Efficient Machine Learning Model Design

Techniques for Fast Inference

ML4FP
2024
Lawrence Berkeley National Lab

Elham E Khoda
San Diego Supercomputing Center, UCSD

Machine Learning for Fundamental Physics School 2024

August 15, 2024

UC San Diego

SDSC
SAN DIEGO SUPERCOMPUTER CENTER

JupyterHub Access

We will use a different Jupyterhub for this session!

JupyterHub access (for efficient_ml tutorial)

- Join hls4ml-tutorial GitHub Organization (check your email for invite)
- Your should be able to see yourself here: https://github.com/orgs/hls4ml-tutorial/people

JupyterHub link

- Open https://tutorials.fastmachinelearning.org in your web browser
- Authenticate with your GitHub account (login if necessary)

Lecture Outline

Motivation behind efficient model design and some highlights

Introduction to Quantization
- Definition
- PTQ vs QAT

Introduction to Pruning
- What is pruning? How to formulate pruning?
- Determine pruning granularity and criteria
- Network performance after pruning

ML on FPGA

hls4ml and Trigger applications

Lecture Outline

Motivation behind efficient model design and some highlights

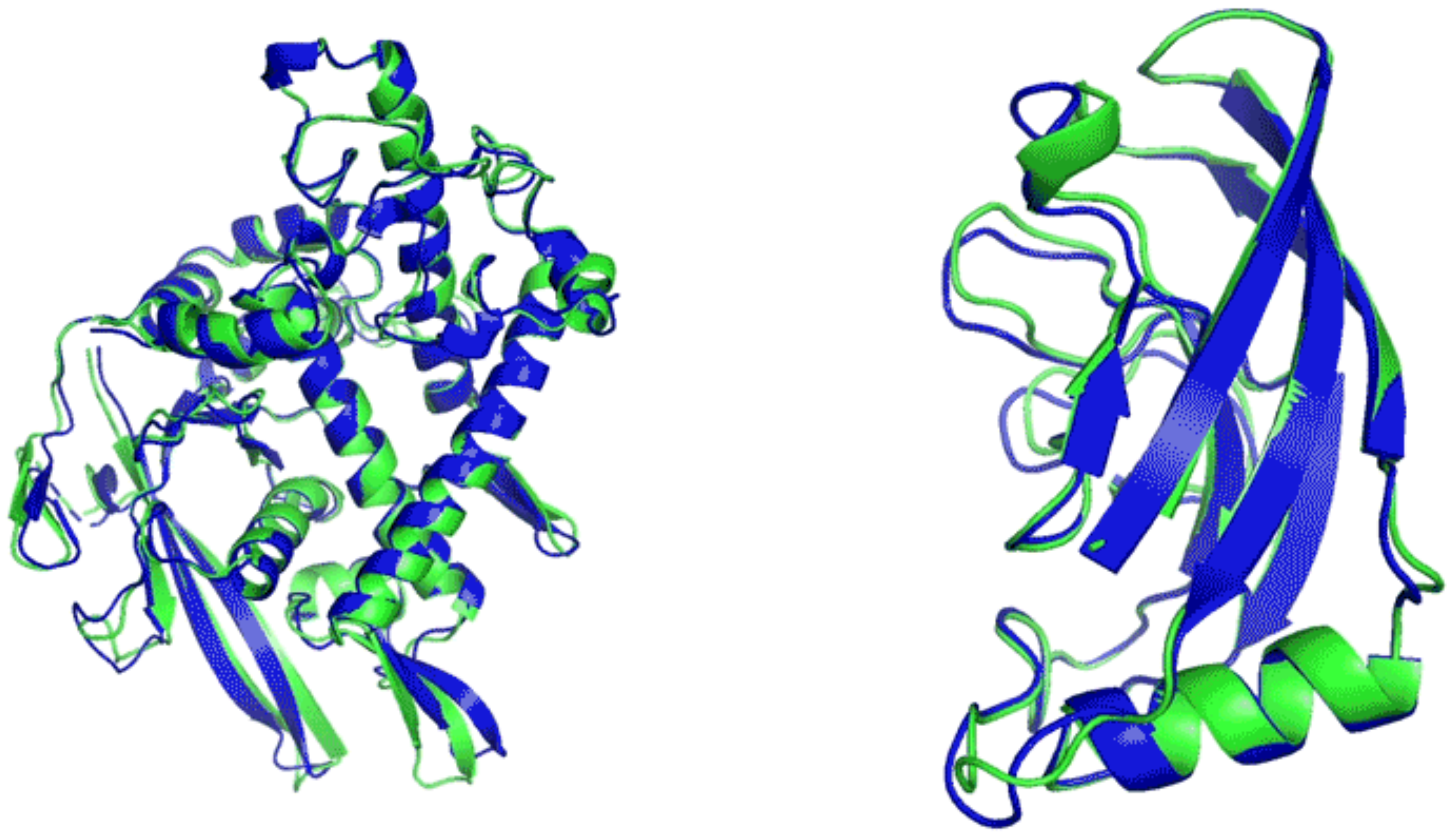
Introduction to Quantization
- Definition
- PTQ vs QAT

Introduction to Pruning
- What is pruning? How to formulate pruning?
- Determine pruning granularity and criteria
- Network performance after pruning

ML on FPGA

hls4ml and Trigger applications

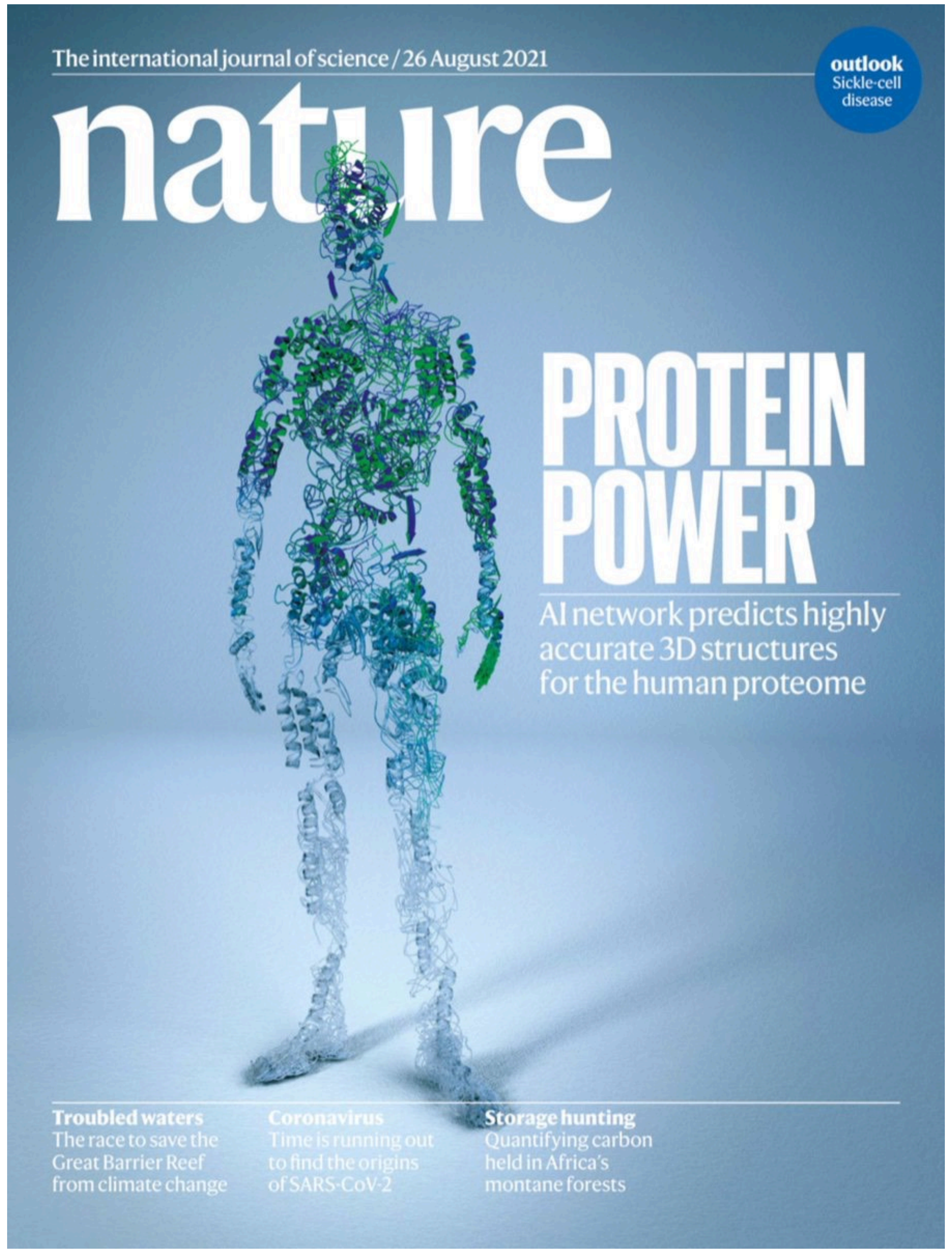
Large Models are everywhere



T1037 / 6vr4
90.7 GDT
(RNA polymerase domain)

T1049 / 6y4f
93.3 GDT
(adhesin tip)

● Experimental result
● Computational prediction



Article
Highly accurate protein structure prediction with AlphaFold

Large Language Models: GPT

what do you know about the Machine Learning for Fundamental Physics School 2024 at LBNL?

Searched 4 sites

The Machine Learning for Fundamental Physics (ML4FP) School 2024 is taking place from August 12 to 16, 2024, at Lawrence Berkeley National Laboratory (LBNL). The program is designed to offer in-depth training on applying machine learning techniques to problems in fundamental physics. This event follows successful similar programs in recent years and is open to participants from the particle physics community, both in-person and virtually.

The curriculum includes a mix of lectures, hands-on tutorials, and interactive sessions, focusing on areas such as anomaly detection, generative models, likelihood-free inference, and physics-aware learning. The school aims to enhance interdisciplinary collaboration by bringing together experts and students in both machine learning and physics.

Additionally, resources such as Jupyter notebooks and learning materials used during the school are publicly available via GitHub, allowing participants and others interested to explore the content in their own time (Berkeley Lab Physics Division (Indico)) (GitHub) (LBL Physics).

Searched 4 sites

- "Machine Learning for Fundamental Physics School 2024 LBNL"
  bing.com
- Berkeley Lab Physics Division (Indico) — Machine Learning for Fundamental Physics School 2024...
  indico.physics.lbl.gov
- GitHub — GitHub - ml4fp/2024-lbnl: This repository contains all the notebooks used for the Machi...
  github.com
- LBL Physics — Machine Learning for Fundamental Physics
  physics.lbl.gov

Example of GPT-4 visual input:

User: What is funny about this image? Describe it panel by panel.

Source: https://www.reddit.com/r/hmmm/comments/ubab5v/hmmm/

GPT-4: The image shows a package for a "Lightning Cable" adapter with three panels.

Panel 1: A smartphone with a VGA connector (a large, blue, 15-pin connector typically used for computer monitors) plugged into its charging port.

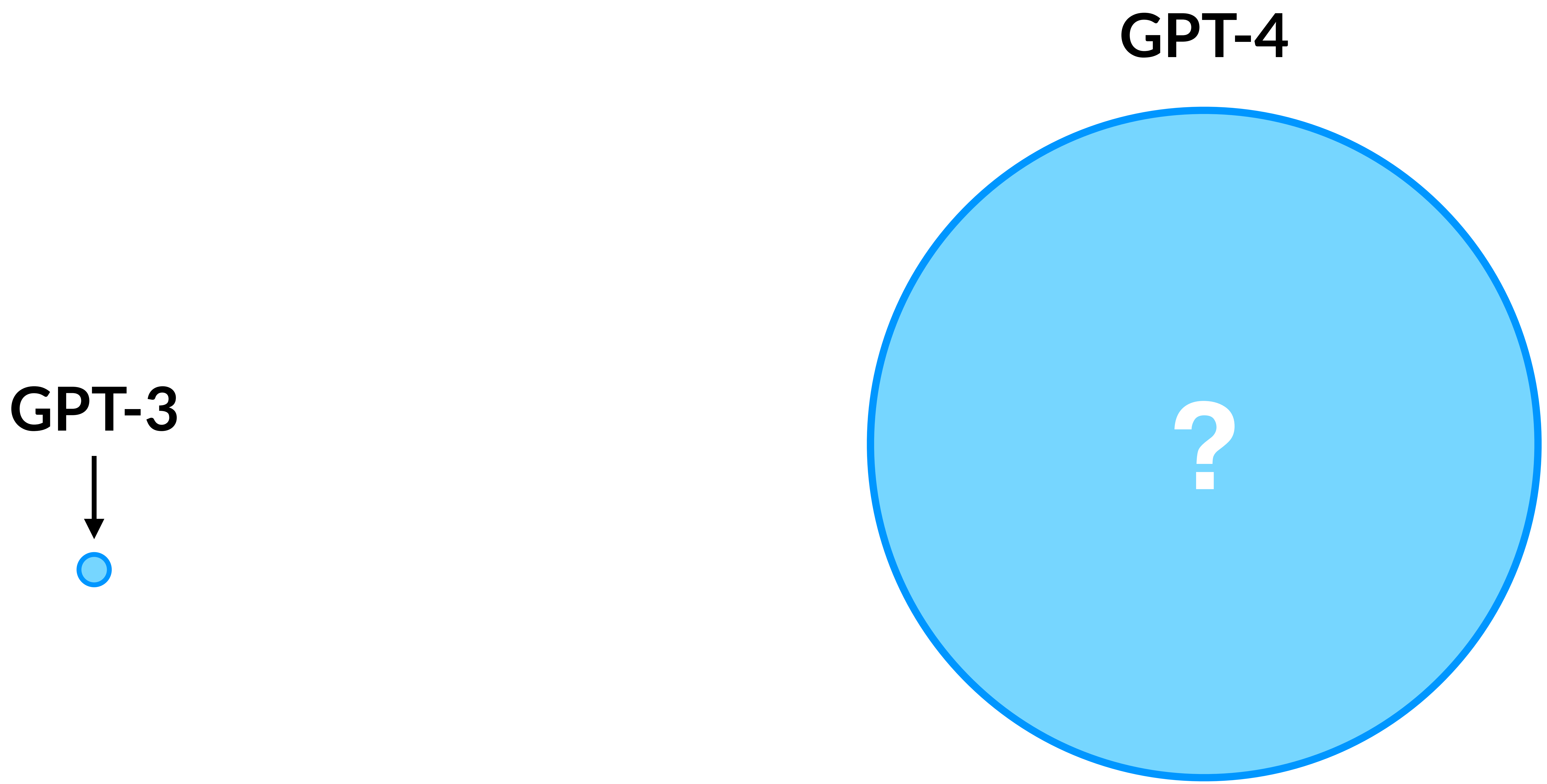
Panel 2: The package for the "Lightning Cable" adapter with a picture of a VGA connector on it.

Panel 3: A close-up of the VGA connector with a small Lightning connector (used for charging iPhones and other Apple devices) at the end.

The humor in this image comes from the absurdity of plugging a large, outdated VGA connector into a small, modern smartphone charging port.

Table 3. Example prompt demonstrating GPT-4's visual input capability. The prompt consists of a question about an image with multiple panels which GPT-4 is able to answer.

Large Language Models



175,000,000,000

~0.16% of parameters of your brain

100,000,000,000,000

Almost all the neurons in your brain?

GPT-3 Training and Inference

GPT-3 Training
- 285, 000 CPUs
- 10,000 GPUs
- 400 Gbits/sec network
- Several weeks

Inference: *Asking Question to ChatGPT*

You
How many GPUs are you using currently?

ChatGPT
As an AI language model, I don't have access to real-time information about my current computational resources or the infrastructure being used to host me. My availability and performance are managed by OpenAI's servers, which may utilize GPUs or other computational resources based on demand and system configuration. Therefore, I cannot provide information on the number of GPUs currently being used.

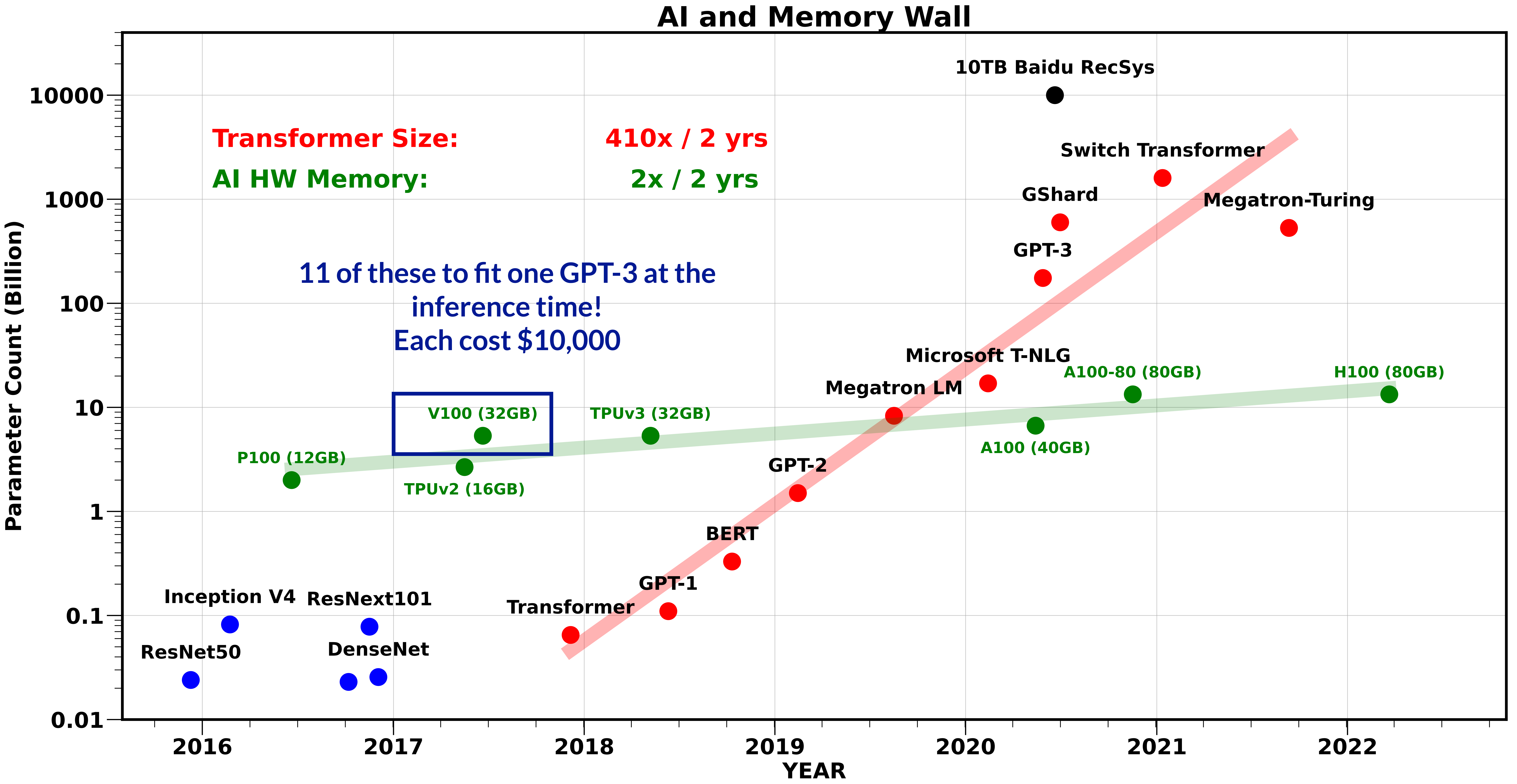
GPT-3: *10x larger than max memory in a single Nvidia A100 GPU*

Millions of queries daily

1 GWh each day ≈ 33,000 U.S. households

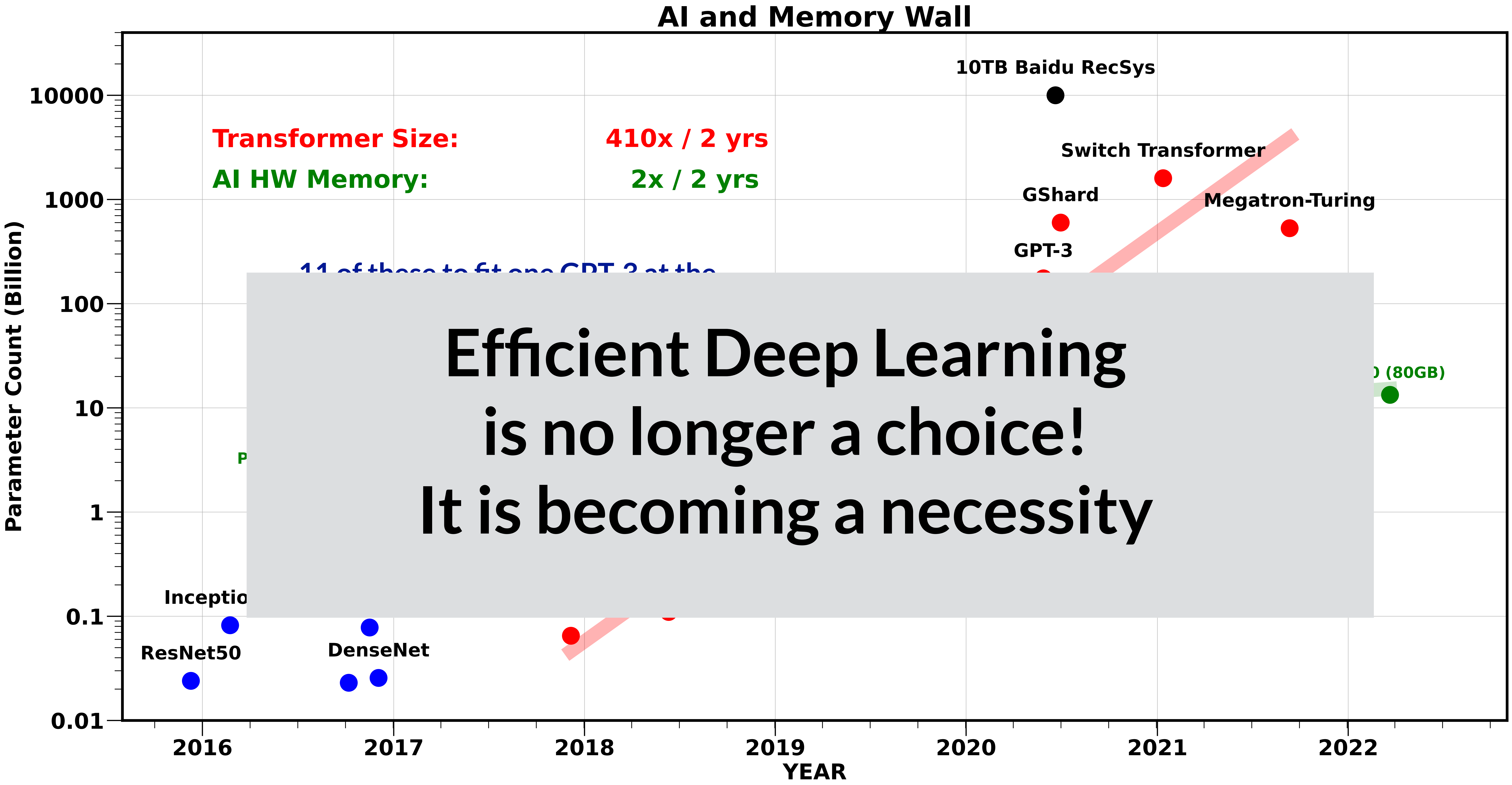
Nvidia Blog

AI and Memory Wall



Medium blog: AI and Memory Wall

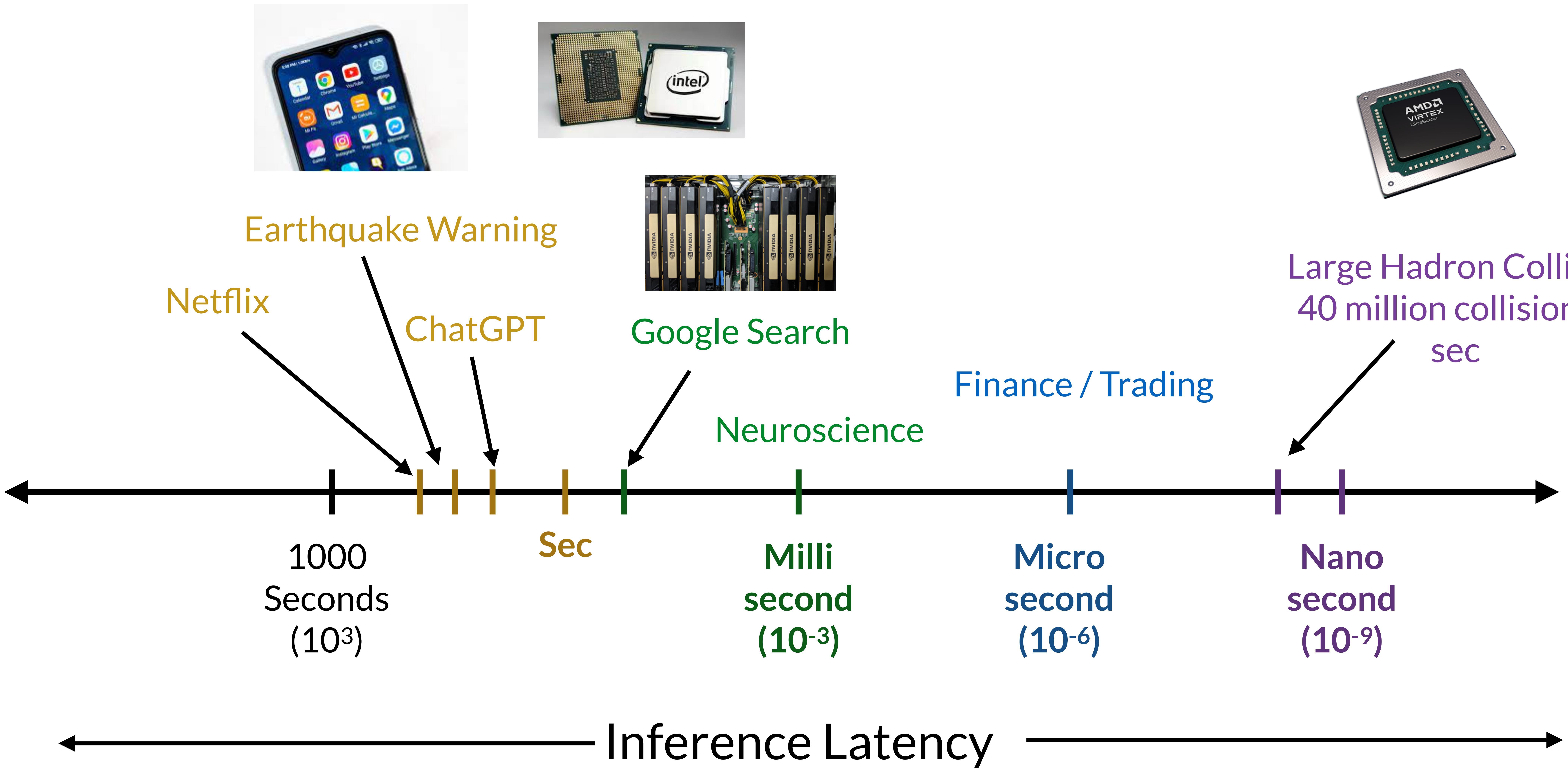
AI and Memory Wall



Efficient Deep Learning
is no longer a choice!
It is becoming a necessity

[Medium blog: AI and Memory Wall]

Machine Learning Inference



Computing Hardware

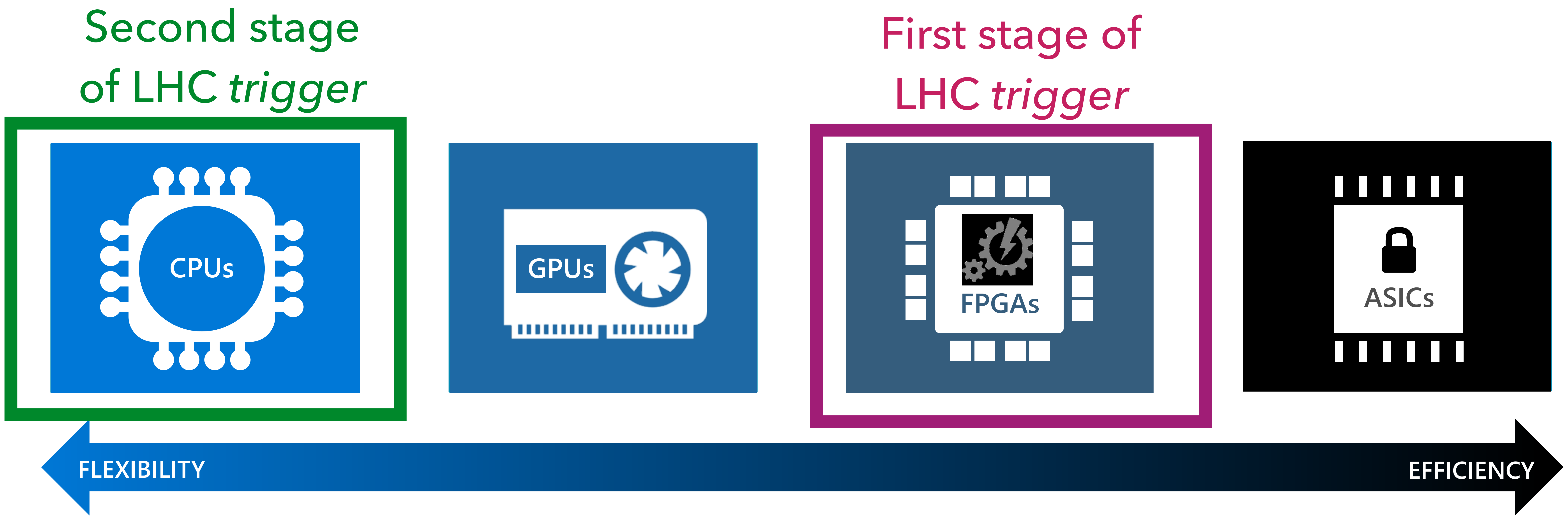
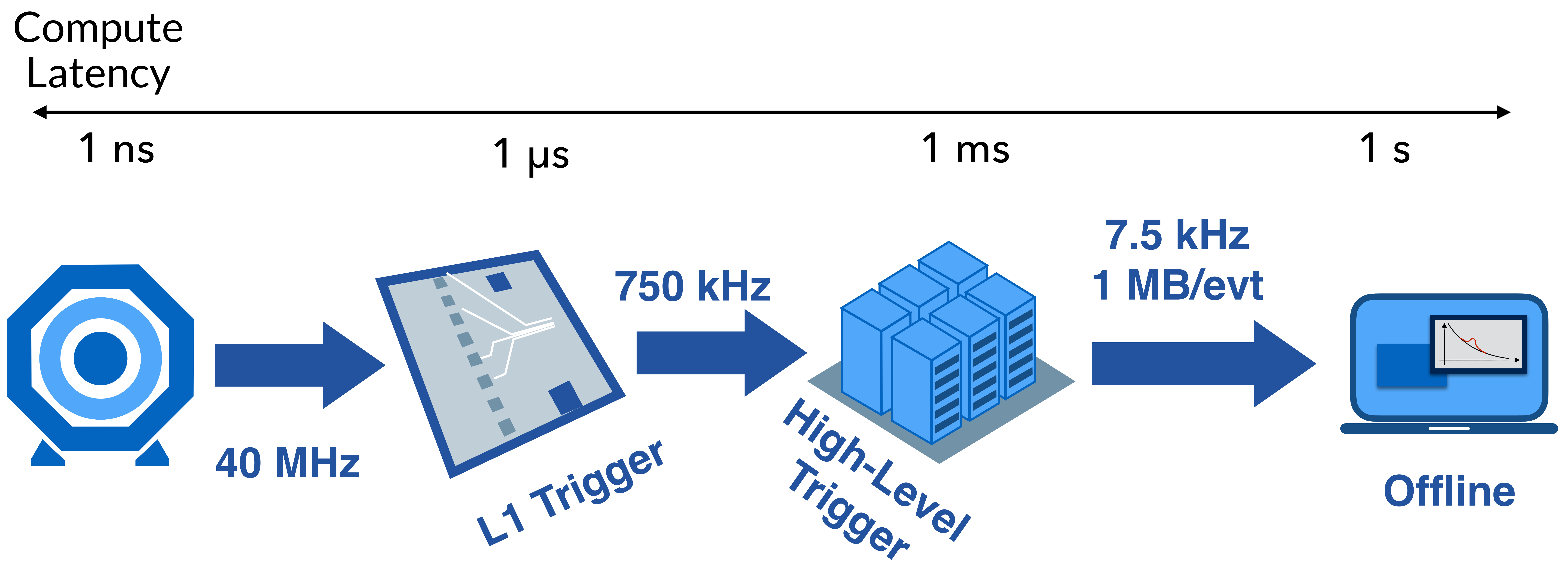


Image: [Microsoft]

HL-LHC Data Processing



ASICs

FPGAs

CPUs
GPUs
FPGAs
Other processors:
IPU, TPU ..

CPUs
GPUs
FPGAs
Other processors:
IPU, TPU ..

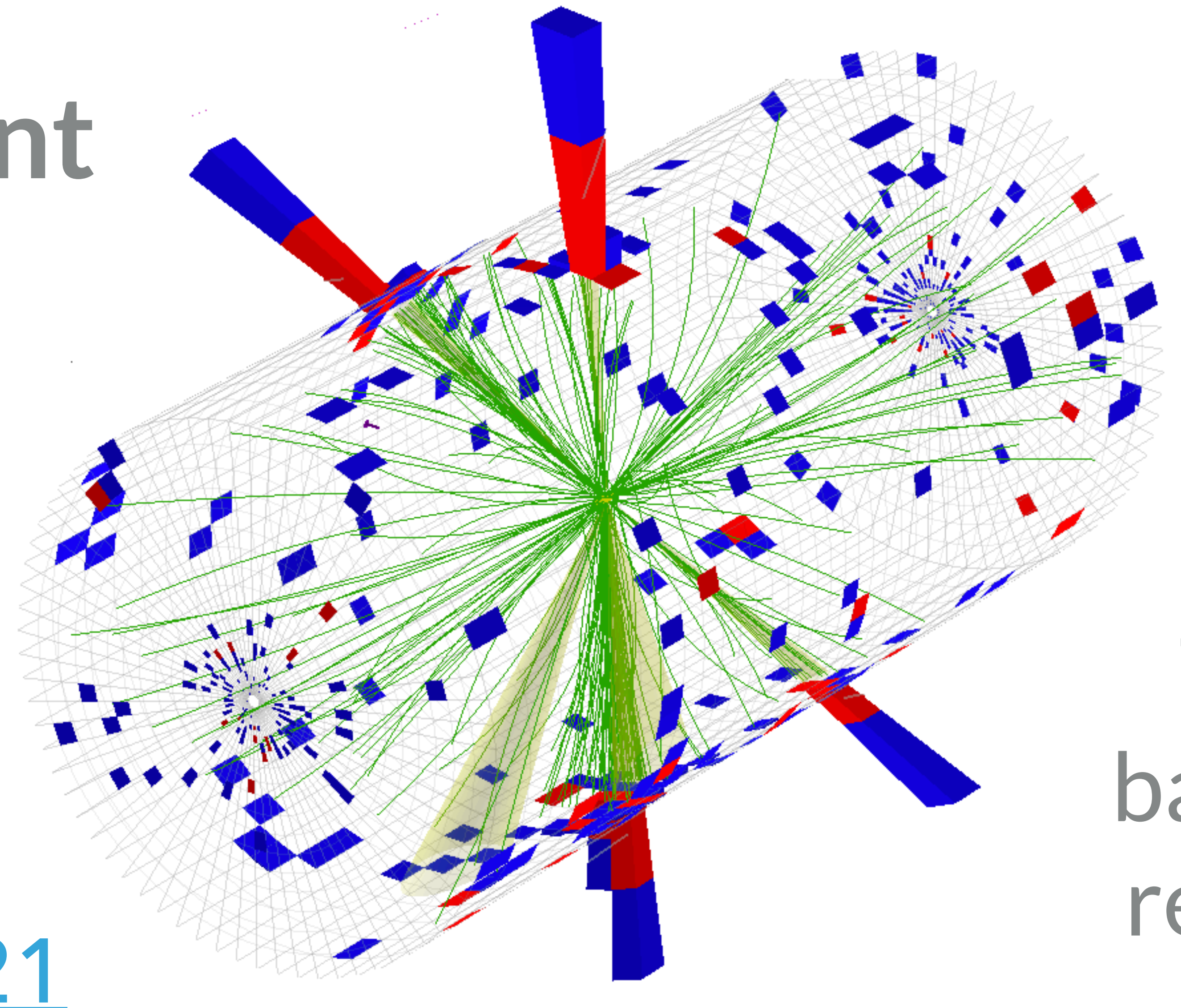
Exabyte-scale datasets

Challenges:
Each collision produces $O(10^3)$ particles
The detectors have $O(10^8)$ sensors
Extreme data rates of O(100 TB/s)

Simplified HL-LHC Trigger

- Single/double/triple muons/electrons
- Photons
- Taus
- Hadronic
- Missing transverse energy
- "Cross" triggers (not shown)

4-jet event



CMS-TDR-021

Thresholds set by backgrounds, limited resolution @ L1, and rate budget

Trigger	Threshold [GeV]
1 μ	22
2 μ	15, 7
3 μ	5, 3, 3
1 e	36
2 e	25, 12
1 γ	36
2 γ	22, 12
1 τ	150
2 τ	90, 90
1 jet	180
2 jet	112, 112
H_T	450
4 jet + H_T	75, 55, 40, 40, 400
p_T^{miss}	200

What could be missing?

- How can we trigger on more complex low-energy hadronic signatures? Long-lived/displaced particles?
- What if we don't know exactly what to look for?
- What if our signatures require complex multivariate algorithms (e.g. b tagging)?
- How can we improve on our traditional (often slow) reconstruction algorithms?

