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Approximate Computing for DNN

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Approximate Deep Learning Accelerators

*Improving performance and energy efficiency of deep-learning
hardware accelerators with controlled arithmetic approximations*

Olivier Sentieys

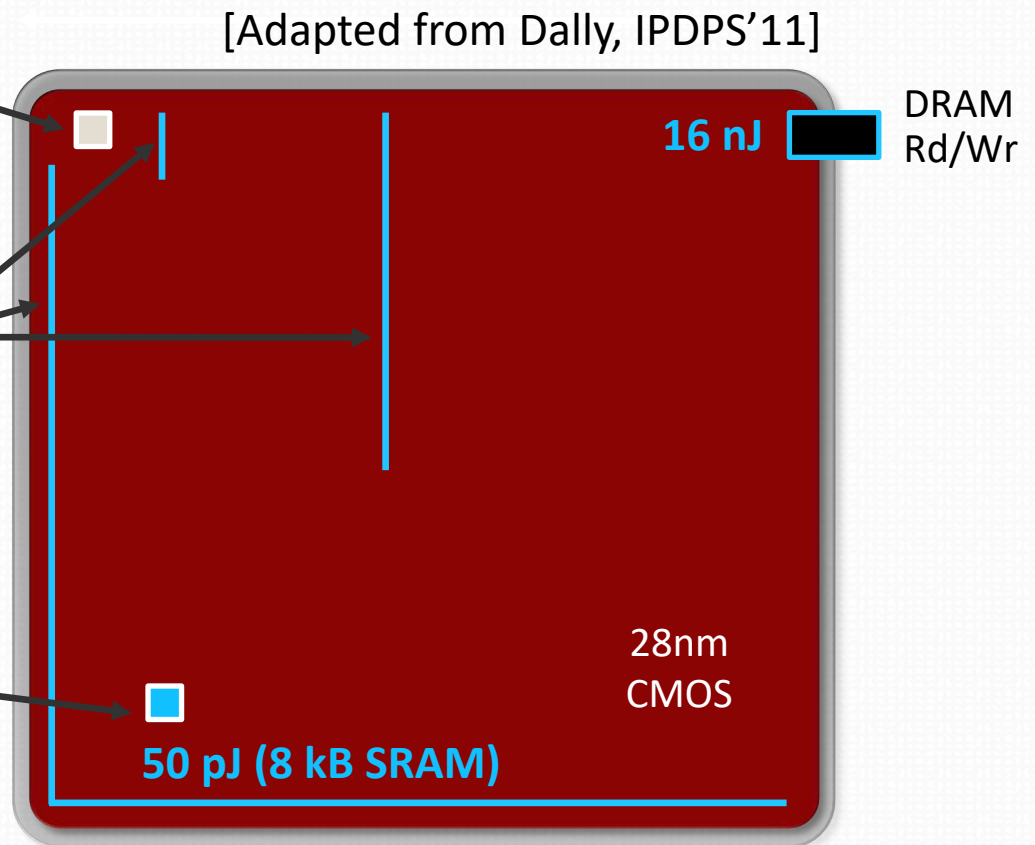
Univ. Rennes, Inria

Inria



Energy Cost in a Processor/SoC

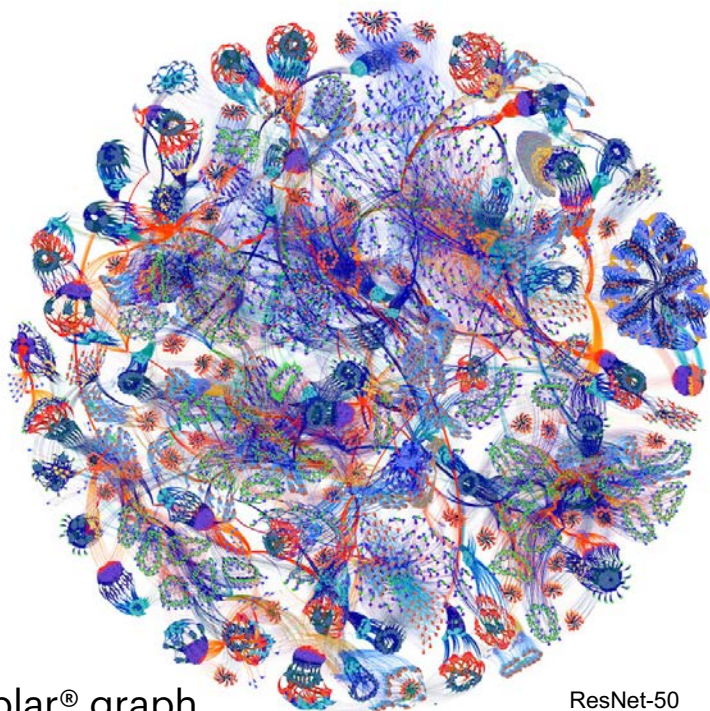
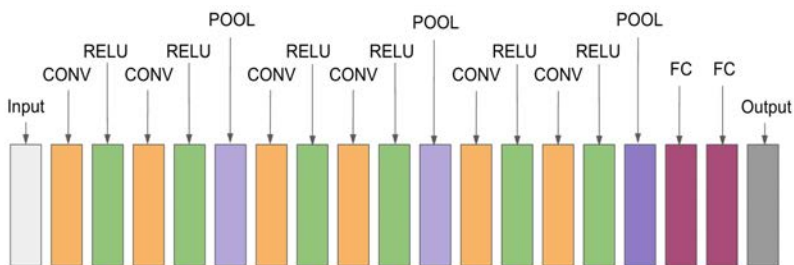
- 64-bit FPU: 20pJ/op
- 32-bit addition: 0.05pJ
- 16-bit multiply: 0.25pJ
- Wire energy
 - 240fJ/bit/mm per $\downarrow\uparrow$
 - 32 bits: 40pJ/word/mm
 - 8 bits: 10pJ/word/mm
- Memory/Register-File
 - Depends on word-length



