



UNIVERSITY OF
TORONTO

Energy-Efficient Machine Learning Acceleration

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SINCLAIR

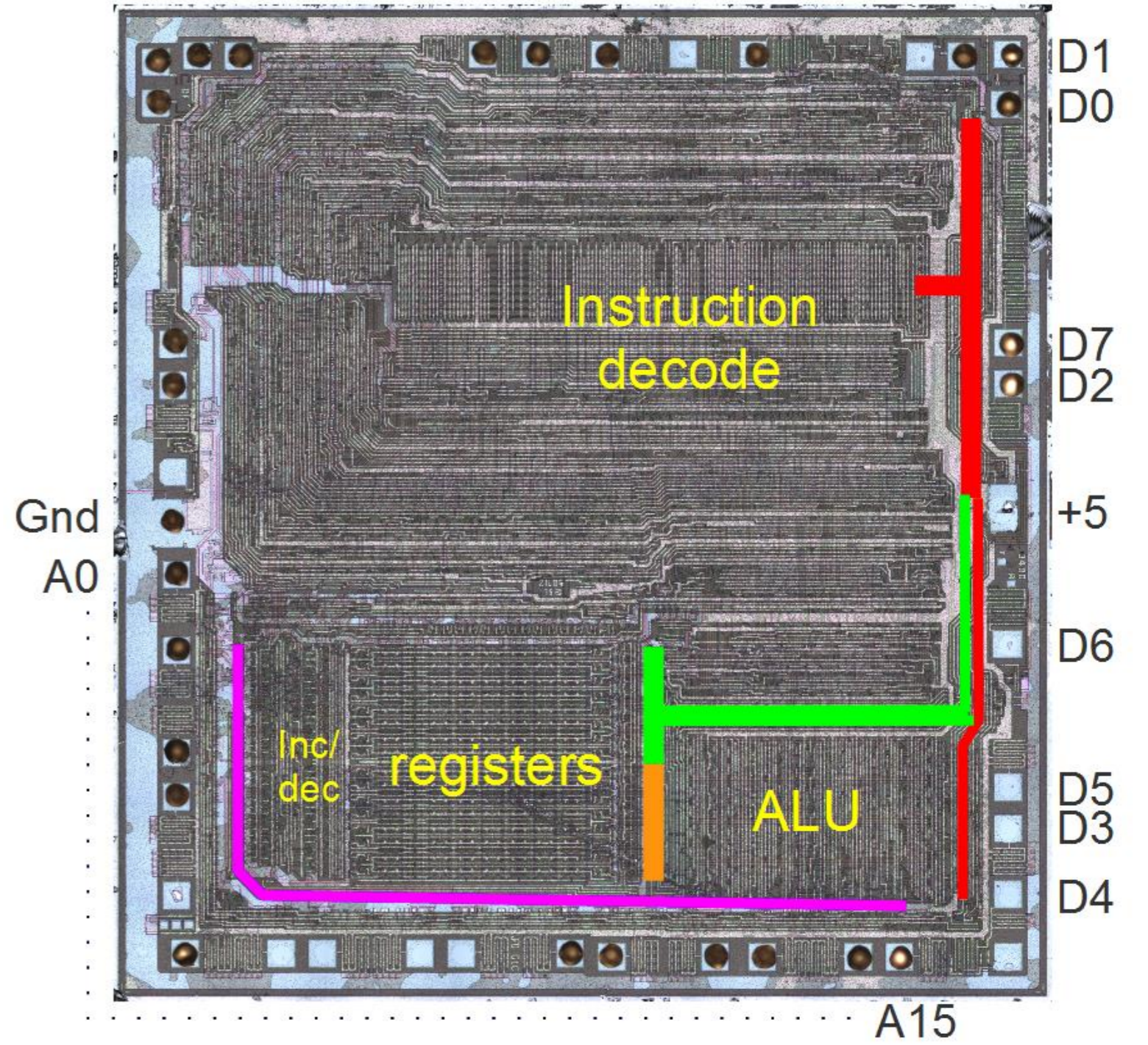
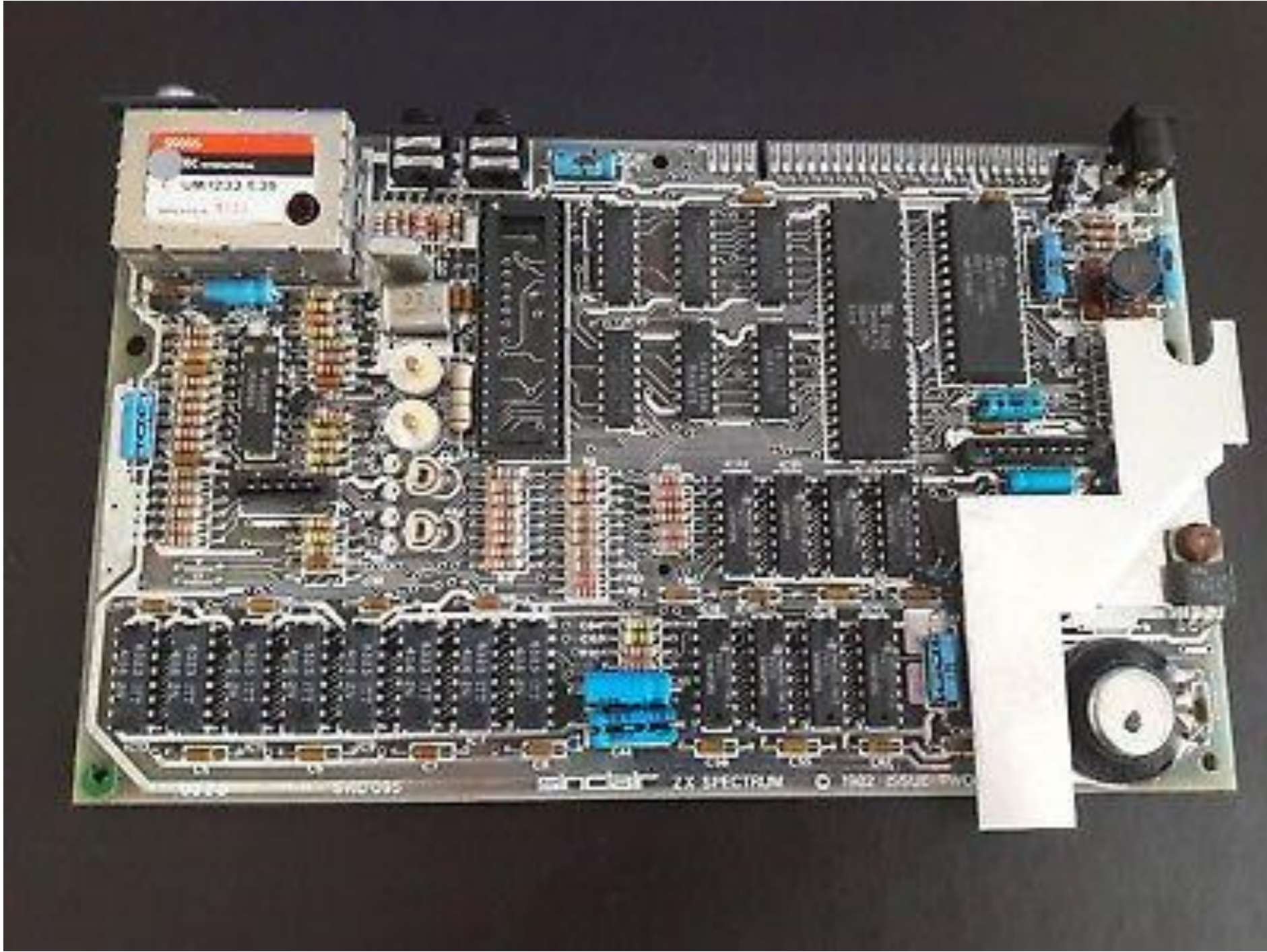
ZX Spectrum

BLUE EDIT 1	RED CAPS LOCK 2	MAGENTA TRUE VIDEO 3	GREEN INV. VIDEO 4	CYAN 5	YELLOW 6	WHITE 7	8	9	BLACK DELETE 0
DEF FN	FN	LINE	OPEN #	CLOSE #	MOVE	ERASE	POINT	CAT	FORMAT
SIN Q	COS W	TAN E	INT R	RND T	STR \$ Y	CHR \$ U	CODE I	PEEK O	TAB P
ASN	ACS	ATN	VERIFY	MERGE	[]	IN	OUT	©
READ A	RESTORE S	DATA D	SGN F	ABS G	SQR H	VAL J	LEN K	USR L	ENTER
~		\	[]	CIRCLE	VAL \$	SCREEN \$	ATTR	
CAPS SHIFT	LN Z	EXP X	L PRINT C	L LIST V	BIN B	IN KEY \$ N	PI M	SYMBOL SHIFT	BREAK SPACE
	BEEP	INK	PAPER	FLASH	BRIGHT	OVER	INVERSE		



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

K





Computing Hardware

We build tools

Used by “everyone” for “everything”

Science, medicine, commerce, ...



← → ↻ 🏠 www.eecg.toronto.edu/~moshovos/CUDA08/doku.php?id=project_presentations_reports_source_code

ECE1742S: Programming Massively Parallel Multiprocessors Using CUDA

Trace: start → [project_presentations_reports_source_code](#)

Convolutional Neural Networks for Object Classification

Alex Krizhevsky

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Abstract I implemented a convolutional neural network with one layer of convolution. I tested it on the CIFAR-10 dataset, which consists of 6000 32×32 colour images in each of 10 classes. The convolutional net does well on the classification task and takes roughly 140x less time to train than a CPU implementation.

- Presentation: [🌐\(pdf\)](#).
- Report: [🌐\(pdf\)](#).
- Source code: [🌐\(zip\)](#).

Our Goal:

Hardware Acceleration of ML

Why?

Hope to... Further Enable ML:

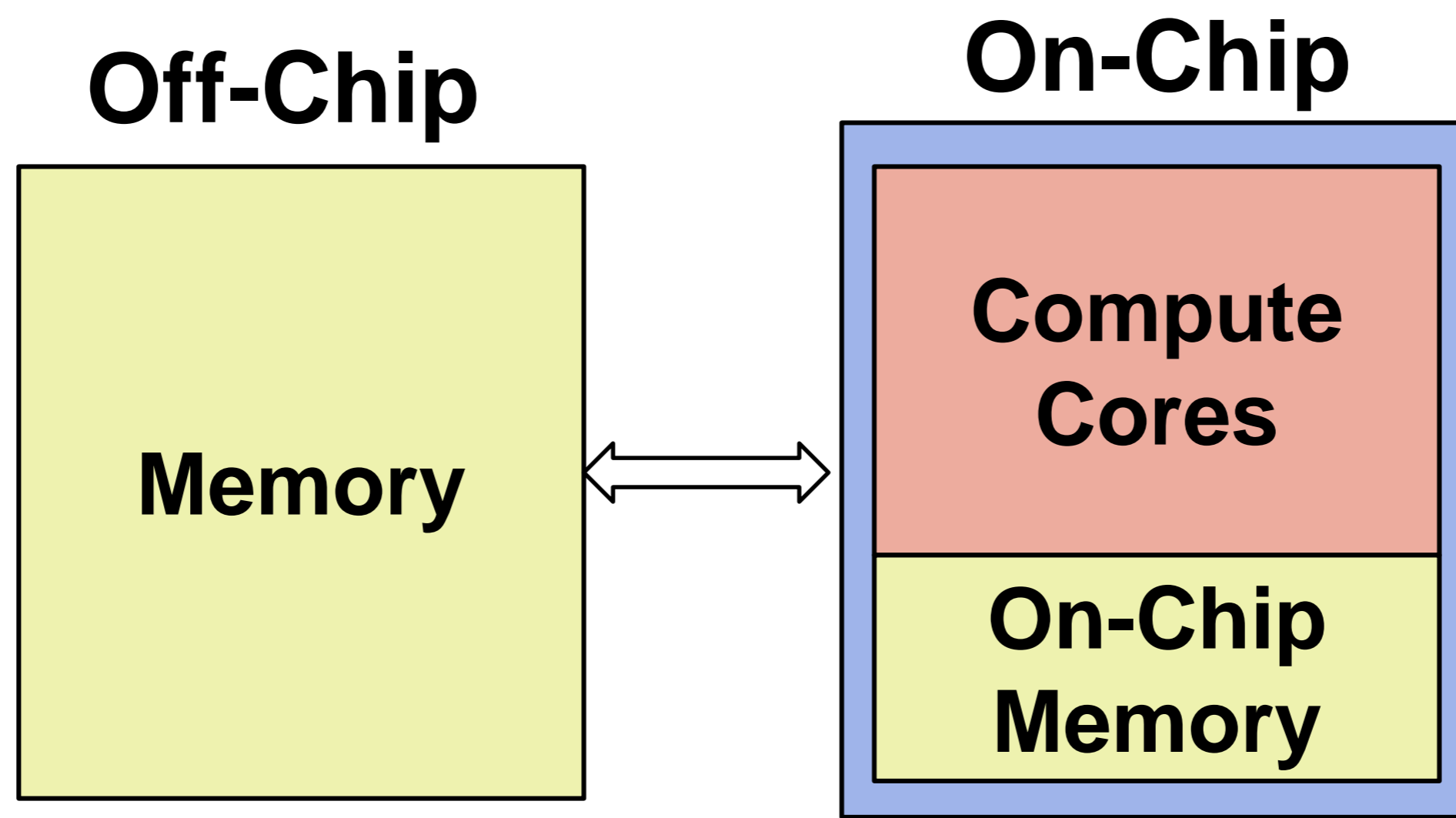
Innovation

Applications

Computing Devices do...

Data “Transformation” \rightarrow **A + B**

Data Movement \rightarrow **A = B**



On- vs. Off-Chip

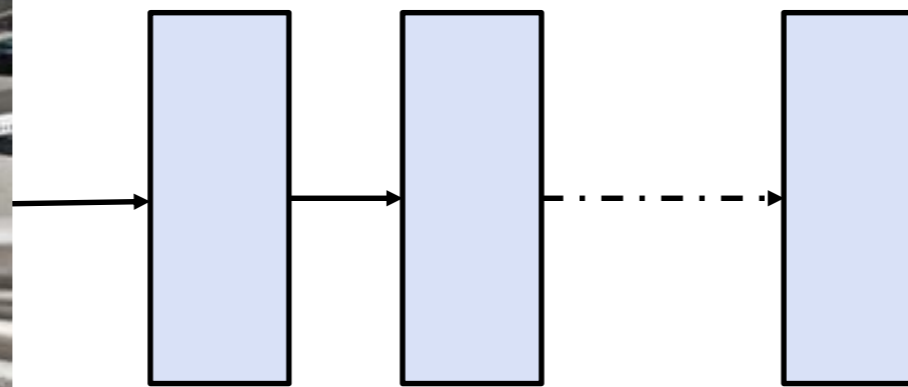
Energy: ~100x

Latency: ~50x

Compute/Watt is the primary design constraint

Example: Convolutional Neural Networks

Layers



LHC
maybe

Tons of **Out** += **A x W**
For other types of networks too

$$\text{Out}_0 += A_0 \times W_0$$

$$\text{Out}_0 += A_1 \times W_1$$

$$\text{Out}_0 += A_2 \times W_2$$

$$\text{Out}_0 += A_3 \times W_3$$

$$\text{Out}_0 += A_4 \times W_4$$

⋮

$$\text{Out}_0 += A_0 \times W_0$$

$$\text{Out}_0 += A_1 \times W_1$$

Lots of Parallelism

$$\text{Out}_0 += A_3 \times W_3$$

$$\text{Out}_0 += A_4 \times W_4$$

⋮

$Out_0 += A_0 \times W_0$
 $Out_1 += A_0 \times W_0$
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 $Out_0 += A_4 \times W_4$
 $Out_1 += A_4 \times W_4$

Do as you are told?