SUEP

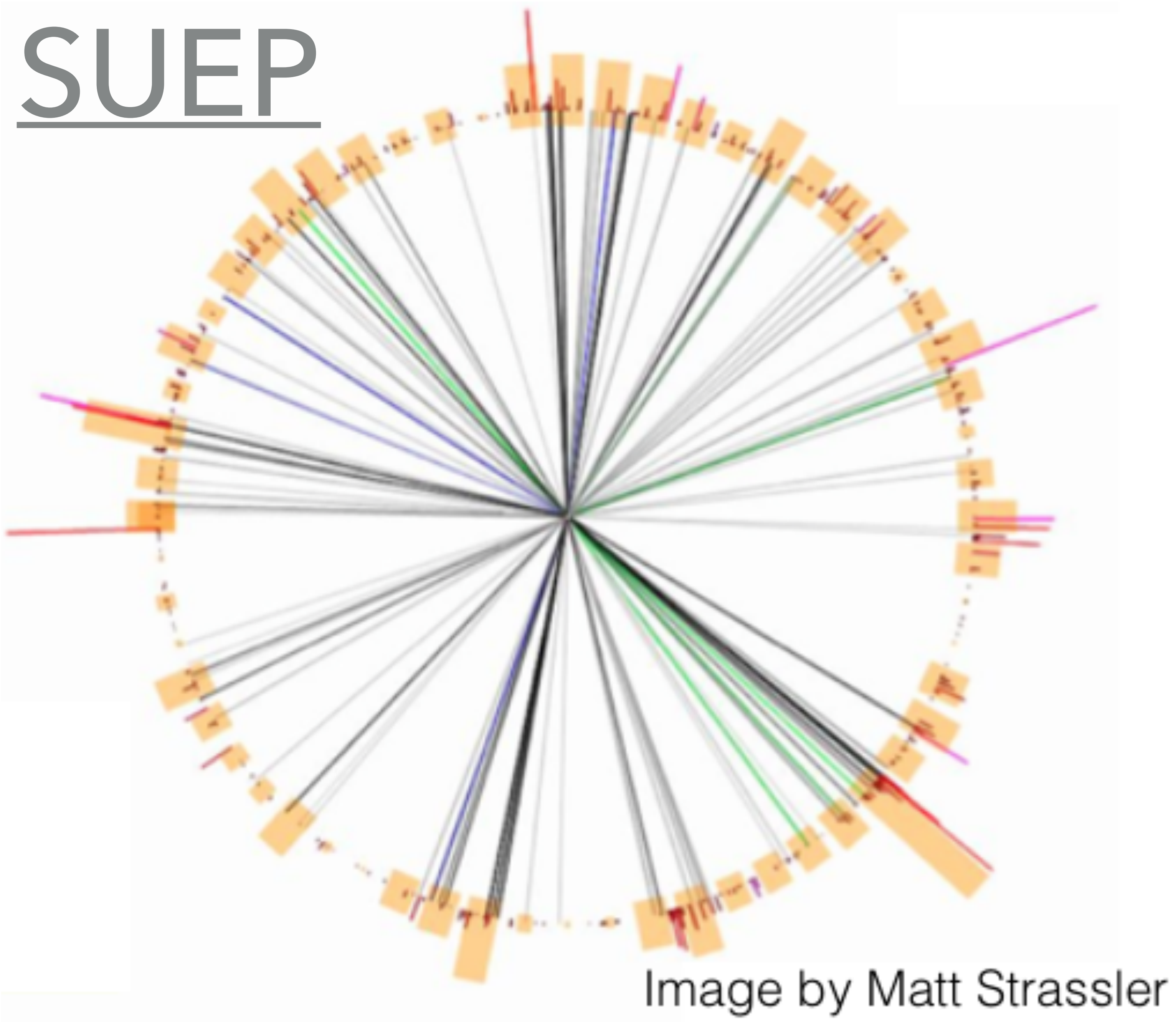
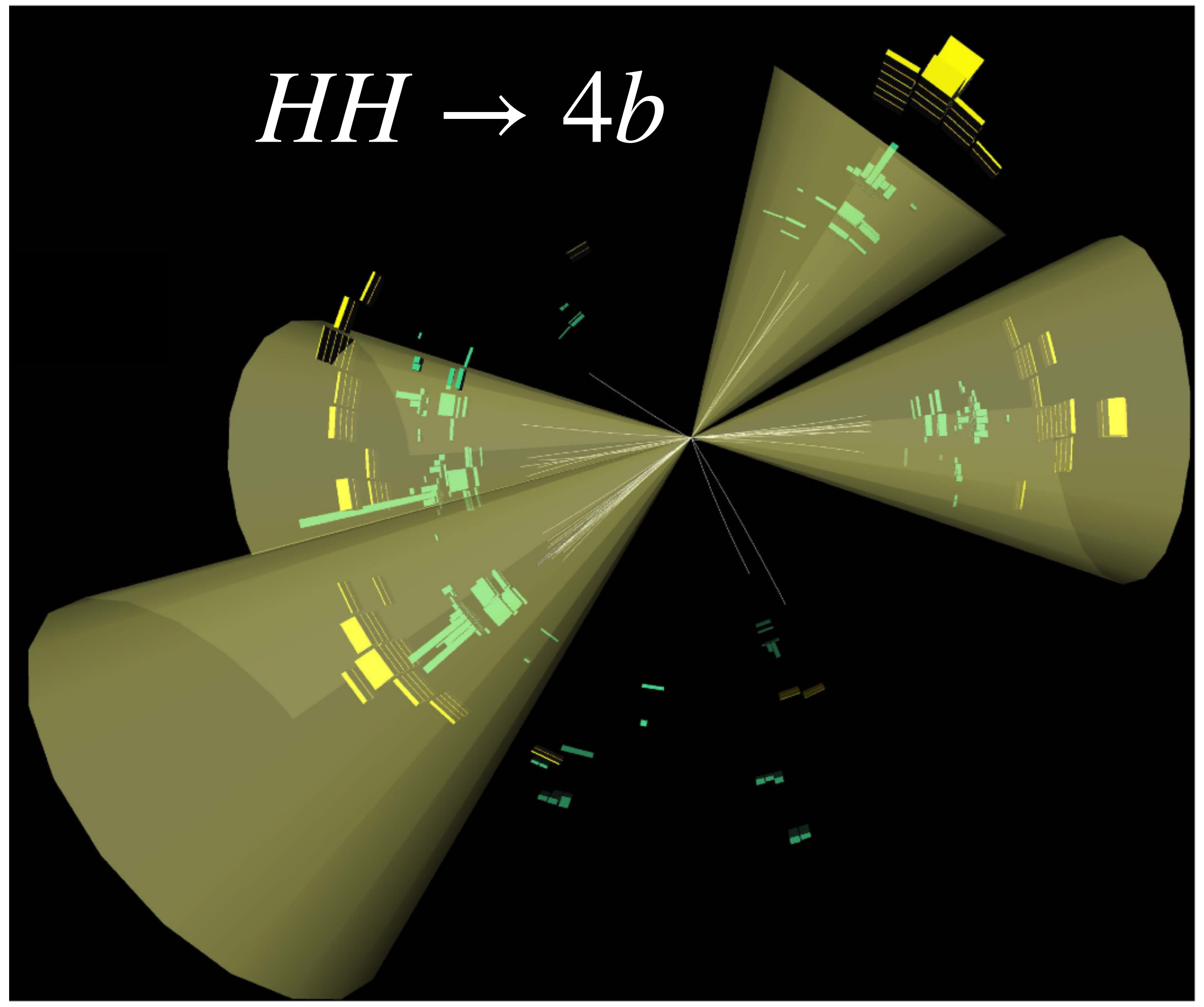
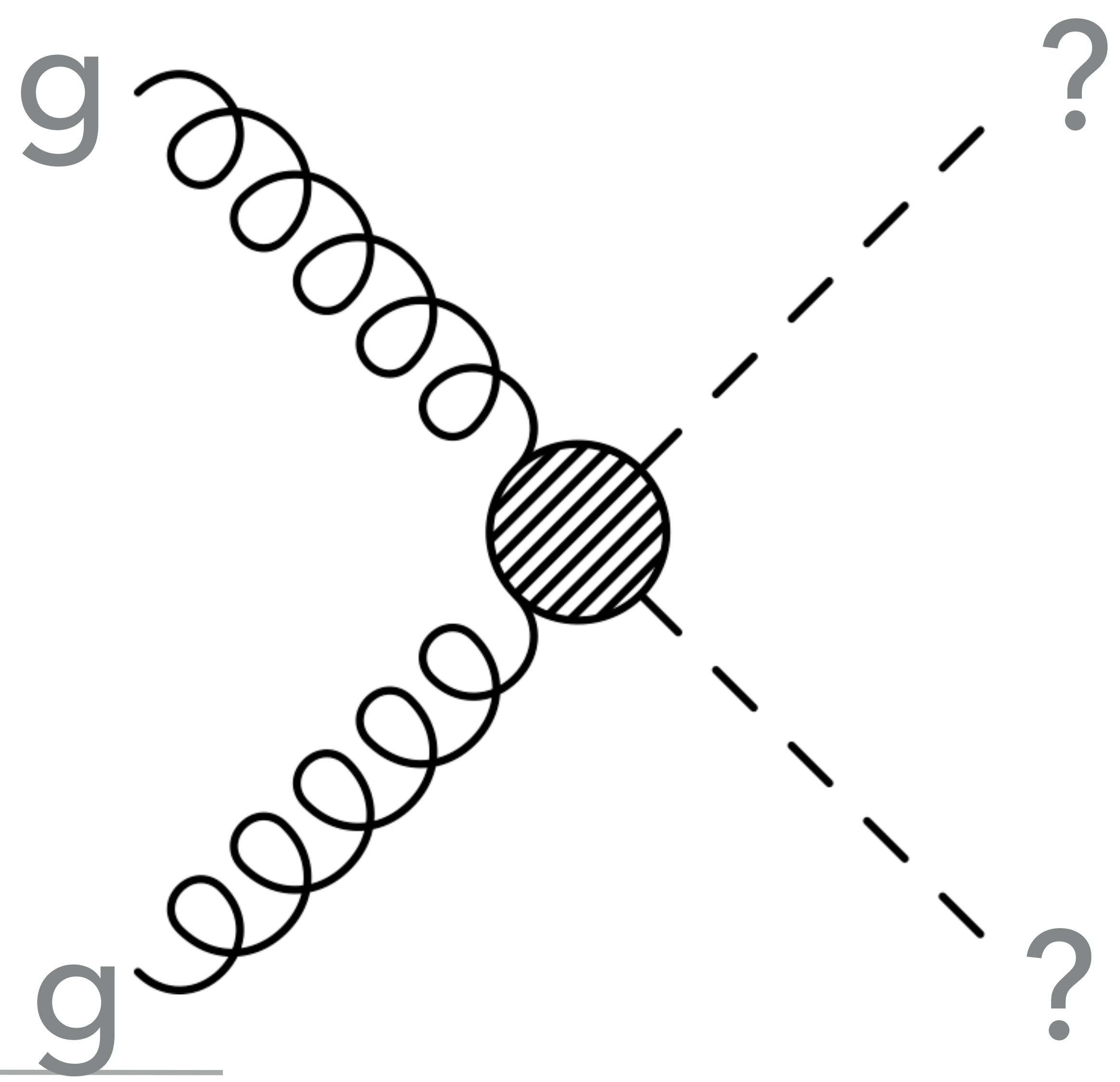
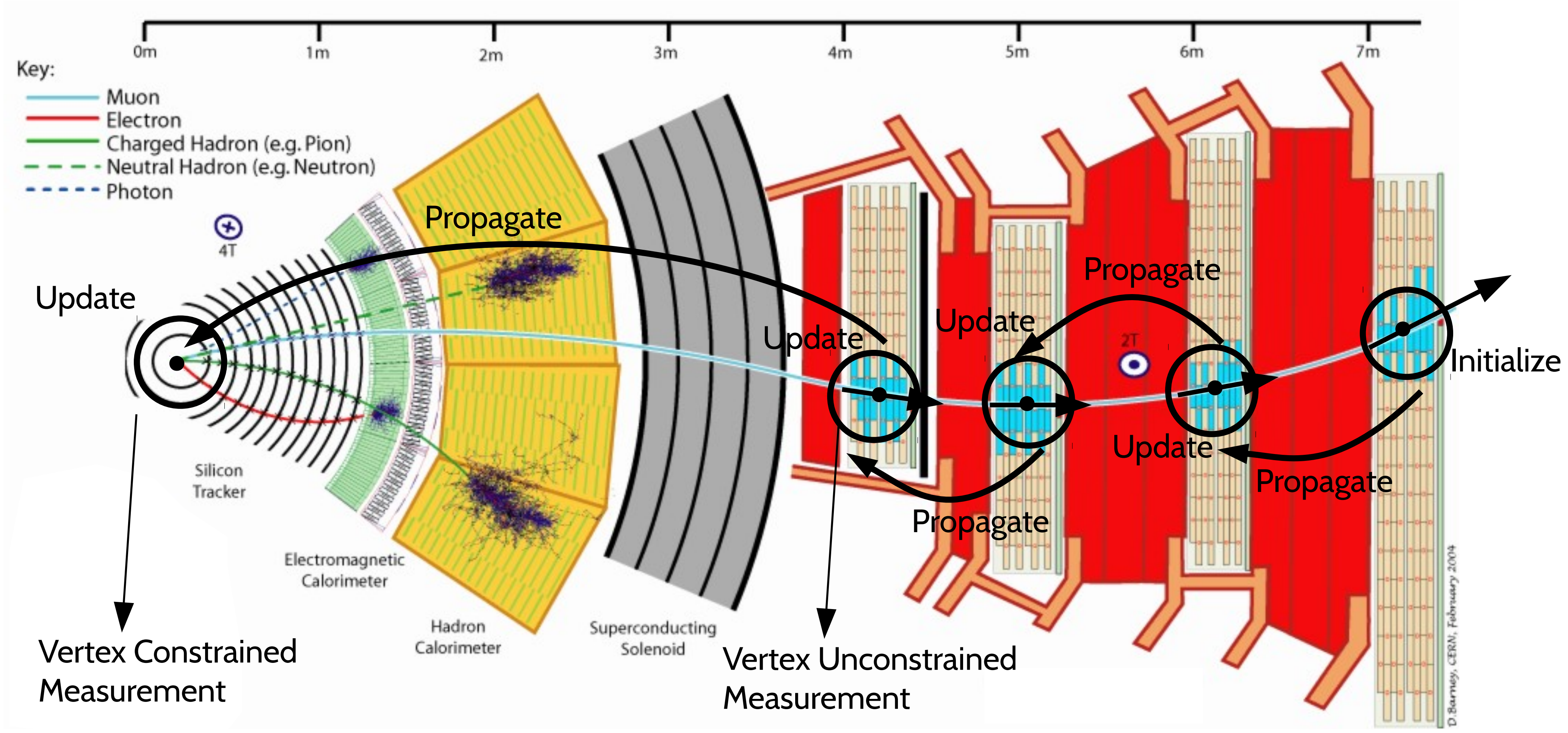


Image by Matt Strassler



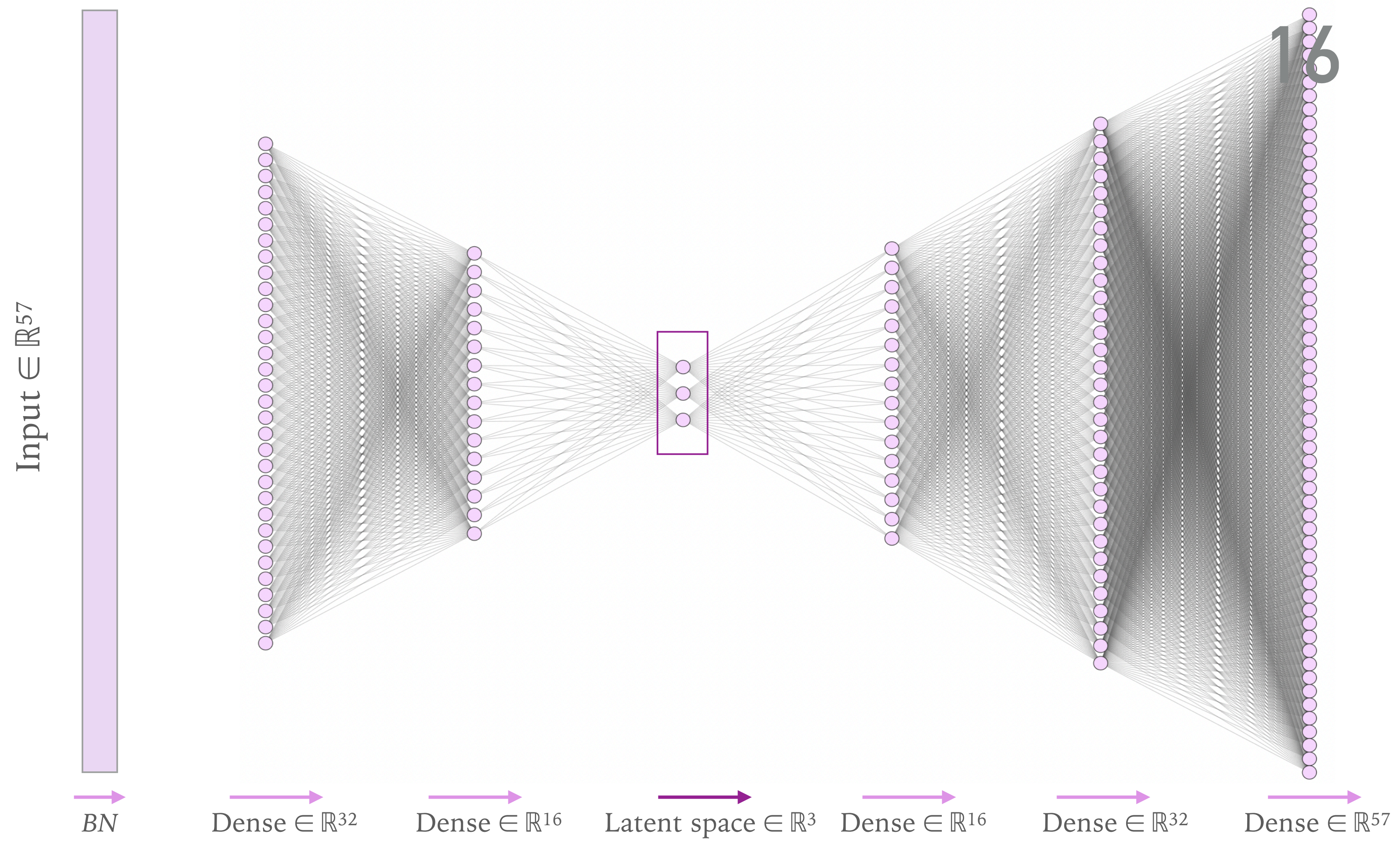


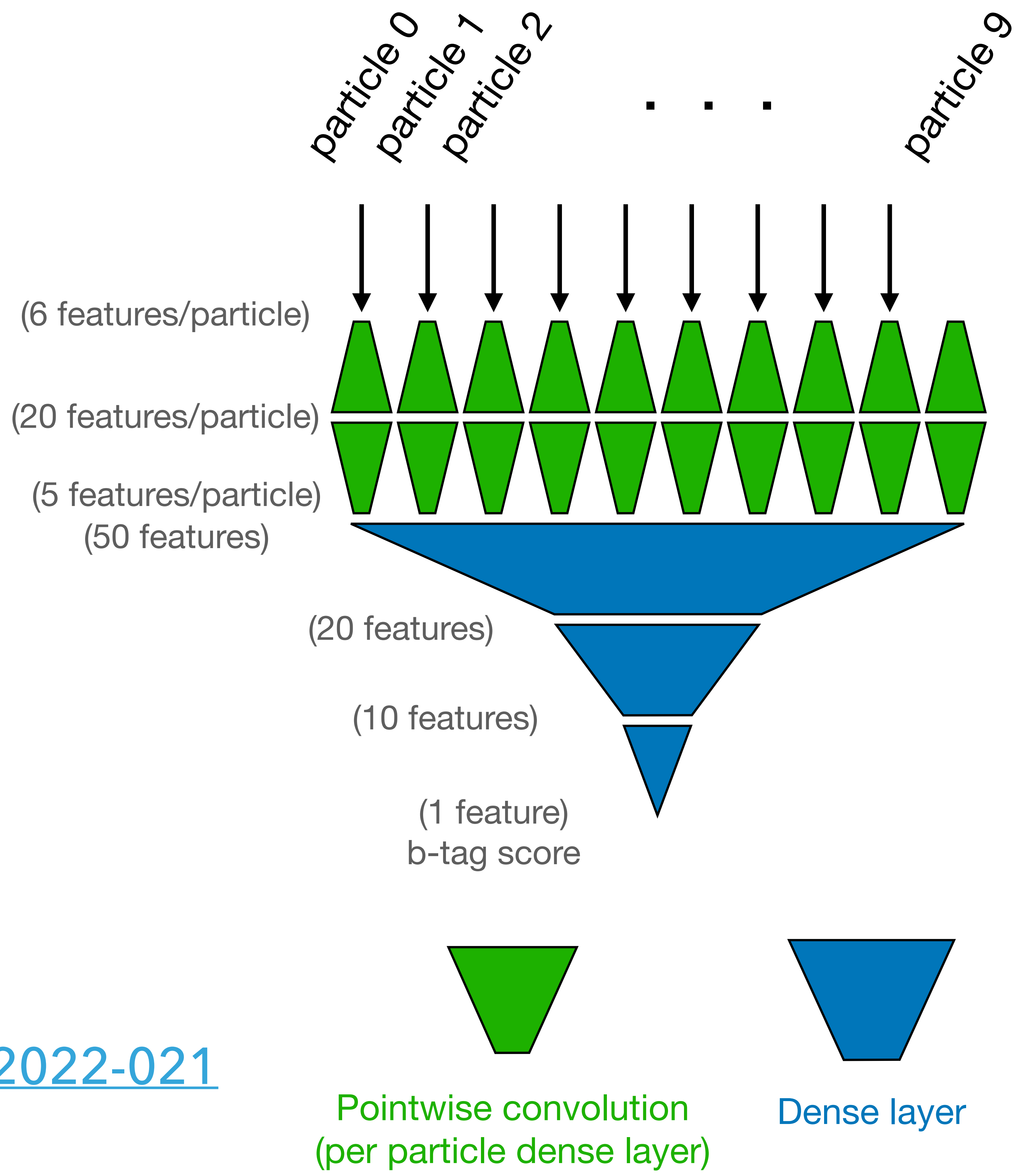


ML in Trigger

- (Variational) autoencoders for anomaly detection
- 1D convolutional neural networks for b-tagging
- Graph neural networks for tracking

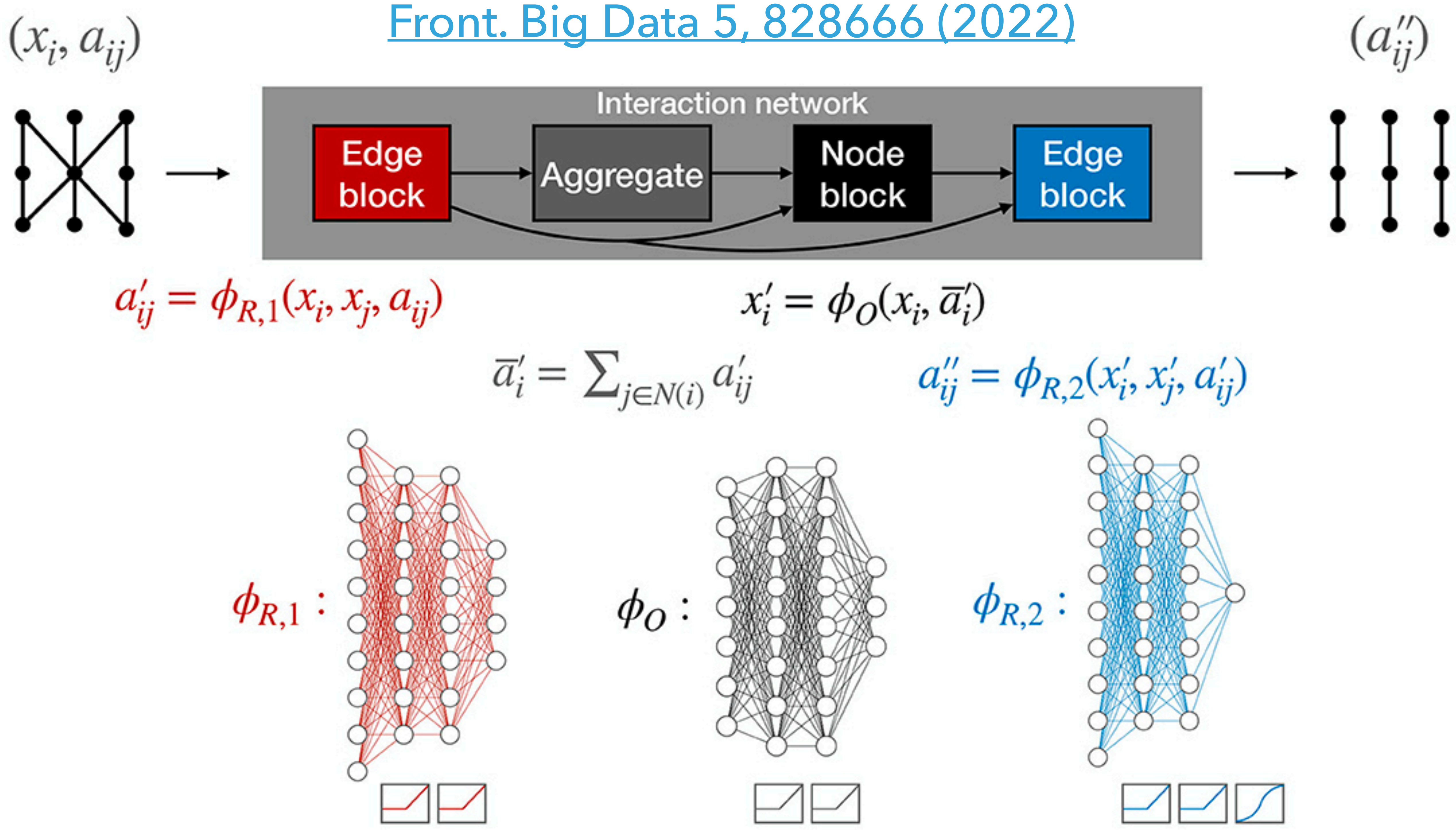
Nat. Mach. Intell. 4, 154 (2022)





CMS-DP-2022-021

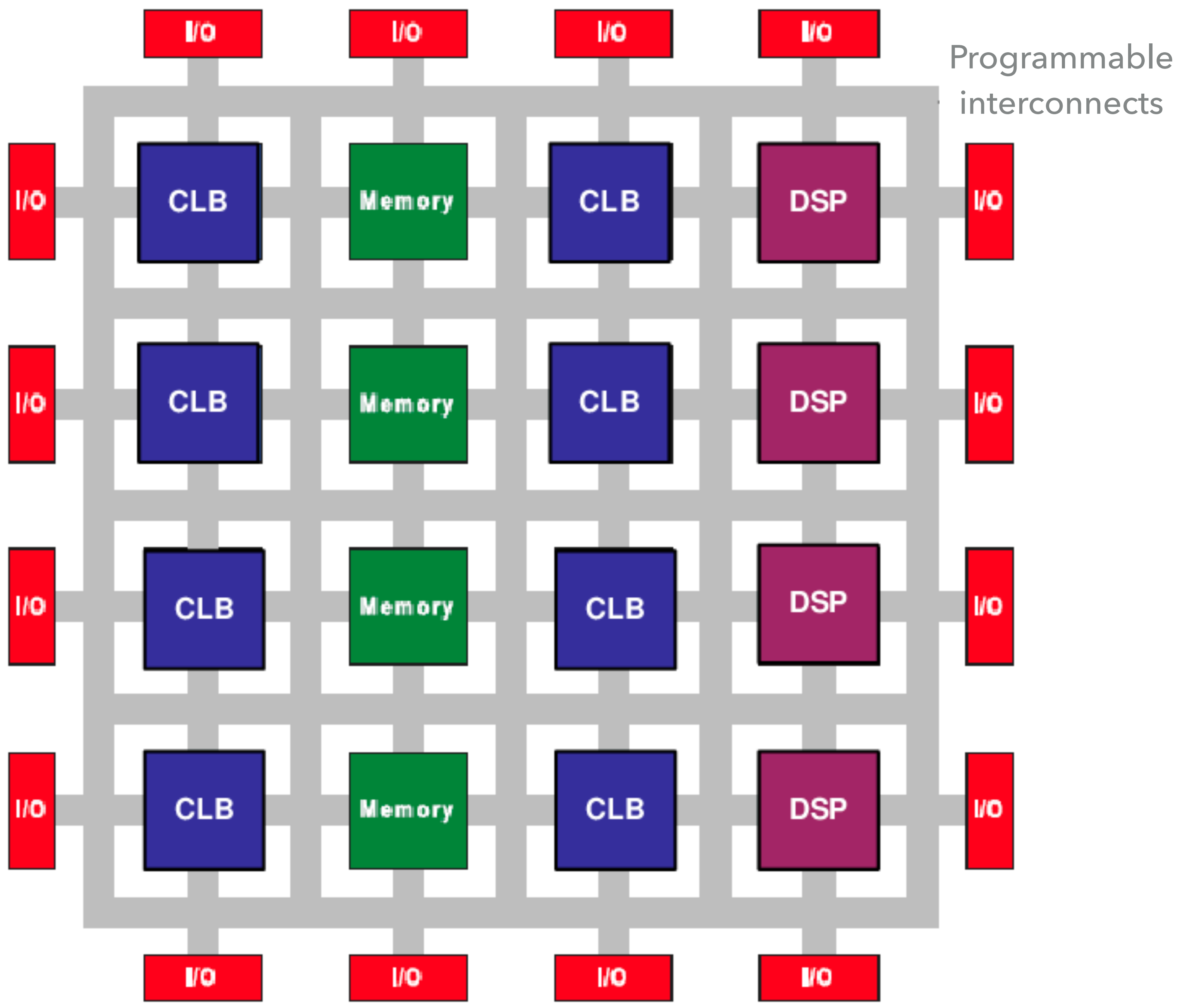
Front. Big Data 5, 828666 (2022)

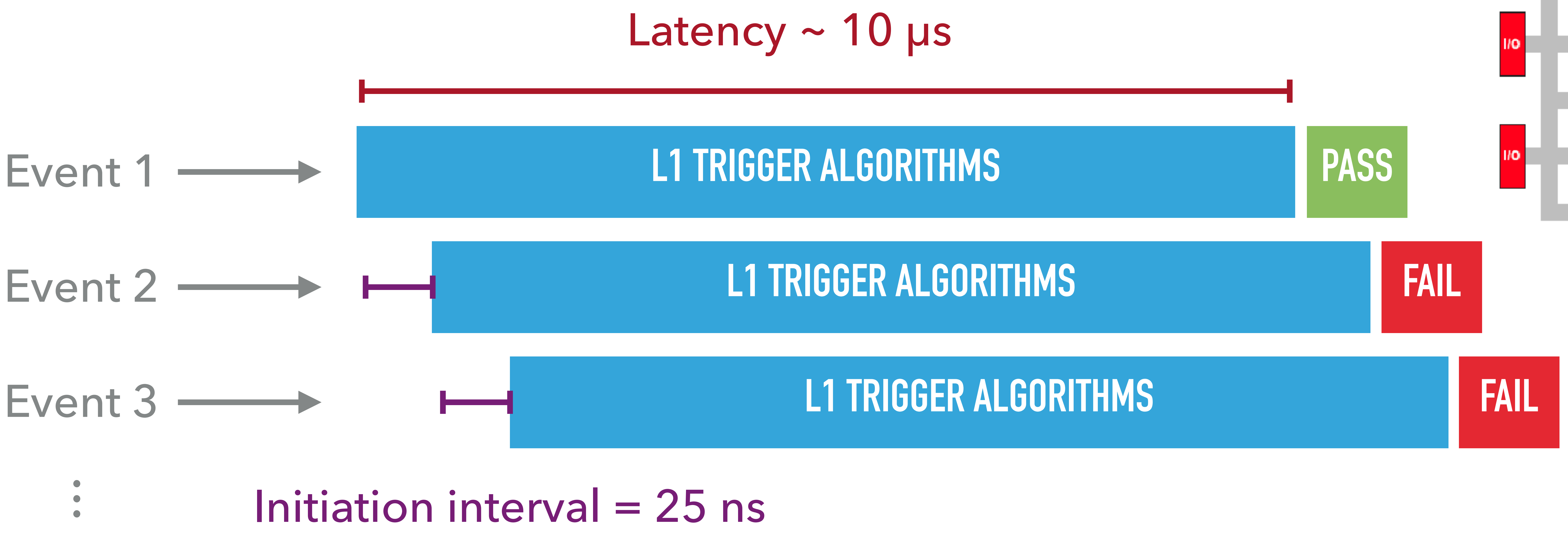


Credit: Javier Duarte

What makes this Hard?

- Reconstruct all events and reject 98% of them in ~10 μs
  - Algorithms have to be <1 μs and process new events every (25 ns) × N_{tmux}
- Latency necessitates all **FPGA** design
  - Algorithms have to fit on <1 FPGA
- How can we satisfy these constraints?

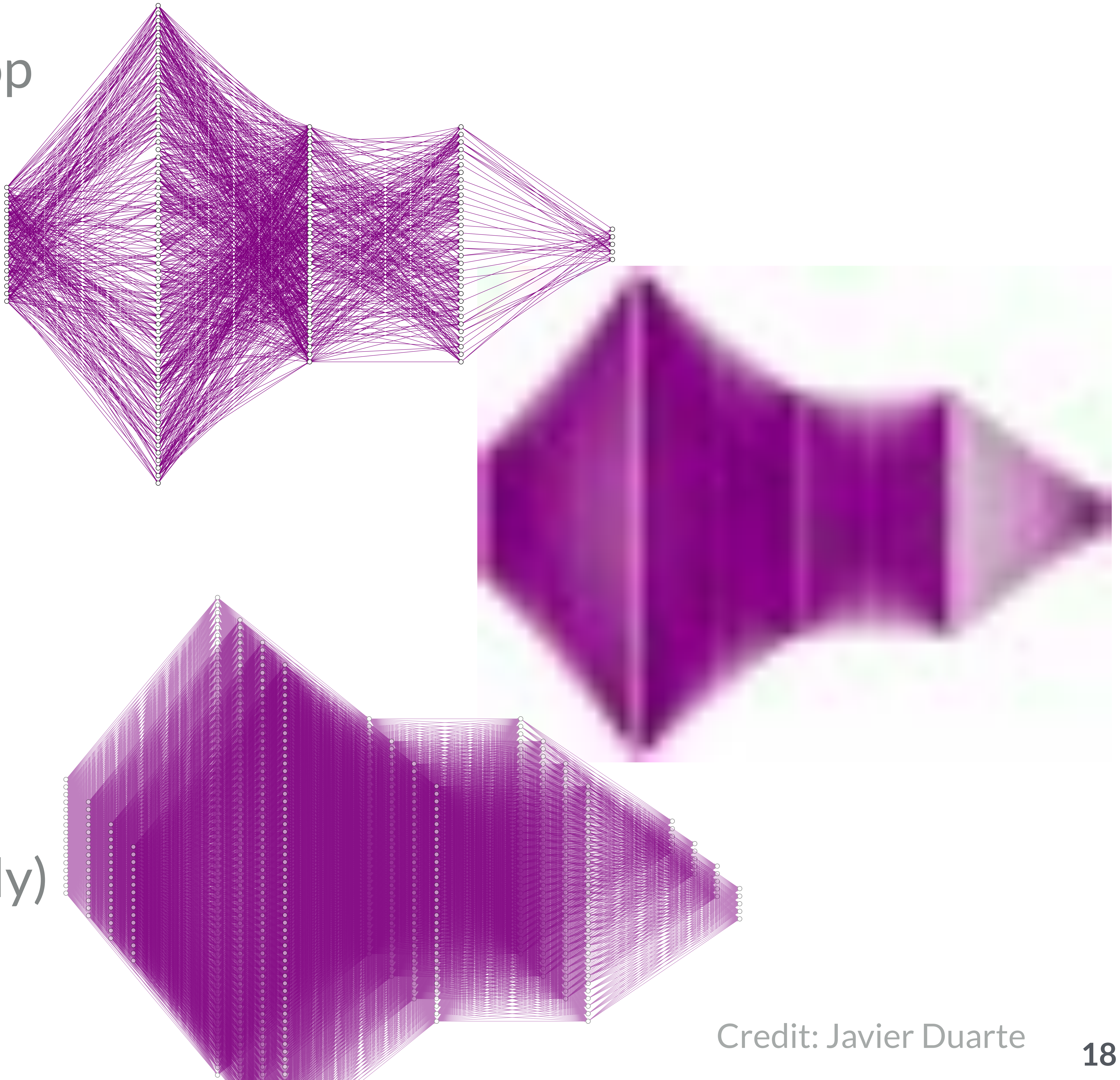




Credit: Javier Duarte

Codesign

- **Codesign**: intrinsic development loop between ML design, training, and implementation
- Pruning
  - Maintain high performance while removing redundant operations
- Quantization
  - Reduce precision from 32-bit floating point to 16-bit, 8-bit, …
- Parallelization
  - Balance parallelization (how fast) with resources needed (how costly)



Credit: Javier Duarte

Question #1

What features / properties do you expect in an "efficient" ML model?

