8-bit Methods for Efficient Deep Learning

Tim Dettmers

Large models are not easily accessible

Model	Inference memory	Fine-tuning memory
T5-11B	22 GB	176 GB
OPT-66B	132 GB	1,056 GB
BLOOM 176B	350 GB	2,800 GB

Raffel et al., 2020, T5. Zhang et al., 2022, OPT., BigScience, 2022, BLOOM.

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LLM.int8()　　8-bit optimizers

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Overview of my work in this talk

8-Bit Approximations for Parallelism in Deep Learning. **Tim Dettmers**, *ICLR* 2015.

8-bit Optimizers via Block-wise Quantization. **Tim Dettmers**, Mike Lewis, Sam Shleifer, Luke Zettlemoyer, *ICLR* 2022 ***Spotlight***.

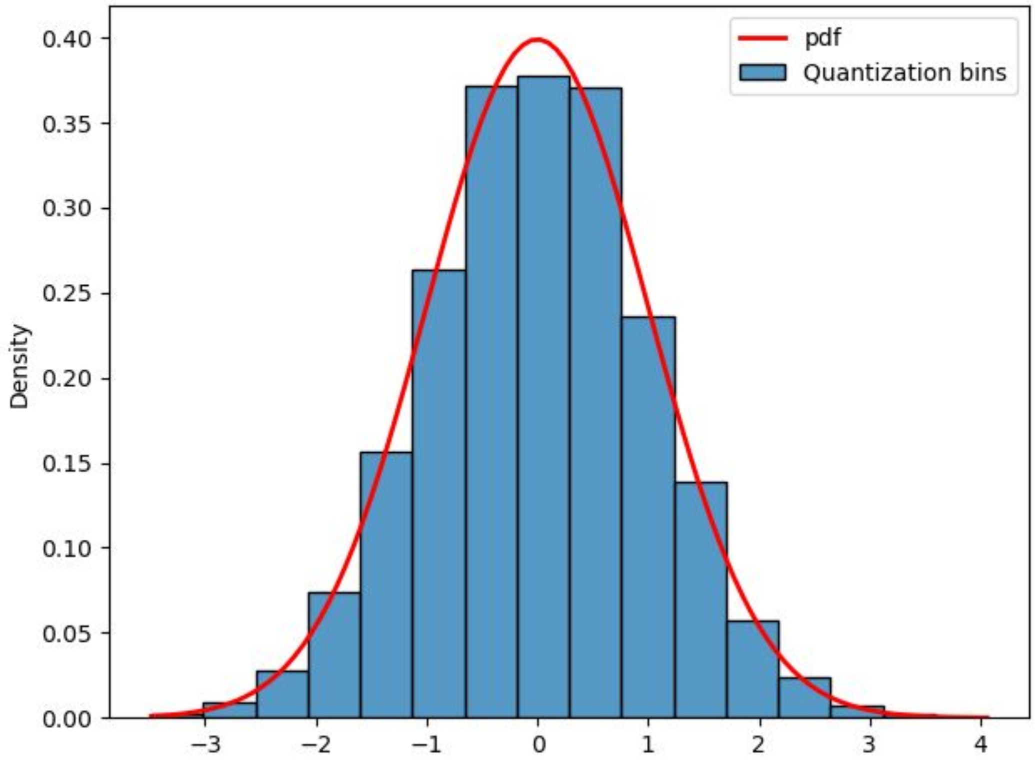
LLM.int8(): 8-bit Matrix Multiplication for Transformers at Scale . **Tim Dettmers**, Mike Lewis, Younes Belkada, Luke Zettlemoyer, *NeurIPS* 2022.

The case for 4-bit precision: k-bit Inference Scaling Laws. **Tim Dettmers**, Luke Zettlemoyer, i*n submission*.

Personalize your own ChatGPT on a single GPU. **Tim Dettmers**, Artidoro Pagnoni, Ari Holtzman, Luke Zettlemoyer, *in progress*.

Background

How does quantization work?



Quantization as a mapping

Most general form of describe quantization is through a mapping from integers to float values normalized to the range -1.0 and 1.0.

Int4	0 1 2 3 4 …	-7 -6 -5 -4 -3 …
FP4	0 1 2 3 4 5 …	-12 -8 -6 -4 -3 …

Quantization as a mapping

Most general form of describe quantization is through a mapping from integers to float values normalized to the range -1.0 and 1.0.

Int4	0	1	2	3	4 …
	-7	-6	-5	-4	-3 …
	-1	-0.86	-0.71	-0.57	-0.43 …

FP4	0	1	2	3	4 …
	-12	-8	-6	-4	-3 …
	-1	-0.67	-0.5	-0.33	-0.25 …

The mapping format { index : float value} generalizes to all data types.

Quantization as a mapping

Most general form of describe quantization is through a mapping from integers to float values normalized to the range -1.0 and 1.0.

Int4 maps -7, -6, … 6, 7 -> -1.0, -0.86 … 0.86, 1.0

Given a tensor X of any real data type. We can apply 8-bit quantization as follows:

1. Normalize X into the range [-1.0, 1.0]
2. Find the closest value in the data type

Step (1) is usually done by dividing by the absolute maximum (absmax) value.

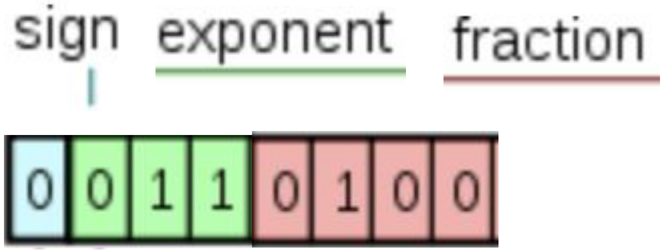
Quantization Example: A non-standard 2-bit data type

Map: {Index: 0, 1, 2, 3 -> Values: -1.0, 0.3, 0.5, 1.0}

Input tensor: [10, -3, 5, 4]

1. Normalize with absmax: [10, -3, 5, 4] -> [1, -0.3, 0.5, 0.4]
2. Find closest value: [1, -0.3, 0.5, 0.4] -> [1.0, 0.3, 0.5, 0.5]
3. Find the associated index: [1.0, 0.3, 0.5, 0.5] -> [3, 1, 2, 2] -> store
4. Dequantization: load -> [3, 1, 2, 2] -> lookup -> [1.0, 0.3, 0.5, 0.5] -> denormalize -> [10, 3, 5, 5]

Floating point data types (FP8)



3 bits for exponent, 4 for fraction:

- Good for large/small numbers
- Bad for precise numbers

1 bits for exponent, 6 for fraction:

- Good for precise numbers
- Bad for large/small numbers

Dynamic exponent quantization

Exponent: 1e-2

Fraction: 0.1 + 0.9*9/16 = 0.606

Sign "-"

Indicator bit

1	0	0	1	1	0	0	1

- 1e-2 * 0.606 = -6.06e-3

Dynamic exponent and fraction bits:

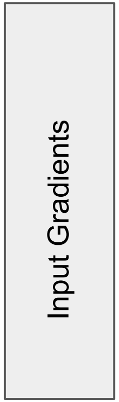
- Good for small and large numbers
- High precision for small and intermediate numbers
- Bad precision for very large numbers

8-bit Approximations for Parallelism in Deep Learning. Dettmers, 2015.

