# Approximate Deep Learning Accelerators

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

Olivier Sentieys

Univ. Rennes, Inria

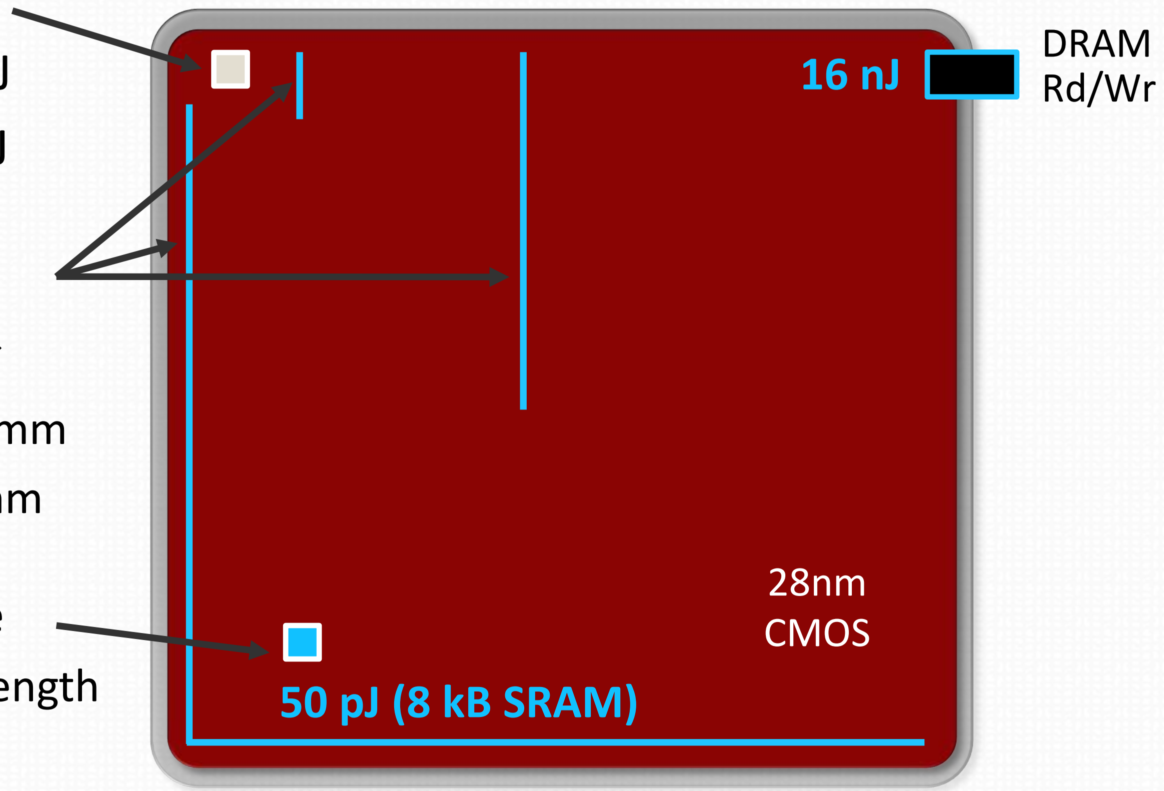
# Energy Cost in a Processor/SoC

- 64-bit FPU: 20pJ/op
- 32-bit addition: 0.05pJ
- 16-bit multiply: 0.25pJ

- Wire energy
  - 240fJ/bit/mm per ⇂↾
  - 32 bits: 40pJ/word/mm
  - 8 bits: 10pJ/word/mm

- Memory/Register-File
  - Depends on word-length

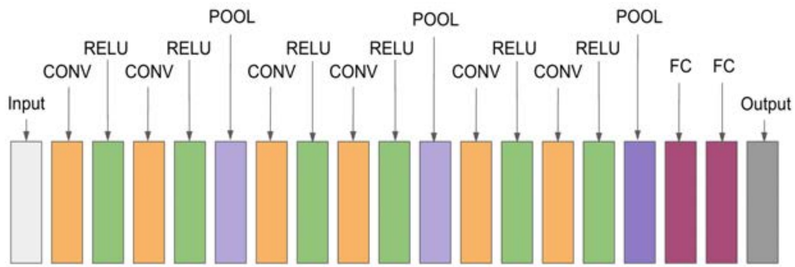
[Adapted from Dally, IPDPS'11]