**Calculate the *same* output
but ... do less work**

$Out_0 += A_0 \times W_0$ $Out_1 += A_0 \times W_0$ $Out_0 += A_0 \times W_0$ $Out_1 += A_0 \times W_0$ $Out_0 += A_0 \times W_0$ $Out_1 += A_0 \times W_0$ $Out_1 += A_0 \times W_0$

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$Out_0 += A_2 \times W_2$

$Out_1 += A_4 \times W_4$

$Out_0 += A_1 \times W_1$

$Out_0 += A_3 \times W_3$

$Out_0 += A_4 \times W_4$

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$Out_0 += A_1 \times W_1$

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2
 $Out_1 += A_3 \times W_3$
 $Out_1 += A_4 \times W_4$

$Out_0 += A_0 \times W_0$
 $Out_0 += A_1 \times W_1$

$Out_1 += A_0 \times W_0$

$Out_0 += A_1 \times W_1$

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$Out_0 += A_4 \times W_4$

$Out_1 += A_0 \times W_0$

$Out_0 += A_0 \times W_0$
 $Out_0 += A_1 \times W_1$

$Out_1 += A_0 \times W_0$

$Out_0 += A_0 \times W_0$

$Out_1 += A_0 \times W_0$

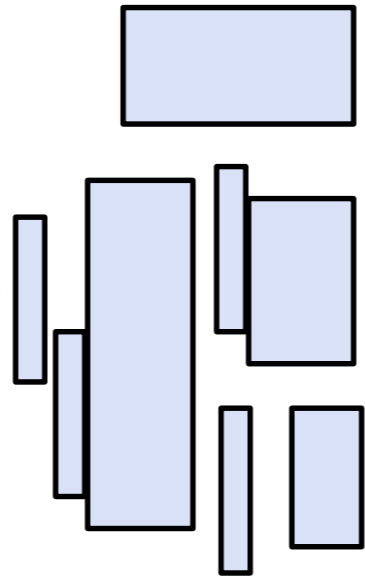
$Out_0 += A_4 \times W_4$

$Out_1 += A_4 \times W_4$

$Out_1 += A_4 \times W_4$

$Out_1 += A_4 \times W_4$





“Compiler”

Runtime

Hardware

Value Properties to Exploit? Many ~0 values

- $\text{Out} += A_0 \times W_0$

0

x

w

~0

x

w

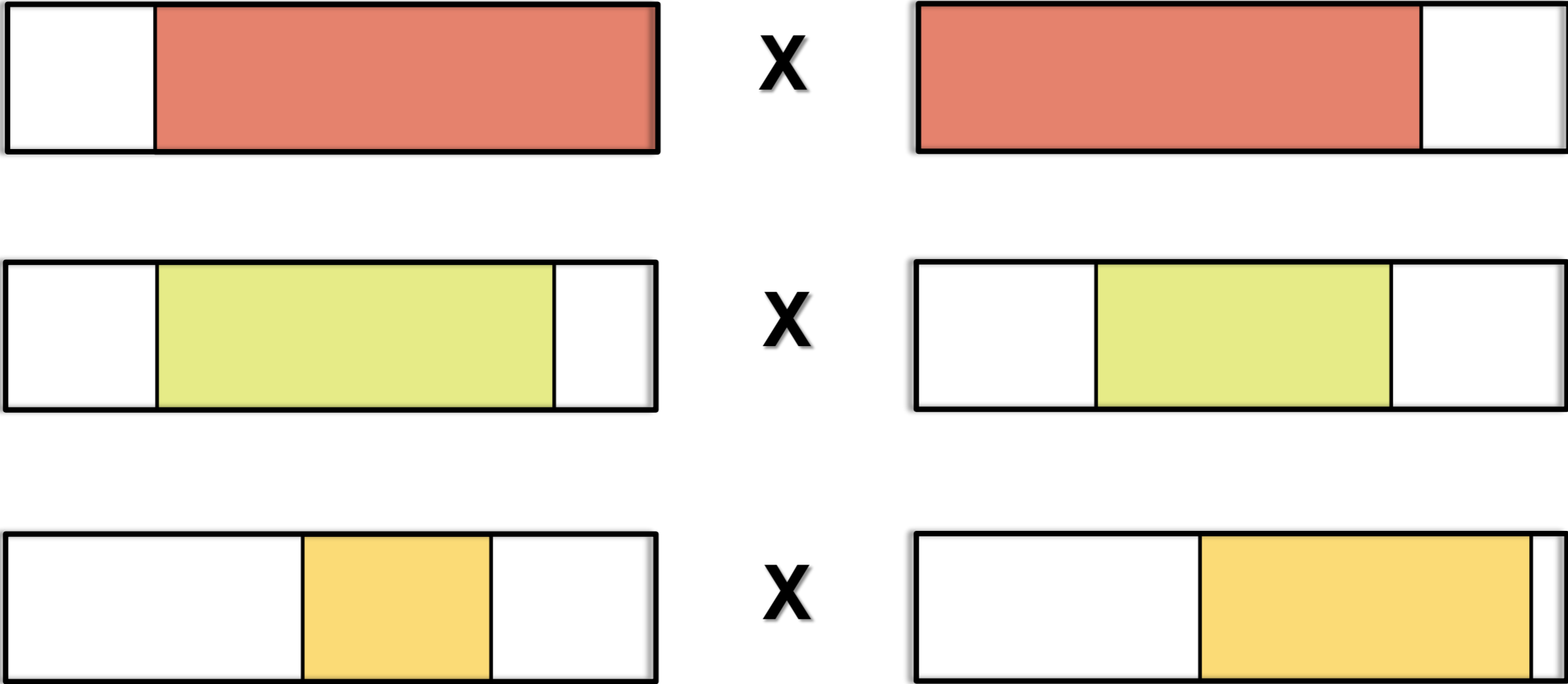
Value Properties to Exploit? Many ~0 values

- $\text{Out} += A_0 \times W_0$

~50%

Value Properties to Exploit? Varying Precision Needs

A **X** **W**



- **At Various Granularities: e.g., Layer or finer**

Value Properties to Exploit? Varying Precision Needs

A **x** **W**

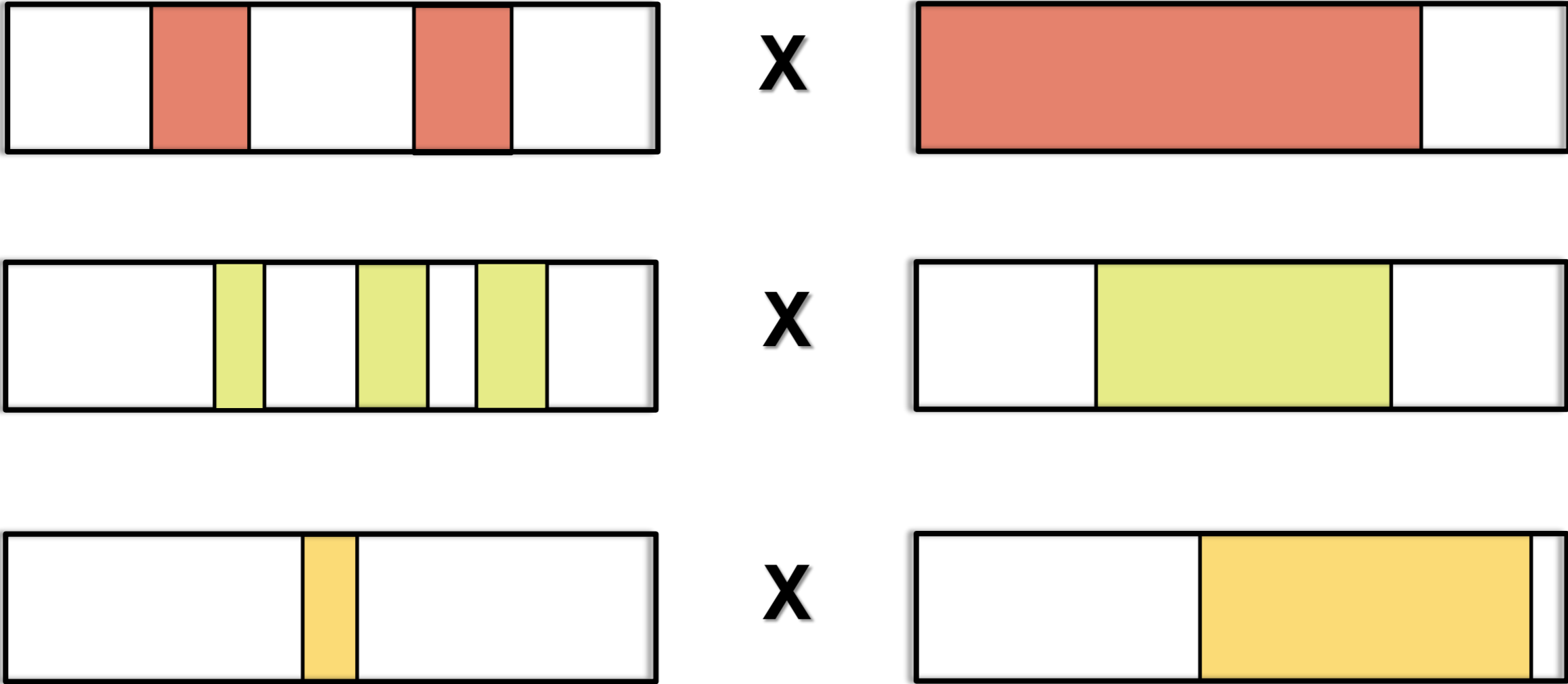
~60%



- At Various Granularities: e.g., say ϵ finer

Value Properties to Exploit? Bits that are "1"