8-bit Optimizers

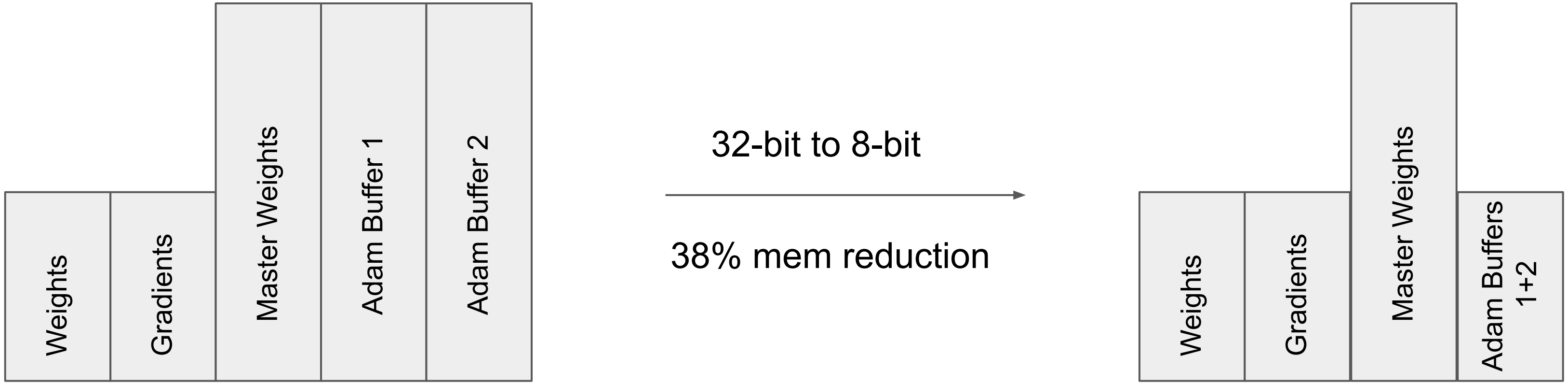
Motivation: Optimizers take up a lot of memory!

Memory depends on seq len, batch size, and model size

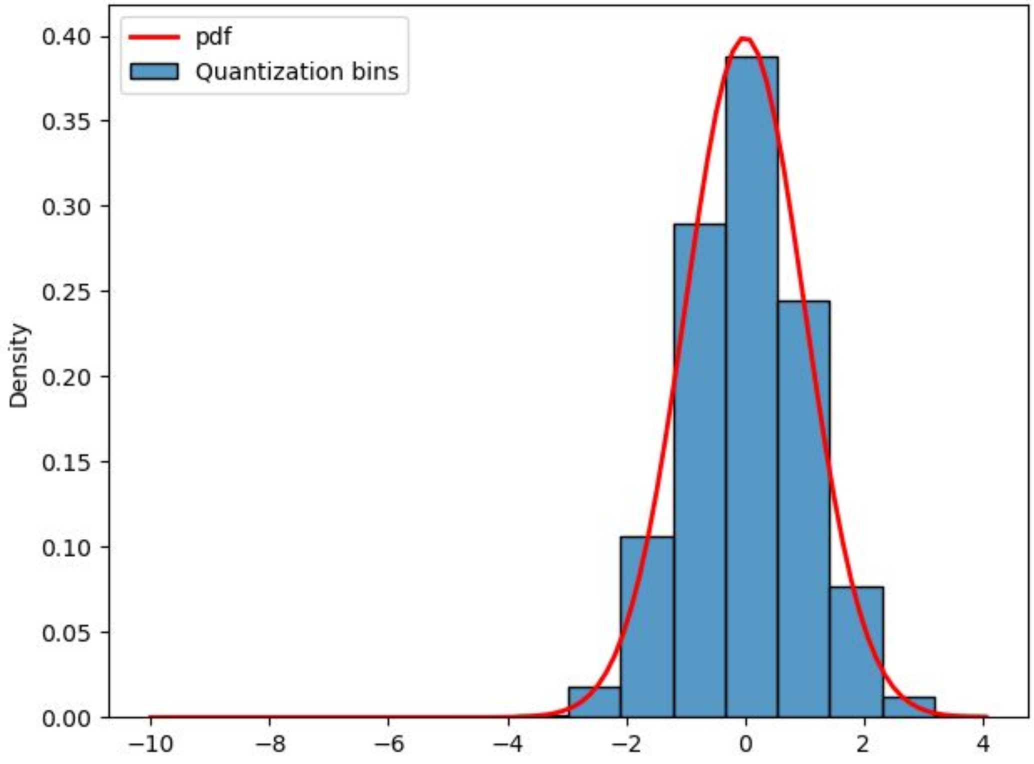


Memory that only depends on model size

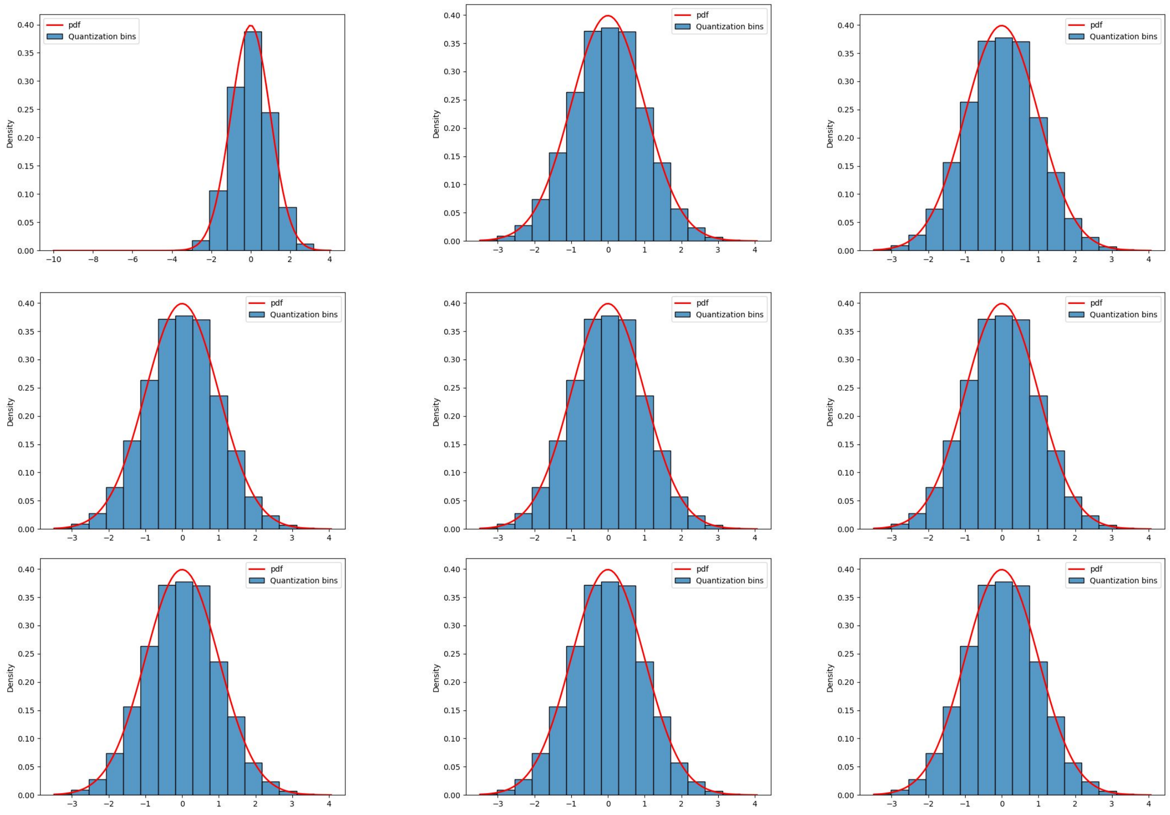
8-bit optimizers reduce memory consumption by 40%



What do outliers in quantization look like?



Block-wise quantization



Putting it together: 8-bit optimizers

Quantization

Updated optimizer states

Optimizer State	-3.1	0.1	-0.03	1.2
Chunk into blocks	$\boxed{-3.1 \quad 0.1}$		$\boxed{-0.03 \quad 1.2}$	
Find block-wise absmax	3.1		1.2	
Normalize with absmax	-1.0	0.032	-0.025	1.0
Find closest 8-bit value	-1.0	0.0329	-0.0242	1.0
Find corresponding index	0	170	80	255

Store index values

Dequantization

Load Index values

Index	0	170	80	255
Lookup values	-1.0	0.0329	-0.0242	1.0
Denormalize by absmax	-1.0*3.1	0.0329*3.1	-0.0242*1.2	1.0*1.2
Dequantized optimizer states	-3.1	0.102	-0.029	1.2

Update optimizer states

Results: Same accuracy/perplexity as 32-bit!