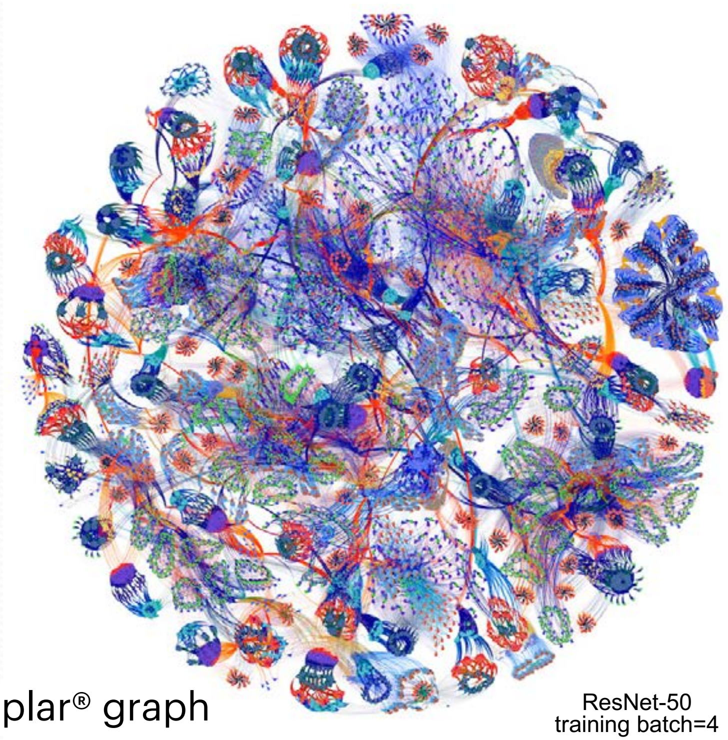



Energy strongly depends on data representation and size

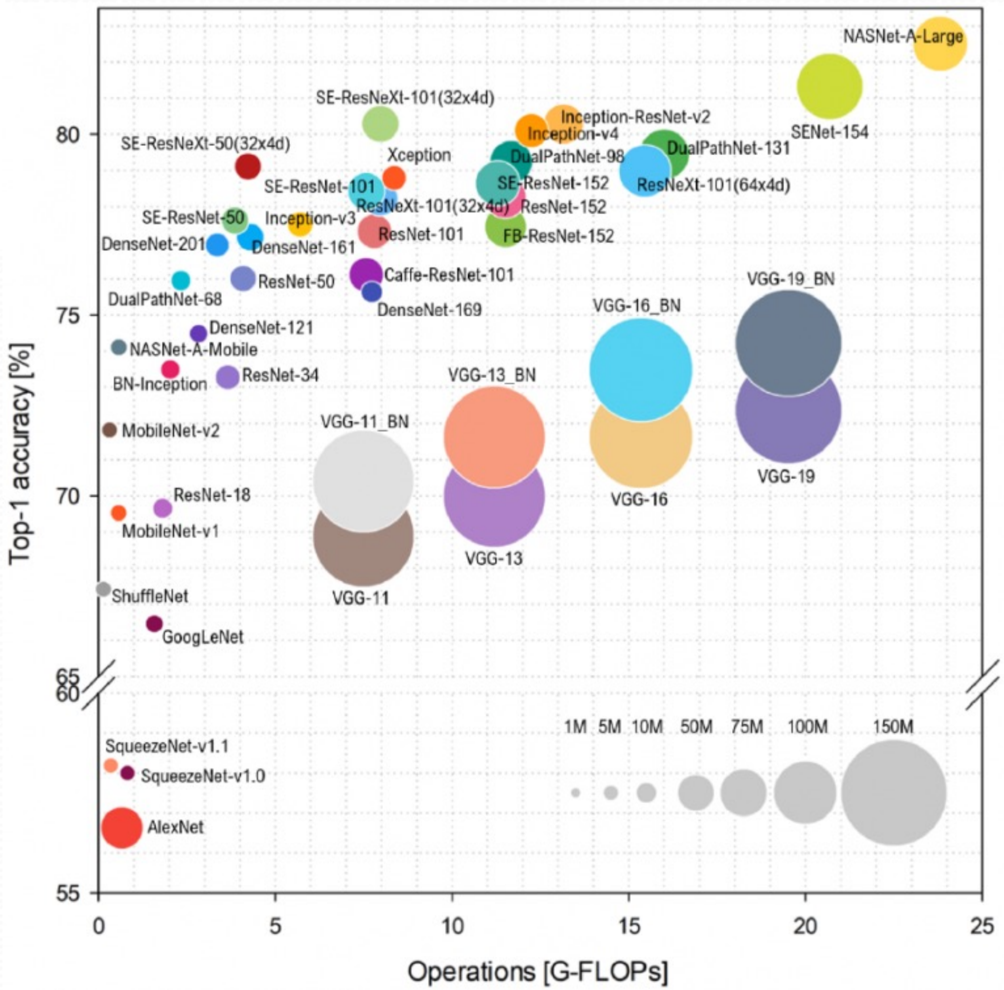
# Complexity Issues of Deep NNs

- Deep (Convolutional) Neural Networks



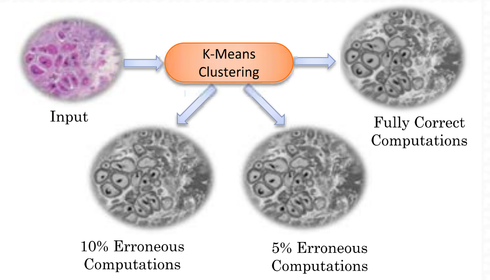




Poplar® graph

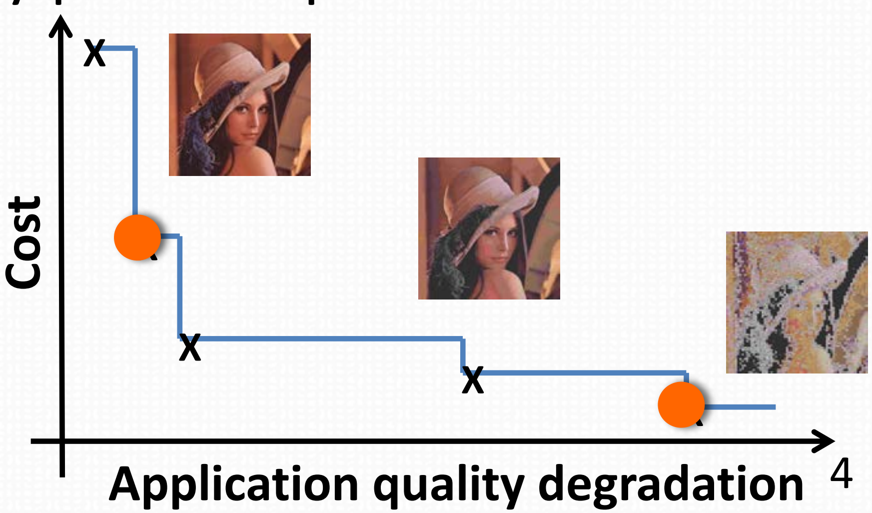


# Approximate Computing

- 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?

**Aoccdrnig to a rscheearch at Cmabrigde Uinervtisy, it deosn't mttaer in waht oredr the ltteers in a wrod are, the olny iprmoatnt tihng is taht the frist and lsat ltteer be at the rghit pclae. And we spnet hlaf our lfie larennig how to splel wrods. Amzanig, 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

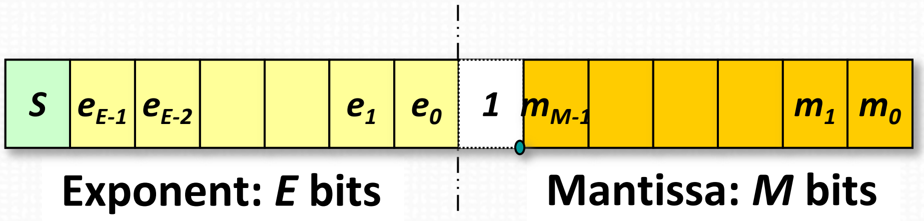
- Approximations in DNNs
- Reducing the numerical precision of arithmetic operations is a general way to increase performance and energy efficiency in computing
  - How does this apply to DNN?
  - Can we design low-precision accelerators for inference and training?

# Number Representations

- Floating-Point (FlP)

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

*s*: sign, *m*: mantissa, *e*: exponent




  – Easy to use
  – High dynamic range
  – IEEE 754

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

- Fixed-Point (FxP)

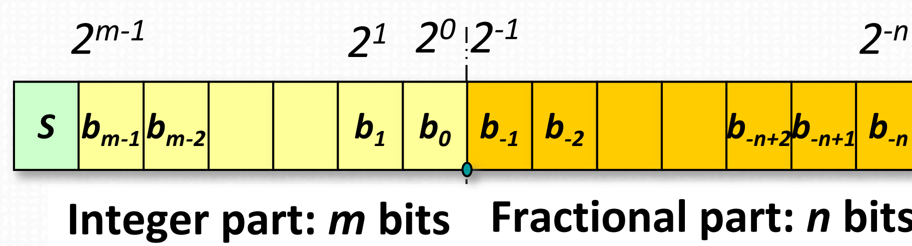
$$x = p \times K$$

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

  – Integer arithmetic
  – Efficient operators
    - Speed, power, cost
  – Hard to use...