Energy strongly depends on data representation and size

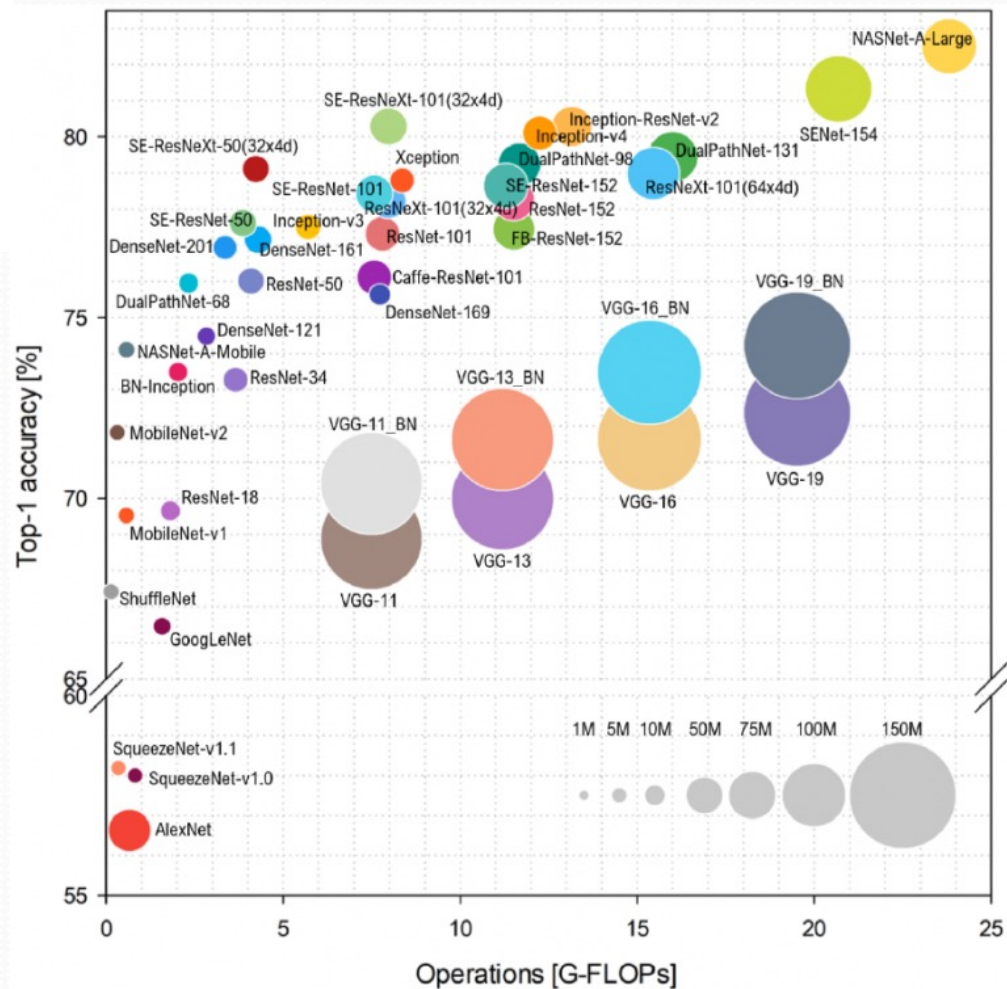
Complexity Issues of Deep NNs

- Deep (Convolutional) Neural Networks



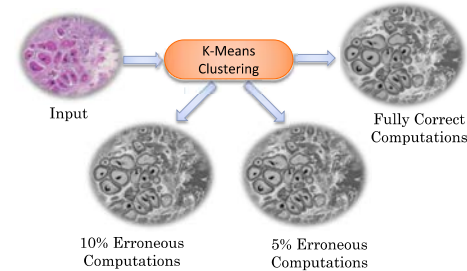
Poplar® graph

ResNet-50
training batch=4



Approximate Computing

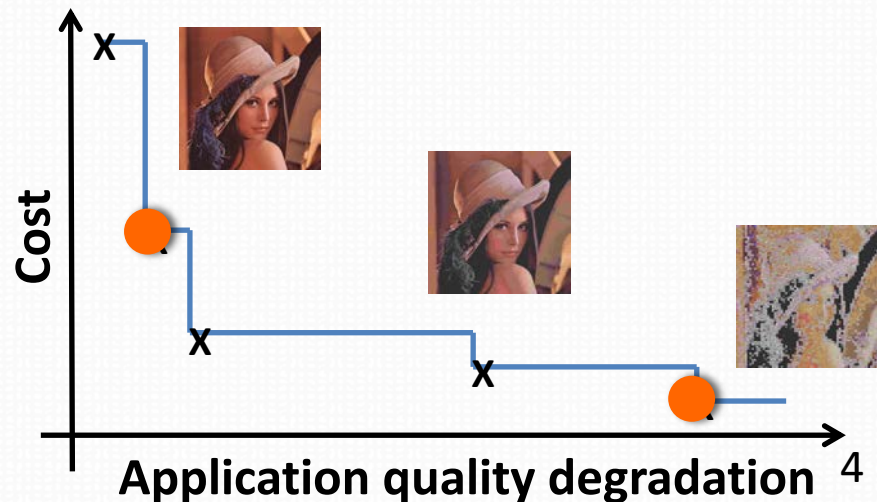
- Many applications are **error resilient**
 - media processing, data mining, machine learning, web search, etc.



- AxC performs **approximations** to reduce **energy** and increase execution speed while keeping **accuracy in acceptable limits**

- Relaxing the need for fully precise operations
- *Number representations and word-length*

- Design-time/run-time
- Different levels



Resilience of ANN?

According to a research at Cambridge University, it doesn't matter in what order the letters in a word are, the only important thing is that the first and last letter be at the right place. And we spend half our life learning how to spell words. Amazing, no!

[O. Temam, ISCA10]

- Our biological neurons are tolerant to computing errors and noisy inputs
- **Quantization** of parameters and computations provides **benefits in throughput, energy, storage**

Even Worse for Training...

- Carbon footprint of DNN training

*Analyzing the carbon footprint of current natural-language processing models shows an alarming trend: **training one huge model for machine translation emits the same amount of CO2 as five cars in their lifetimes (fuel included)***

[Strubell *et al.*, ACL 2019]

- Many more operations than inference
- More pressure on memory access
- Much more difficult to accelerate

Need for a Significant Reduction of the Carbon Footprint of Neural Network Training Hardware

This rest of this talk is about

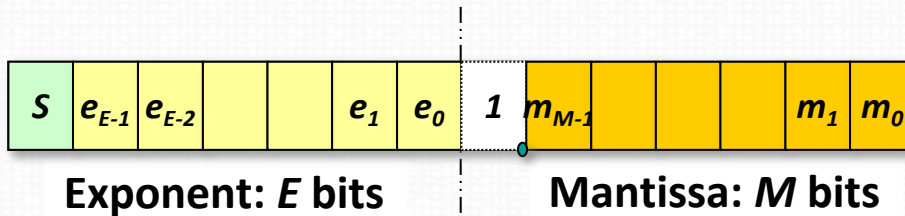
- Approximations in DNNs
- Reducing the **numerical precision** of arithmetic operations is a general way to increase performance and energy efficiency in computing
 - How does this apply to DNN?
 - Can we design low-precision accelerators for inference and **training**?

