

Parasitic Effects on Dual-Granularity Cooperative Quantization (DGCQ) System



B11901027 王仁軒

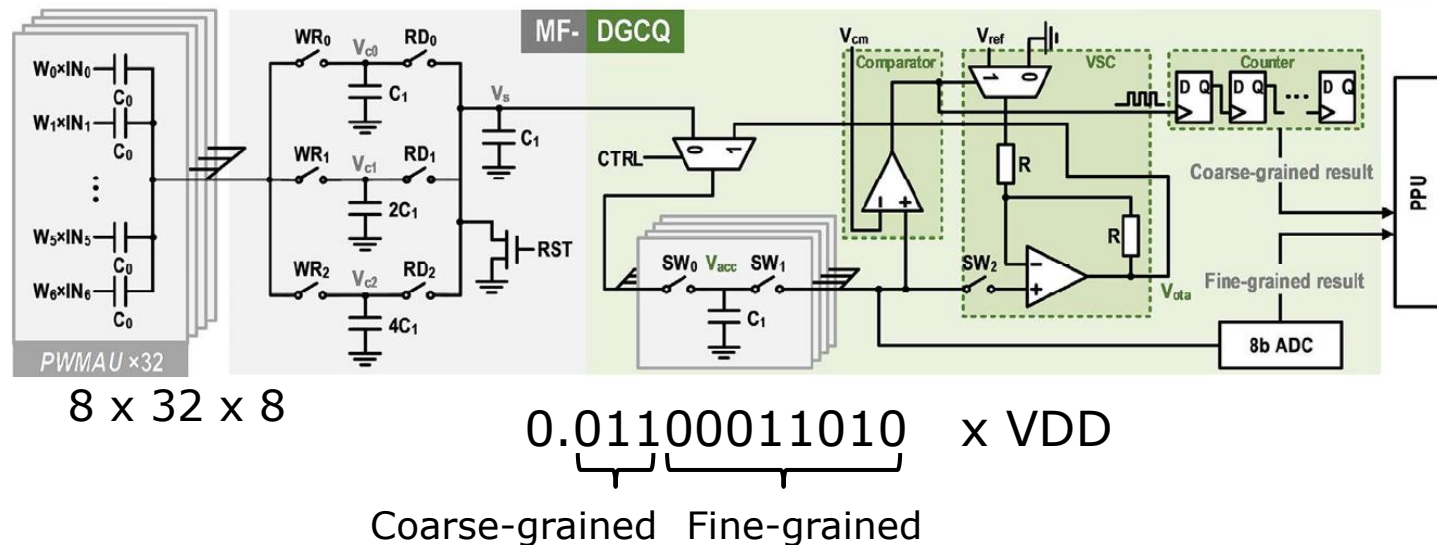
Quantizing MAC Voltage

■ Coarse-grained method

- Takes 2^n iterations to get n bit precision
- Area is roughly a fixed value

■ SAR ADC

- Takes n iterations to get n bit precision
- Area is proportional to 2^n (dominated by caps)



Quantizing MAC Voltage

■ Partition of coarse/fine grained result

□ Suppose $V_{ref} = V_{DD}$

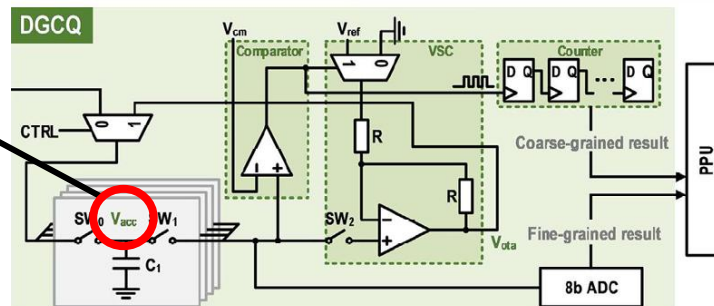
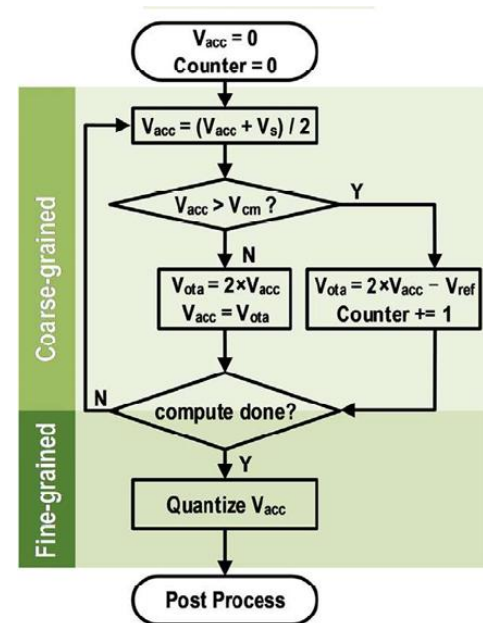
$0.\underbrace{011}_{\text{Coarse-grained}}\underbrace{100011010}_{\text{Fine-grained}} \times V_{DD}$