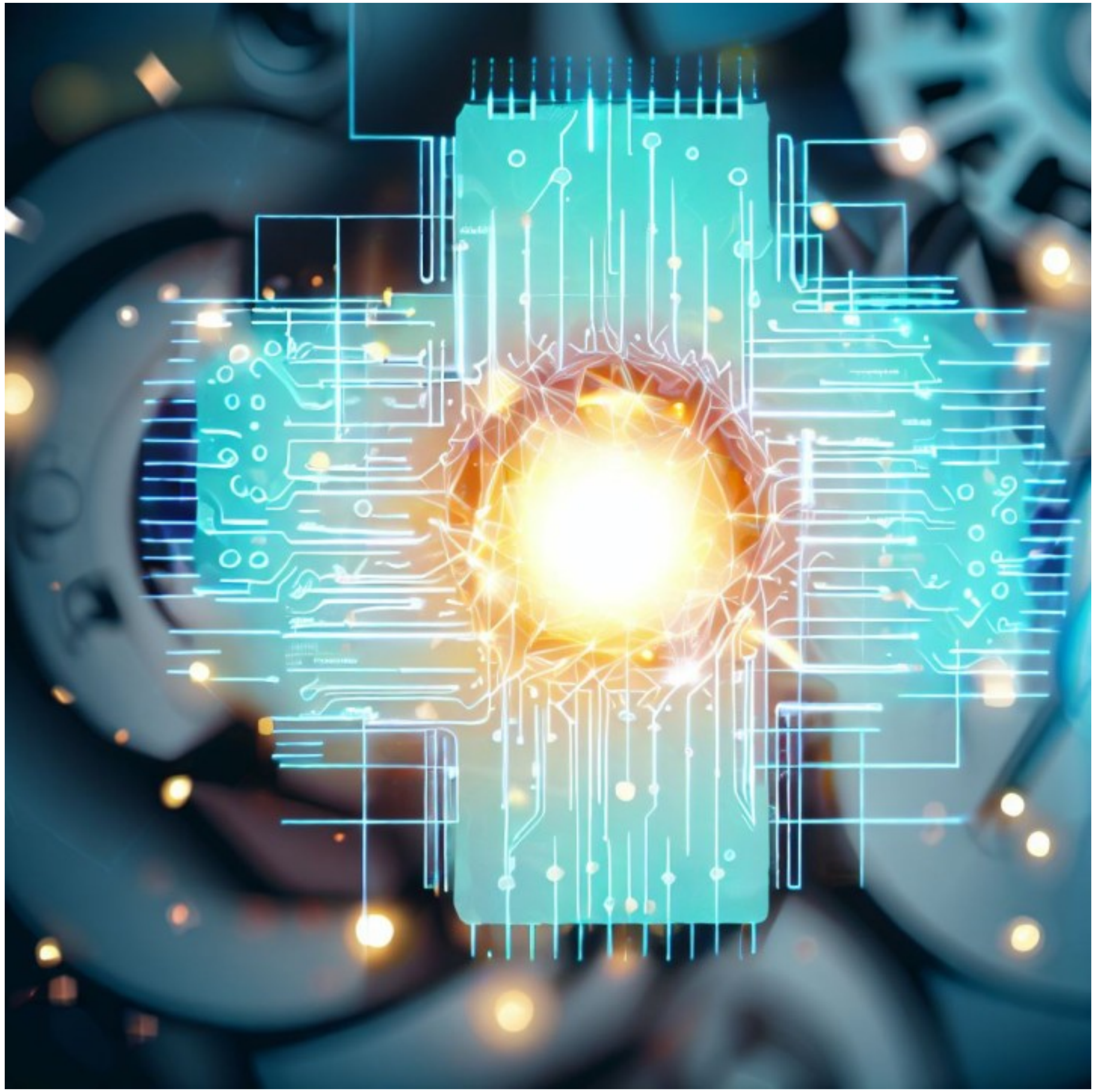
Think about it for 30 seconds and share your answer

Question #1

What features / properties do you expect in an “efficient” ML model?

Think about it for 30 seconds and share your answer

- Smaller in size
- Requires less computing resources for training and / or inference
- Runs faster during inference (prediction stage)
- Uses less power
- Should scale well with increasing data volume



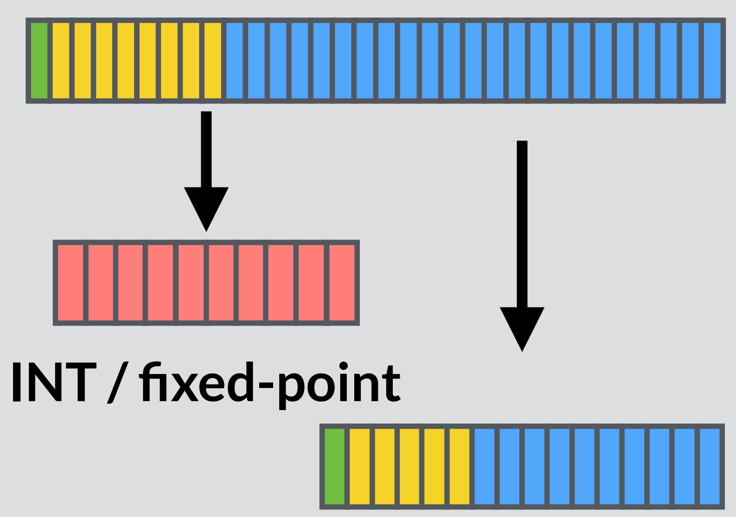
Lets discuss

some of the techniques to design Efficient Deep Learning models

Efficient Model Design

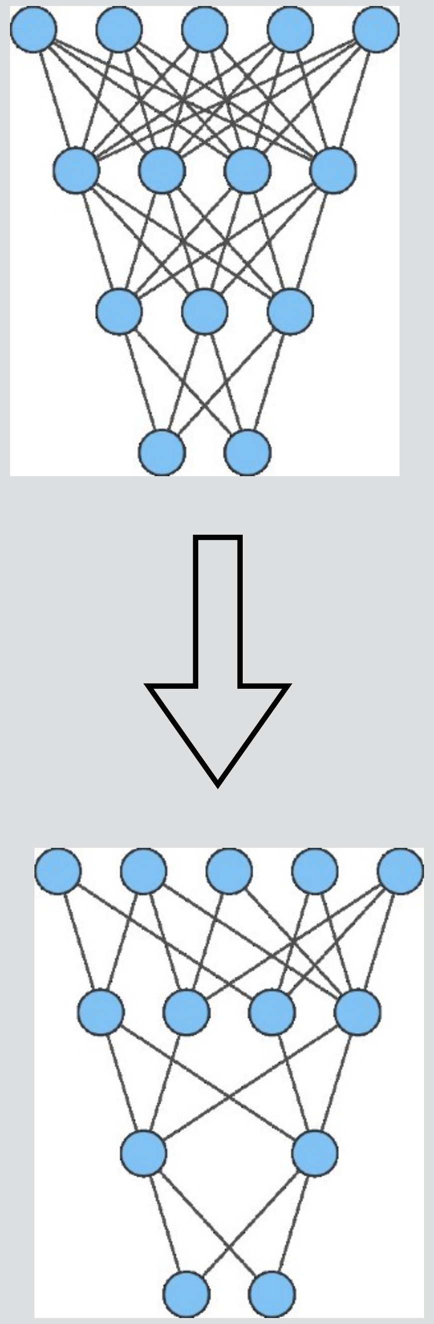
Quantization

Finding the optimal model architecture



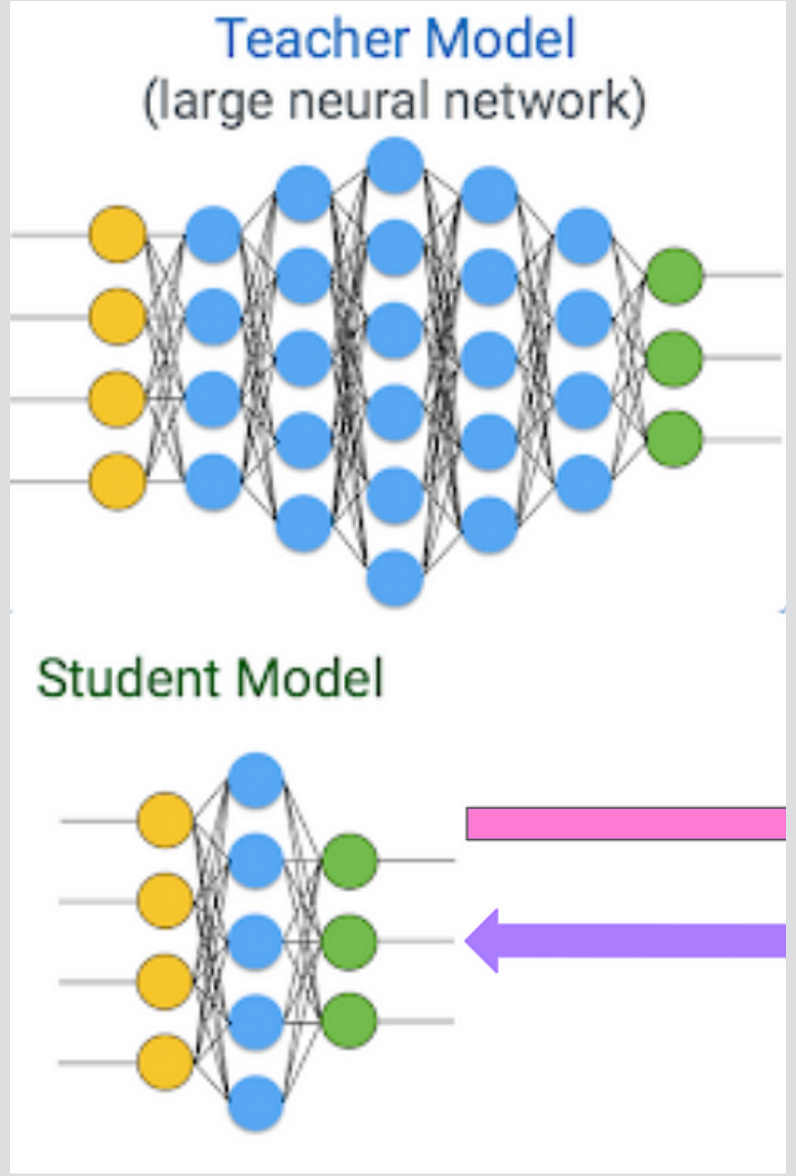
Pruning

Remove synapses and neurons



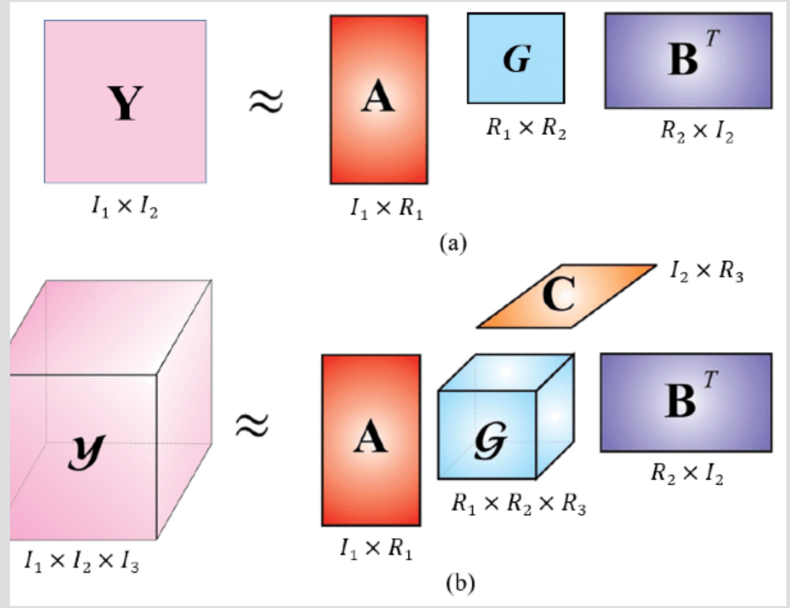
Knowledge Distillation

Train a smaller model using a bigger model



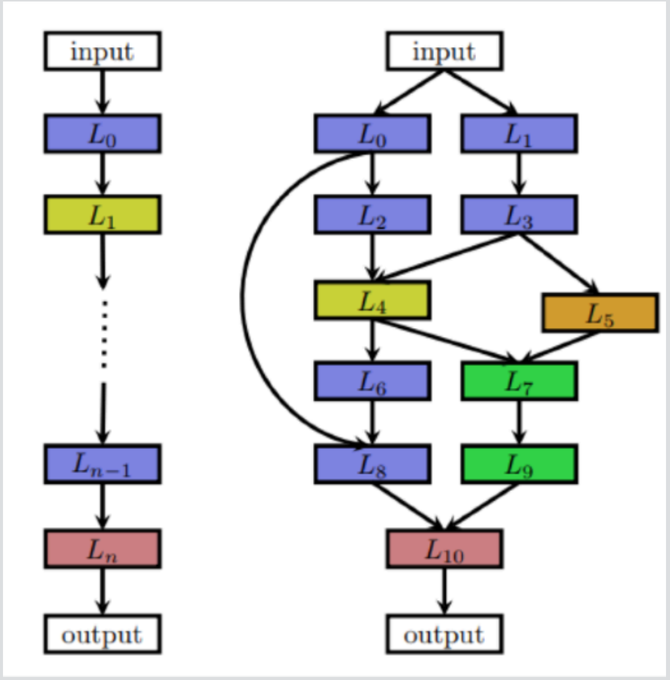
Tensor Decomposition

Reduce the dimension of the weight matrix / tensor



Neural Architecture Search

Finding the optimal model architecture



Lecture Outline

Motivation behind efficient model design and some highlights

Introduction to Quantization
- Definition
- PTQ vs QAT

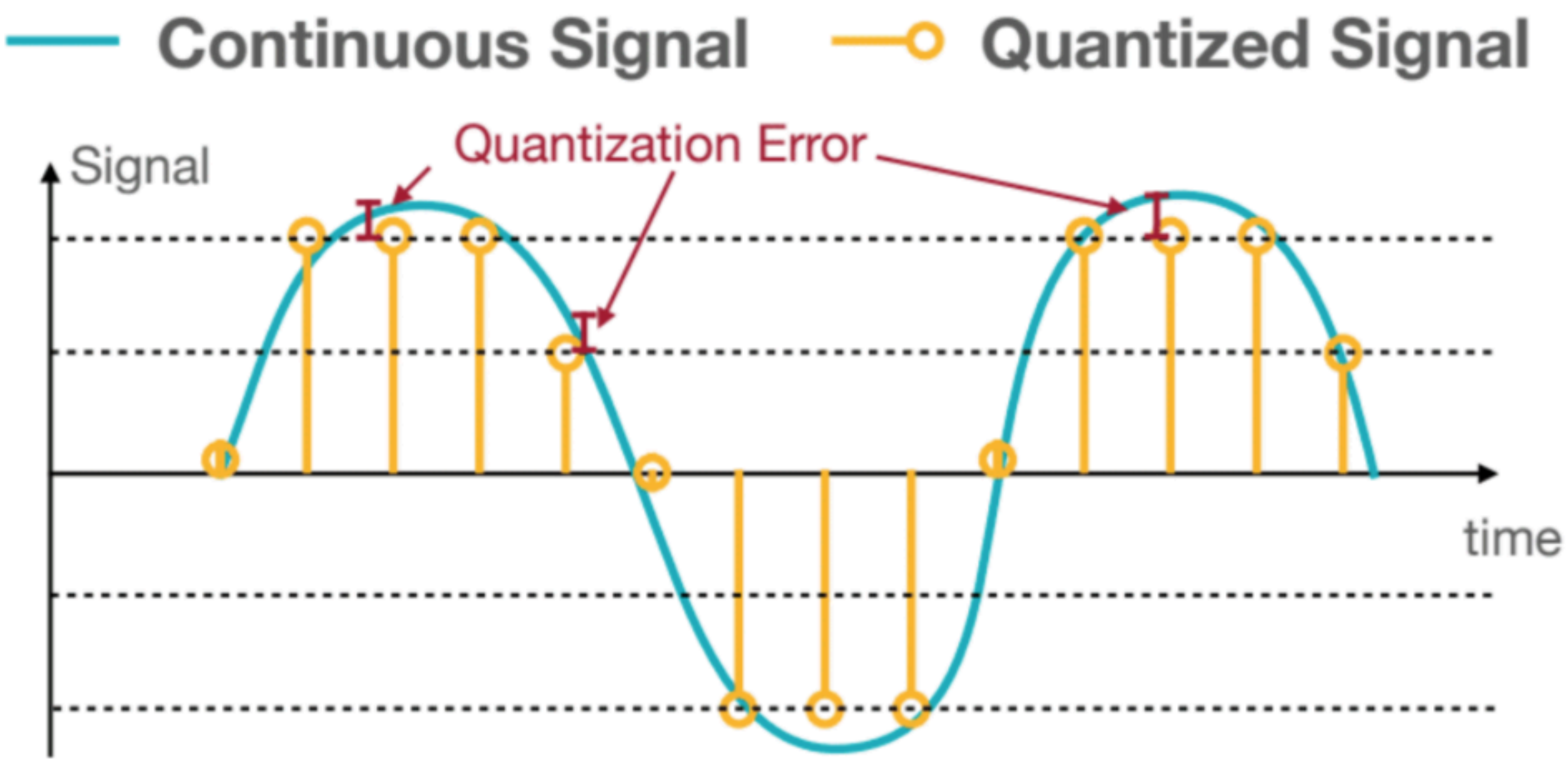
Introduction to Pruning
- What is pruning? How to formulate pruning?
- Determine pruning granularity and criteria
- Network performance after pruning

ML on FPGA

hls4ml and Trigger applications

Quantization

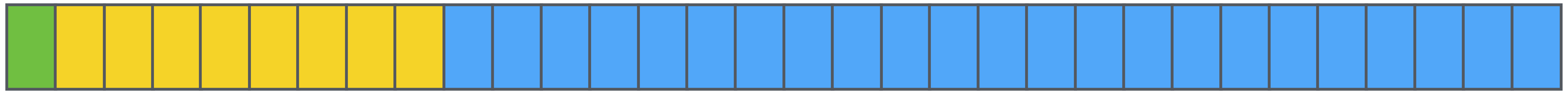
Quantization is the process of constraining an input from a continuous or otherwise large set of values to a discrete set



Numerical Data Types

32-bit floating-point (FP32)

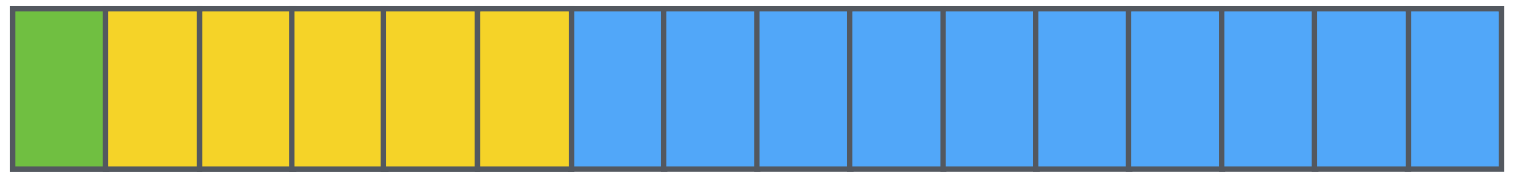
Range: 10^{-38} - 10^{38}



Sign bit 8 bit Exponent 23 bit Mantissa

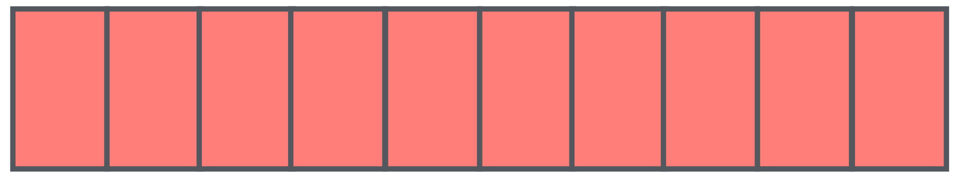
16-bit floating-point (FP16)

Range: $6x10^{-5}$ - $6x10^{4}$

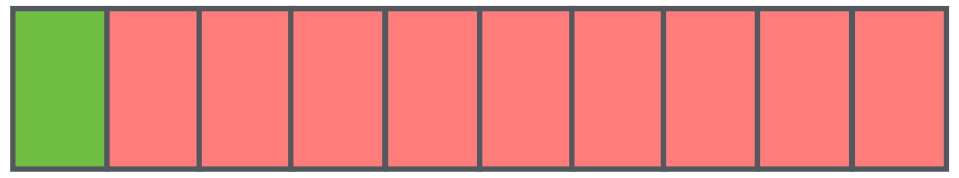


Sign bit 5 bit Exponent 10 bit Mantissa

Unsigned Integer



Signed Integer

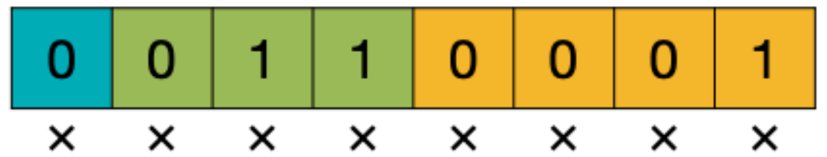


Sign bit

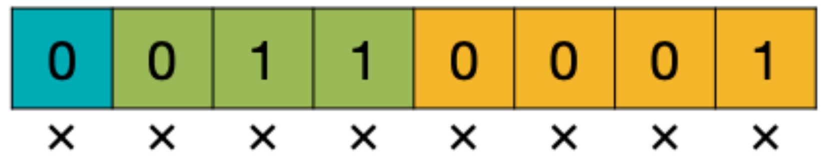
Fixed-point Number

Integer . Fraction

"Decimal" Point



$$-2^3+2^2+2^1+2^0+2^{-1}+2^{-2}+2^{-3}+2^{-4} = 3.0625$$



$$(-2^7+2^6+2^5+2^4+2^3+2^2+2^1+2^0) \times 2^{-4} = 49 \times 0.0625 = 3.0625$$

(using 2's complement representation)

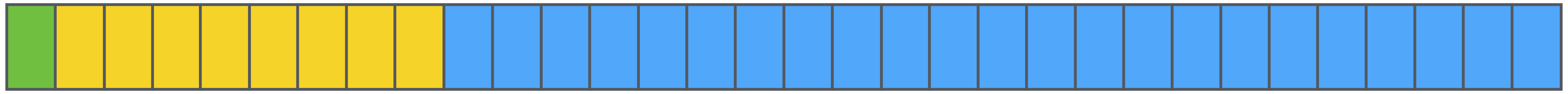
17

GPT-3 Memory

GPT-3

~175,000,000,000

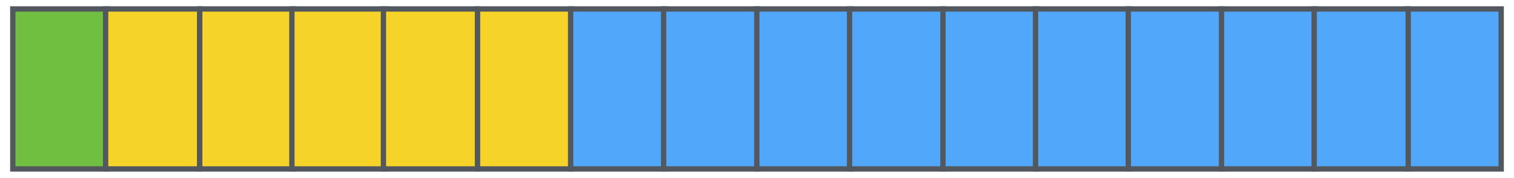
32-bit floating-point (FP32) Range: 10^{-38} - 10^{38}



Sign bit 8 bit Exponent 23 bit Mantissa

~700 GB of memory
(175 B par x 4 bytes/par)
~10x larger than max memory in a single Nvidia A100 GPU

16-bit floating-point (FP16) Range: 6×10^{-5} - 6×10^{4}



Sign bit 5 bit Exponent 10 bit Mantissa

~350 GB of memory
(175 B par x 2 bytes/par)
~ 5 Nvidia A100 GPUs
~ 11 Nvidia V100 GPUs

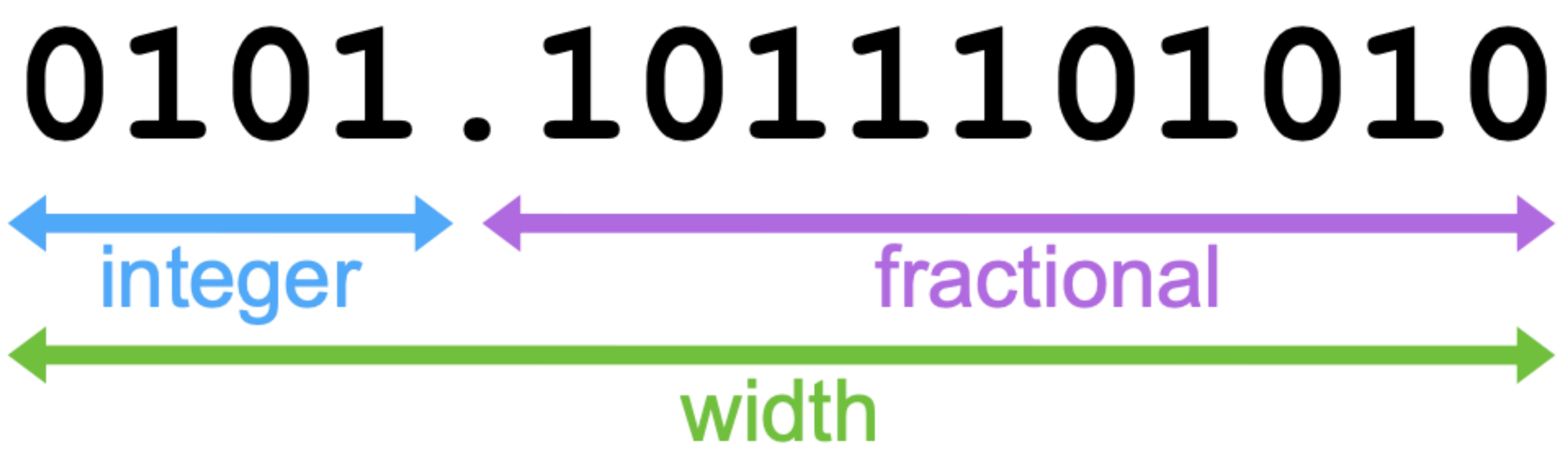
Quantization Types

[arXiv:2004.09602](https://arxiv.org/abs/2004.09602)

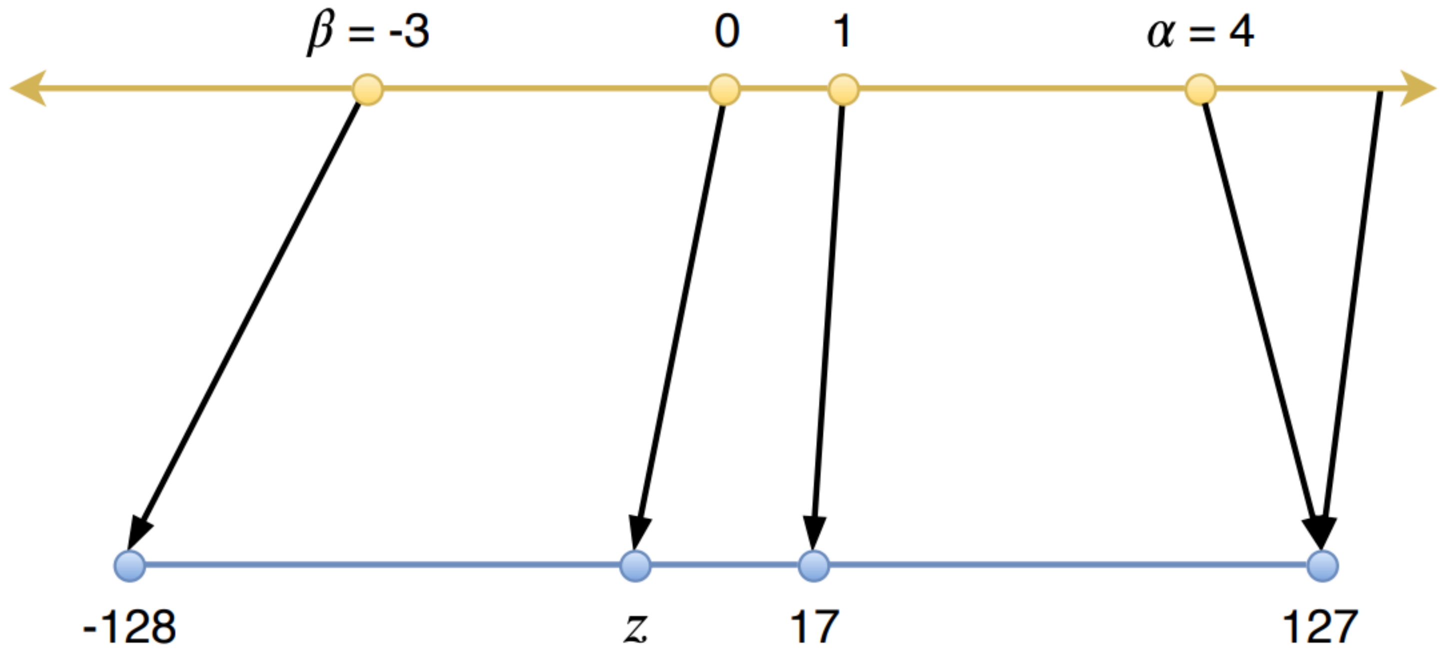
Quantization: using reduced precision for parameters and operations

Fixed-point precision

ap_fixed<width bits, integer bits>

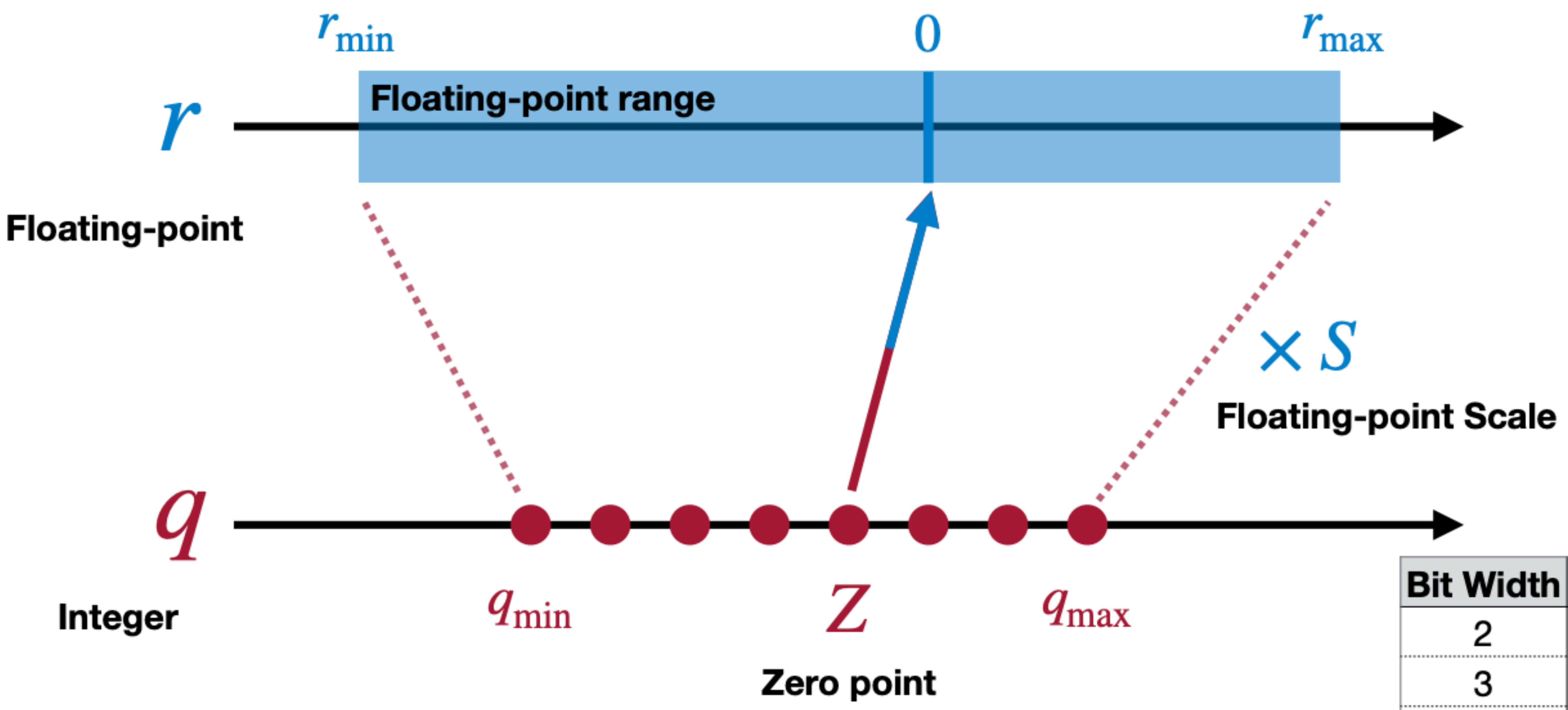


Affine Integer Quantization



Affine Integer Quantization

An affine mapping of integers to real numbers $r = S(q - Z)$



Bit Width	q_{min}	q_{max}
2	-2	1
3	-4	3
4	-8	7
N	-2^{N-1}	$2^{N-1}-1$

Quantization and Training of Neural Networks for Efficient Integer-Arithmetic-Only Inference [Jacob et al., CVPR 2018]

Quantization Strategies

Usual ML software workflow

(Q) K + TensorFlow

(Q) ONNX

PYTORCH

Post Training Quantization

- QKeras
- Bravitas
- PyTorch (limited options)
- TensorFlow (limited options)
- ONNX (in development)

Initial Model

Usual ML software workflow

(Q) K + TensorFlow

(Q) ONNX

PYTORCH

Quantization-Aware Training

- QKeras
- PyTorch (limited options)
- TensorFlow (limited options)
- QONNX (in development)

Question #2

Post-training Quantization (PTQ) vs Quantization-Aware Training (QAT)

Advantages and disadvantages of PTQ?

Post-training Quantization (PTQ) vs Quantization-Aware Training (QAT)

PTQ	QAT
Usually fast	Slow
No re-training of the model	Model needs to be trained/finetuned
Plug and play of quantization schemes	Plug and play of quantization schemes (requires re-training)
Less control over final accuracy of the model	More control over final accuracy since *q-params* are learned during training.

Quantization References

Quantization Survey paper
https://arxiv.org/pdf/2103.13630

MIT Efficient ML Course:
https://hanlab.mit.edu/courses/2023-fall-65940

TensorFlow model_optimization:
https://www.tensorflow.org/lite/performance/model_optimization

PyTorch Quantization:
https://pytorch.org/docs/stable/quantization.html

Lecture Outline

Motivation behind efficient model design and some highlights

Introduction to Quantization
- Definition
- PTQ vs QAT

Introduction to Pruning
- What is pruning? How to formulate pruning?
- Determine pruning granularity and criteria
- Network performance after pruning

ML on FPGA

hls4ml and Trigger applications

Neural Network Pruning

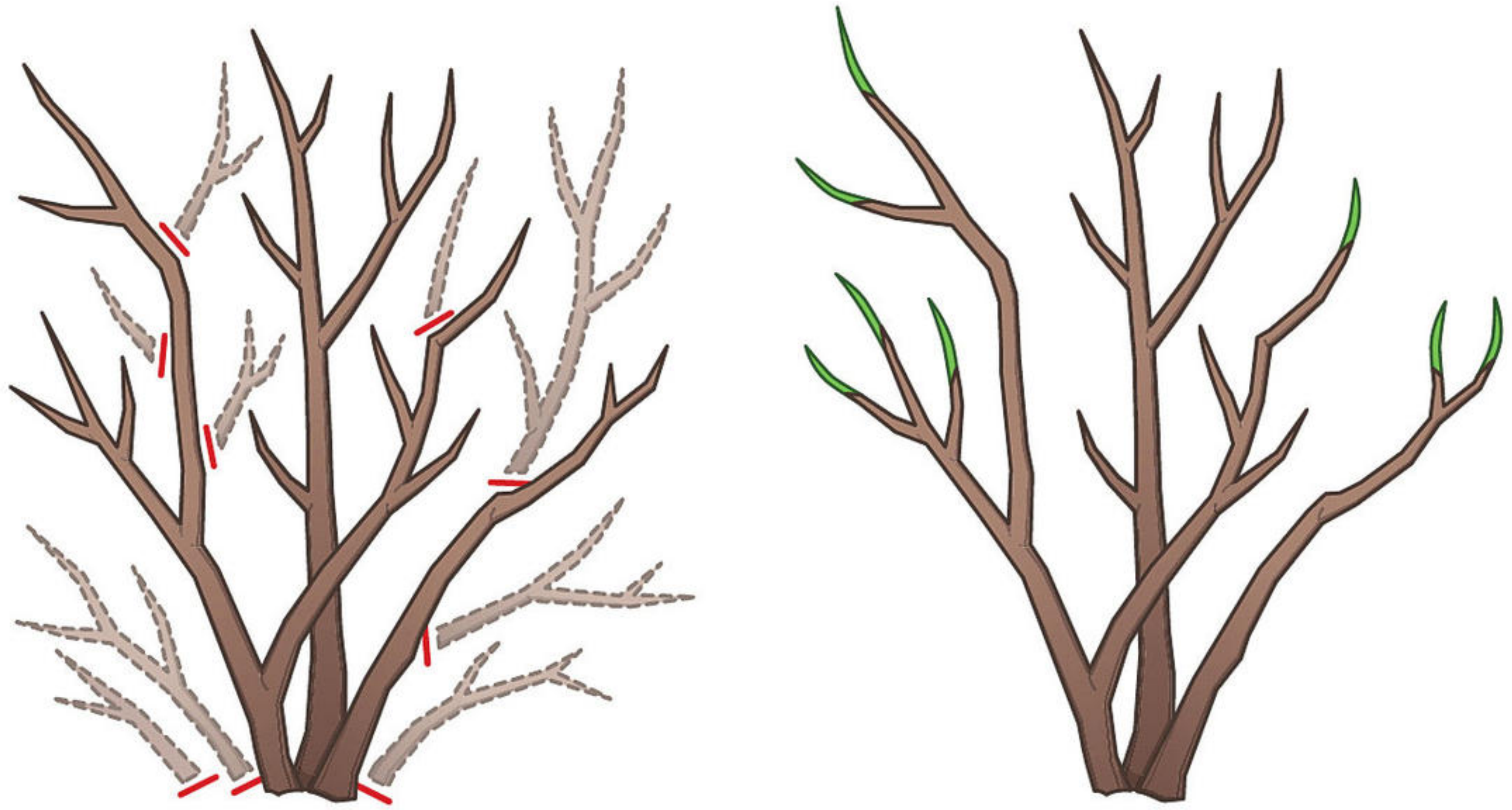
- > 90% reduction in parameter count
- Decreasing the storage requirements
- Improving computation efficiency

Model accuracy loss was negligible

Neural Network	#Parameters		
	Before Pruning	After Pruning	Reduction
AlexNet	61 M	6.7 M	9 ×
VGG-16	138 M	10.3 M	12 ×
GoogleNet	7 M	2.0 M	3.5 ×
ResNet50	26 M	7.47 M	3.4 ×

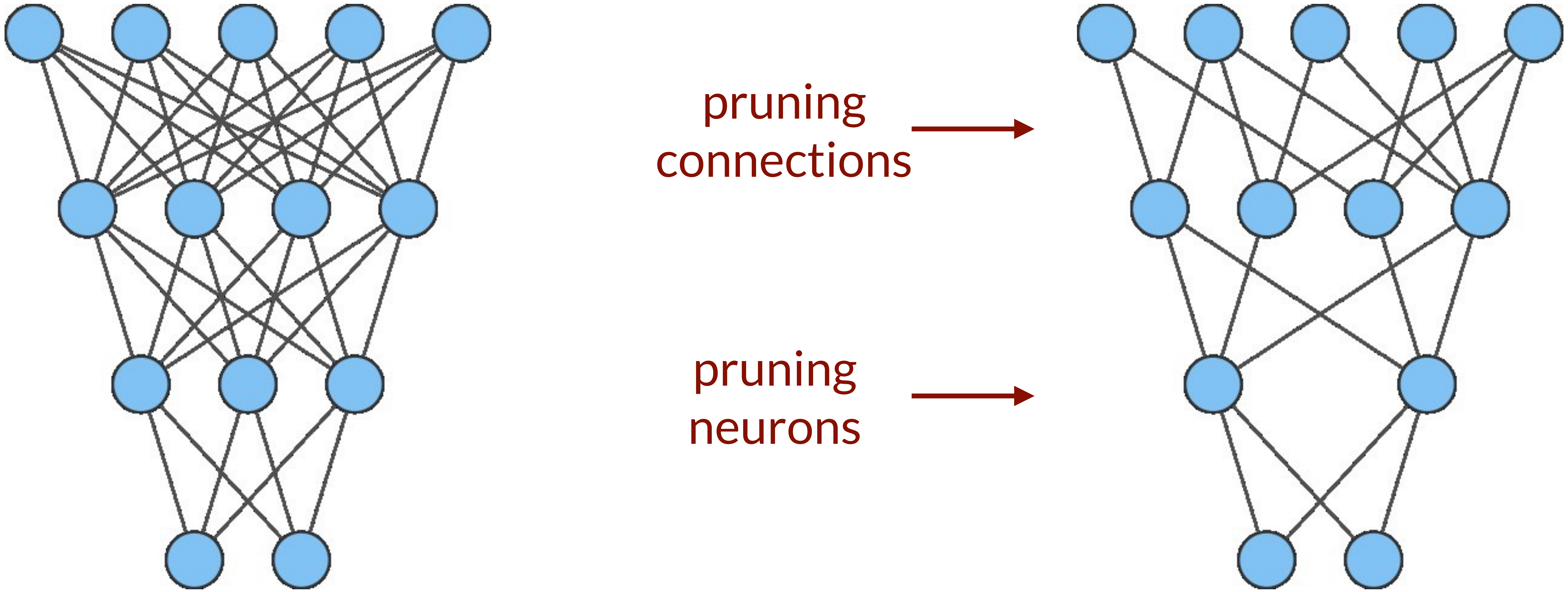
Results are from Efficient Methods and Hardware for Deep Learning [Han, S, Stanford University]

What is pruning?