Number Representations

- Floating-Point (FIP)

$$x = (-1)^s \times m \times 2^{e-127}$$

s : sign, m : mantissa, e : exponent



- Easy to use
- High dynamic range
- IEEE 754

- Fixed-Point (FxP)

$$x = p \times K$$

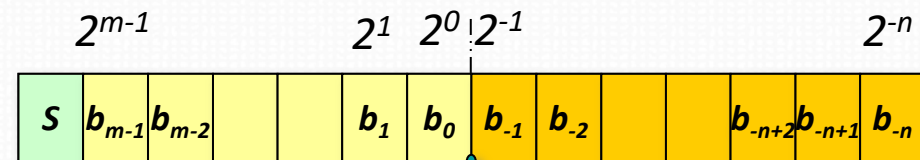
p : integer, $K=2^{-n}$: fixed scale factor

- Integer arithmetic
- Efficient operators
 - Speed, power, cost

- Hard to use...

$$x = s \cdot (-2)^m + \sum_{i=-n}^{m-1} b_i \cdot 2^i$$

s : sign, m : magnitude, n : fractional



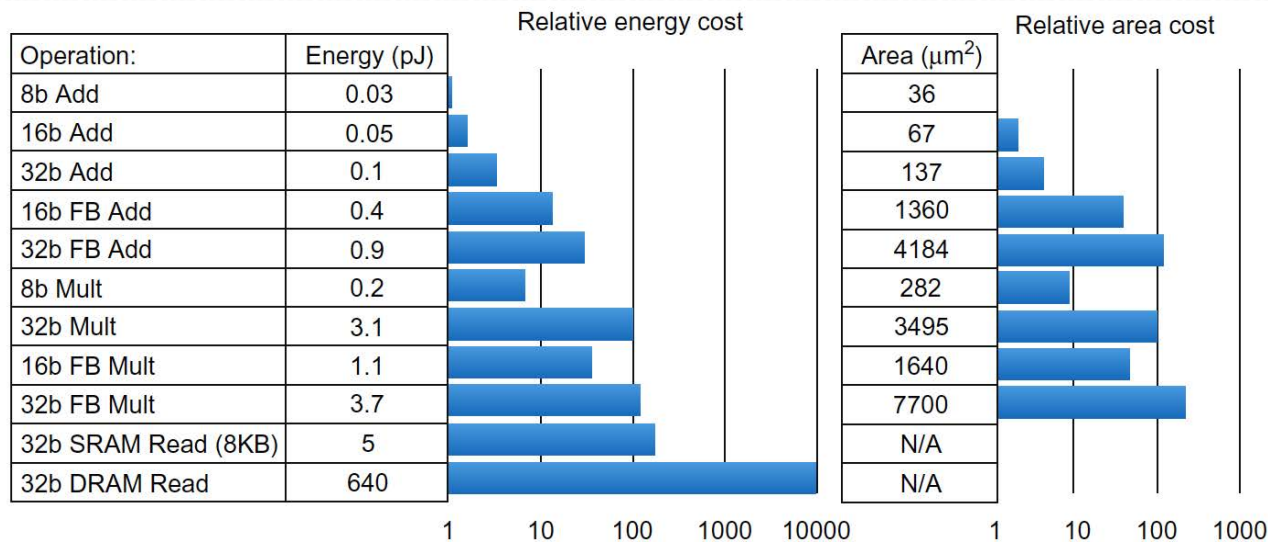
Integer part: m bits Fractional part: n bits

Format	e	m	bias
Single Precision	8	23	127
Double Precision	11	52	1023

Number Representations

- Energy, delay, and area vary a lot between numeric formats and word-length

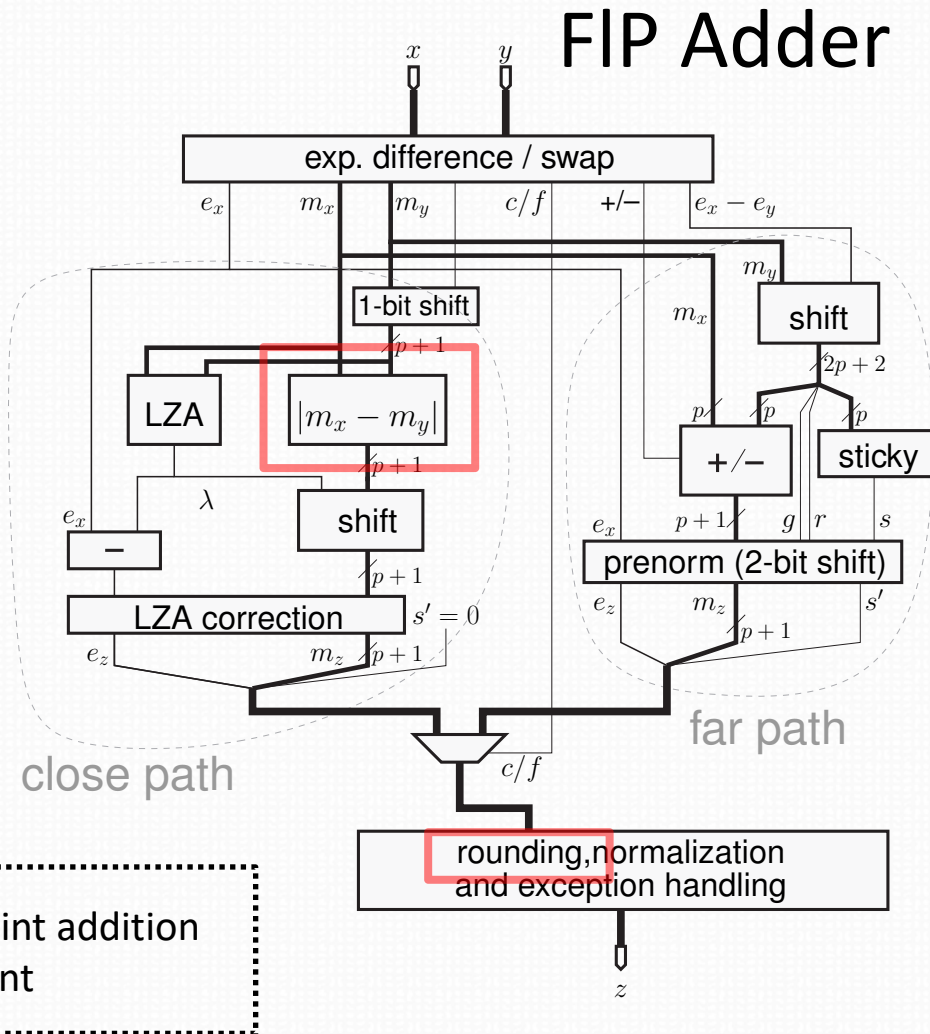
	Addition	Multiplication
8-bit integer	0.03pJ / 36 μm^2	0.2pJ / 282 μm^2
32-bit float	0.9pJ / 4184 μm^2	3.7pJ / 7700 μm^2



Energy numbers are from Mark Horowitz *Computing's Energy problem (and what we can do about it)*. ISSCC 2014
 Area numbers are from synthesized result using Design compiler under TSMC 45nm tech node. FP units used DesignWare Library.