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

$s$: sign, $m$: magnitude, $n$: fractional

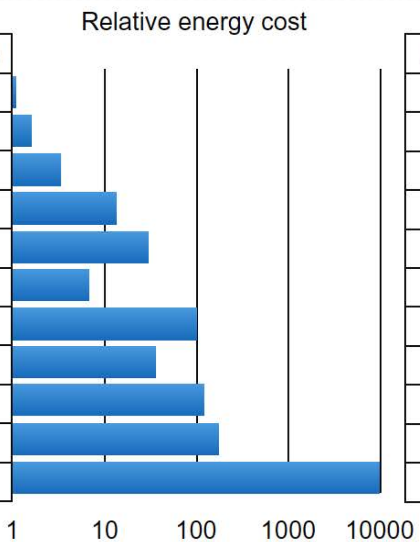


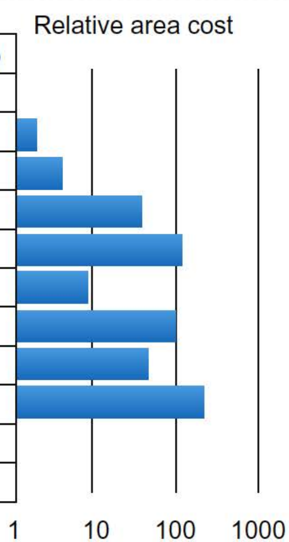
# Number Representations

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

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

| Operation: | Energy (pJ) | Area (μm$^2$) |
|---|---|---|
| 8b Add | 0.03 | 36 |
| 16b Add | 0.05 | 67 |
| 32b Add | 0.1 | 137 |
| 16b FB Add | 0.4 | 1360 |
| 32b FB Add | 0.9 | 4184 |
| 8b Mult | 0.2 | 282 |
| 32b Mult | 3.1 | 3495 |
| 16b FB Mult | 1.1 | 1640 |
| 32b FB Mult | 3.7 | 7700 |
| 32b SRAM Read (8KB) | 5 | N/A |
| 32b DRAM Read | 640 | N/A |



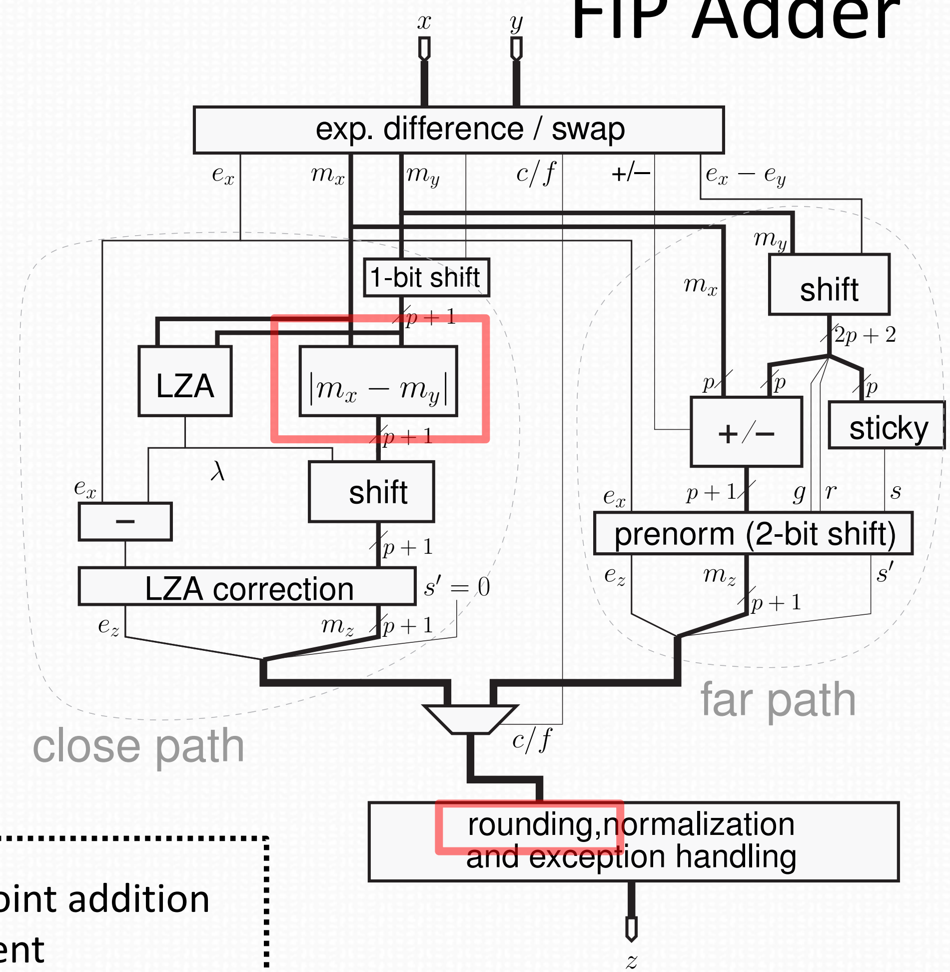




Energy numbers are from Mark Horowitz *Computing's Energy problem (and what we can do about it)*. ISSCC 2014
Area numbers are from synthesized result using Design compiler under TSMC 45nm tech node. FP units used DesignWare Library.