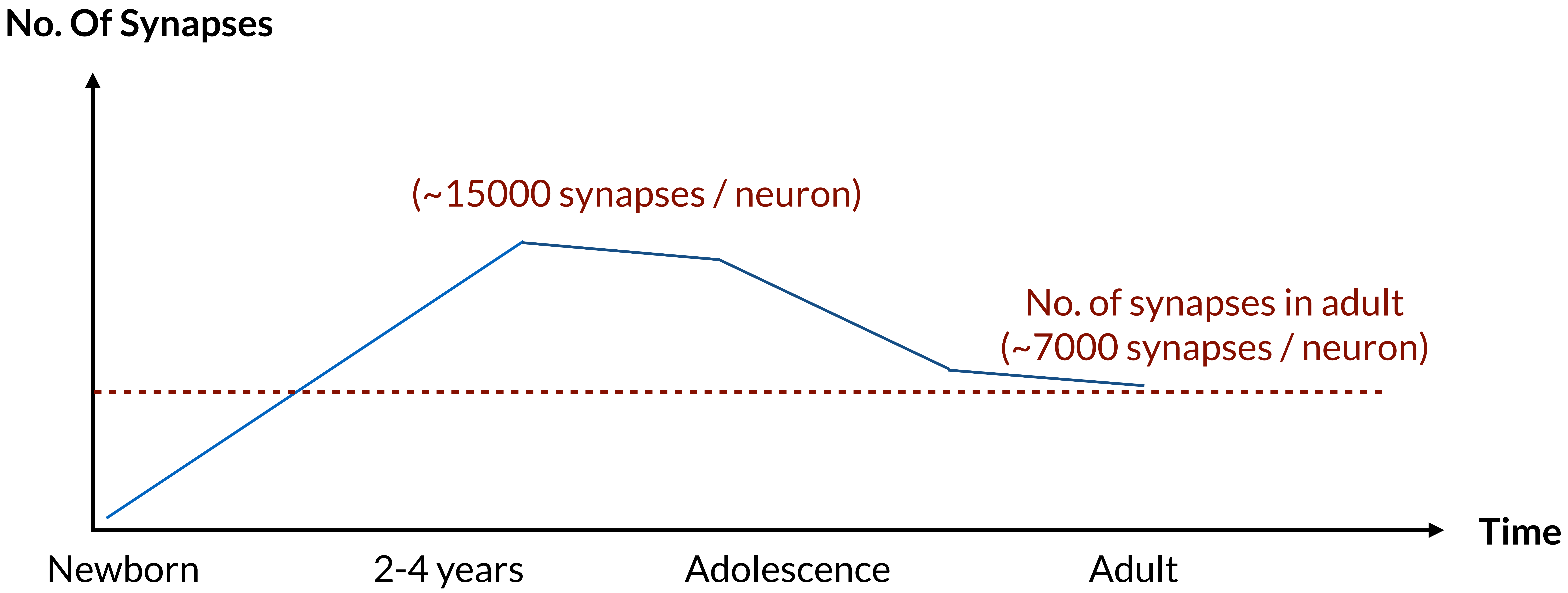


Neural Network Pruning

Pruning is the technique to remove less important connections and neurons

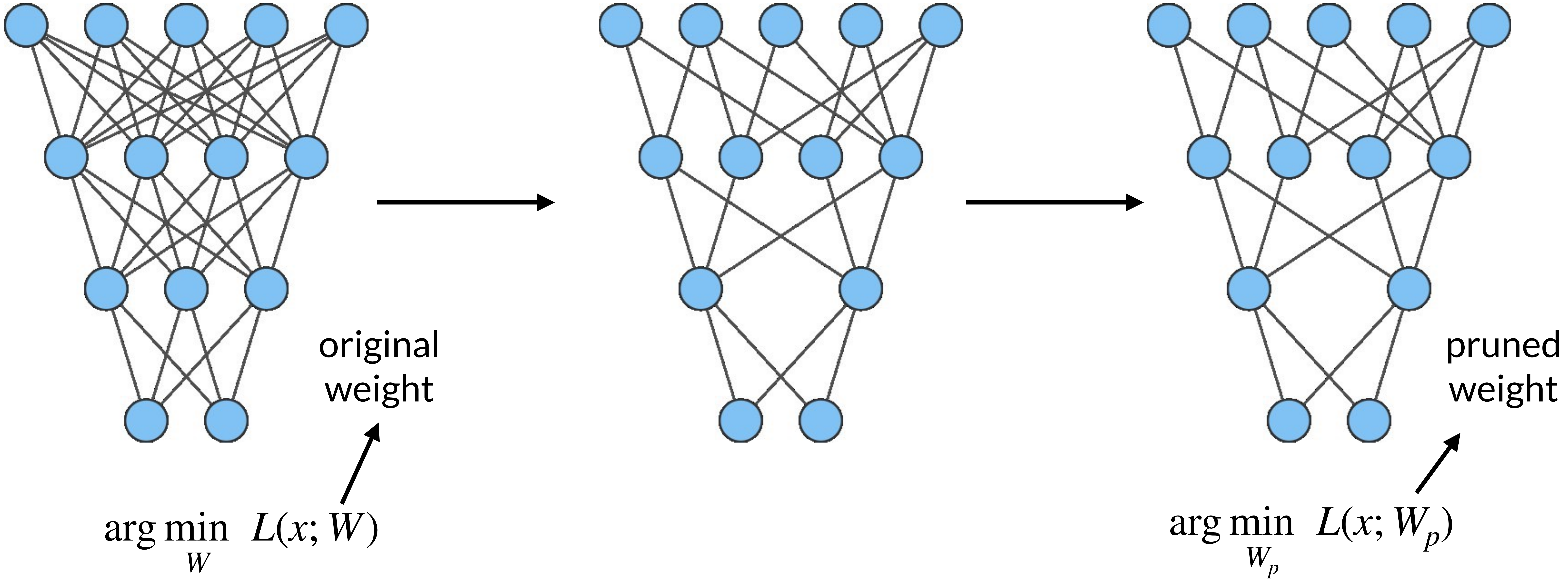


Pruning happens in Human Brain



Pruning workflow

Initialize → **Train** → **Prune** → **Train**



Weight Pruning: Formulation

Remove least important connections such that $||W_p||_0 < N$

W_p is the pruned weight matrix

N = target #non-zero weights

$$\text{Sparsity} = \frac{\text{\# of non-zero weights}}{\text{Total \# of weights}} = \frac{||W_p||_0}{||W_p||}$$

Example
50% sparsity means half of the weight are pruned

Lecture Outline

Motivation behind efficient model design and some highlights

Introduction to Quantization

- Definition
- PTQ vs QAT

Introduction to Pruning

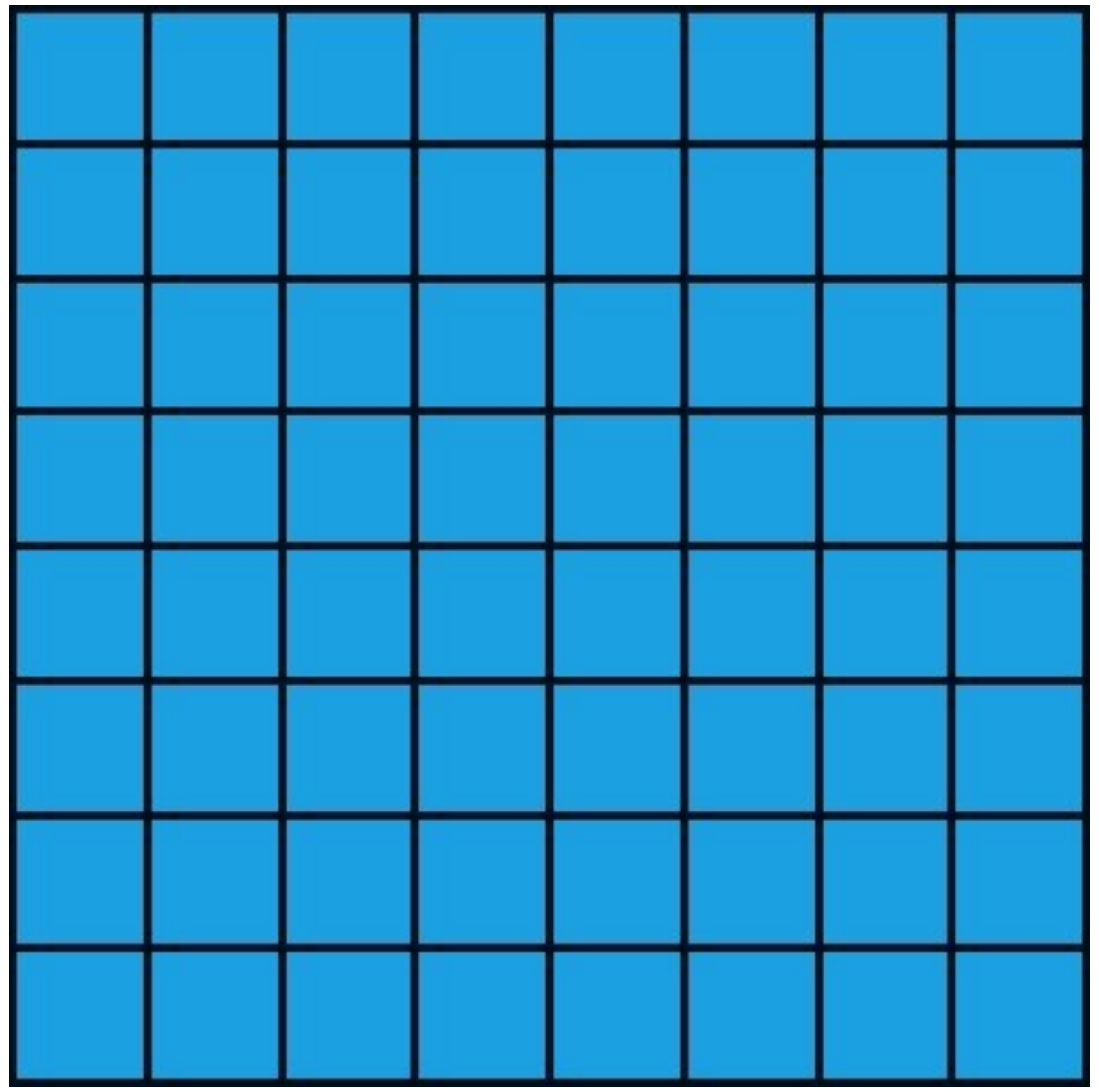
- What is pruning? How to formulate pruning?
- Determine pruning granularity and criteria
- Network performance after pruning

ML on FPGA

hls4ml and Trigger applications

Different Pruning Granularity: Structured and Unstructured

Example: 2D weight matrix (8x8)



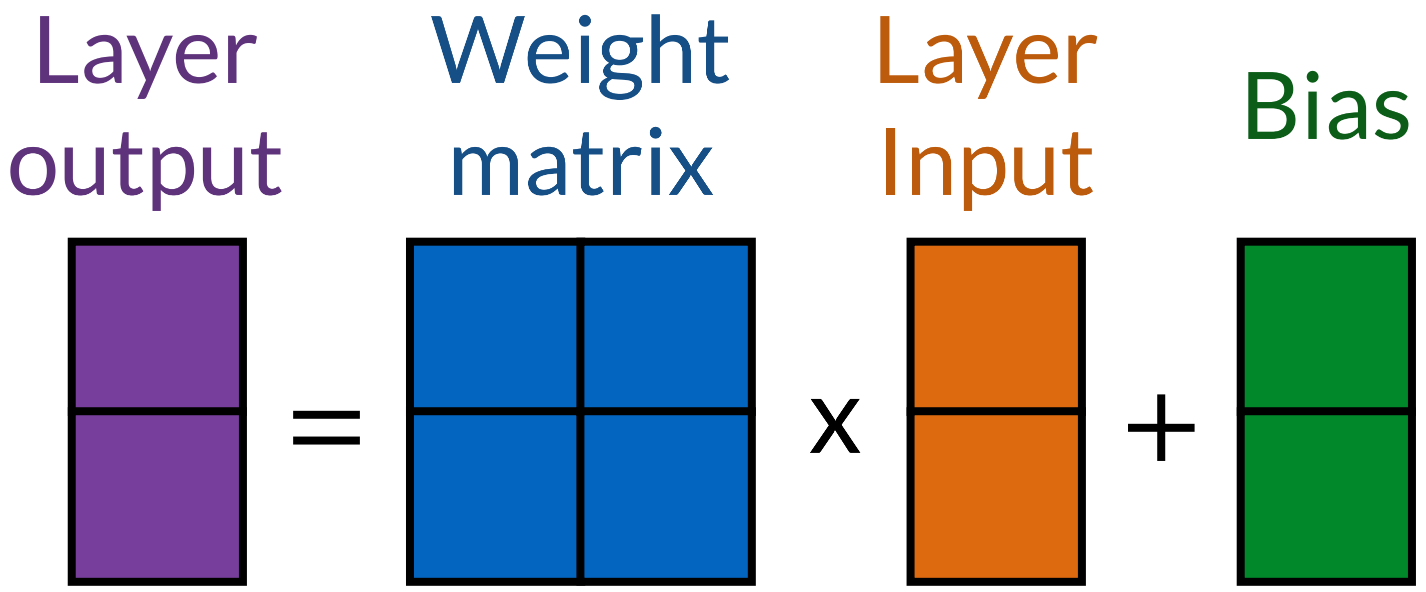
NN layer computation

Layer input $= x_1 \in \mathbb{R}^{m_1}$

Weight $= \mathbf{W}_1 \in \mathbb{R}^{m_2 \times m_1}$, Bias $= b_1 \in \mathbb{R}^{m_2}$

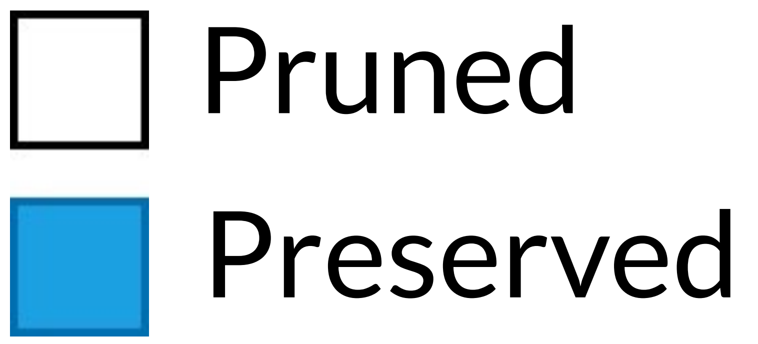
Layer output $= x_2 \in \mathbb{R}^{m_2}$

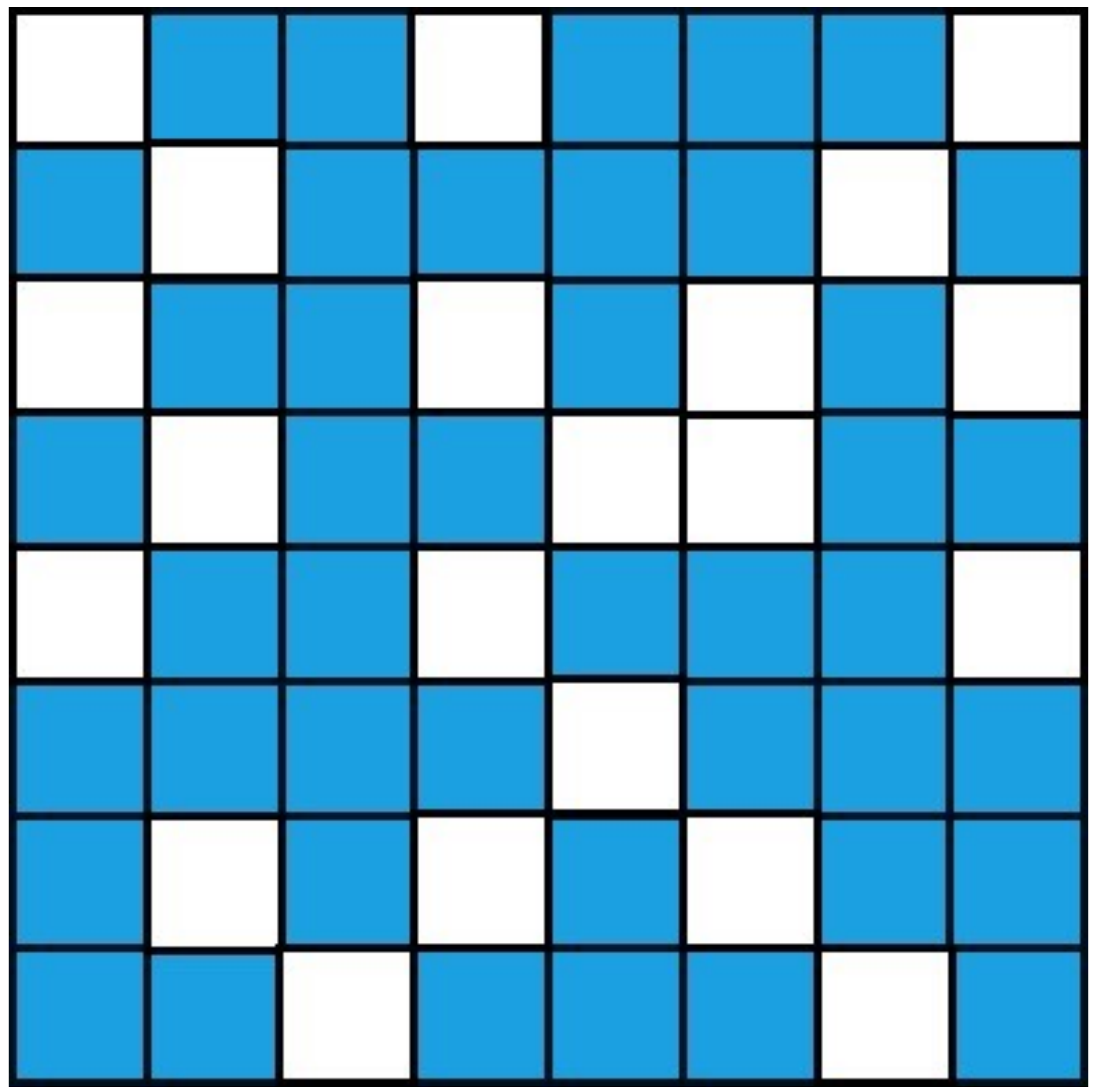
$$x_2 = \mathbf{W}_1 \cdot x_1 + b_1$$



Different Pruning Granularity: Structured and Unstructured

Example: 2D weight matrix (8x8)





Fine-grained / Unstructured Pruning

- Flexible pruning index

Different Pruning Granularity: Structured and Unstructured

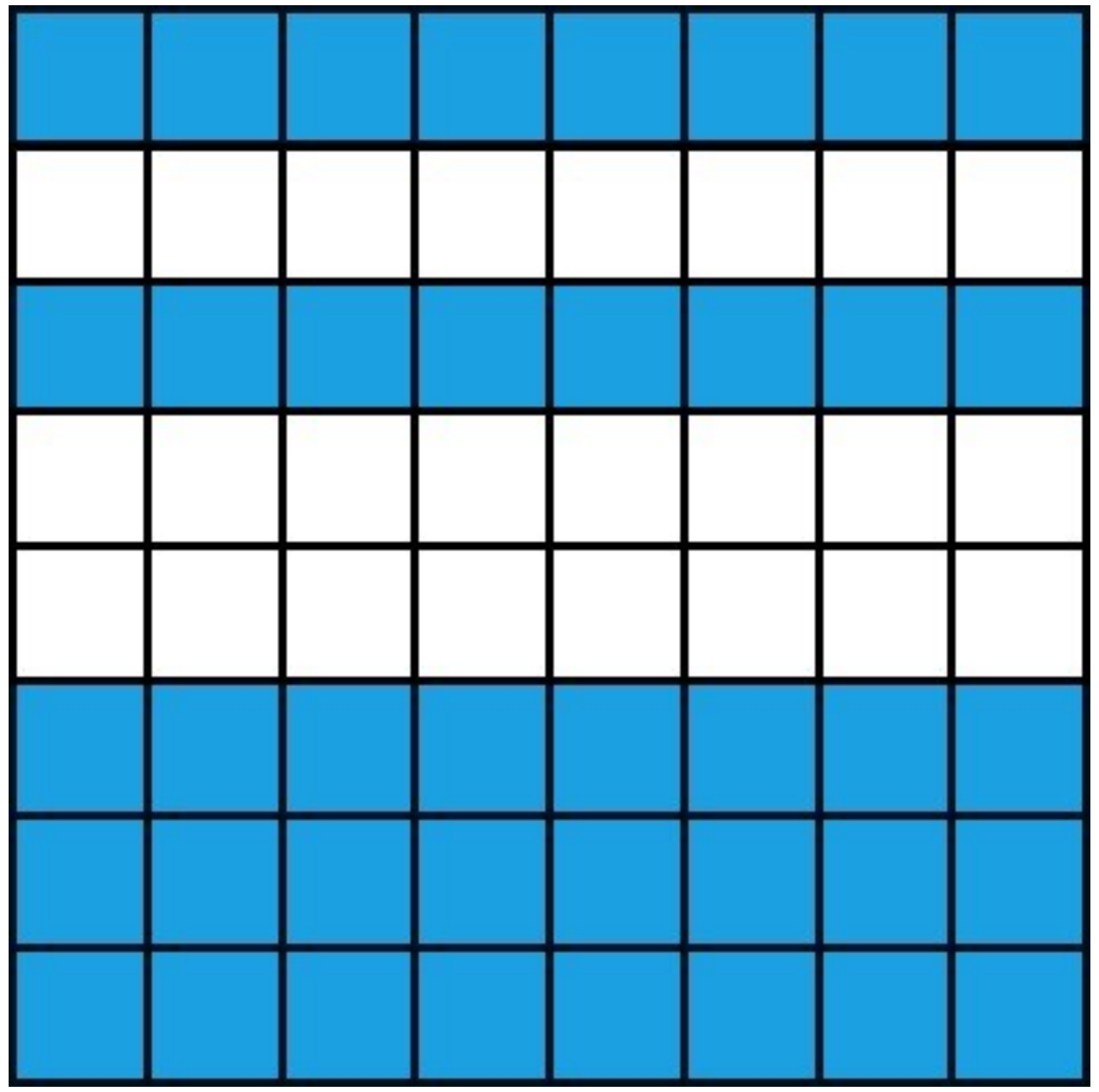
Example: 2D weight matrix (8x8)

Pruned

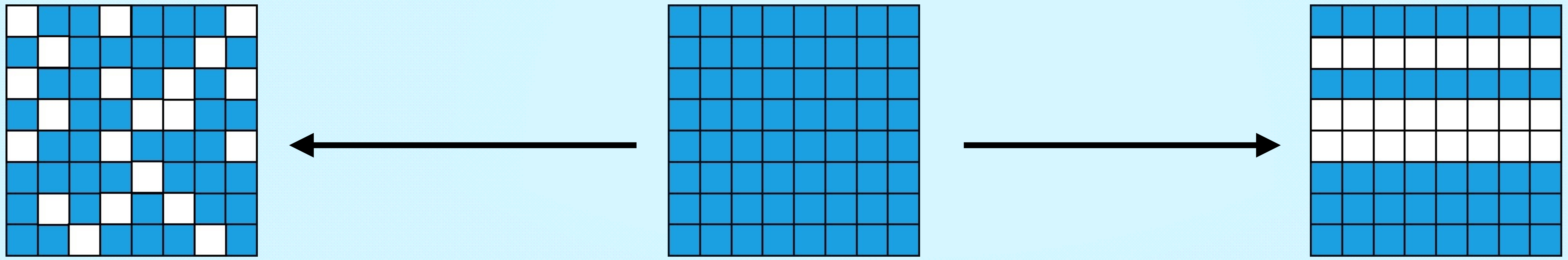
Preserved

Coarse-grained / Structured Pruning

- Less flexible pruning index



Question #3



Unstructured Pruning | Original Matrix | Structured Pruning

Which statement is more accurate?

Context: *neural network (NN) inference / prediction stage*

NN layer computation

Layer input $= x_1 \in \mathbb{R}^{m_1}$

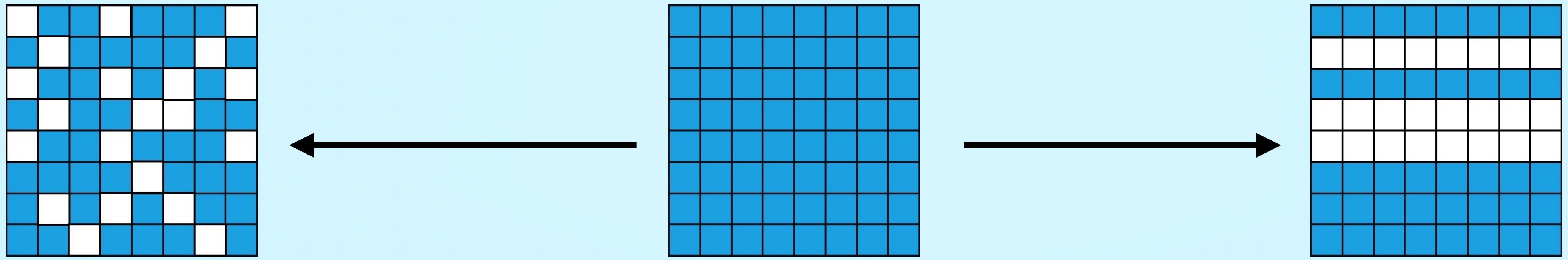
Weight $= \mathbf{W}_1 \in \mathbb{R}^{m_2 \times m_1}$, Bias $= b_1 \in \mathbb{R}^{m_2}$

Layer output $= x_2 \in \mathbb{R}^{m_2}$

$$x_2 = \mathbf{W}_1 \cdot x_1 + b_1$$

A. Accelerating NN models is easier after unstructured pruning (weight matrix)
B. Accelerating NN models is easier after structured pruning (weight matrix)
C. Both methods offer similar ease of acceleration
D. The original network (before pruning) will be faster

Question #3



Unstructured Pruning | Original Matrix | Structured Pruning

NN layer computation

$\text{Layer input} = x_1 \in \mathbb{R}^{m_1}$

$\text{Weight} = \mathbf{W}_1 \in \mathbb{R}^{m_2 \times m_1}, \quad \text{Bias} = b_1 \in \mathbb{R}^{m_2}$

$\text{Layer output} = x_2 \in \mathbb{R}^{m_2}$

$$x_2 = \mathbf{W}_1 \cdot x_1 + b_1$$

Which statement is more accurate?

Context: *neural network (NN) inference / prediction stage*

A. Accelerating NN models is easier after unstructured pruning (weight matrix)

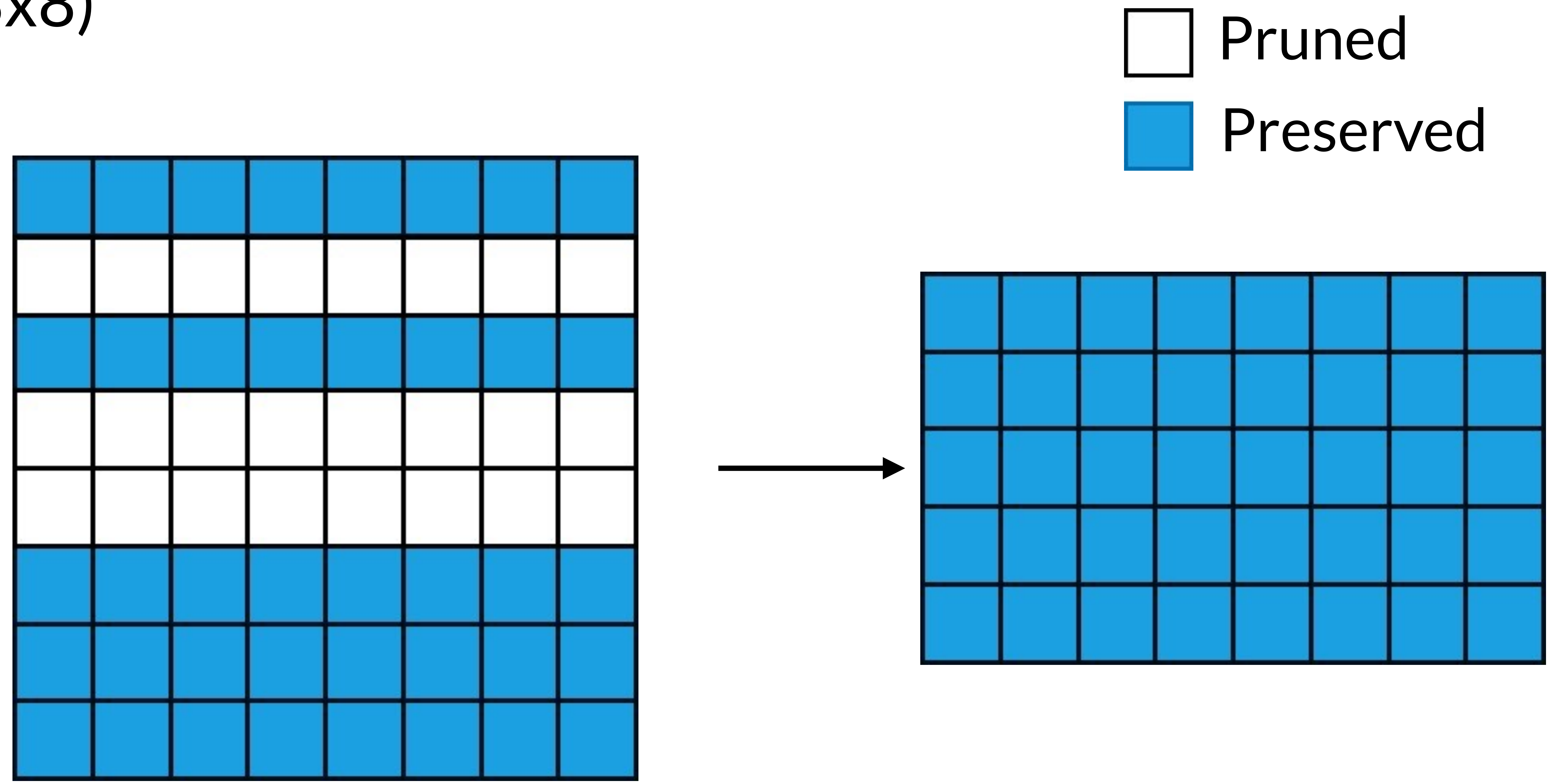
B. Accelerating NN models is easier after structured pruning (weight matrix)

C. Both methods offer similar ease of acceleration

D. The original network (before pruning) will be faster

Different Pruning Granularity: Structured and Unstructured

Example: 2D weight matrix (8x8)



Coarse-grained / Structured Pruning

- Less flexible pruning index
- Small regular matrix → easy to accelerate

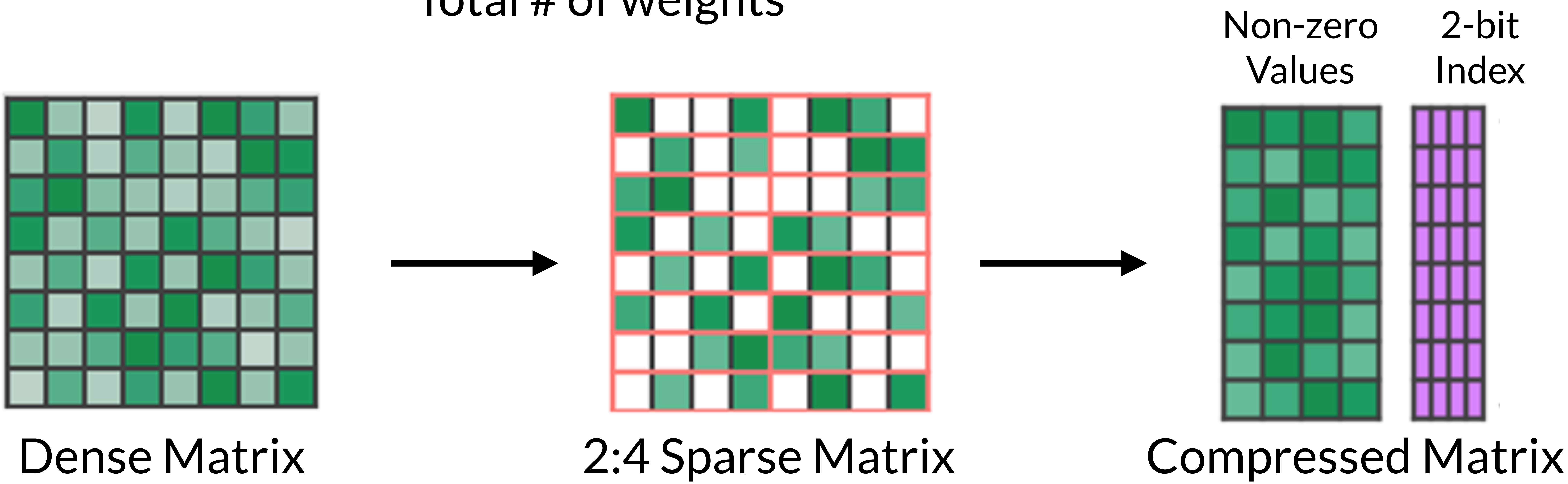
Mention hardware

Pattern-based Pruning

Pruning with N:M sparsity = In each M contiguous elements, N of them are pruned
Example: 2:4 sparsity (50% sparsity)

It is supported by Nvidia's Ampere GPU architecture (eg A100)

$$\text{Sparsity} = \frac{\text{\# of non-zero weights}}{\text{Total \# of weights}}$$



Accelerating Inference with Sparsity Using the NVIDIA Ampere Architecture and NVIDIA TensorRT

Lecture Outline

Motivation behind efficient model design and some highlights

Introduction to Quantization
- Definition
- PTQ vs QAT

Introduction to Pruning
- What is pruning? How to formulate pruning?
- Determine pruning granularity and criteria
- Network performance after pruning

