Boosting Machine Learning Innovation: Computing Systems that Learn and Adapt

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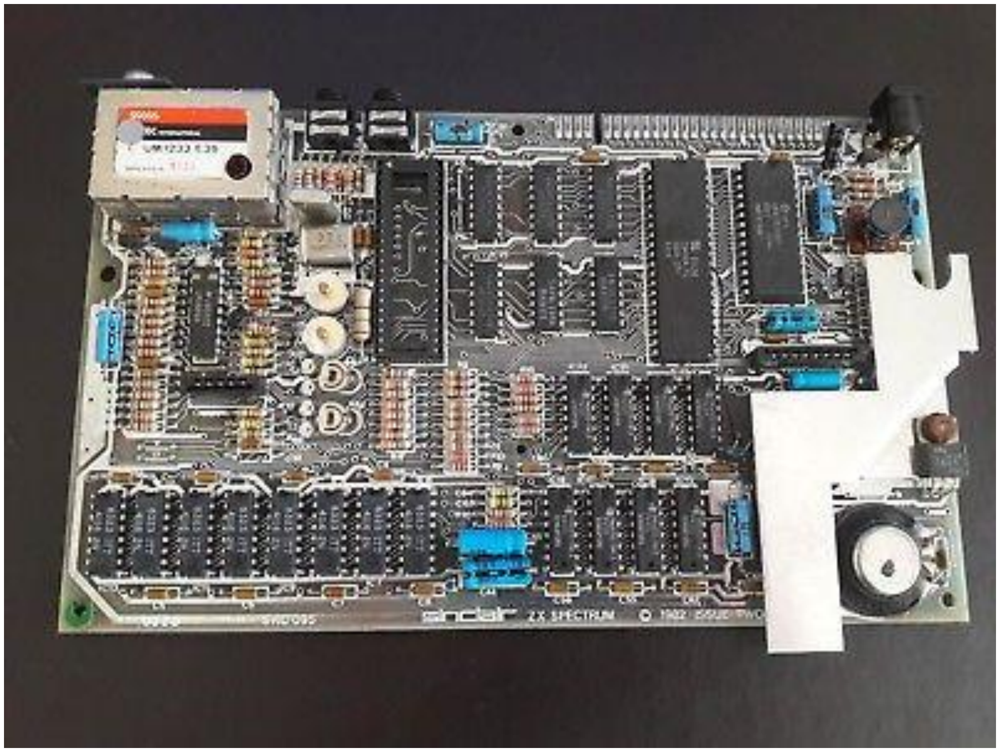
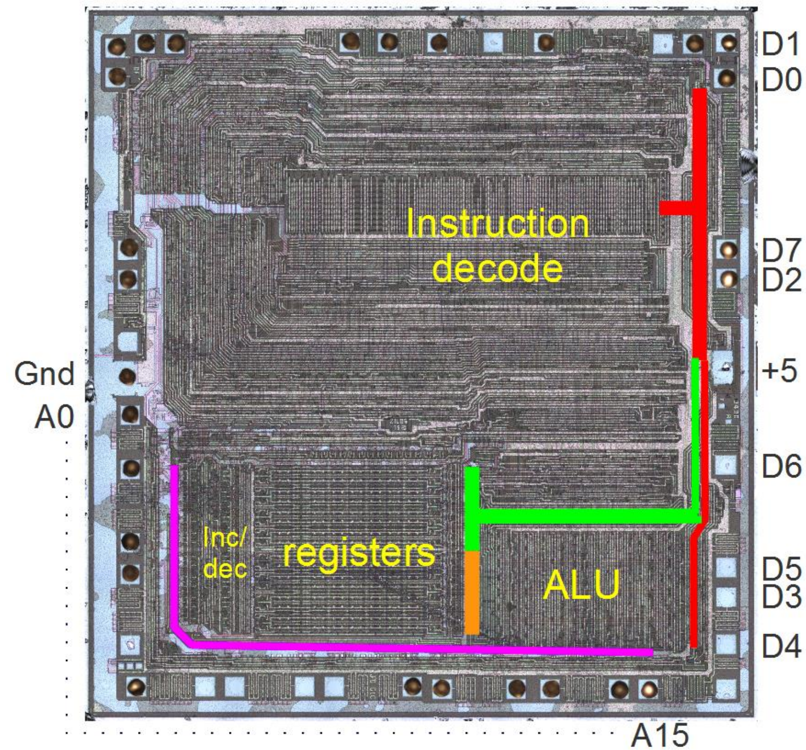
A bit about my background


sinclair
ZX Spectrum
BLUE EDIT 1 DEF FN
RED CAPS LOCK 2 FN
MAGENTA TRUE VIDEO 3 LINE
GREEN INV. VIDEO 4 OPEN #
CYAN 5 CLOSE #
YELLOW 6 MOVE
WHITE 7 ERASE
8 POINT
GRAPHICS 9 CAT
BLACK DELETE 0 FORMAT
SIN Q PLOT ASN
COS W DRAW ACS
TAN E REM ATN
INT R RUN VERIFY
RND T RAND MERGE
STR $ Y AND RETURN
CHR $ U OR IF
CODE I AT INPUT IN
PEEK O POKE OUT
TAB P PRINT
READ A STOP NEW
RESTORE S NOT SAVE
DATA D STEP DIM
SGN F TO FOR
ABS G THEN GOTO
SQR H GOSUB CIRCLE
VAL J LOAD VAL $
LEN K LIST SCREEN $
USR L LET ATTR
ENTER
CAPS SHIFT
LN Z COPY BEEP
EXP X CLEAR INK
L PRINT C CONT PAPER
L LIST V CLS FLASH
BIN B BORDER BRIGHT
IN KEY $ N NEXT OVER
PI M PAUSE INVERSE
SYMBOL SHIFT
BREAK SPACE

```
10>LET a=10
20 PRINT a
```

K




D1
D0
Instruction
decode
D7
D2
Gnd
+5
A0
D6
Inc/
dec
registers
ALU
D5
D3
D4
A15


12
10

Computing Hardware

We build tools

Used by “everyone” for “everything”

Science, medicine, commerce, …

Our Current Goal

- **Enabling Further Innovation in Machine Learning**
  - **Reduce compute, memory footprint and communication**
  - **Edge, Server, IoT**

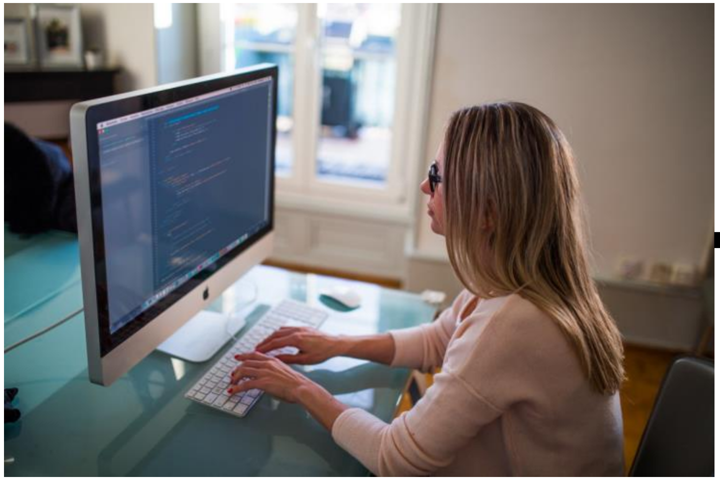
- **Two Guiding Principles…**

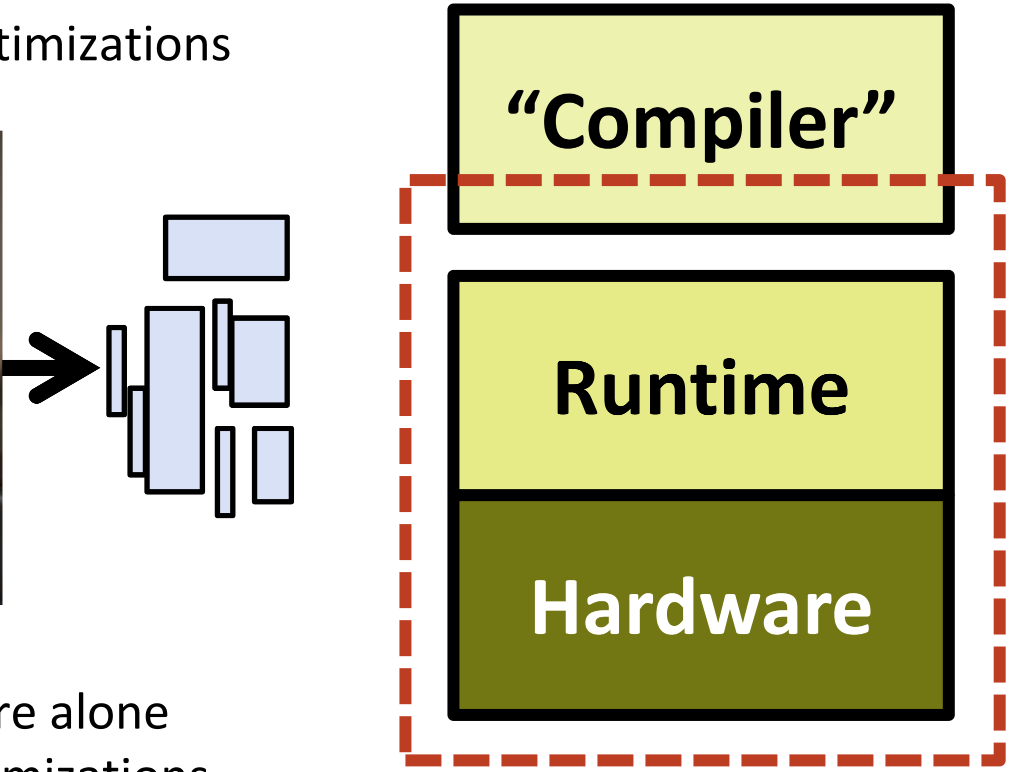
Principle #1

The advantage of natural occurring properties in Deep Learning Models

Do not require any changes
In the ML network/software
Developing software is hard…

But, …Reward model optimizations

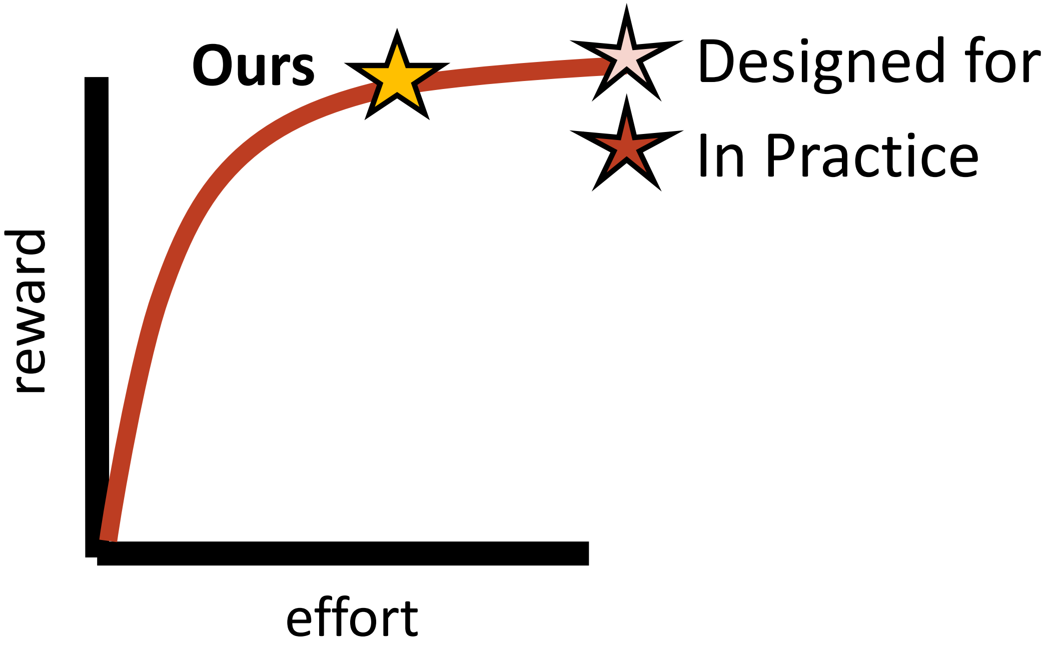




Improvements come from hardware alone
or low-level runtime/compiler optimizations

Principle #2

Balance hardware (area/energy) cost vs. reward (compute/memory amplification)



Behaviour-based approach to ML acceleration

7+ years of research

Family of techniques:

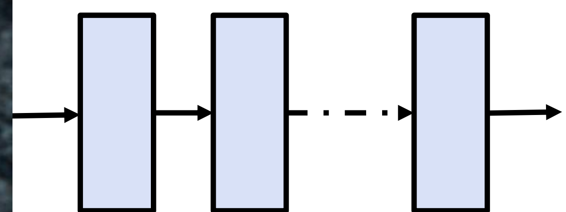
- Zero/near zero activation skipping
- Bit-serial designs → static + dynamic precision
- Memory compression (data width + delta) / on-chip /off-chip
- Bit-skipping designs
  - Computational Imaging
- Sparsity
- Inference + Training
- Software Tools:
  - Training Algorithm → bitwidth selection
  - Profiling

- **Apack**
  - Lossless compression for fixed-point inference
- **Mokey**
  - Quantization for Transformers

- **Schrödinger's FP**
  - Dynamic Adaptation of Floating-Point Containters

Example: Convolutional Neural Networks

Layers



Poutine
maybe

Tons of **Out += A x W**

For other types of networks too

Neural Nets do...

Out_0 += A_0 x W_0	Out_1 += A_0 x W_0	Out_0 += A_0 x W_0	Out_1 += A_0 x W_0	Out_0 += A_0 x W_0	Out_1 += A_0 x W_0	Out_0 += A_0 x W_0	Out_1 += A_0 x W_0
Out_0 += A_1 x W_1	Out_1 += A_1 x W_1	Out_0 += A_1 x W_1	Out_1 += A_1 x W_1	Out_0 += A_1 x W_1	Out_1 += A_1 x W_1	Out_0 += A_1 x W_1	Out_1 += A_1 x W_1
Out_0 += A_2 x W_2	Out_1 += A_2 x W_2	Out_0 += A_2 x W_2	Out_1 += A_2 x W_2	Out_0 += A_2 x W_2	Out_1 += A_2 x W_2	Out_0 += A_2 x W_2	Out_1 += A_2 x W_2
Out							W_3
Out							W_4
Out_0 += A_0 x W_0	Out_1 += A_0 x W_0	Out_0 += A_0 x W_0	Out_1 += A_0 x W_0	Out_0 += A_0 x W_0	Out_1 += A_0 x W_0	Out_0 += A_0 x W_0	Out_1 += A_0 x W_0
Out_0 += A_1 x W_1	Out_1 += A_1 x W_1	Out_0 += A_1 x W_1	Out_1 += A_1 x W_1	Out_0 += A_1 x W_1	Out_1 += A_1 x W_1	Out_0 += A_1 x W_1	Out_1 += A_1 x W_1
Out_0 += A_2 x W_2	Out_1 += A_2 x W_2	Out_0 += A_2 x W_2	Out_1 += A_2 x W_2	Out_0 += A_2 x W_2	Out_1 += A_2 x W_2	Out_0 += A_2 x W_2	Out_1 += A_2 x W_2
Out_0 += A_3 x W_3	Out_1 += A_3 x W_3	Out_0 += A_3 x W_3	Out_1 += A_3 x W_3	Out_0 += A_3 x W_3	Out_1 += A_3 x W_3	Out_0 += A_3 x W_3	Out_1 += A_3 x W_3
Out							W_4
Out							W_0
Out_0 += A_1 x W_1	Out_1 += A_1 x W_1	Out_0 += A_1 x W_1	Out_1 += A_1 x W_1	Out_0 += A_1 x W_1	Out_1 += A_1 x W_1	Out_0 += A_1 x W_1	Out_1 += A_1 x W_1
Out_0 += A_2 x W_2	Out_1 += A_2 x W_2	Out_0 += A_2 x W_2	Out_1 += A_2 x W_2	Out_0 += A_2 x W_2	Out_1 += A_2 x W_2	Out_0 += A_2 x W_2	Out_1 += A_2 x W_2
Out_0 += A_3 x W_3	Out_1 += A_3 x W_3	Out_0 += A_3 x W_3	Out_1 += A_3 x W_3	Out_0 += A_3 x W_3	Out_1 += A_3 x W_3	Out_0 += A_3 x W_3	Out_1 += A_3 x W_3
Out_0 += A_4 x W_4	Out_1 += A_4 x W_4	Out_0 += A_4 x W_4	Out_1 += A_4 x W_4	Out_0 += A_4 x W_4	Out_1 += A_4 x W_4	Out_0 += A_4 x W_4	Out_1 += A_4 x W_4

Many MACs

Lots of **data to transfer**

When we started we assumed: Everyone in industry will target parallelism and data blocking first.

We wanted to be ready with the next technologies once these two are “perfected”.

We targeted “behavior” based optimizations: what ML does at runtime that we can take advantage of.
The programmer specifies a way to compute a result, as long as we produce the same result we can play tricks at the hardware level to improve efficiency. Lots of experience from CPUs: caches, branch prediction, etc.

Do as you are told?