Optimizer	Task	Data	Model	Metric†	Time	Mem saved
32-bit AdamW	GLUE	Multiple	RoBERTa-Large	88.9	–	Reference
32-bit AdamW	GLUE	Multiple	RoBERTa-Large	88.6	17h	0.0 GB
32-bit Adafactor	GLUE	Multiple	RoBERTa-Large	**88.7**	24h	1.3 GB
8-bit AdamW	GLUE	Multiple	RoBERTa-Large	**88.7**	**15h**	**2.0 GB**
32-bit Momentum	CLS	ImageNet-1k	ResNet-50	77.1	–	Reference
32-bit Momentum	CLS	ImageNet-1k	ResNet-50	77.1	118h	0.0 GB
8-bit Momentum	CLS	ImageNet-1k	ResNet-50	**77.2**	**116 h**	**0.1 GB**
32-bit Adam	MT	WMT'14+16	Transformer	29.3	–	Reference
32-bit Adam	MT	WMT'14+16	Transformer	29.0	126h	0.0 GB
32-bit Adafactor	MT	WMT'14+16	Transformer	29.0	127h	0.3 GB
8-bit Adam	MT	WMT'14+16	Transformer	**29.1**	**115h**	**1.1 GB**
32-bit Momentum	MoCo v2	ImageNet-1k	ResNet-50	67.5	–	Reference
32-bit Momentum	MoCo v2	ImageNet-1k	ResNet-50	67.3	30 days	0.0 GB
8-bit Momentum	MoCo v2	ImageNet-1k	ResNet-50	**67.4**	**28 days**	**0.1 GB**
32-bit Adam	LM	Multiple	Transformer-1.5B	9.0	308 days	0.0 GB
32-bit Adafactor	LM	Multiple	Transformer-1.5B	**8.9**	316 days	5.6 GB
8-bit Adam	LM	Multiple	Transformer-1.5B	9.0	**297 days**	**8.5 GB**
32-bit Adam	LM	Multiple	GPT3-Medium	10.62	795 days	0.0 GB
32-bit Adafactor	LM	Multiple	GPT3-Medium	10.68	816 days	1.5 GB
8-bit Adam	LM	Multiple	GPT3-Medium	**10.62**	**761 days**	**1.7 GB**
32-bit Adam	Masked-LM	Multiple	RoBERTa-Base	3.49	101 days	0.0 GB
32-bit Adafactor	Masked-LM	Multiple	RoBERTa-Base	3.59	112 days	0.7 GB
8-bit Adam	Masked-LM	Multiple	RoBERTa-Base	**3.48**	**94 days**	**1.1 GB**

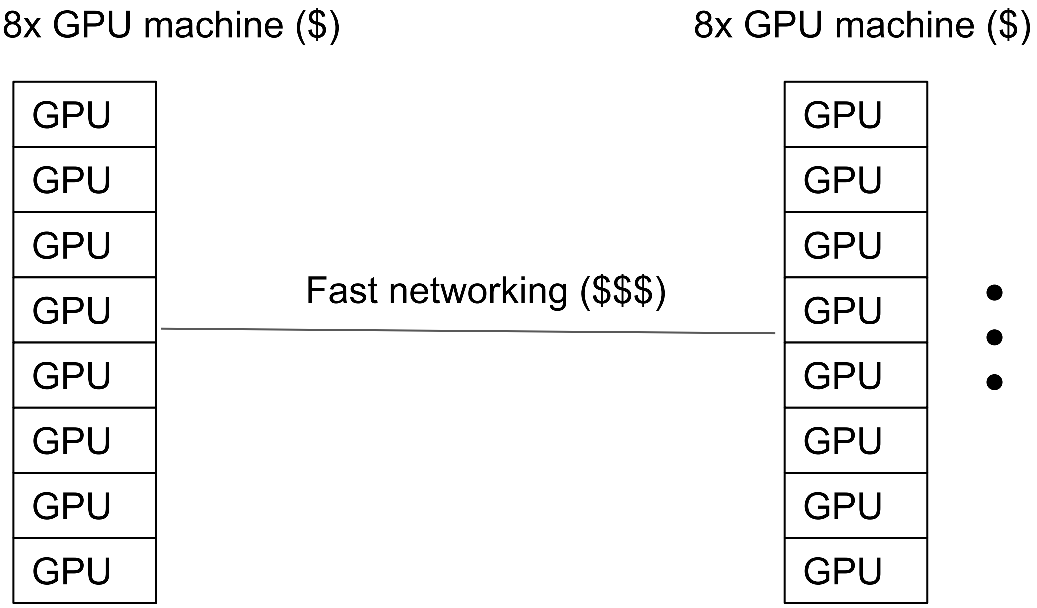
†**Metric**: GLUE=Mean Accuracy/Correlation. CLS/MoCo = Accuracy. MT=BLEU. LM=Perplexity.

Ablations on Language Modeling: All components needed!

Parameters	Optimizer	Dynamic	Block-wise	Stable Emb	Unstable (%)	Perplexity
209M	32-bit Adam				0	16.7
	32-bit Adam			✓	0	**16.3**
	8-bit Adam				90	253.0
	8-bit Adam			✓	50	**194.4**
	8-bit Adam	✓			10	18.6
	8-bit Adam	✓		✓	0	**17.7**
	8-bit Adam	✓	✓		0	16.8
	8-bit Adam	✓	✓	✓	0	**16.4**
1.3B	32-bit Adam				0	10.4
1.3B	8-bit Adam	✓			100	N/A
1.3B	8-bit Adam	✓		✓	80	10.9
1.5B	32-bit Adam				0	9.0
1.5B	8-bit Adam	✓	✓	✓	0	9.0

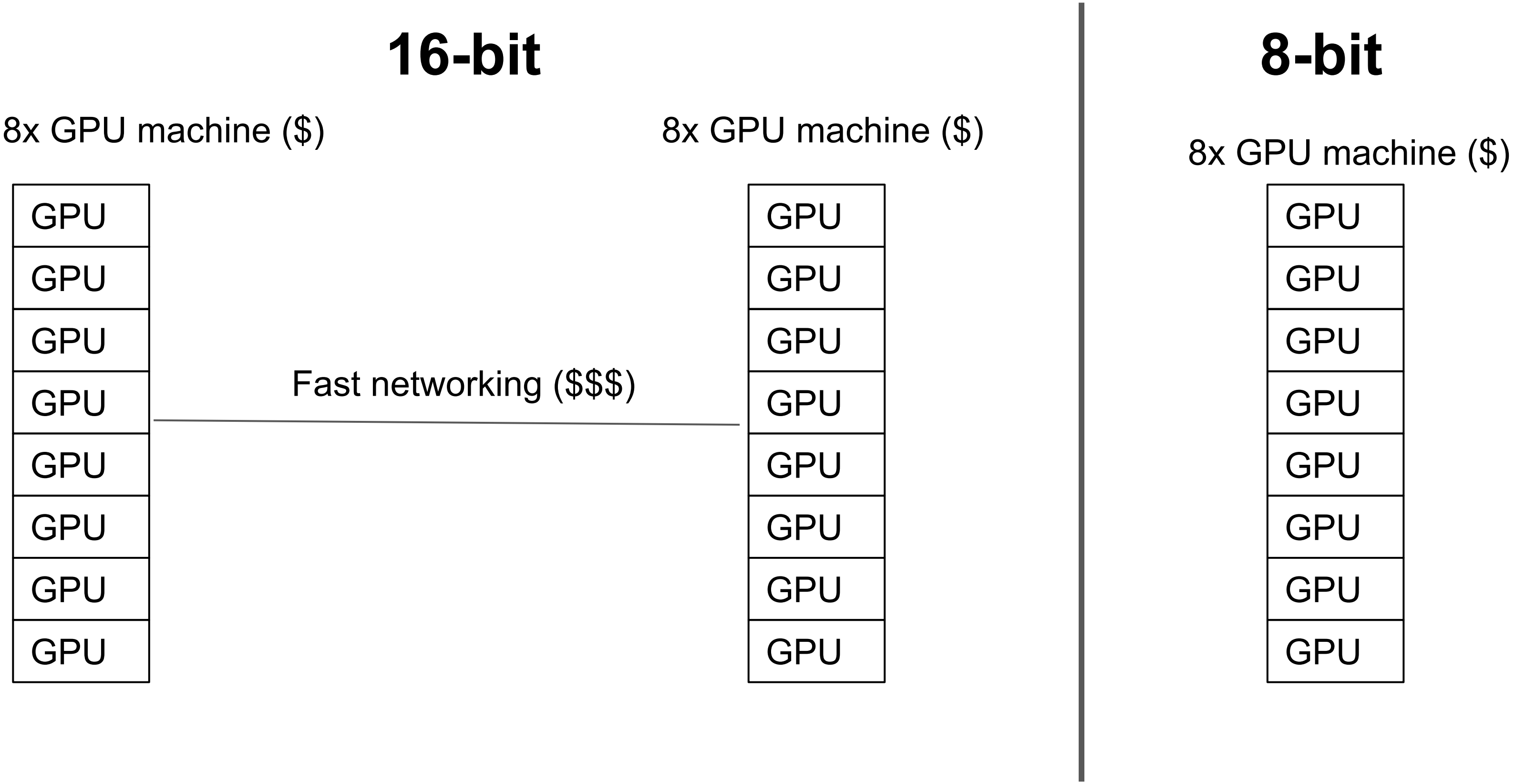
LLM.int8()

