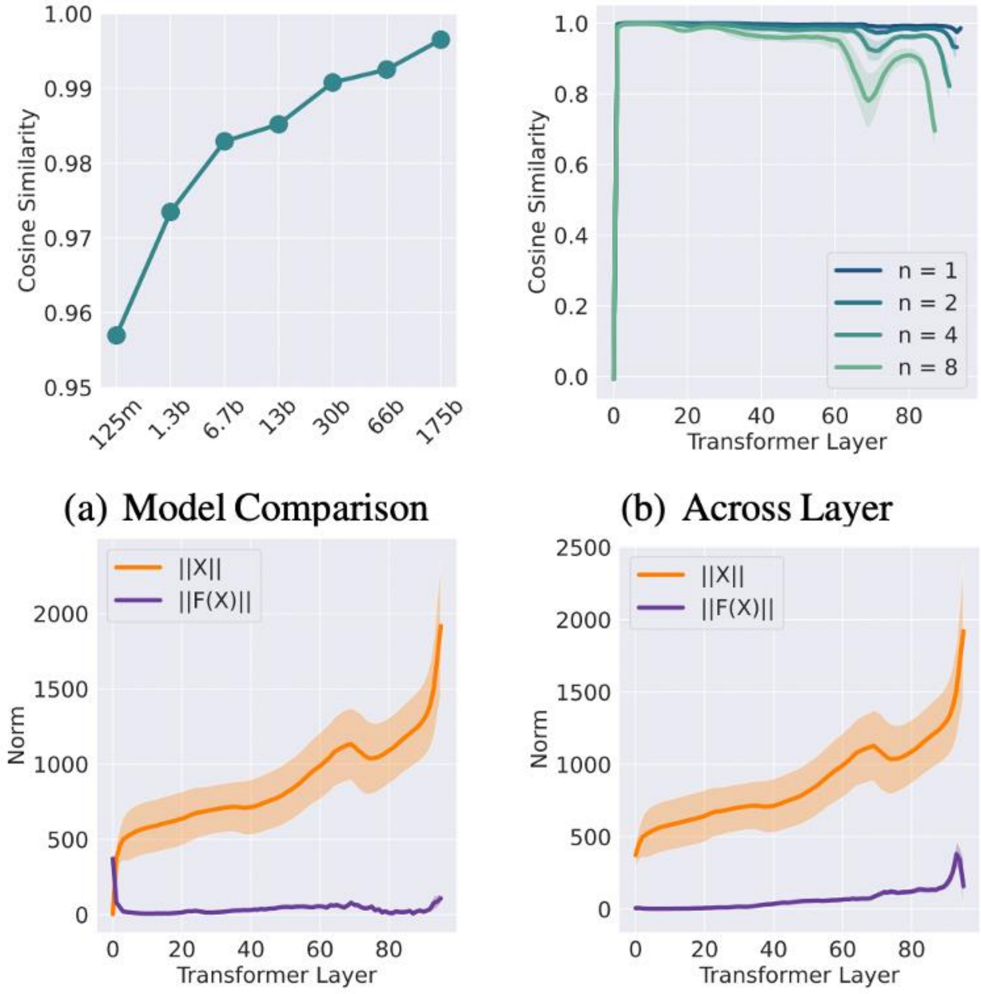
Only 25% of the FFN parameters are used for a single token



Switch Transformers: Scaling to Trillion Parameter Models with Simple and Efficient Sparsity [Fedus et al., CoRR 2021]

Deja Vu: Contextual Sparsity

Observation 1: Model activations change very little between consecutive layers of a network



(a) Model Comparison (b) Across Layer

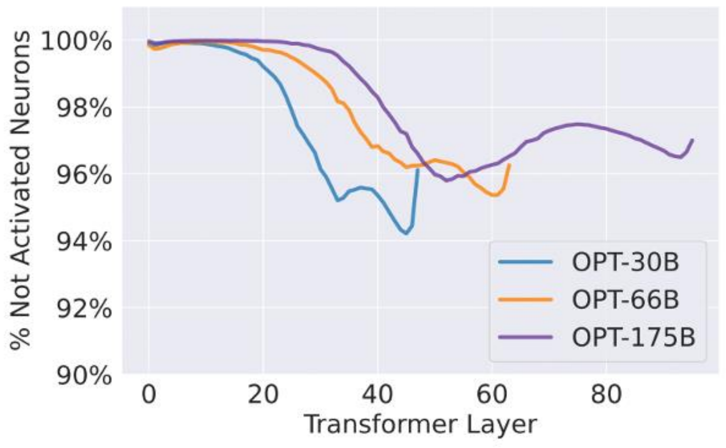
(c) Residual Around Attention (d) Residual Around MLP

Deja Vu: Contextual Sparsity for Efficient LLMs at Inference Time [Liu et al., 2023]

Deja Vu: Contextual Sparsity

Observation 2: Most attention heads and most neurons are not used

(a) Contextual sparsity in Attention Head

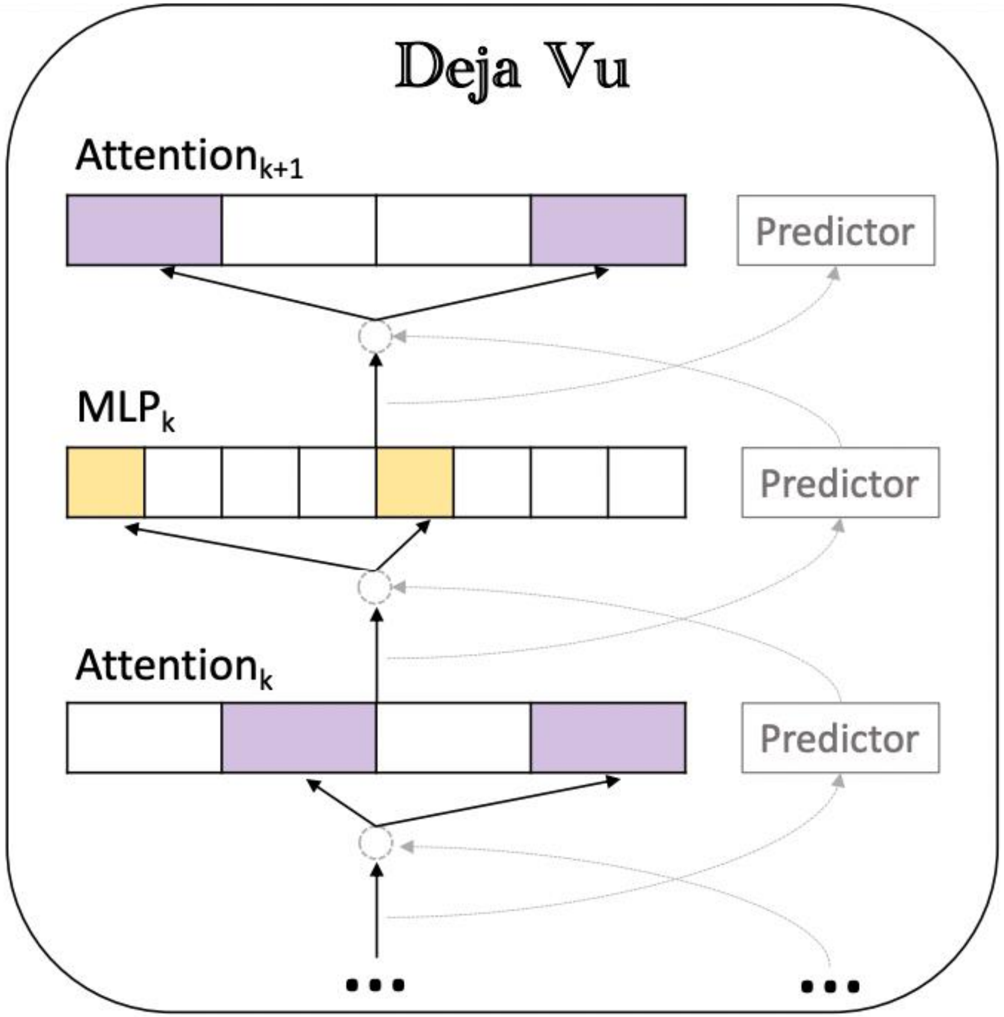


(b) Contextual sparsity in MLP Block

Deja Vu: Contextual Sparsity for Efficient LLMs at Inference Time [Liu et al., 2023]

Deja Vu: Contextual Sparsity

Sparsification: Use predictors in each layer to determine which neurons to activate and which attention heads to use – ignore all unpredicted heads/neurons