Floating-Point Arithmetic

- Floating-point hardware is doing the job for you!
- FIP operators are therefore more complex

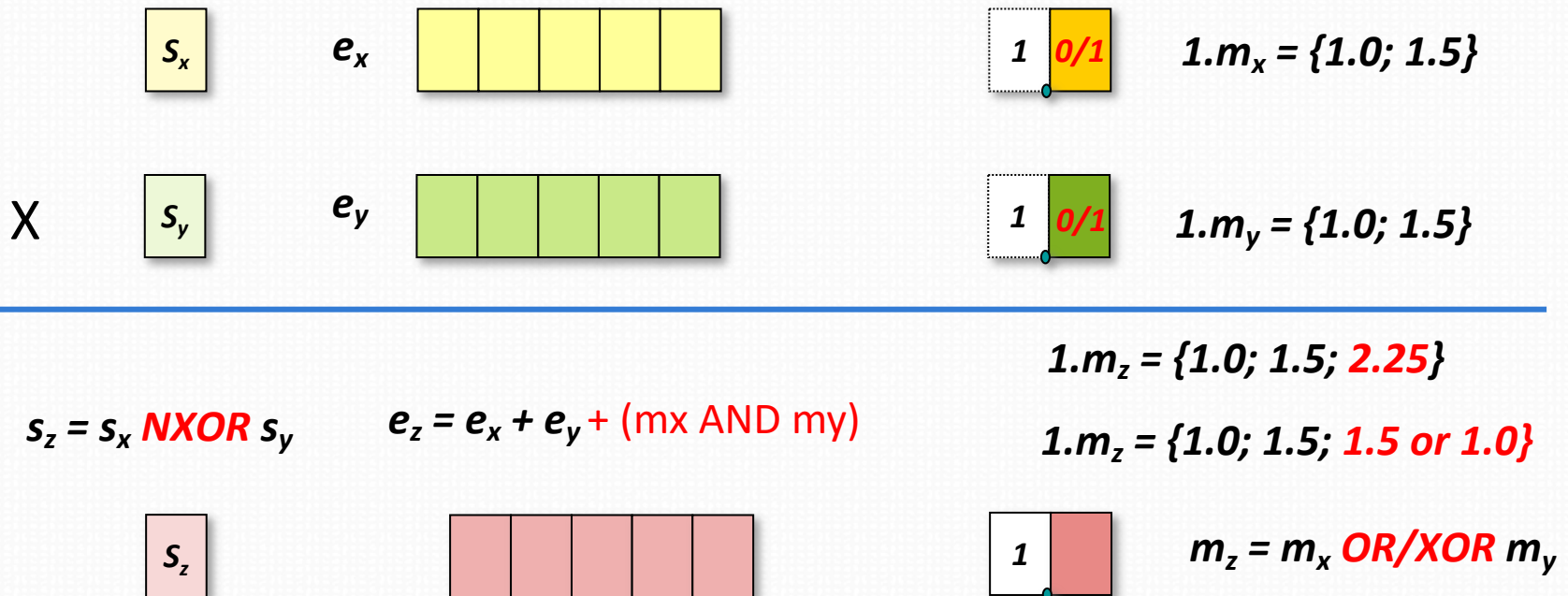


What can be customized?

- Of course precision
 - Exponent (E) and Mantissa (M) bit-width
 - *e* and *m* both impact accuracy
- Play with exponent **bias**
- **Sub-normal** numbers or not?
- 0, ∞ , NaN?
- **Rounding** modes
 - to nearest, truncation, to 0/ ∞
- Inexact integer operators

LP-Floating-Point Multiplication

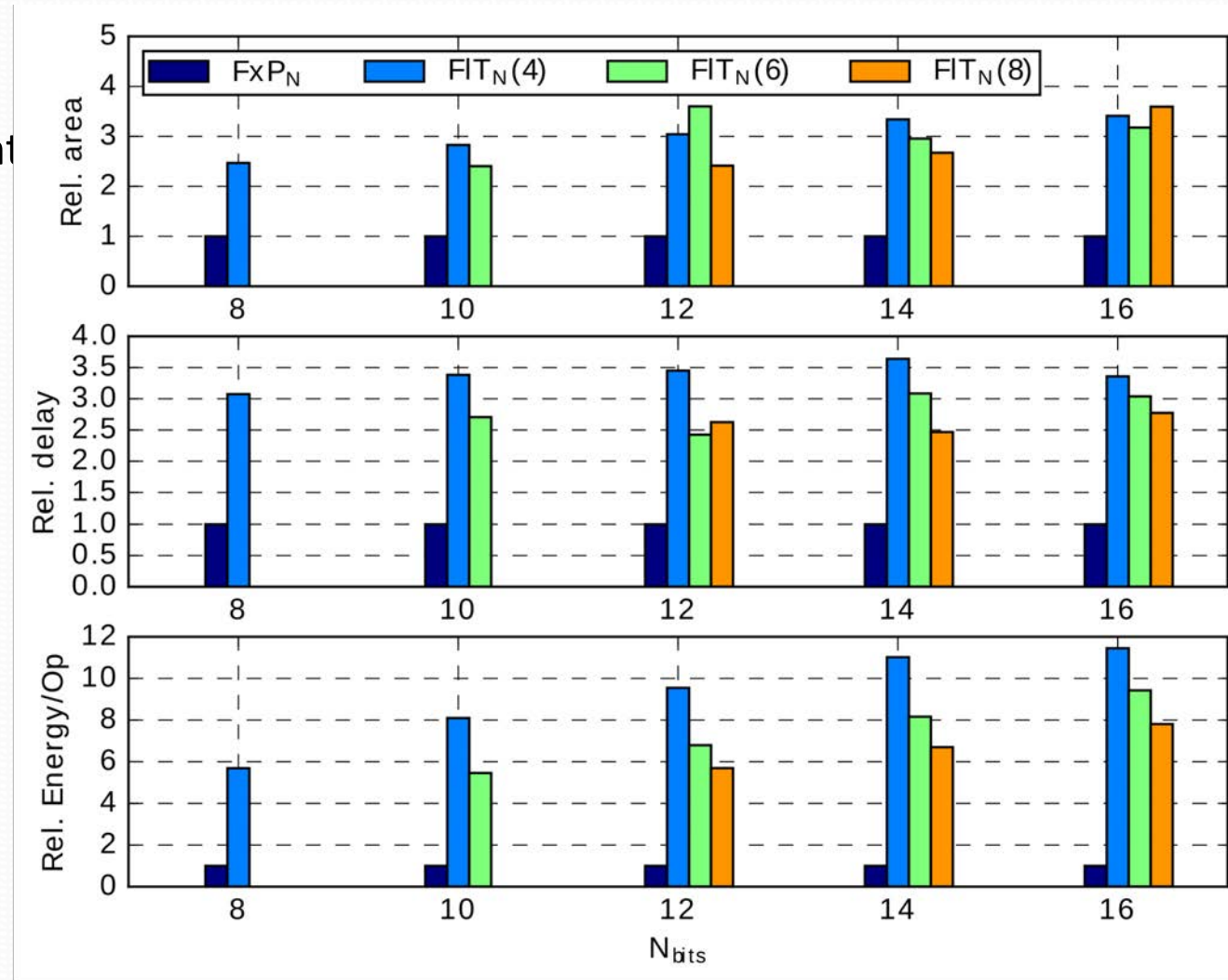
- Example: 7 bits, (2,5)



- 5-bit adder and 3 gates!