Large models such as OPT-175B need more than one computer to be run



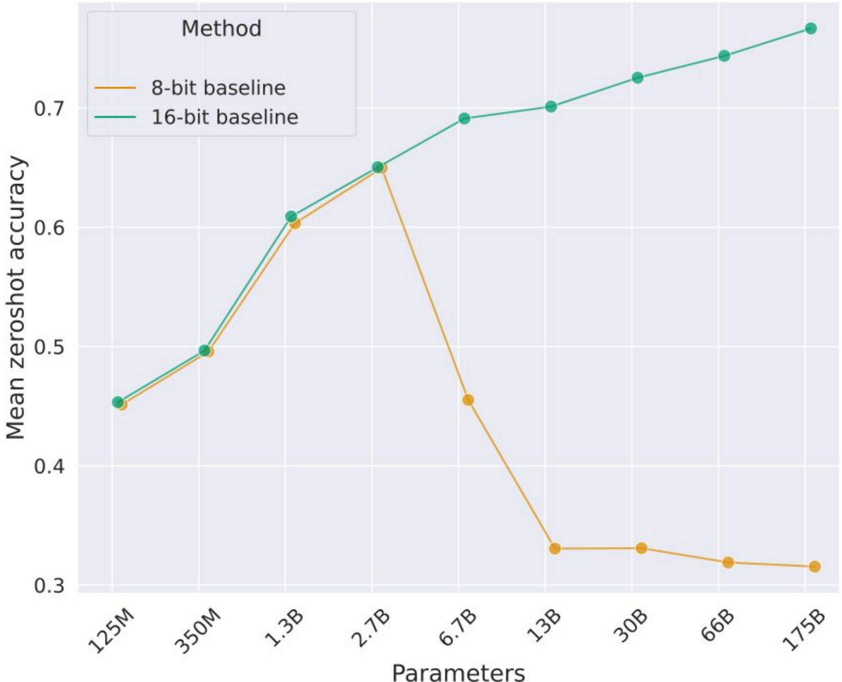
- OPT-175B requires 350 GB of GPU memory
- 15 consumer GPUs required for OPT-175B
- 7 high-end GPUs required ($15k per GPU)

With 8-bit weights we only need a single machine with consumer GPUs



Using OPT-175B on a single machine via 8-bit weights

With 8-bit weights we can reduce memory usage from 350 GiB to 175 GiB. This fits into a single machine with 8 consumer GPUs! Does it work?



The problem with quantizing outliers with large values

Absmax linear quantization with very large outliers:

3.50, 0.10, 0.02, 1.00, 0.30, 0.01, 0.05, 0.10 -> 127, 5, 1, 50, 15, 0, 2, 5

7.50, 0.10, 0.02, 1.00, 0.30, 0.01, 0.05, 0.10 -> 127, 2, 0, 25, 6, 0, 1, 2

15.0, 0.10, 0.02, 1.00, 0.30, 0.01, 0.05, 0.10 -> 127, 0, 0, 10, 3, 0, 0, 1

Vector-wise quantization

Matrix multiplication is a series of inner products

Use two unique normalization constants for each inner product.

A @ B = C: [b x h] @ [h x o] -> [b x o]

1. Normalize A and B:
    a. absmaxA_vec = A16.absmax(1): [b x h] -> [b]
    b. absmaxB_vec = B16.absmax(0): [h x o] -> [o]
    c. A8 = 127*A16/absmaxA_vec; B8 = 127*B16/absmaxB_vec: [b x h] * [b] -> [b x h]
2. C32 = A8 @ B8
3. C16f = C32/(127*127) * (absmaxA_vec @ absmaxB_vec): [b x o] + ([b] @ [o] -> [b x o])

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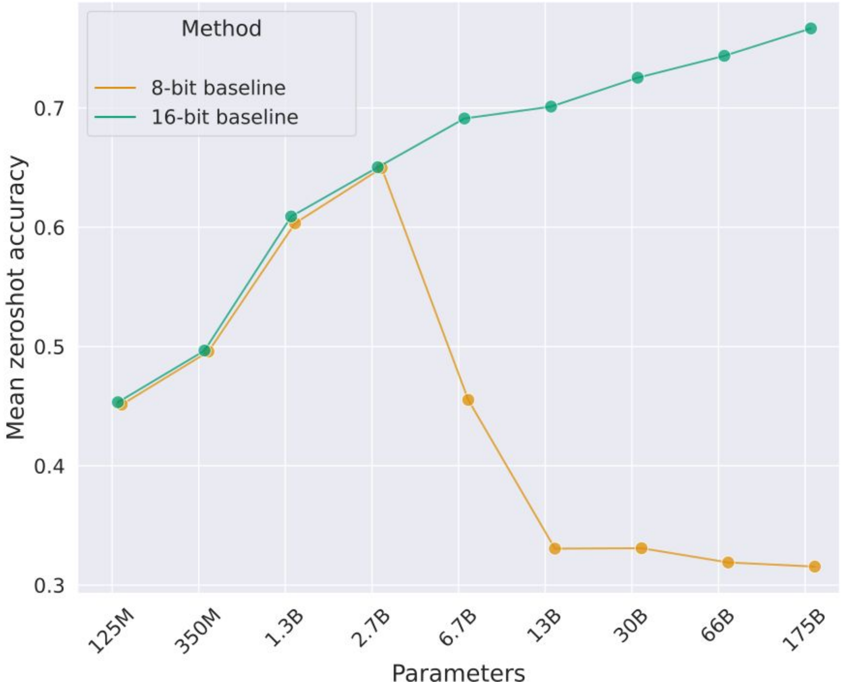


Emergent Features

Finding outlier features in transformer hidden states

Hidden states with dimension [sequence, hidden_dim], outliers are in some hidden dimension.

You need to look in the right spots. At 2.7B there are 262,144 different hidden state values and only 960 are outliers (0.3%). Its easy to miss!

Fortunately, it becomes more common and highly systematic with scale.

Hidden states in transformers: 125m

98.5% of the time

[0.3, -0.1, 0.4]

[-0.2, 0.5, 0.1]

[0.3, 0.9, -0.7]

Sequence dimension

Hidden/feature dimension

1.5% of the time

[0.3, -0.1, -3.0]

[-0.2, 0.5, -6.0]

[0.3, 0.9, -7.0]

Hidden states in transformers: 350m

95% of the time

[0.3, -0.1, 0.4]

[-0.2, 0.5, 0.1]

[0.3, 0.9, -0.7]

5% of the time

[0.3, -0.1, 5.0]

[-0.2, 0.5, 6.0]

[0.3, 0.9, 8.0]

Hidden states in transformers: 2.7B

91% of the time

[0.3, -0.1, 0.4]

[-0.2, 0.5, 0.1]

[0.3, 0.9, -0.7]

9% of the time

[0.3, -0.1, -16.0]

[-0.2, 0.5, -10.0]

[0.3, 0.9, -27.0]

Hidden states in transformers: 6.0B

83% of the time

[0.3, -0.1, 0.4]

[-0.2, 0.5, 0.1]

[0.3, 0.9, -0.7]

17% of the time

[0.3, -0.1, -15.0]

[-0.2, 0.5, -17.0]

[0.3, 0.9, -22.0]

Hidden states in transformers: 6.7B. Phase shift!