Out_0 += A_3 x W_3 Out_1 += A_3 x W_3 Out_0 += A_3 x W_3 Out_1 += A_3 x W_3 Out_0 += A_3 x W_3 Out_1 += A_3 x W_3 Out_0 += A_3 x W_3 Out_1 += A_3 x

Out_0 += A_4 x W_4 Out_1 += A_4 x W_4 Out_0 += A_4 x W_4 Out_1 += A_4 x W_4 Out_0 += A_4 x W_4 Out_1 += A_4 x W_4 Out_0 += A_4 x W_4 Out_1 += A_4 x

Instead calculate the *same* output but … do less work

Out_0 += A_2 x W_2 Out_1 += A_2 x W_2 Out_0 += A_2 x W_2 Out_1 += A_2 x W_2 Out_0 += A_2 x W_2 Out_1 += A_2 x W_2 Out_0 += A_2 x W_2 Out_1 += A_2 x

Out_0 += A_3 x W_3 Out_1 += A_3 x W_3 Out_0 += A_3 x W_3 Out_1 += A_3 x W_3 Out_0 += A_3 x W_3 Out_1 += A_3 x W_3 Out_0 += A_3 x W_3 Out_1 += A_3 x

Out_0 += A_4 x W_4 Out_1 += A_4 x W_4 Out_0 += A_4 x W_4 Out_1 += A_4 x W_4 Out_0 += A_4 x W_4 Out_1 += A_4 x W_4 Out_0 += A_4 x W_4 Out_1 += A_4 x

$Out_0 \mathrel{+}= A_0 \times W_0$

$Out_0 \mathrel{+}= A_4 \times W_4$

$Out_0 \mathrel{+}= A_2 \times W_2$

$Out_0 \mathrel{+}= A_3 \times W_3$

$Out_0 \mathrel{+}= A_4 \times W_4$

$Out_0 \mathrel{+}= A_4 \times W_4$

$Out_1 \mathrel{+}= A_0 \times W_0$

$Out_1 \mathrel{+}= A_3 \times W_3$

$Out_1 \mathrel{+}= A_0 \times W_0$

$Out_1 \mathrel{+}= A_1 \times W_1$

$Out_1 \mathrel{+}= A_0 \times W_0$

$Out_0 \mathrel{+}= A_0 \times W_0$

$Out_0 \mathrel{+}= A_0 \times W_0$

$Out_0 \mathrel{+}= A_1 \times W_1$

$Out_0 \mathrel{+}= A_0 \times W_0$

$Out_0 \mathrel{+}= A_1 \times W_1$

$Out_1 \mathrel{+}= A_0 \times W_0$

$Out_1 \mathrel{+}= A_1 \times W_1$

$Out_1 \mathrel{+}= A_4 \times W_4$

2

$Out_1 \mathrel{+}= A_3 \times W_3$

$Out_1 \mathrel{+}= A_4 \times W_4$

$Out_1 \mathrel{+}= A_0 \times W_0$

$Out_1 \mathrel{+}= A_4 \times W_4$

$Out_0 \mathrel{+}= A_0 \times W_0$

$Out_0 \mathrel{+}= A_0 \times W_0$

$Out_0 \mathrel{+}= A_1 \times W_1$

$Out_1 \mathrel{+}= A_0 \times W_0$

$Out_1 \mathrel{+}= A_1 \times W_1$

$Out_1 \mathrel{+}= A_0 \times W_0$

$Out_1 \mathrel{+}= A_4 \times W_4$

$Out_0 \mathrel{+}= A_4 \times W_4$

$Out_0 \mathrel{+}= A_1 \times W_1$

$Out_0 \mathrel{+}= A_0 \times W_0$

$Out_1 \mathrel{+}= A_0 \times$

$Out_1 \mathrel{+}= A_4 \times$

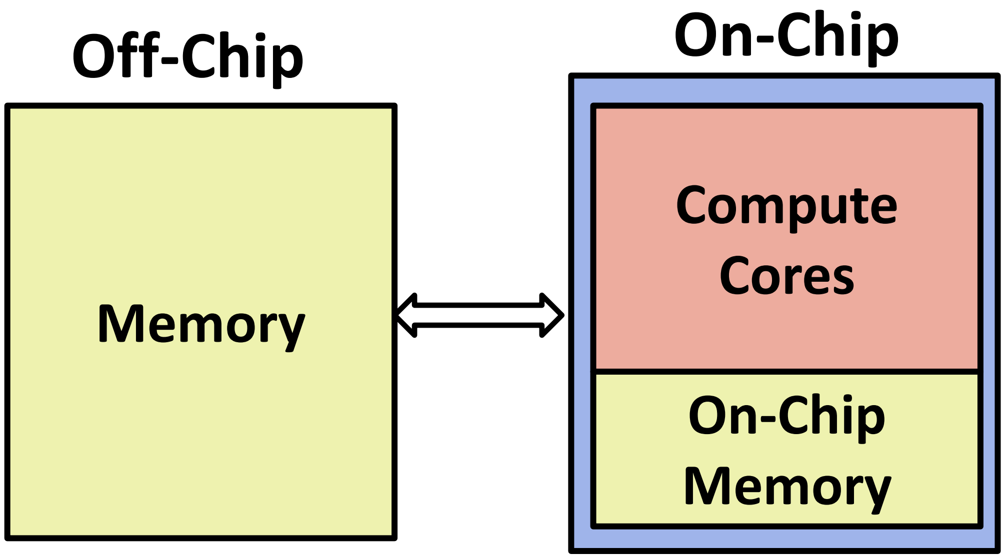
$Out_1 \mathrel{+}= A_0 \times$

$Out_1 \mathrel{+}= A_1 \times$

$Out_1 \mathrel{+}= A_0 \times$

$Out_1 \mathrel{+}= A_4 \times$

Technology #1: Memory Transfers: Shapeshifter



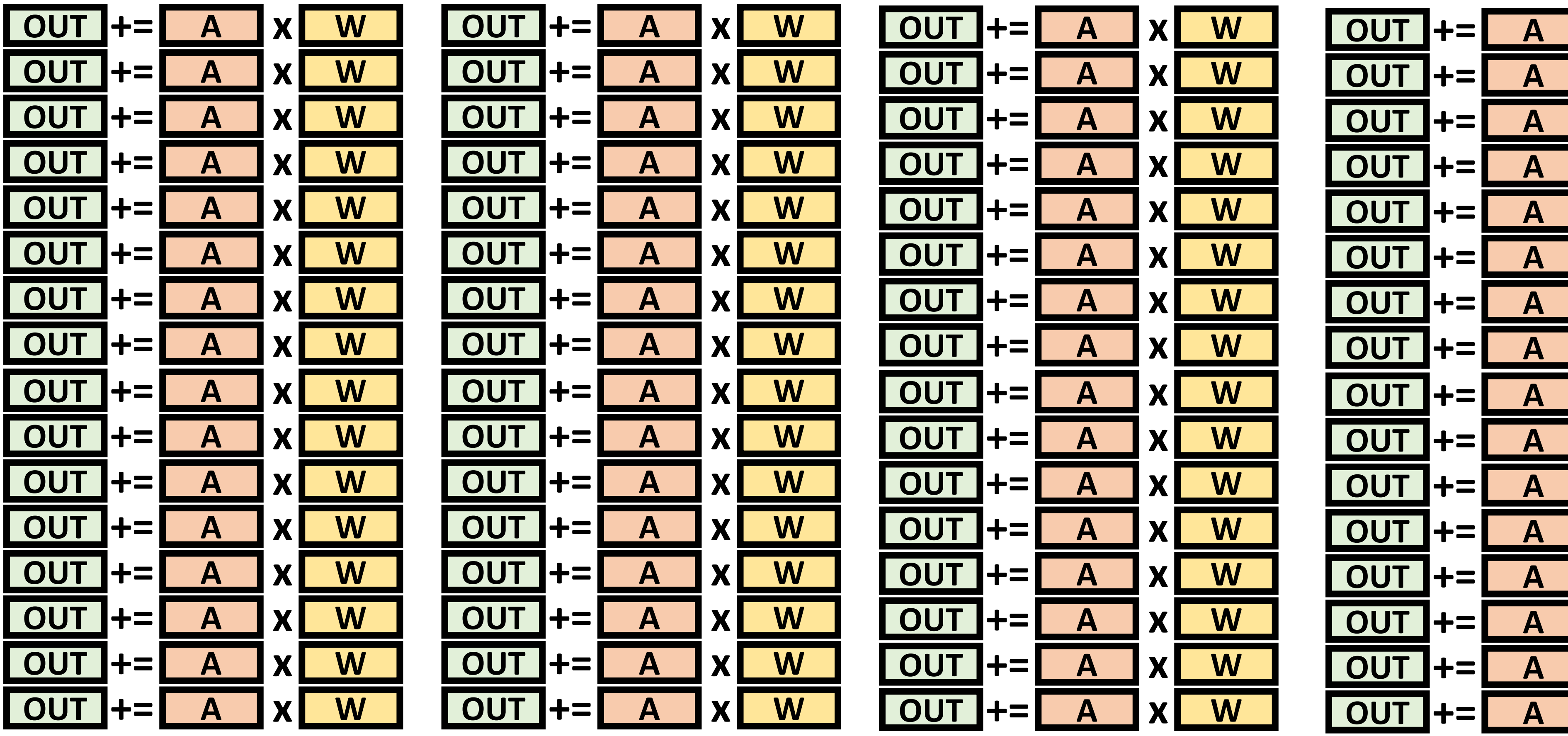
On- vs. Off-Chip

Energy: ~100x

Latency: ~50x

Compute/Watt is the primary design constraint

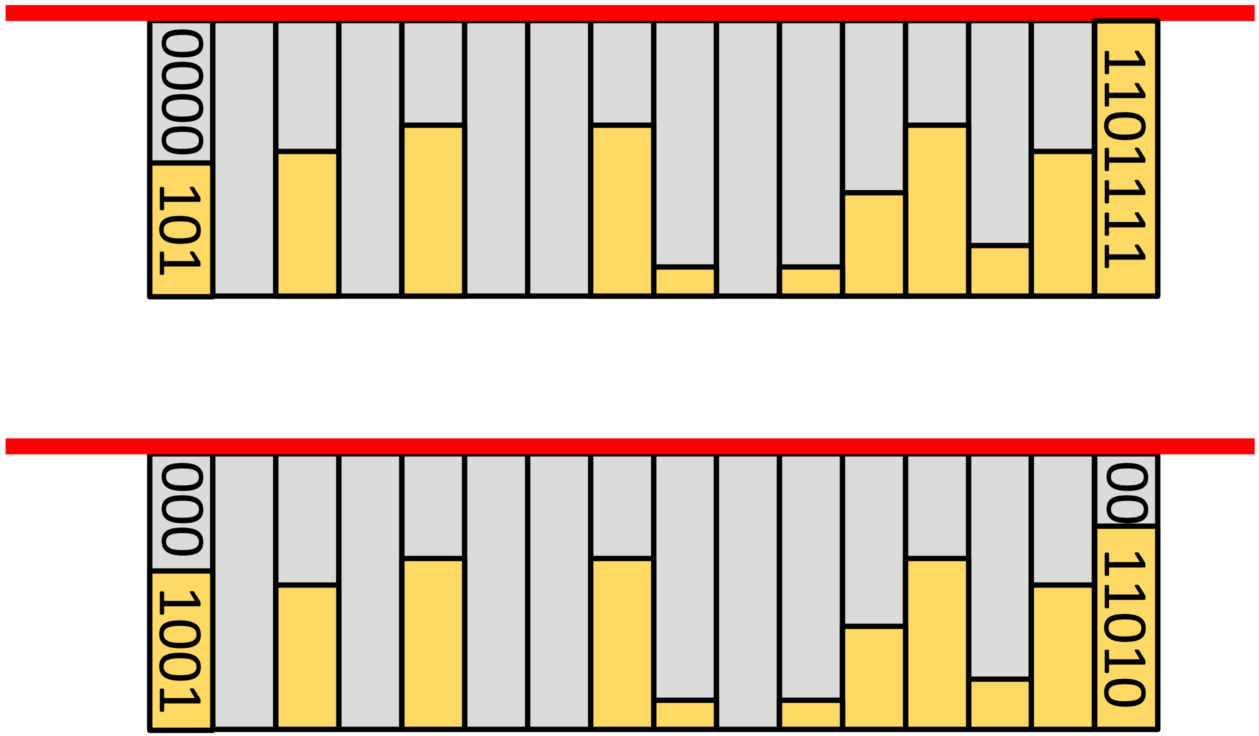
Conventional Approach:
One Datawidth to Rule them All



Pick a datatype that fits the range of *all* values… this proves excessive for ML workloads…

Conventional Data Transfers: Fixed Size Container Per Value

e.g., transfer 16 values at a time all using 8b each



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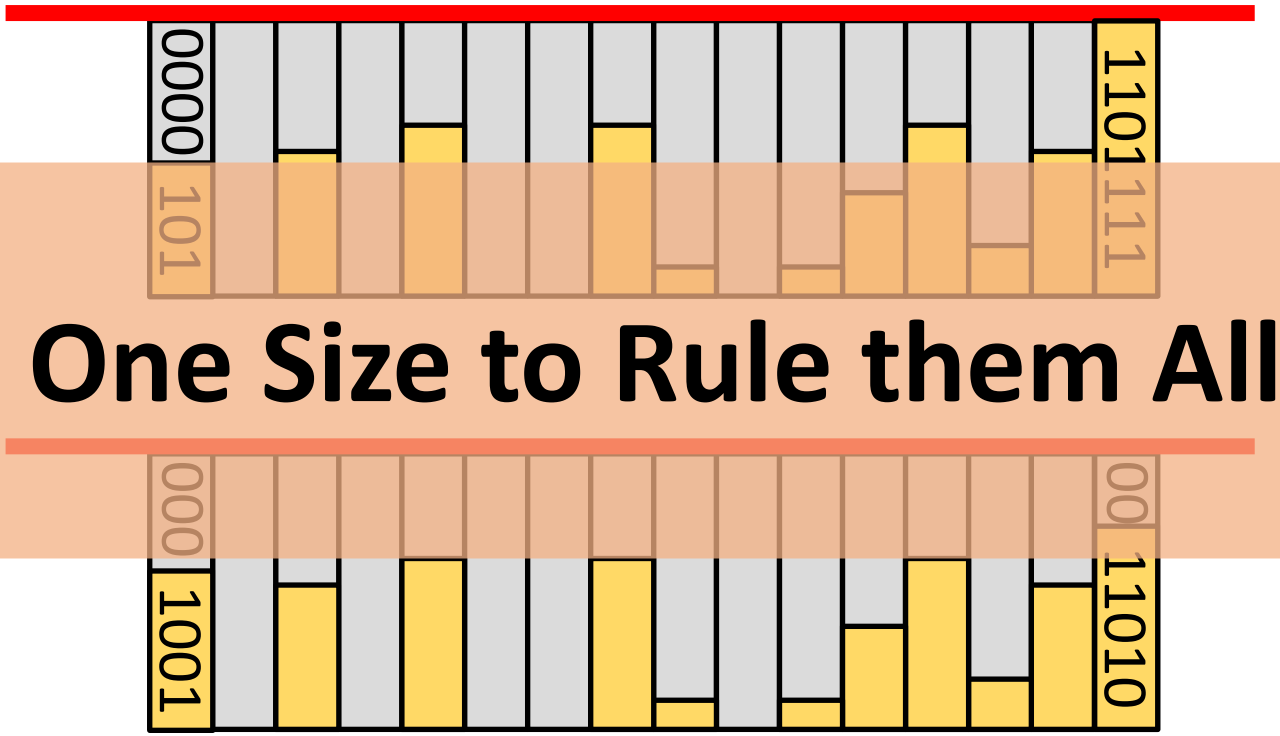
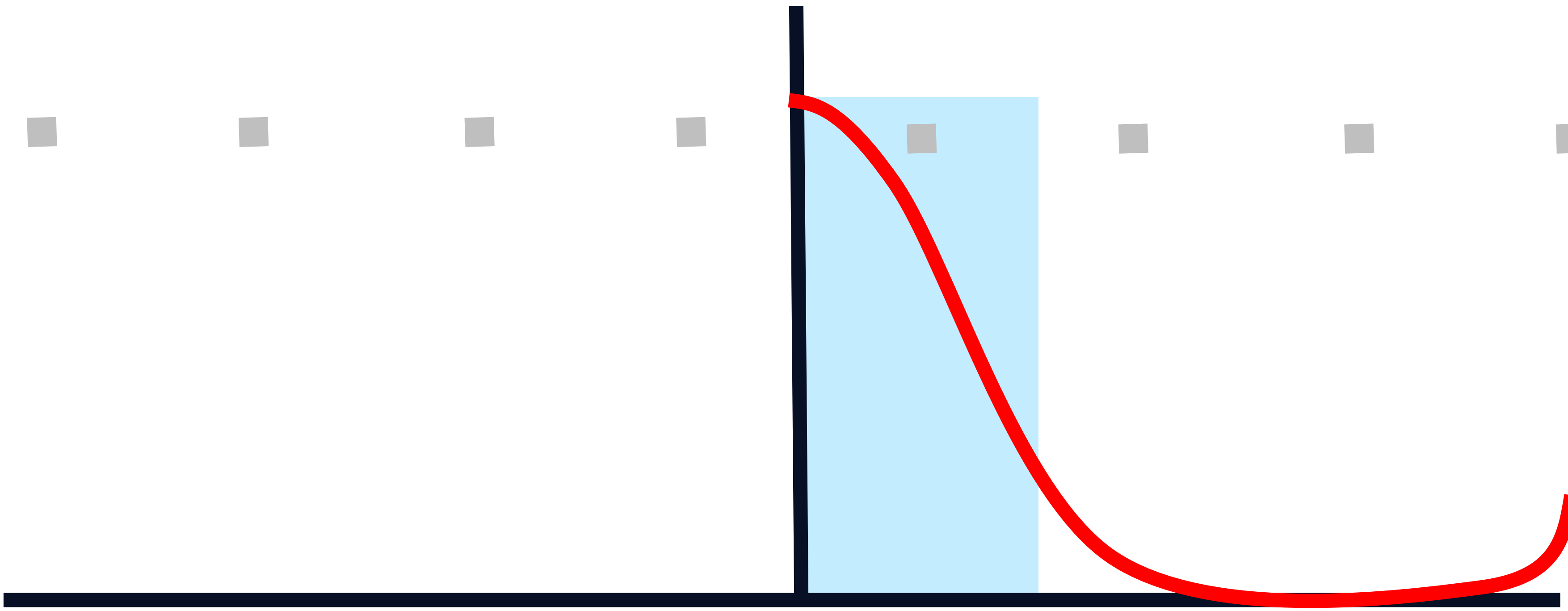
e.g., transfer 16 values at a time all using 8b each