A **X** **W**



Ineffectual Computations Explained

W 0001 0100

A 0010 1010

0000 0000

0010 1010

0000 0000

0010 1010

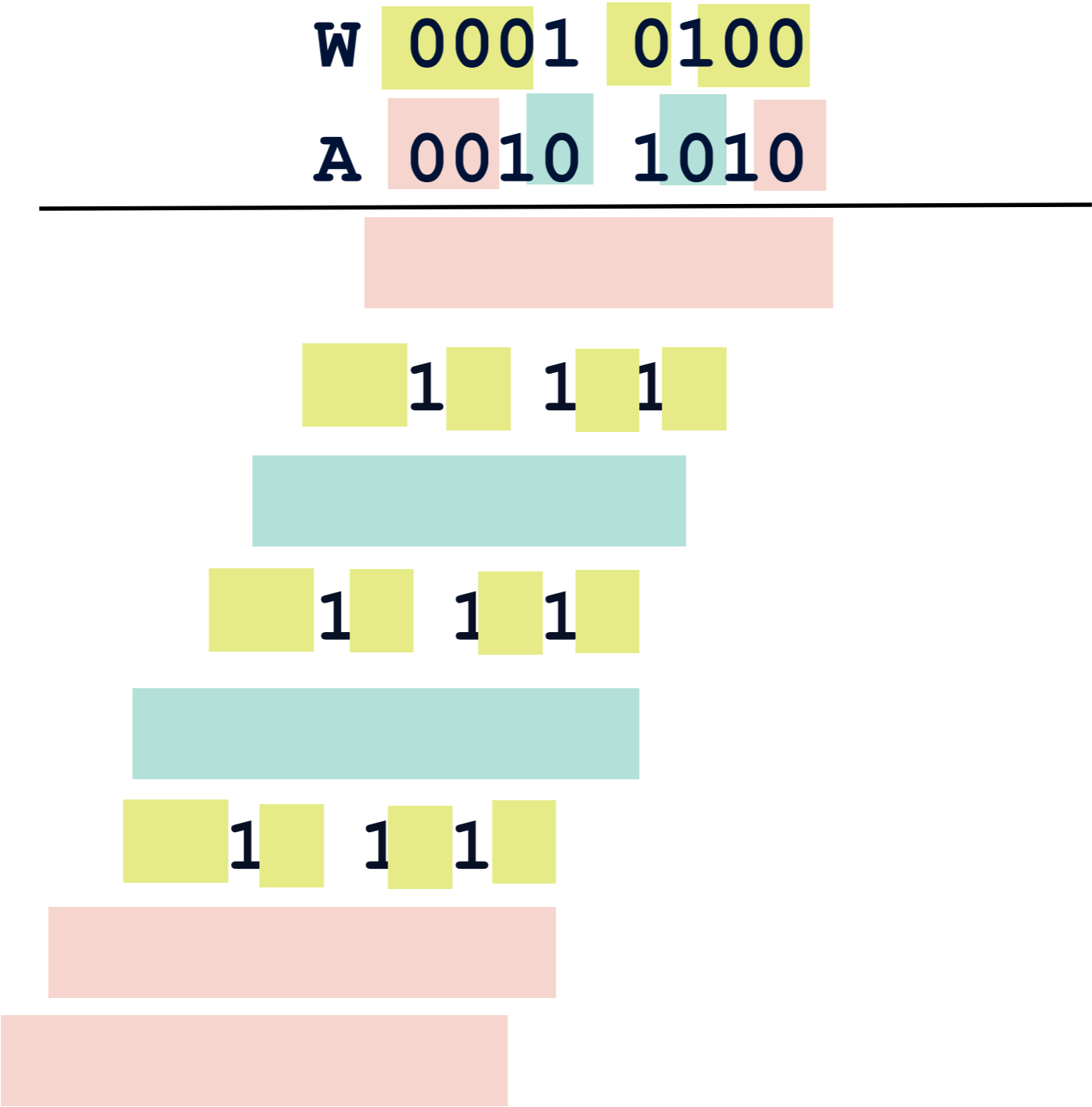
0000 0000

0010 1010

0000 0000

0000 0000

Ineffectual Computations Explained

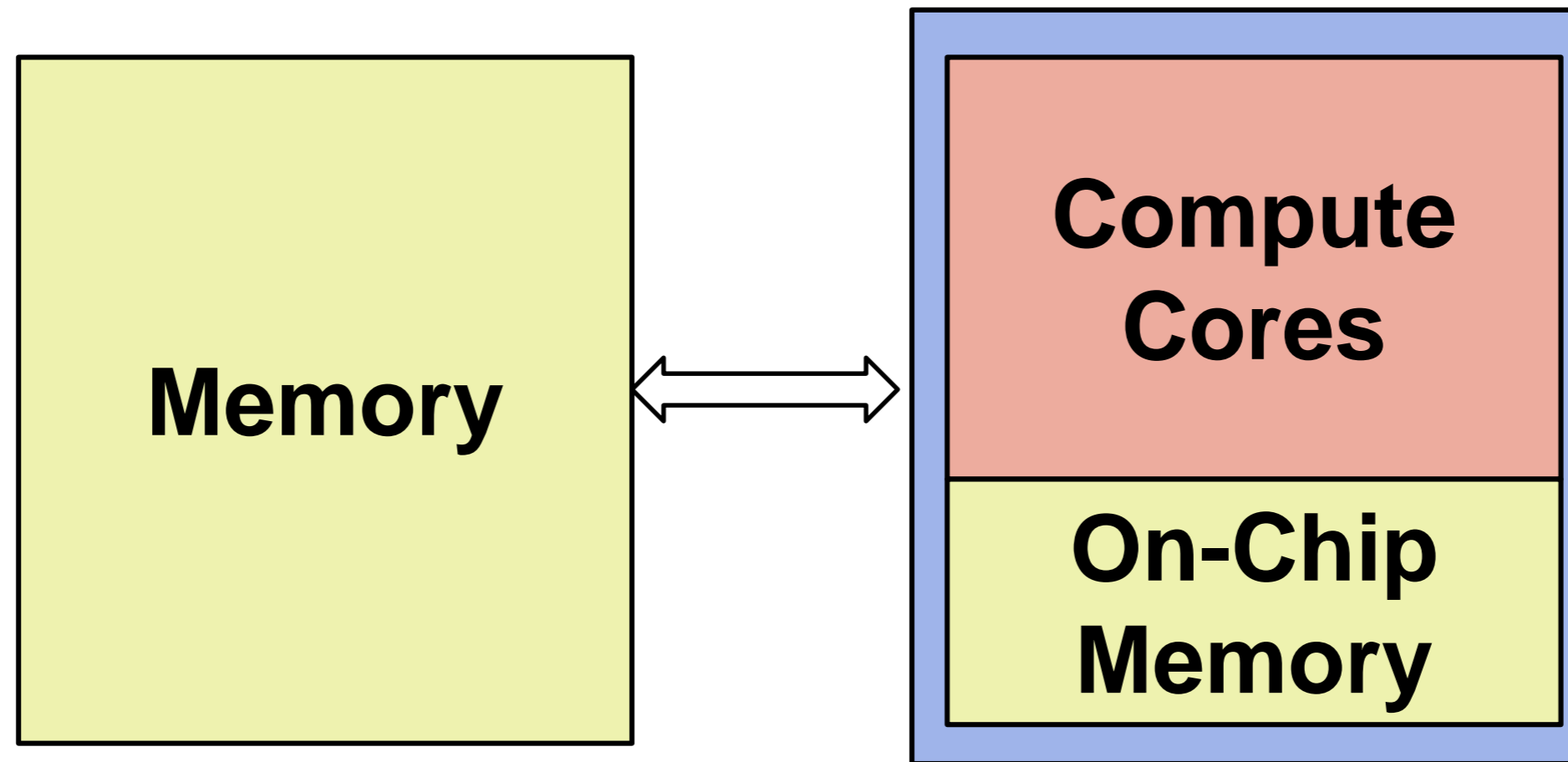


Value Properties to Exploit? Bits that are "1"

A **x** **W**

75% - 99%





On- vs. Off-Chip

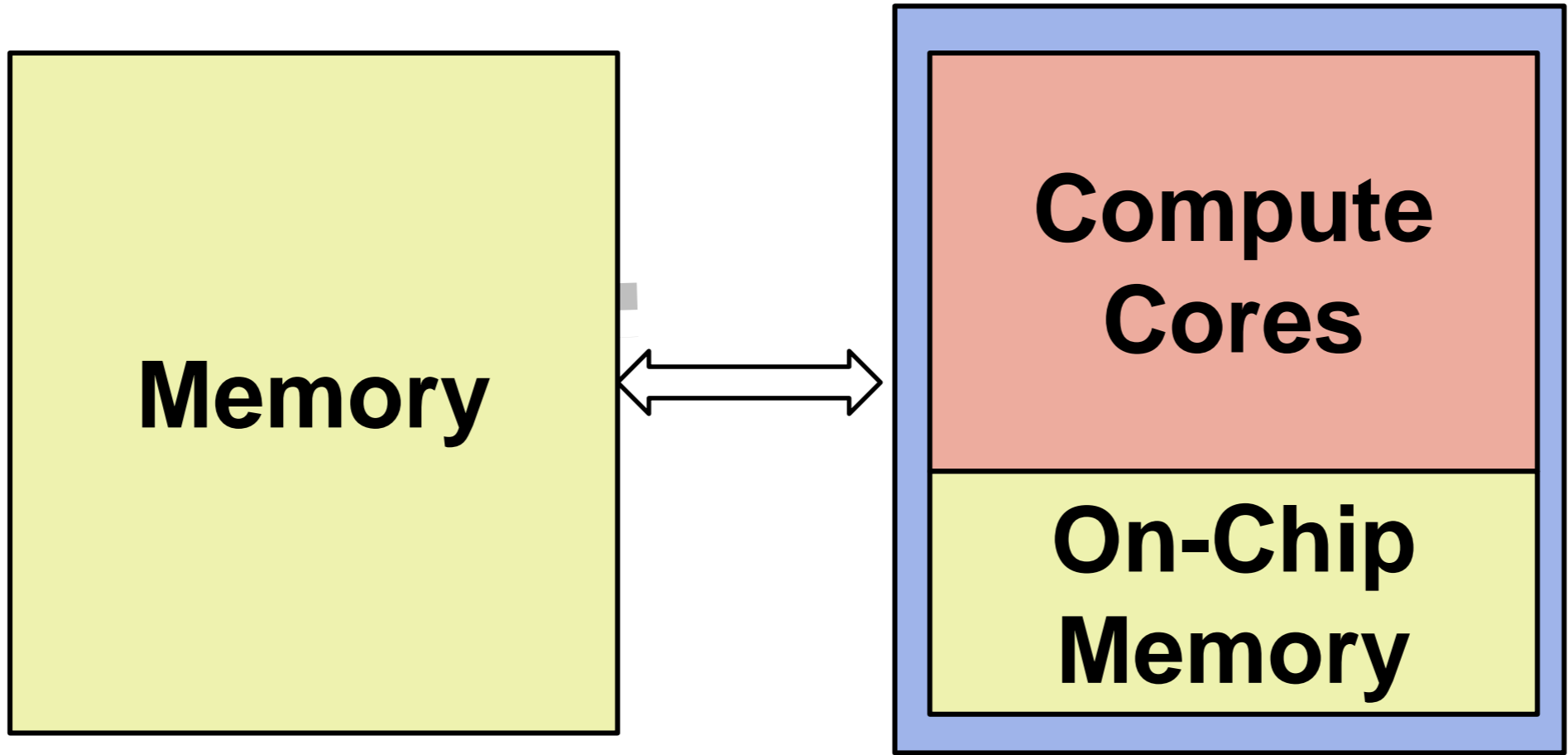
Energy: ~100x

Latency: ~50x

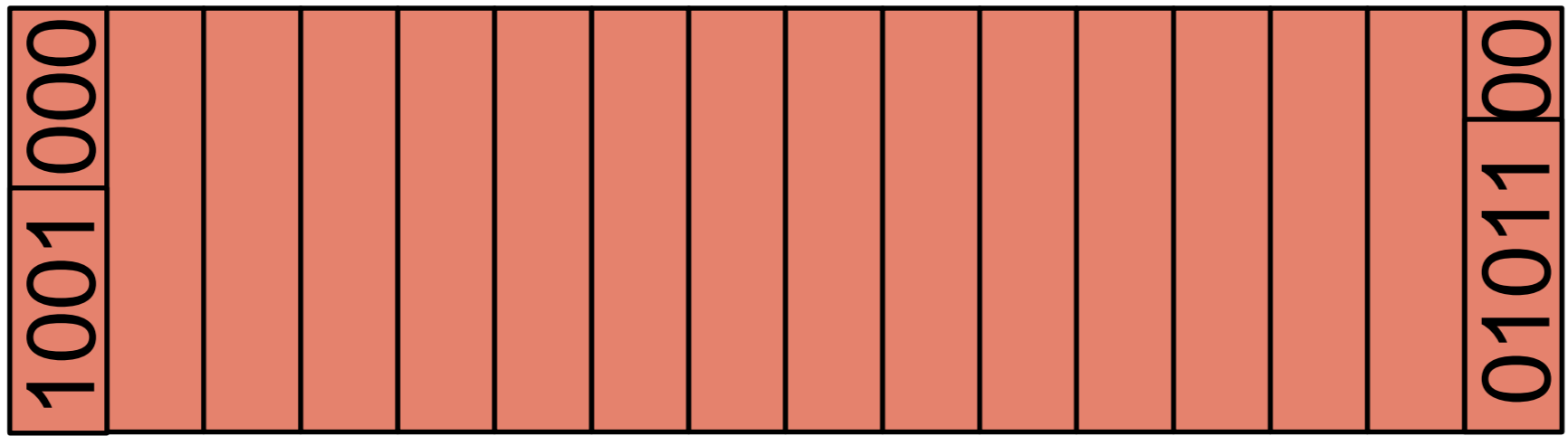
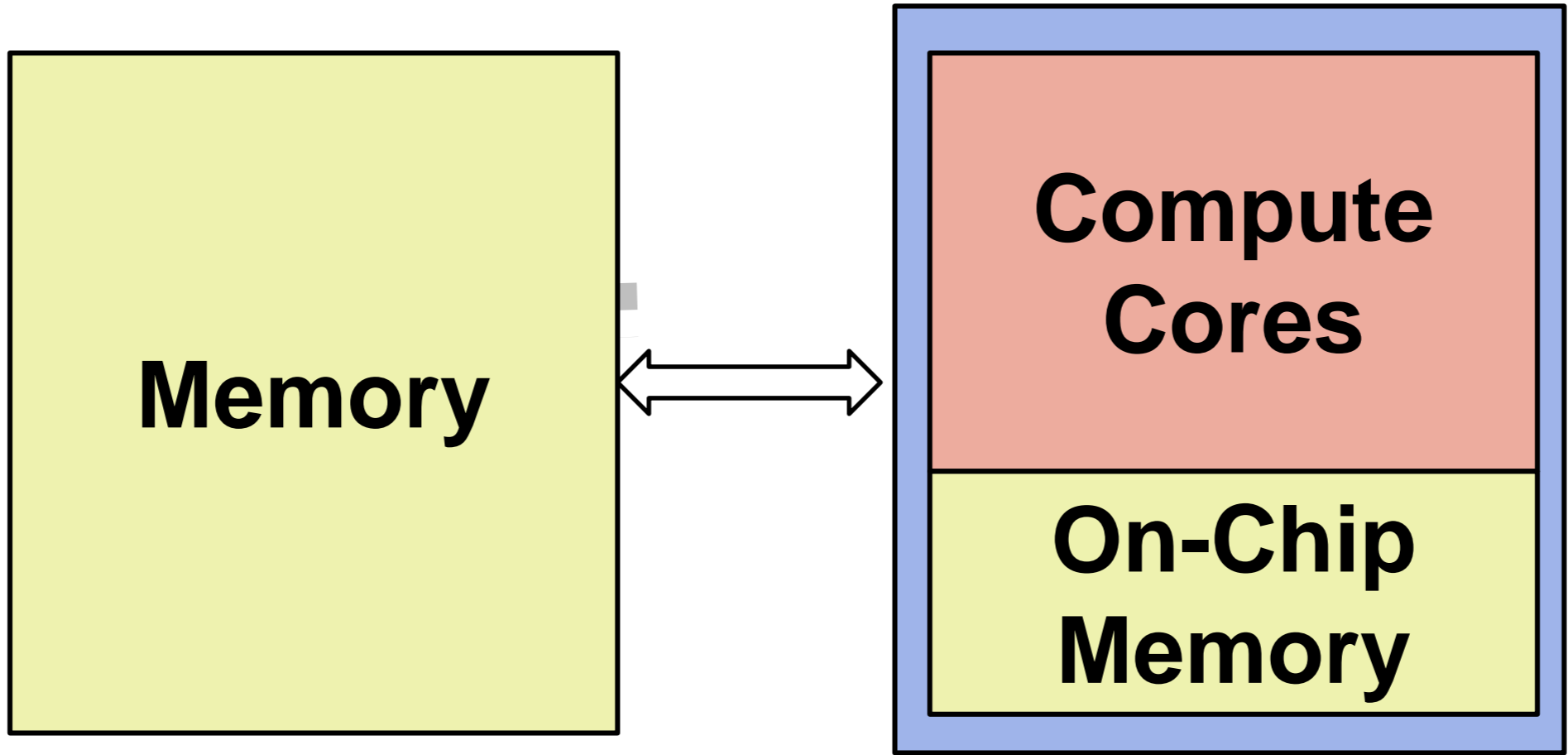
$Out_0 += A_0 \times W_0$ $Out_1 += A_0 \times W_0$ $Out_0 += A_0 \times W_0$ $Out_1 += A_0 \times W_0$ $Out_0 += A_0 \times W_0$ $Out_1 += A_0 \times W_0$ $Out_0 += A_0 \times W_0$ $Out_1 += A_0 \times W_0$ $Out_0 += A_0 \times W_0$ $Out_1 += A_0 \times W_0$



$$\text{Out}_0 += A_0 \times W_0 \text{Out}_1 += A_0 \times W_0 \text{Out}_0 += A_0 \times W_0 \text{Out}_1 += A_0 \times W_0 \text{Out}_0 += A_0 \times W_0 \text{Out}_1 += A_0 \times W_0 \text{Out}_0 += A_0 \times W_0 \text{Out}_1 += A_0 \times W_0$$