25% of the time

[0.3, -0.1, 0.4]

[-0.2, 0.5, 0.1]

[0.3, 0.9, -0.7]

75% of the time

[0.3, -0.1, -40.0]

[-0.2, 0.5, -45.0]

[0.3, 0.9, -61.0]

Hidden states in transformers: 13B

~25% of the time

[0.3, -0.1, 0.4]

[-0.2, 0.5, 0.1]

[0.3, 0.9, -0.7]

~75% of the time

[0.3, -0.1, -75.0]

[-0.2, 0.5, -65.0]

[0.3, 0.9, -50.0]

Hidden states in transformers: 66B

~25% of the time

[0.3, -0.1, 0.4]

[-0.2, 0.5, 0.1]

[0.3, 0.9, -0.7]

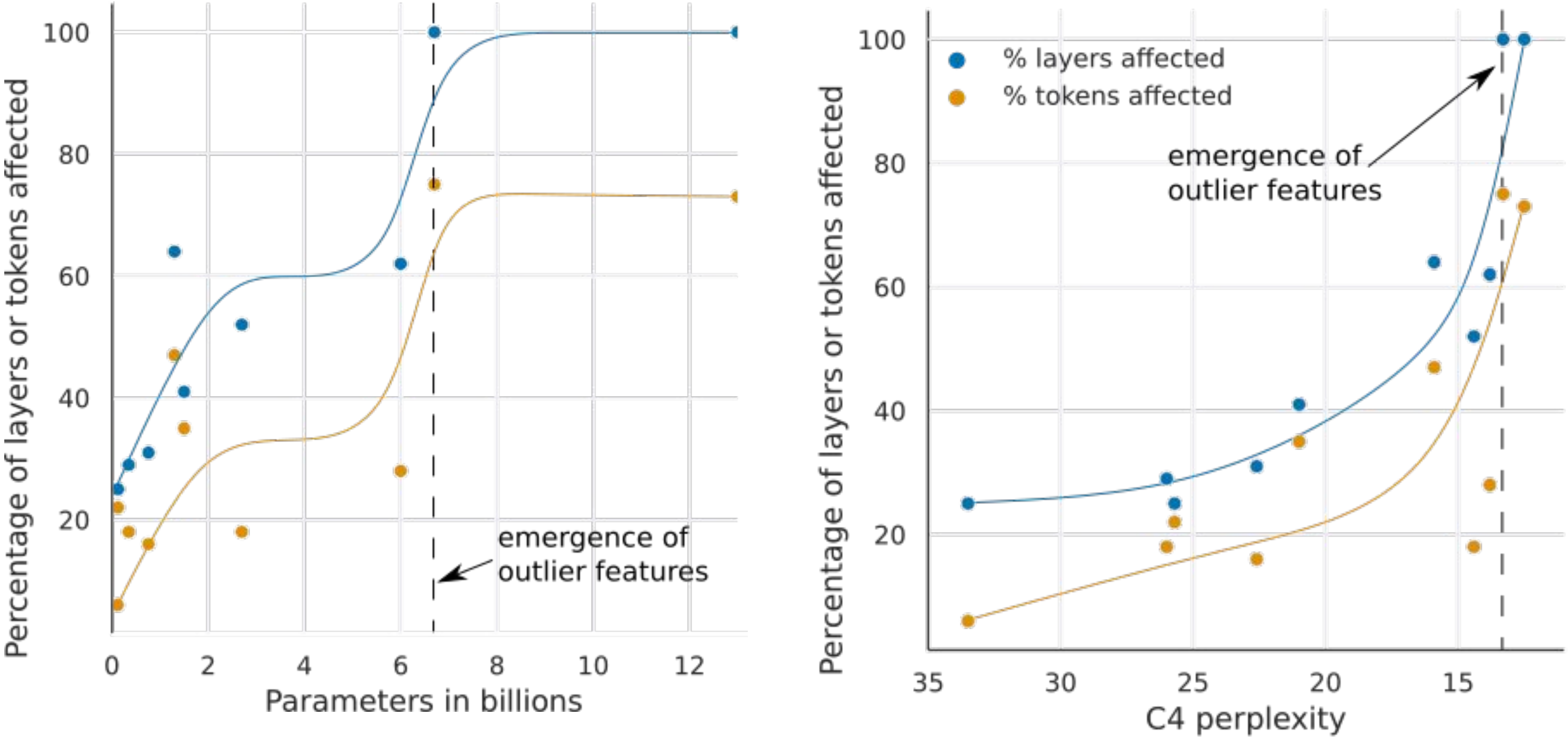
~75% of the time

[0.3, -0.1, -95.0]

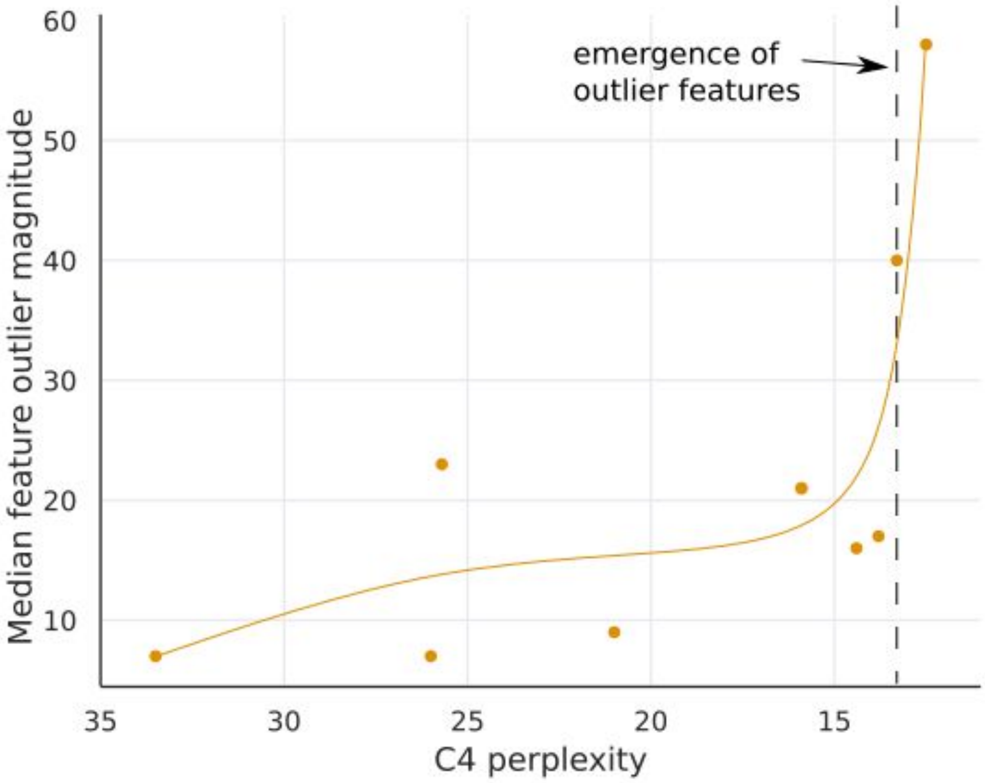
[-0.2, 0.5, -113.0]

[0.3, 0.9, -87.0]

Emergent features: sudden vs. smooth emergence



Emergent features: very large outliers after emergence



Further Analysis: Outliers are important for performance

Take 6.7B transformer language model.