After 8 iteration, $V_{acc} = 8V_S - [8V_S]$

$8V_S = 011.00011010 \times V_{DD}$

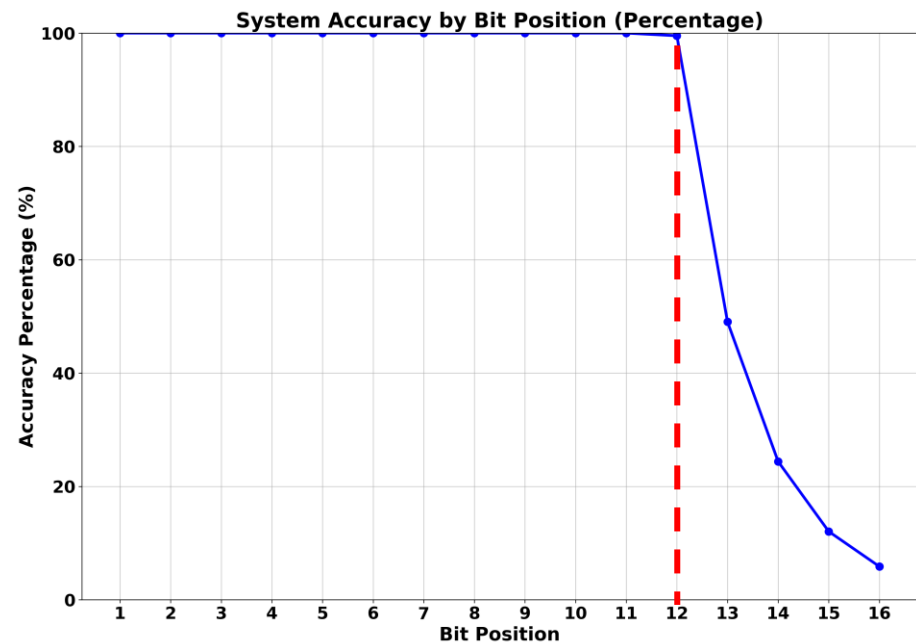
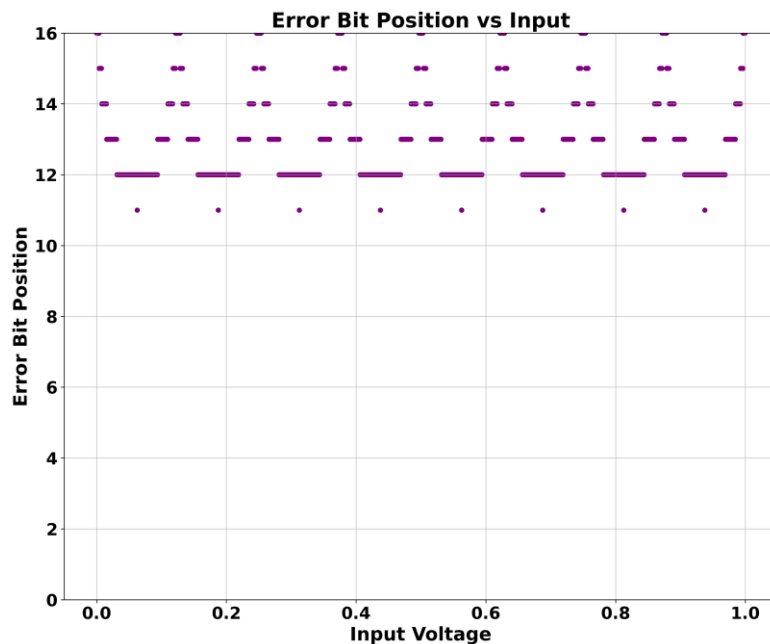
$[8V_S] = 011.00000000 \times V_{DD}$