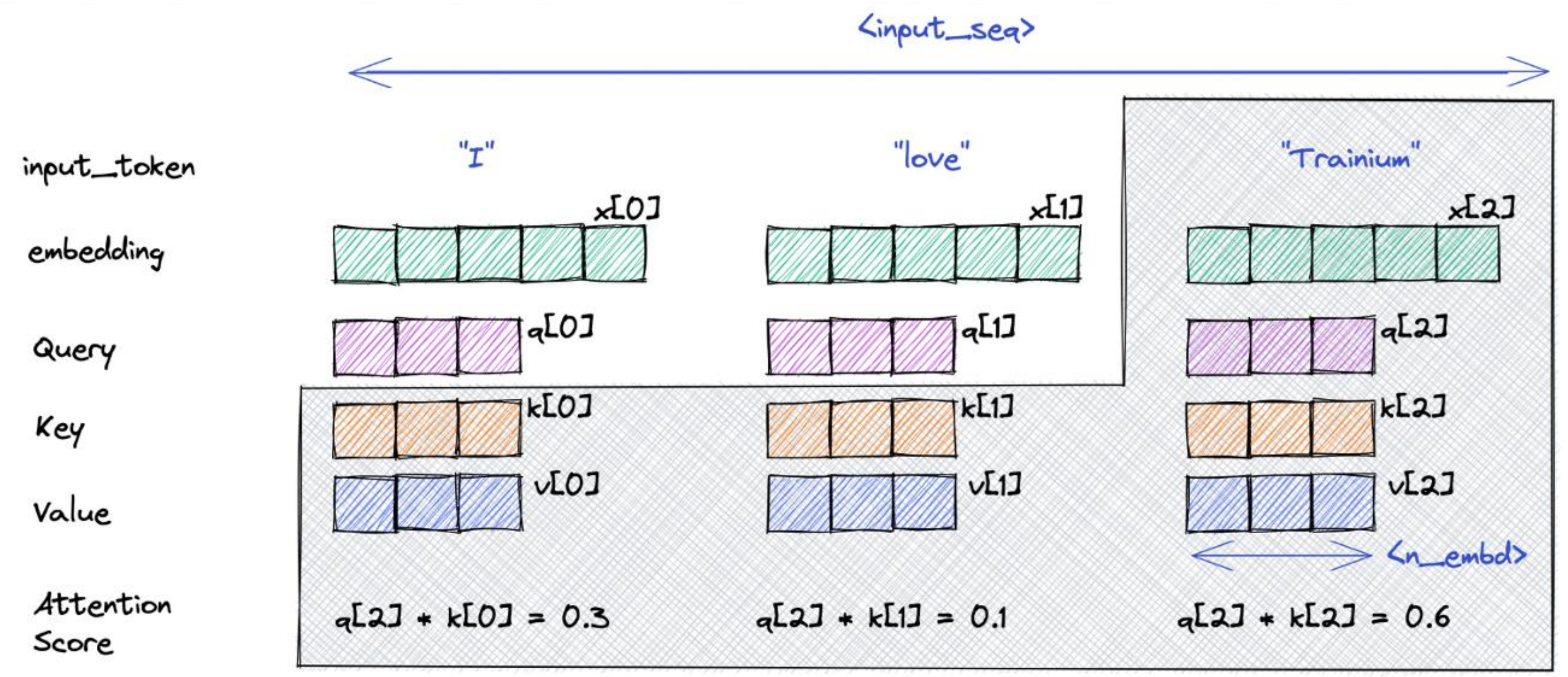
Deja Vu: Contextual Sparsity for Efficient LLMs at Inference Time [Liu et al., 2023]

Efficient LLMs

- Quantization
  - Background
  - K-Means vs. Linear Quantization
  - Quantization Granularity
  - Quantization Aware Training (QAT) vs Post-Training Quantization (PTQ)
  - LLM Quantization (LLM.int8(), SmoothQuant, AWQ, 1-bit LLMs)
- Sparsity (Mixture of Experts, Deja Vu: Contextual Sparsity)
- **Efficient Inference Systems (vLLM, StreamingLLM, MHA/GQA/MQA)**
- Parameter Efficient Fine-Tuning (BitFit, Adapter, Prompt Tuning, LoRA)

The KV-Cache

The transformer needs to have access to the keys and values for all previous tokens in all layers for all heads when



https://awsdocs-neuron.readthedocs-hosted.com/en/latest/general/appnotes/transformers-neuronx/generative-llm-inference-with-neuron.html

The KV-Cache

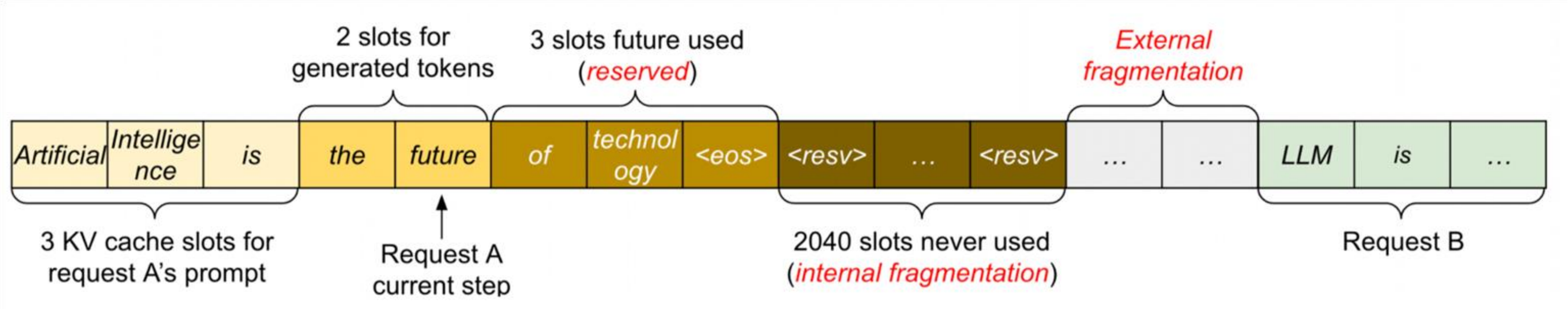
In total, we must store

Batch_size * seq_len * num_heads * num_layers * emb_dim * 2

separate values in the kv cache

vLLM

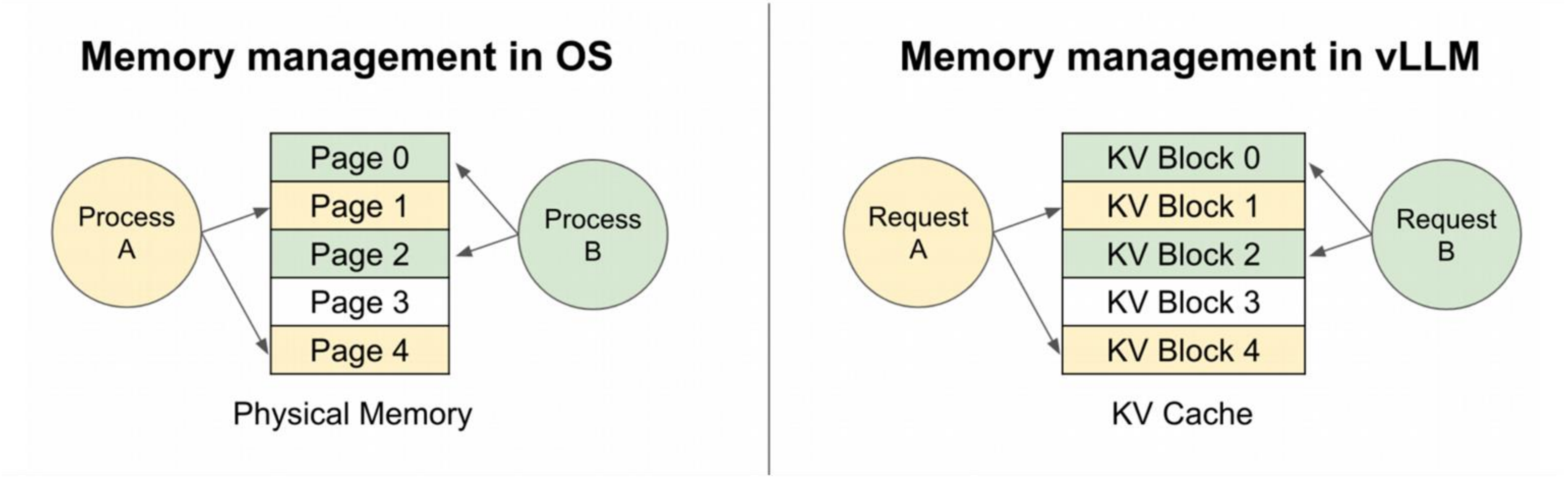
How does a large LLM service (large ChatGPT) handle multiple incoming requests with respect to the KV-cache?
-Originally, most systems just assign fixed sized blocks of memory to each incoming request. How to improve?



Efficient Memory Management for Large Language Model Serving with PagedAttention (Kwon et al., 2023)

vLLM

Let's adopt a similar approach to that found in virtual memory!



