Deep Learning Applications for collider physics Lecture 3

Maurizio Pierini

Plan for these lectures

	Day1	Day2	Day3	Day4	Day5
1st hour	Introduction	ConvNN	LHC & fast Inference	Autoencoders	Graphs
2nd hour	Dense NNNs	GANs	RNNs	Anomaly Detection	Graphs
Tutorial	Dense NNNs	ConvNN	RNNs	AE	Graphs

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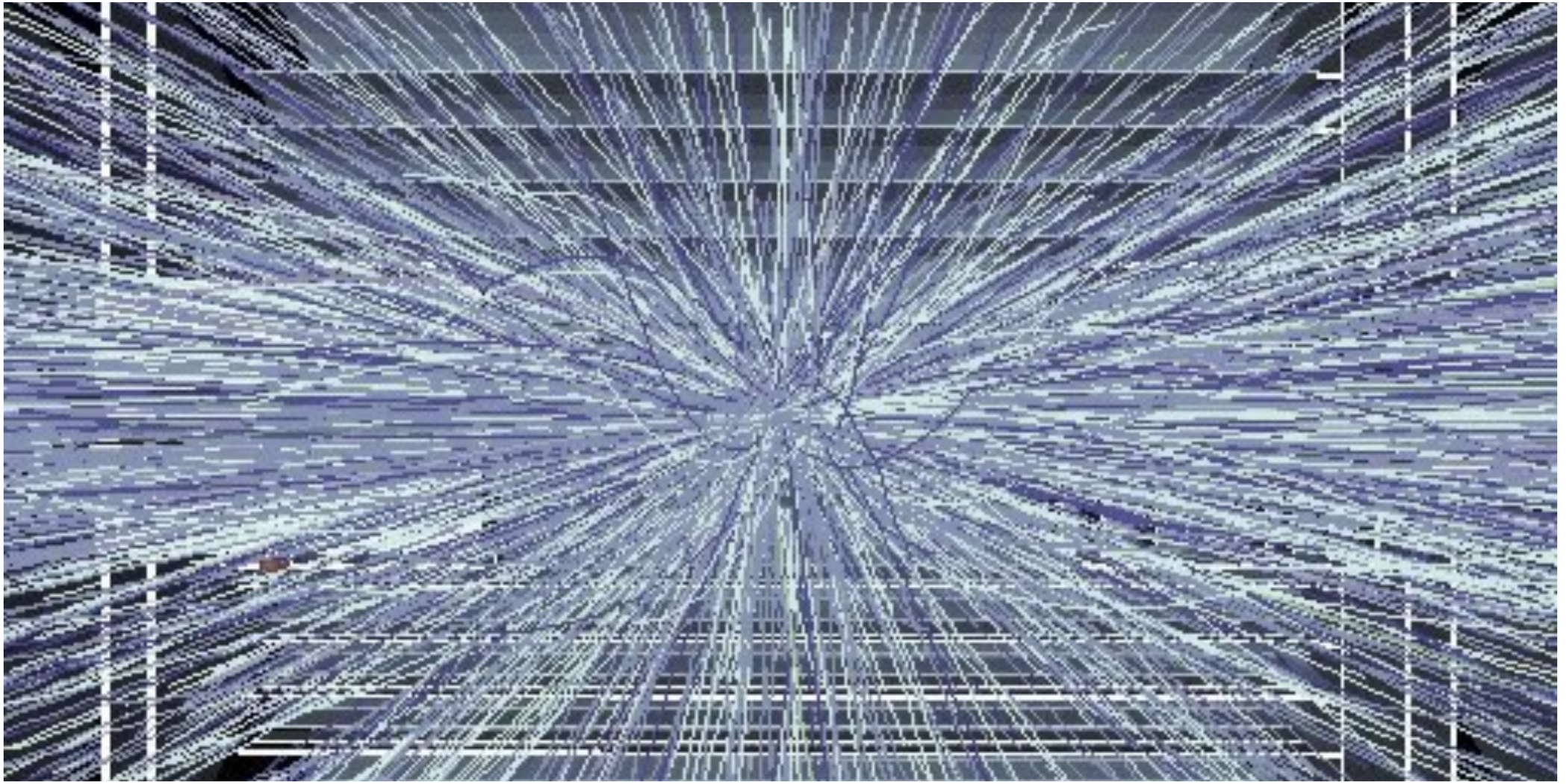


Why Deep Learning for HEP?

