Big Models Quantization

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Contents

- → Intro
- → Training Pipelines
- → F8Net
- → StatQuant
- → Automatic Mixed Precision

Quantization Introduction

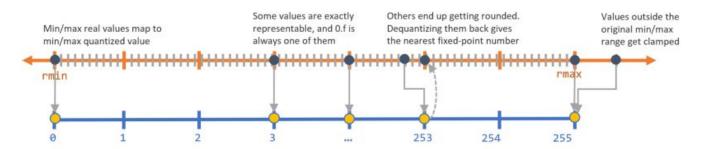
Idea: Use an integer weight and activation representation, reducing the precision.

Motivation:

- 1. Reduce memory footprint
- 2. Reduce inference latency
- 3. Reduce training time*

INT8 compared to FP32:

- 4x size reduction
- 2-4x memory reduction
- 2-4x inference acceleration



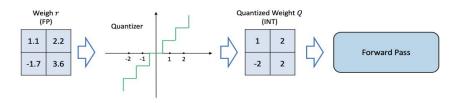
Quantization Training Pipelines

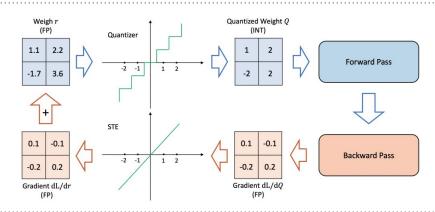
Post-training Quantization:

- → collecting statistics
- → no re-training

Quantization-Aware Training:

- → fine-tuning quantized model
- → using STE* to approximate gradients





*Fully Quantized Training:

- → fine-tuning quantized model
- → gradients are quantized

F8Net Framework

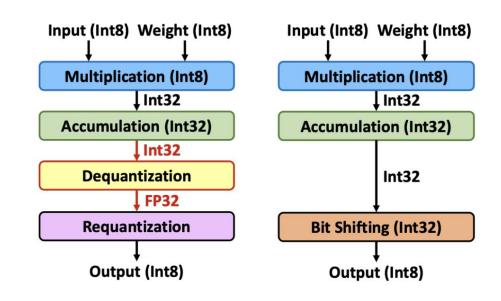
Idea: Quantize inputs and weights, perform all operations with 8-bit integers

Pros:

- → hardware-friendly forward pass
- → adjustable tensor representation in fixed-point format

Cons:

→ full-precision gradients



Considered quantization settings: Simulated quant. (left) and Fixed-point quant. (right)

StatQuant Framework

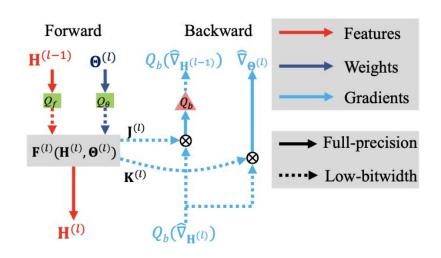
Idea: Consider FQT gradient as an unbiased estimate of QAT gradient and reduce its variance via Per-sample and Block Householder quantizers

Pros:

- → speed-up on specialized hardware
- → almost no performance degradation
- → solid theoretical foundations

Cons:

→ no significant memory reduction



StatQuant FQT pipeline



Automatic Mixed Precision

Idea: use 16-bit precision to speed up training **Problem:** small values vanish (underflowing)

Tricks:

- → Some operations in fp16, some in fp32
- → Apply updates to fp32 weights
- → Loss scaling

Algorithm	Test Accuracy	GPU Memory	Total Training Time
B - 1080 Ti	94.13	10737MB	64.9m
B - 2080 Ti	94.17	10855MB	54.3m
AMP - 1080 Ti	94.07	6615MB	64.7m
AMP - 2080 Ti	94.23	7799MB	37.3m

CONV3 Operation Norm1 Operation CONV1 CONV1 CONV1 ACCELERATED BY GPU FP32 Operation FP16 Operation Rum On Tensor Cores

Our Results: Fine-tuning GPT2 on Max Korzh texts 5 epochs

	16-bit AMP	32-bit
Training time	01:01	01:32
GPU Mem	6691 MB	8325 MB
Loss	2.7372	2.7370

Quantization Team







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Thank you for your attention!