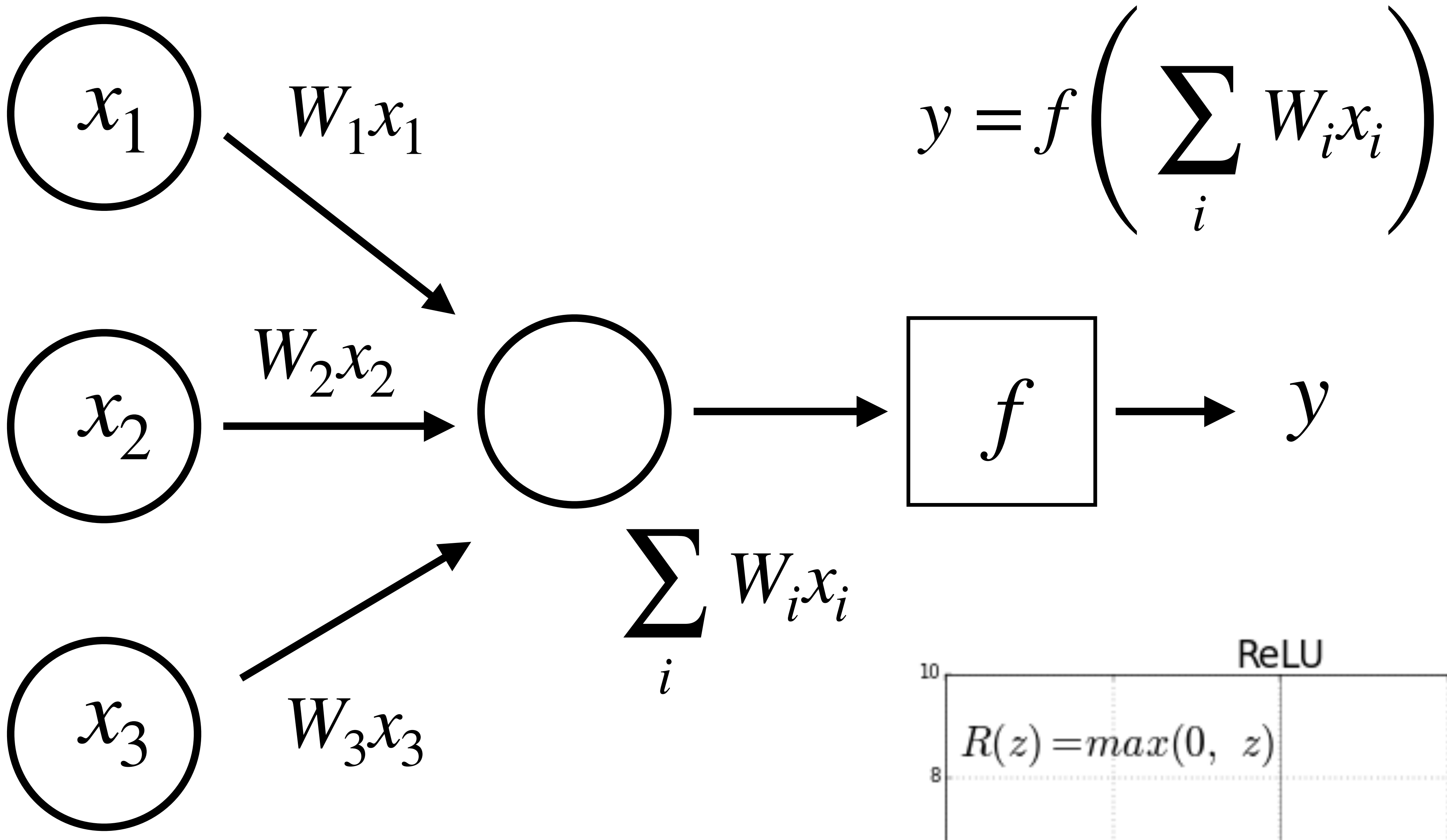
ML on FPGA

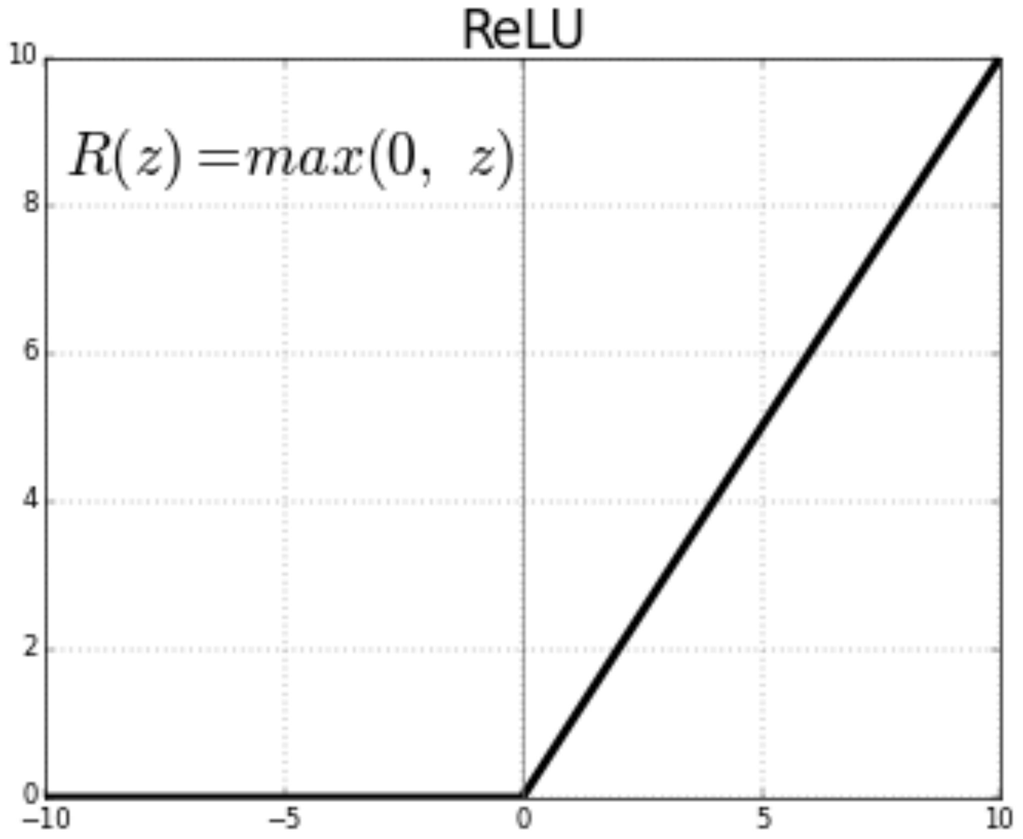
hls4ml and Trigger applications

Pruning Criteria

Goal:

Remove less important parameters from a neural network





Example

ReLU Activation

$$f(\cdot) = \mathrm{ReLU}(\cdot)$$

Weights: $W = [-5,\ 12,\ 0.2]$

$$y = \mathrm{ReLU}(-5x_1 + 12x_2 + 0.2x_3)$$

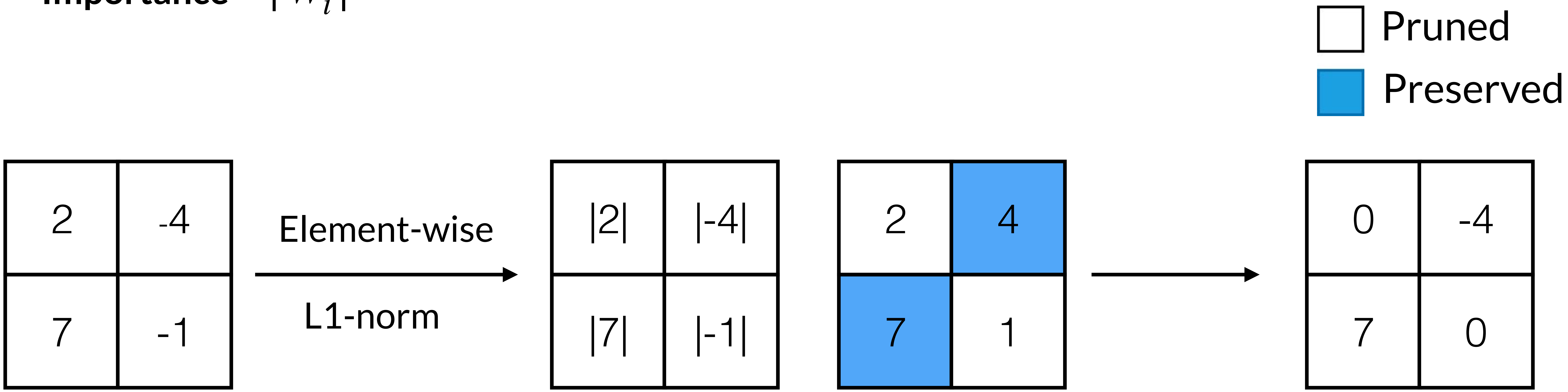
If we want to remove one weight, then which one?

Magnitude-based Pruning

Element-wise pruning using absolute magnitude

Magnitude-based pruning considers weights with larger absolute values are more important than other weights.

Importance = $|W_i|$



Original Weight

Importance

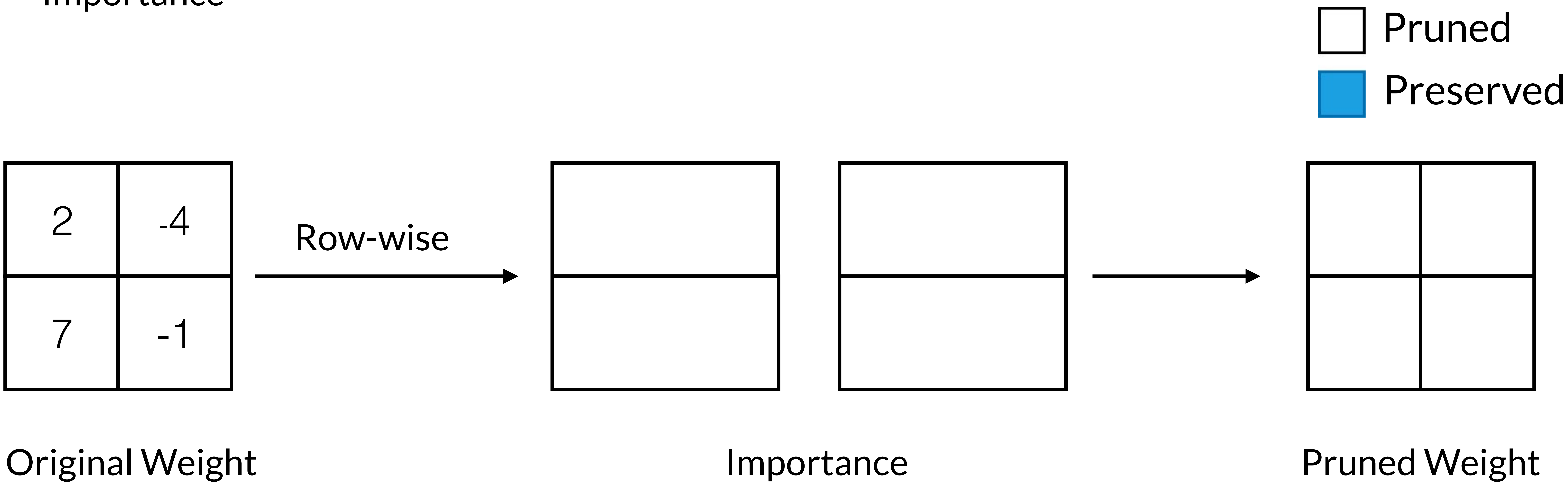
Pruned Weight

Magnitude-based Pruning

Row-wise pruning

Magnitude-based pruning considers weights with larger absolute values are more important than other weights.

Importance =



Question #4

Row-wise pruning

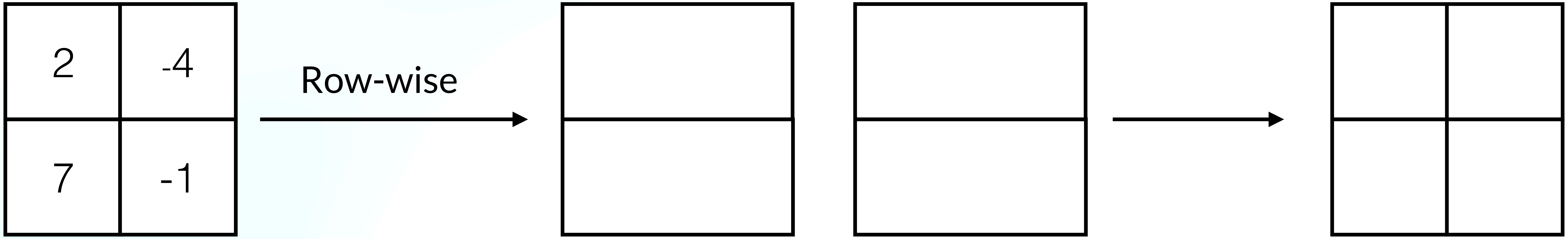
Come up with a strategy to prune a whole row.

2 minutes

Importance = *define it as a function of the weights*

Pruned

Preserved



Original Weight

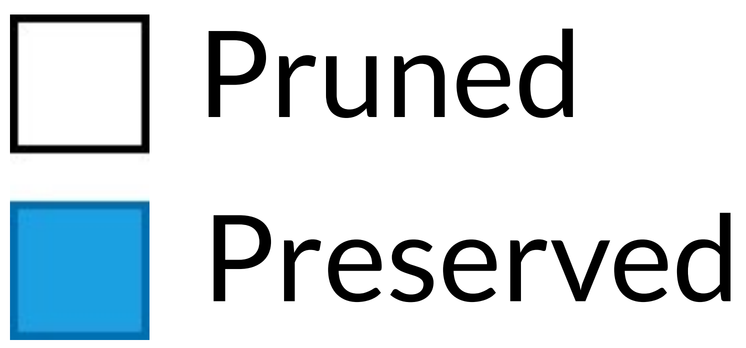
Importance

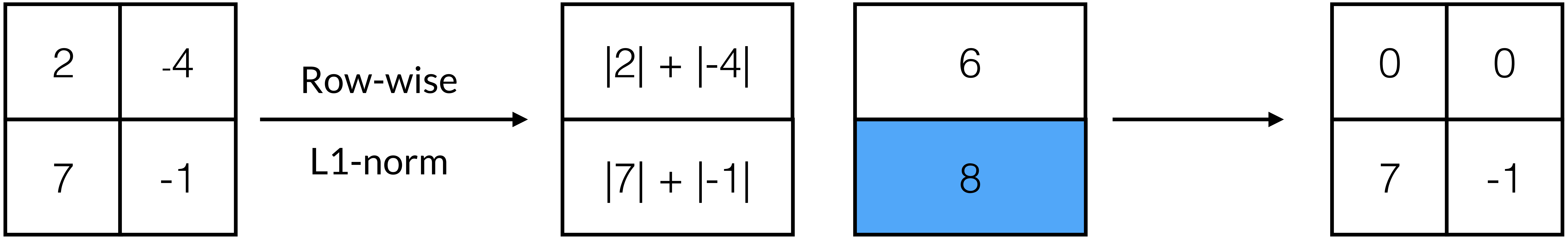
Pruned Weight

Magnitude-based Pruning

Row-wise pruning using *L1*-norm

Importance = $\sum_{i \in S} |w_i|$ sum of weighs within the structural set (S)





Original Weight

Importance

Pruned Weight

Magnitude-based Pruning

Row-wise pruning using *L2*-norm

Importance = $\sqrt{\sum_{i \in S} |w_i|^2}$ sum of weighs square within the structural set (S)

Pruned

Preserved

$$\underbrace{\begin{bmatrix} 2 & -4 \\ 7 & -1 \end{bmatrix}}_{\text{Original Weight}} \xrightarrow[\text{L2-norm}]{\text{Row-wise}} \underbrace{\begin{bmatrix} \sqrt{|2|^2 + |-4|^2} = \sqrt{20} \\ \sqrt{|7|^2 + |-1|^2} = \sqrt{50} \end{bmatrix} \begin{bmatrix} \sqrt{20} \\ \sqrt{50} \end{bmatrix}}_{\text{Importance}} \longrightarrow \underbrace{\begin{bmatrix} 0 & 0 \\ 7 & -1 \end{bmatrix}}_{\text{Pruned Weight}}$$

There are many other ways!

We highlighted **magnitude-based weight pruning**

→ You can use any fancy or complicated function that meets your requirements

- **Neuron Pruning**

Some other methods:

- **Second-order derivative-based pruning**

→ Minimizes the error on loss function introduced by pruned synapses

$$\delta L = L(x; W) - L(x; W_p = W - \delta W)$$

- **Channel pruning for convolution neural networks**

- **Regression pruning**

→Minimize error of a corresponding layer's output: before and after pruning

Lecture Outline

Motivation behind efficient model design and some highlights

Introduction to Quantization
- Definition
- PTQ vs QAT

Introduction to Pruning
- What is pruning? How to formulate pruning?
- Determine pruning granularity and criteria
- Network performance after pruning

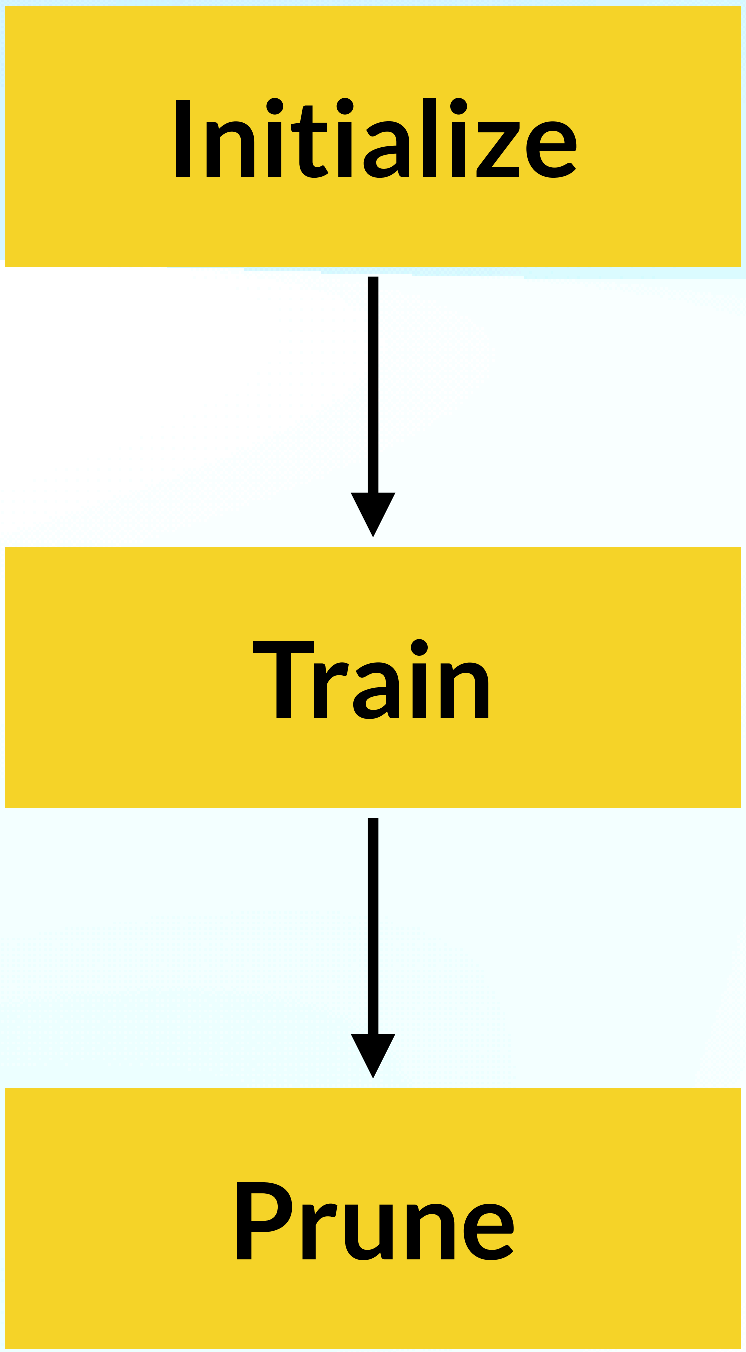
ML on FPGA

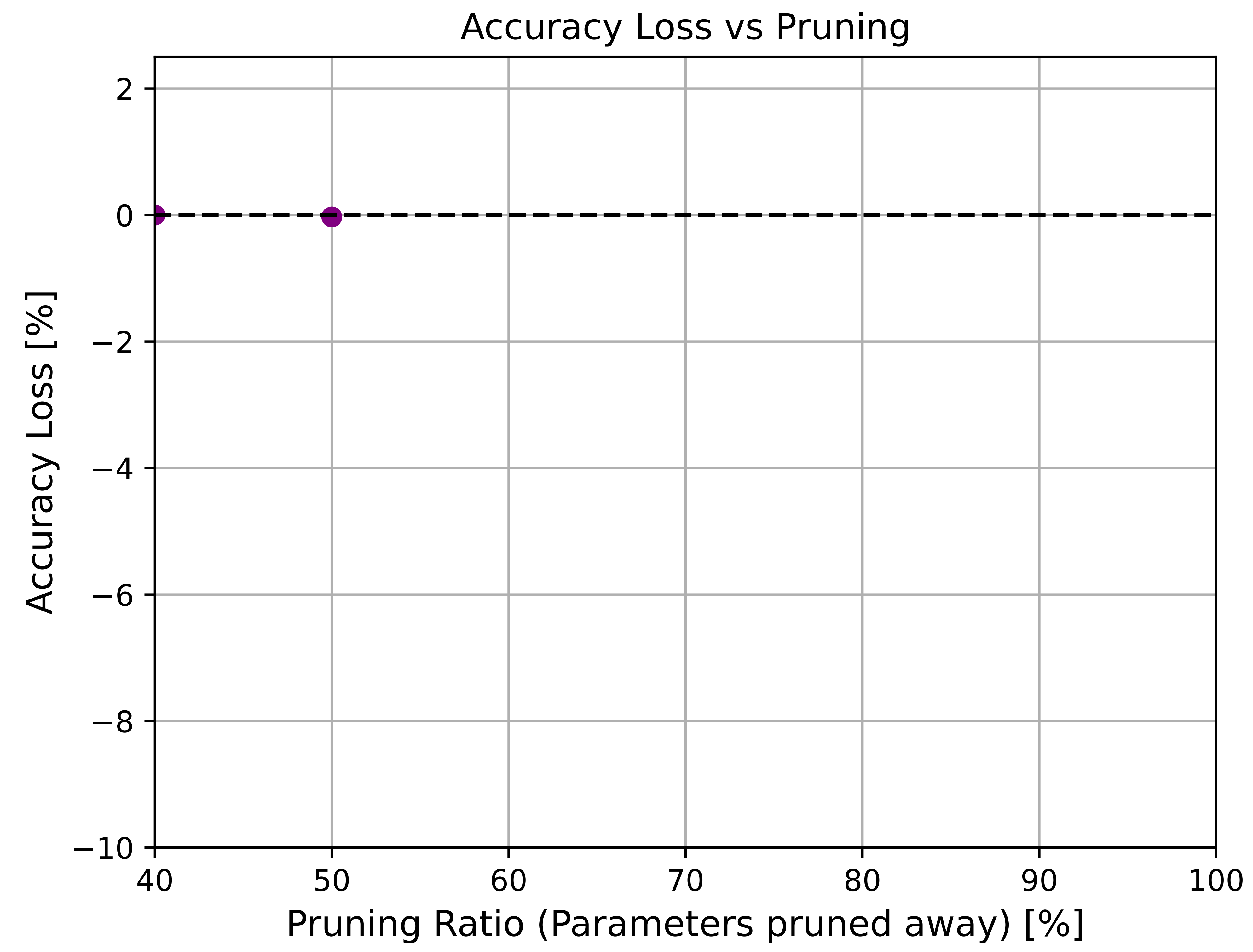
hls4ml and Trigger applications

Question #5

What trend do you expect in the accuracy-loss vs pruning ratio plot beyond 50% pruning ratio?

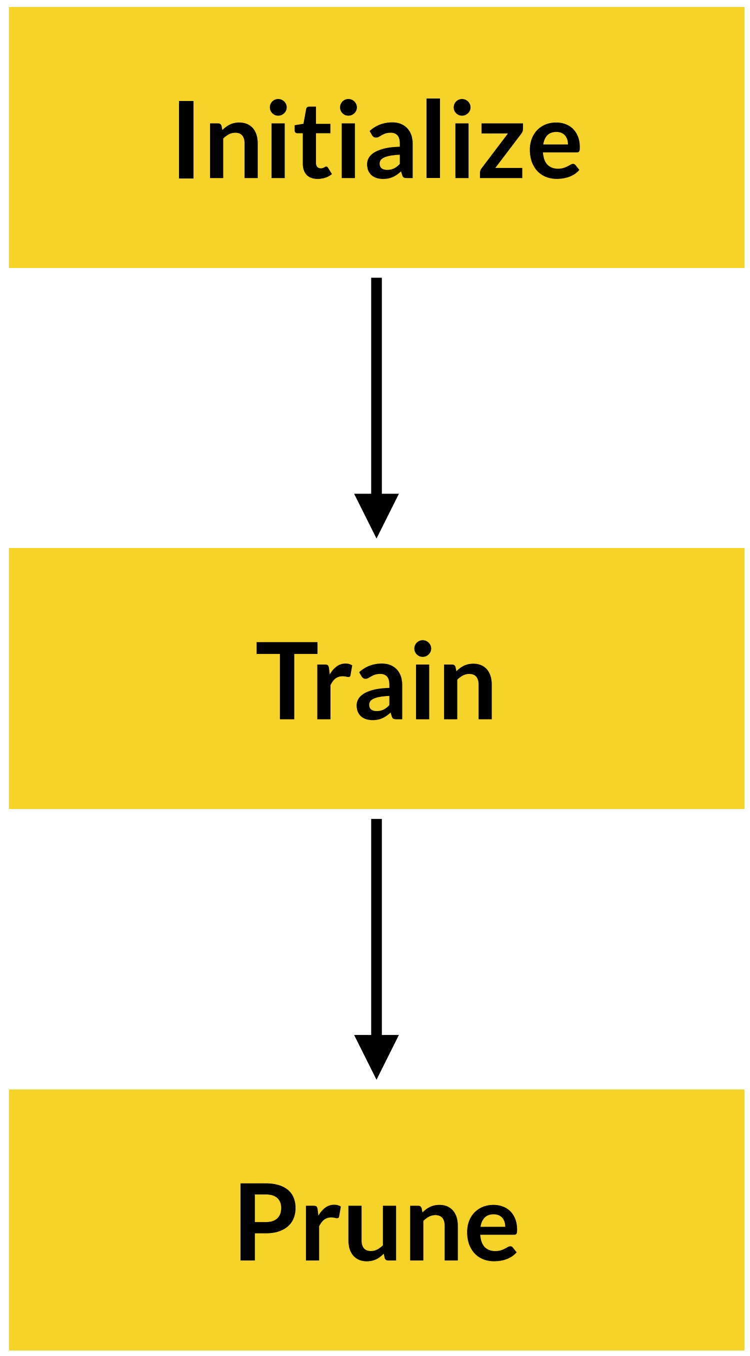
Assume: *the model performance did not degrade after 50% pruning*

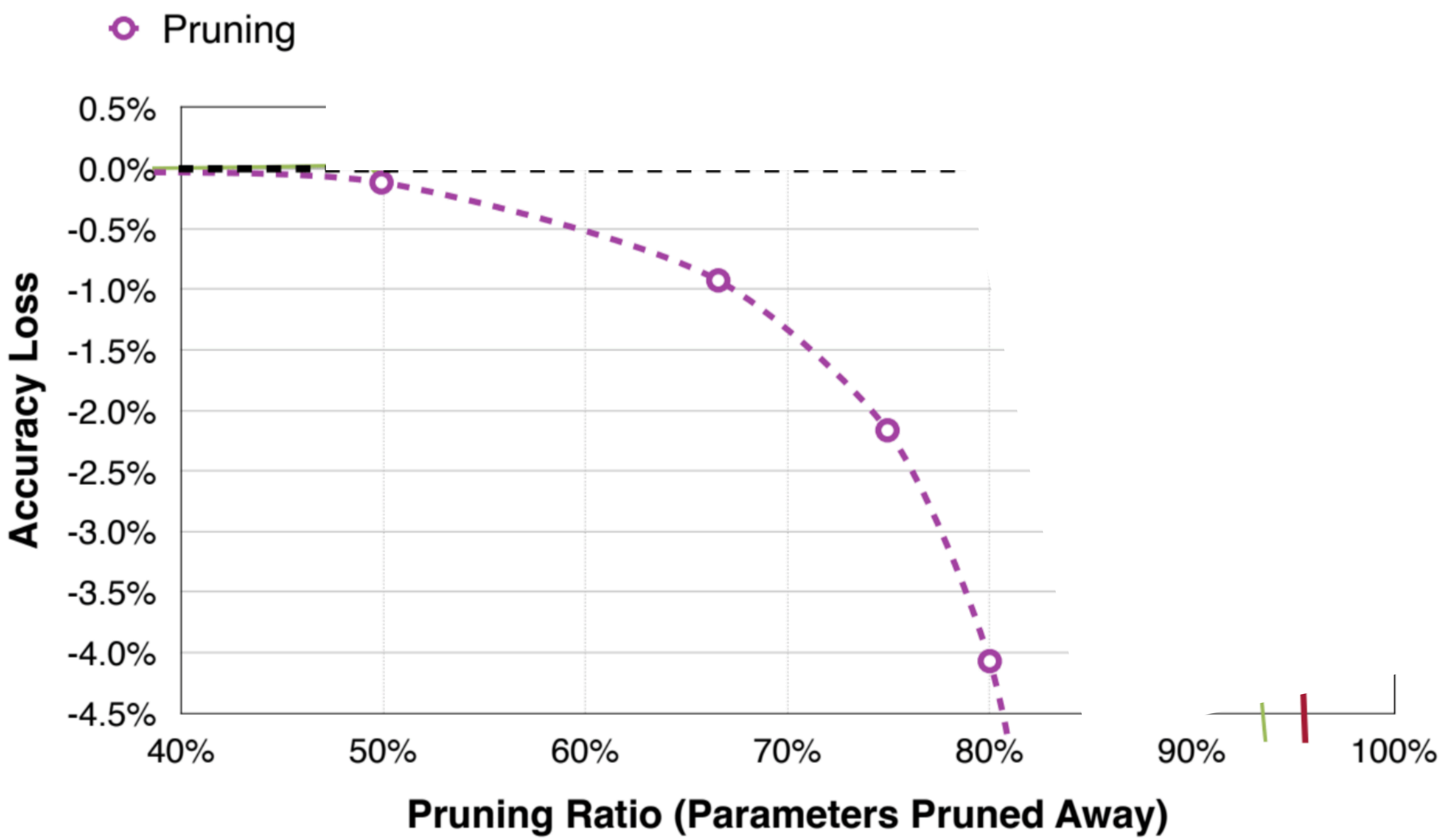




Accuracy loss in pruning

The model performance may decrease after pruning

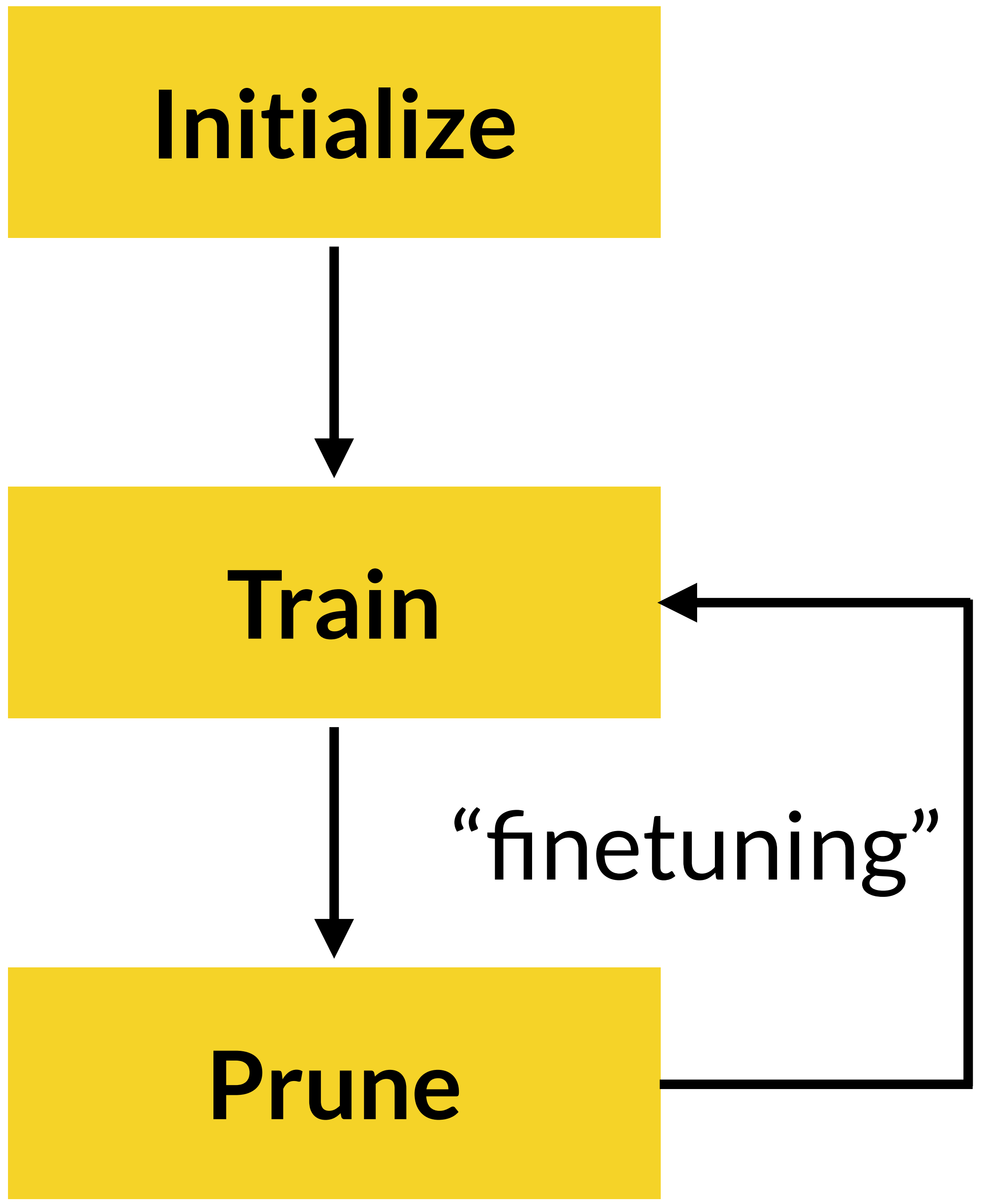


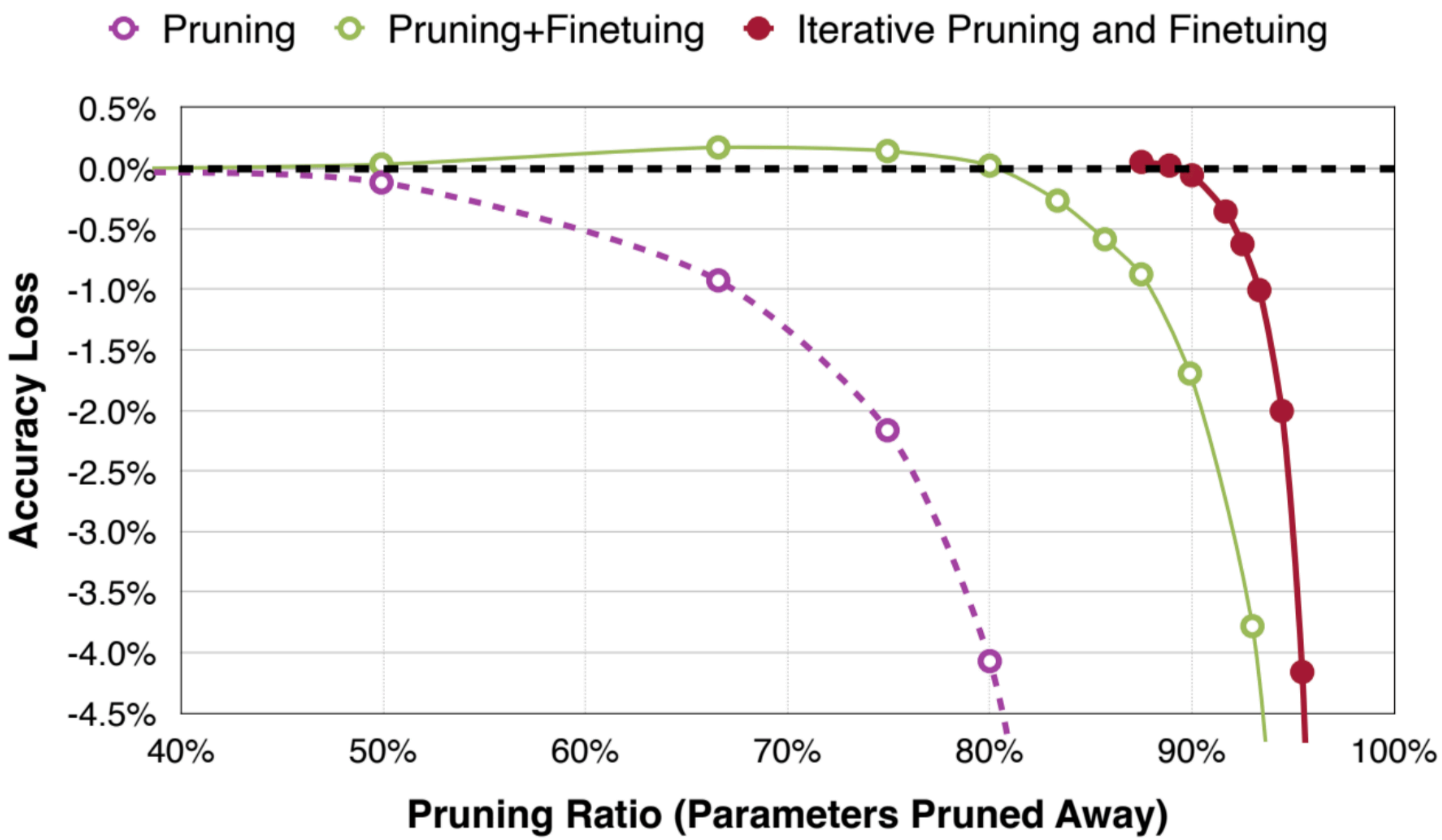


Learning both Weights and Connections for Efficient Neural Networks {Han et al. , NeurIPS 2015

Accuracy loss in pruning

The model performance may decrease after pruning





Learning both Weights and Connections for Efficient Neural Networks {Han et al. , NeurIPS 2015

Pruning References

Neural Network pruning survey paper:
https://arxiv.org/abs/2308.06767

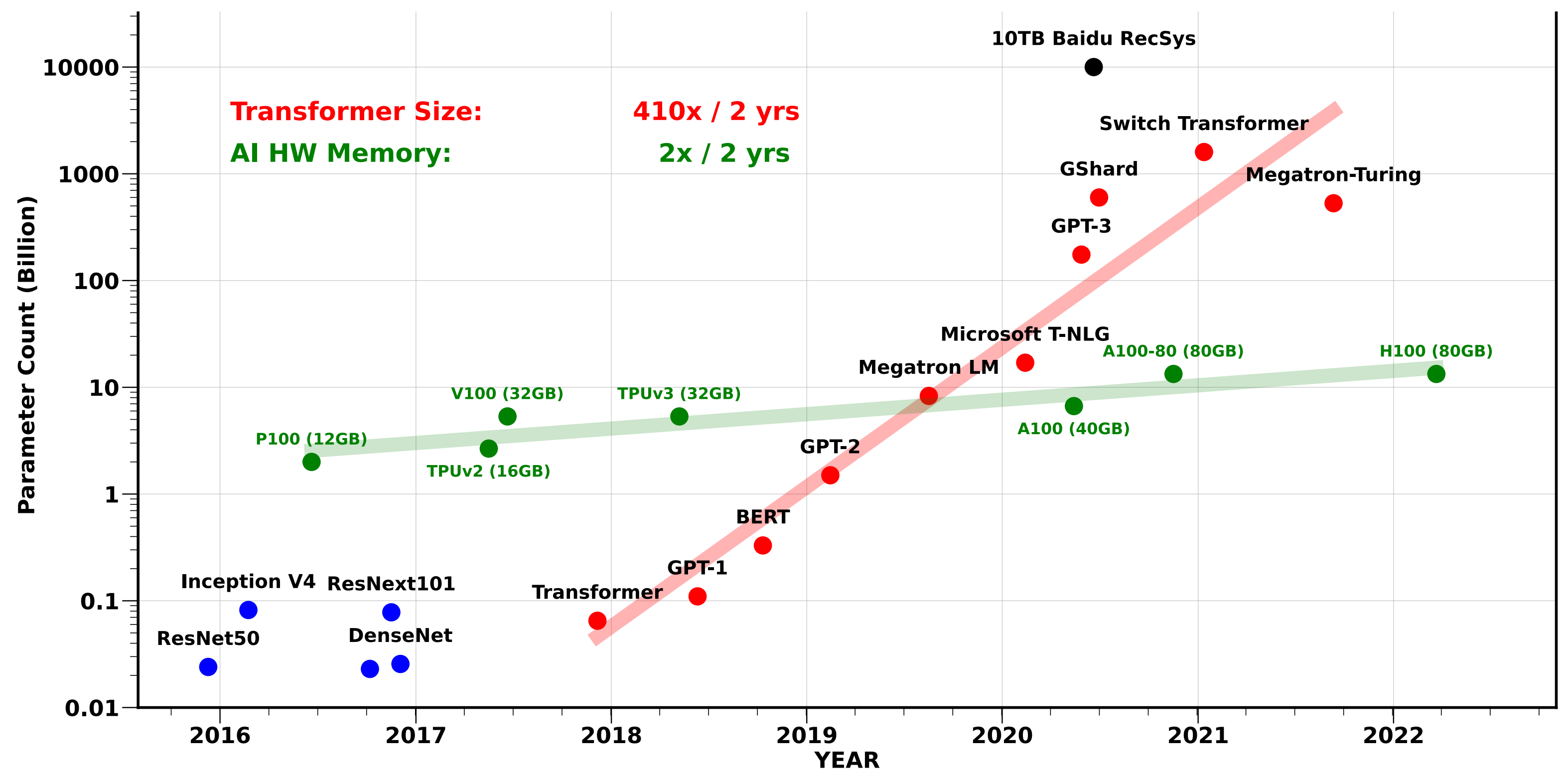
MIT Efficient ML Course:
https://hanlab.mit.edu/courses/2023-fall-65940