# Floating-Point Arithmetic

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

## FlP Adder




Fixed-point addition equivalent

[J.-M. Muller et al., Handbook of Floating-point arithmetic, Springer, 2009]

# 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)

$s_x$ $\quad e_x$ $\quad$ 1 0/1 $\quad 1.m_x = \{1.0; 1.5\}$

X $\quad s_y$ $\quad e_y$ $\quad$ 1 0/1 $\quad 1.m_y = \{1.0; 1.5\}$

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$1.m_z = \{1.0; 1.5; 2.25\}$

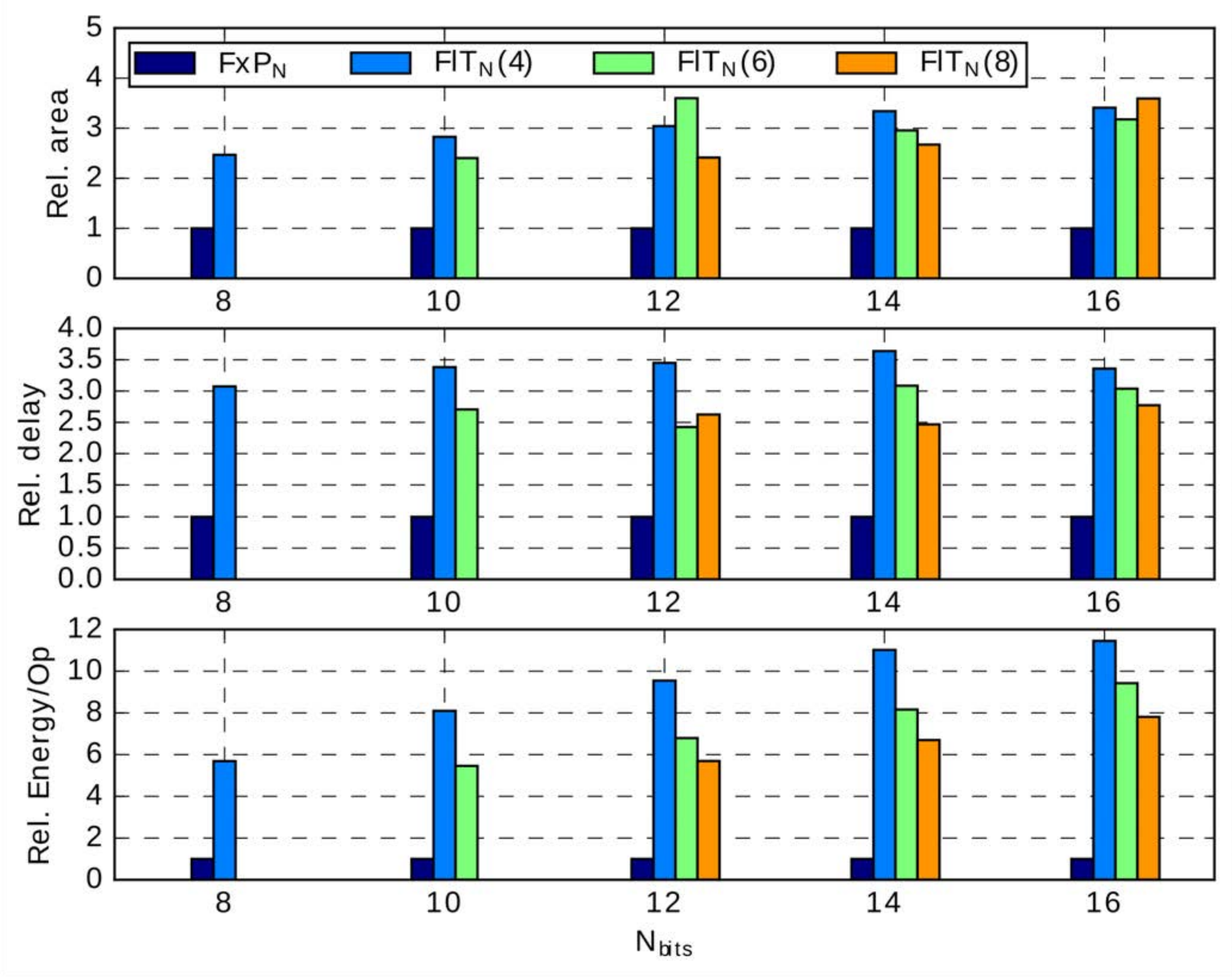
$s_z = s_x$ **NXOR** $s_y$ $\quad e_z = e_x + e_y$ + (mx AND my) $\quad 1.m_z = \{1.0; 1.5;$ **1.5 or 1.0**$\}$

$s_z$ $\quad$ 1 $\quad m_z = m_x$ **OR/XOR** $m_y$

- 5-bit adder and 3 gates!

# FxP vs. FlP: Adders

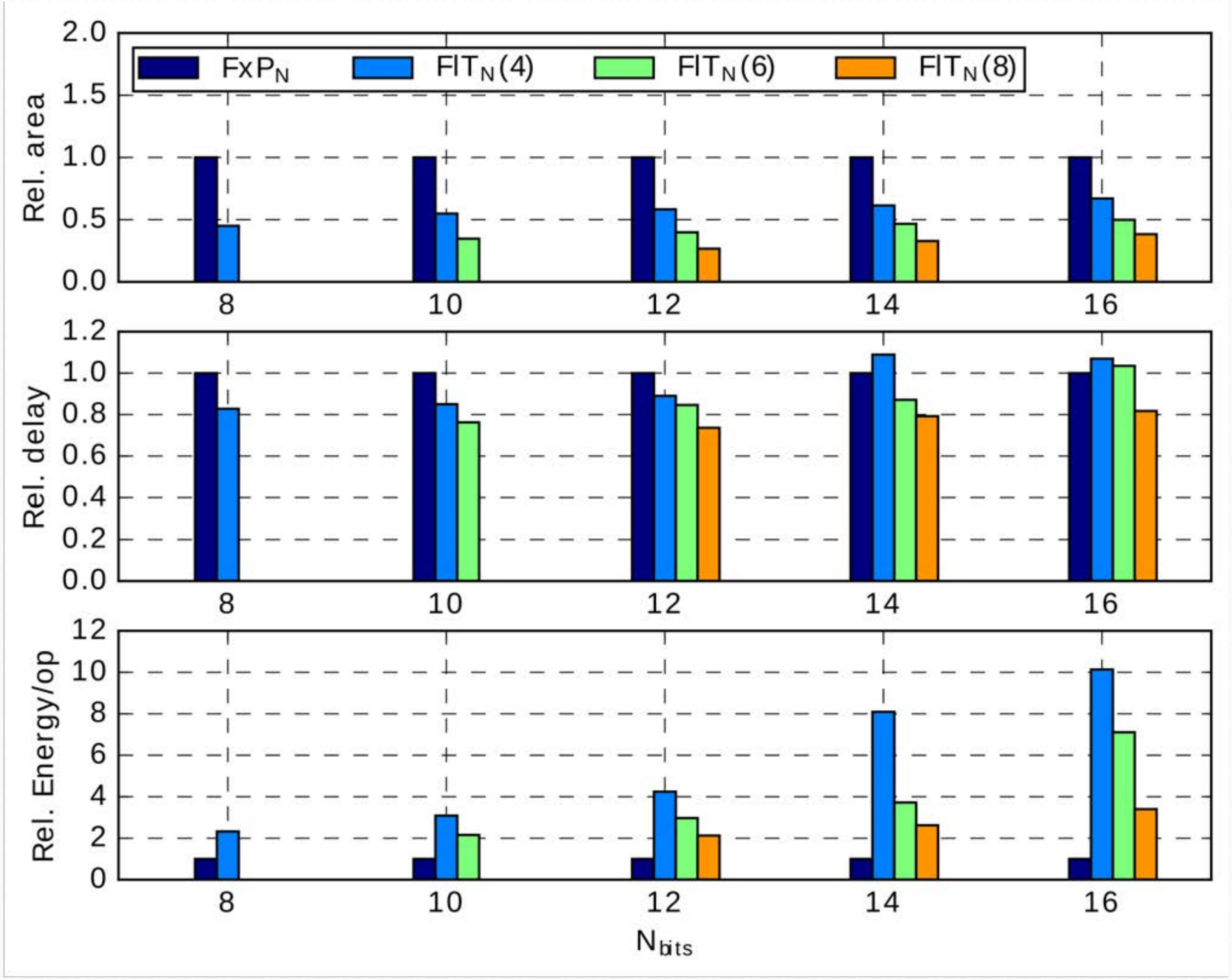
- $FxP_N$
  - *N*-bit Fixed-Point
- $FlT_N(E)$
  - *N*-bit Float
  - Exponent *E* bits
- FxP adders are always smaller, faster, less energy