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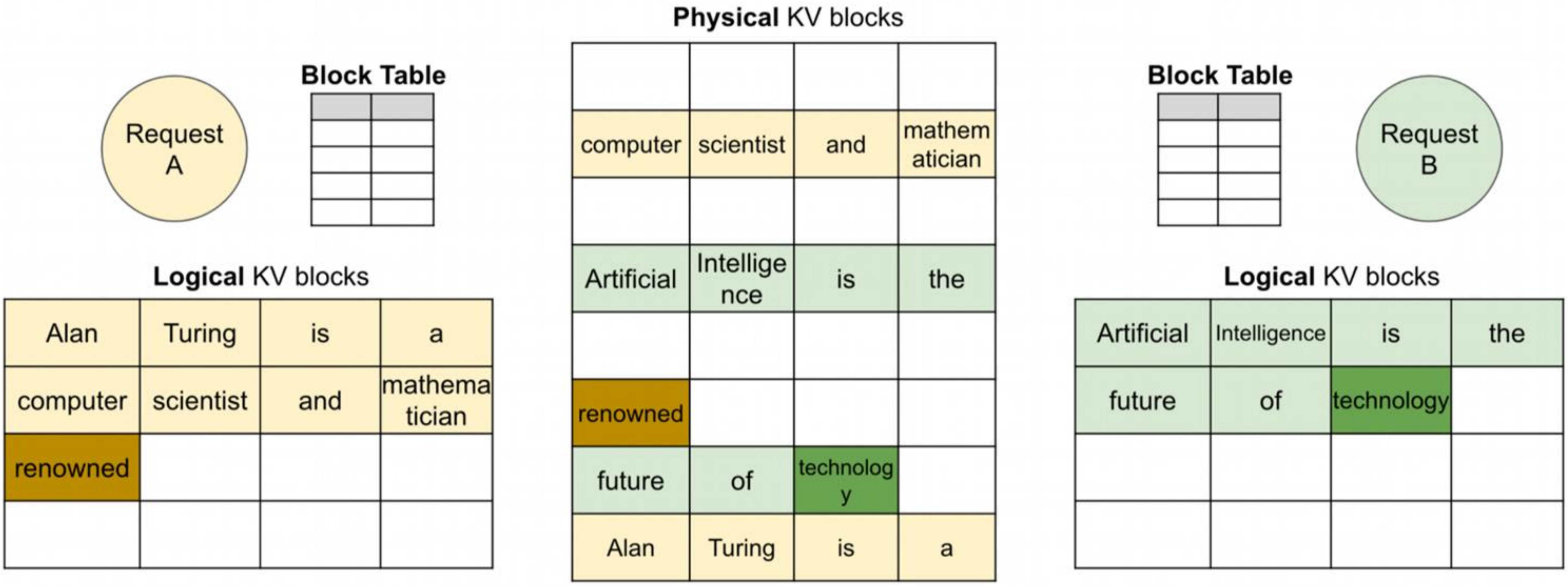
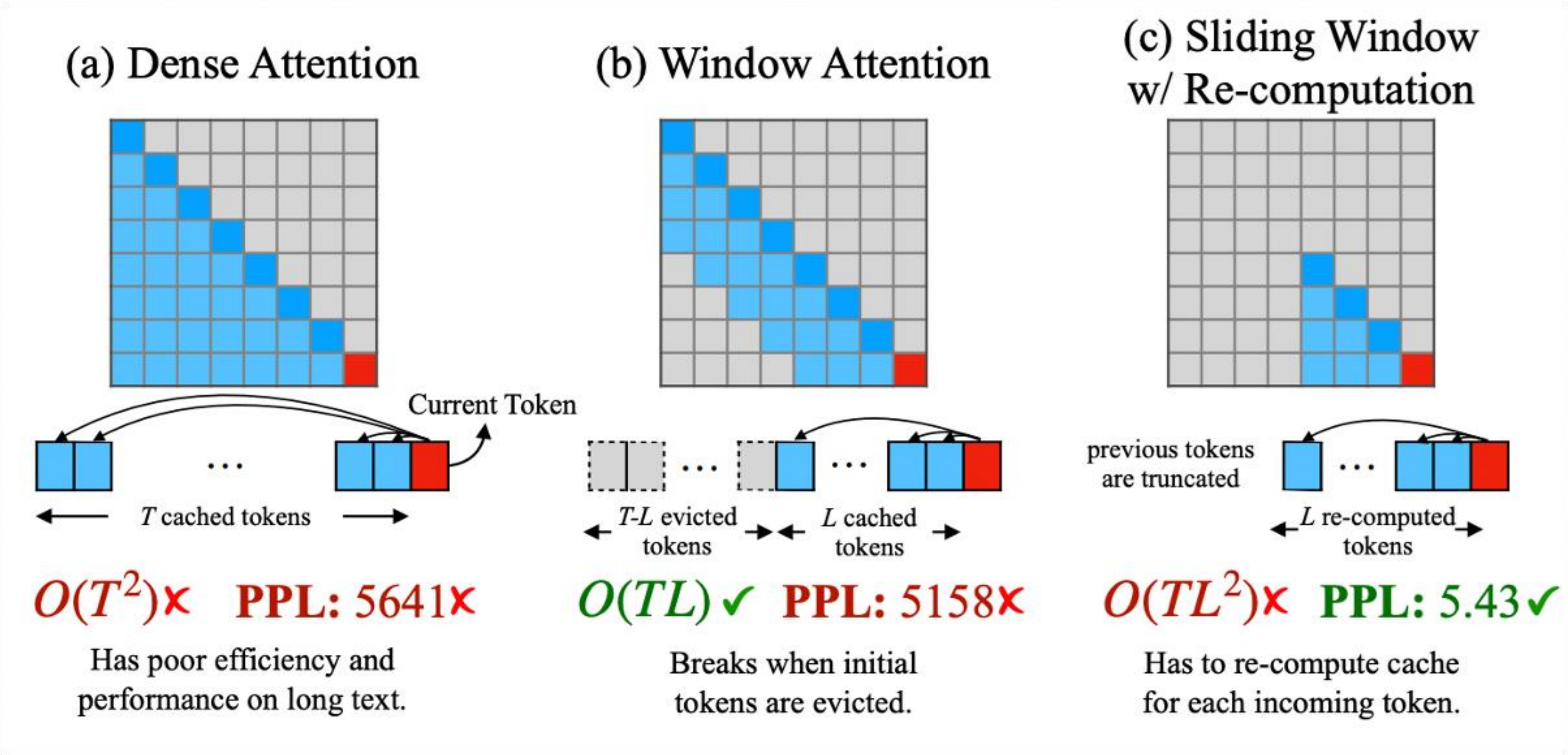
vLLM



Efficient Memory Management for Large Language Model Serving with PagedAttention (Kwon et al., 2023)

StreamingLLM

How can we extend models to have much longer context length at minimal cost?

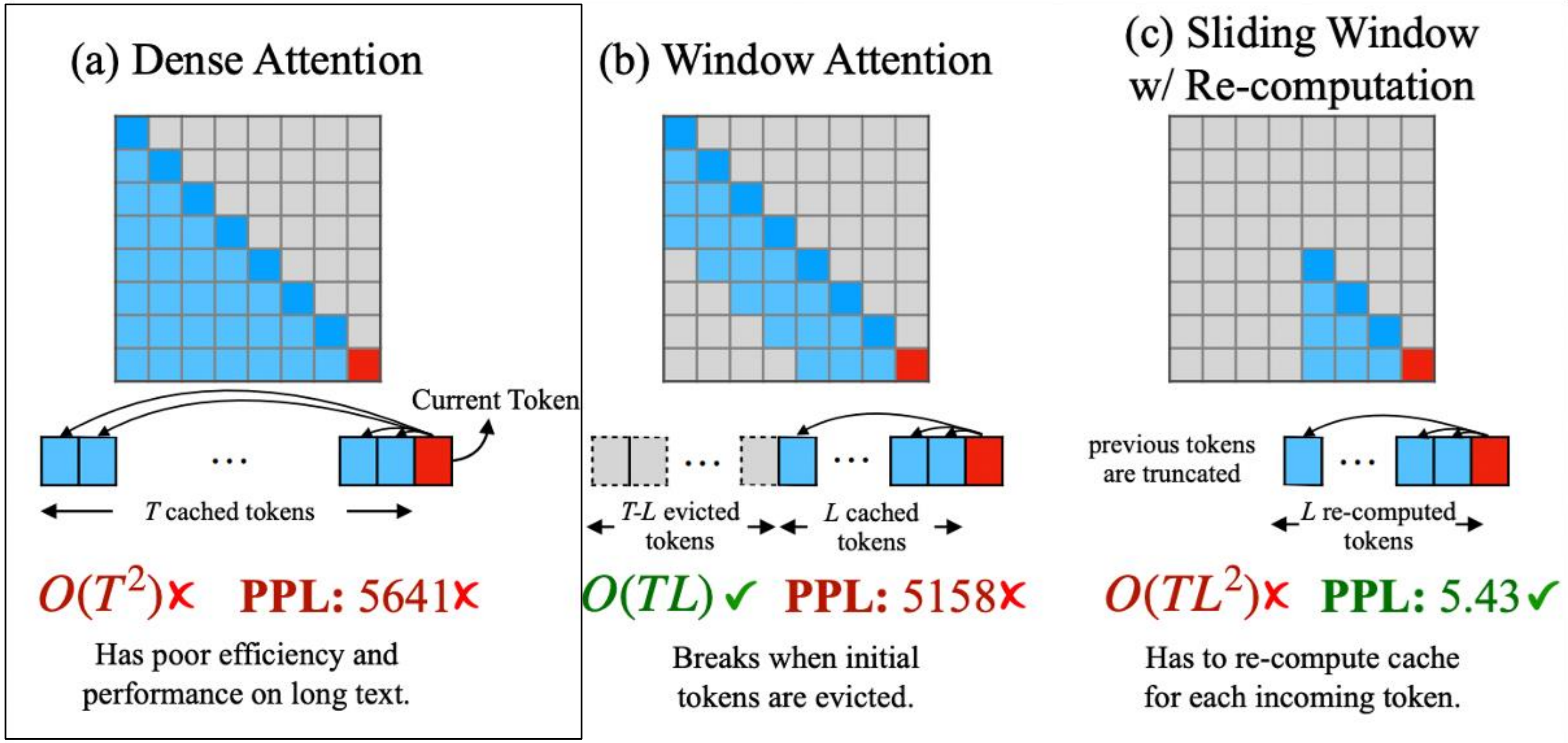


Efficient Streaming Language Models with Attention Sinks [Xiao et al., 2023]

StreamingLLM

How can we extend models to have much longer context length at minimal cost?