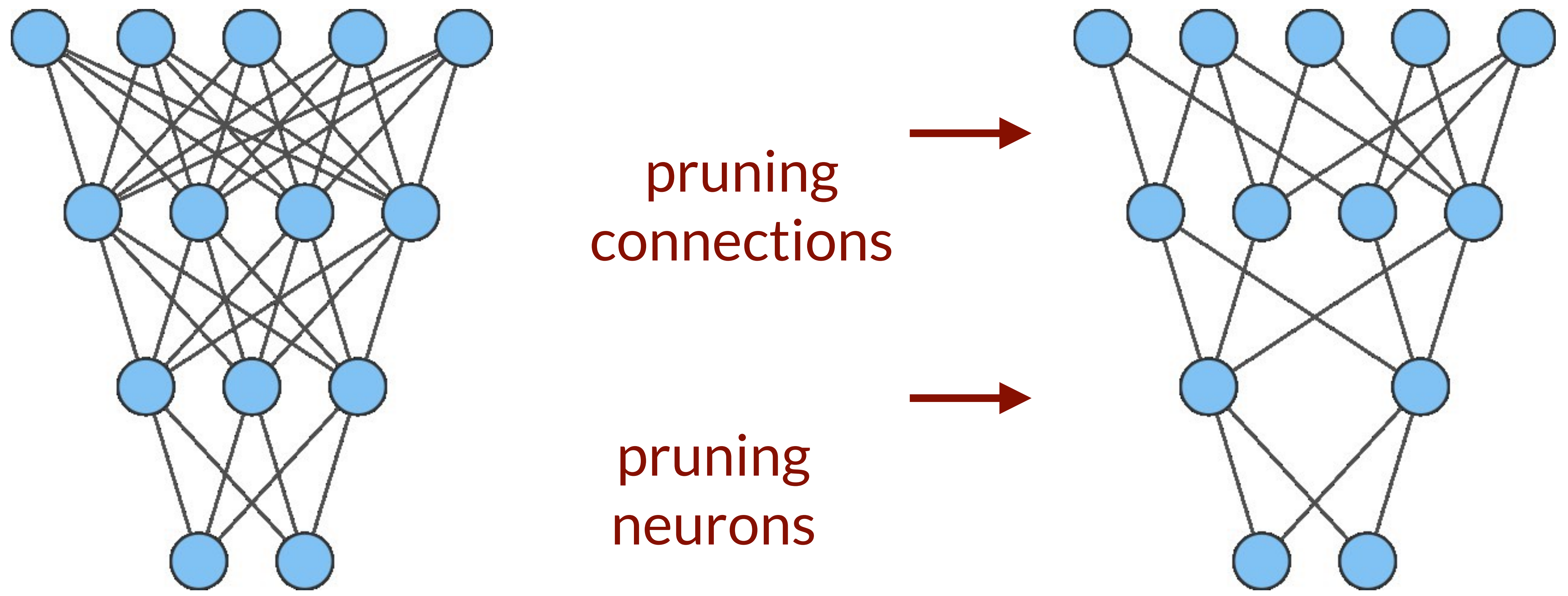
TensorFlow pruning guide:
https://www.tensorflow.org/model_optimization/guide/pruning/comprehensive_guide

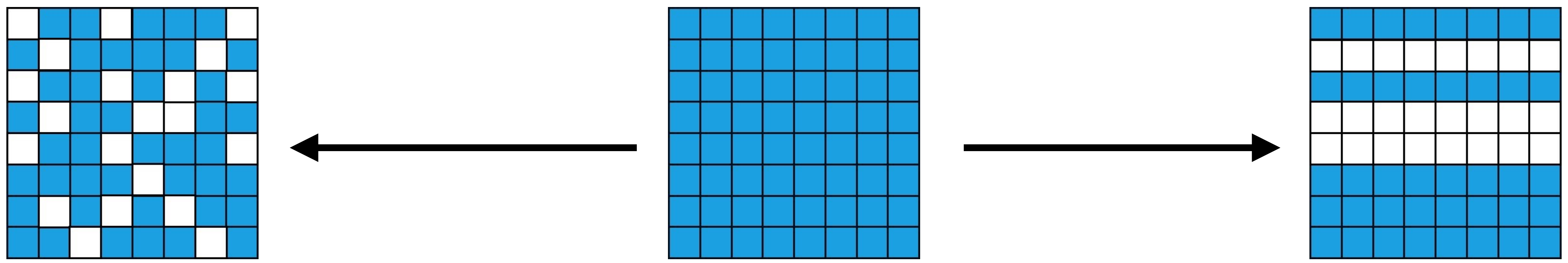
PyTorch pruning tutorial:
https://pytorch.org/tutorials/intermediate/pruning_tutorial.html

Key Points

Expensive large models



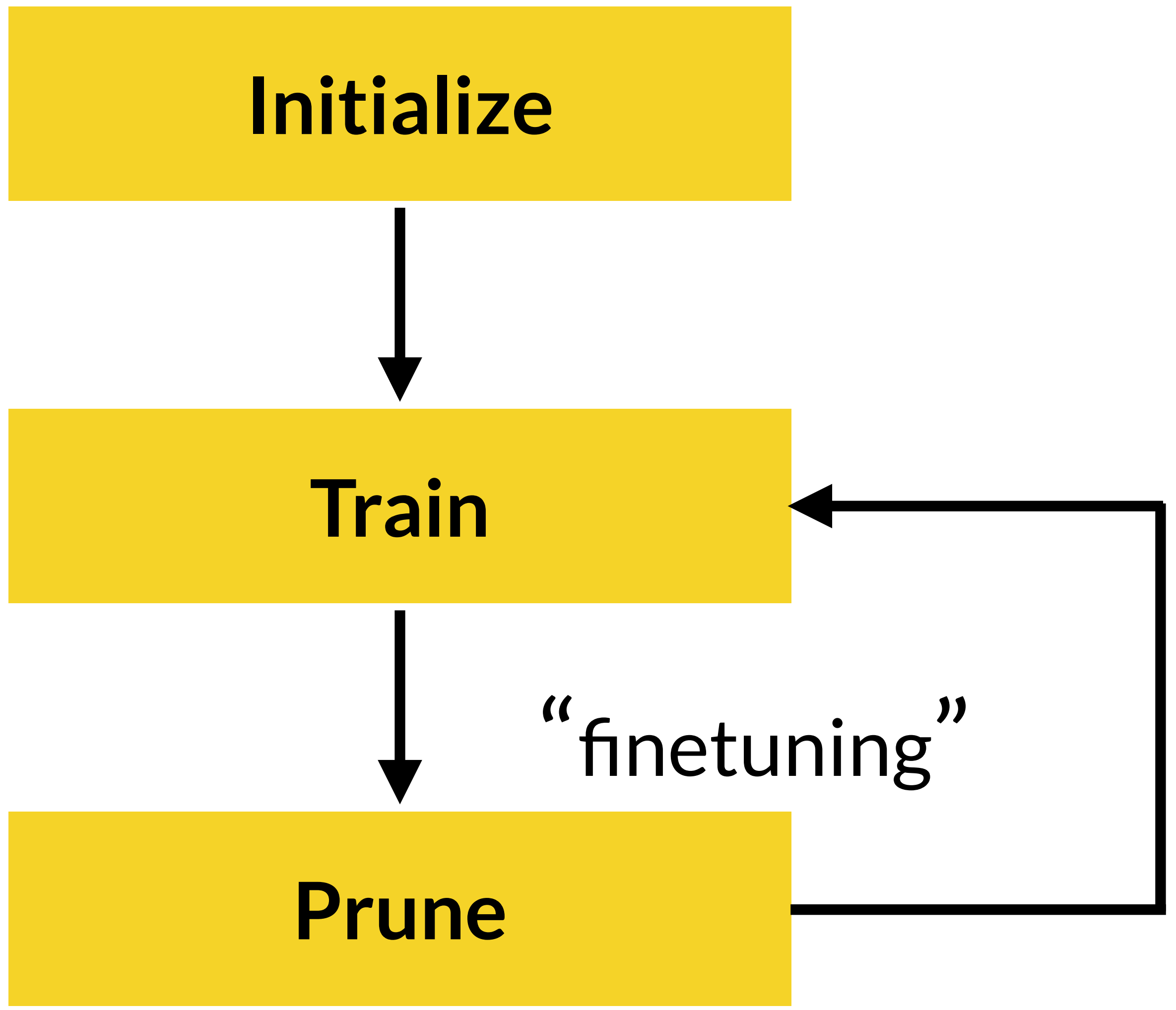




Unstructured Pruning

Original Matrix

Structured Pruning



Let's practice it

Jupyter Link

https://tutorials.fastmachinelearning.org

Instructions are also on GitHub

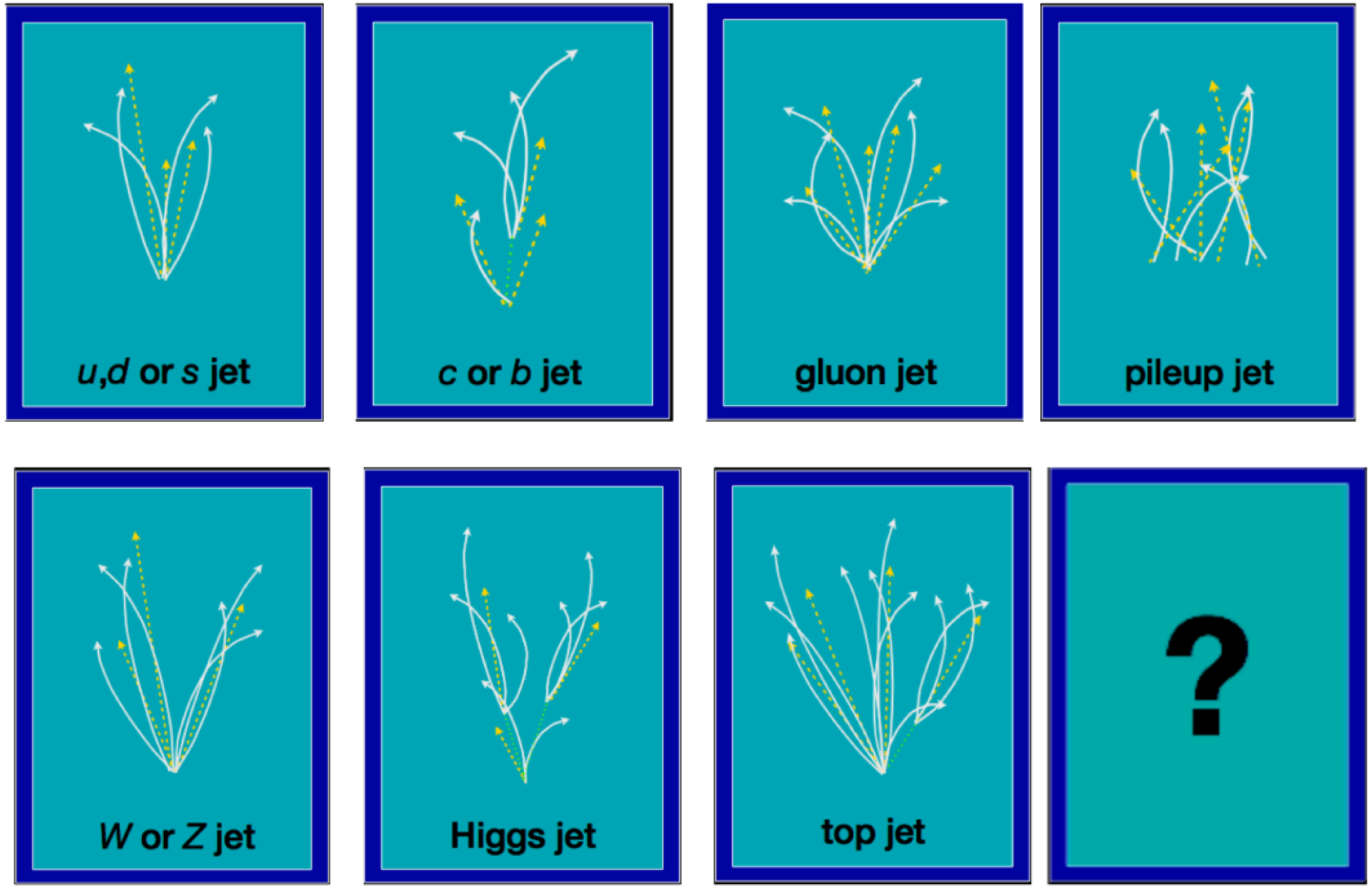
https://github.com/ml4fp/2024-lbnl/tree/main/efficient_ml

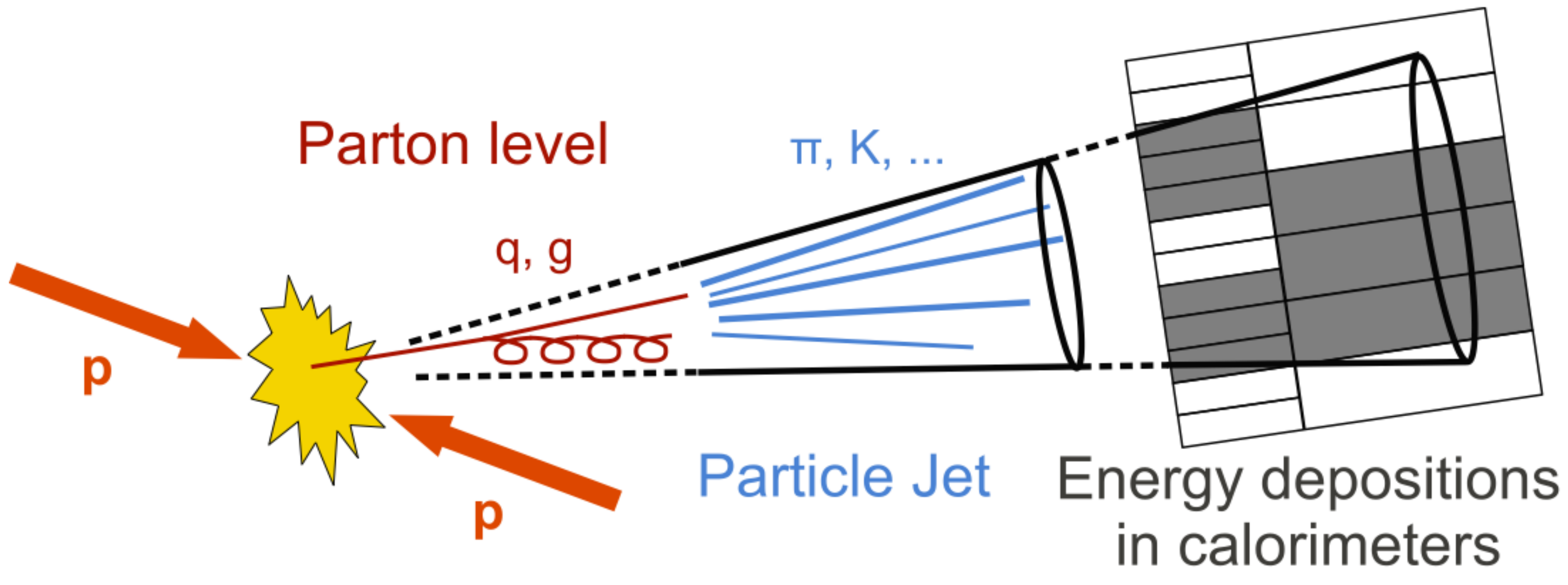
Start your Jupyterhub

Note it is a different jupyterhub compared to the other days

Checkout the tutorial repo: https://github.com/ml4fp/2024-lbnl.git

Example: Jet Classification

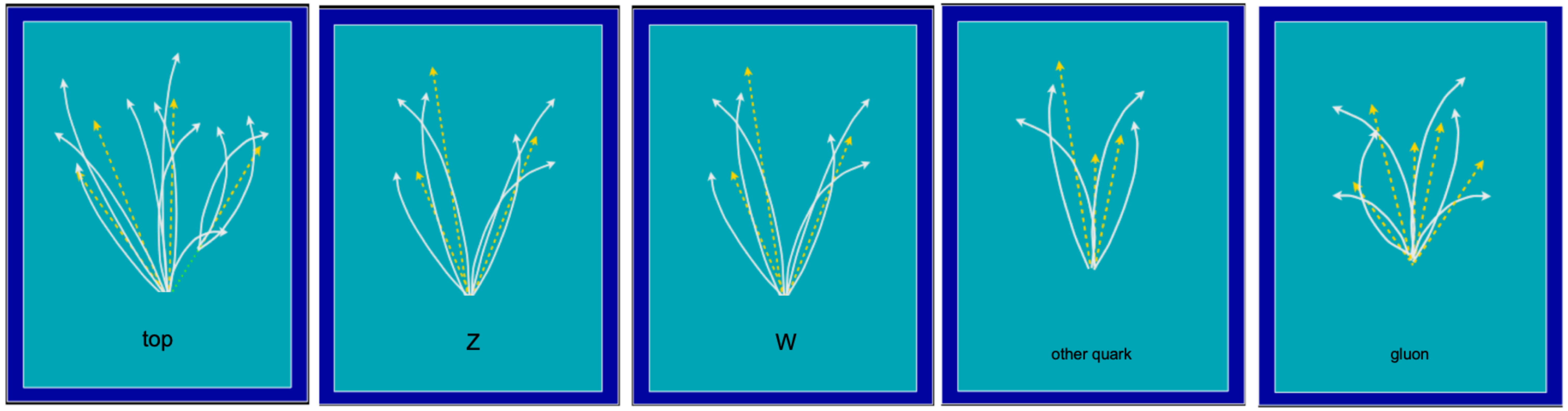




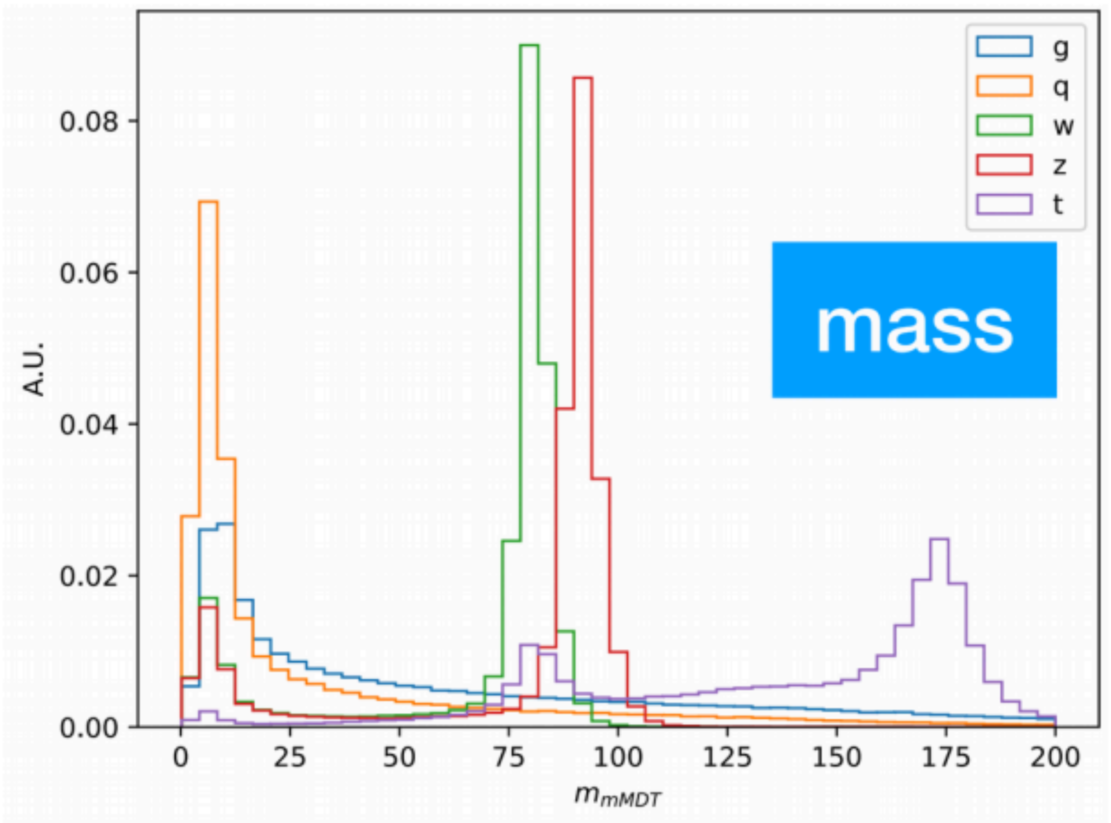
Jet Classification: 5-Class classifier

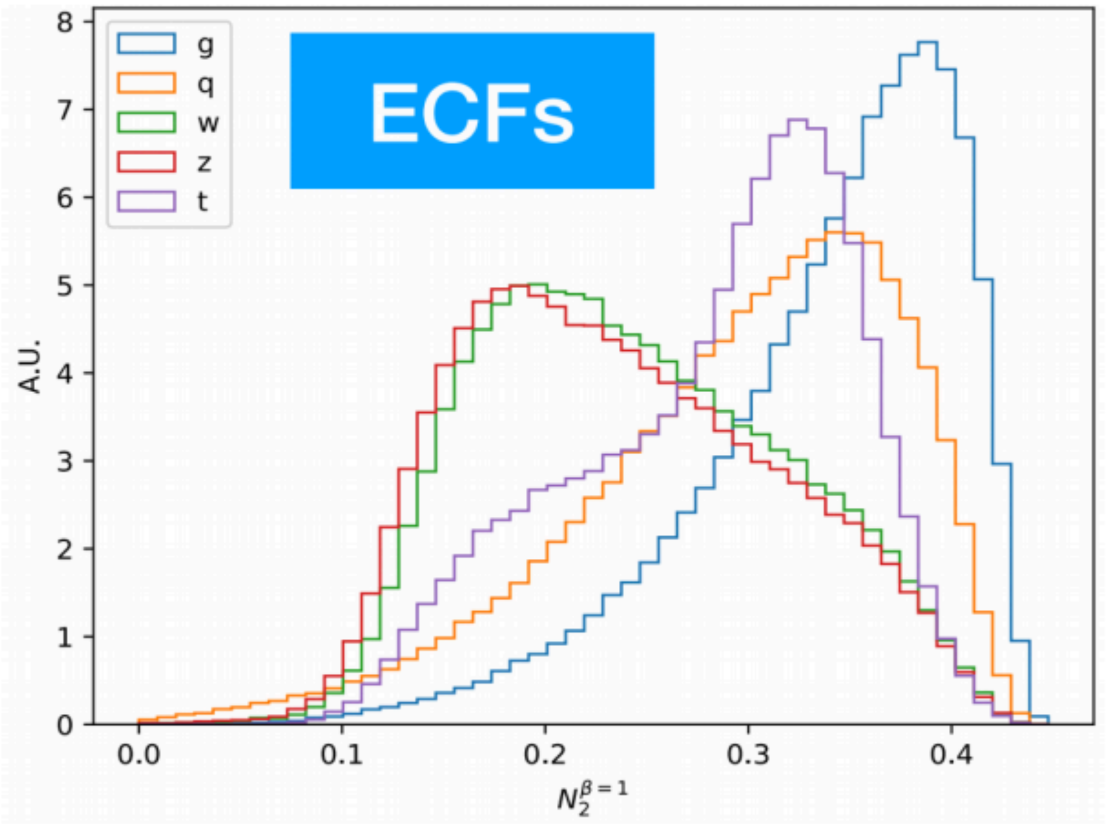
Five class classifier

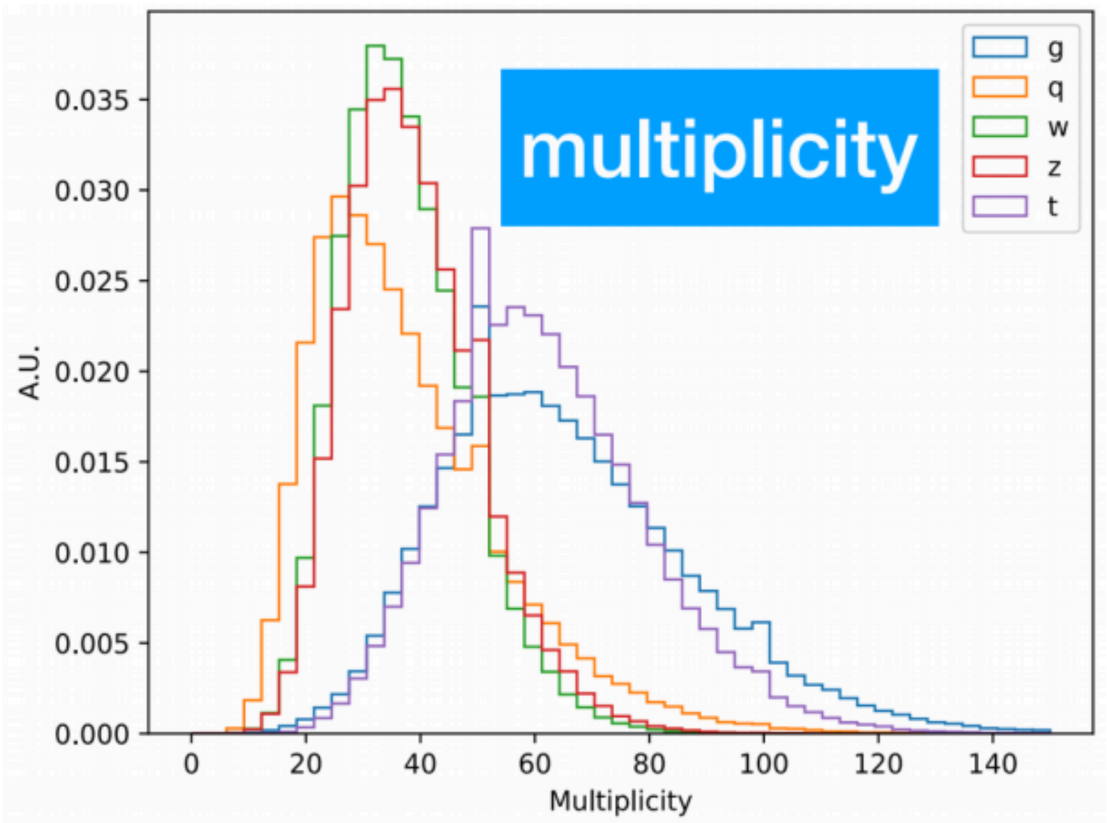
Sample: ~ 1M events with two boosted WW/ZZ/tt/qq/gg anti-kT jets



t→bW→bqq　　Z→qq　　W→qq　　q/g background







Observables

m_{mMDT}

$N_2^{\beta=1,2}$

$M_2^{\beta=1,2}$

$C_1^{\beta=0,1,2}$

$C_2^{\beta=1,2}$

$D_2^{\beta=1,2}$

$D_2^{(\alpha,\beta)=(1,1),(1,2)}$

$\sum z \log z$

Multiplicity

Lecture Outline

Motivation behind efficient model design and some highlights

Introduction to Quantization
- Definition
- PTQ vs QAT

Introduction to Pruning
- What is pruning? How to formulate pruning?
- Determine pruning granularity and criteria
- Network performance after pruning

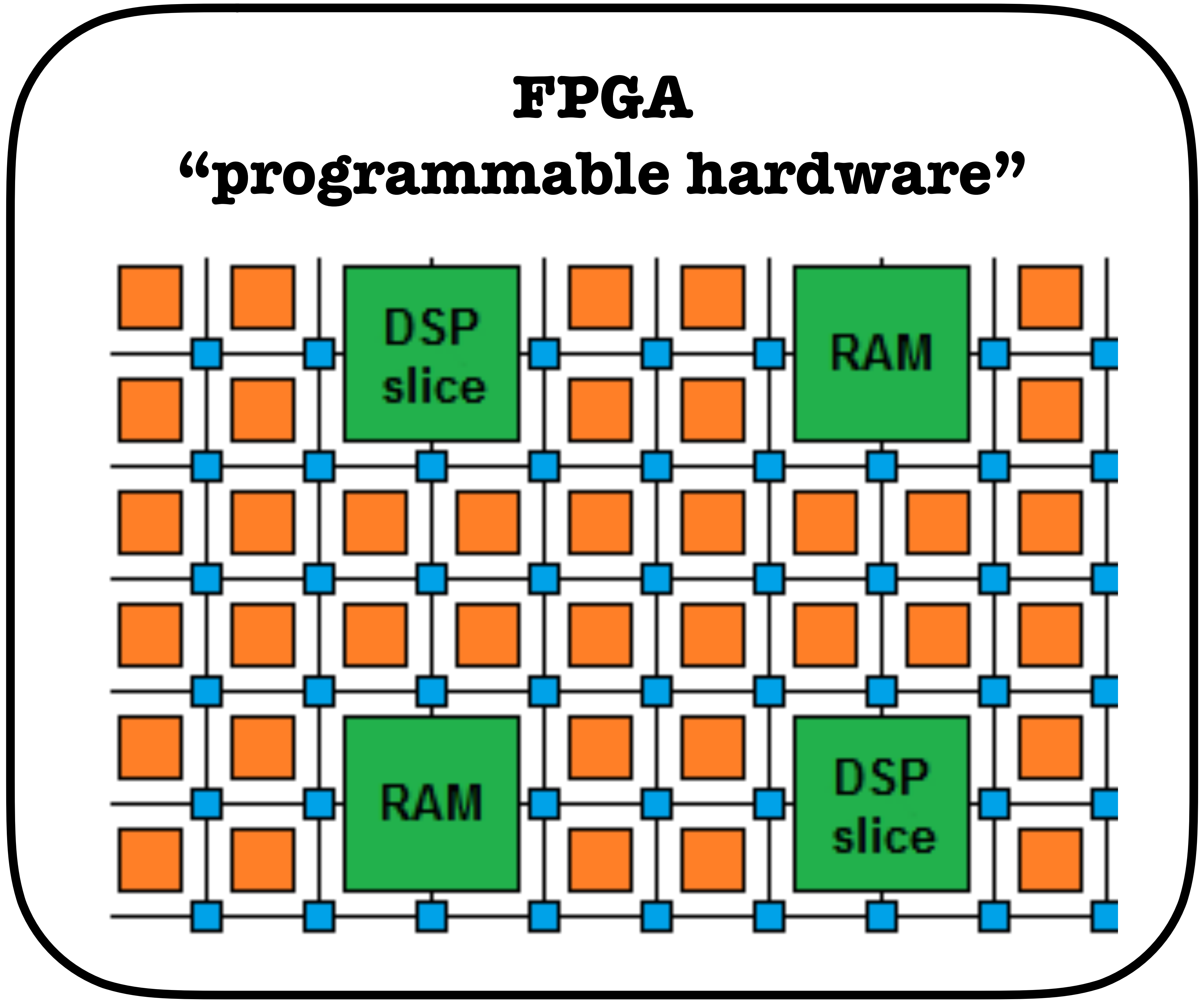
ML on FPGA

hls4ml and Trigger applications

Modern FPGAs

Pros:

- Reprogrammable interconnects between embedded components that perform multiplication (DSPs), apply logical functions (LUTs), or store memory (BRAM)
- High throughput I/O: O(100) optical transceivers running at O(15) Gbps
- Massively parallel
- Low power



Cons:

- Requires domain knowledge to program (using VHDL/Verilog)

Why FPGA at LHC?