Most ML values can fit in much narrow containers

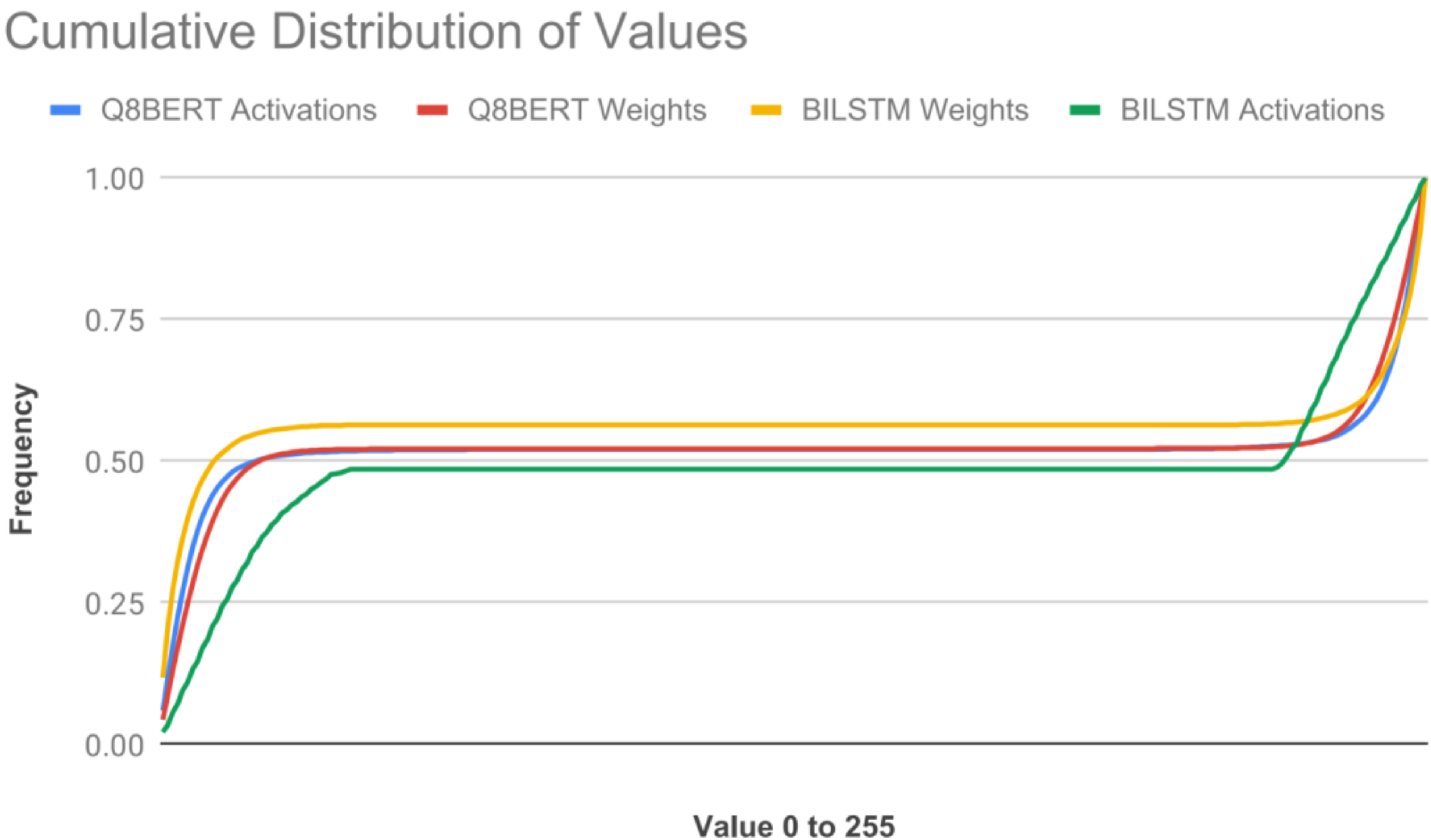
Out_0 += A_0 x W_0 Out_1 += A_0 x W_0 Out_0 += A_0 x W_0 Out_1 += A_0 x W_0 Out_0 += A_0 x W_0 Out_1 += A_0 x W_0 Out_0 += A_0 x W_0 Out_1 += A_0 x W



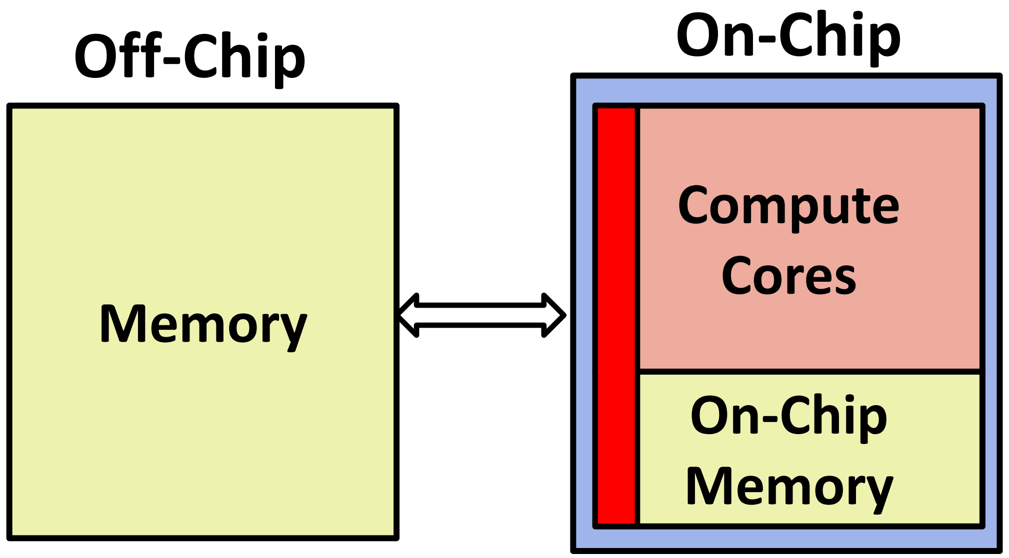
DPRed: Making Typical Activation and Weight Values Matter In Deep Learning Computing, Delmas et al.,
https://arxiv.org/abs/1804.06732

Value Distribution During Inference

Far from Uniform: Few Values -> Most Frequent



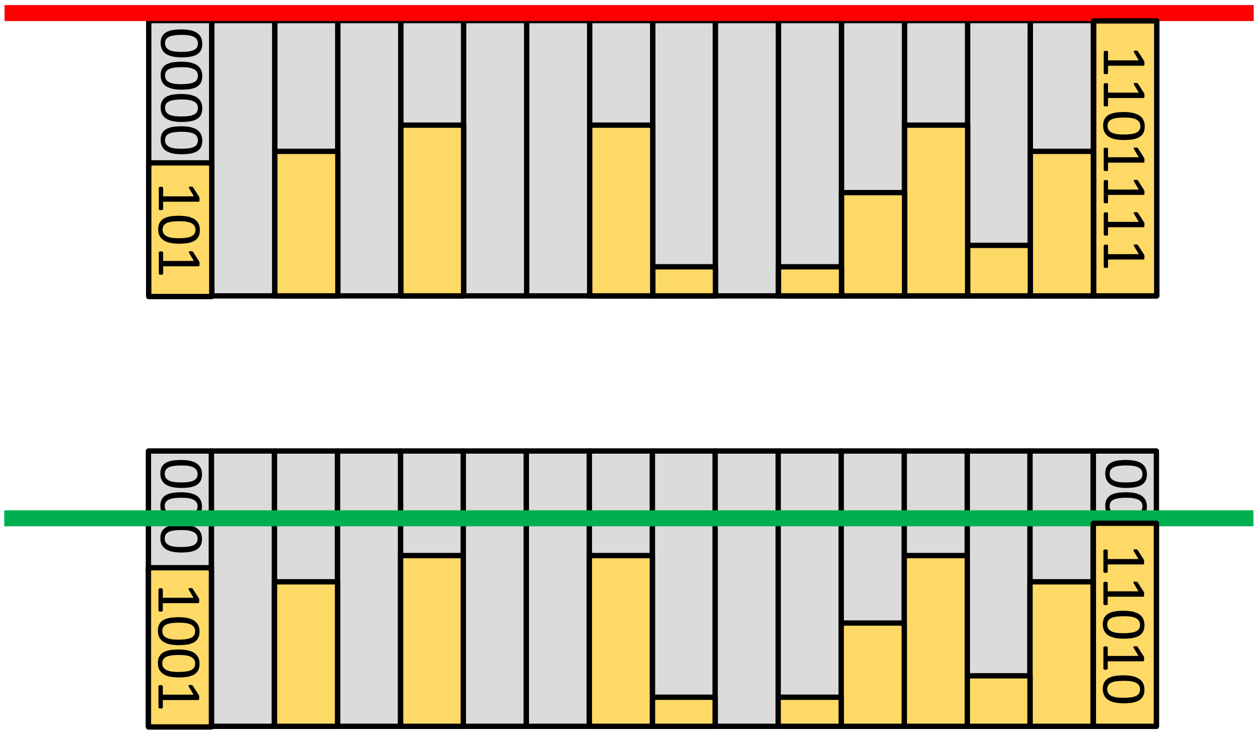
Technology #1: Memory Transfers: Shapeshifter



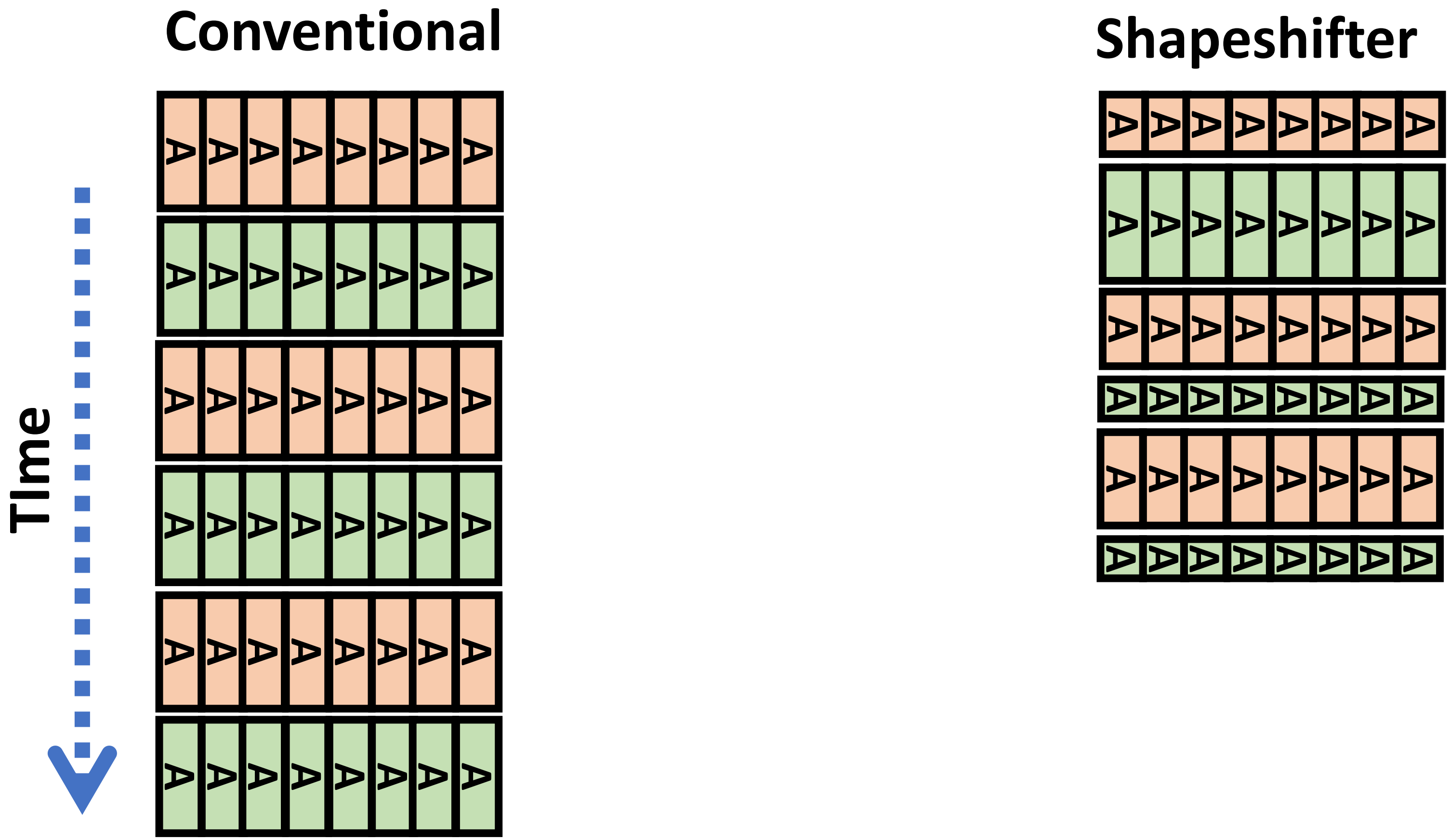
Encode/Decode Value to/from Memory

Shapeshifter: Make Typical Values Matter

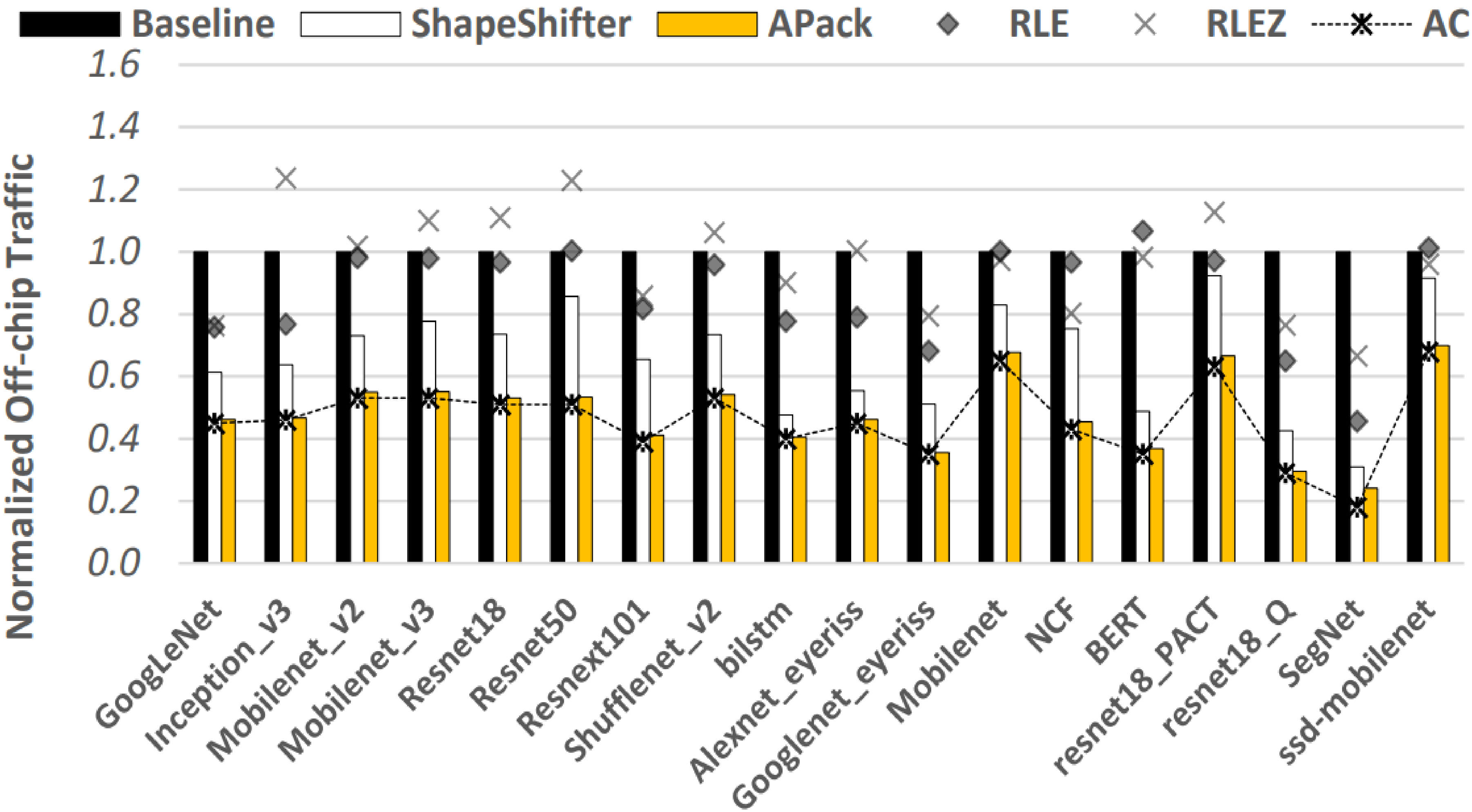
Container adapts to value content. Weights and activations.



Memory Transfers

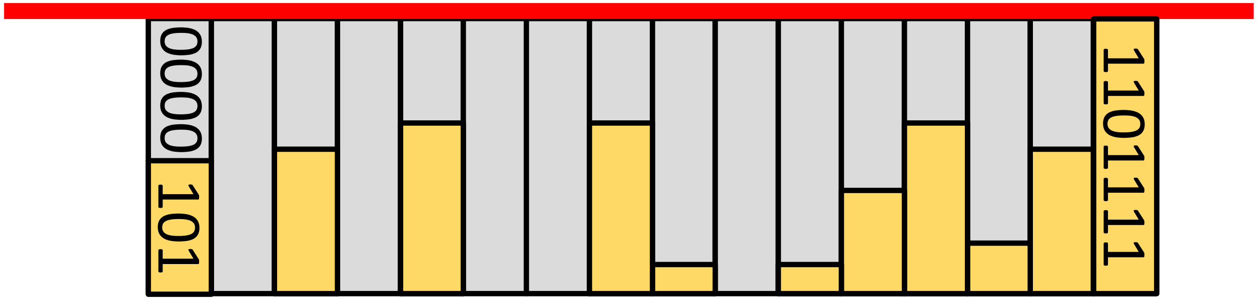


Shapeshifter Effectiveness



Shapeshifter: Life is not always fair

This may happen often depending on the network



APACK

12 0 23 45 67 127 18 22 88 103 234 22 1 0 2 3 5 8 19 9 0 9 8 20 28 220 20 20 244 223 2 1 1 0 1 0
19 9 0 9 8 20 28 220 20 20 244 223 2 1 1 0 1 0 12 0 23 45 67 127 18 22 88 103 234 22 1 0 2 3 5 8
234 22 1 0 2 3 5 8 9 8 20 28 220 20 20 244 223 2 1 1 0 1 0 12 0 23 45 19 9 0 67 127 18 22 88 103

….

28 220 20 20 244 223 2 1 1 0 1 0 234 22 1 0 2 3 19 9 0 67 127 18 22 88 103 5 8 9 8 20 12 0 23 45

0.10238464892028374628298383933….333292

12 0 23 45 67 127 18 22 88 103 234 22 1 0 2 3 5 8 19 9 0 9 8 20 28 220 20 20 244 223 2 1 1 0 1 0
19 9 0 9 8 20 28 220 20 20 244 223 2 1 1 0 1 0 12 0 23 45 67 127 18 22 88 103 234 22 1 0 2 3 5 8
234 22 1 0 2 3 5 8 9 8 20 28 220 20 20 244 223 2 1 1 0 1 0 12 0 23 45 19 9 0 67 127 18 22 88 103

….