Too much storage

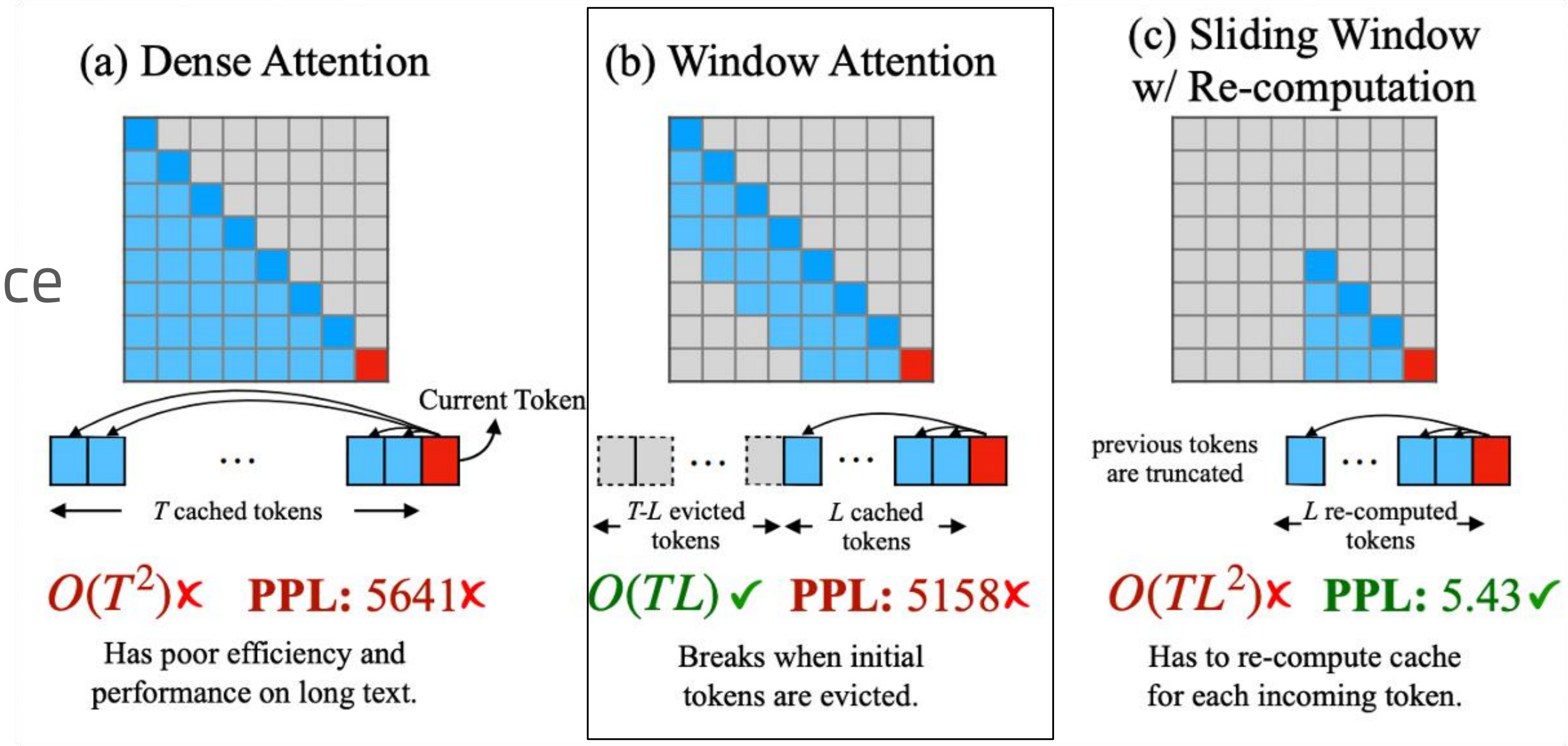


Efficient Streaming Language Models with Attention Sinks [Xiao et al., 2023]

StreamingLLM

How can we extend models to have much longer context length at minimal cost?

Bad performance

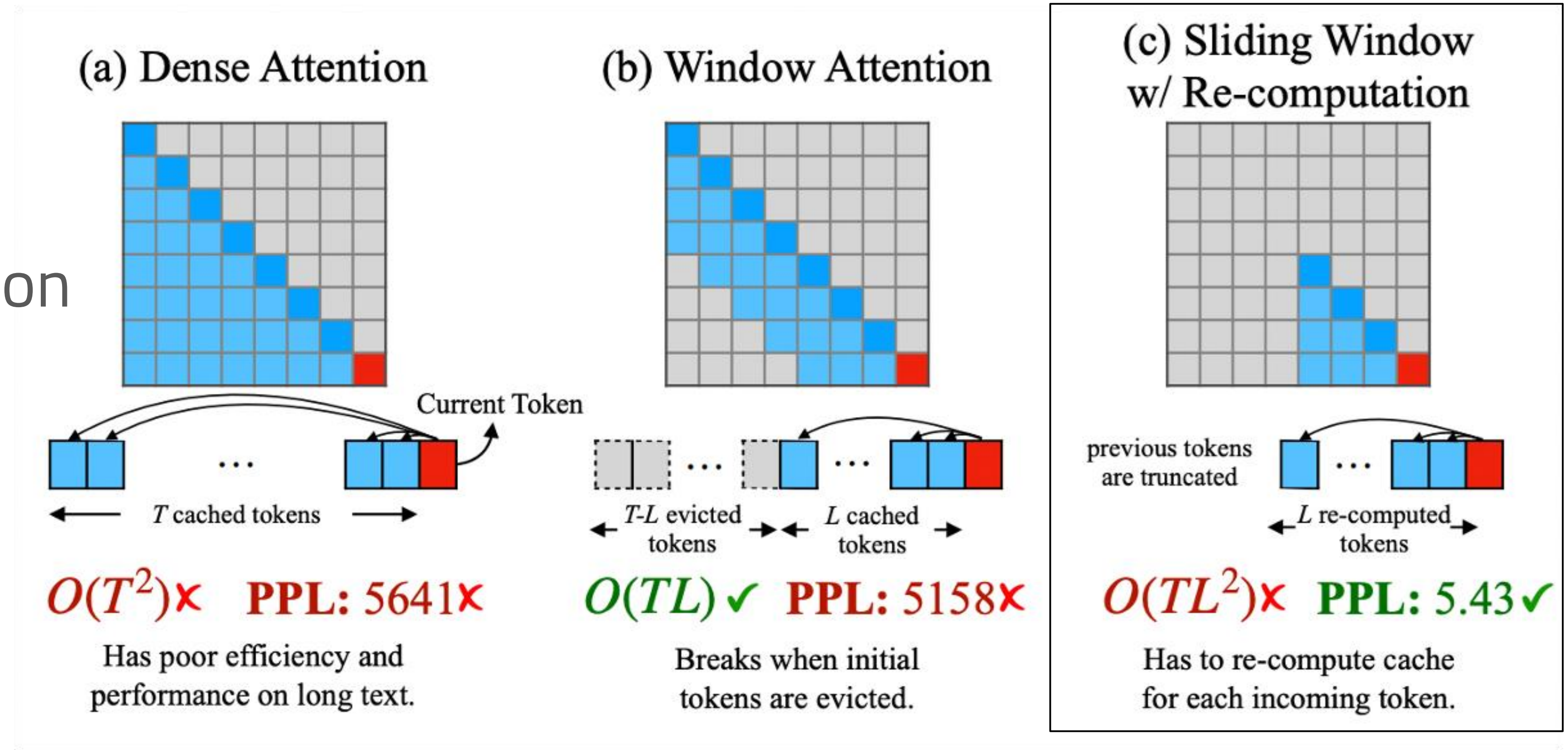


Efficient Streaming Language Models with Attention Sinks [Xiao et al., 2023]

StreamingLLM

How can we extend models to have much longer context length at minimal cost?

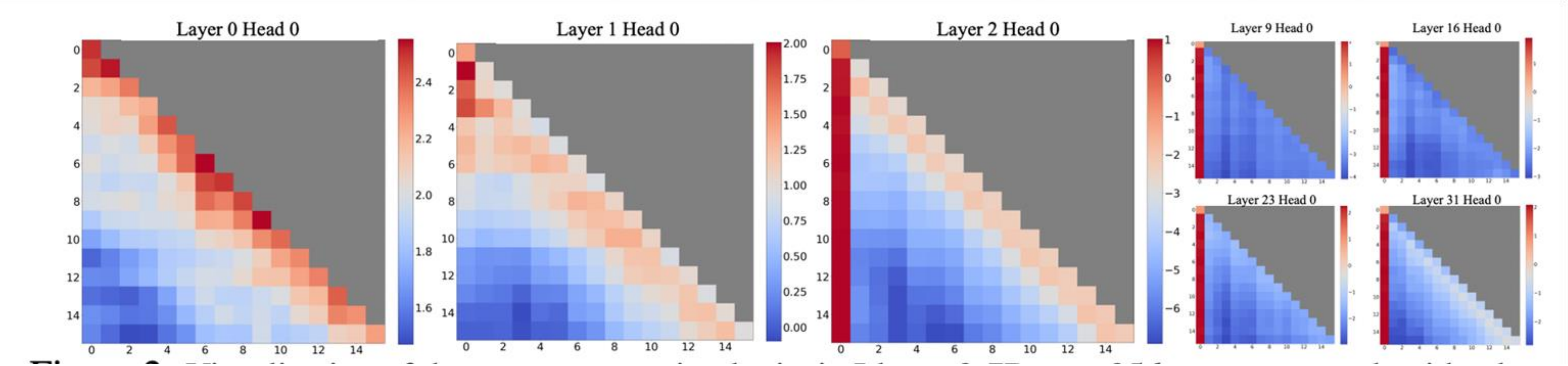
Too much recomputation



Efficient Streaming Language Models with Attention Sinks [Xiao et al., 2023]

StreamingLLM

Observation: Most attention is either placed on the first token or to tokens that the model has recently seen.