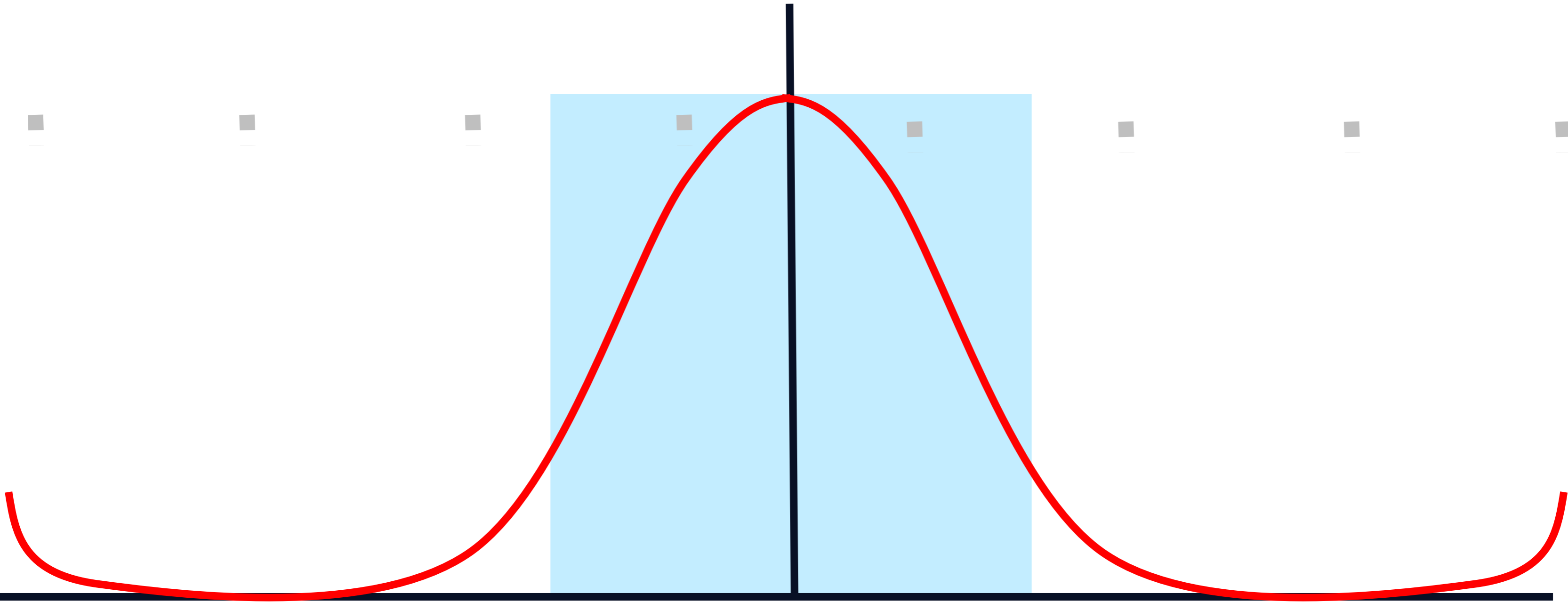


$Out_0 += A_0 \times W_0$ $Out_1 += A_0 \times W_0$ $Out_0 += A_0 \times W_0$ $Out_1 += A_0 \times W_0$ $Out_0 += A_0 \times W_0$ $Out_1 += A_0 \times W_0$ $Out_0 += A_0 \times W_0$ $Out_1 += A_0 \times W_0$ $Out_0 += A_0 \times W_0$ $Out_1 += A_0 \times W_0$



Making Typical Values Matter

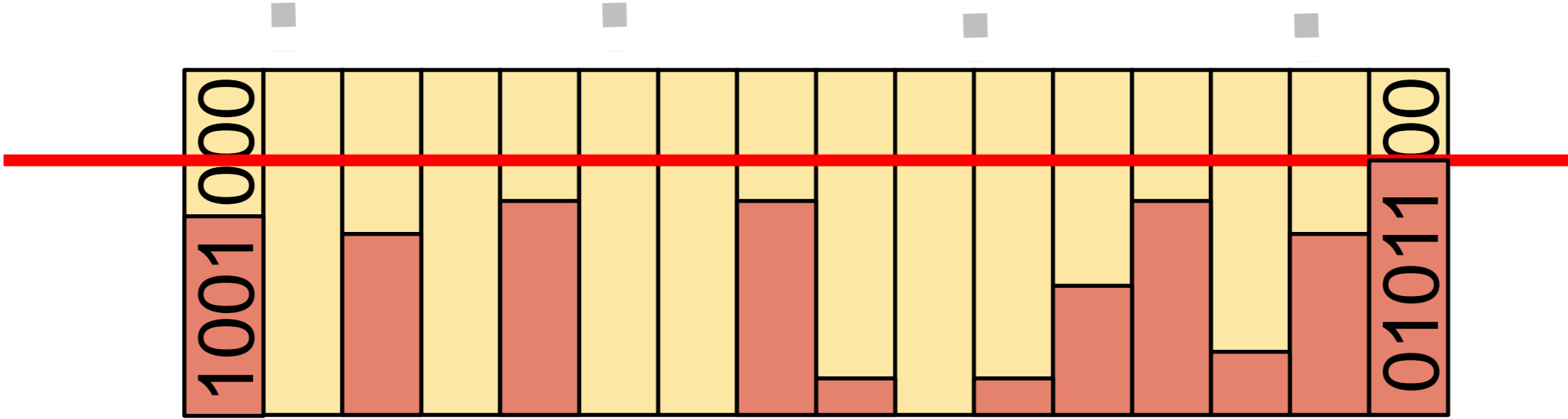
$$\text{Out}_0 += A_0 \times W_0 \text{Out}_1 += A_0 \times W_0 \text{Out}_0 += A_0 \times W_0 \text{Out}_1 += A_0 \times W_0 \text{Out}_0 += A_0 \times W_0 \text{Out}_1 += A_0 \times W_0 \text{Out}_0 += A_0 \times W_0 \text{Out}_1 += A_0 \times W_0$$



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

Making Typical Values Matter

$$\text{Out}_0 += A_0 \times W_0 \quad \text{Out}_1 += A_0 \times W_0 \quad \text{Out}_0 += A_0 \times W_0 \quad \text{Out}_1 += A_0 \times W_0 \quad \text{Out}_0 += A_0 \times W_0 \quad \text{Out}_1 += A_0 \times W_0 \quad \text{Out}_0 += A_0 \times W_0 \quad \text{Out}_1 += A_0 \times W_0 \quad \text{Out}_0 += A_0 \times W_0 \quad \text{Out}_1 += A_0 \times W_0$$



Reduces traffic to 50% -- 25% of the original

Effective Precisions w/ Per Group Adaptation: 16b case

Precisions are much lower

GoogleNet	6.19-5.94-5.74-6.77-6.91-6.77-6.86-6.77
	-6.92-6.31-5.96-6.31-6.00-6.31-6.55-5.33
	-5.33-5.33-5.33-5.33-5.48-6.74-6.33-6.74
	-6.51-6.74-7.07-6.35-6.17-6.35-5.88-6.35
	-6.56-5.07-4.69-5.07-4.82-5.07-5.31-5.53
	-4.89-5.53-5.70-5.53-5.86-7.88-7.62-7.88
	-8.07-7.88-8.31-4.97-3.85-4.97-3.61-4.97-5.36

Also: Computation Speed:

Ineffectual Computations Explained

W 0001 0100

A 0010 1010

0000 0000

0010 1010

0000 0000

0010 1010

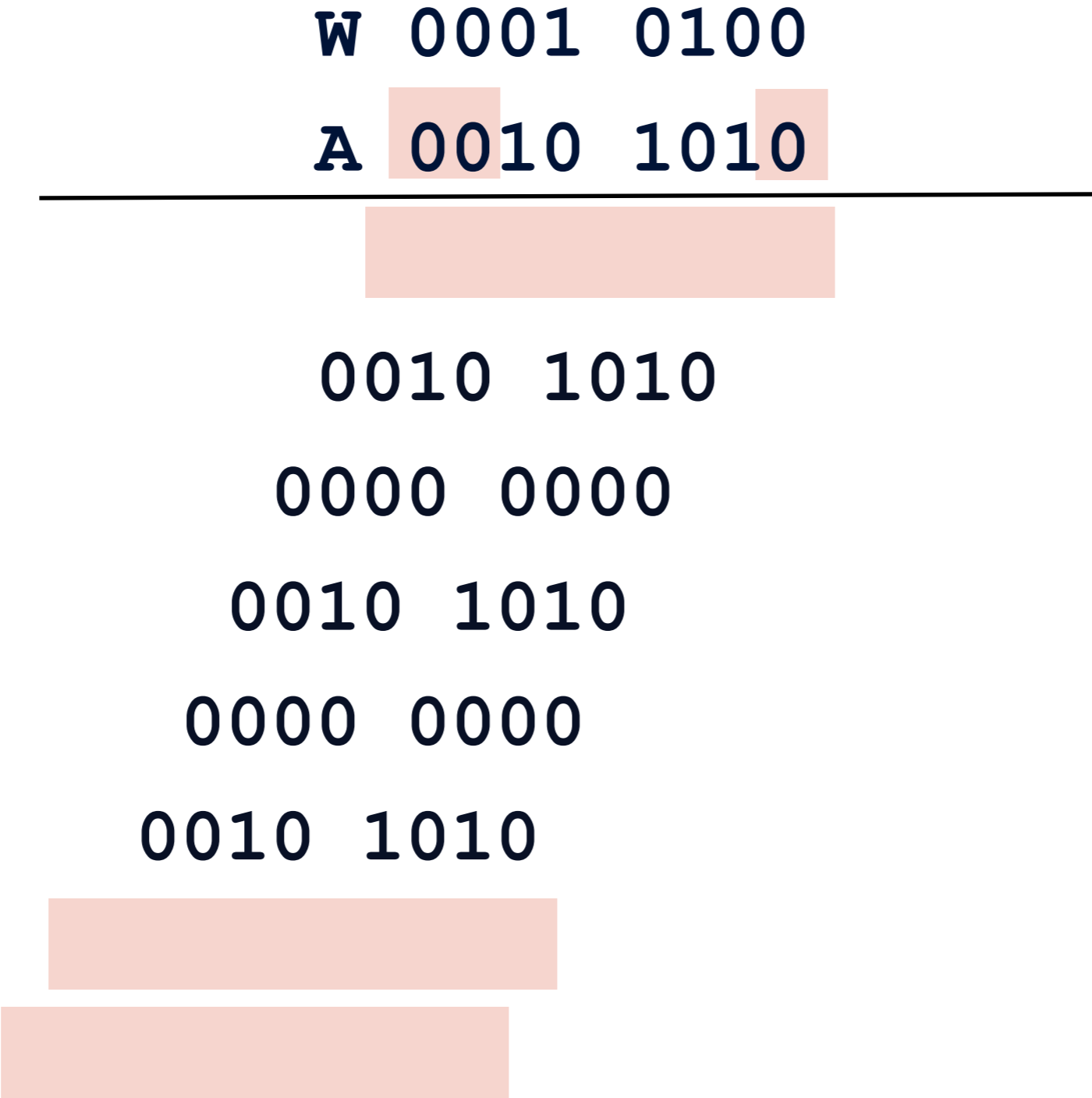
0000 0000

0010 1010

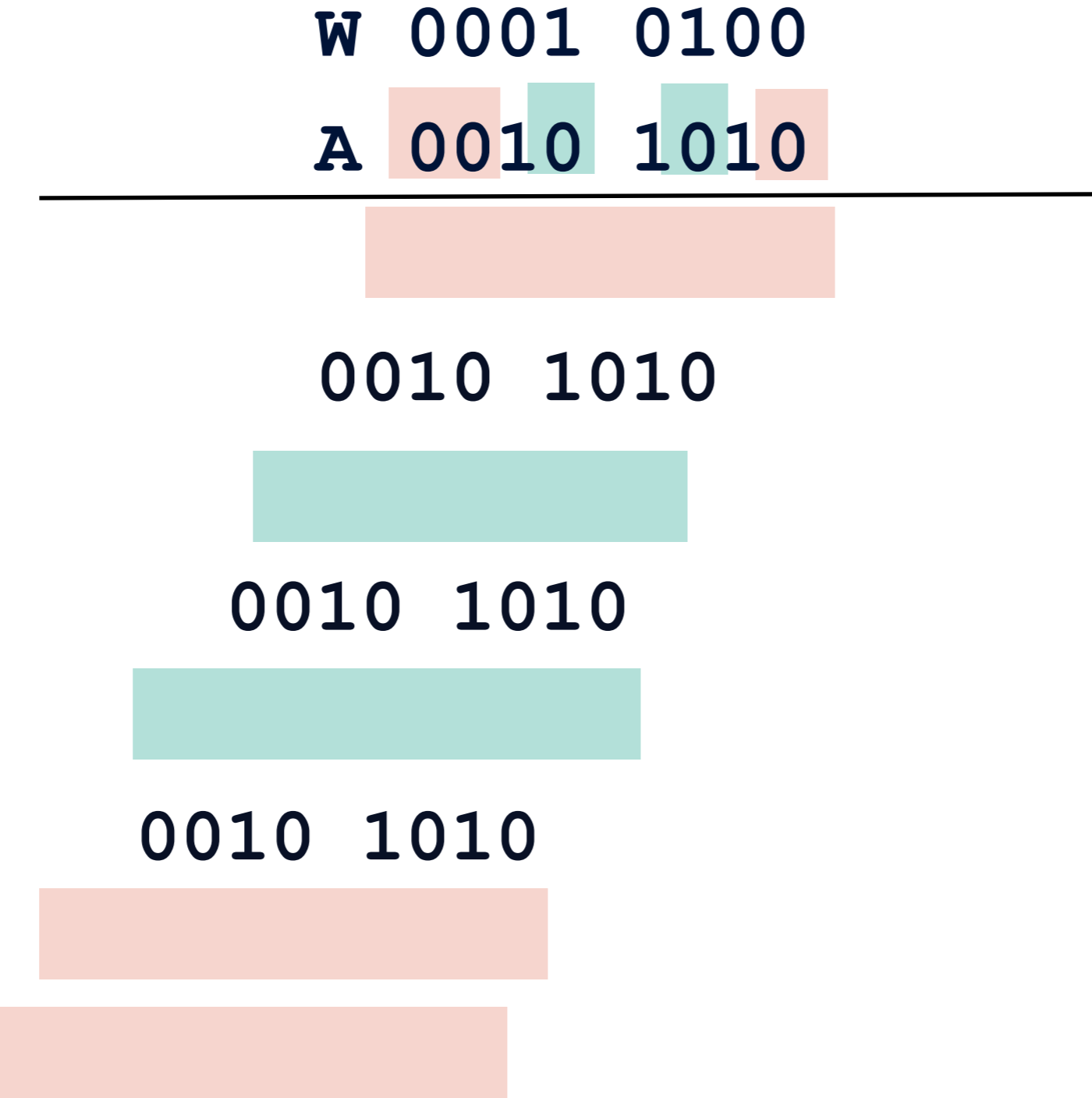
0000 0000

0000 0000

Ineffectual Computations Explained



Ineffectual Computations Explained

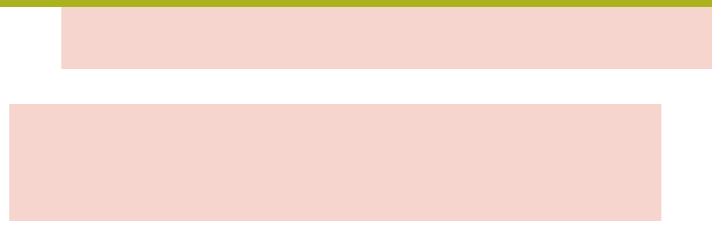


Ineffectual Computations Explained

W 0001 0100

A 0010 1010

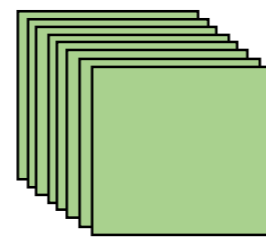
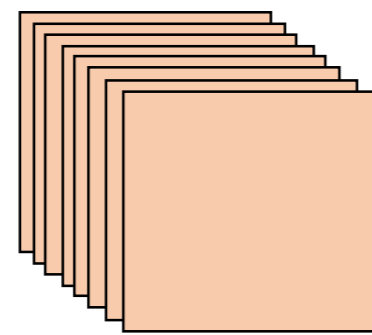
75% - 95%