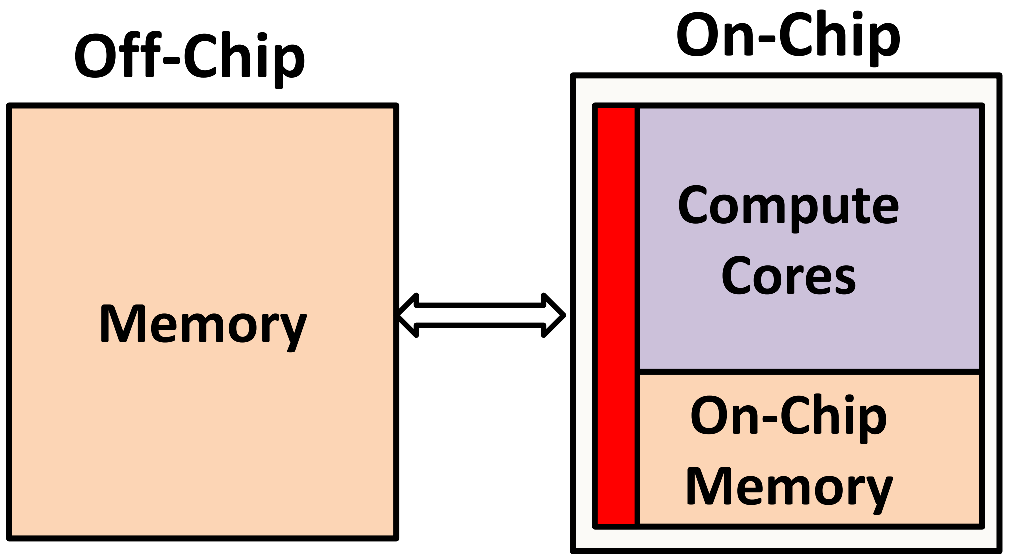
28 220 20 20 244 223 2 1 1 0 1 0 234 22 1 0 2 3 19 9 0 67 127 18 22 88 103 5 8 9 8 20 12 0 23 45

0.1023846489202837462829838393….333292

$0.1101010101010101010111101 01…111001_{(2)}$

Frequent values → less than ONE BIT

Technology #1: Memory Transfers: Shapeshifter



Encode/Decode Value to/from Memory

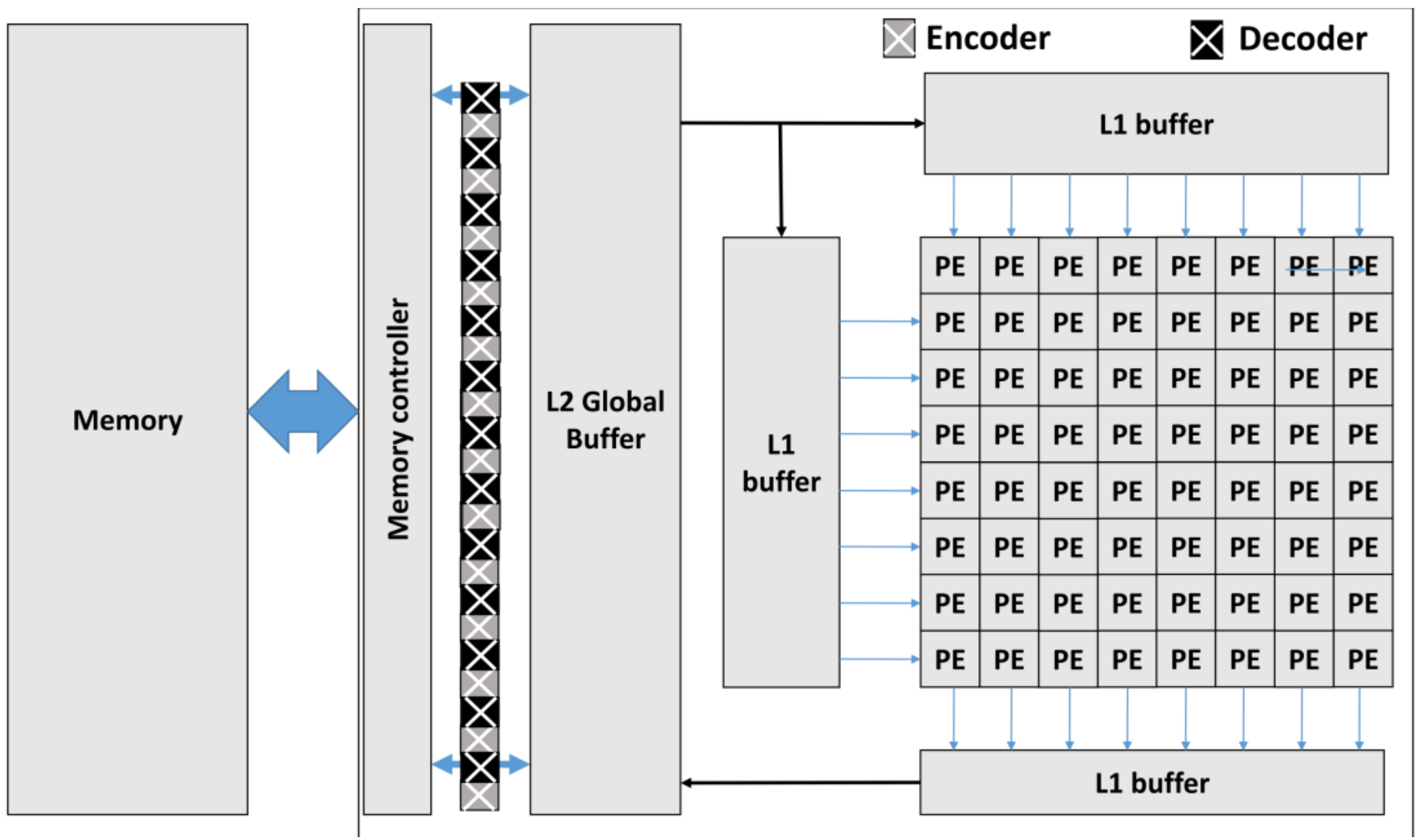
APACK: Lossless Compression for fixed-point

- Based on Arithmetic Coding
  - Encode a TENSOR with unique REAL number
- Precision needed:
  - Sequence Length
  - Frequency of values

- Outline:
  - Classical Arithmetic Coding
    - Too expensive – too slow
  - Apack

Key Idea: Encode Values According to Frequency

- Transparently encode/decode
- Lossless
- Weights in advance / Activations Profiling



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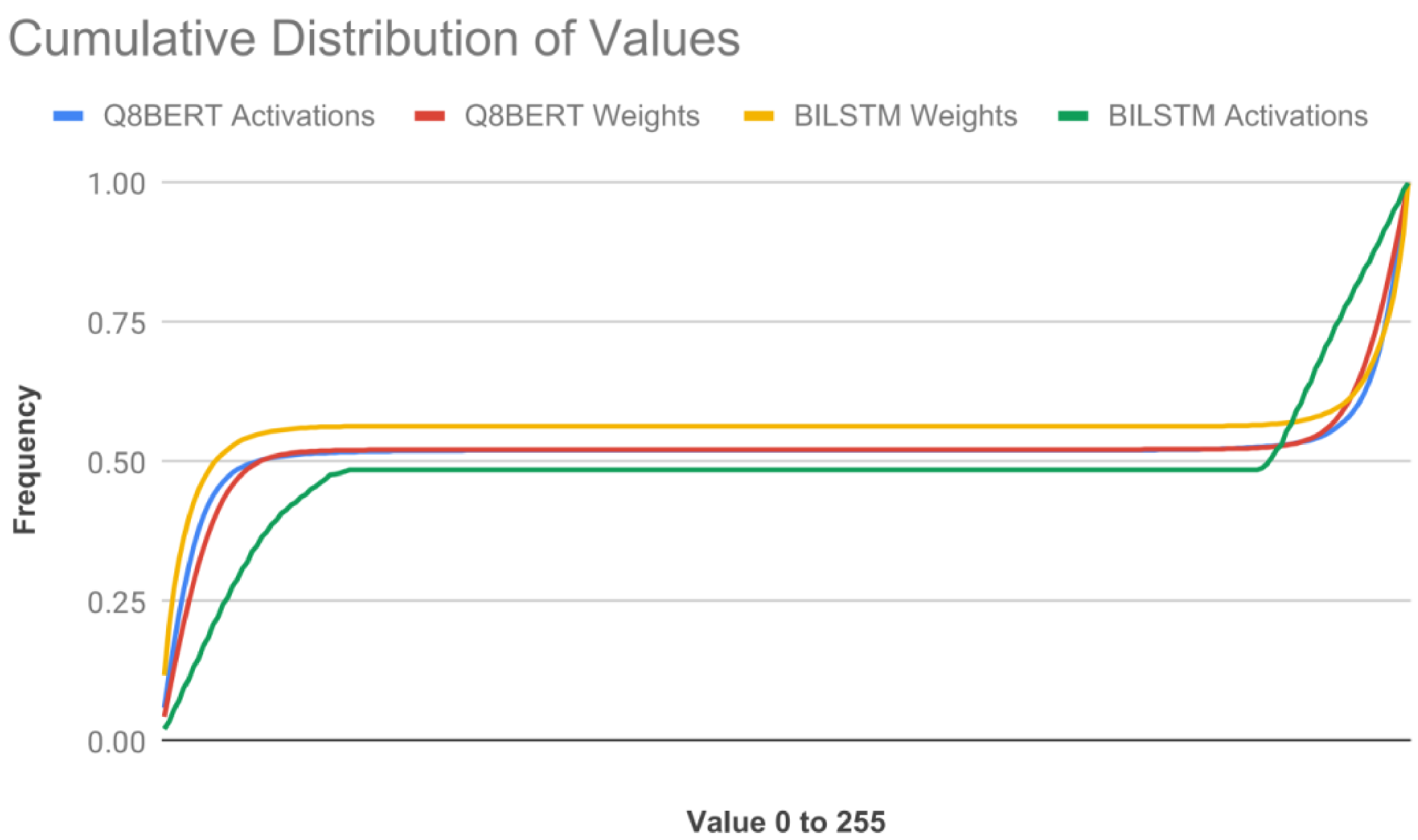
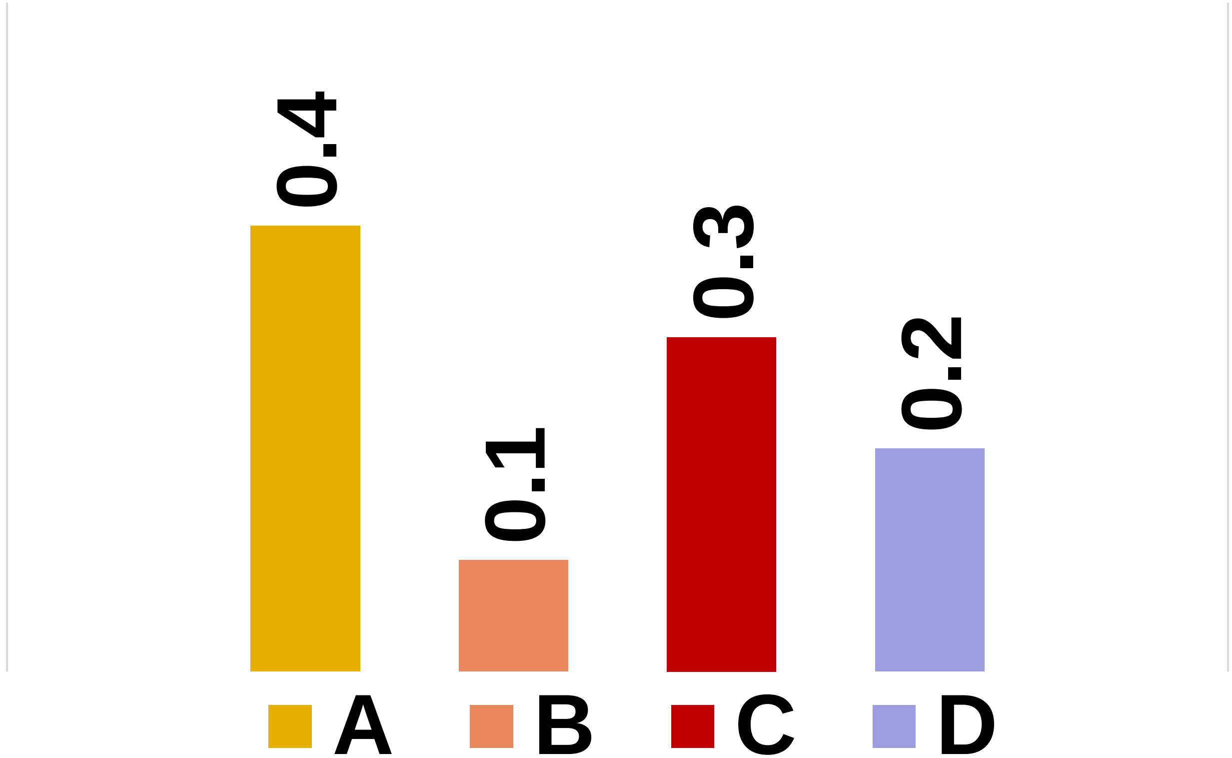
Far from Uniform: Few Values -> Most Frequent



Values change with input → Distributin not so much

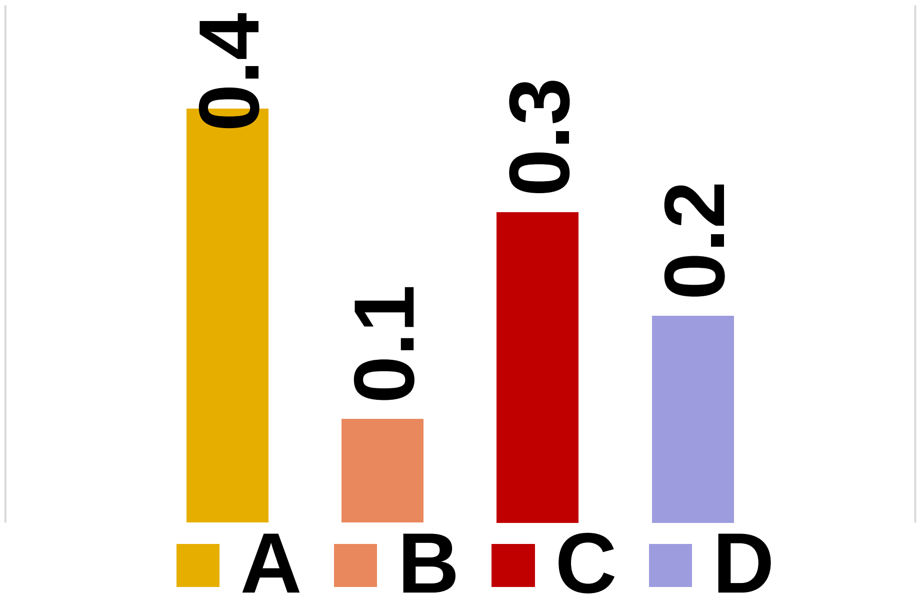
Classical Arithmetic Coding

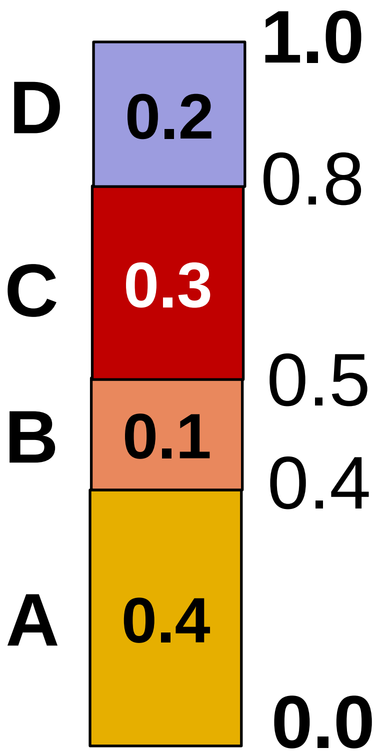
- Symbols w/ Frequencies



Classical Arithmetic Coding

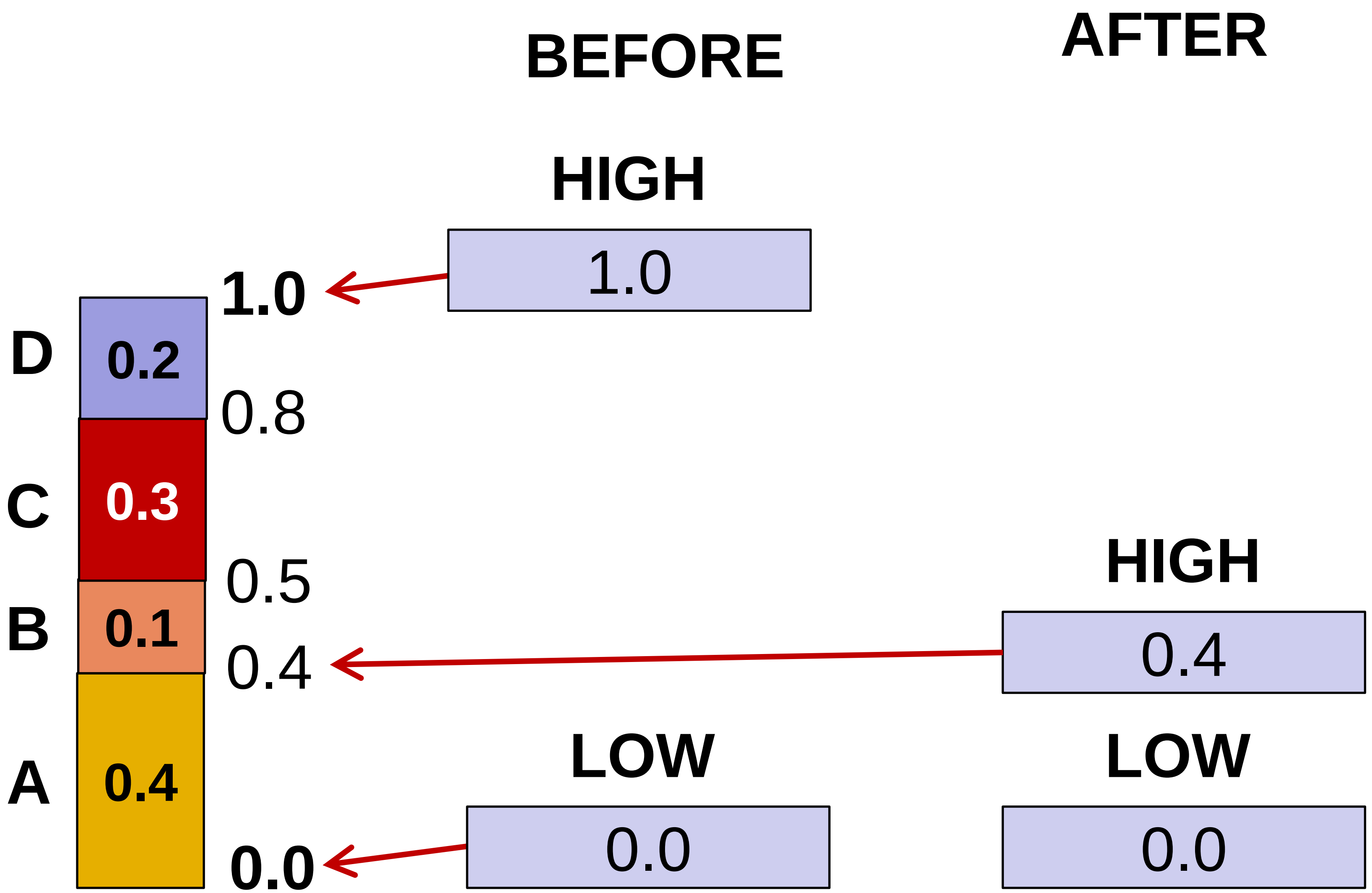
- #1 Range/Probability Assignment
  - All the info needed to encode decode