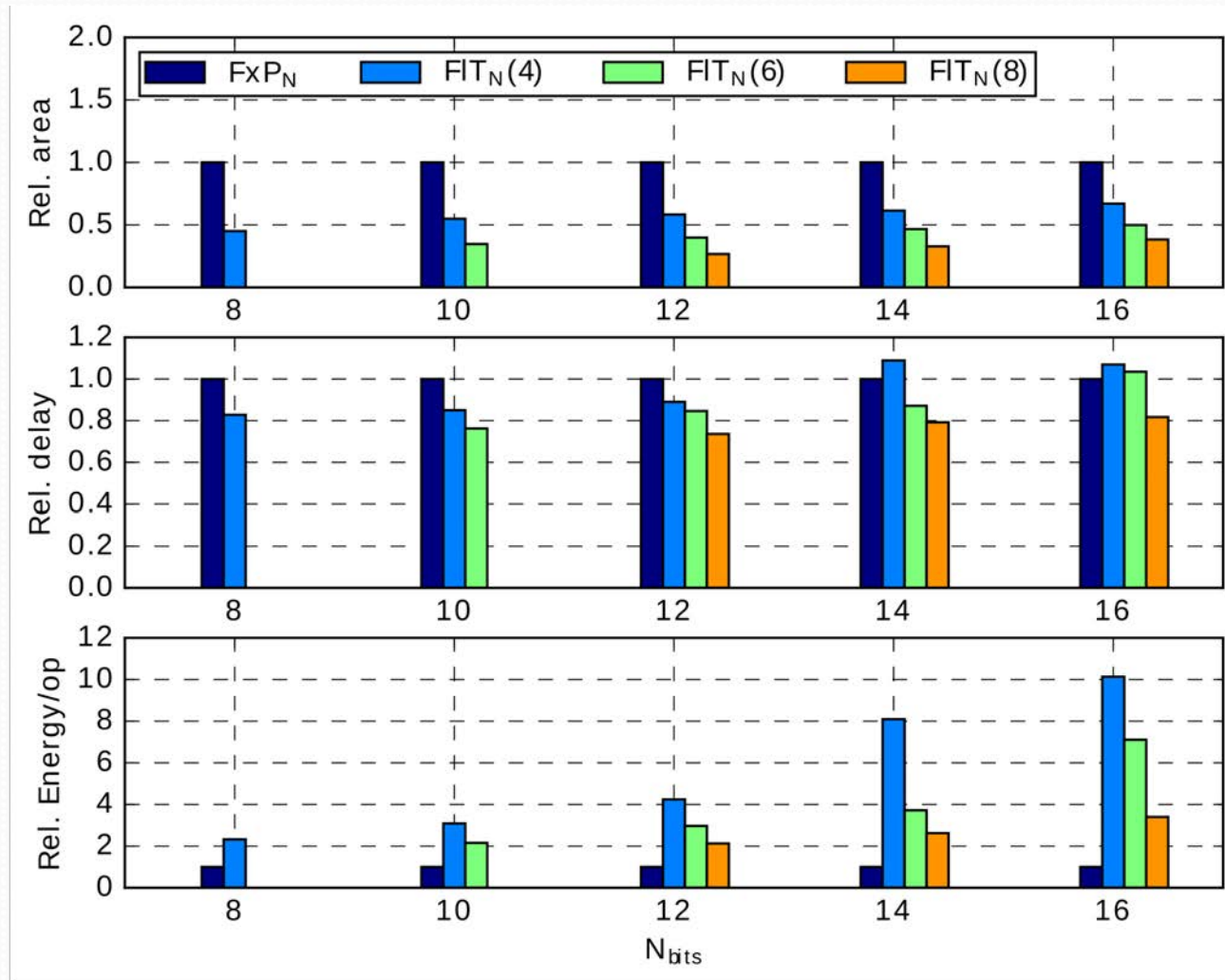
FxP vs. FIP: Adders

- FxP_N
 - N -bit Fixed-Point
- $FIT_N(E)$
 - N -bit Float
 - Exponent E bits
- FxP adders are always smaller, faster, less energy



FxP vs. FIP: Multipliers

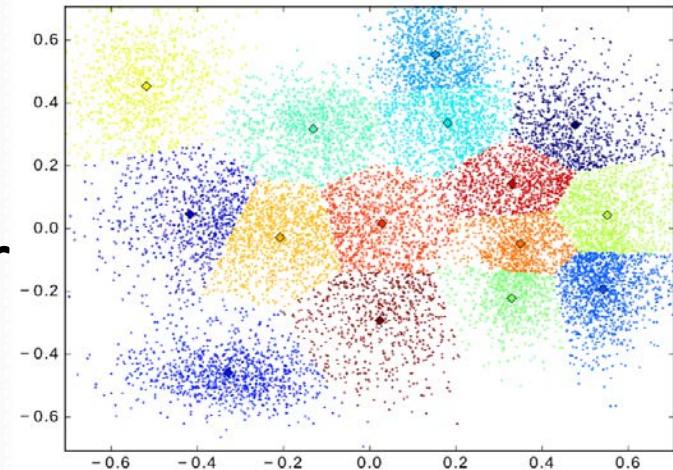
- FxP_N
 - Fixed-Point
 - N bits
- $FIT_N(E)$
 - Floating-Point
 - N bits
 - Exponent E bits
- FIP multipliers are smaller, faster, but consume more energy



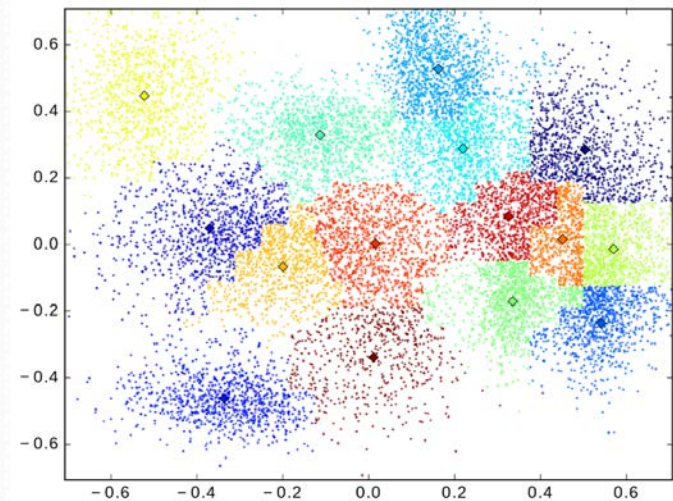
Custom Floating-Point

- Difference in cost/energy between float/fixed is smaller for low-precision operators
- Slower increase of errors for floating-point
 - e.g., 8-bit float is still effective for K-means clustering [SiPS'17]