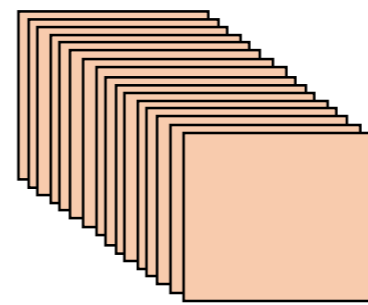
ImageNet $\approx 230 \times 230$



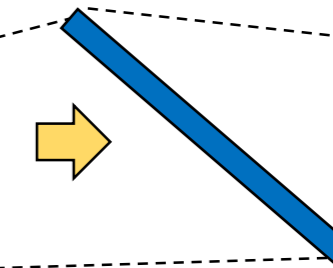
Fixed Resolution



pooling



pooling



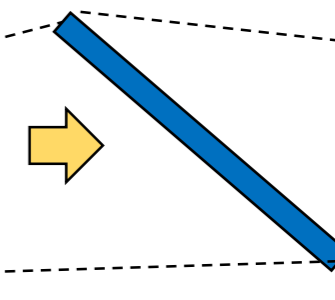
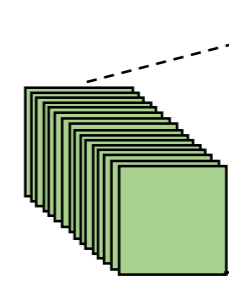
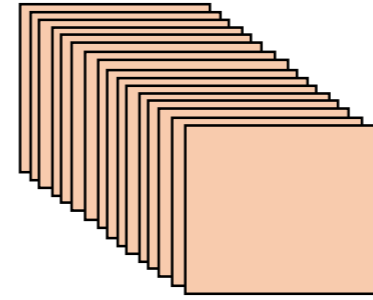
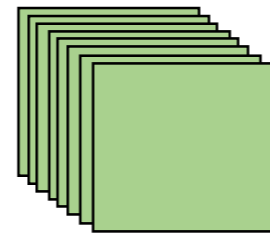
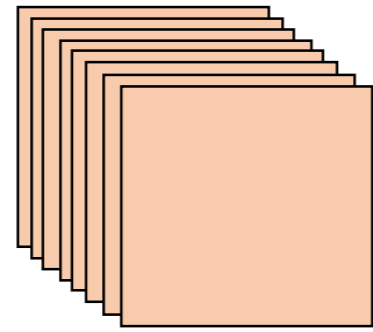
Fully
Connected

Dog
Cat
Lion

Different resolution (typically lower)



ImageNet $\approx 230 \times 230$



Dog
Cat
Lion

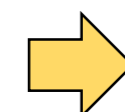
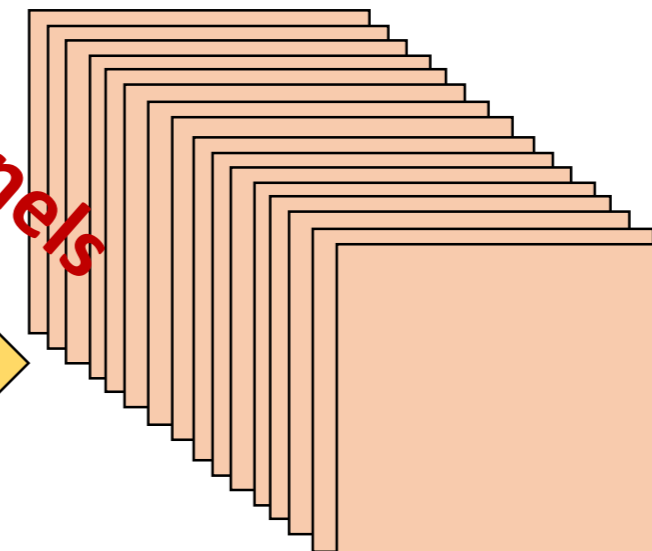
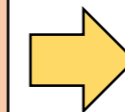
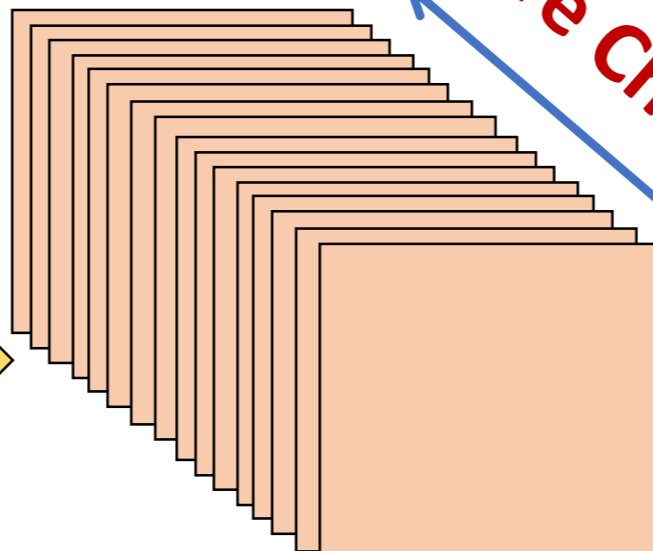
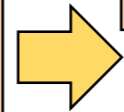
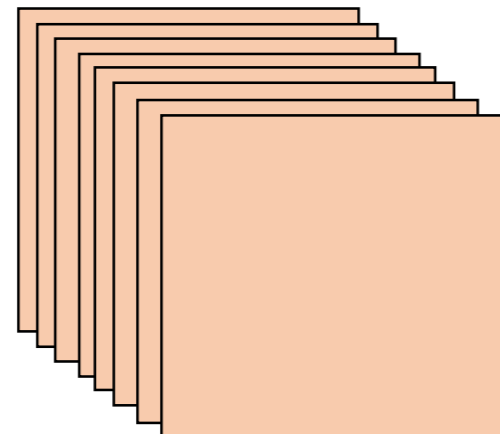
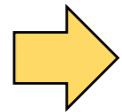
Fixed Resolution

pooling

pooling

Fully
Connected

Different resolution (typically lower)