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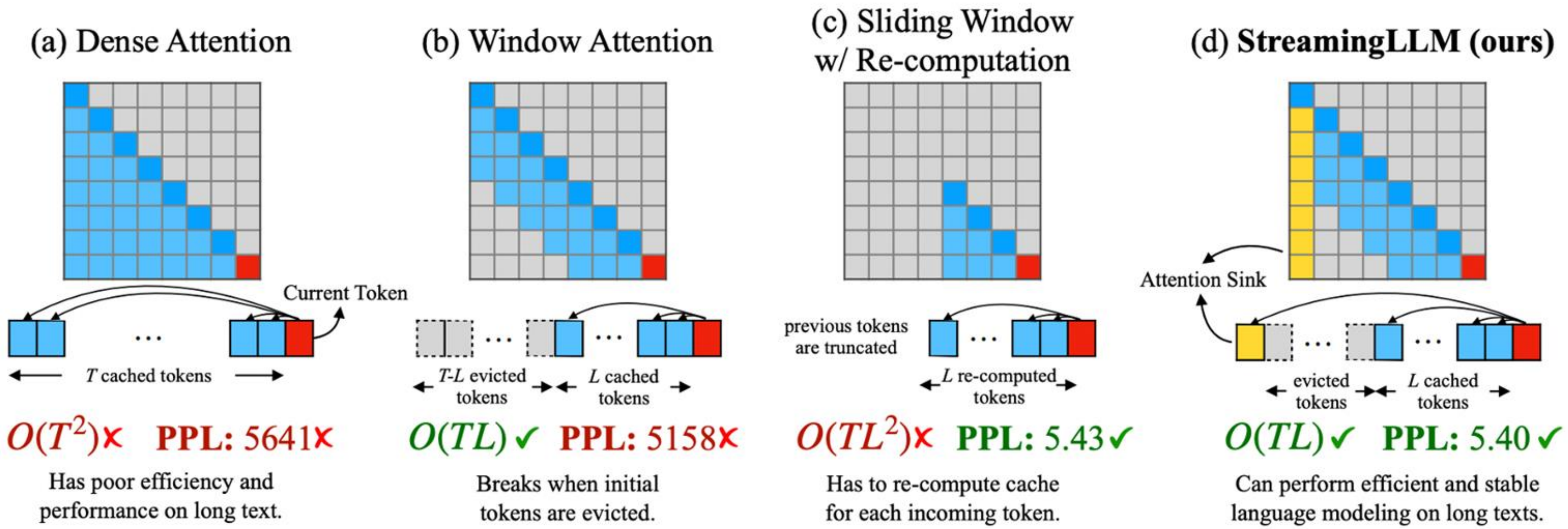
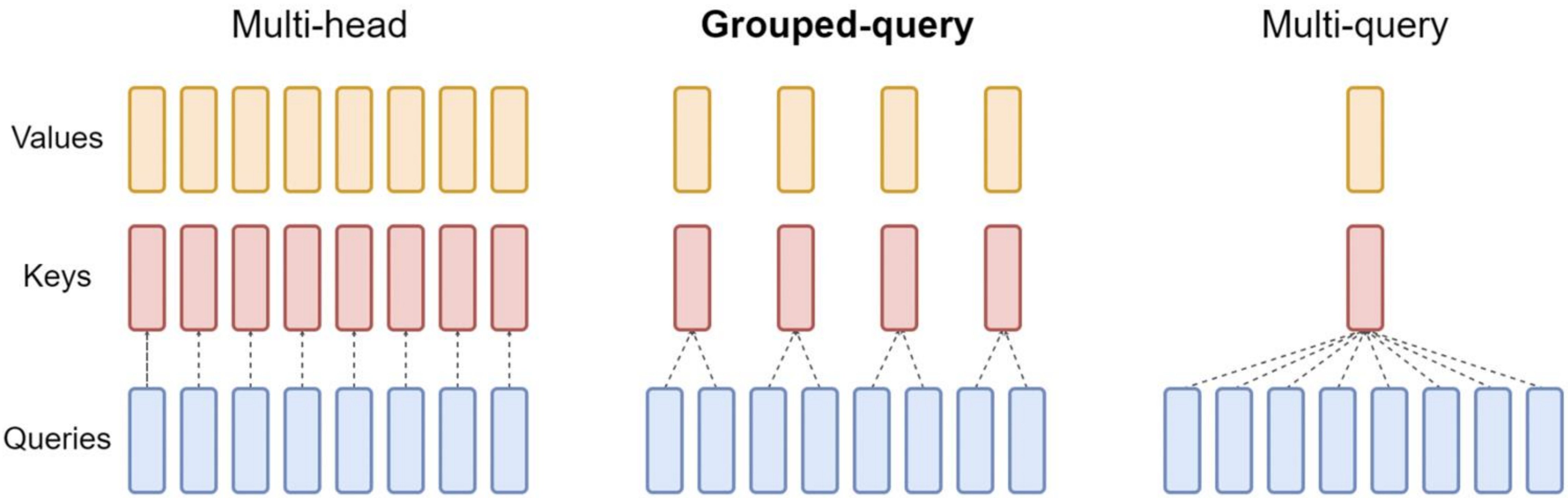
StreamingLLM



Efficient Streaming Language Models with Attention Sinks [Xiao et al., 2023]

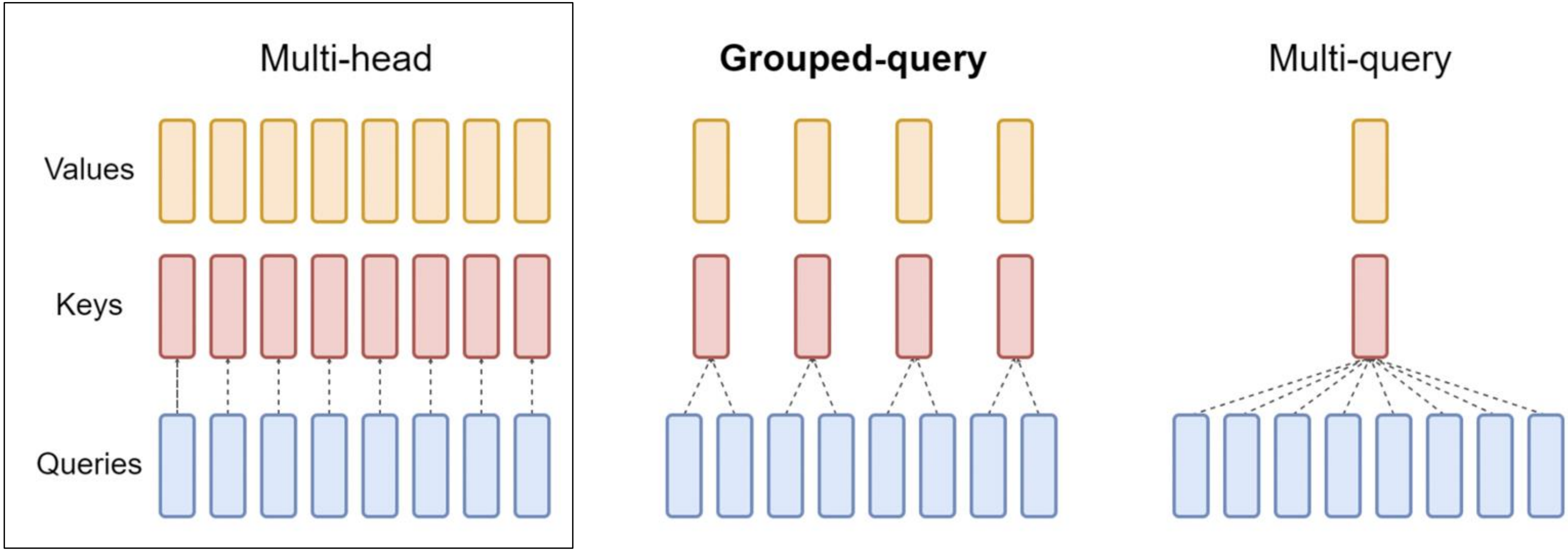
MHA/GQA/MQA



GQA: Training Generalized Multi-Query Transformer Models from Multi-Head Checkpoints

MHA/GQA/MQA

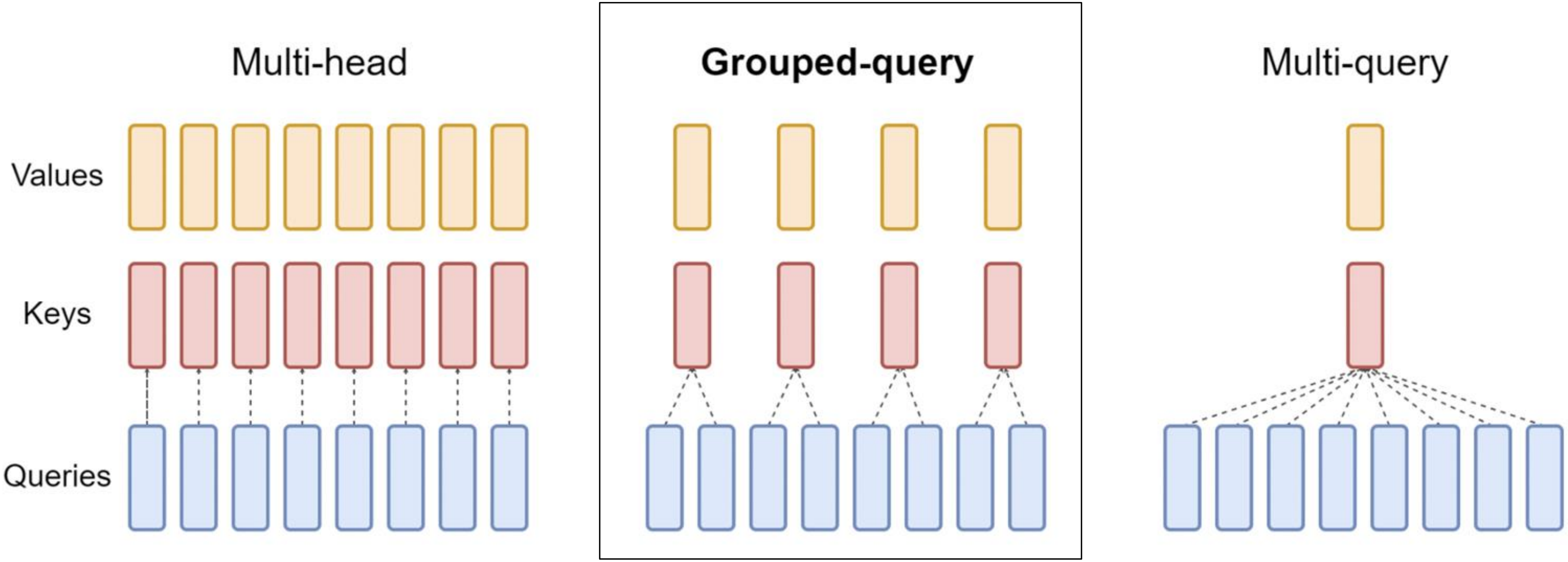
Each attention head calculates separate keys and values for each token