28nm FDSOI technology, Catapult (HLS), Design Compiler, PrimeTime

# FxP vs. FlP: Multipliers

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

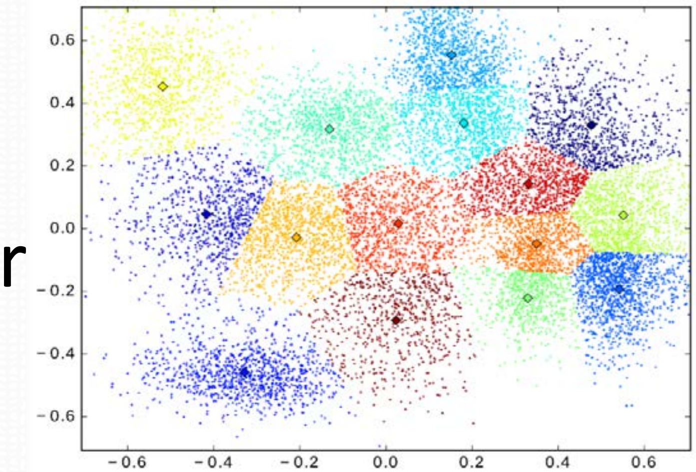



28nm FDSOI technology, Catapult (HLS), Design Compiler, PrimeTime

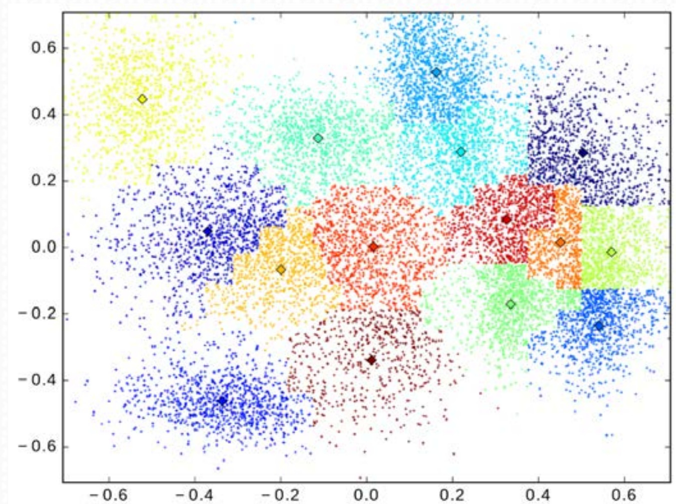
# Custom Floating-Point

- 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: $ct\_float_8$
5-bit exponent
3-bit mantissa

# Custom Floating-Point

- `ct_float`: a Custom Floating-Point C++ Library `https://gitlab.inria.fr/sentieys/ctfloat`
  - Synthesizable (with HLS) library
  - Templated C++ class

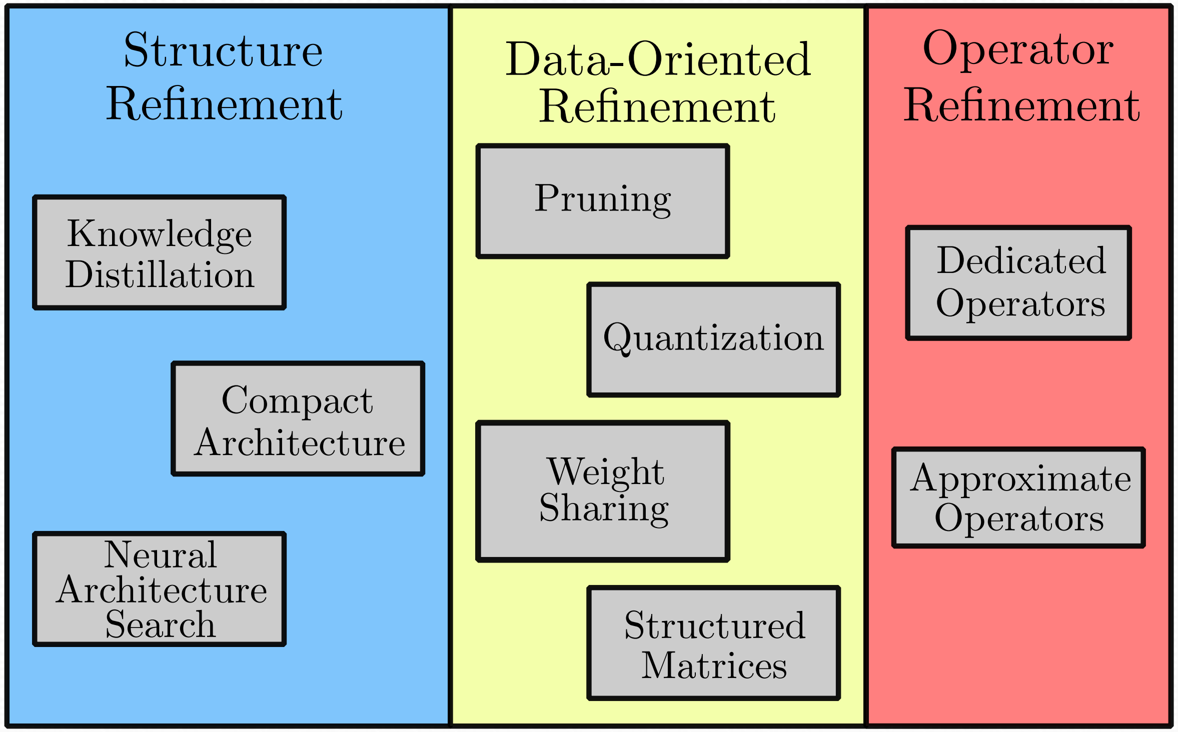
    `ct_float`<*e*,*m*,*r*>

    - 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.