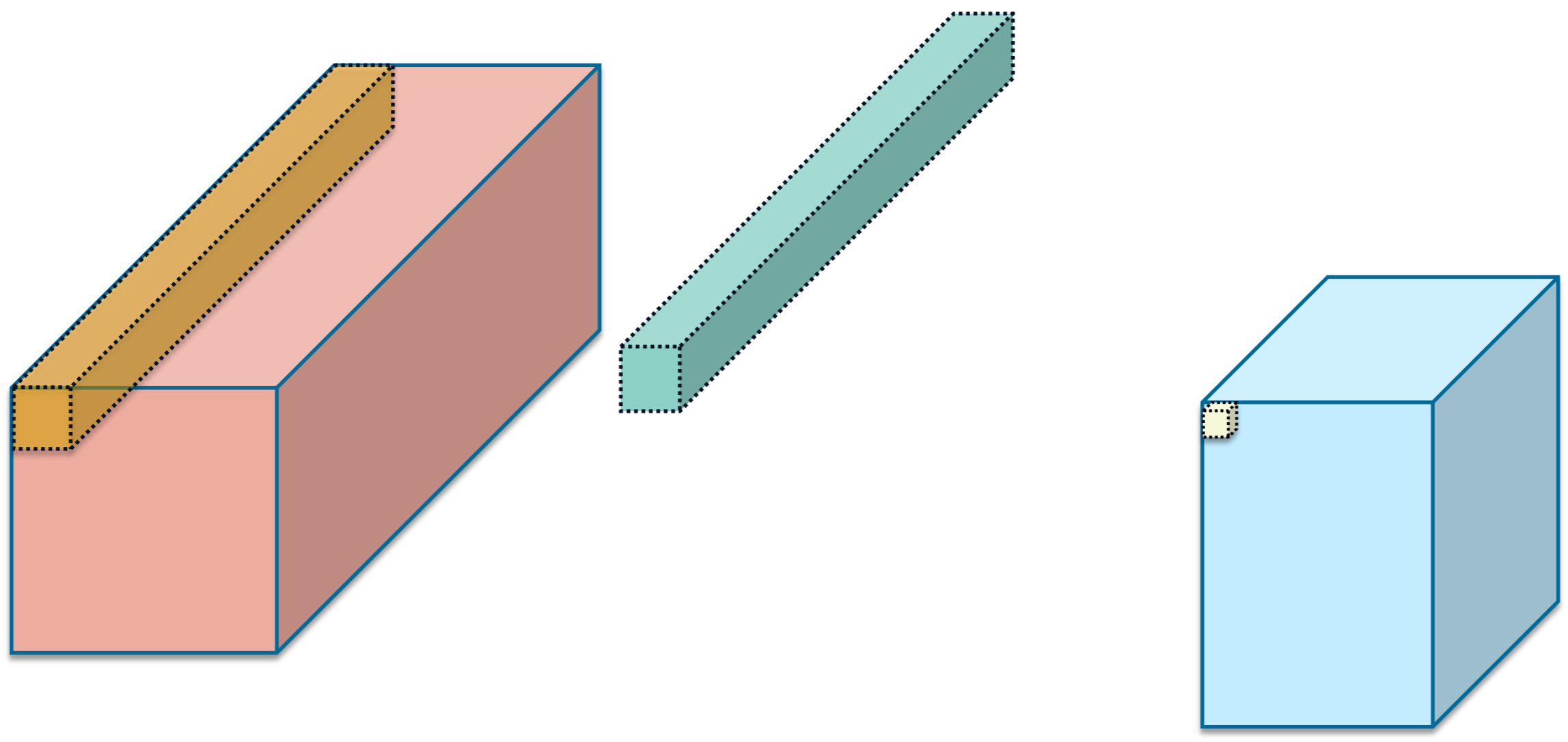
More Channels

Any resolution

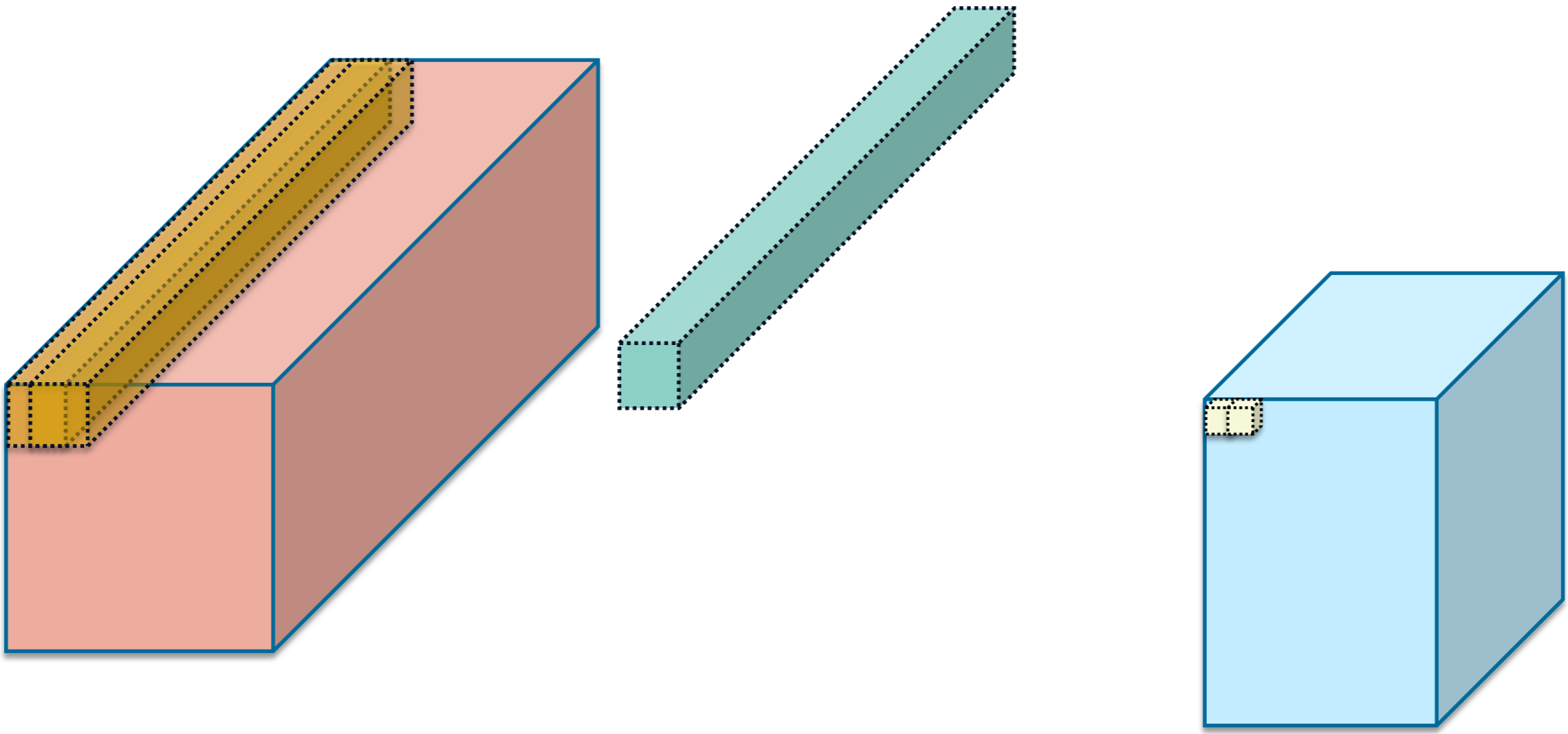
Same resolution

Per-pixel
Prediction

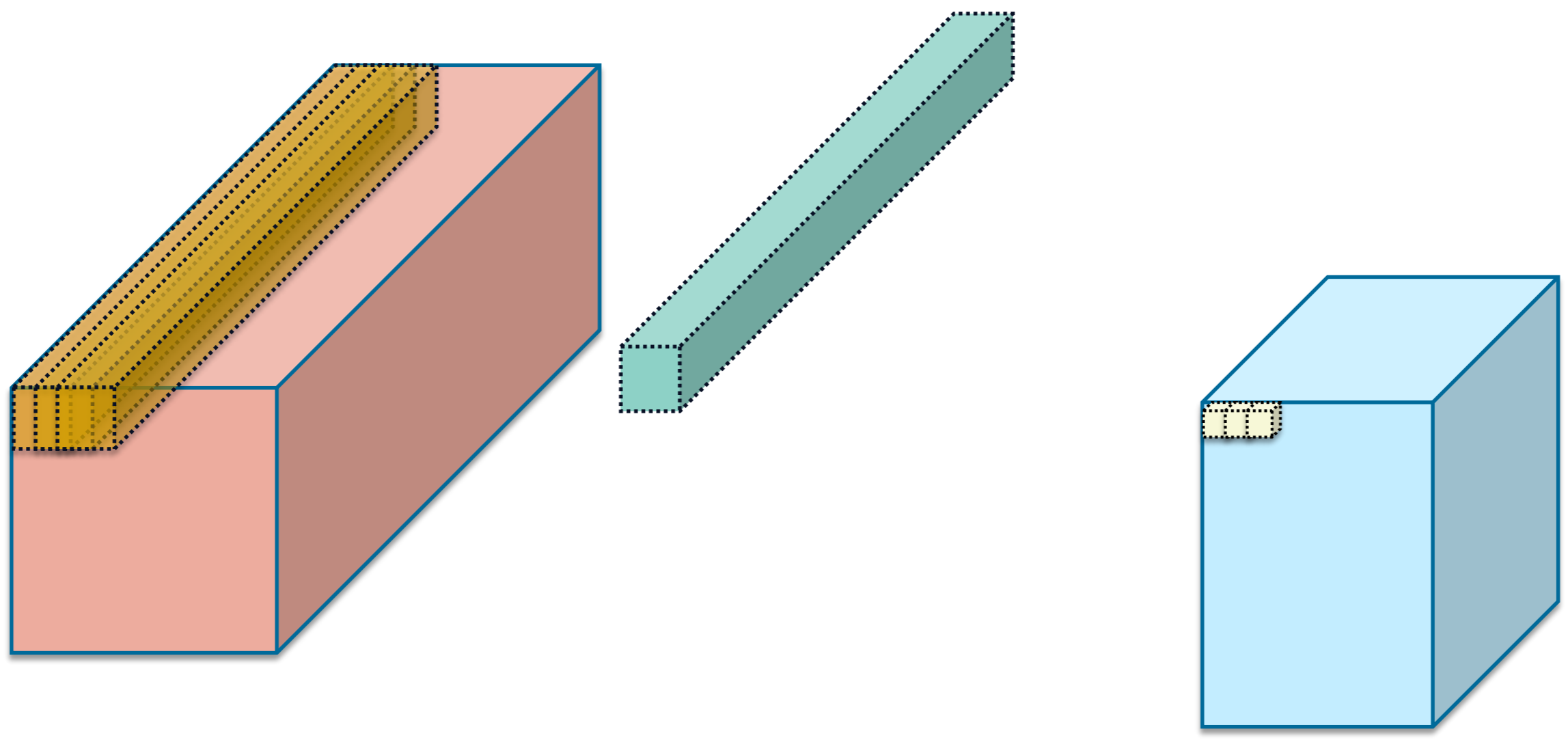
Deep Learning: Convolutional Networks



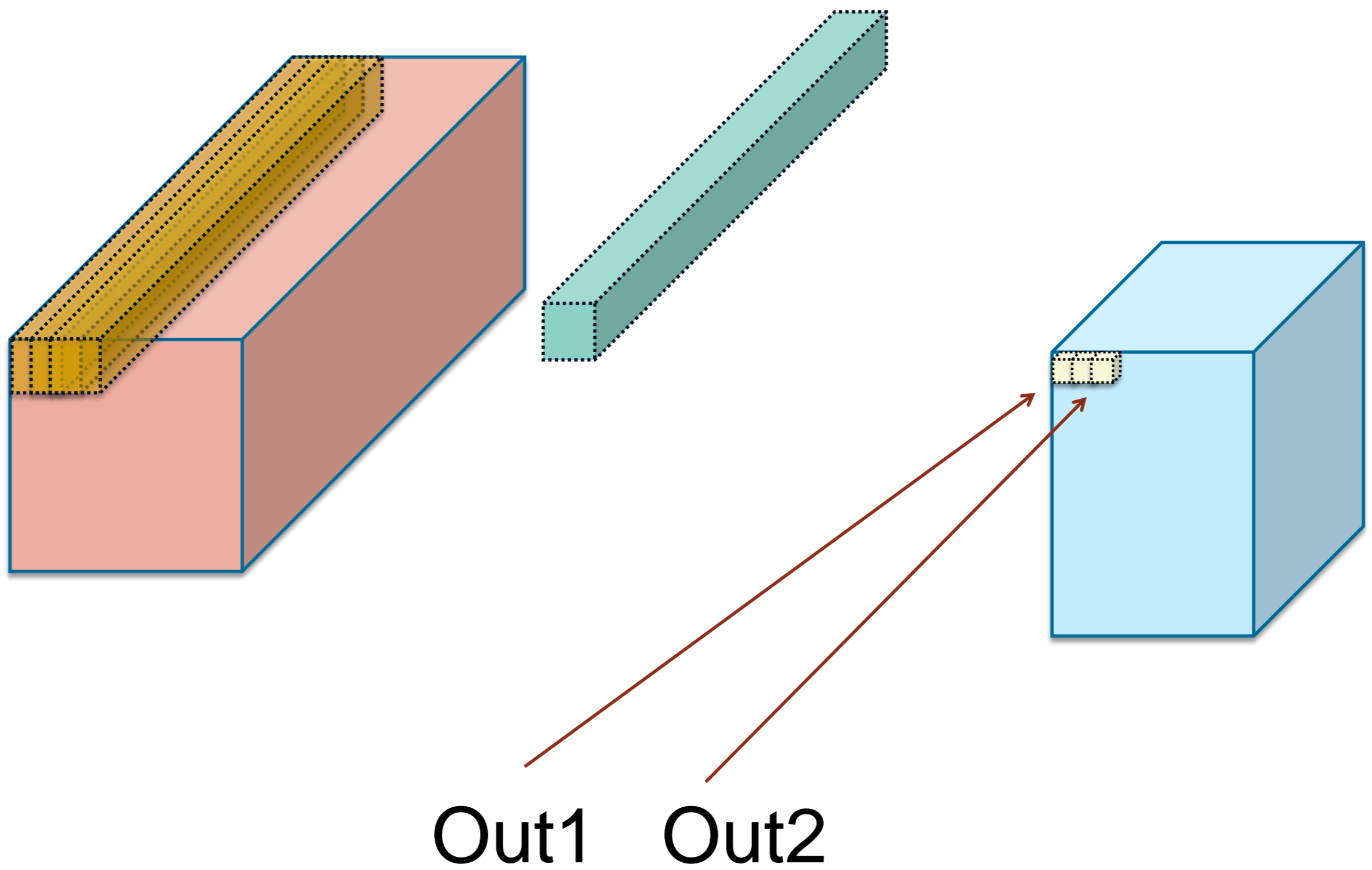
Deep Learning: Convolutional Networks



Deep Learning: Convolutional Networks



Deep Learning: Convolutional Networks



$$\text{Out1} += A_0 \times W_0$$

$$\text{Out1} += A_1 \times W_1$$

$$\text{Out1} += A_2 \times W_2$$

$$\text{Out1} += A_3 \times W_3$$

⋮

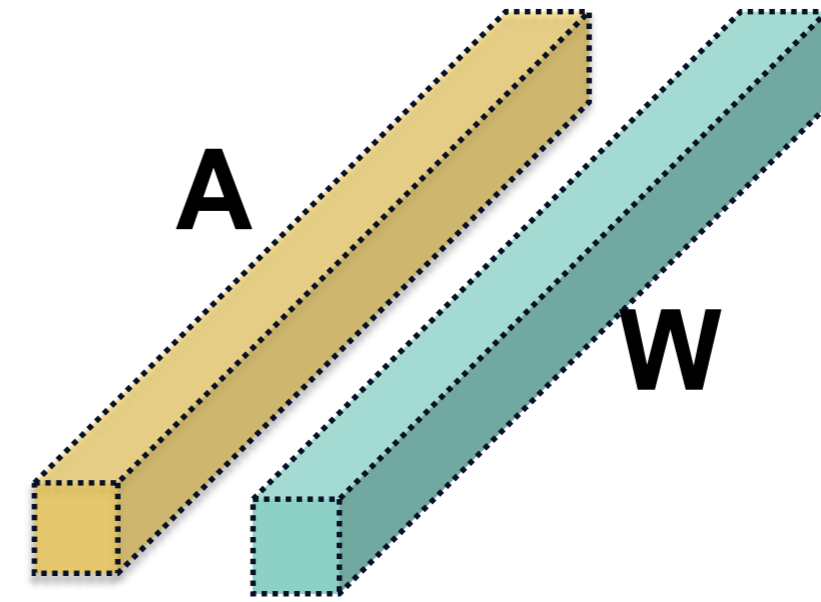
$$\text{Out2} += A'_0 \times W_0$$

$$\text{Out2} += A'_1 \times W_1$$

$$\text{Out2} += A'_2 \times W_2$$

$$\text{Out2} += A'_3 \times W_3$$

⋮



$$\text{Out1} += A_0 \times W_0$$

$$\text{Out2} += A'_0 \times W_0$$

$$\text{Out1} += A_0 \times W_0 = 0110 \times W_0$$

Cost = 2



$$\text{Out2} += A'_0 \times W_0 = 0111 \times W_0$$

Cost = 3

$$\text{Out1} += A_0 \times W_0 = 0110 \times W_0$$

$$\text{Cost} = 2$$

$$\text{Out2} += A'_0 \times W_0 = 0111 \times W_0$$

$$\text{Out2} += \text{Out1} + (A'_0 - A_0) \times W_0$$

$$\text{Out1} += A_0 \times W_0 = 0110 \times W_0$$

$$\text{Cost} = 2$$

$$\text{Out2} += A'_0 \times W_0 = 0111 \times W_0$$

$$\text{Out2} += \text{Out1} + (A'_0 - A_0) \times W_0$$

$$\text{Out2} += \text{Out1} + (0111 - 0110) \times W_0$$

$$\text{Out1} += A_0 \times W_0 = 0110 \times W_0$$

$$\text{Cost} = 2$$

$$\text{Out2} += A'_0 \times W_0 = 0111 \times W_0$$

$$\text{Out2} += \text{Out1} + (A'_0 - A_0) \times W_0$$

$$\text{Out2} += \text{Out1} + (0111 - 0110) \times W_0$$

$$\text{Out2} += \text{Out1} + 0001 \times W_0$$

$$\text{Cost} = 1$$

Pruning and Sparsity

Do as you are told?

$$\text{Out} += A_0 \times W_0$$

$$\text{Out} += A_1 \times W_1$$

$$\text{Out} += A_2 \times W_2$$

$$\text{Out} += A_3 \times W_3$$

$$\text{Out} += A_4 \times W_4$$



Do as you are told?

$$\text{Out} += A_0 \times W_0$$

$$\text{Out} += A_1 \times 0$$

$$\text{Out} += A_2 \times W_2$$

$$\text{Out} += A_3 \times W_3$$

$$\text{Out} += A_4 \times W_4$$

⋮

Do as you are told?

$$\text{Out} += A_0 \times W_0$$

$$\text{Out} += A_2 \times W_2$$

$$\text{Out} += A_3 \times W_3$$

$$\text{Out} += A_4 \times W_4$$

⋮

Do as you are told?