Approximate K-Means Clustering



Reference: double



Floating-Point: ct_float₈
5-bit exponent
3-bit mantissa 15

Custom Floating-Point

- `ct_float`: a Custom Floating-Point

C++ Library

<https://gitlab.inria.fr/sentieys/ctfloat>

- **Synthesizable** (with HLS) library

- Templated C++ class

```
ct_float<e,m,r>
```

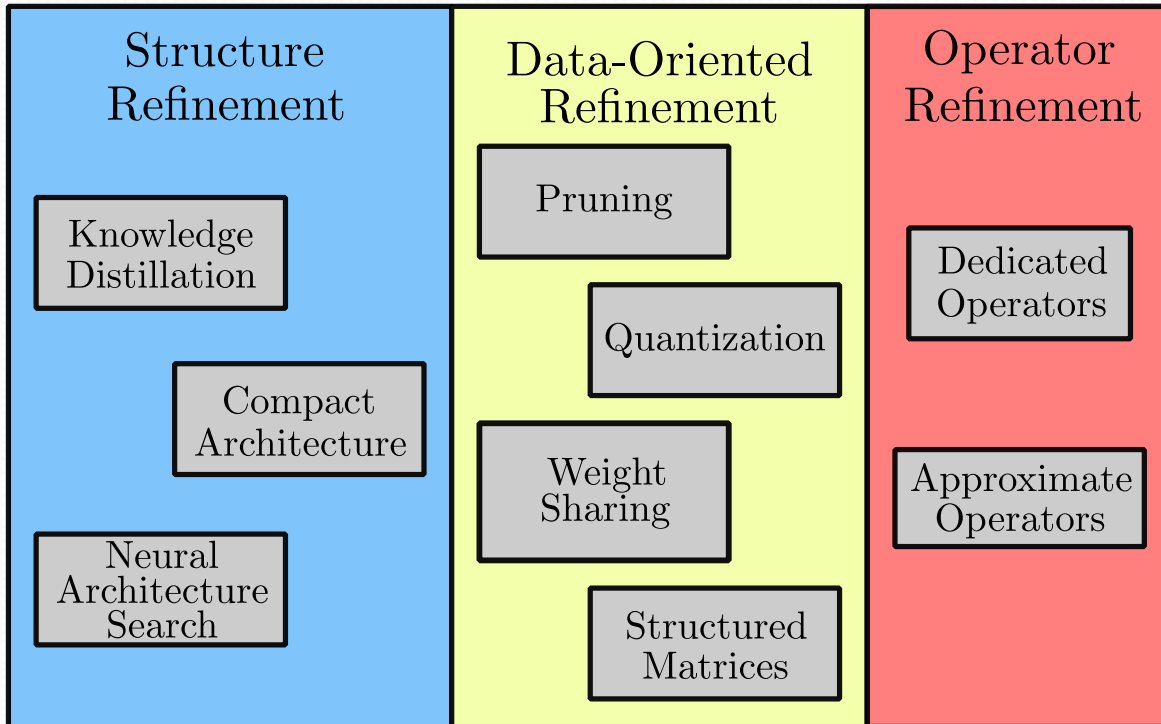
- Exponent width e (int)
- Mantissa width m (int)
- Rounding method r
- Bias b

```
ct_float<8,12,CT_RD> x,y,z;  
x = 1.5565e-2;  
z = x + y;
```

- **Many possible design points**

- latency constraints, rounding modes, etc.

Approximate DNNs

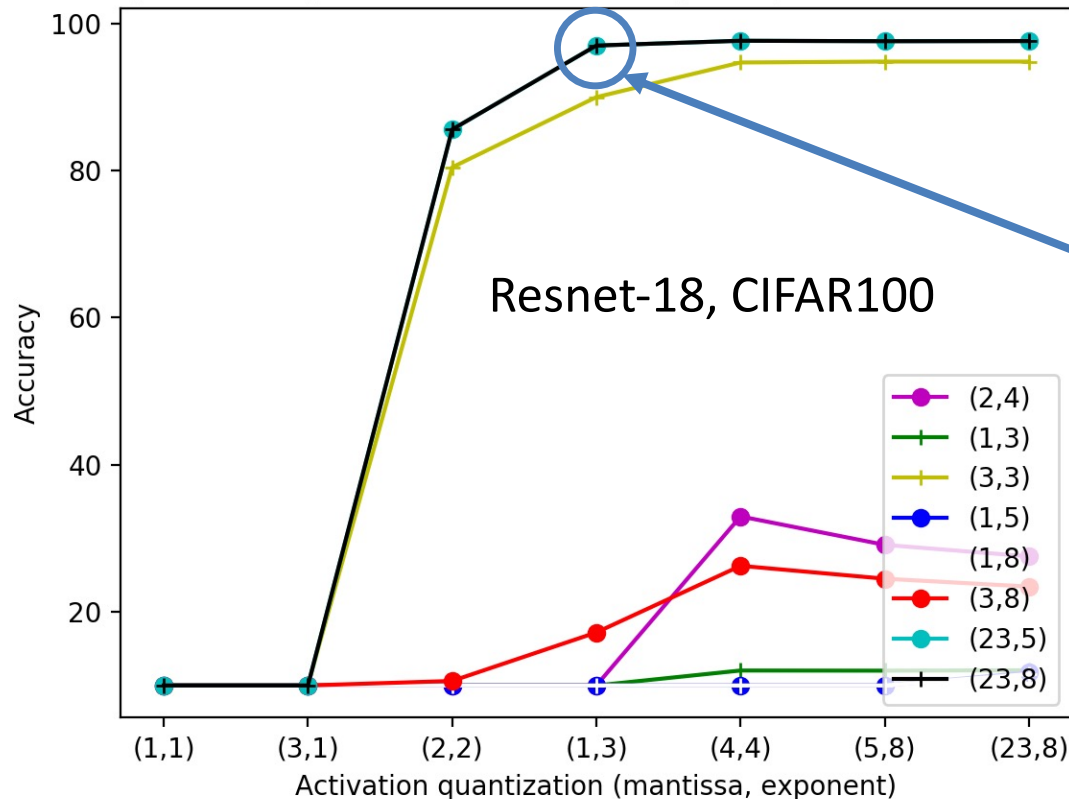


- Float
 - half-precision
 - Bfloat16
- Fixed-point
 - INT8
- Block floating-point
- BNN/TNN

Approximate DNNs: Low-Precision

- Not only **Weights**, but also **Activations**, **Per-Layer Quantization**, etc.