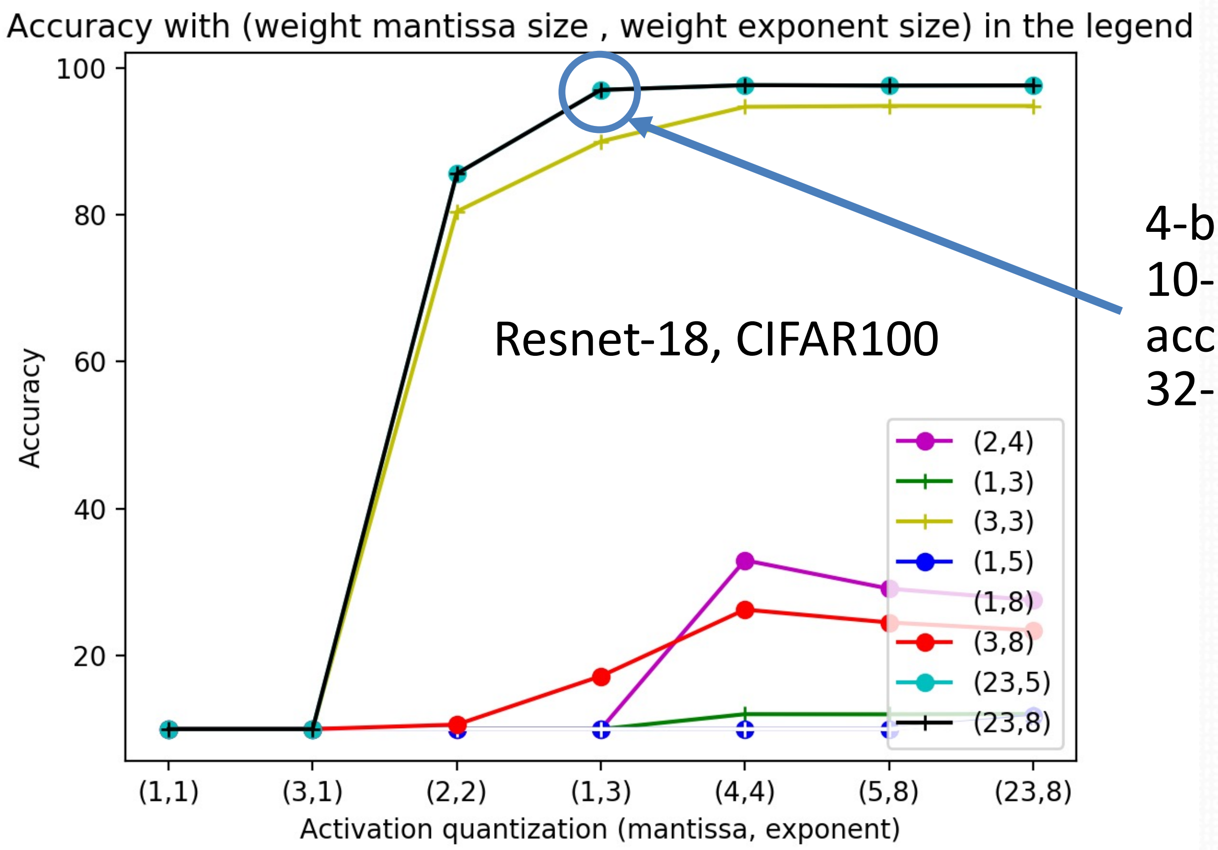
# Approximate DNNs




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

# Approximate DNNs: Low-Precision

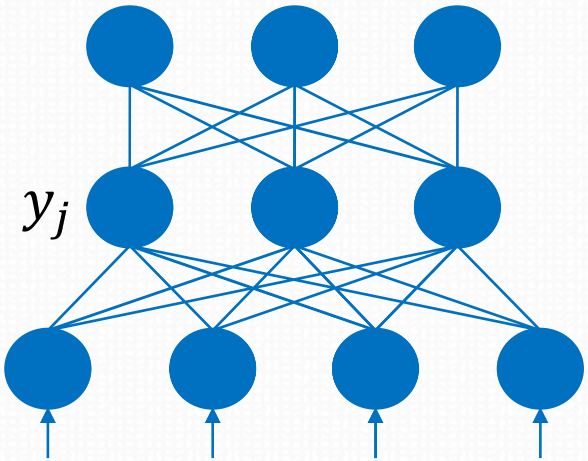
- Not only Weights, but also Activations, Per-Layer Quantization, etc.