$$\text{Out} += A_0 \times W_0$$

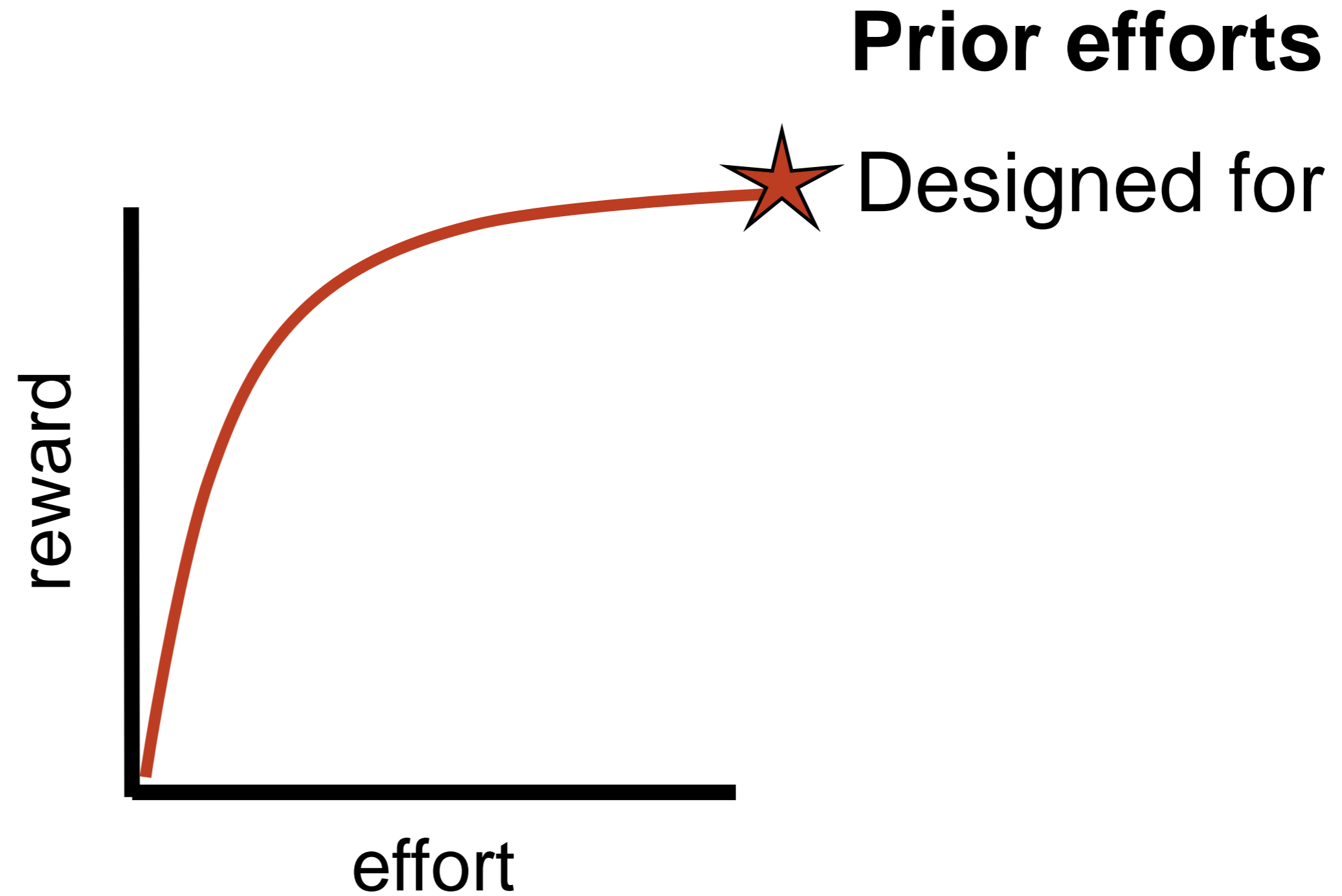
$$\text{Out} += A_2 \times W_2$$

$$\text{Out} += A_3 \times W_3$$

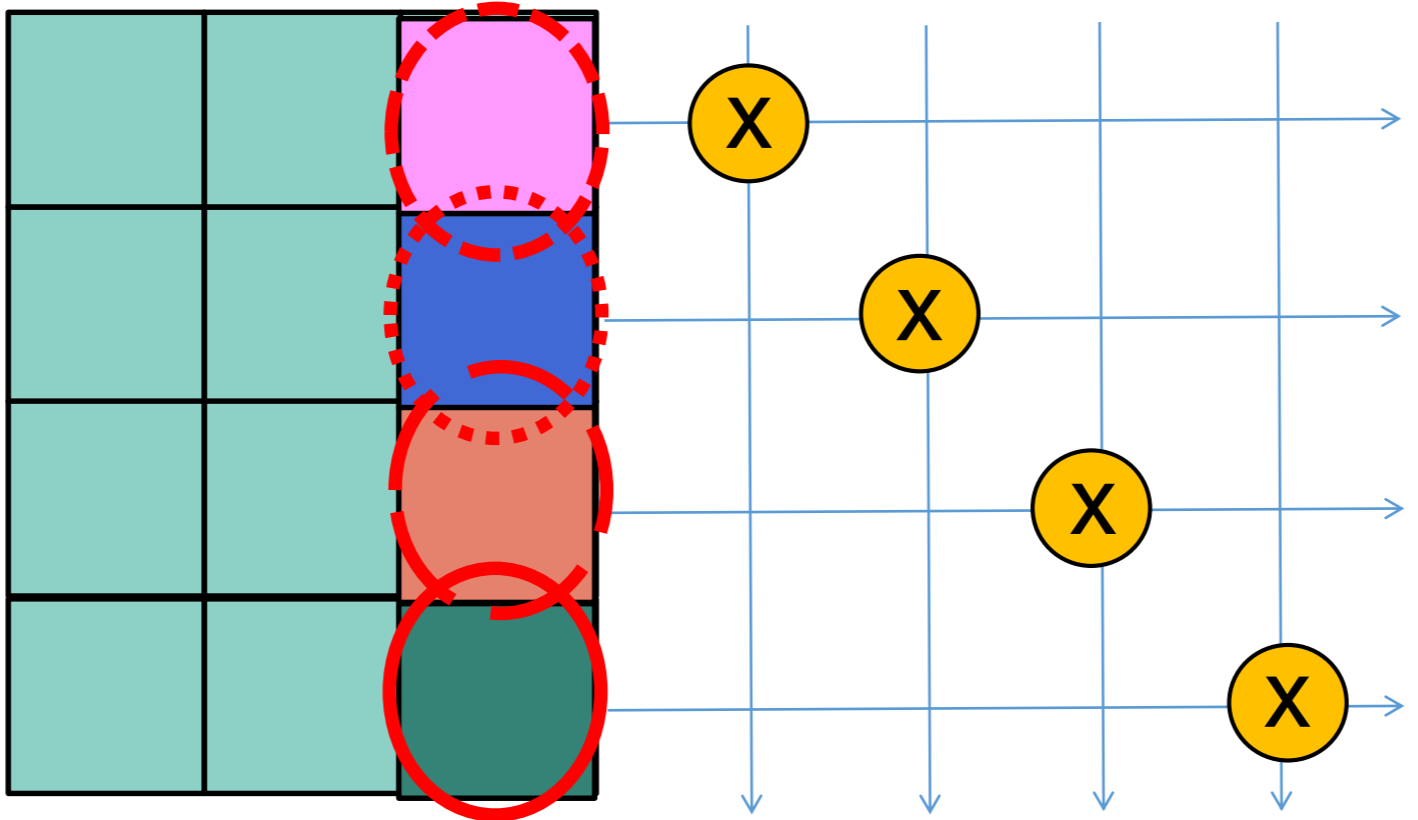
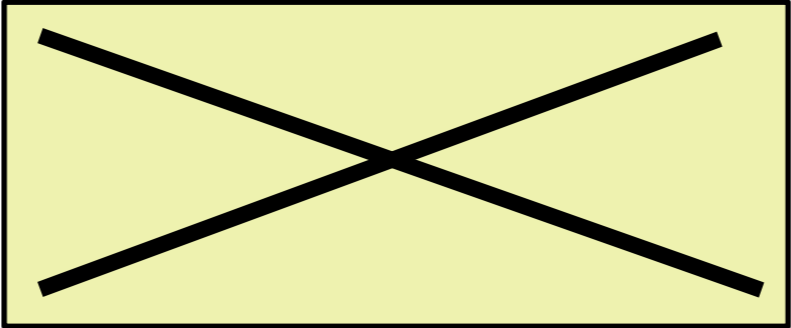
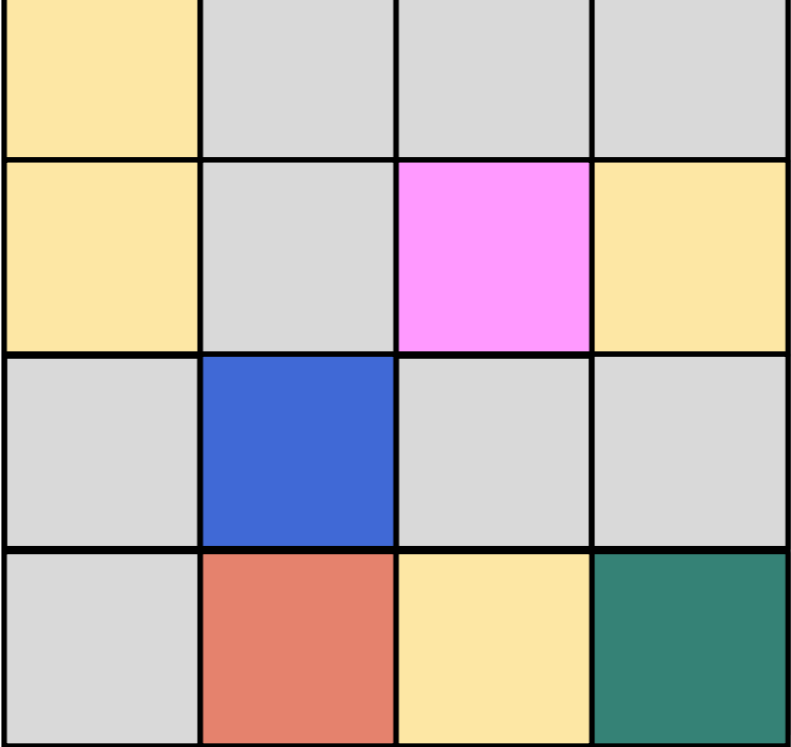
$$\text{Out} += A_4 \times W_4$$