Attention Top-1 probability (single layer):

- Baseline: 40%
- Remove random dimensions: 39.9%
- Remove outliers: 15%

C4 validation perplexity (all layers)

- Baseline: 14.4 ppl
- Remove random dimensions: 14.4 ppl
- Remove outliers: 44.0 ppl

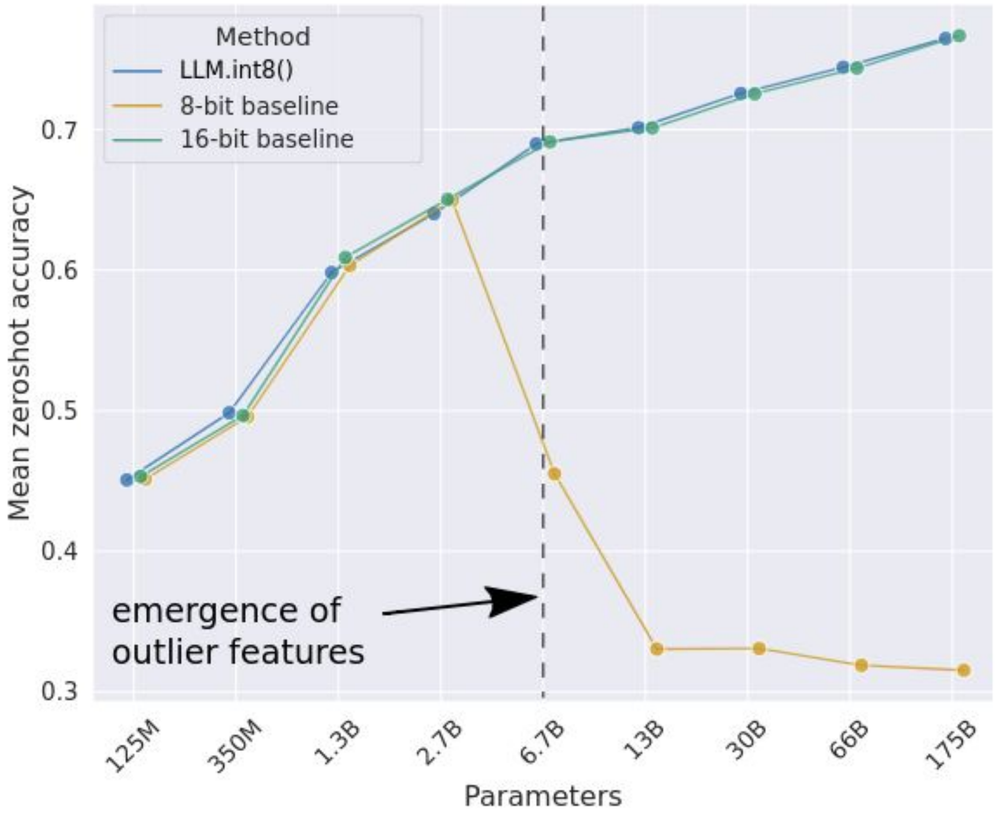
Mixed precision decomposition

Multiply outlier hidden/features dimensions (0.1%) in 16-bit.

Multiply other hidden/features dimensions (99.9%) in 8-bit.

$$\mathbf{C}_{f16} \approx \sum_{h \in O} \mathbf{X}^h_{f16} \mathbf{W}^h_{f16} + \mathbf{S}_{f16} \cdot \sum_{h \notin O} \mathbf{X}^h_{i8} \mathbf{W}^h_{i8}$$

No performance degradation with LLM.int8()



Quantization as a practical tool for memory reduction

Table 2: Different hardware setups and which methods can be run in 16-bit vs. 8-bit precision. We can see that our 8-bit method makes many models accessible that were not accessible before, in particular, OPT-175B/BLOOM.

			Largest Model that can be run	
Class	Hardware	GPU Memory	8-bit	16-bit
Enterprise	8x A100	80 GB	**OPT-175B / BLOOM**	**OPT-175B / BLOOM**
Enterprise	8x A100	40 GB	**OPT-175B / BLOOM**	OPT-66B
Academic server	8x RTX 3090	24s GB	**OPT-175B / BLOOM**	OPT-66B
Academic desktop	4x RTX 3090	24 GB	**OPT-66B**	OPT-30B
Paid Cloud	Colab Pro	15 GB	**OPT-13B**	GPT-J-6B
Free Cloud	Colab	12 GB	**T0/T5-11B**	GPT-2 1.3B

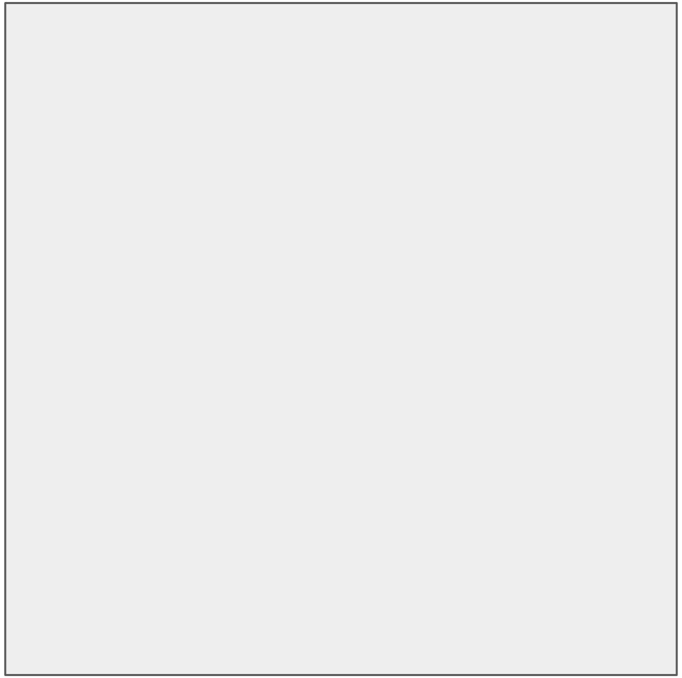
Bit-level Inference Scaling Laws

Inference cost are mostly loading the bits in the weight matrix!

Moderns GPUs can multiply 200 elements in the same time it takes to load 1 element from memory.