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

# What is still difficult: learning

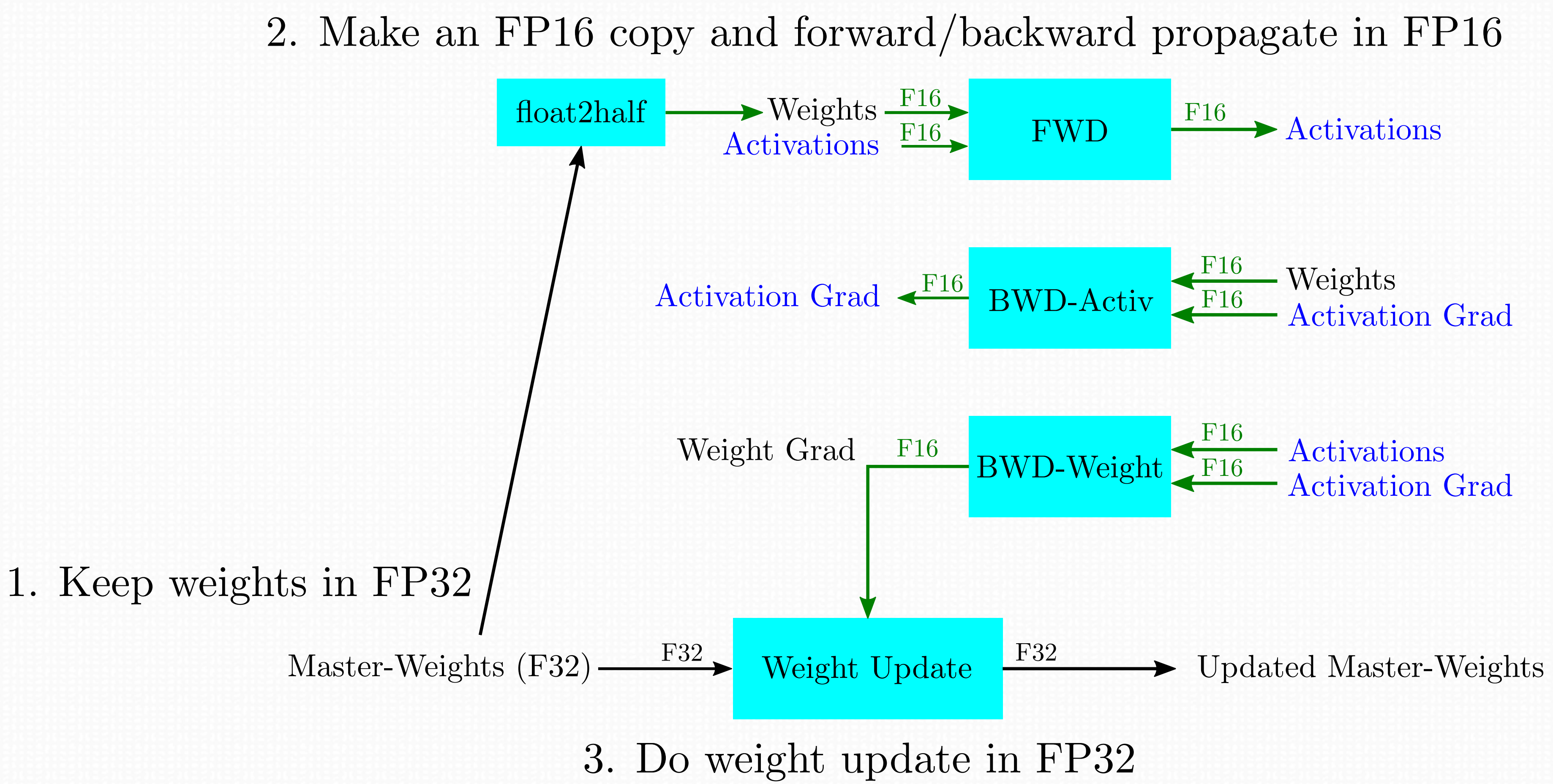
- Learning: gradient descent and backpropagation




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

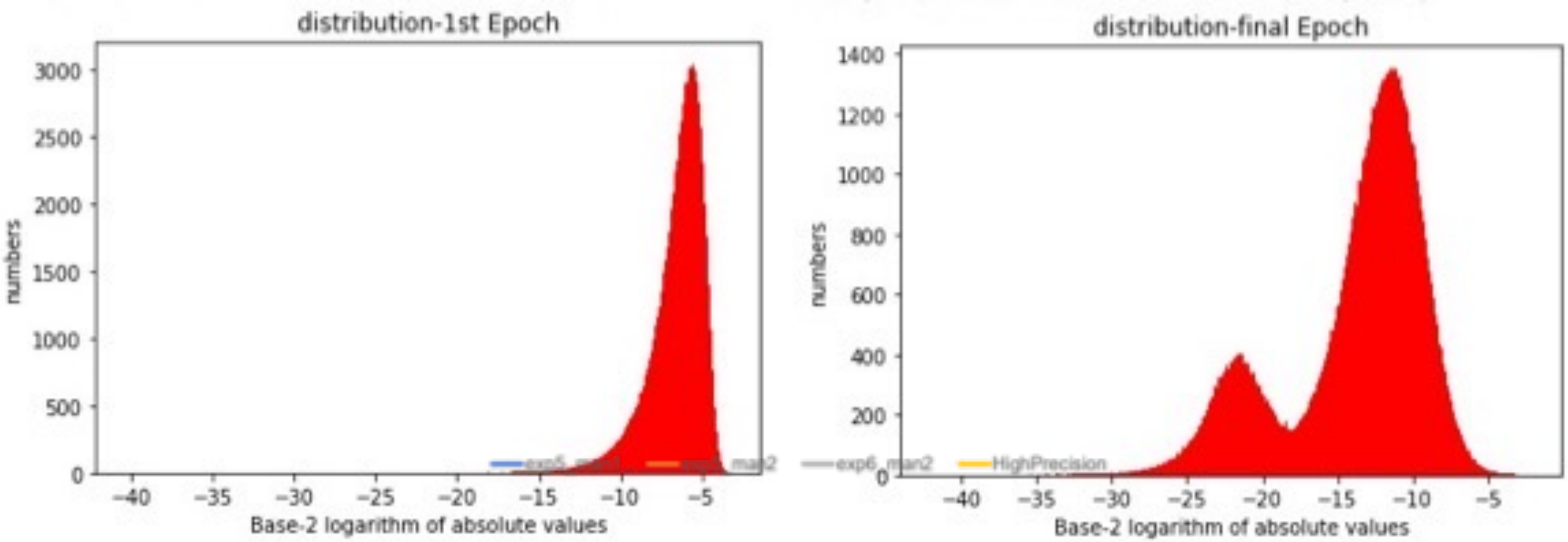
- This is very expensive to compute, even in HW
  - Approximating and accelerating learning is much more difficult