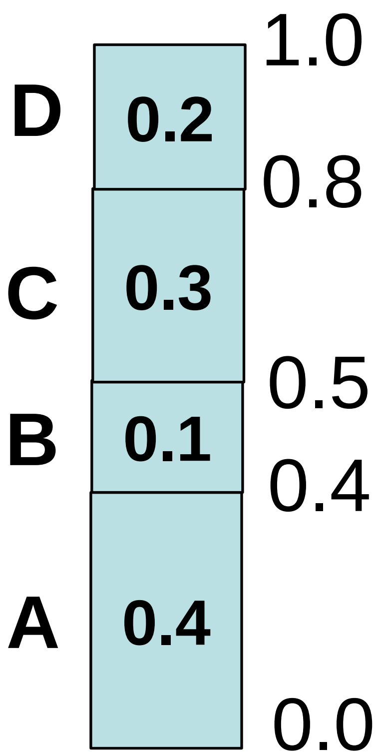
Encoding ABA

- Incoming Symbol: A



Encoding the first value: A

- A



BEFORE

HIGH

1.0

LOW

0.0

AFTER

HIGH

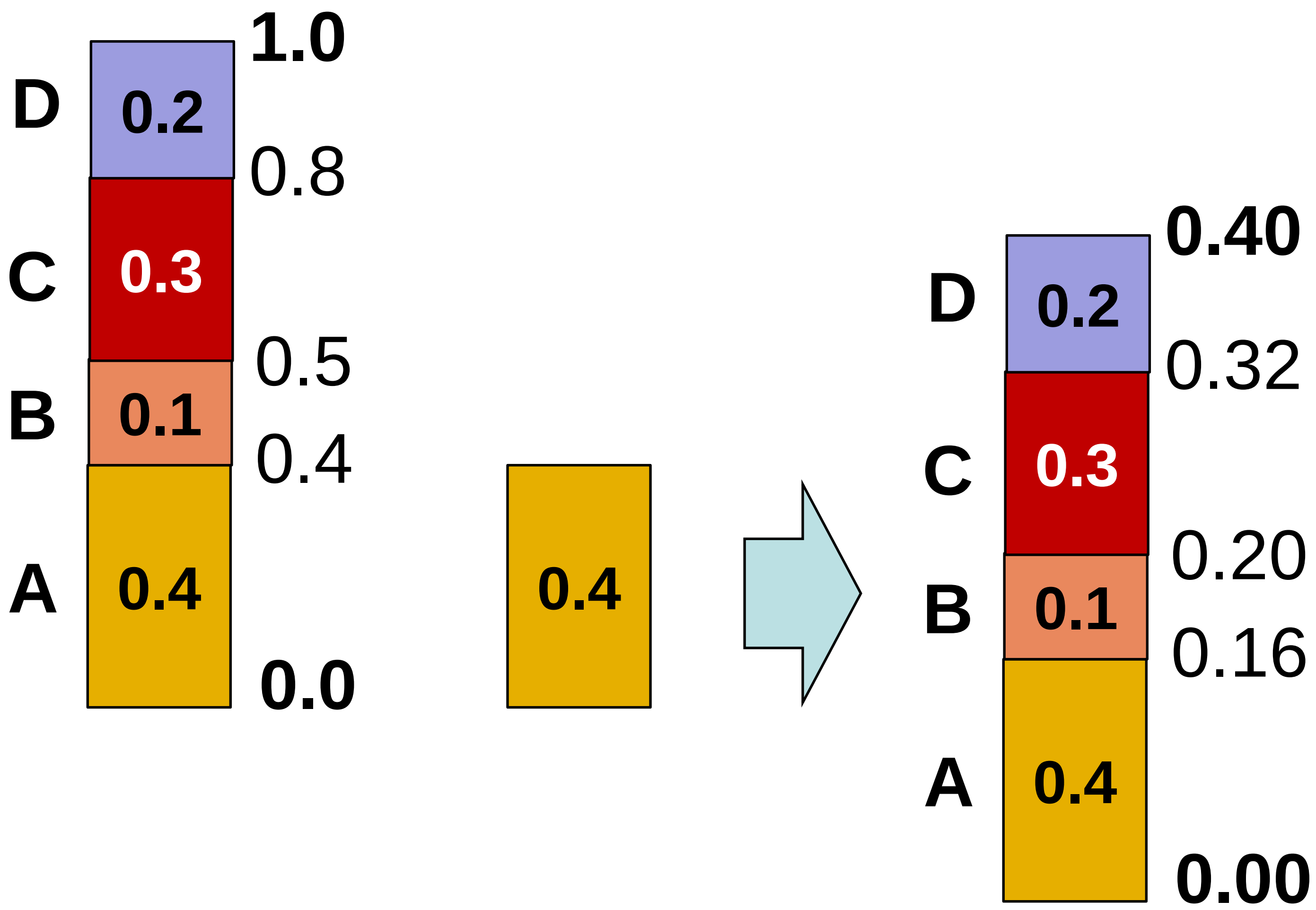
0.4

LOW

0.0

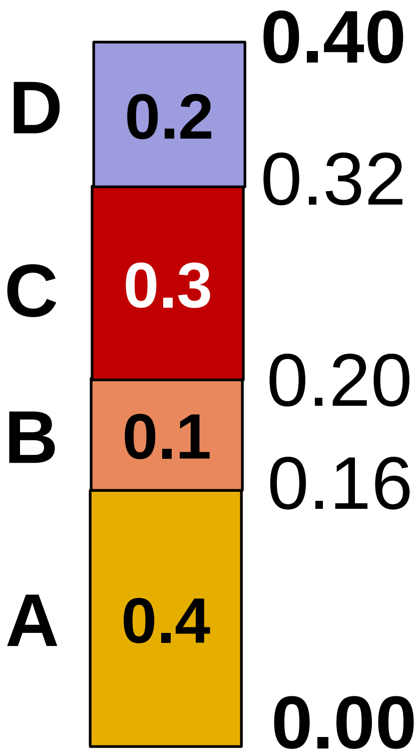
After Encoding A

- How our range table looks



Encoding the second value: B

- B

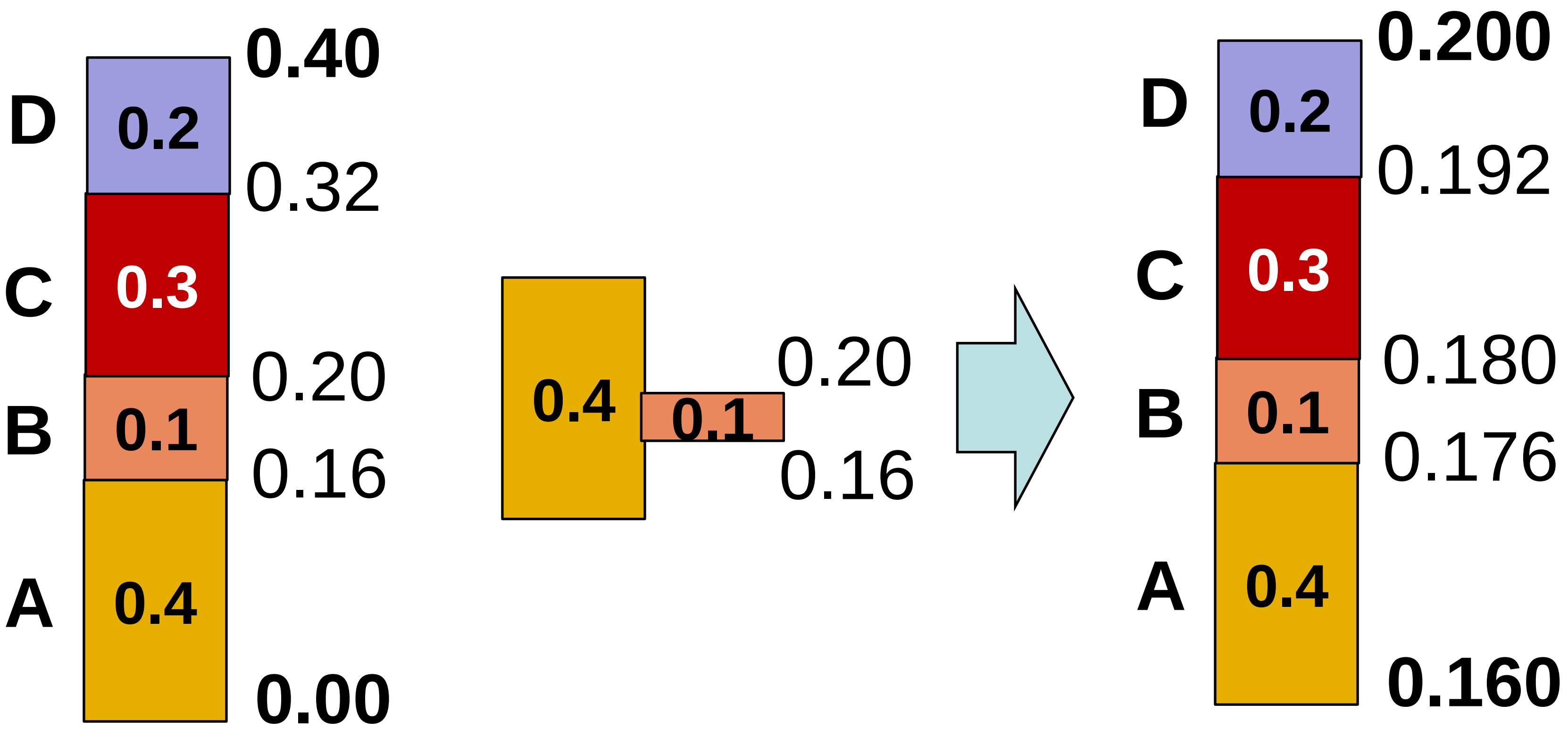


	BEFORE	AFTER
HIGH	0.4	0.20
LOW	0.0	0.16

Initial range: HIGH – LOW = 0.4
B's prob = 0.1
B's offset = 0.4
New offset = LOW x B's offset = 0.16
New range = initial range x B's prob = 0.04
LOW = 0.16
HIGH = 0.16 + 0.04

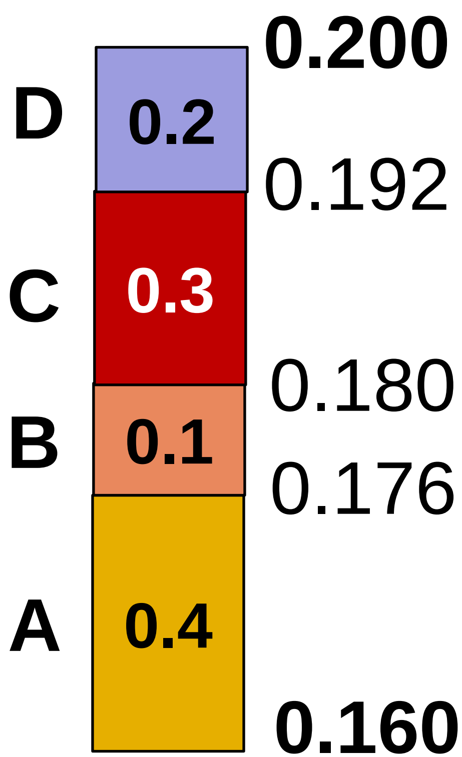
Enconding the B

- Incoming Symbols: **A****B**



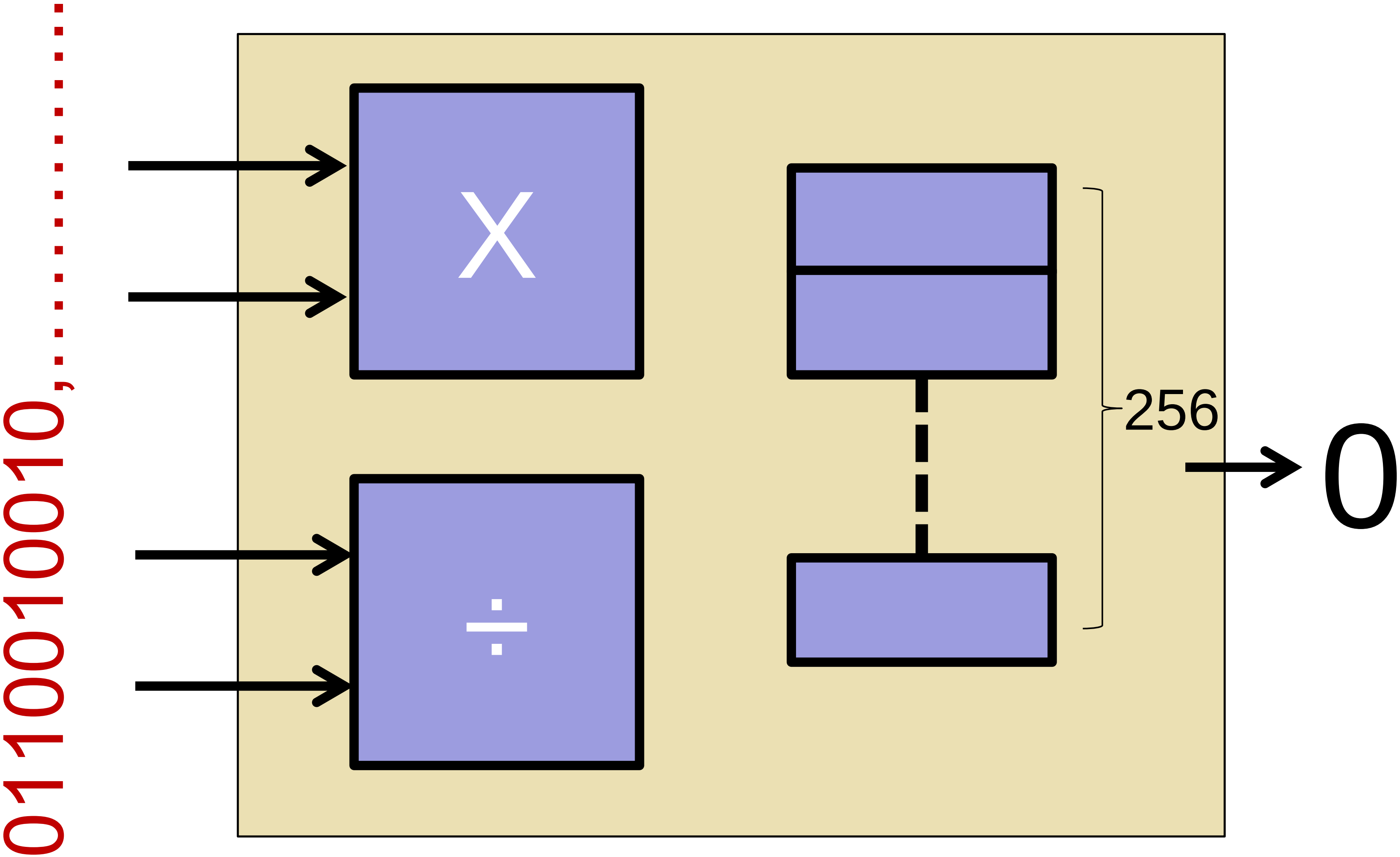
Encoding the third value: A

- A



	BEFORE	AFTER
HIGH	0.20	0.176
LOW	0.16	0.160

Initial range: HIGH – LOW = 0.04
A's prob = 0.4
B's offset = 0.0
New offset = LOW x A's offset = 0.16 + 0.0
New range = initial range x A's prob = 0.016
LOW = 0.16
HIGH = 0.16 + 0.016 = 0.176


0110010010,
X
÷
256
0

Challenges with Arithmetic Coding

- Arbitrary Precision Arithmetic
  - Multiplications and Divisions
- Expensive Range Table
  - 256 entries for 8b fixed-point
- Low Bandwidth
  - 1 bit per invocation

APACK Key Idea

V = PREFIX + OFFSET

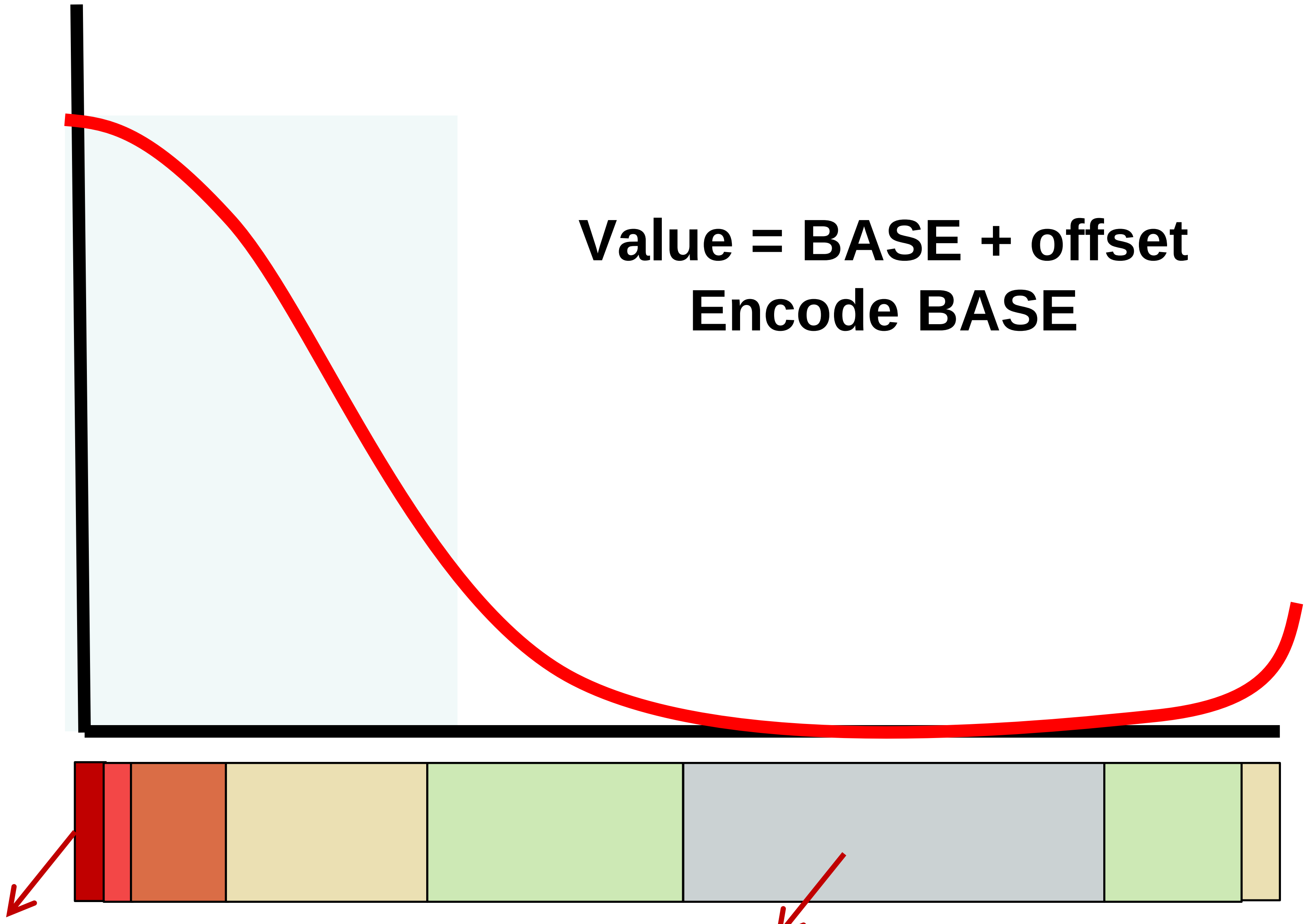
APACK Key Idea

0000 0000 = 0

0101 0111 =

01000 0000+1 0111

Apack Key Idea



Value = BASE + offset
Encode BASE

0x00 → 0x00,0b
0x01 → 0x00,1b

0x8F → 0x80, 001111b
0x91 → 0x80, 010001b

Table Generation: Done in Advance

IDX	v_min	v_max	OL	tlow	thigh	p
0	0x00	0x03	2	0x000	0x1EB	0.4795
1	0x04	0x07	2	0x1EB	0x229	0.0605
2	0x08	0x0F	3	0x229	0x238	0.0146
3	0x10	0x3F	6	0x238	0x23A	0.0020
4	0x40	0x4F	4	0x23A	0x23A	0.0000
5	0x50	0x5F	4	0x23A	0x23A	0.0000
6	0x60	0x6F	4	0x23A	0x23A	0.0000
7	0x70	0x7F	4	0x23A	0x23A	0.0000
8	0x80	0x8F	4	0x23A	0x23A	0.0000
9	0x90	0x9F	4	0x23A	0x23A	0.0000
10	0xA0	0xAF	4	0x23A	0x23A	0.0000
11	0xB0	0xBF	4	0x23A	0x23A	0.0000
12	0xC0	0xCF	4	0x23A	0x23A	0.0000
13	0xD0	0xF3	6	0x23A	0x23C	0.0020
14	0xF4	0xFB	3	0x23C	0x276	0.0566
15	0xFC	0xFF	2	0x276	0x3FF	0.3838