High parallelism ⇧ = Low latency ⇩

- Can work on different data simultaneously (pipelining)! High bandwidth

Power efficient

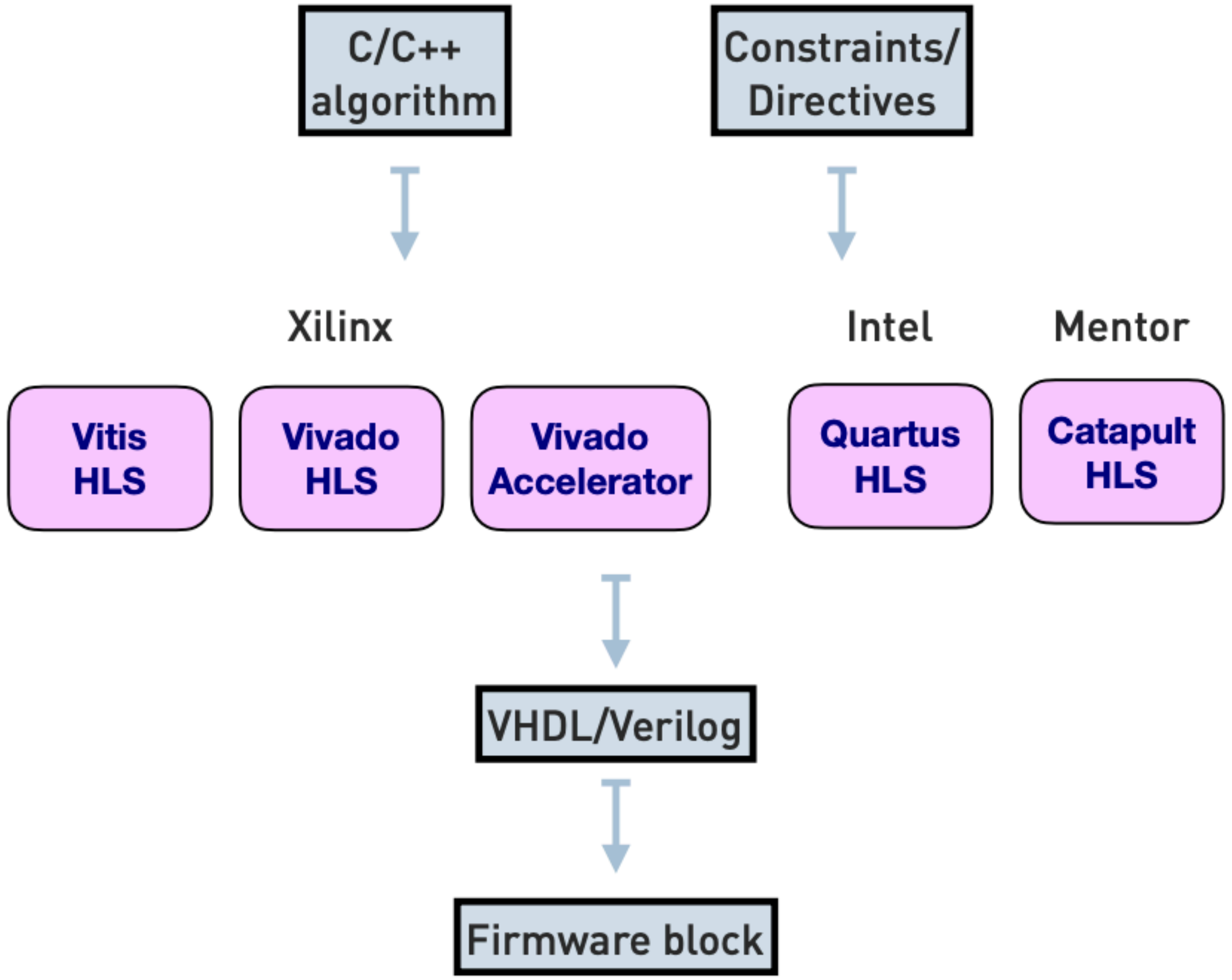
- FPGAS ~x10 more power efficient than GPUs

Latency deterministic

- FPGAs repeatable and predictable latency

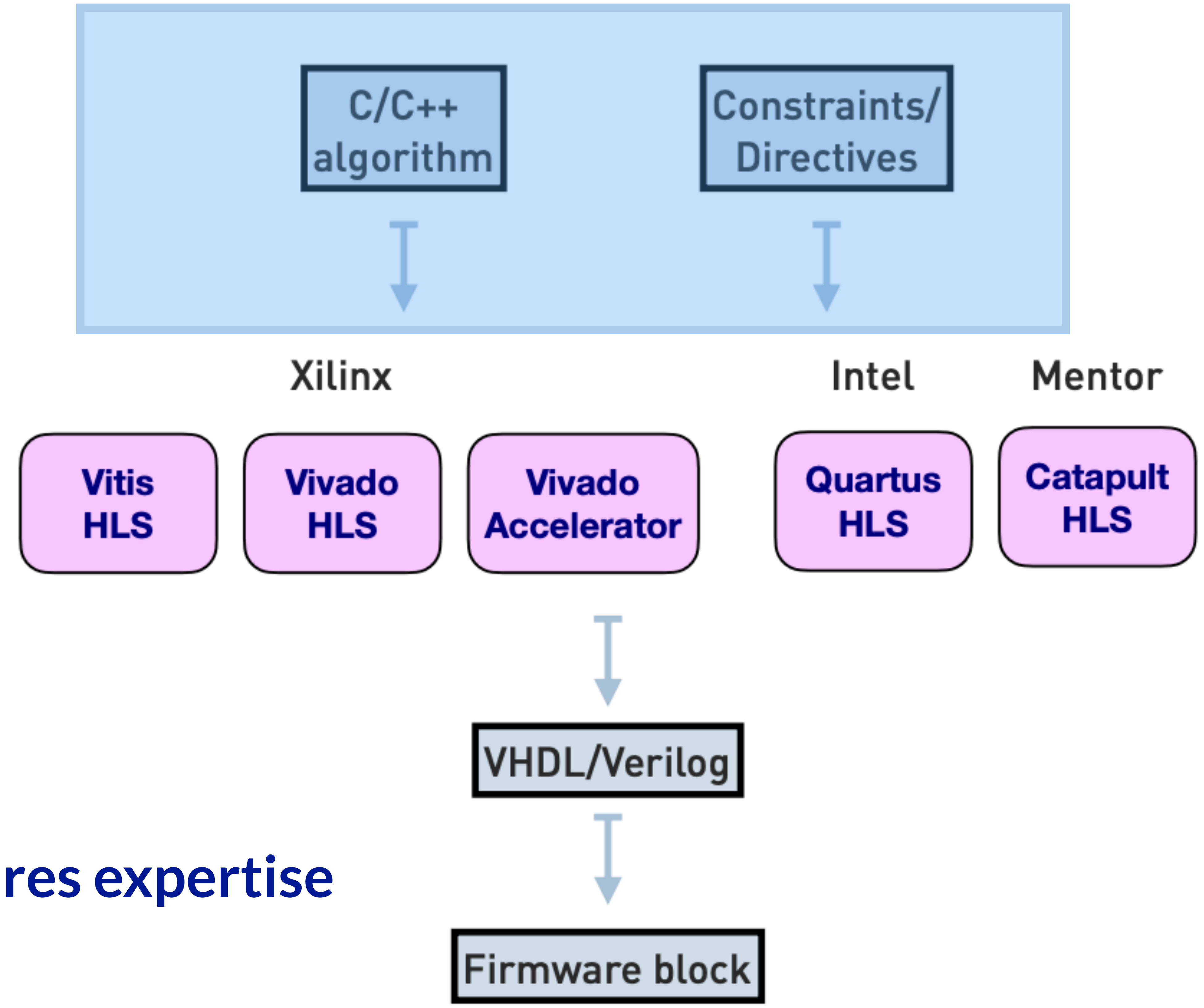
Latency is fixed by proton collisions occurring at 40 MHz, cannot tolerate slack

FPGA Programming



1. Write C-style code of function
2. Pass to a high-level synthesis (HLS) tool
3. HLS translates to hardware-description language (HDL)
4. Build firmware

FPGA Programming



1. Write C-style code of function

2. Pass to a high-level synthesis (HLS) tool

3. HLS translates to hardware-description language (HDL)

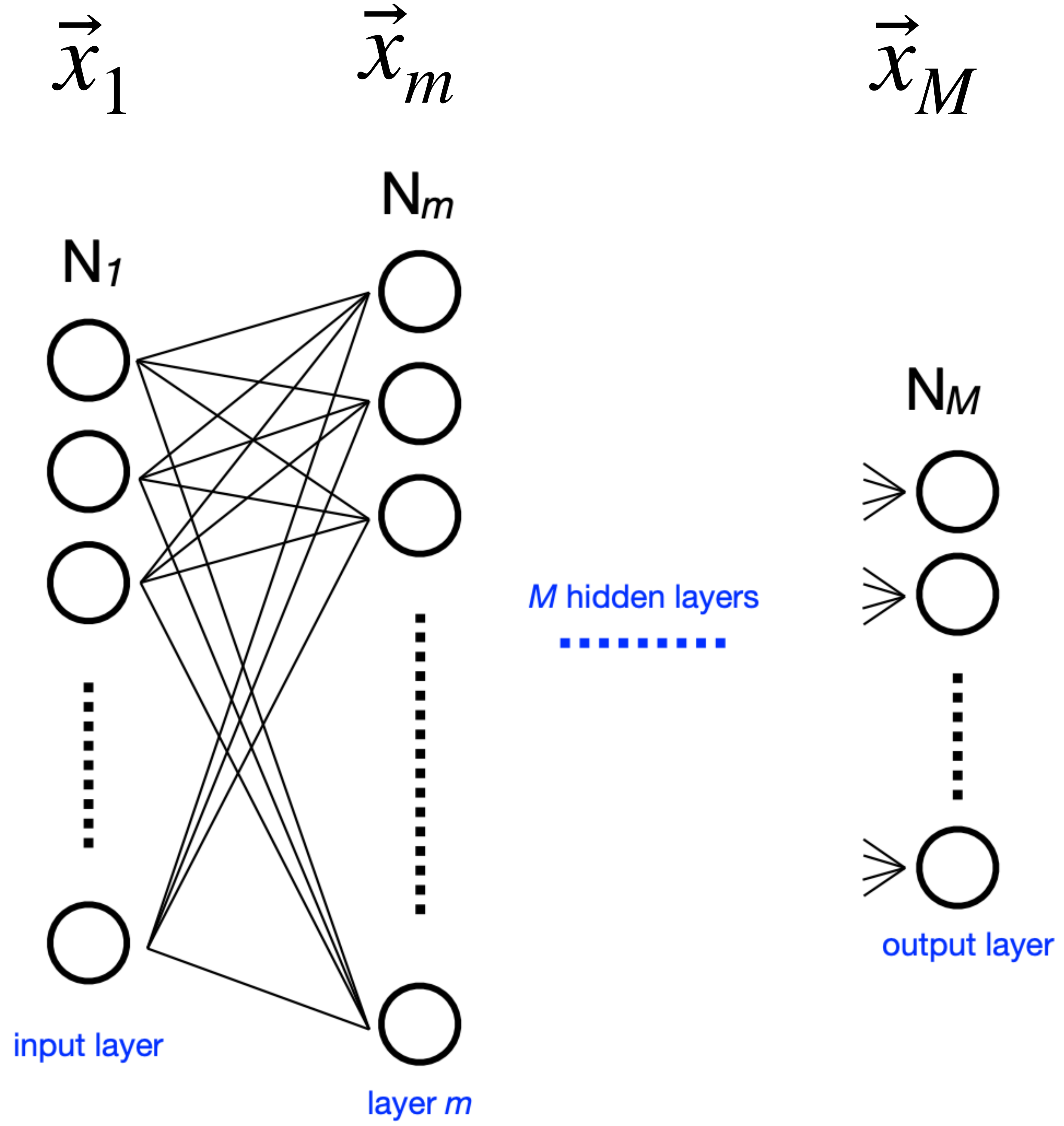
4. Build firmware

Efficient L1T firmware design requires expertise

- FPGA deployment in busy devices
- « 1µs latency target

Not well served by industry tools!

Inference on FPGA

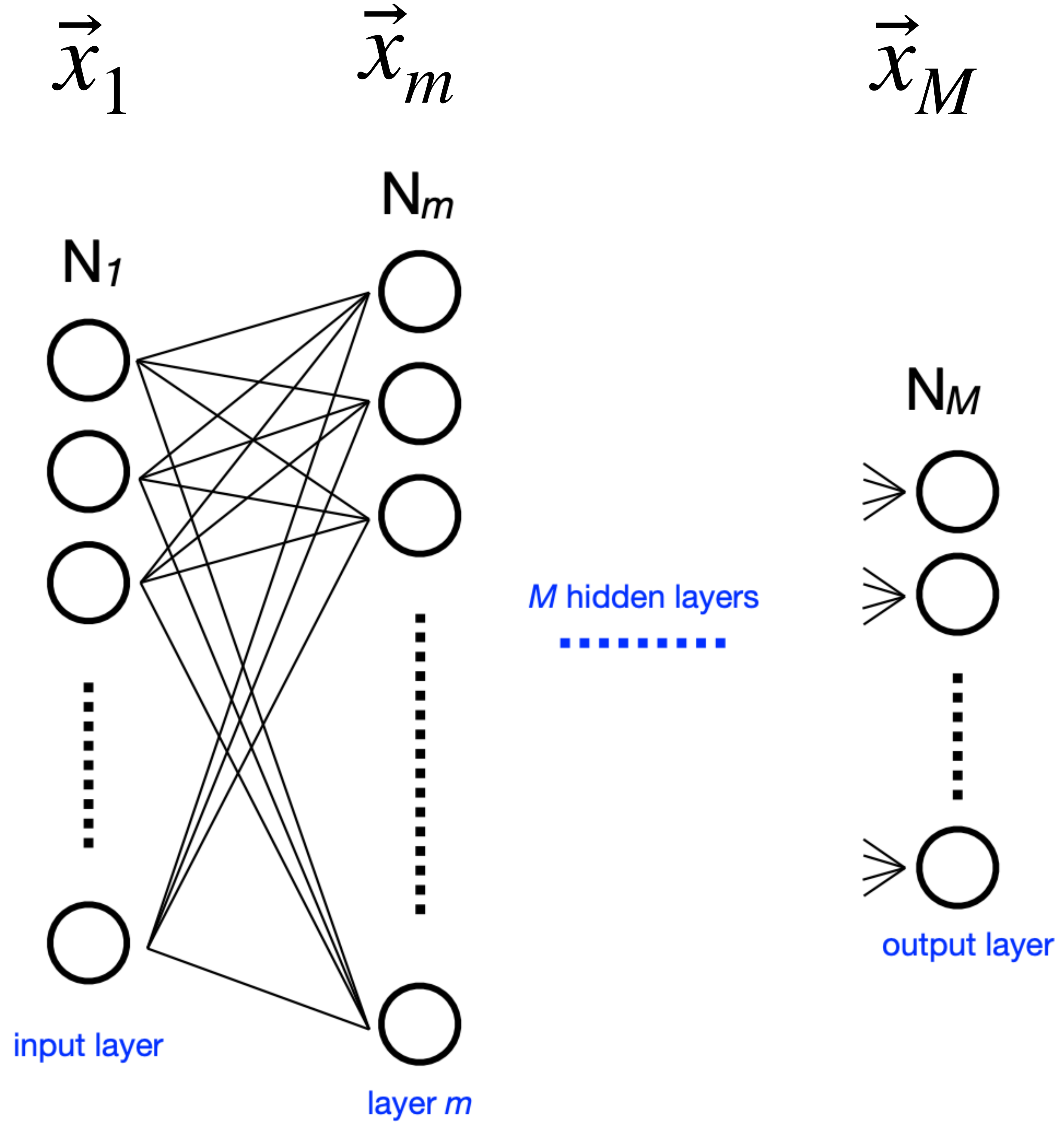


multiplication

$$\vec{x}_m = g_m\left(W_{m,m-1}\vec{x}_{m-1} + \vec{b}_m\right)$$

activation function

addition



$$\vec{x}_m = g_m\left(W_{m,m-1}\vec{x}_{m-1} + \vec{b}_m\right)$$

multiplication

activation function

addition

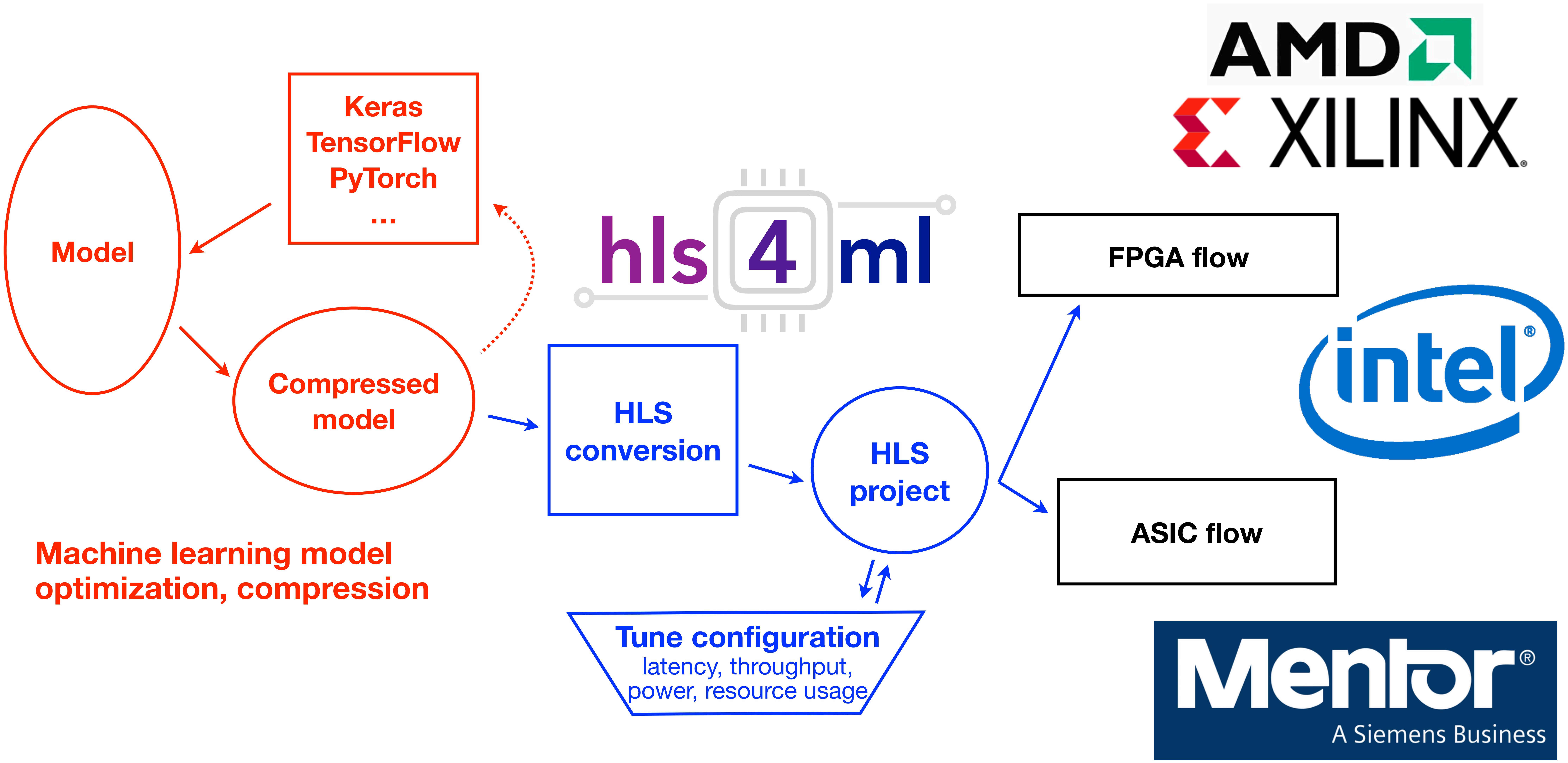
Multiplier Unit (DSP)

up to ~6k parallel operation (VU9P)

Design Exploration with hls4ml

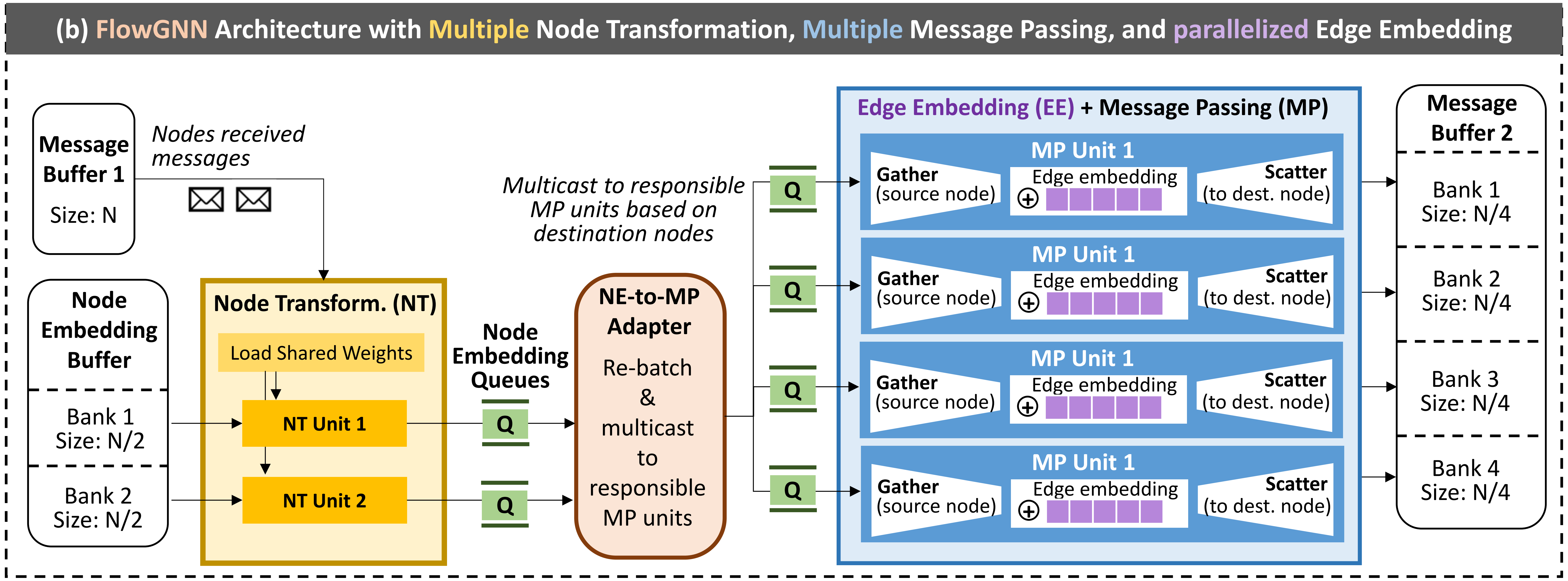
JINST 13, P07027 (2018)

- hls4ml for scientists or ML experts to translate ML algorithms into RTL firmware



Many tools with different strengths

- FINN (NNs): https://finn.readthedocs.io/en/latest/
- Conifer (BDTs): https://github.com/thesps/conifer
- fwXMachina (BDTs): http://fwx.pitt.edu/
- FlowGNN: https://github.com/sharc-lab/flowgnn



Lecture Outline

Motivation behind efficient model design and some highlights

Introduction to Quantization
- Definition
- PTQ vs QAT

Introduction to Pruning
- What is pruning? How to formulate pruning?
- Determine pruning granularity and criteria
- Network performance after pruning

ML on FPGA

hls4ml and Trigger applications

Let’t Go through the hls4ml Demo

Official hls4ml tutorials:
https://fastmachinelearning.org/hls4ml-tutorial/README.html

JupyterHub access (for efficient_ml tutorial)

- Join hls4ml-tutorial GitHub Organization (check your email for invite)
- Your should be able to see yourself here:
  https://github.com/orgs/hls4ml-tutorial/people

JupyterHub link

- Open https://tutorials.fastmachinelearning.org in your web browser
- Authenticate with your GitHub account (login if necessary)

Quantization

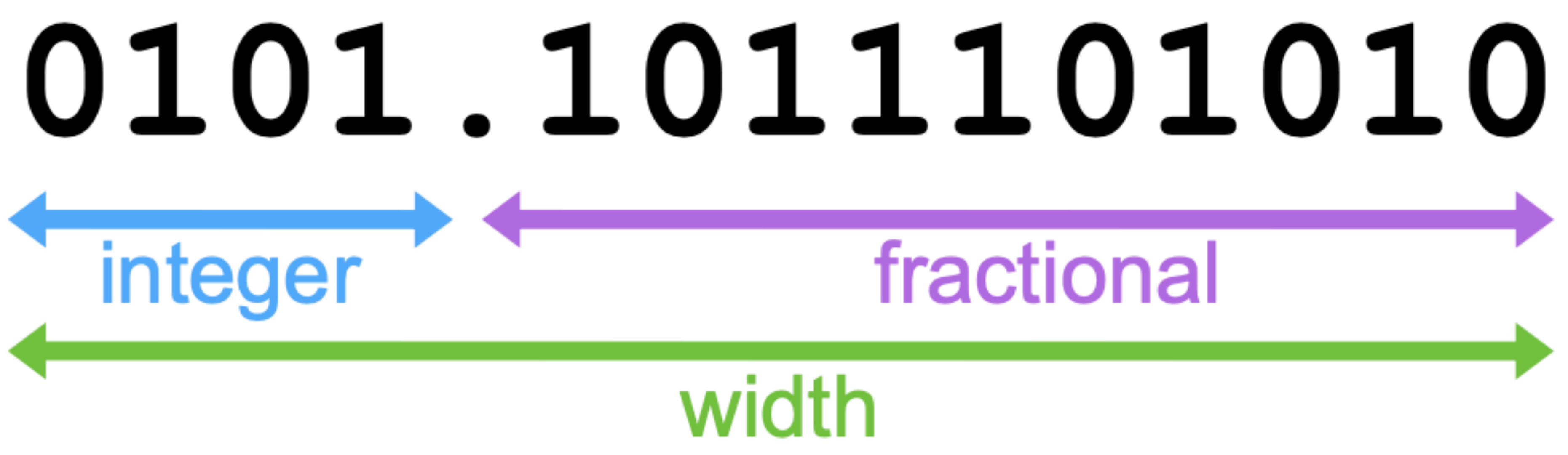
Quantization – Reducing the bit precision used for NN arithmetic

Why this is necessary?

- Floating-point operations (32 bit numbers) on an FPGA consumes large resources
- Not necessary to do it for desired performance

- **hls4ml uses fixed-point representation for all computations**
  - Operations are integer ops, but we can represent fractional values

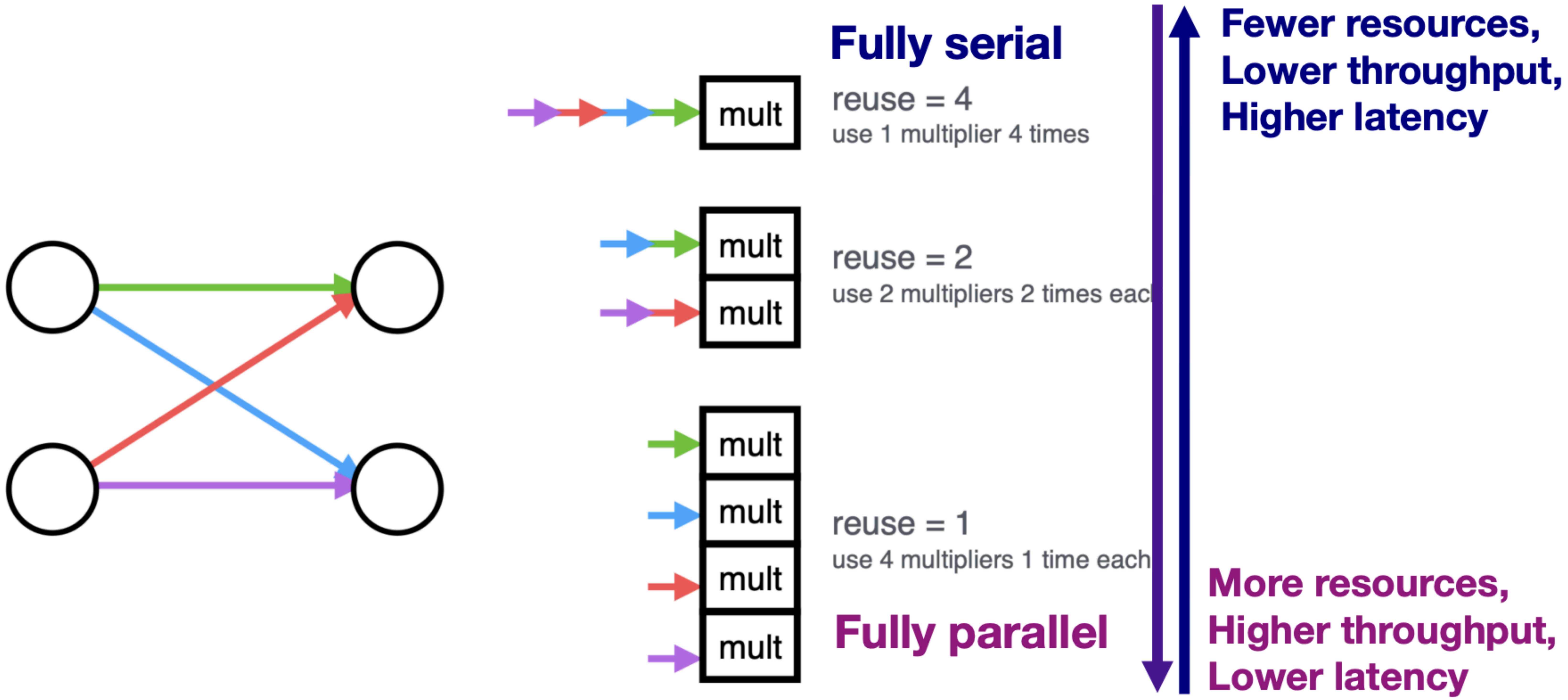
ap_fixed<width bits, integer bits>



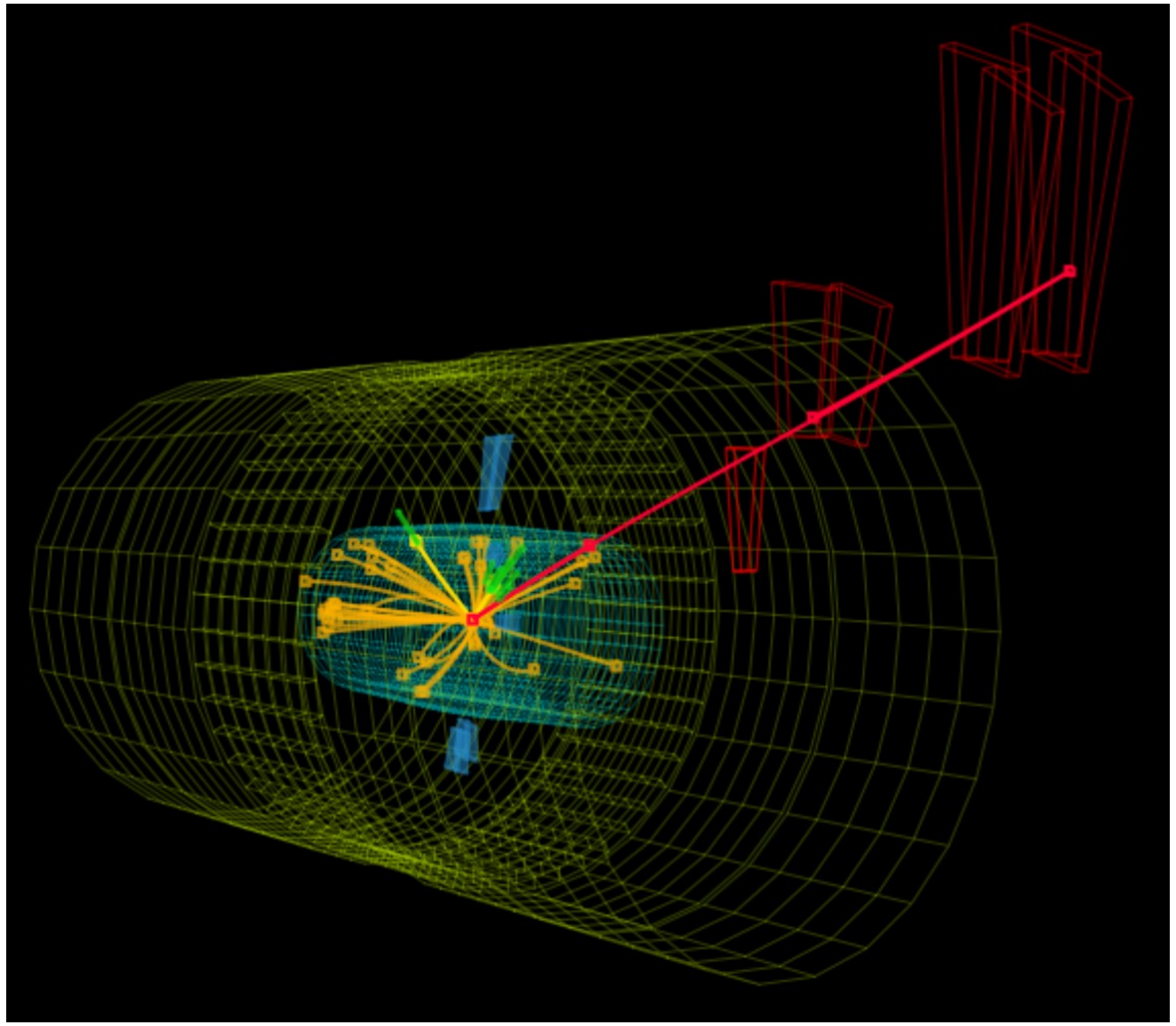
Parallelization

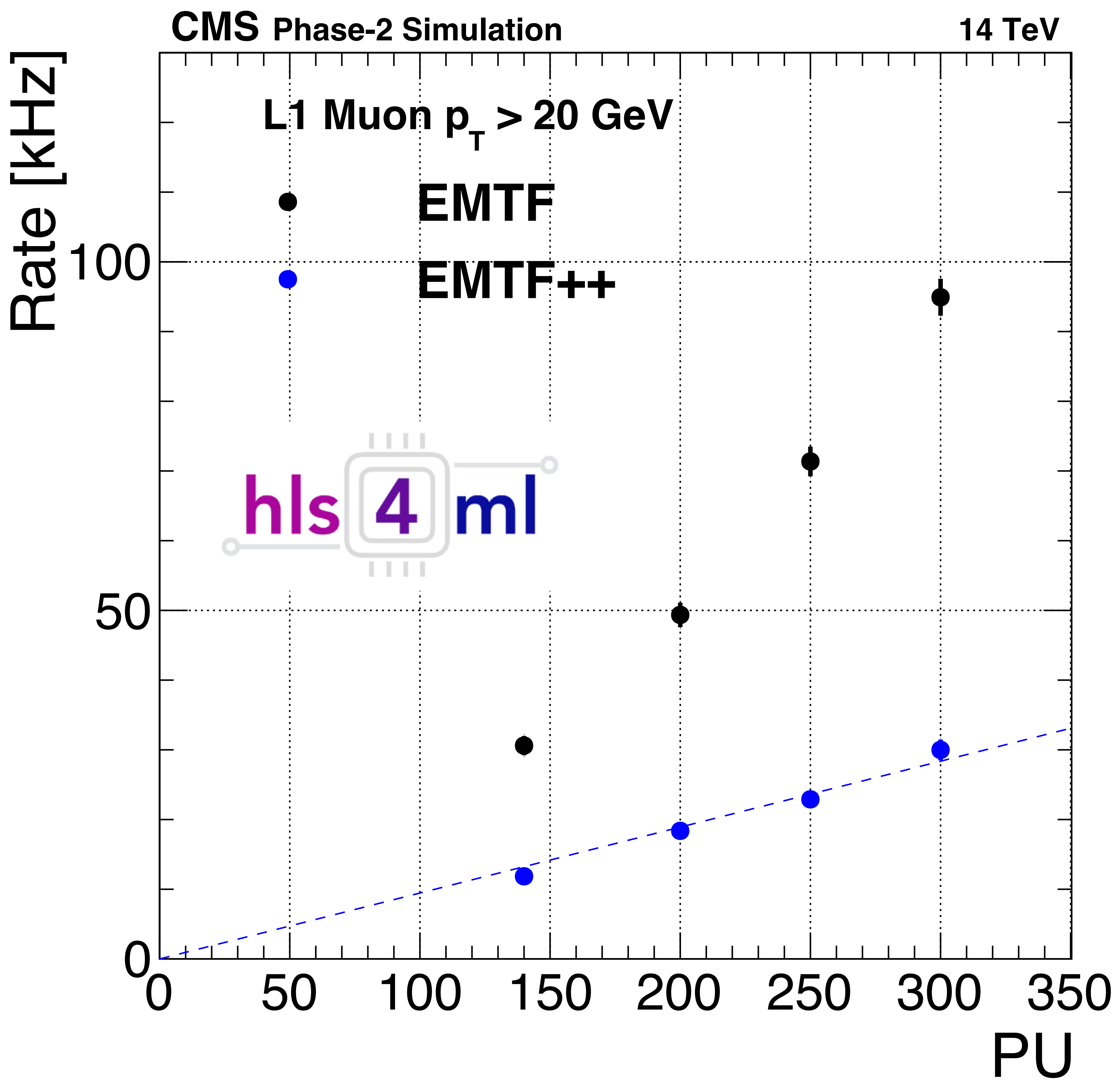
- Trade-off between latency and FPGA resource usage determined by the parallelization of the calculations in each layer

- Configure the "reuse factor" = number of times a multiplier is used to do a computation

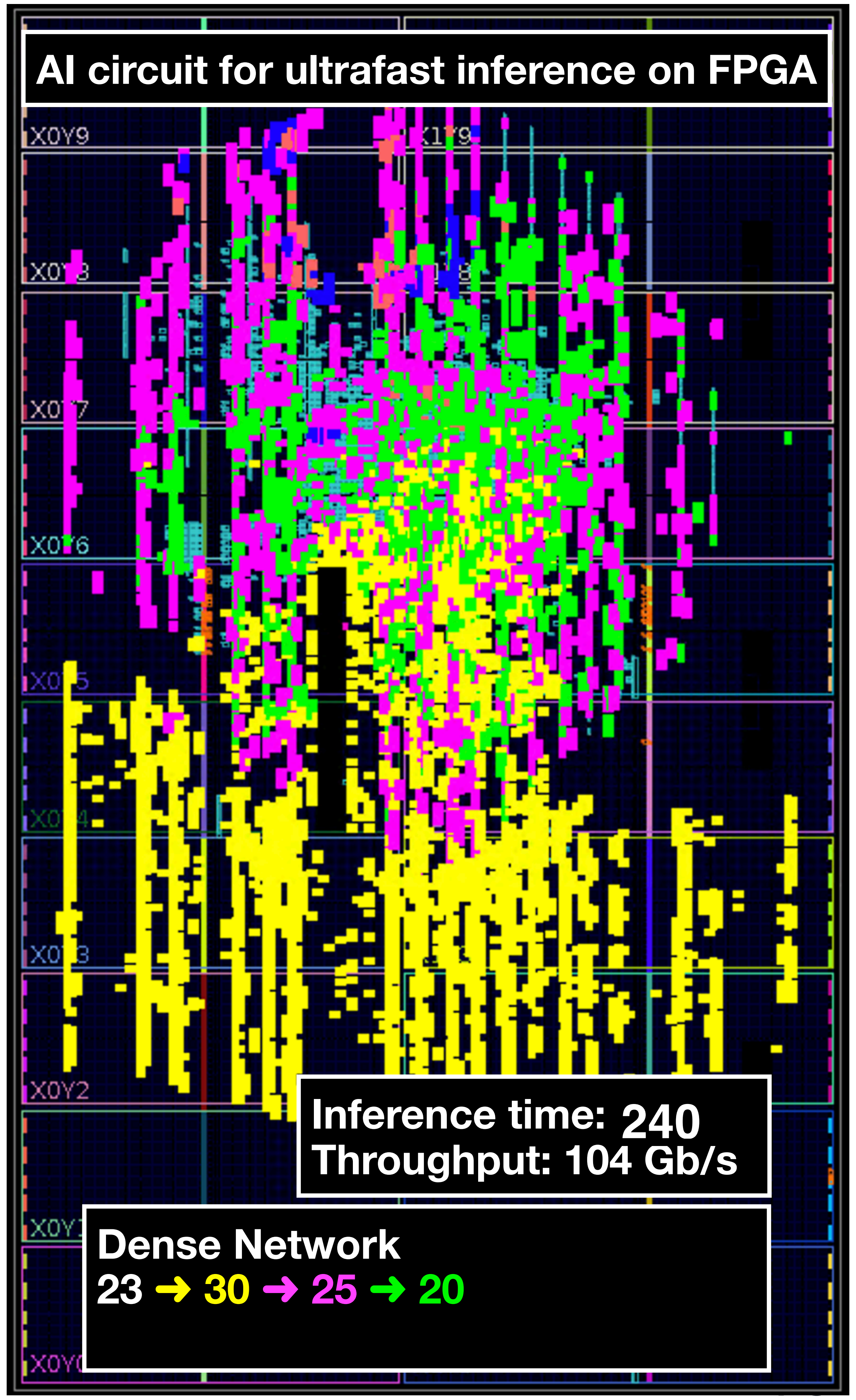


Application: Measure Muon p_T at 40 MHz





CMS-TDR-021



- NN measures muon momentum
  - 3× reduction in the trigger rate for NN!
- Fits within L1 trigger latency (240 ns!) and FPGA resource requirements (less then 30%)