GQA: Training Generalized Multi-Query Transformer Models from Multi-Head Checkpoints

MHA/GQA/MQA

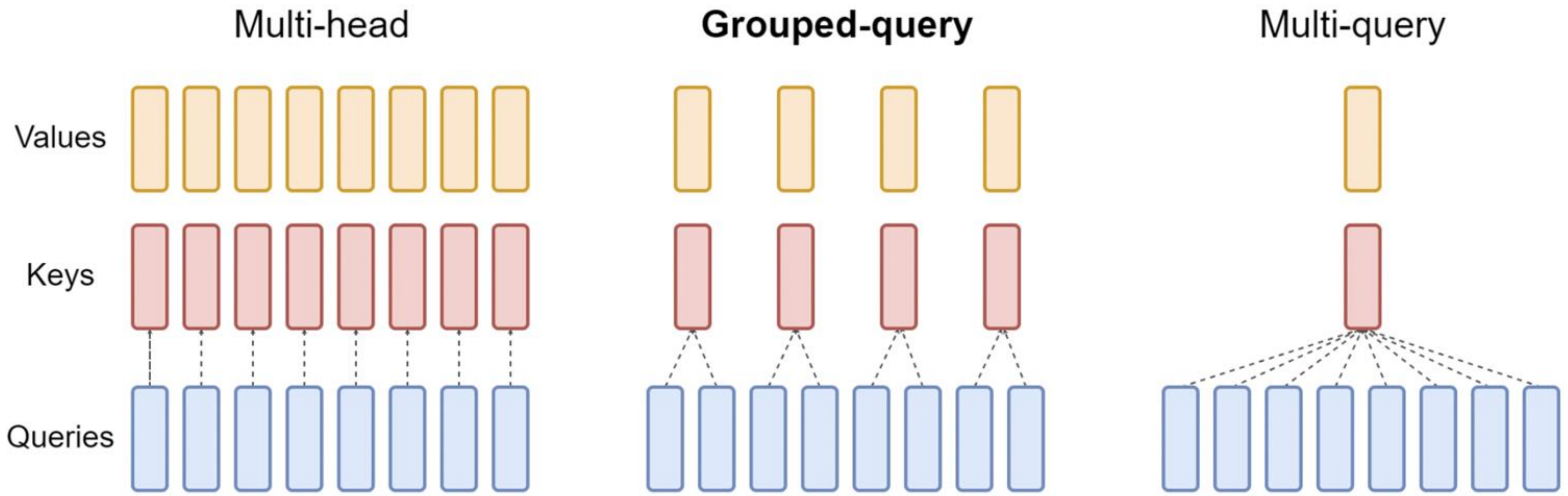
Attention heads are split into groups.
Each group has one key/value per token.



GQA: Training Generalized Multi-Query Transformer Models from Multi-Head Checkpoints

MHA/GQA/MQA

Attention heads share the same keys and values for each token



GQA: Training Generalized Multi-Query Transformer Models from Multi-Head Checkpoints

Efficient LLMs

- Quantization
  - Background
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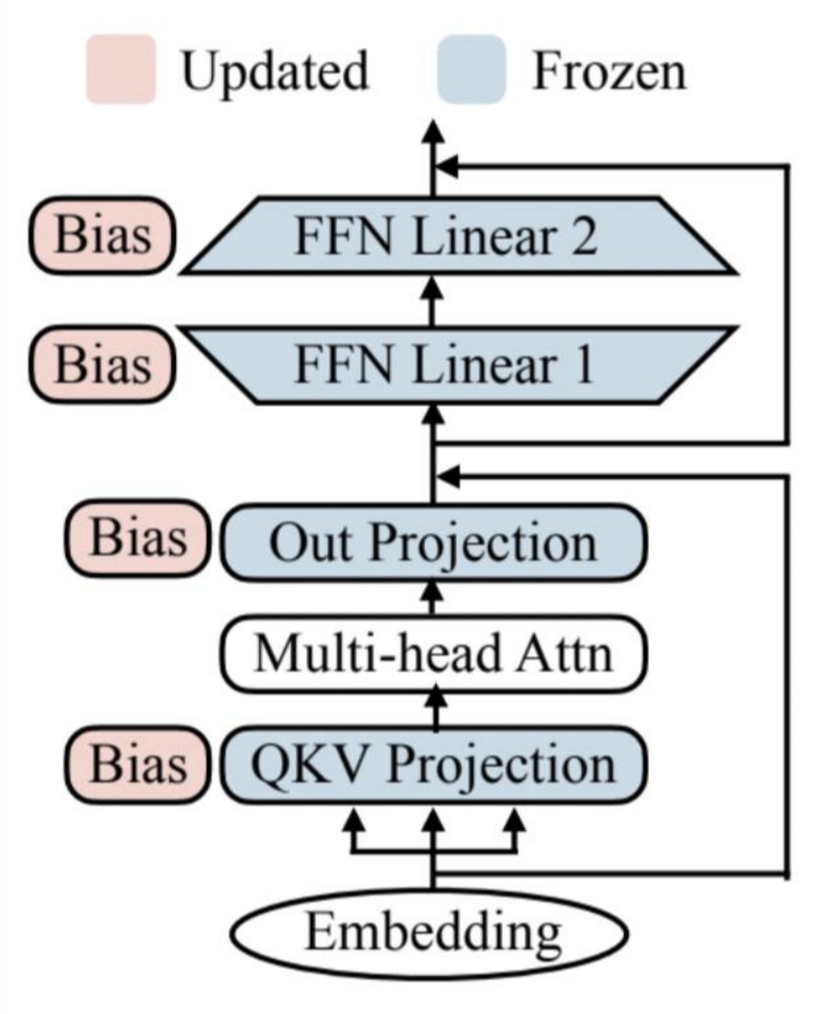
BitFit



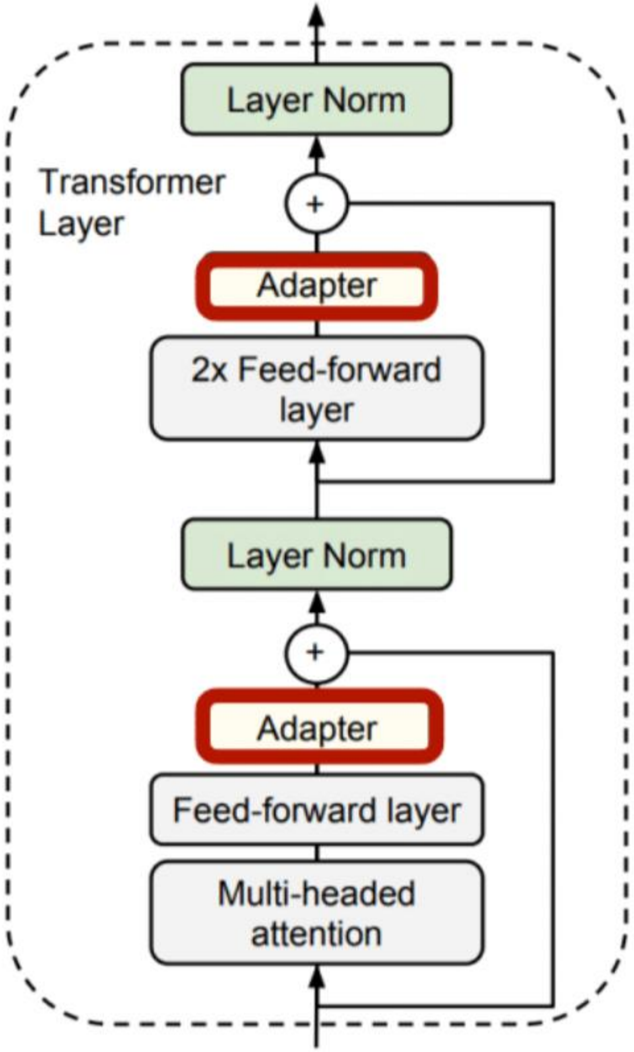
Update only the bias parameters

		%Param	QNLI	SST-2	MNLI_m	MNLI_{mm}	CoLA	MRPC	STS-B	RTE	QQP	Avg.
	Train size		105k	67k	393k	393k	8.5k	3.7k	7k	2.5k	364k	
(V)	Full-FT†	100%	**93.5**	**94.1**	**86.5**	**87.1**	**62.8**	**91.9**	89.8	71.8	**87.6**	**84.8**
(V)	Full-FT	100%	91.7±0.1	93.4±0.2	85.5±0.4	85.7±0.4	62.2±1.2	90.7±0.3	**90.0±0.4**	**71.9±1.3**	87.5±0.4	84.1
(V)	Diff-Prune†	0.5%	**93.4**	**94.2**	**86.4**	**86.9**	63.5	91.3	89.5	71.5	**86.6**	**84.6**
(V)	BitFit	0.08%	91.4±2.4	93.2±0.4	84.4±0.2	84.8±0.1	**63.6±0.7**	**91.7±0.5**	**90.3±0.1**	**73.2±3.7**	85.4±0.1	84.2
(T)	Full-FT‡	100%	91.1	**94.9**	86.7	85.9	**60.5**	**89.3**	**87.6**	70.1	**72.1**	**81.8**
(T)	Full-FT†	100%	**93.4**	94.1	86.7	**86.0**	59.6	88.9	86.6	**71.2**	71.7	81.5
(T)	Adapters‡	3.6%	90.7	94.0	84.9	85.1	59.5	89.5	**86.9**	71.5	**71.8**	81.1
(T)	Diff-Prune†	0.5%	**93.3**	94.1	**86.4**	**86.0**	**61.1**	**89.7**	86.0	70.6	71.1	**81.5**
(T)	BitFit	0.08%	92.0	**94.2**	84.5	84.8	59.7	88.9	85.5	**72.0**	70.5	80.9