Table Generation: Done in Advance

IDX	v_min	v_max	OL	tlow	thigh	p
0	0x00	0x03	2	0x000	0x1EB	0.4795
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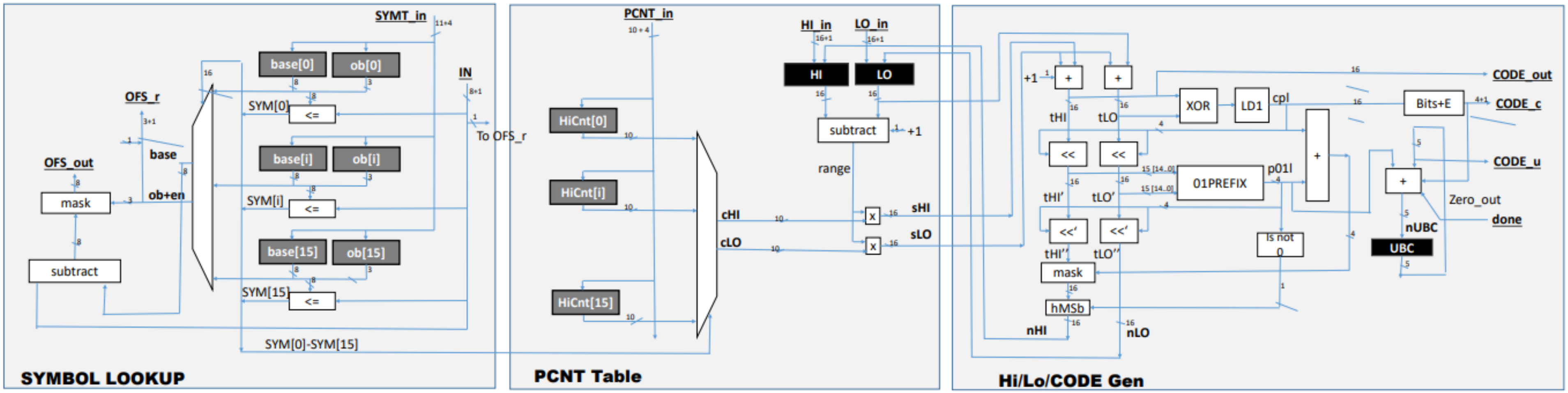
4	0x40	0x4F	4	0x23A	0x23A	0.0000
5	0x50	0x5F	4	0x23A	0x23A	0.0000
6	0x60	0x6F	4	0x23A	0x23A	0.0000
7	0x70	0x7F	4	0x23A	0x23A	0.0000
8	0x80	0x8F	4	0x23A	0x23A	0.0000
9	0x90	0x9F	4	0x23A	0x23A	0.0000
10	0xA0	0xAF	4	0x23A	0x23A	0.0000
11	0xB0	0xBF	4	0x23A	0x23A	0.0000
12	0xC0	0xCF	4	0x23A	0x23A	0.0000
13	0xD0	0xF3	6	0x23A	0x23C	0.0020
14	0xF4	0xFB	3	0x23C	0x276	0.0566
15	0xFC	0xFF	2	0x276	0x3FF	0.3838
	8b		3b		10b	

$0.11010101010101010\ldots1011110101_{(2)}$

$0.11010101010101010\ldots101111010111001_{(2)}$

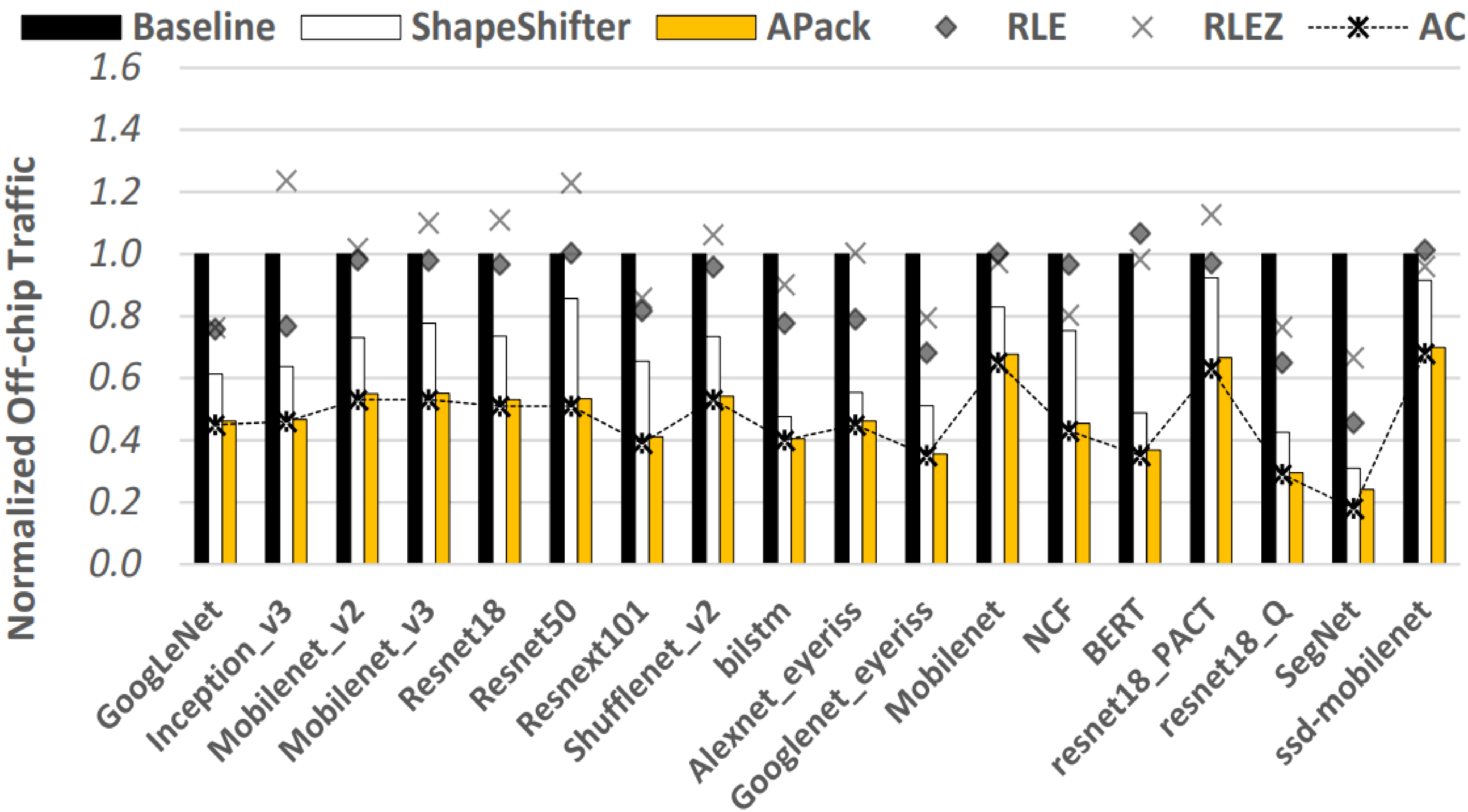
APACK Encoder



Hardware

- Fixed-Point
- 10b x 16b Multiplications and 16b comparisons
- A few leading 1
- One value per “cycle”
- Use multiple to sustain BW needed
- Externally: Sequential Streams

APACK Activations



Mokey

Enabling Narrow Fixed-Point Inference

for Out-of-the-Box Floating-Point Transformer Models

Challenges

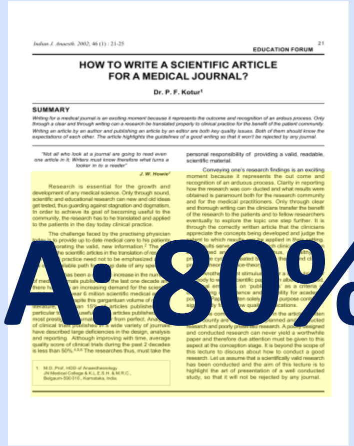
Weights

2018
1.2GB

2021
2TB

Activations

A: 5%



A: 80%

Challenges

Weights

2021

2TB

Activations

A:80%

Memory:

Performance & Energy Bottleneck

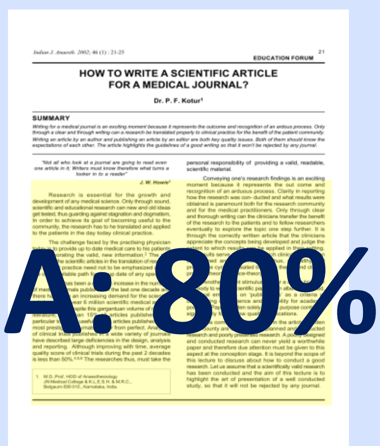
Challenges

Weights

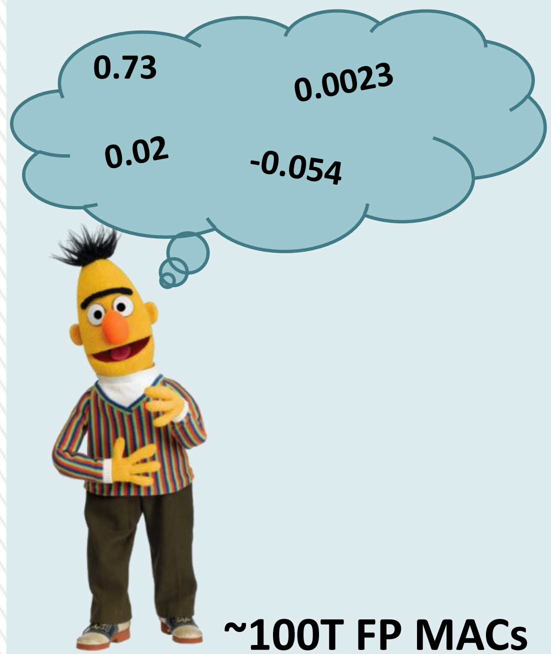
2018
1.2GB

2021
2TB

Activations

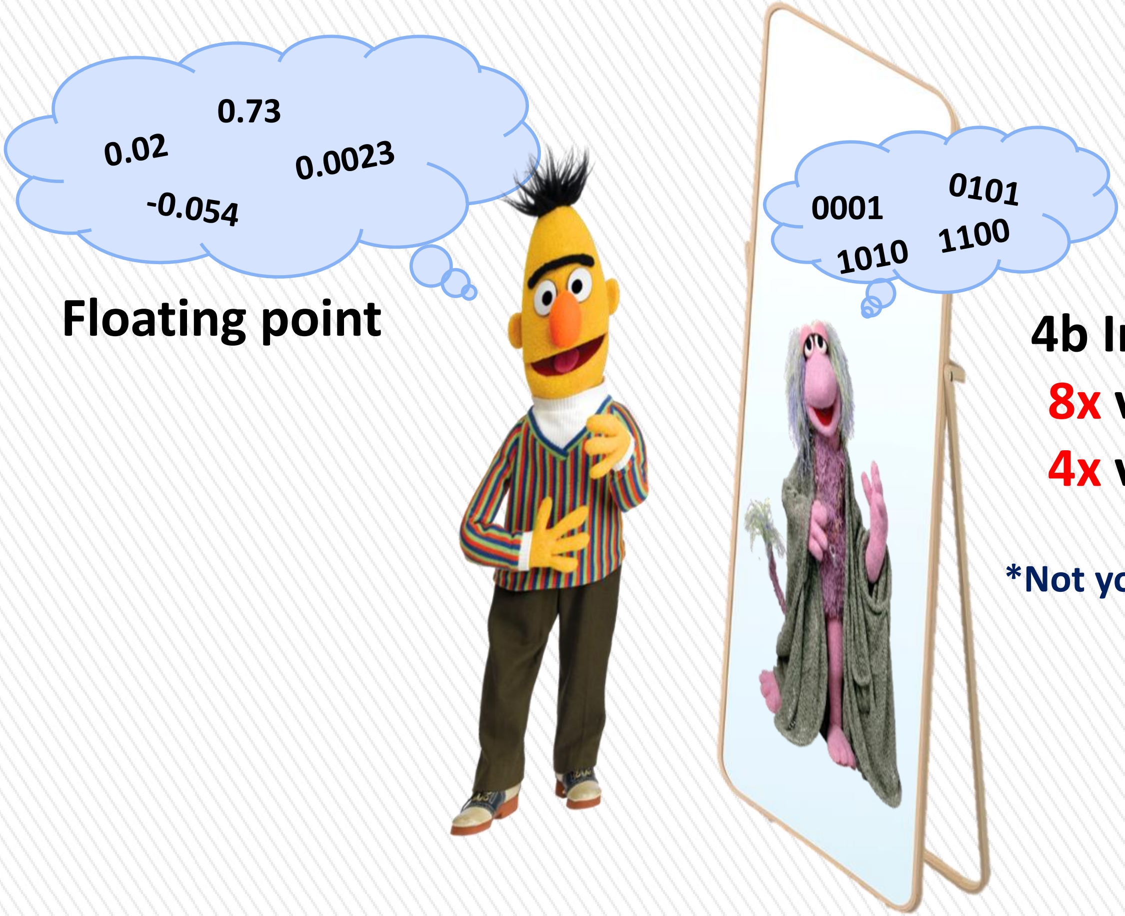


FP Compute



~100T FP MACs

Mokey: BERT's Better Self

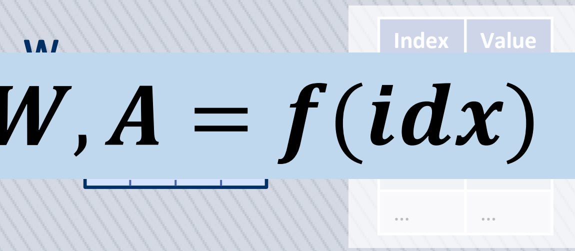


4b Int index
8x vs FP32
4x vs FP16

***Not your typical 4b quantization ;)**

Mokey

4-bit Quantization: W+A



$$W, A = f(idx)$$

Post-training

+= A x W. ➔ Count idx

Fixed-point compute

Mokey HW Accelerator

Vs. Tensor Cores: ***15x*** Faster + ***100x*** Energy Efficient

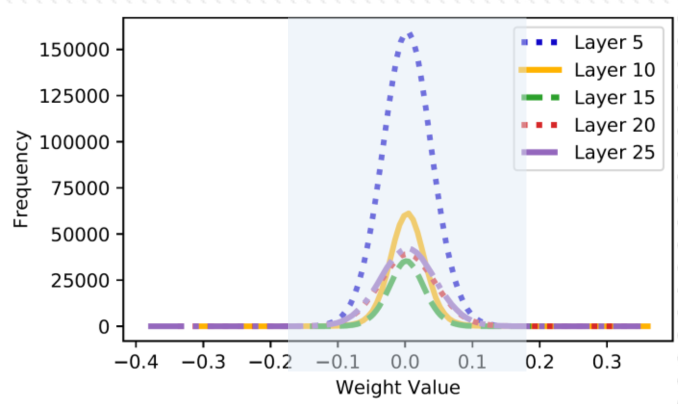
Mokey Memory Compression

For Tensor Cores:

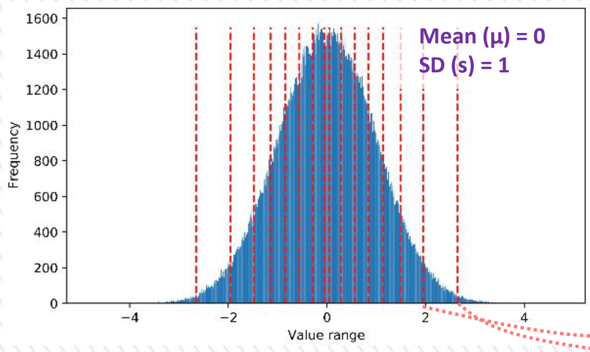
Off-chip Only: ***4x*** Faster + ***8x*** Energy Efficient

Off- and on-chip*: ***10x*** Faster + ***50x*** Energy Efficient

A Dictionary for All Layers



Reference Distribution



Golden Dict. (GD)

Index	Value
I	-2.7
II	-1.98
…	…
VI	1.98
XVI	2.7

Scale and **Shift** is All You Need

Inference Computation

Original

A = 0.2 W = 0.7

A×W += 0.2 × 0.7 = 0.14

Dictionary Quant.

A = I W= II

Index	Value
I	0.2
II	0.7
III	1.1
IV	1.4
…	…

A × W += I × II

A × W += 0.2 × 0.7 = 0.14

Mokey Quant.

A = I W= II

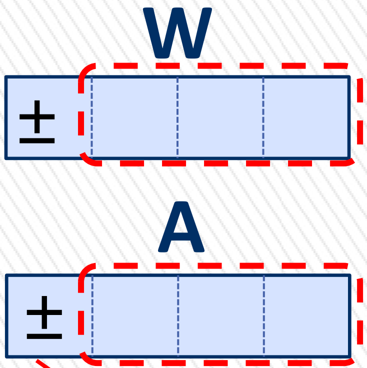
How?!