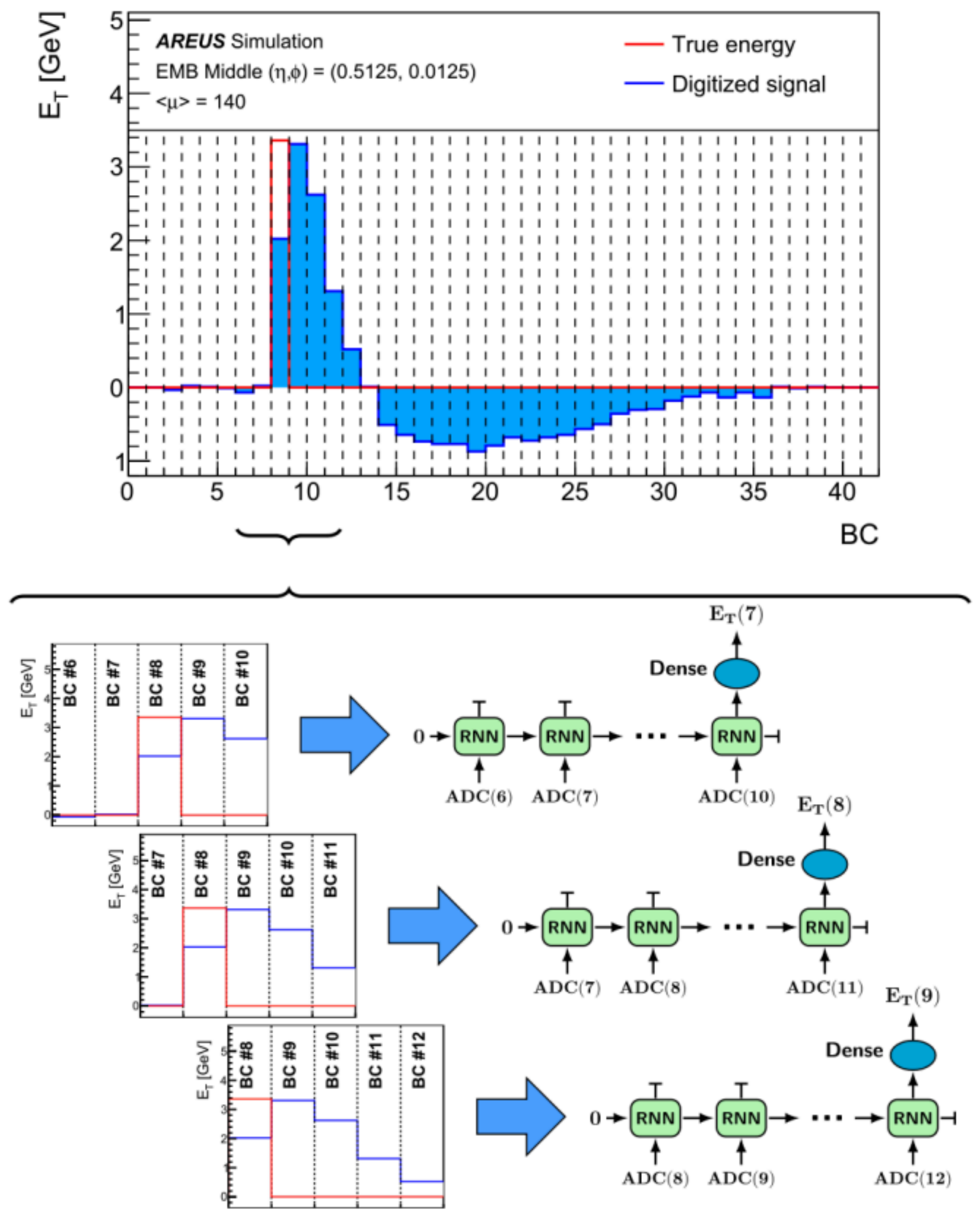
Application: ATLAS LAr Calorimeter

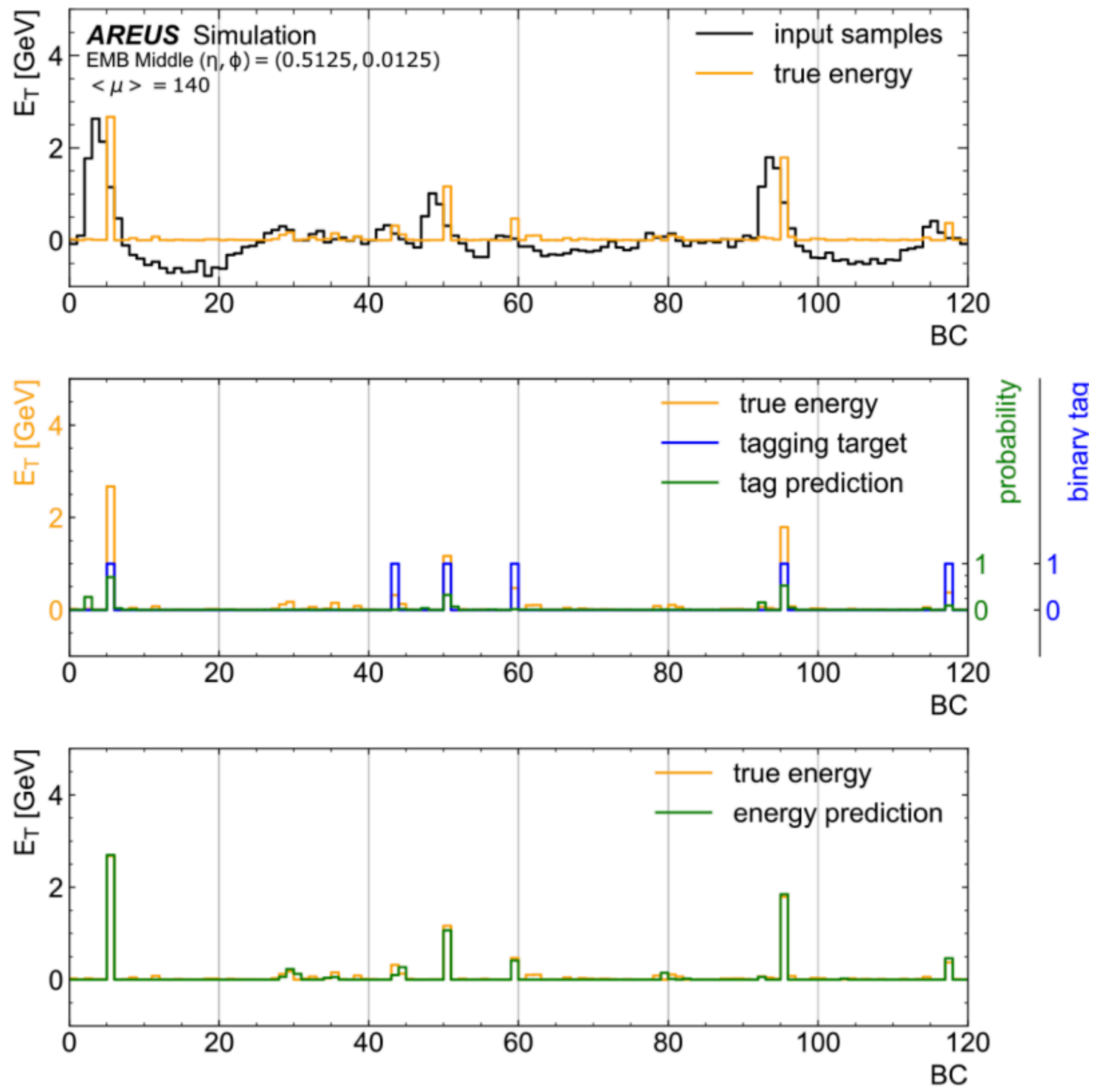
10.1007/s41781-021-00066-y

Convolutional and **Recurrent Neural Networks**
for real-time energy reconstruction of ATLAS LAr Calorimeter for Phase 2

- Up to around 600 calorimeter channels processed by on device
- 200 ns latency of predictions

- Implemented on Intel FPGAs (previous examples are all AMD)
  - Team contributed majorly to RNN and Intel implementations of hls4ml

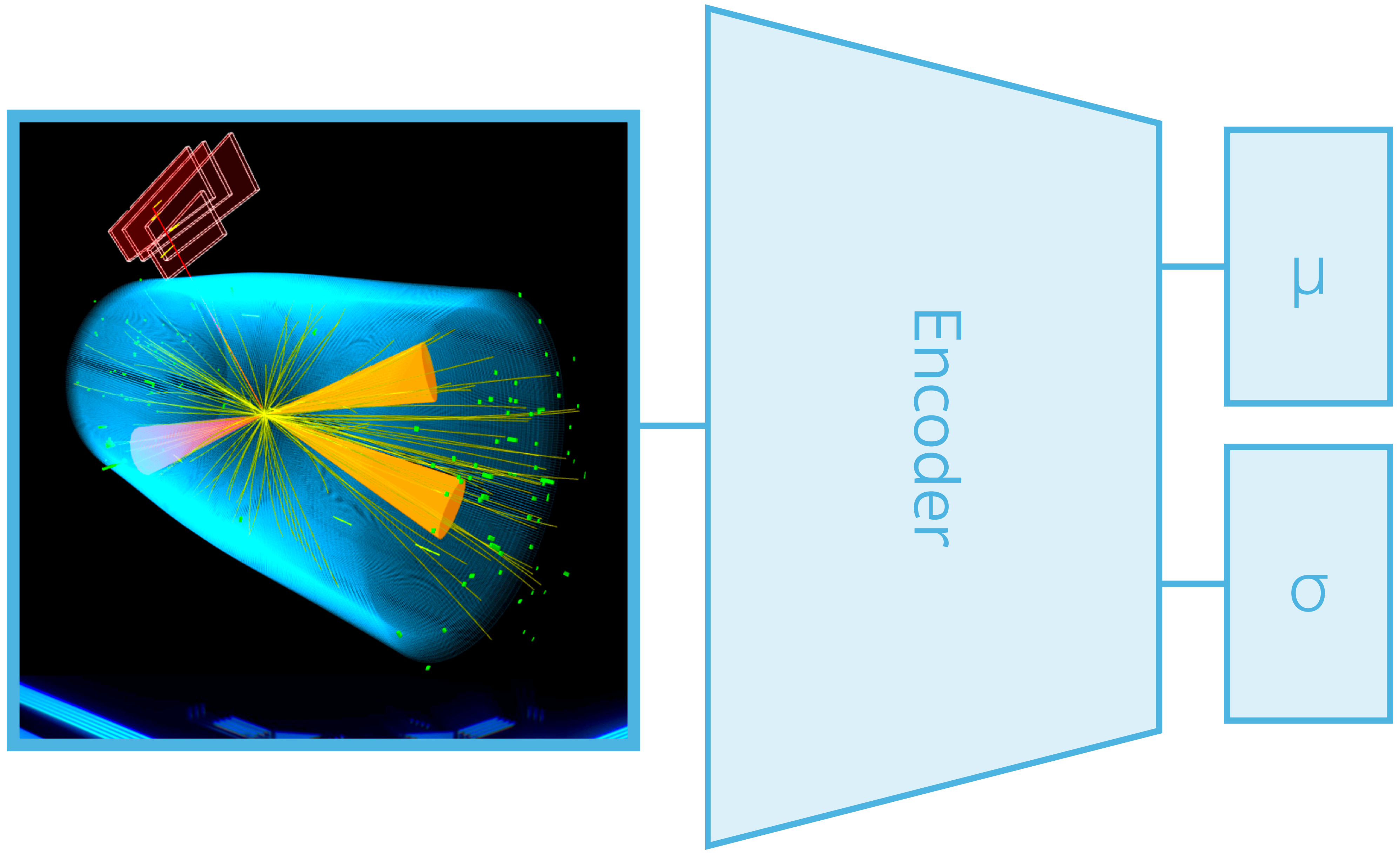




Application: Anomaly Detection

Nat. Mach. Intell. 4, 154 (2022)
Data challenge: mpp-hep.github.io/ADC2021

- **Challenge:** if new physics has an unexpected signature that doesn't align with existing triggers, precious BSM events may be discarded at trigger level
- Can we use unsupervised algorithms to detect non-SM-like anomalies?
  - **Autoencoders (AEs):** compress input to a smaller dimensional latent space then decompress and calculate difference
  - **Variational autoencoders (VAEs):** model the latent space as a probability distribution; possible to detect anomalies purely with latent space variables



Key observation: Can build an anomaly score from the latent space of VAE directly! No need to run decoder!

$$R_z = \sum_i \frac{\mu_i^2}{\sigma_i^2}$$

Application: CMS Anomaly Trigger

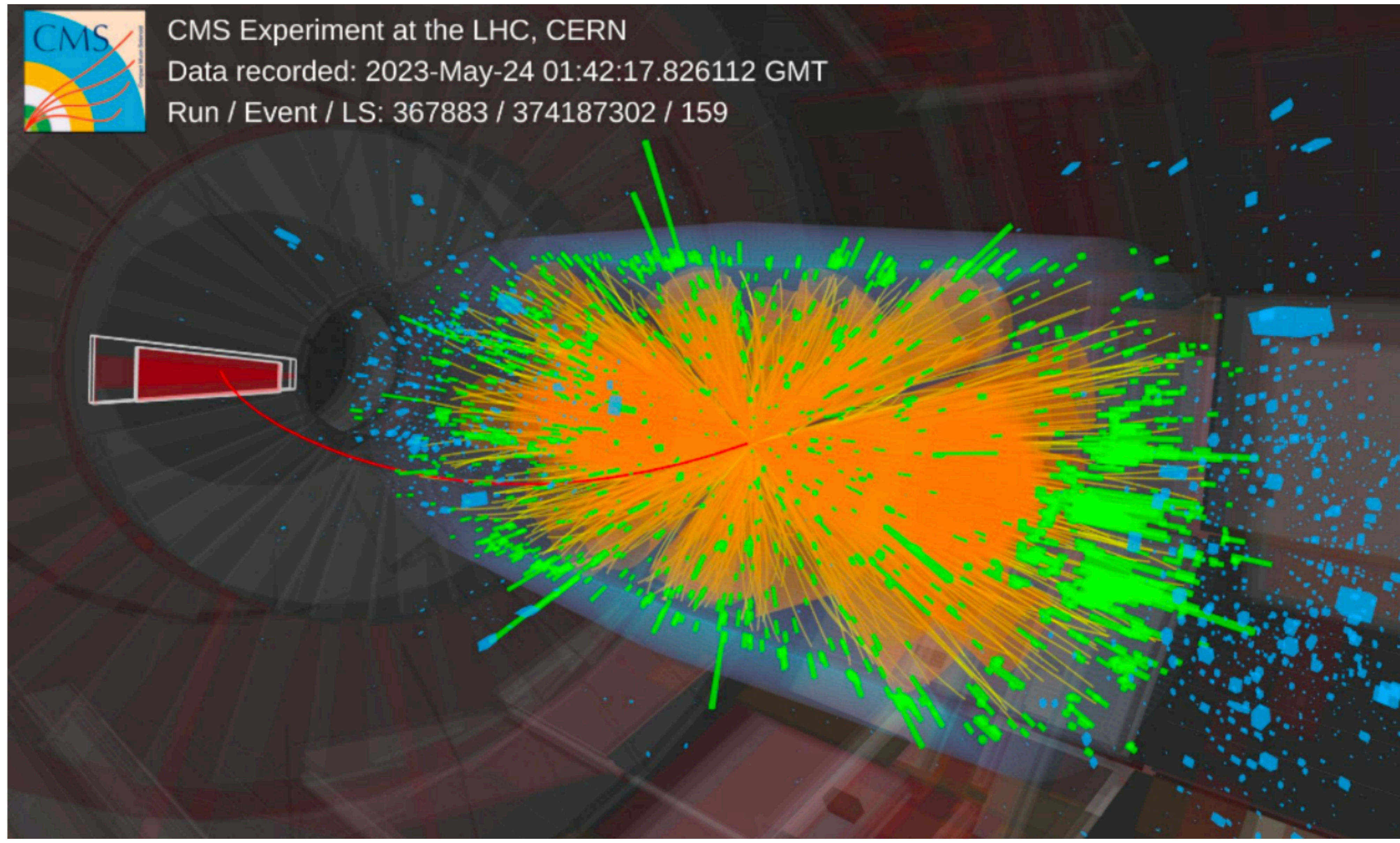
CMS has implemented a similar idea: **AXOL1TL**

AXOL1TL

- L1 Hardware implemented VAE-based AD trigger (based on https://arxiv.org/abs/2108.03986)
- Trained on 2018 zerobias data, ran in 2023 Global Trigger Test Crate
- CMS is also developing CICADA, a calorimeter only AD trigger

Similar effort is ongoing in ATLAS

Event display of the highest anomaly score

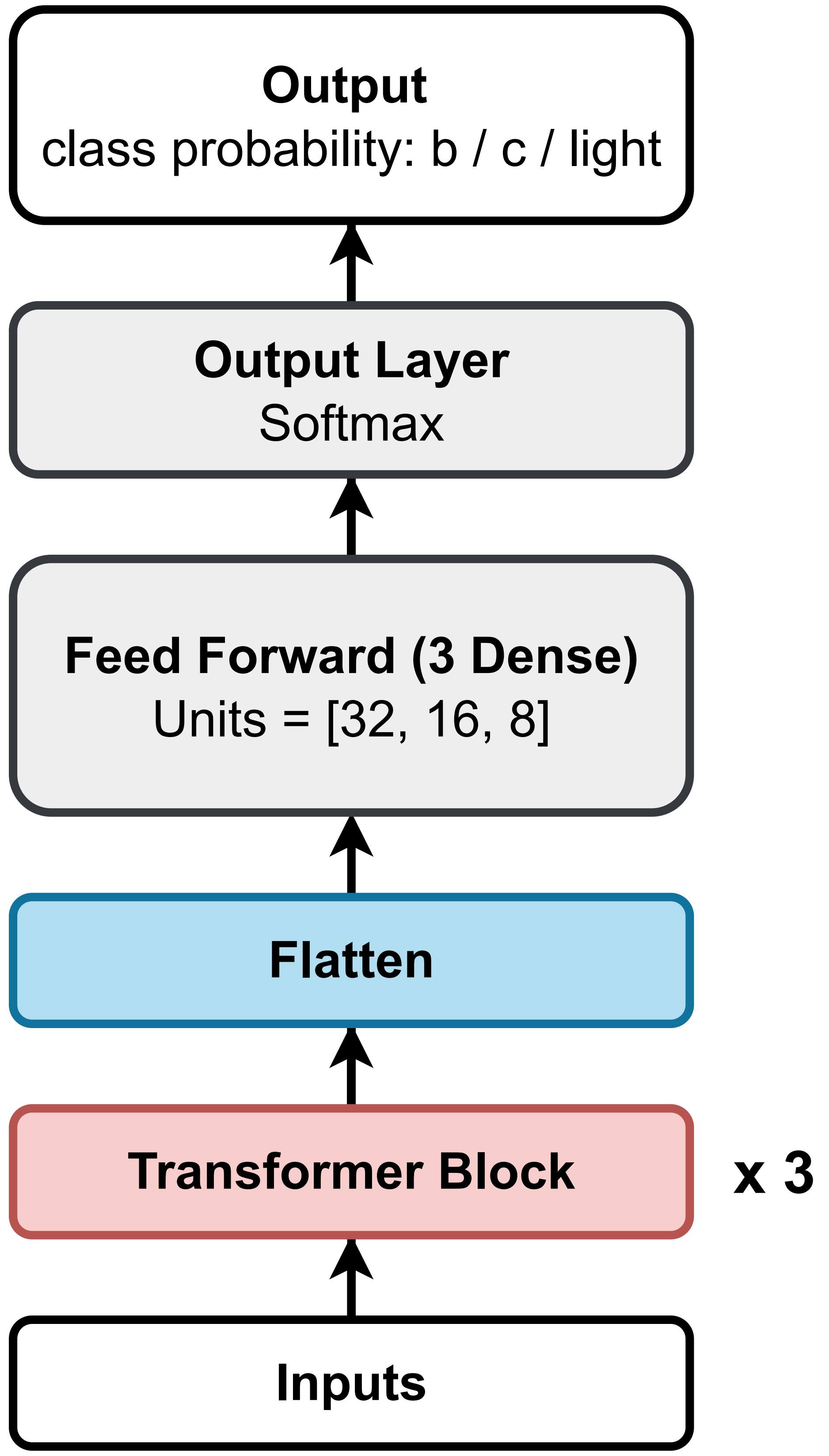


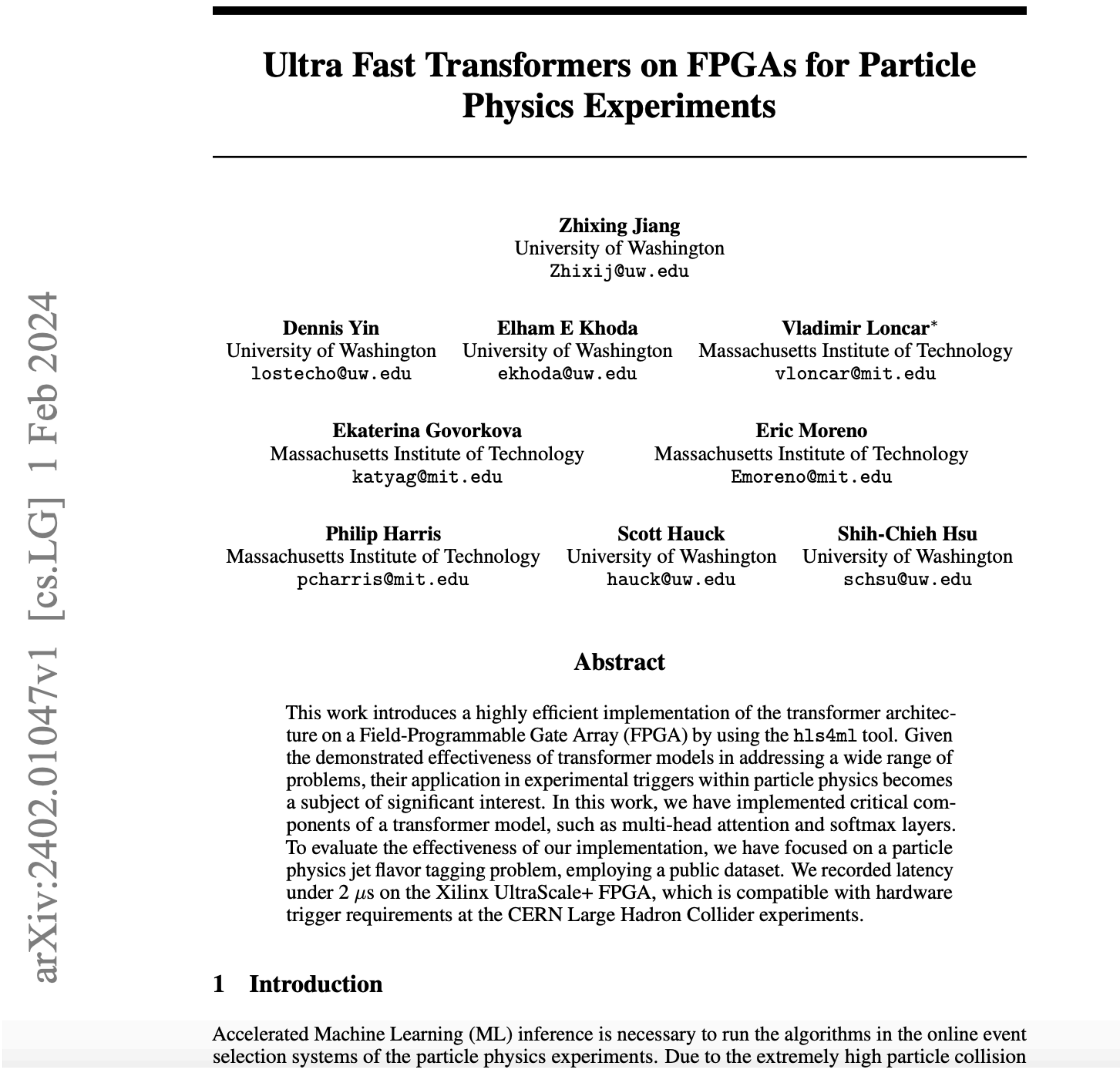
CMS-DP-2023-079

Low-latency Transformers

arXiv:2402.01047

Reuse and clk	Interval (cycle)	Latency (cycles)	Latency(time)
R1 (6.577 ns)	49	269	2.077 us
R2 (6.215 ns)	65	449	3.467 us
R4 (4.723 ns)	100	768	5.853 us





arXiv:2402.01047v1 [cs.LG] 1 Feb 2024

Ultra Fast Transformers on FPGAs for Particle Physics Experiments

Zhixing Jiang
University of Washington
Zhixij@uw.edu

Dennis Yin
University of Washington
lostecho@uw.edu

Elham E Khoda
University of Washington
ekhoda@uw.edu

Vladimir Loncar*
Massachusetts Institute of Technology
vloncar@mit.edu

Ekaterina Govorkova
Massachusetts Institute of Technology
katyag@mit.edu

Eric Moreno
Massachusetts Institute of Technology
Emoreno@mit.edu

Philip Harris
Massachusetts Institute of Technology
pcharris@mit.edu

Scott Hauck
University of Washington
hauck@uw.edu

Shih-Chieh Hsu
University of Washington
schsu@uw.edu

Abstract

This work introduces a highly efficient implementation of the transformer architecture on a Field-Programmable Gate Array (FPGA) by using the `hls4ml` tool. Given the demonstrated effectiveness of transformer models in addressing a wide range of problems, their application in experimental triggers within particle physics becomes a subject of significant interest. In this work, we have implemented critical components of a transformer model, such as multi-head attention and softmax layers. To evaluate the effectiveness of our implementation, we have focused on a particle physics jet flavor tagging problem, employing a public dataset. We recorded latency under 2 μs on the Xilinx UltraScale+ FPGA, which is compatible with hardware trigger requirements at the CERN Large Hadron Collider experiments.

1 Introduction

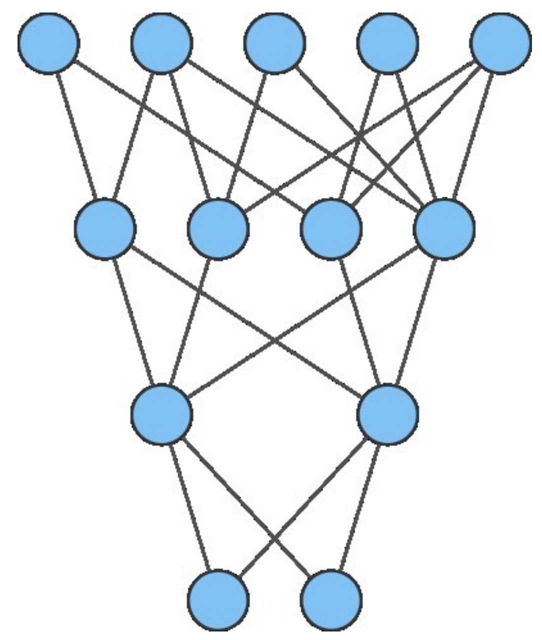
Accelerated Machine Learning (ML) inference is necessary to run the algorithms in the online event selection systems of the particle physics experiments. Due to the extremely high particle collision

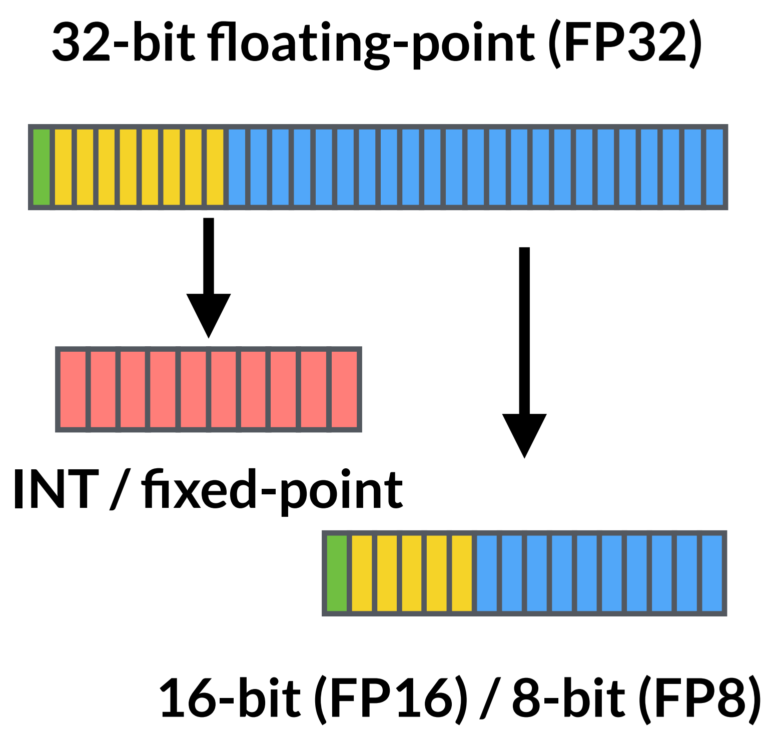
Observed Inference Latency ~ 2-6 μs

Summary

- **Efficient model design is becoming more important as the models are getting bigger**

- **Several tricks to design efficient ML inference**
  - Some popular method: Pruning and Quantization
  - Need to optimize pruning and quantization strategy for satisfactory results
  - *Another effective technique: Knowledge Distillation*





- **ML-based algorithms are getting popular for experimental trigger applications**

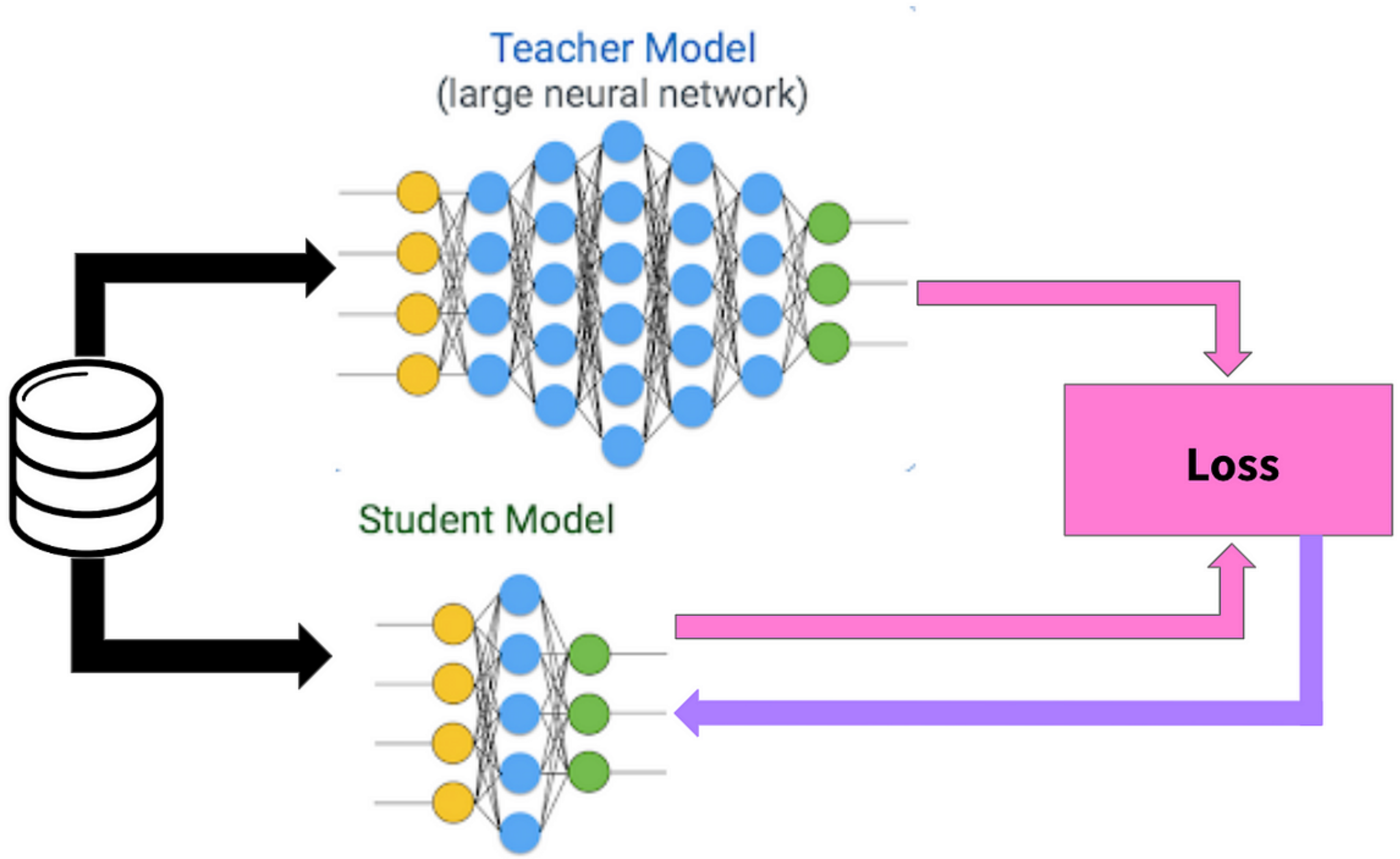
- **Efficient ML techniques are crucial for real-time inference**

End of the Lesson

Thank you for your attention and participation

Knowledge Distillation

One Example: particle physics application



Efficient and Robust Jet Tagging at the LHC with Knowledge Distillation

Ryan Liu
University of California, Berkeley
Berkeley, CA 94720

Abhijith Gandrakota
Fermi National Accelerator Laboratory
Batavia, IL 60510

Jennifer Ngadiuba
Fermi National Accelerator Laboratory
Batavia, IL 60510

Maria Spiropulu
California Institute of Technology
Pasadena, CA 91125

Jean-Roch Vlimant
California Institute of Technology
Pasadena, CA 91125

Thank You!

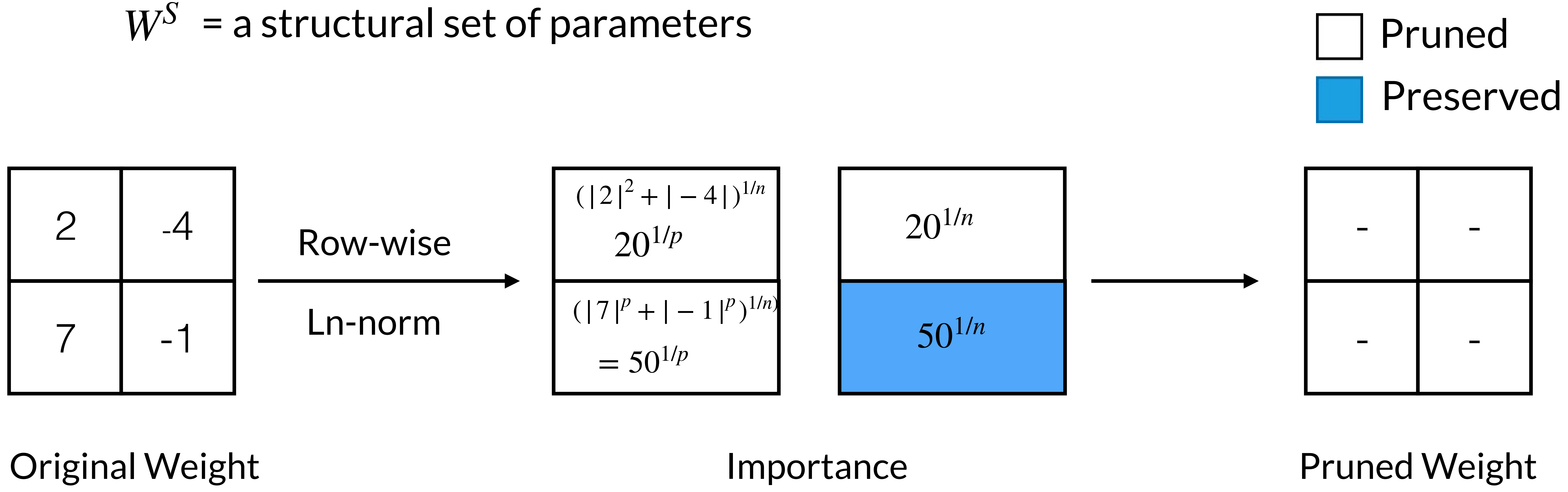
Extra Slides

Magnitude-based Pruning

Row-wise pruning using L_n-norm

We can define L_n norm as: $$||W^{(S)}|| = \left(\sum_{i\in S} |w_i|^n\right)^{\frac{1}{n}}$$

W^S = a structural set of parameters



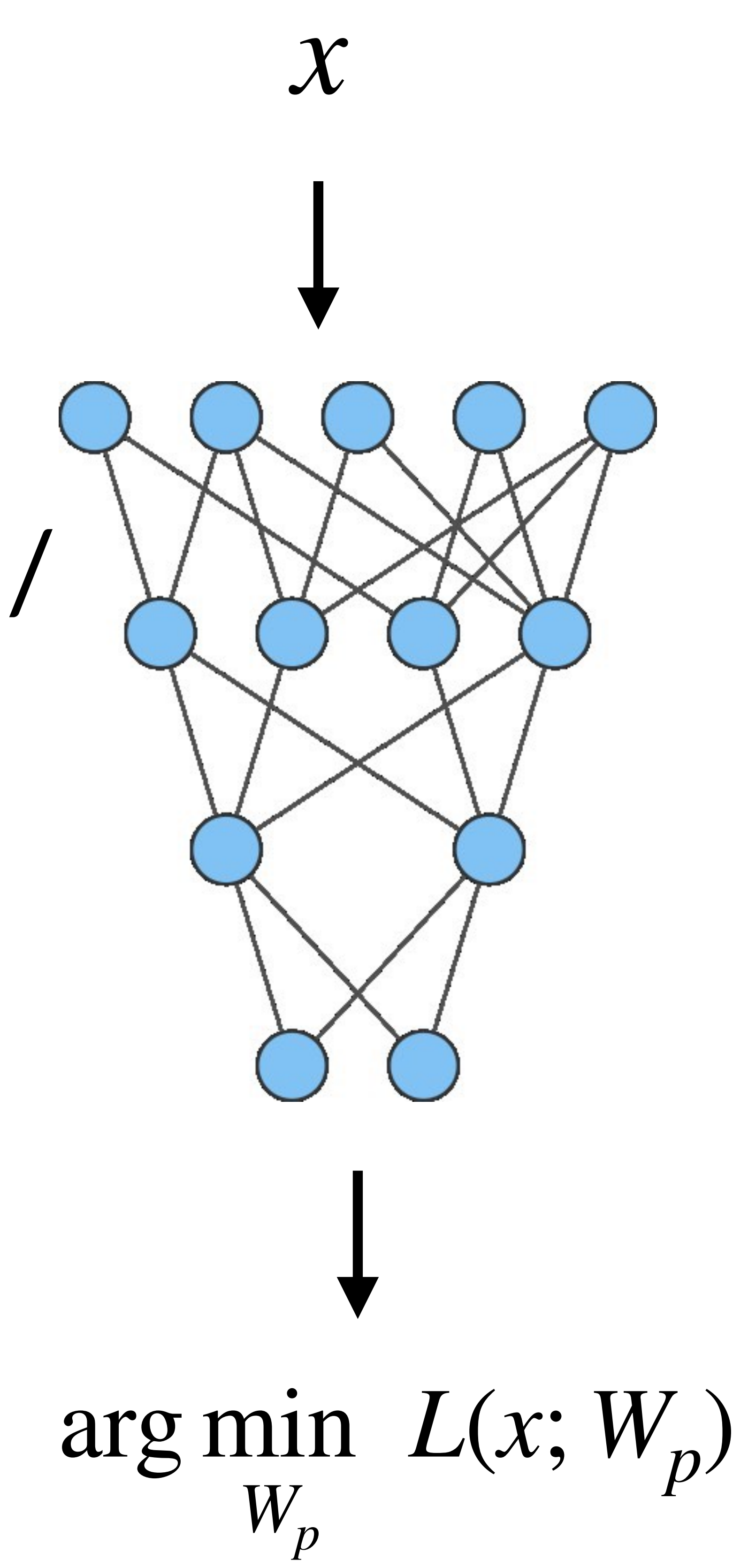
Neural Network Pruning: Formulation

Neural network model $f(x; W)$ Remove least important connections such that

Pruning $\arg\min_{W_p} L(x; W_p)$ $\|W_p\|_0 < N$

Calculate

subject to sparsity ratio —> least significant / important connections /



Sparsity = $\dfrac{\text{\# of non-zero weights}}{\text{Total \# of weights}}$

$\odot$

Element-wise product operator

Pruned model

$f(x; M \odot W'_p)$

$M \in \{0,1\}^{|W'|}$

M is binary mask tensor that fixes certain parameters to 0