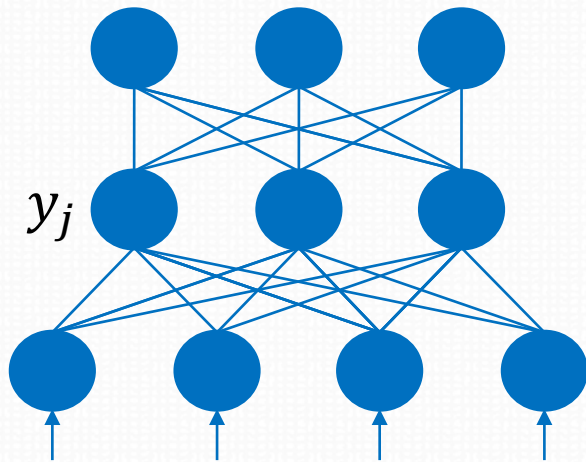
Accuracy with (weight mantissa size , weight exponent size) in the legend



4-bit activations and 10-bit weights keeps accuracy near (98.4%) 32-bit float reference

What is still difficult: learning

- Learning: gradient descent and backpropagation

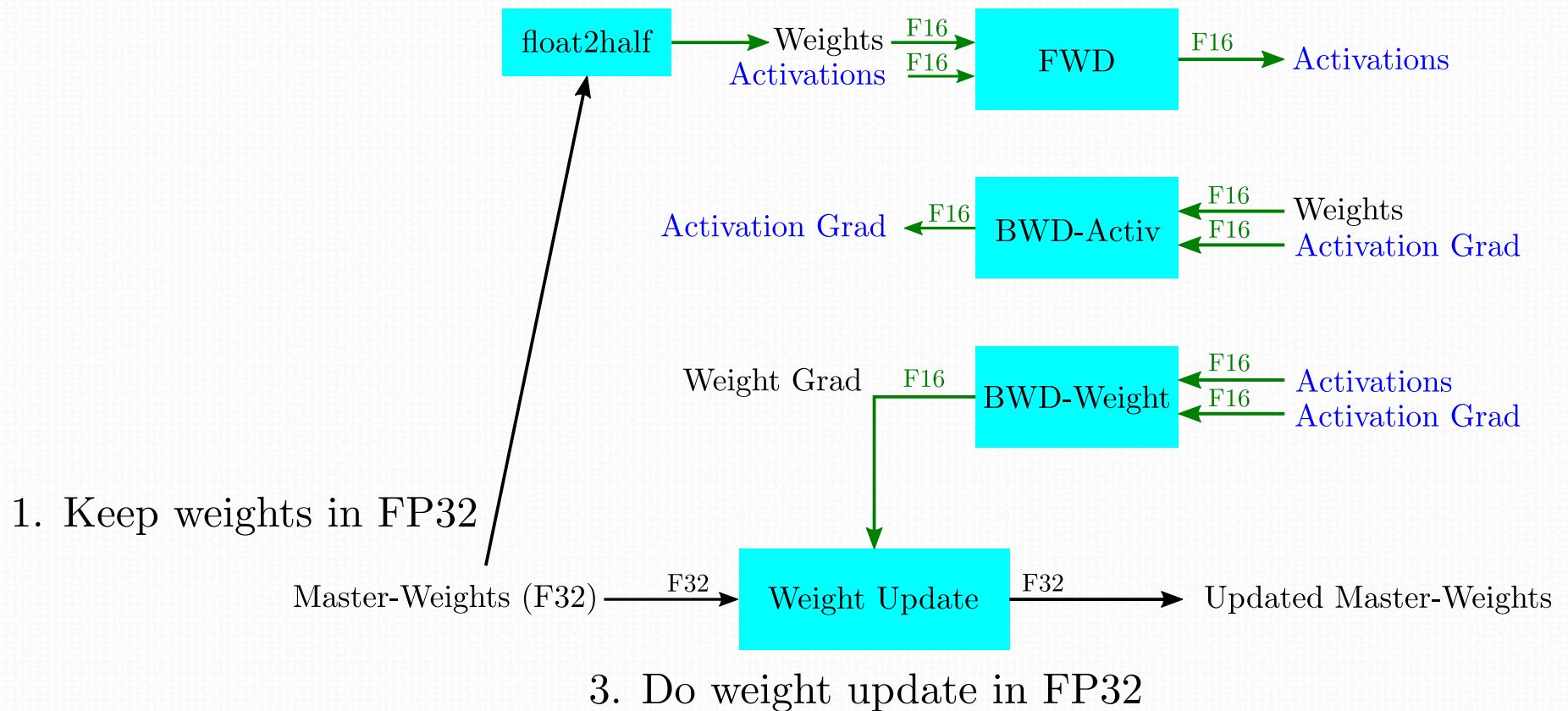


$$w_{ij}^t = w_{ij}^{t-1} - \alpha \frac{\partial \ell}{\partial w_{ij}^{t-1}}$$

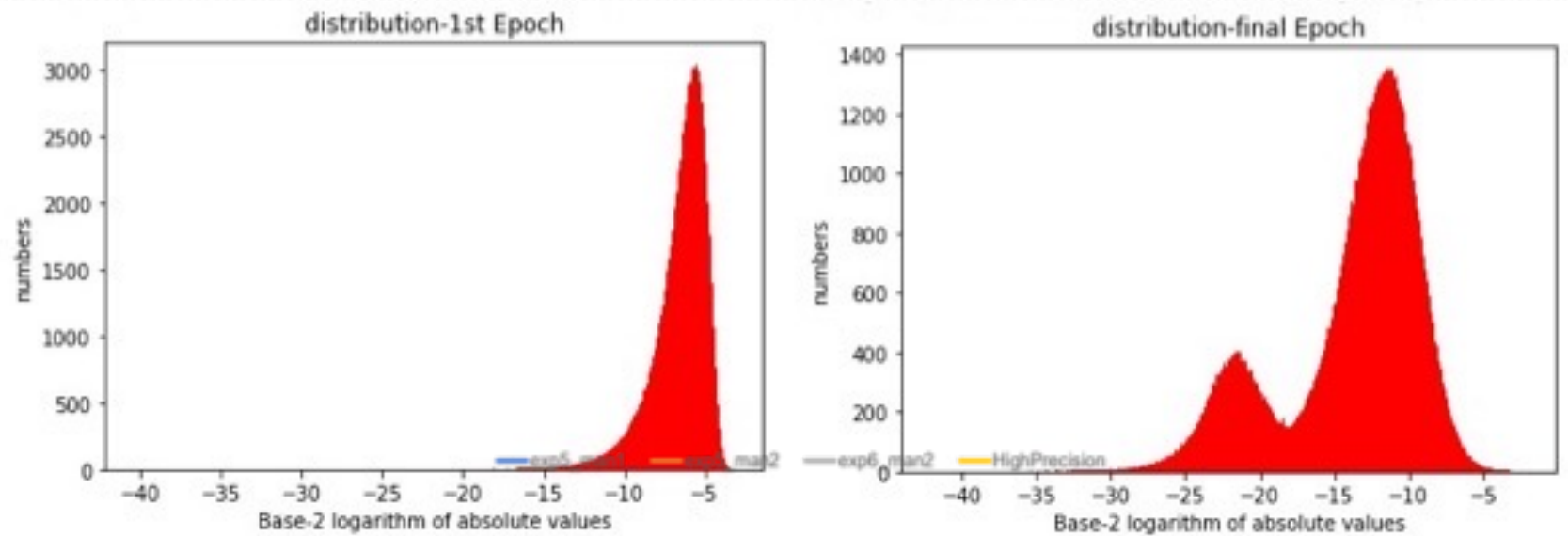
- This is very expensive to compute, even in HW
 - Approximating and accelerating learning is much more difficult