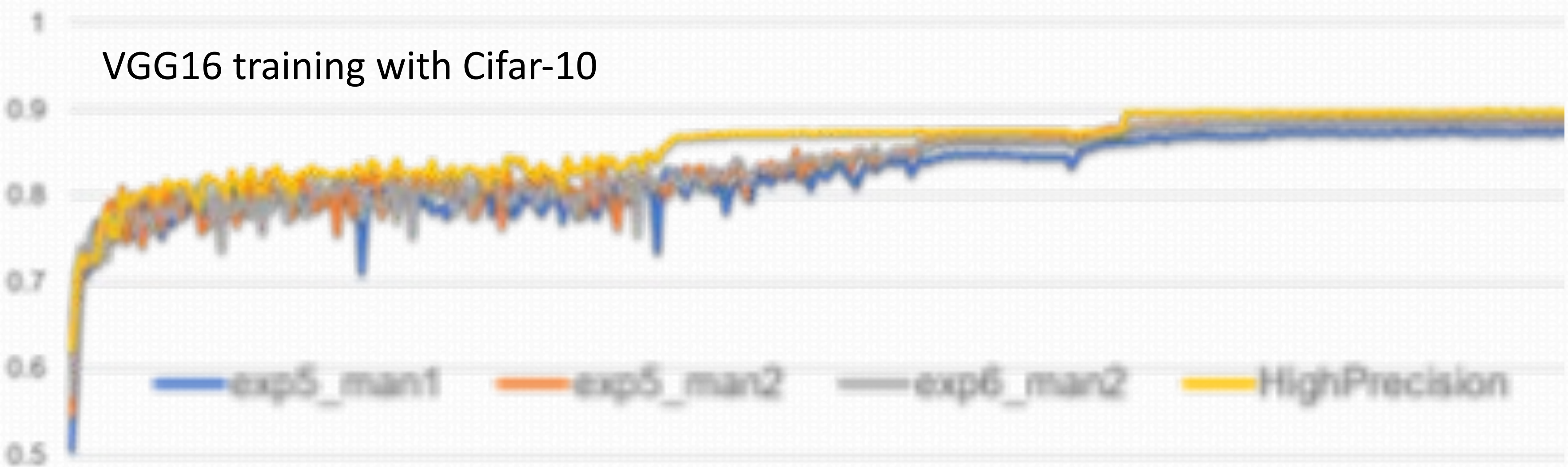
# Mixed-Precision Training



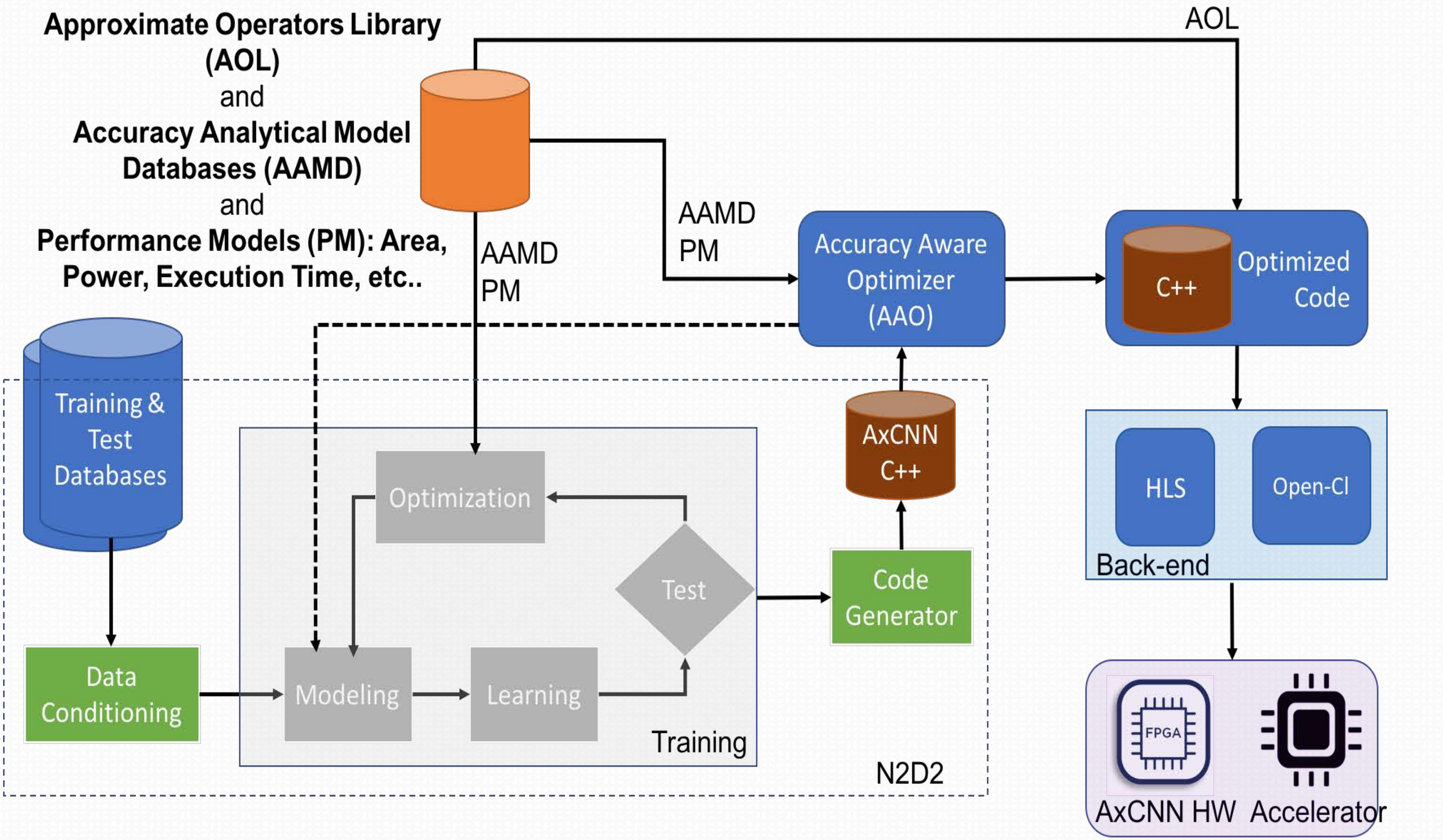

[NVIDIA, Mixed precision training, 2018]

# Low-Precision Training of DNNs



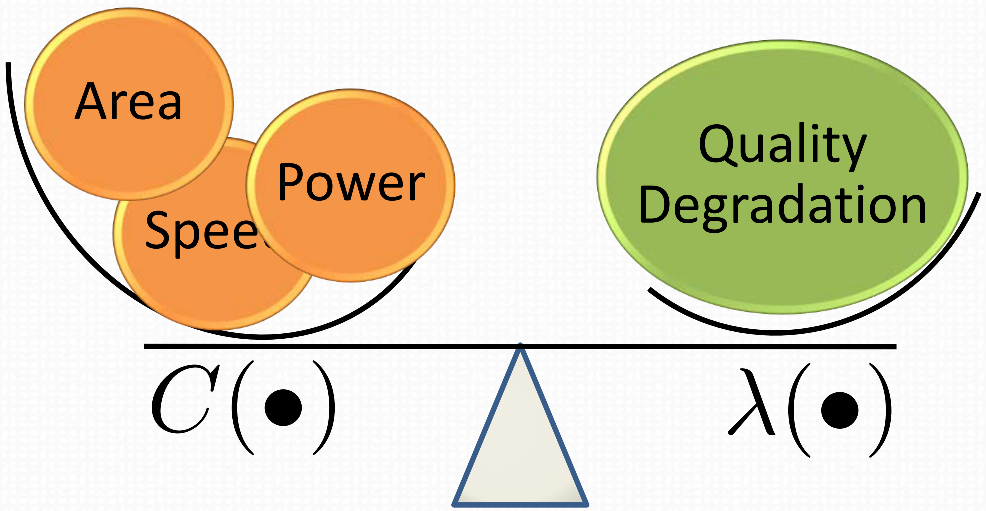



# Accuracy and Hw Aware Exploration



# Accuracy and Hw Aware Exploration

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




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

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

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

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

# 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
  - Automatizing 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