A × W += I × II = 0.14

Values Format

Index	Value
I	0.05
II	0.35
…	…
VI	1.97
VII	2.6

Golden Dict. (GD)



$$\text{Values} = \pm(a^{i} + b)$$

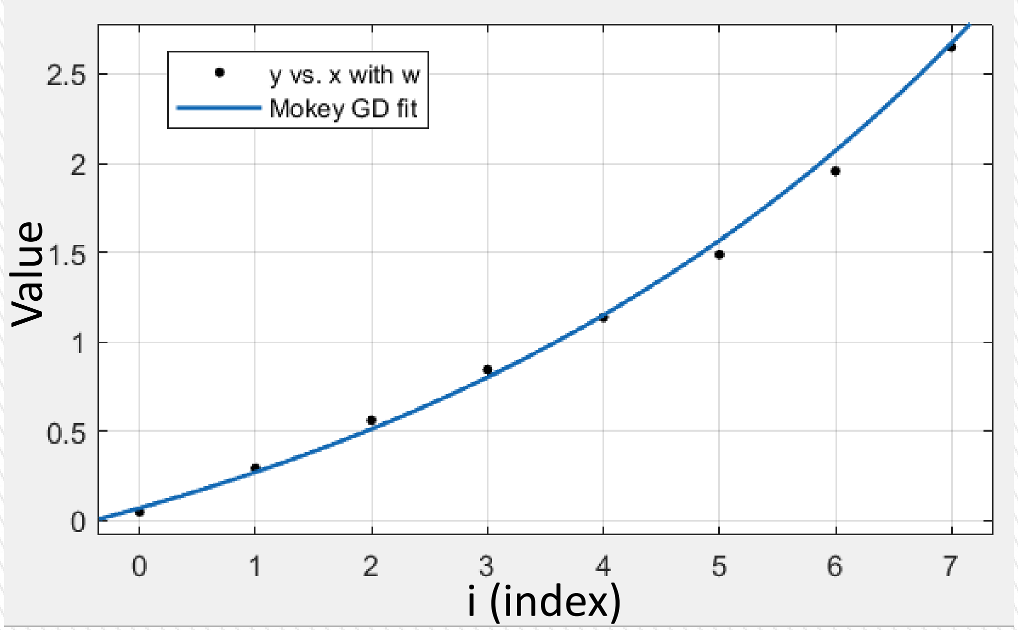
per value

Fixed

Exponential Function

Index	Value
I	0.05
II	0.35
…	…
VI	1.97
VII	2.6

Golden Dict. (GD)



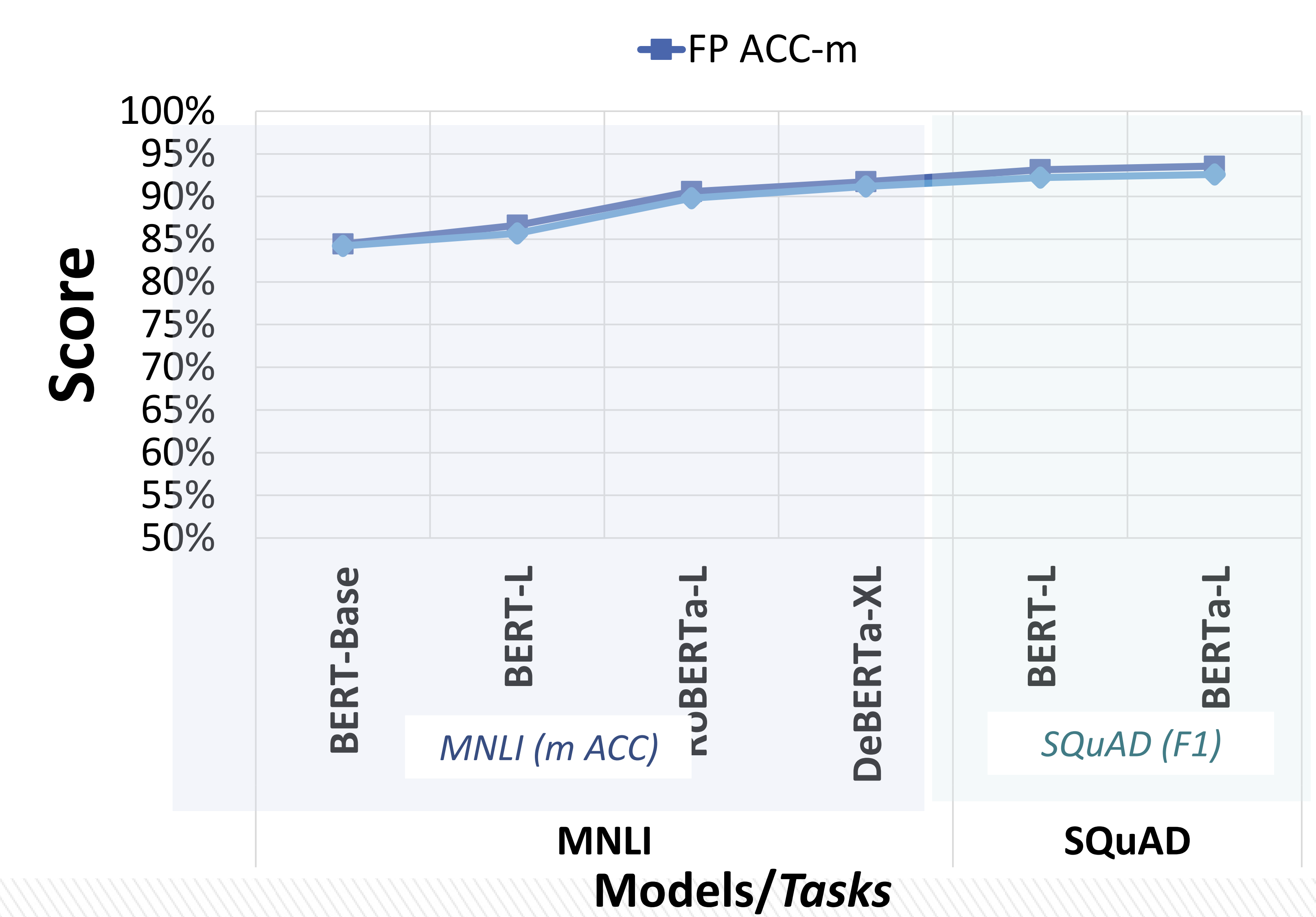
$GD = a^i + b$

Evaluation

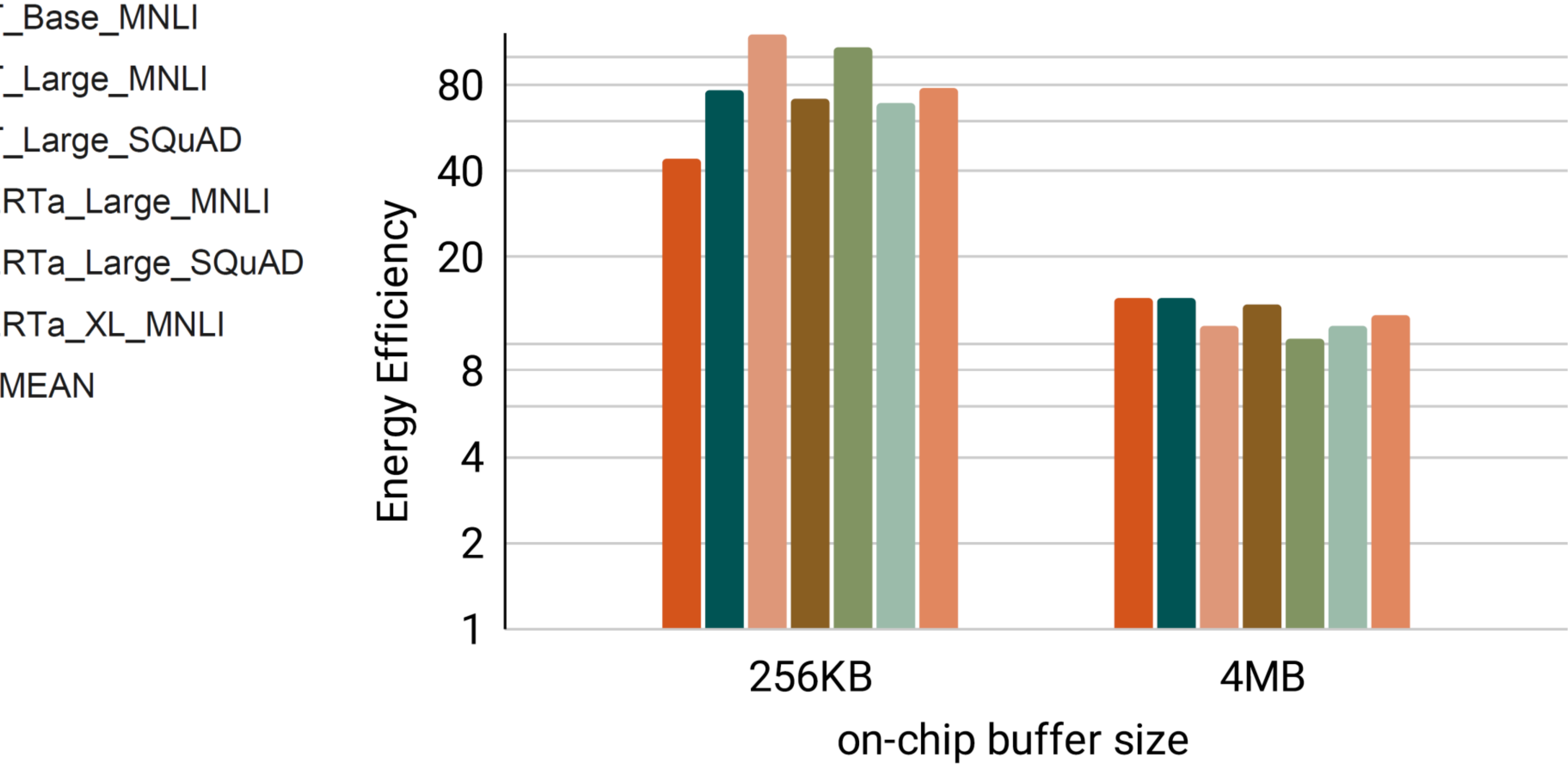
- FP16 Tensor Cores baseline
- Wide range of on-chip buffers
- 110M - 750M parameter models

- Custom cycle accurate simulator.
  - DRAMsim3: Dual Channel DDR4-3200
- On-chip Memory: CACTI
- Synthesis: Synopsis Design Compiler
  - 65nm TSMC – 1Ghz
- Layout: Cadence Innovus
- Signal Activity: Modelsim
- Power Estimation: Cadence Innovus