Mixed-Precision Training

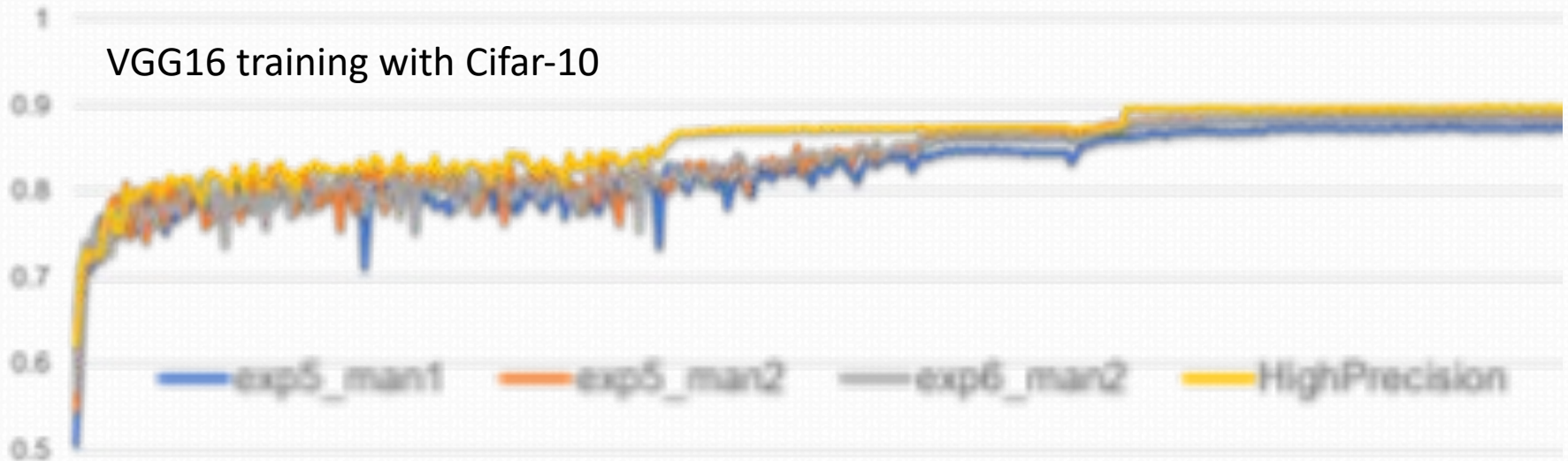
2. Make an FP16 copy and forward/backward propagate in FP16



Low-Precision Training of DNNs

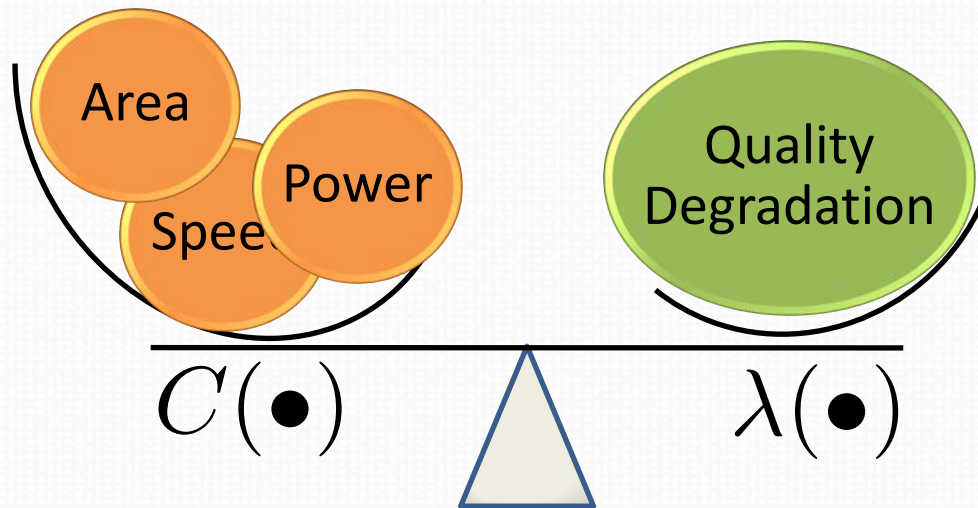


VGG16 training with Cifar-10



Accuracy and Hw Aware Exploration

- Optimization process
 - Determine the number format and word-length for each data
 - Constrained by quality degradation



$$\min (C(\mathbf{w}, \mathbf{t})) \quad \text{s.t.}$$

$$\lambda(\mathbf{w}, \mathbf{t}) \leq \lambda_{obj}$$

$$\max (\lambda(\mathbf{w}, \mathbf{t})) \quad \text{s.t.}$$

$$C(\mathbf{w}, \mathbf{t}) \leq C_{max}$$

Conclusions

- Most applications tolerate imprecision
- Playing with precision is an effective way to save energy consumption
 - Number representations, low-precision
 - Not only computation, but also **memory and transfers**
 - **Run-time** accuracy adaptation would increase energy efficiency even further
- Low-Precision **Training** and Inference

Open Issues

- Exploring number representations and word-length is a difficult problem for **large** applications
 - Mainly limited by simulation time to evaluate accuracy
 - Automating the choice between (or combining) **float and fixed** is a challenge
 - Towards an automatic optimizing compiler framework
 - **Domain-specific knowledge is a key**
- Evaluating **cost** is also an important (and less studied) issue
 - e.g., #weights alone is not a good metric
 - e.g., unstructured pruning reduces performance
 - **Hardware-aware pruning/quantization requires a good cot model**