$V_{acc} = 000.00011010 \times V_{DD}$



Quantizing MAC Voltage

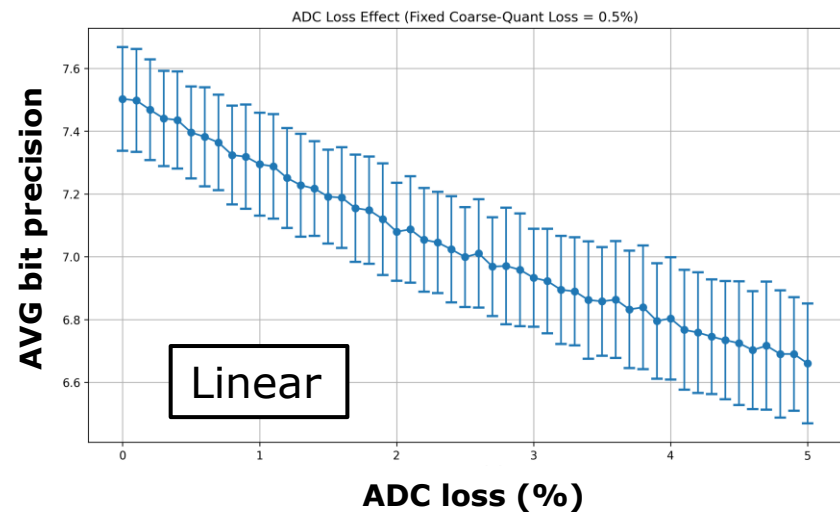
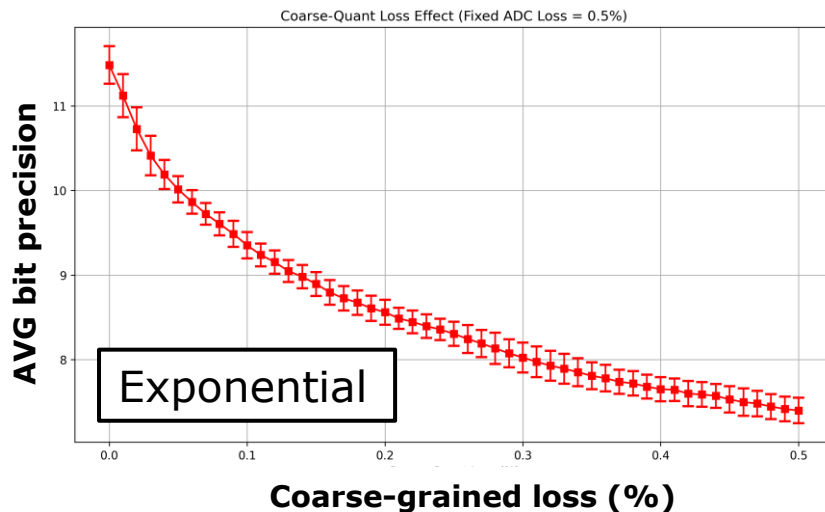
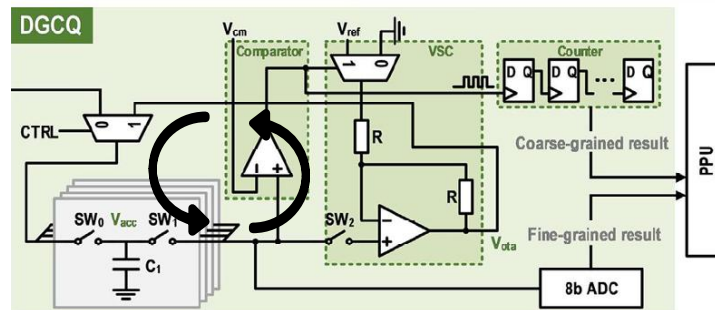
■ 3-bit coarse, 8-bit fine



Bit precision can reach 12 bit in most situation
(lossless)