Inputs

Weight matrix

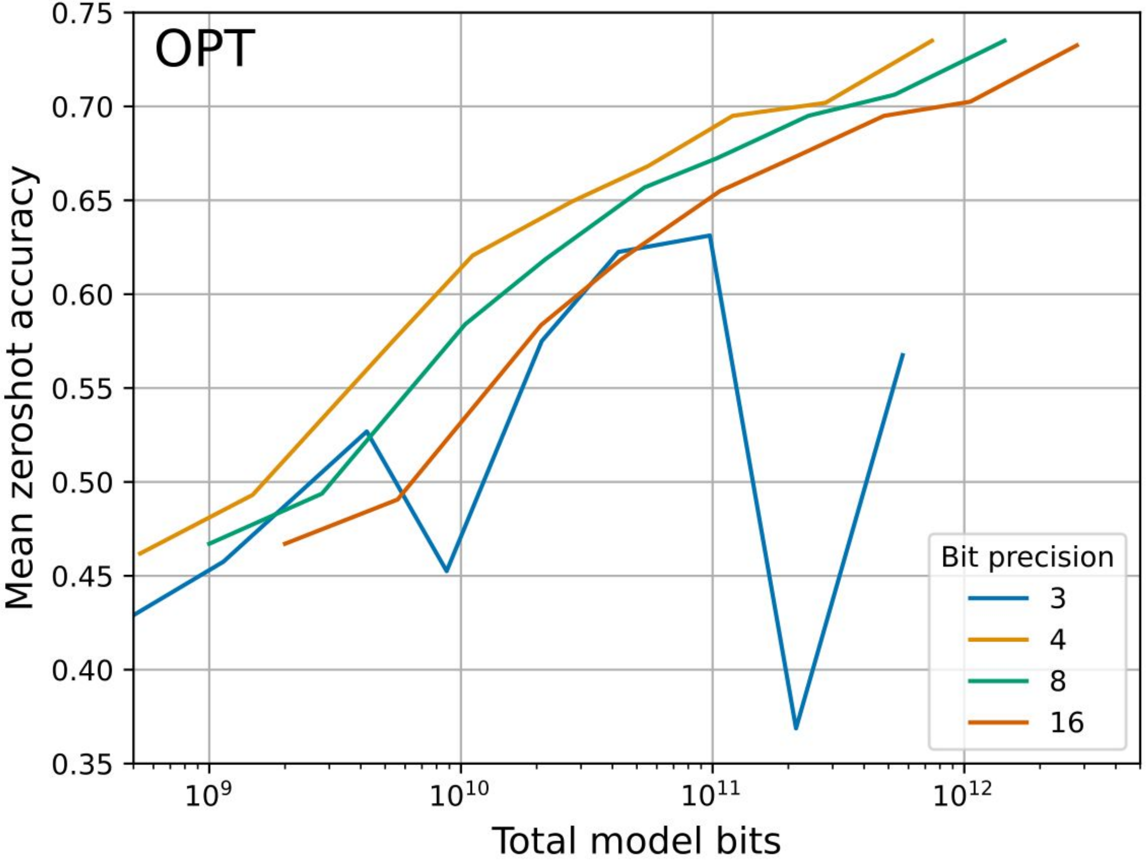


Inference costs of
4-bit 60B and 8-bit 30B LLMs similar

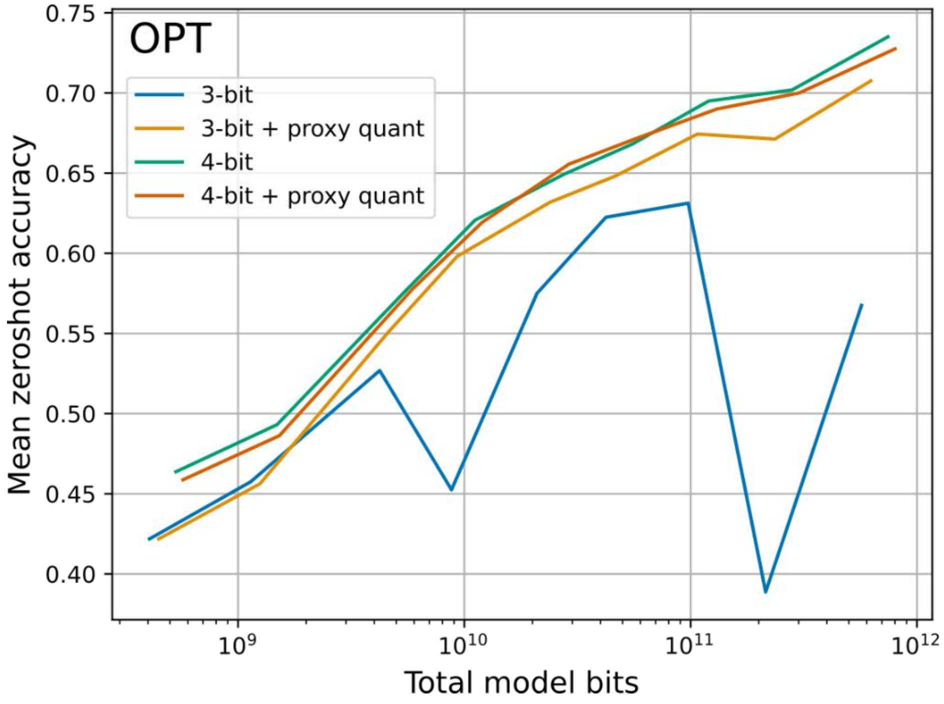
Bit-level scaling laws experimental setup overview

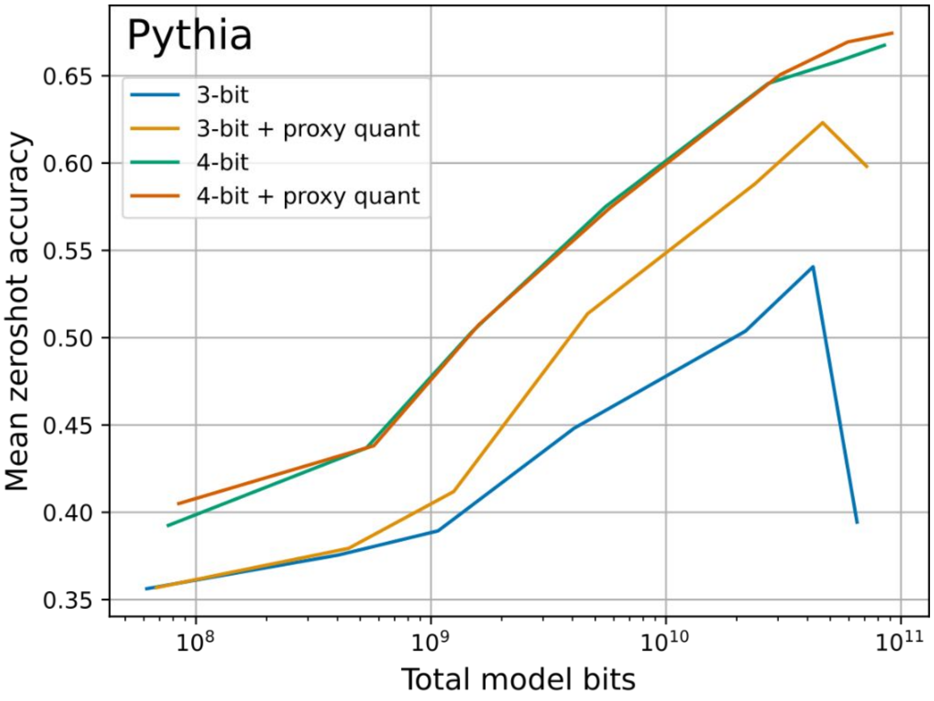
- 35,000 zero-shot experiments (Lambada, Winogrande, PiQA, HellaSwag)
- 19m to 176B parameters
- OPT, BLOOM, BLOOMZ, Pythia/NeoX, GPT-2
- 3 to 8 bit precision (2-bit -> random performance)
- Two quantization concepts: centralization, blocking/grouping
- 4 data types: Integer, Float, dynamic exponent, quantile quantization

Given a zero-shot accuracy, what is the best k-bit quantization?

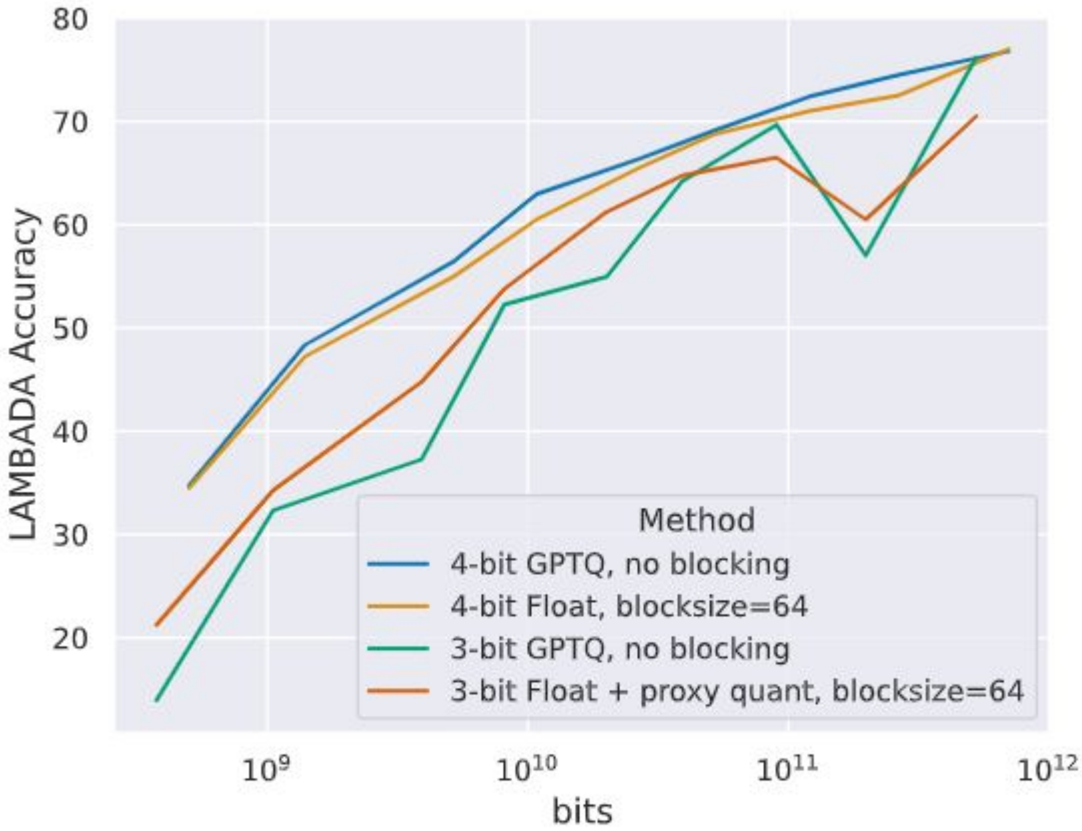


Does it help to treat outliers separately?