⋮

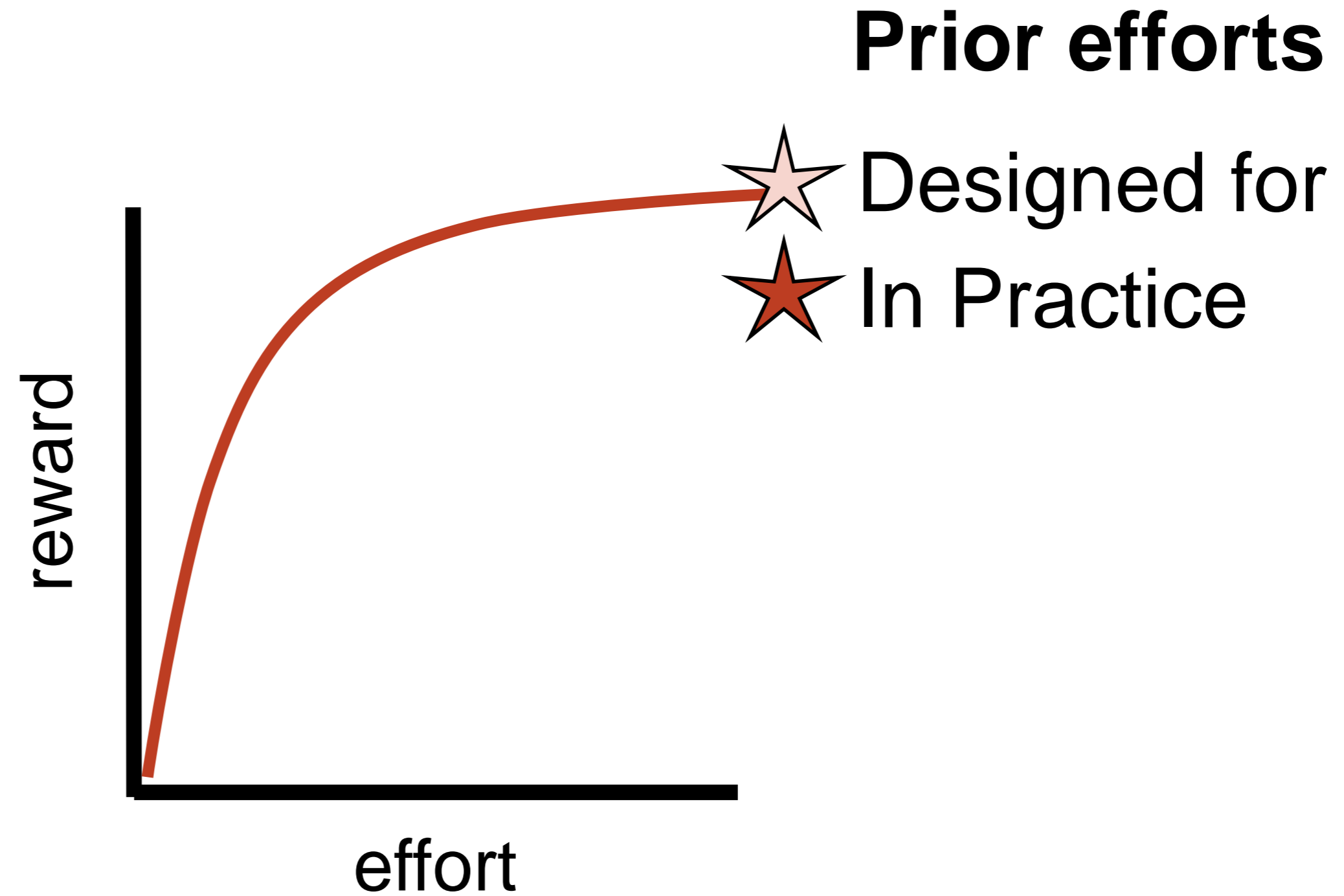
Removing Zero Weights



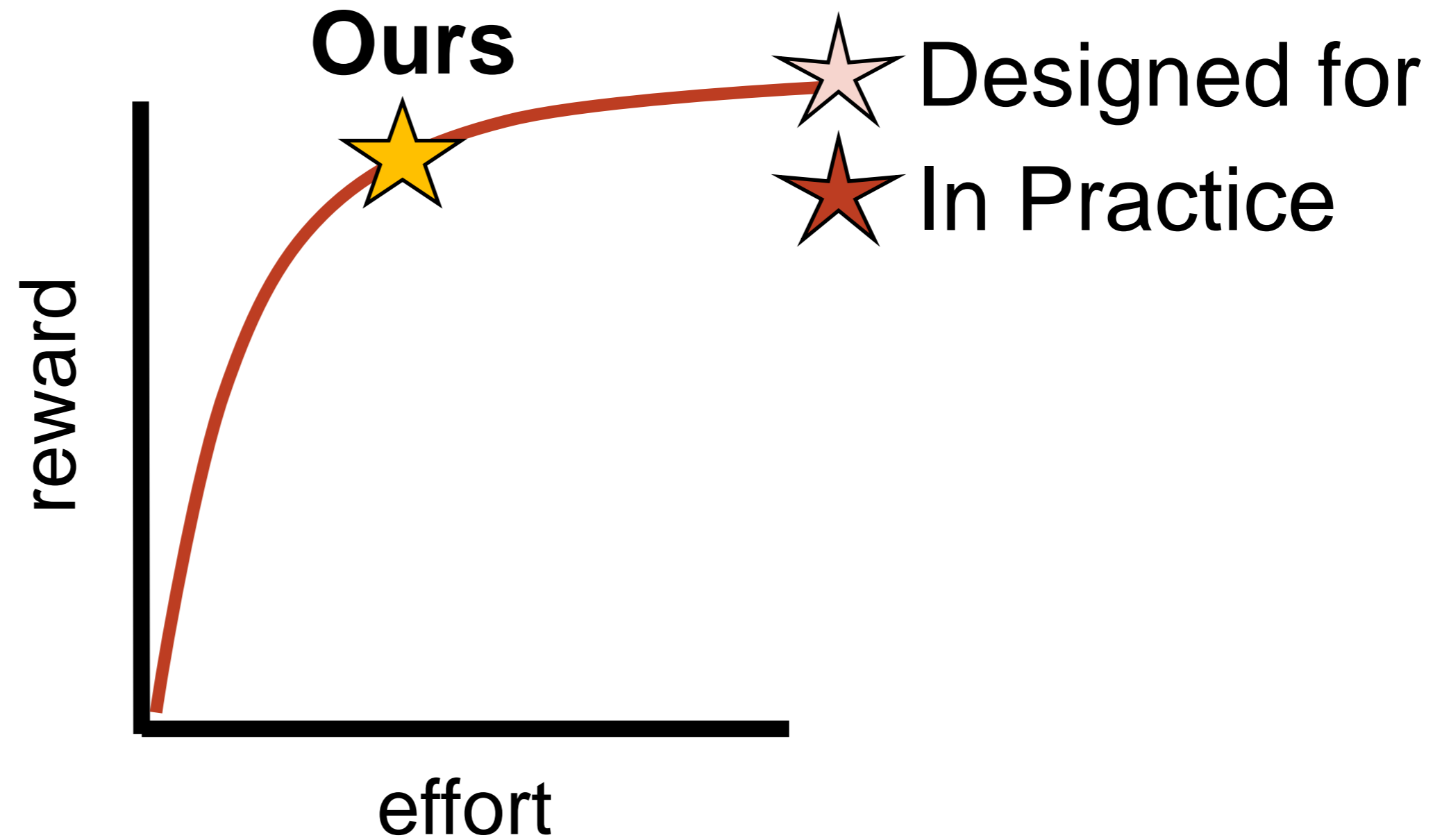
Cambricon-X



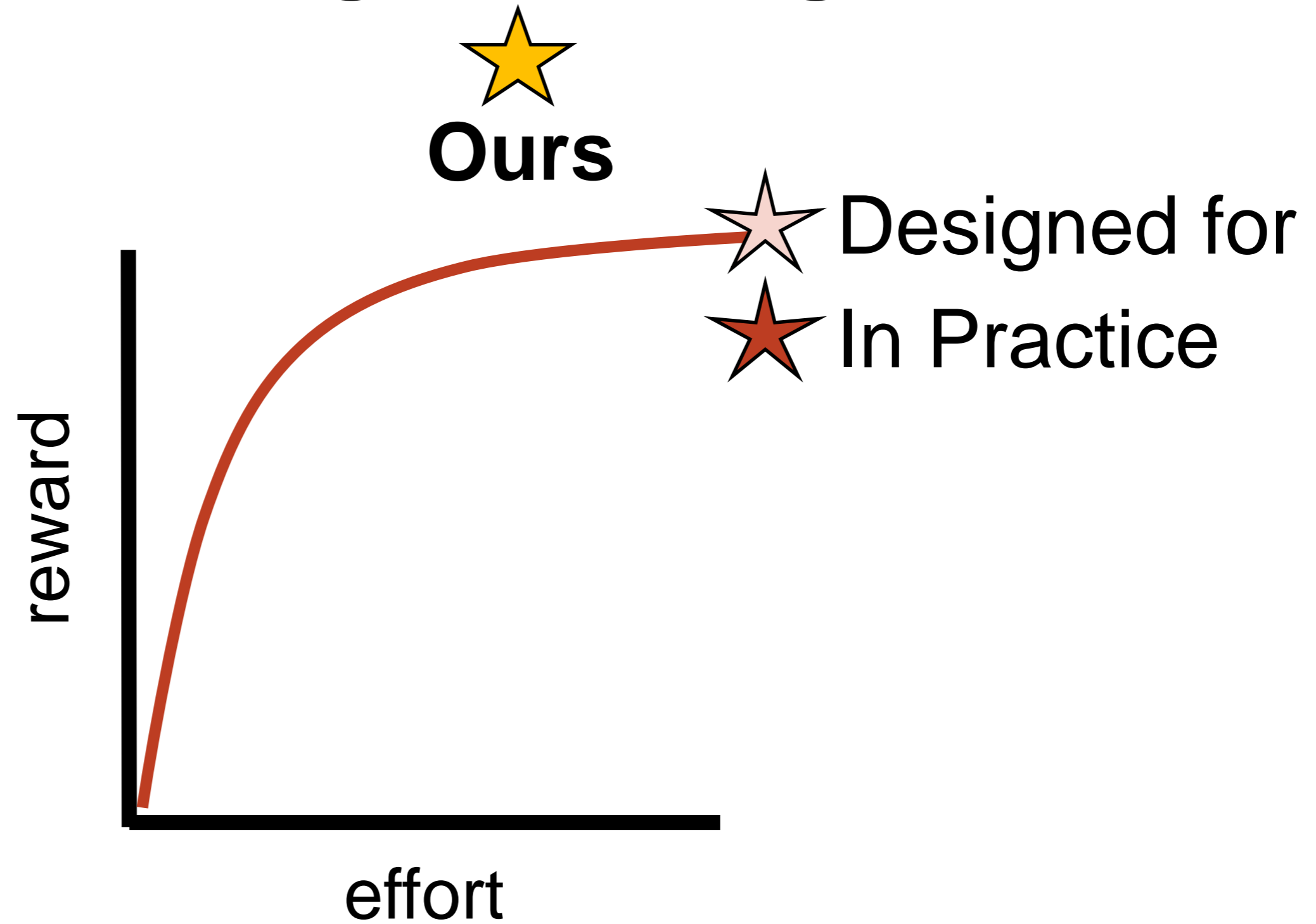
Removing Zero Weights



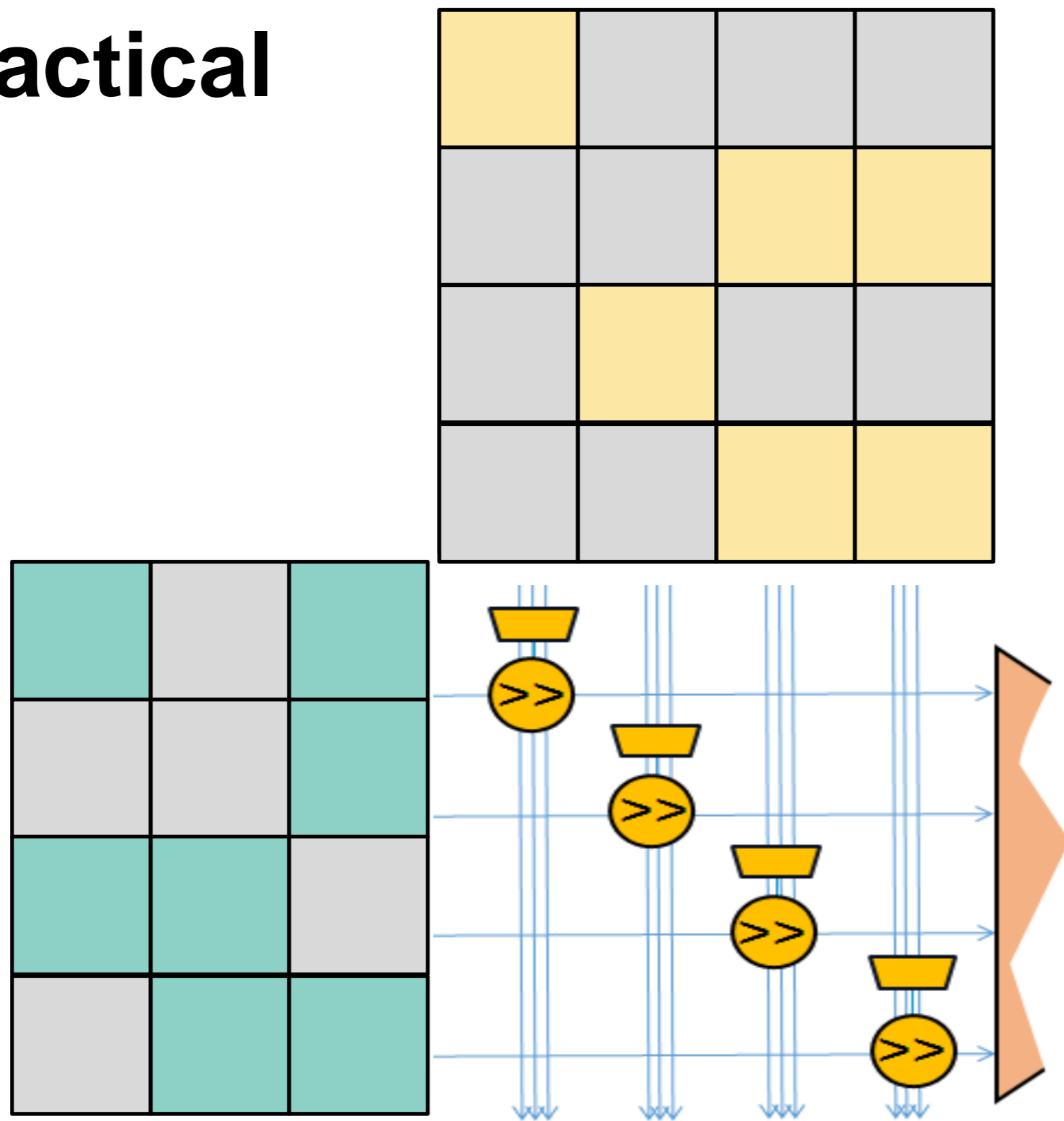
Removing Zero Weights



Removing Zero Weights



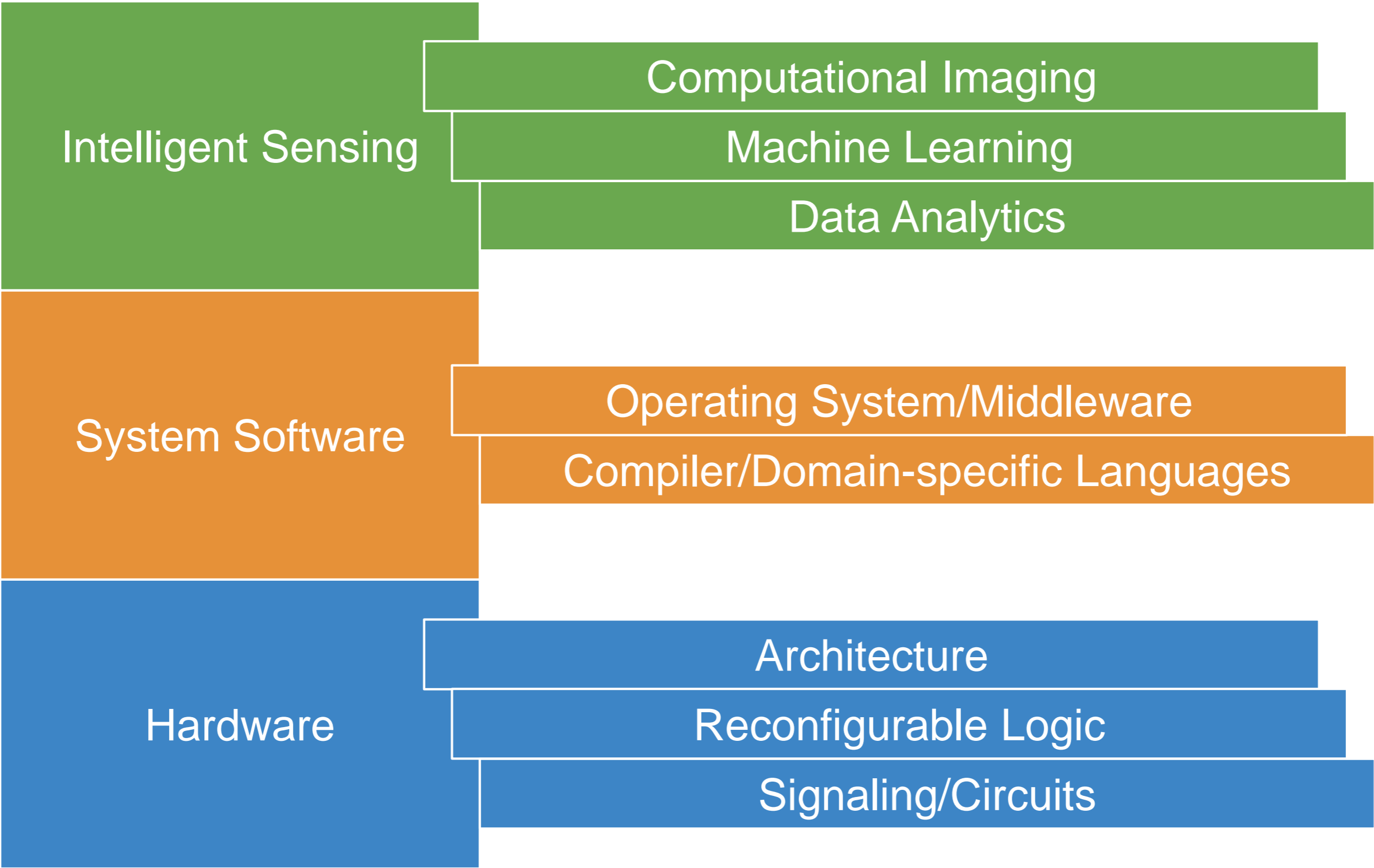
Bit-Tactical

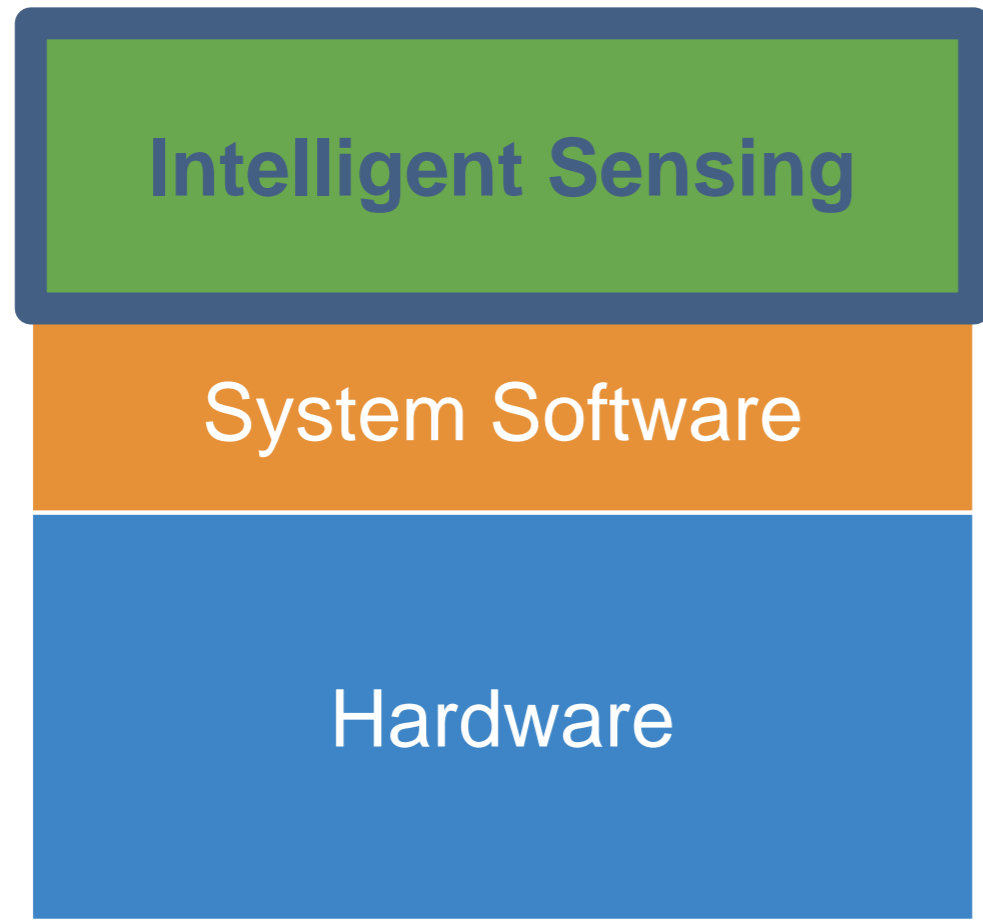


- We build tools
- Used by “everyone” for “everything”
- Science, medicine, commerce, ...





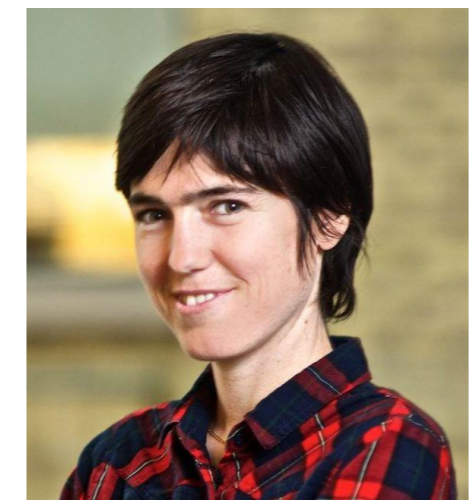




Sanja Fidler



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Raquel Urtasun



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