Quantization Accuracy



Accelerator Energy Efficiency



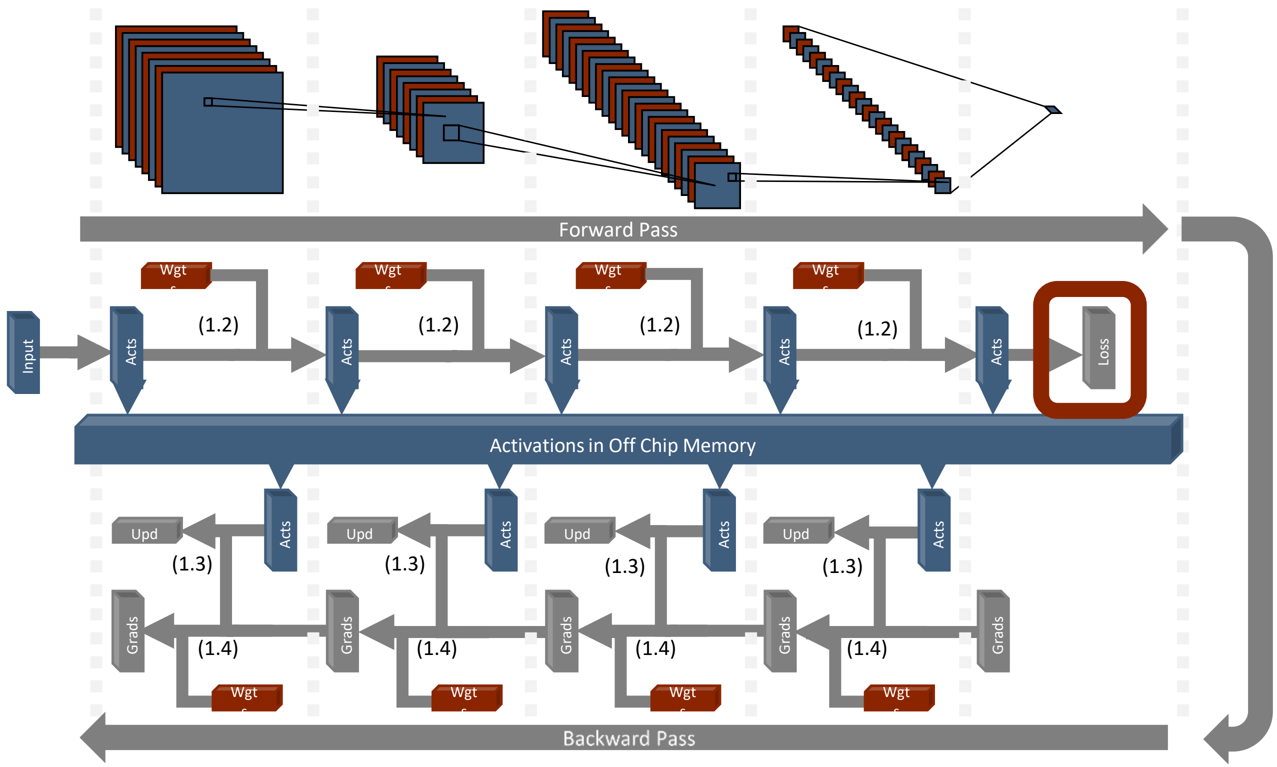
Memory Compression and more in paper ☺

Schrödinger's FP
Dynamic Adaptation of Floating-Point Containers During Training

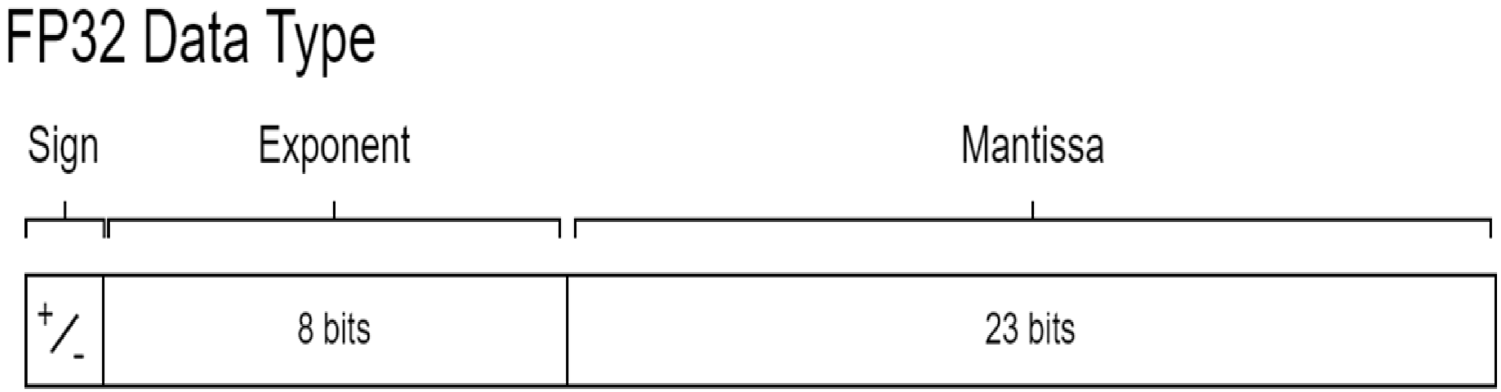
Gradient Descent – Overview

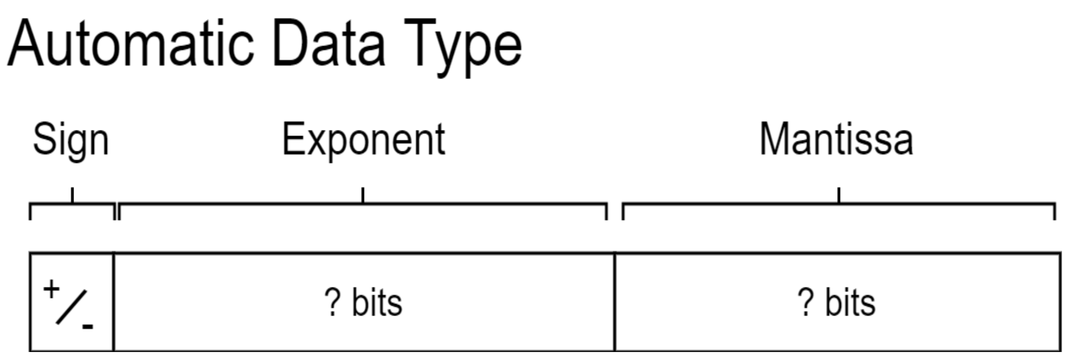
- Loss function

$$w_i^l = w_i^l - LR \times \frac{\partial L}{\partial w_i^l}$$

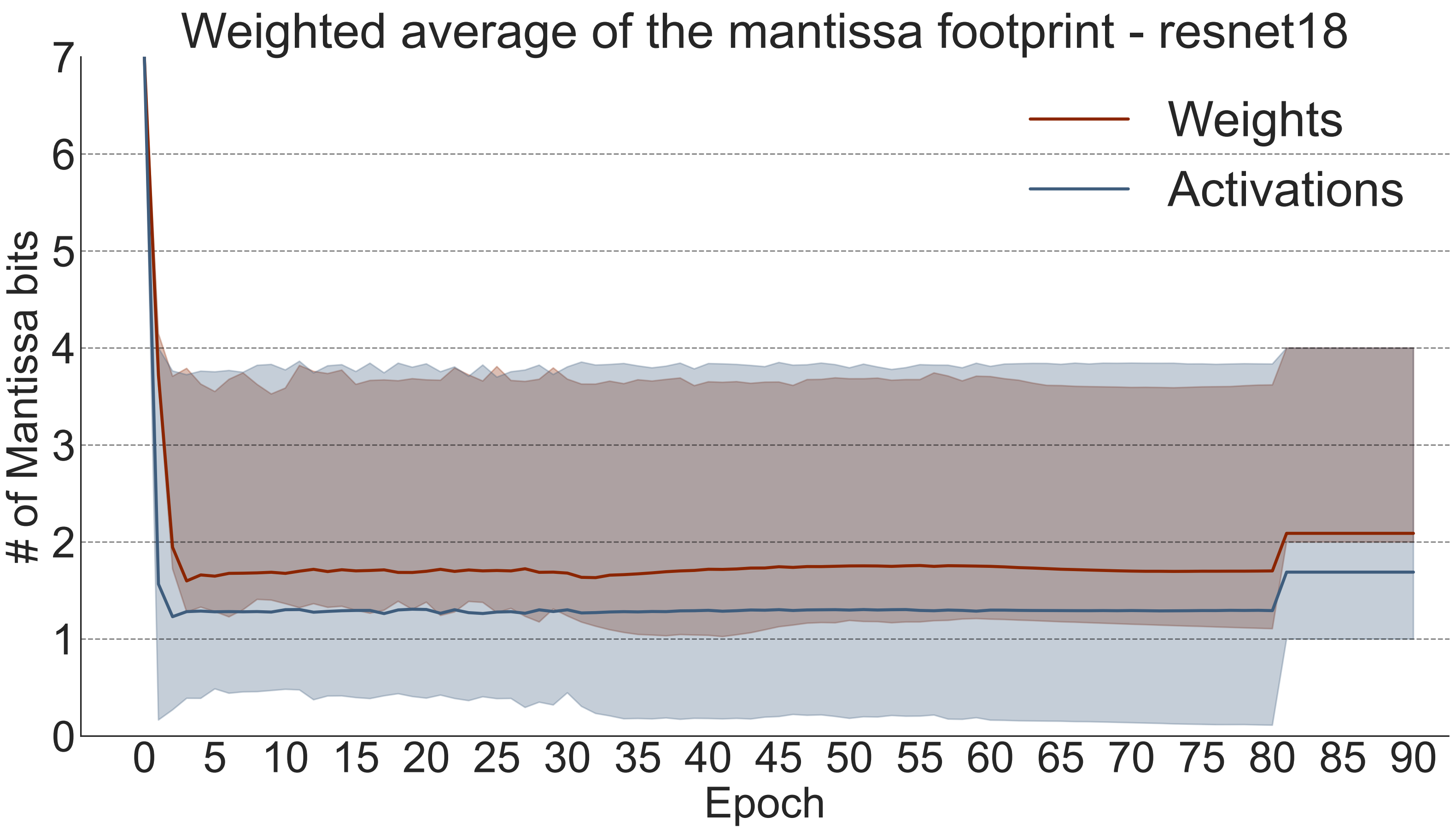


The Precision Problem

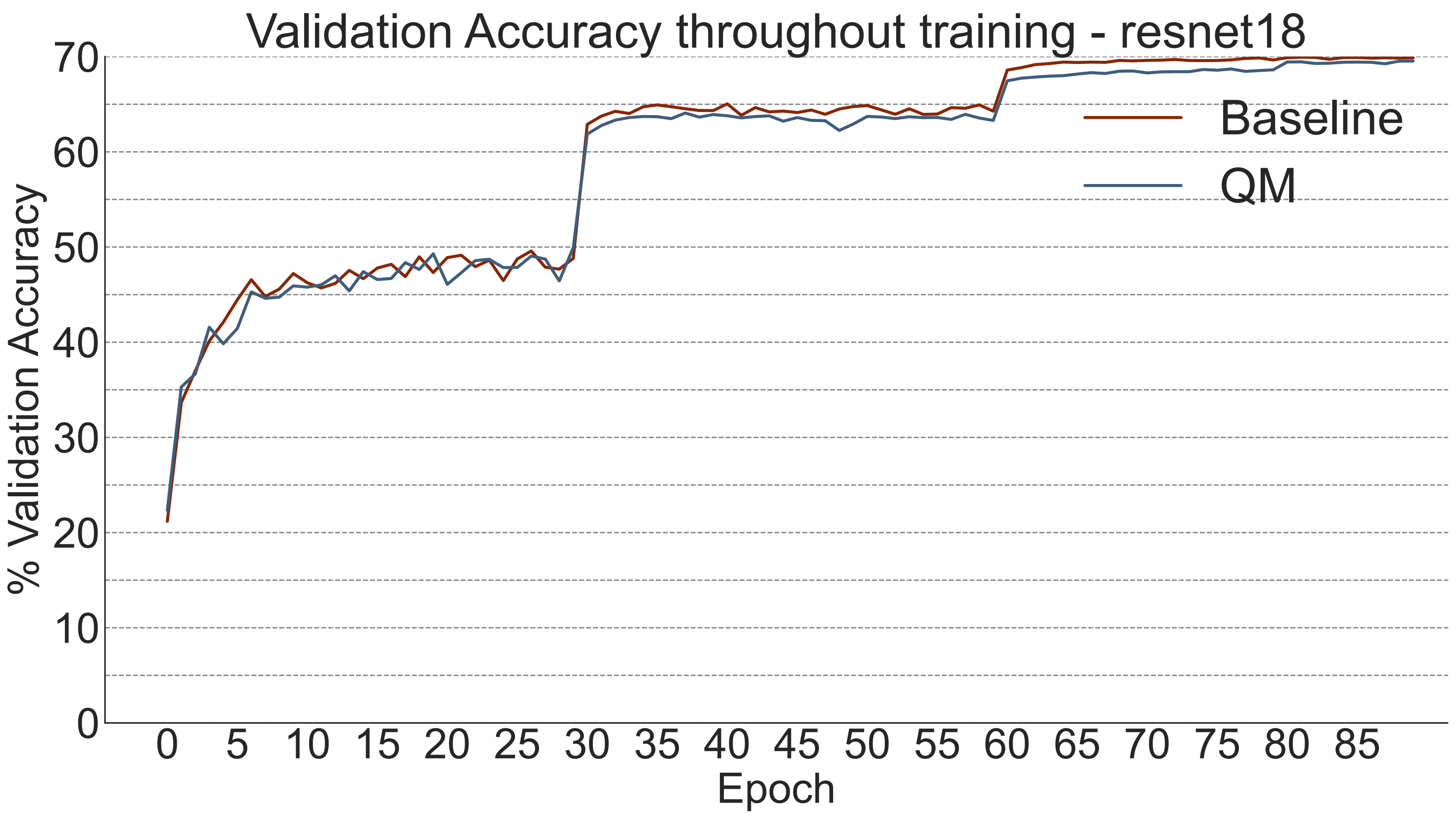




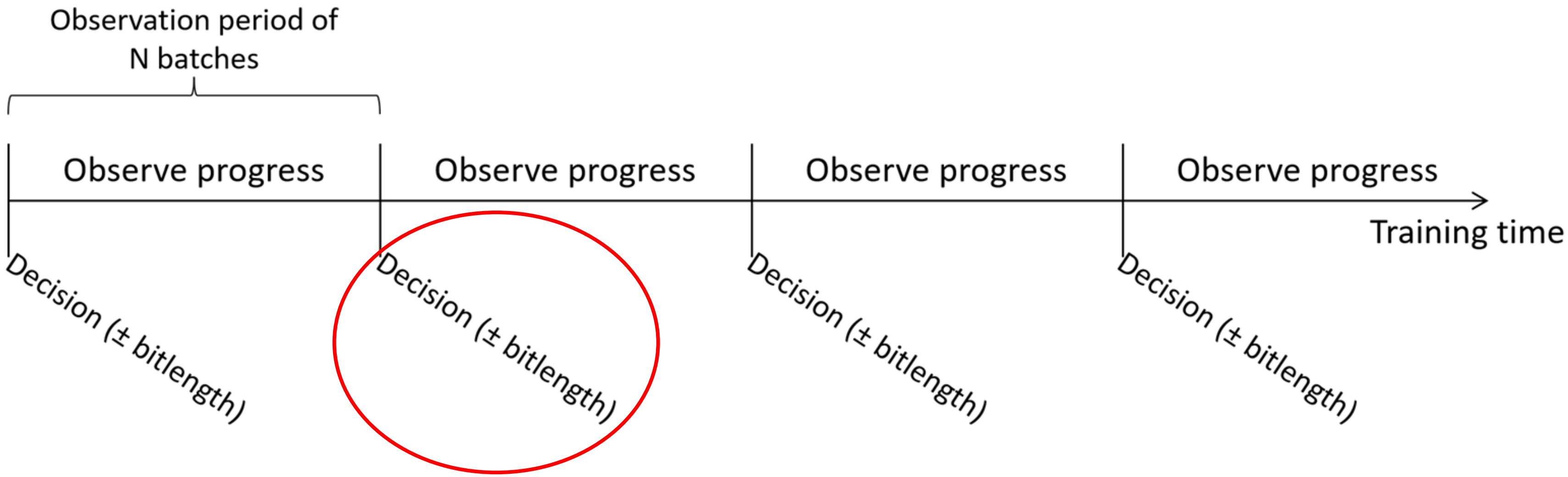
Datatype – Does it work?



Datatype – Does it work?



BitChop


Observation period of
N batches
Observe progress
Observe progress
Observe progress
Observe progress
Training time
Decision (± bitlength)
Decision (± bitlength)
Decision (± bitlength)
Decision (± bitlength)

BitChop - Moving Average Policy

- Exponential decay factor and dynamic threshold:

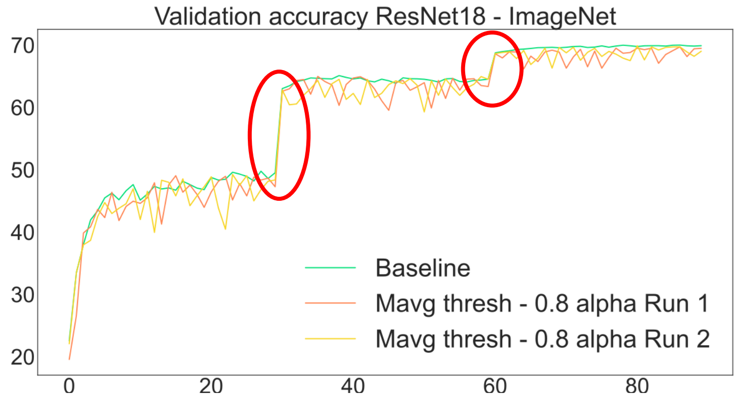
$$Mavg_{i+1} = Mavg_i + \alpha \times (L_i - Mavg_i)$$

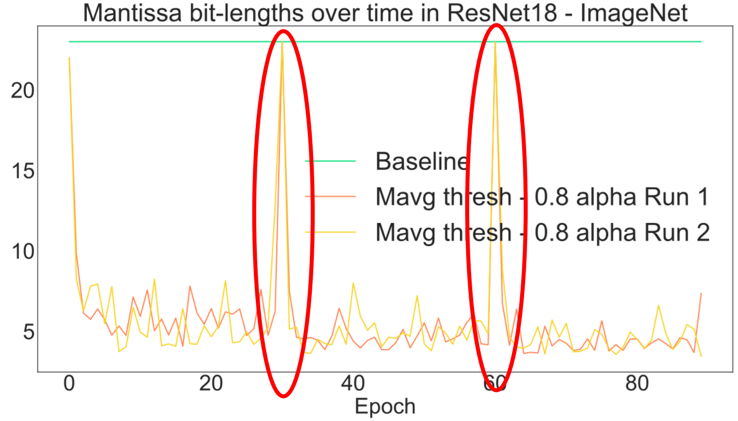
- Full precision on learning rate change
- 4 bits mantissa on average
  - Slight volatility in accuracy
- 75% mantissa footprint reduction on average

$$ErrAvg_i = \frac{\sum_{n=i-N}^{i-1} \frac{|Mavg_n - L_n|}{L_n}}{N}$$

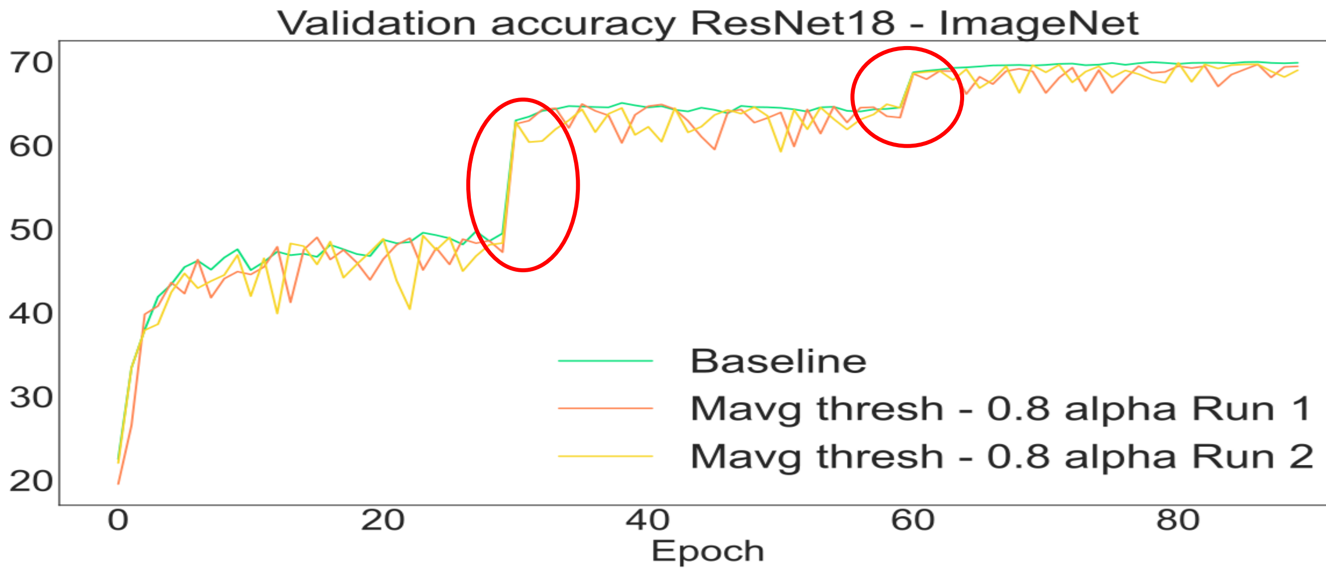
$$\epsilon_i = Mavg_i \times ErrAvg_i$$

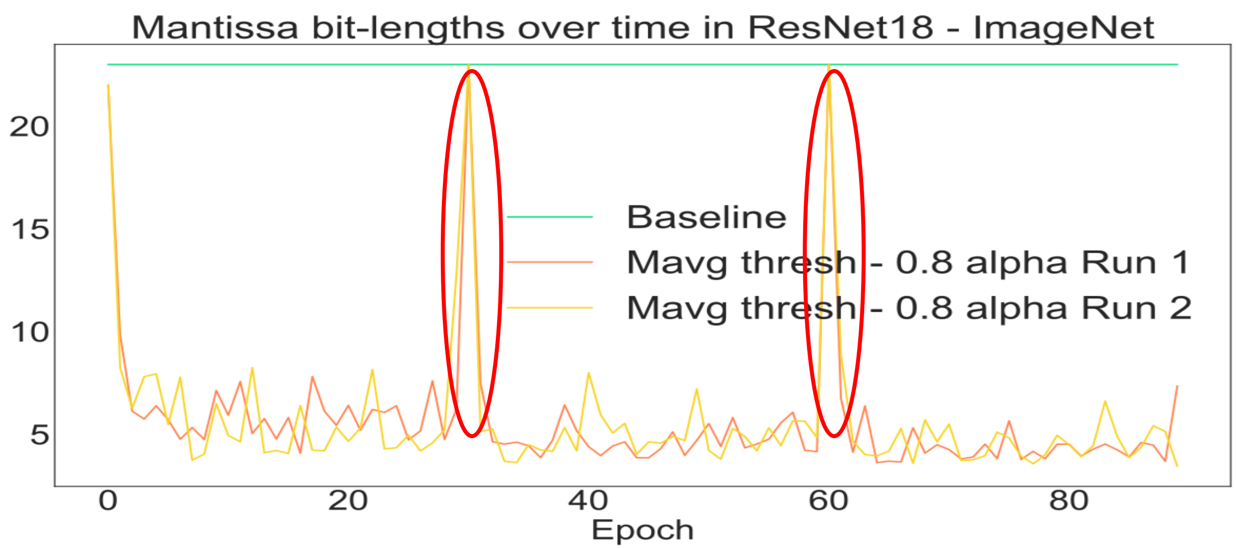
$$bitlength_{i+1} = \begin{cases} bitlength_i - 1, & \text{when } Mavg_i > L_i + \epsilon \\ bitlength_i, & \text{when } L_i - \epsilon_i \le Mavg_i \le L_i + \epsilon_i \\ bitlength_i + 1, & \text{when } Mavg_i < L_i - \epsilon \end{cases}$$





BitChop - Moving Average Policy





Datatype – Does it work?

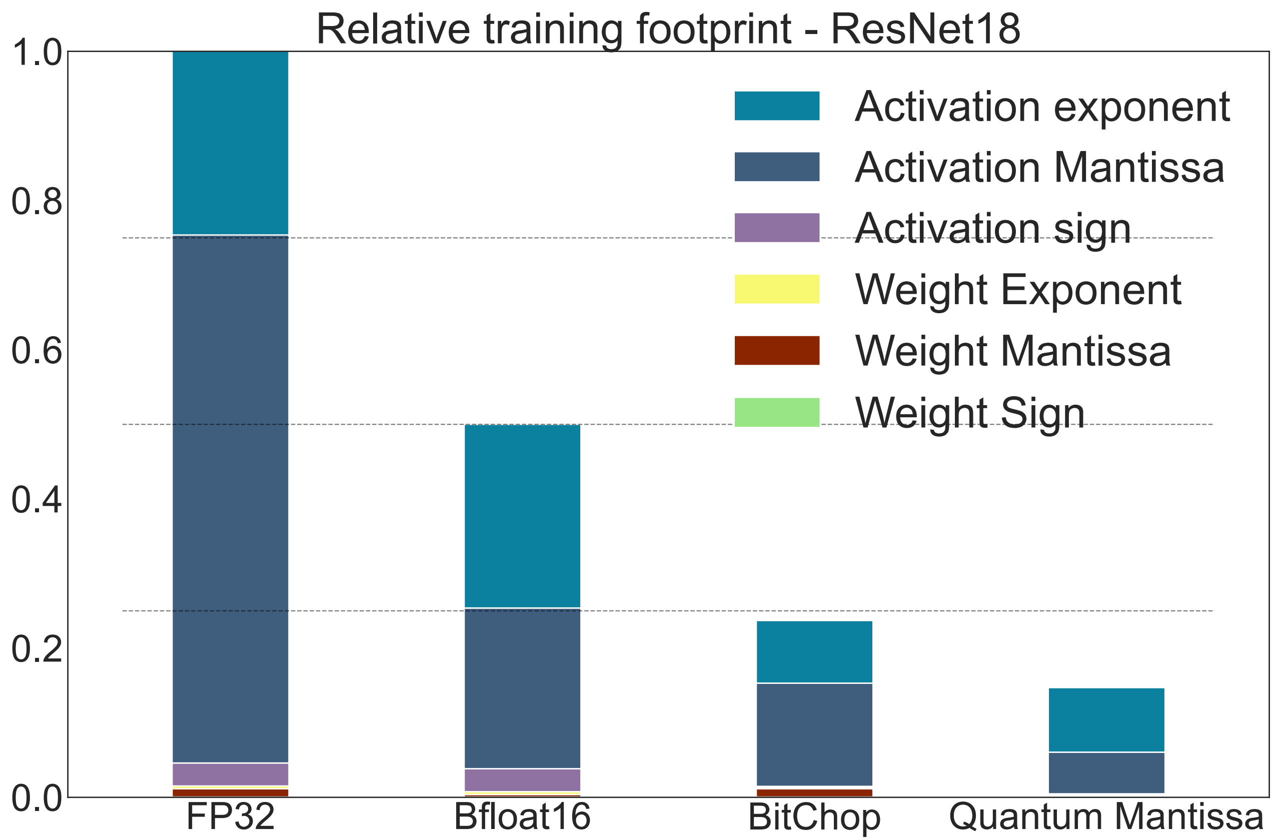


Table 2: Performance and Energy Efficiency gains in comparison w/ FP32

Network	Performance			Energy Efficiency		
	Bfloat 16	SFP_{QM}	SFP_{BC}	**Bfloat 16**	SFP_{QM}	SFP_{BC}
ResNet18	1.53×	2.30×	2.09×	2.00×	6.12×	4.22×
MobileNet V3 Small	1.72×	2.37×	2.14×	2.00×	3.95×	3.60×

Summary

- HW and SW that improves performance and energy efficiency
- w/o requiring any changes to the models
- Rewards further optimizations
- Apack
- Mokey
- Schrödinger's FP