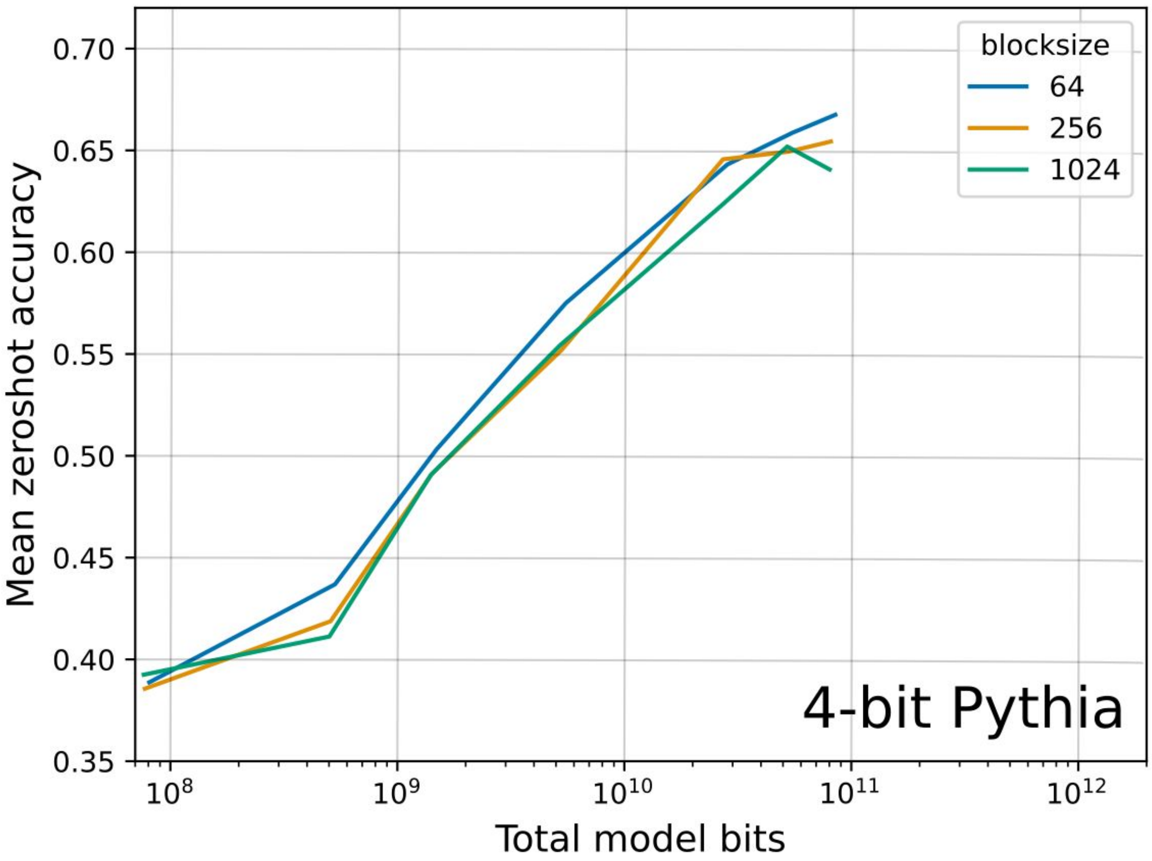




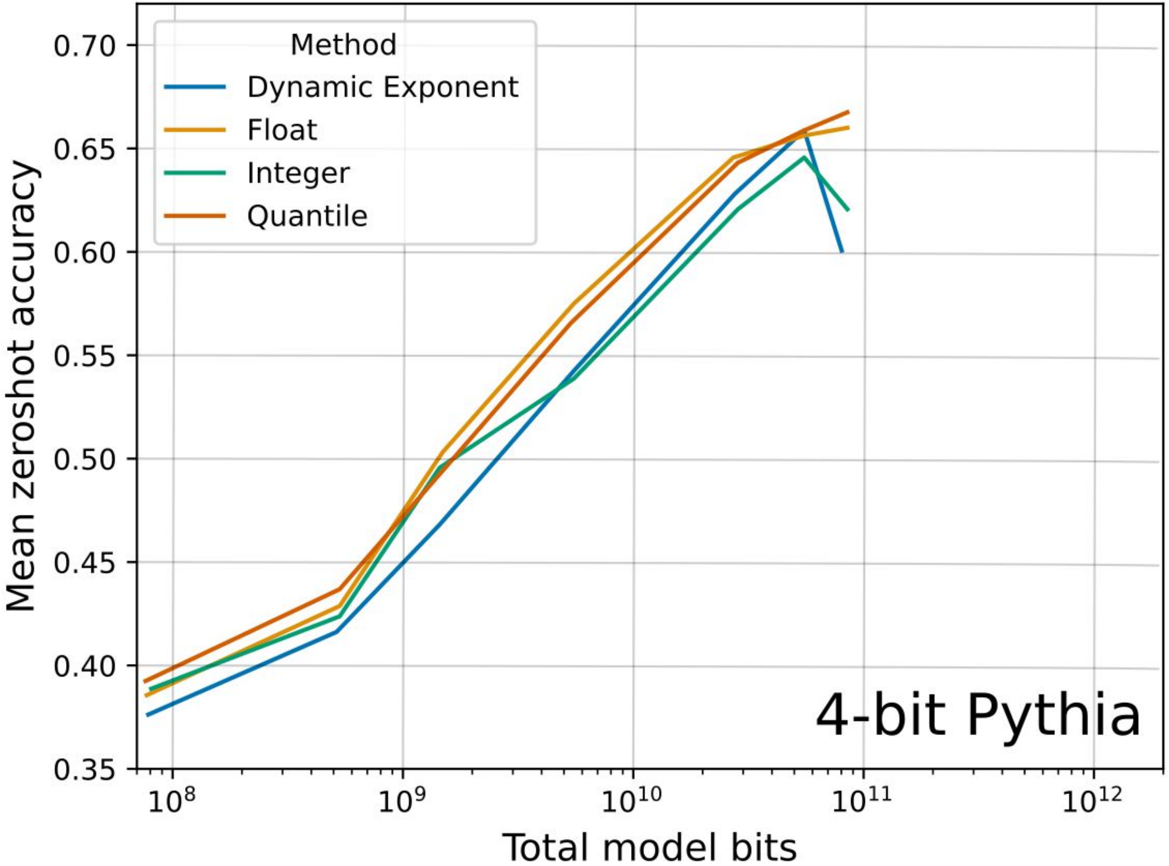
Comparison with GPTQ



What does help to improve scaling? Block size



What does help to improve scaling? Data types



Conclusion

8-bit optimizers make the training and fine-tuning more accessible.

LLM.int8() makes large language models more accessible, for example, zeroshot prompting for OPT-175 on a single node or 65B LLaMA on a single GPU.

Currently, 4-bit precision seems to be best for bit-level scaling of LLM inference. Improving bit-level scaling laws as a measure to improve inference latency.

k-bit methods work well in a variety settings and scales and can make deep learning more efficient and more accessible.