Table 1: $\text{BERT}_{\text{LARGE}}$ model performance on the GLUE benchmark validation set (V) and test set (T). Lines with † and ‡ indicate results taken from Guo et al. (2020) and Houlsby et al. (2019) (respectively).

BitFit: Simple Parameter-efficient Fine-tuning for Transformer-based Masked Language-models [Zeken et al, ACL 2021]

Adapter



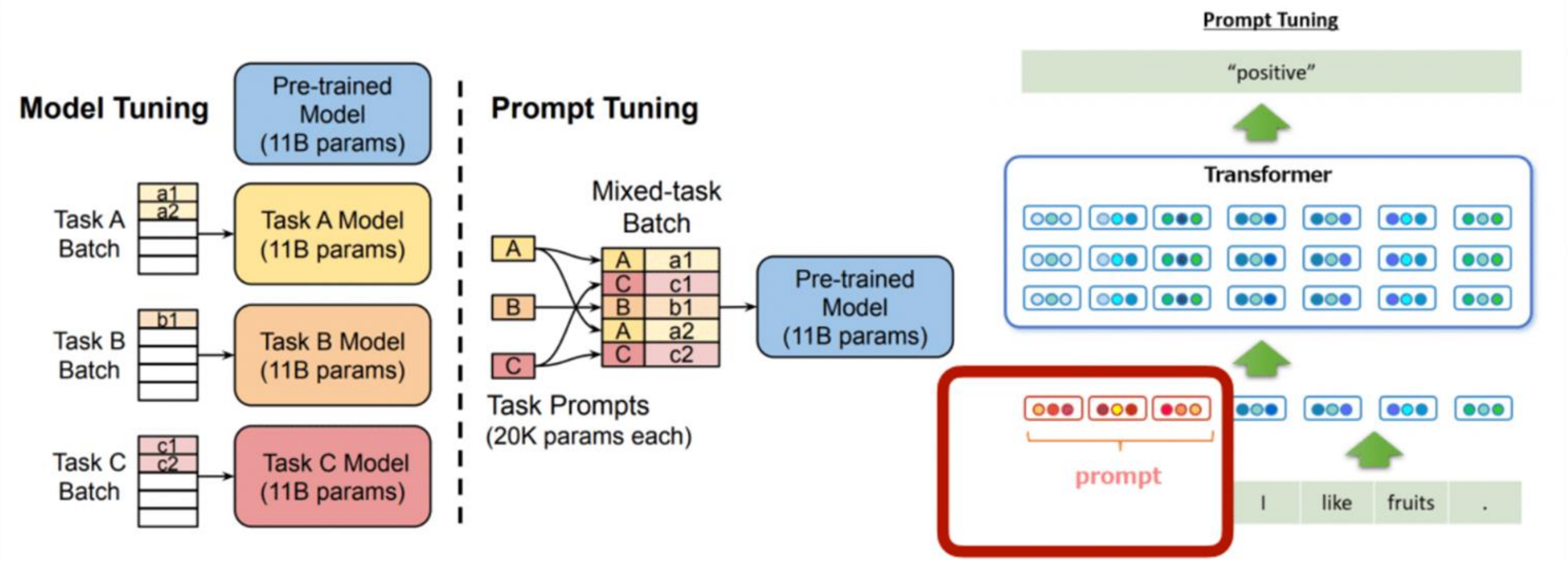
Add trainable layers after each feedforward layer

	Total num params	Trained params / task	CoLA	SST	MRPC	STS-B	QQP	MNLI_{m}	MNLI_{mm}	QNLI	RTE	Total
$\text{BERT}_{\text{LARGE}}$	9.0×	100%	60.5	94.9	89.3	87.6	72.1	86.7	85.9	91.1	70.1	80.4
Adapters (8-256)	1.3×	3.6%	59.5	94.0	89.5	86.9	71.8	84.9	85.1	90.7	71.5	80.0
Adapters (64)	1.2×	2.1%	56.9	94.2	89.6	87.3	71.8	85.3	84.6	91.4	68.8	79.6

Parameter-Efficient Transfer Learning for NLP [Houlsby et al, ICML 2019]

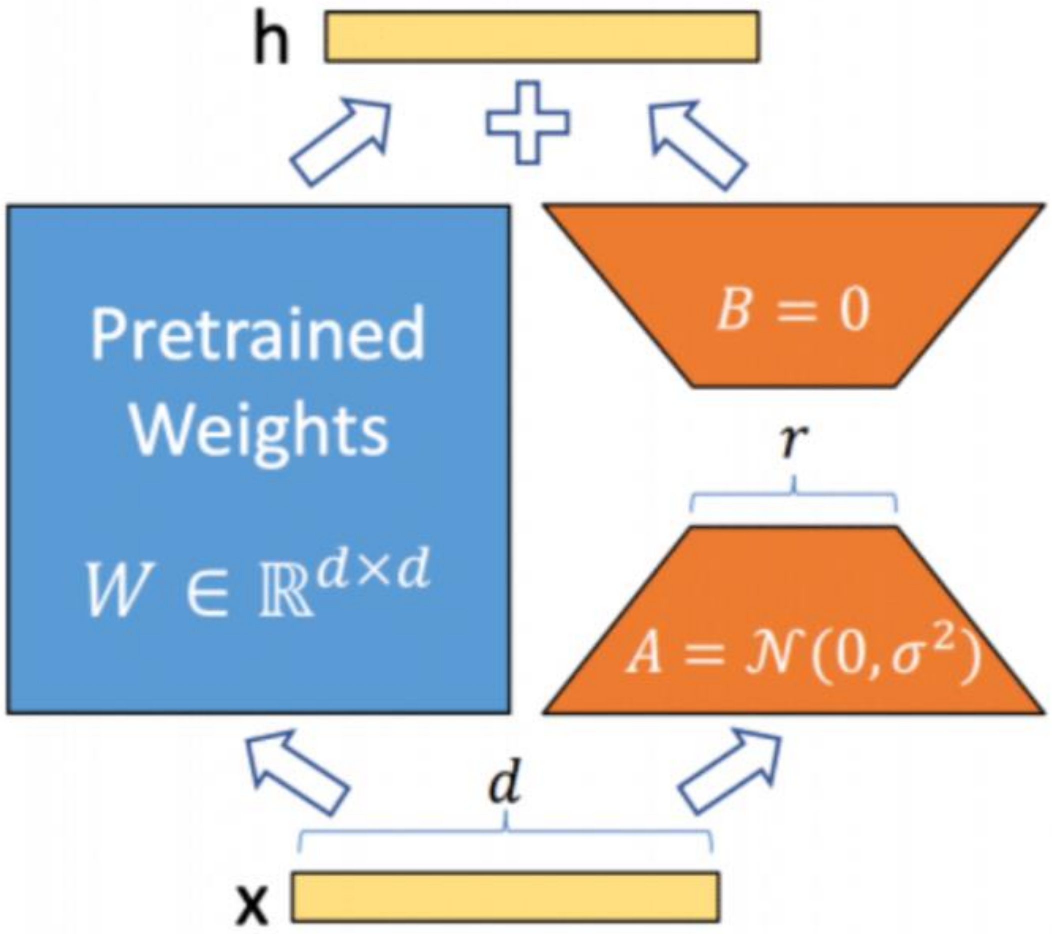
Prompt Tuning (Soft Prompting)

Train a continuous, learnable prompt in embedding space for each task we are training on



The Power of Scale for Parameter-Efficient Prompt Tuning [Lester, ACL 2021]