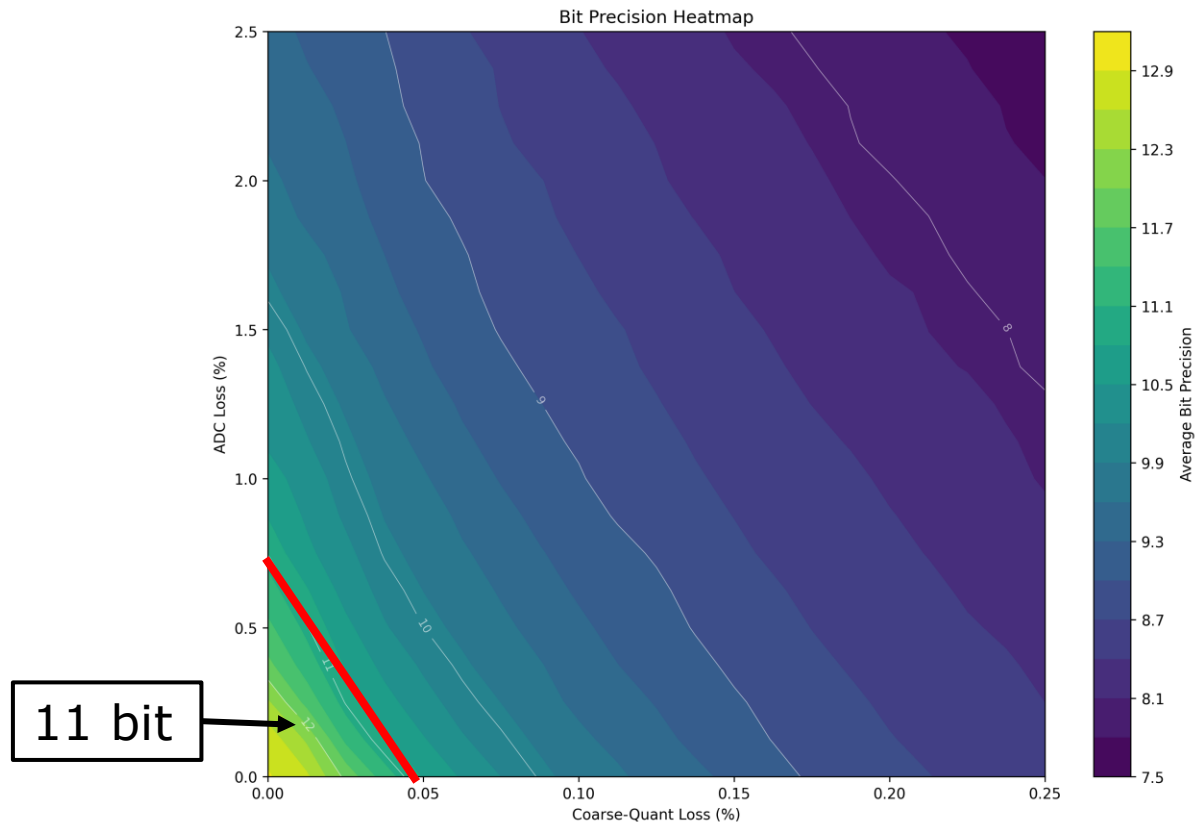
Parasitic Effect

- Coarse-grained method is iterative
 - Loss in each iteration accumulates
 - ADC is also a source of noise



Parasitic Effect

- Coarse-grained method is iterative
 - Loss in each iteration accumulates
 - ADC is also a source of noise



Effect of DGCQ (Lossy Case)

- ADC : Large area, larger loss
- Coarse-grained : Time-consuming
- Dual-granularity : Less area, low loss, fast



Effect of DGCQ on ML Tasks

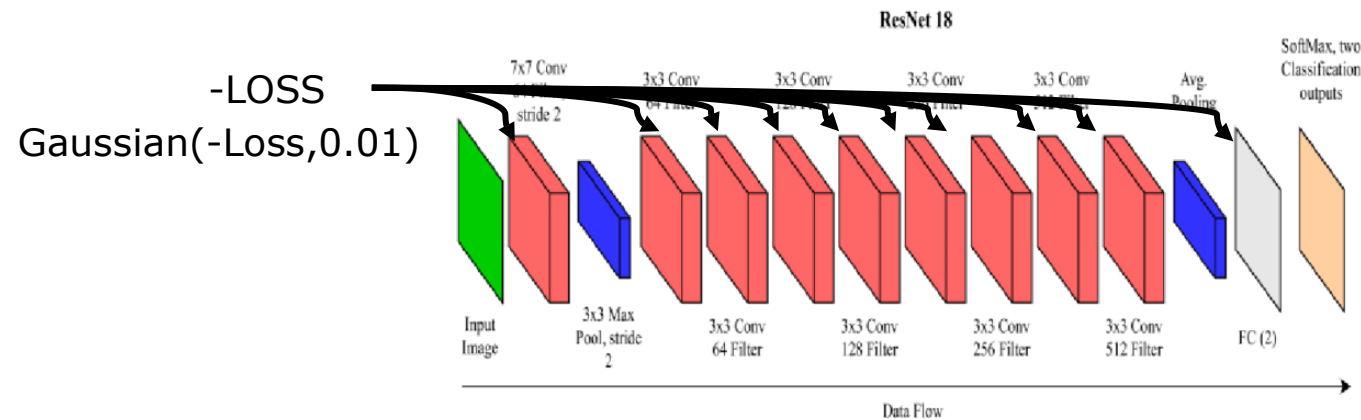
■ The dataset used in the paper is ImageNet

- ImageNet is not implemented in torch
- Use a simpler dataset CIFAR-10

Model	ResNet-18
Dataset	ImageNet
Data precision	INT8
Task	Classification
Metric	Accuracy

■ ResNet-18

- Trained using fp32 precision
- Quantize to int8 after training
- Compute MAC result for each layer and apply loss



Effect of DGCQ on ML Tasks

■ Comparison between coarse/fine-grained value

DGCQ : Merge 2 types of granularity