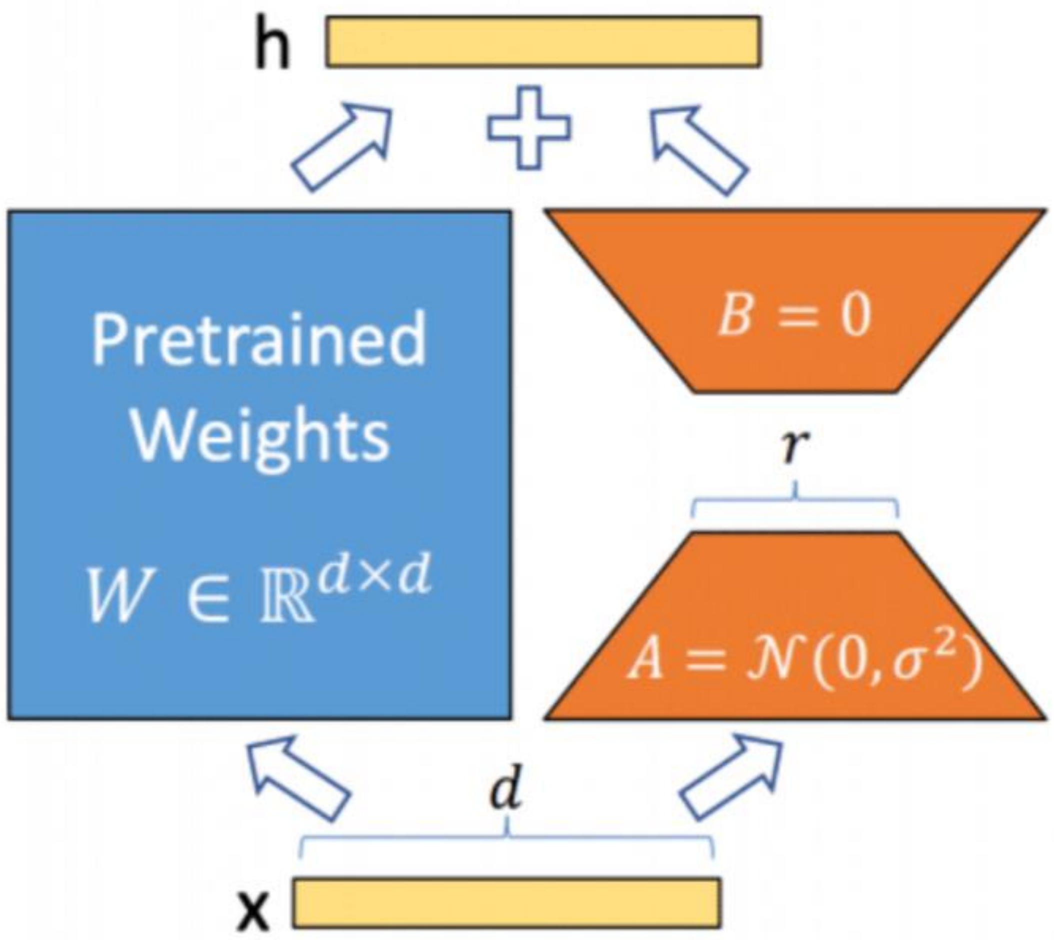
LoRA



- ❑ Hypothesizes that fine-tuning results in only low rank updates
- ❑ Thus, we may approximate the updates themselves as low-rank and train on this low-rank approximation directly

The Power of Scale for Parameter-Efficient Prompt Tuning [Lester, ACL 2021]

LoRA



h = Wx

h = Wx + BAx

The Power of Scale for Parameter-Efficient Prompt Tuning [Lester, ACL 2021]

LoRA

Model & Method	# Trainable Parameters	MNLI	SST-2	MRPC	CoLA	QNLI	QQP	RTE	STS-B	Avg.
RoB_{base} (FT)*	125.0M	**87.6**	94.8	90.2	**63.6**	92.8	**91.9**	78.7	91.2	86.4
RoB_{base} (BitFit)*	0.1M	84.7	93.7	**92.7**	62.0	91.8	84.0	81.5	90.8	85.2
RoB_{base} (Adpt^{D})*	0.3M	$87.1_{\pm.0}$	$94.2_{\pm.1}$	$88.5_{\pm1.1}$	$60.8_{\pm.4}$	$93.1_{\pm.1}$	$90.2_{\pm.0}$	$71.5_{\pm2.7}$	$89.7_{\pm.3}$	84.4
RoB_{base} (Adpt^{D})*	0.9M	$87.3_{\pm.1}$	$94.7_{\pm.3}$	$88.4_{\pm.1}$	$62.6_{\pm.9}$	$93.0_{\pm.2}$	$90.6_{\pm.0}$	$75.9_{\pm2.2}$	$90.3_{\pm.1}$	85.4
RoB_{base} (LoRA)	0.3M	$87.5_{\pm.3}$	$\mathbf{95.1}_{\pm.2}$	$89.7_{\pm.7}$	$63.4_{\pm1.2}$	$\mathbf{93.3}_{\pm.3}$	$90.8_{\pm.1}$	$\mathbf{86.6}_{\pm.7}$	$\mathbf{91.5}_{\pm.2}$	**87.2**
$\text{RoB}_{\text{large}}$ (FT)*	355.0M	90.2	**96.4**	**90.9**	68.0	94.7	**92.2**	86.6	92.4	88.9
$\text{RoB}_{\text{large}}$ (LoRA)	0.8M	$\mathbf{90.6}_{\pm.2}$	$96.2_{\pm.5}$	$\mathbf{90.9}_{\pm1.2}$	$\mathbf{68.2}_{\pm1.9}$	$\mathbf{94.9}_{\pm.3}$	$91.6_{\pm.1}$	$\mathbf{87.4}_{\pm2.5}$	$\mathbf{92.6}_{\pm.2}$	**89.0**
$\text{RoB}_{\text{large}}$ (Adpt^{P})†	3.0M	$90.2_{\pm.3}$	$96.1_{\pm.3}$	$90.2_{\pm.7}$	$\mathbf{68.3}_{\pm1.0}$	$\mathbf{94.8}_{\pm.2}$	$\mathbf{91.9}_{\pm.1}$	$83.8_{\pm2.9}$	$92.1_{\pm.7}$	88.4
$\text{RoB}_{\text{large}}$ (Adpt^{P})†	0.8M	$\mathbf{90.5}_{\pm.3}$	$\mathbf{96.6}_{\pm.2}$	$89.7_{\pm1.2}$	$67.8_{\pm2.5}$	$\mathbf{94.8}_{\pm.3}$	$91.7_{\pm.2}$	$80.1_{\pm2.9}$	$91.9_{\pm.4}$	87.9
$\text{RoB}_{\text{large}}$ (Adpt^{H})†	6.0M	$89.9_{\pm.5}$	$96.2_{\pm.3}$	$88.7_{\pm2.9}$	$66.5_{\pm4.4}$	$94.7_{\pm.2}$	$92.1_{\pm.1}$	$83.4_{\pm1.1}$	$91.0_{\pm1.7}$	87.8
$\text{RoB}_{\text{large}}$ (Adpt^{H})†	0.8M	$90.3_{\pm.3}$	$96.3_{\pm.5}$	$87.7_{\pm1.7}$	$66.3_{\pm2.0}$	$94.7_{\pm.2}$	$91.5_{\pm.1}$	$72.9_{\pm2.9}$	$91.5_{\pm.5}$	86.4
$\text{RoB}_{\text{large}}$ (LoRA)†	0.8M	$\mathbf{90.6}_{\pm.2}$	$96.2_{\pm.5}$	$\mathbf{90.2}_{\pm1.0}$	$68.2_{\pm1.9}$	$\mathbf{94.8}_{\pm.3}$	$91.6_{\pm.2}$	$\mathbf{85.2}_{\pm1.1}$	$\mathbf{92.3}_{\pm.5}$	**88.6**
DeB_{XXL} (FT)*	1500.0M	91.8	**97.2**	92.0	72.0	**96.0**	92.7	93.9	92.9	91.1
DeB_{XXL} (LoRA)	4.7M	$\mathbf{91.9}_{\pm.2}$	$96.9_{\pm.2}$	$\mathbf{92.6}_{\pm.6}$	$\mathbf{72.4}_{\pm1.1}$	$\mathbf{96.0}_{\pm.1}$	$\mathbf{92.9}_{\pm.1}$	$\mathbf{94.9}_{\pm.4}$	$\mathbf{93.0}_{\pm.2}$	**91.3**

Table 2: $\text{RoBERTa}_{\text{base}}$, $\text{RoBERTa}_{\text{large}}$, and $\text{DeBERTa}_{\text{XXL}}$ with different adaptation methods on the GLUE benchmark. We report the overall (matched and mismatched) accuracy for MNLI, Matthew's correlation for CoLA, Pearson correlation for STS-B, and accuracy for other tasks. Higher is better for all metrics. * indicates numbers published in prior works. † indicates runs configured in a setup similar to Houlsby et al. (2019) for a fair comparison.

The Power of Scale for Parameter-Efficient Prompt Tuning [Lester, ACL 2021]

Summary

- Efficient inference algorithms in LLMs lead to lower cost, faster inference, and smaller models
- Quantization and sparsity are the primary techniques for realizing these efficiencies
- PEFT techniques allow for faster fine-tuning with smaller storage requirements

Open Source Models

- Llama (Meta) ⟶ https://huggingface.co/docs/transformers/en/model_doc/llama
- Mixtral (Mistral) ⟶ https://huggingface.co/docs/transformers/en/model_doc/mixtral
- DBRX (Databricks) ⟶ https://huggingface.co/databricks/dbrx-base
- Grok (xai)⟶ https://huggingface.co/xai-org/grok-1
- Gemma (Google) ⟶ https://huggingface.co/google/gemma-2b-it

Repos to Make Models More Efficient

- Megablocks (MoE library)⟶ https://github.com/databricks/megablocks
- LLM.int8() ⟶ https://huggingface.co/blog/hf-bitsandbytes-integration
- AutoAWQ (AWQ integration) ⟶ https://github.com/casper-hansen/AutoAWQ
- LoRA ⟶ https://huggingface.co/docs/diffusers/en/training/lora
- QLoRA (not covered here) ⟶ https://huggingface.co/blog/4bit-transformers-bitsandbytes