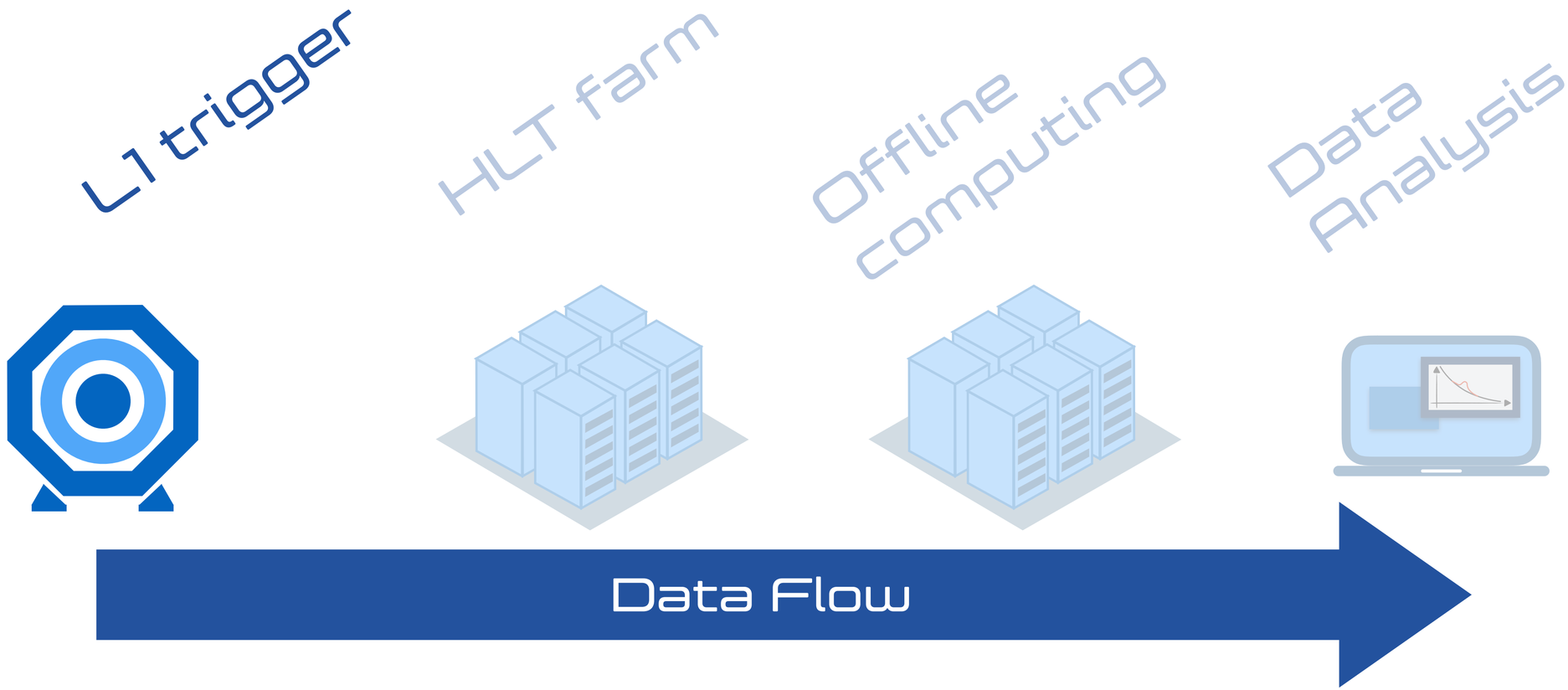
European Research Council

The LHC Big-data problem

- *The LHC generates 40 million collisions every second*
- *The technology to store all these data doesn't exist*
- *Keeping data costs money (for disk, tape, and CPU for processing)*
- *We need to select in real time what we want to keep*
- *Some event is more interesting than other (A BIG THEORETICAL BIAS that we have to pay)*

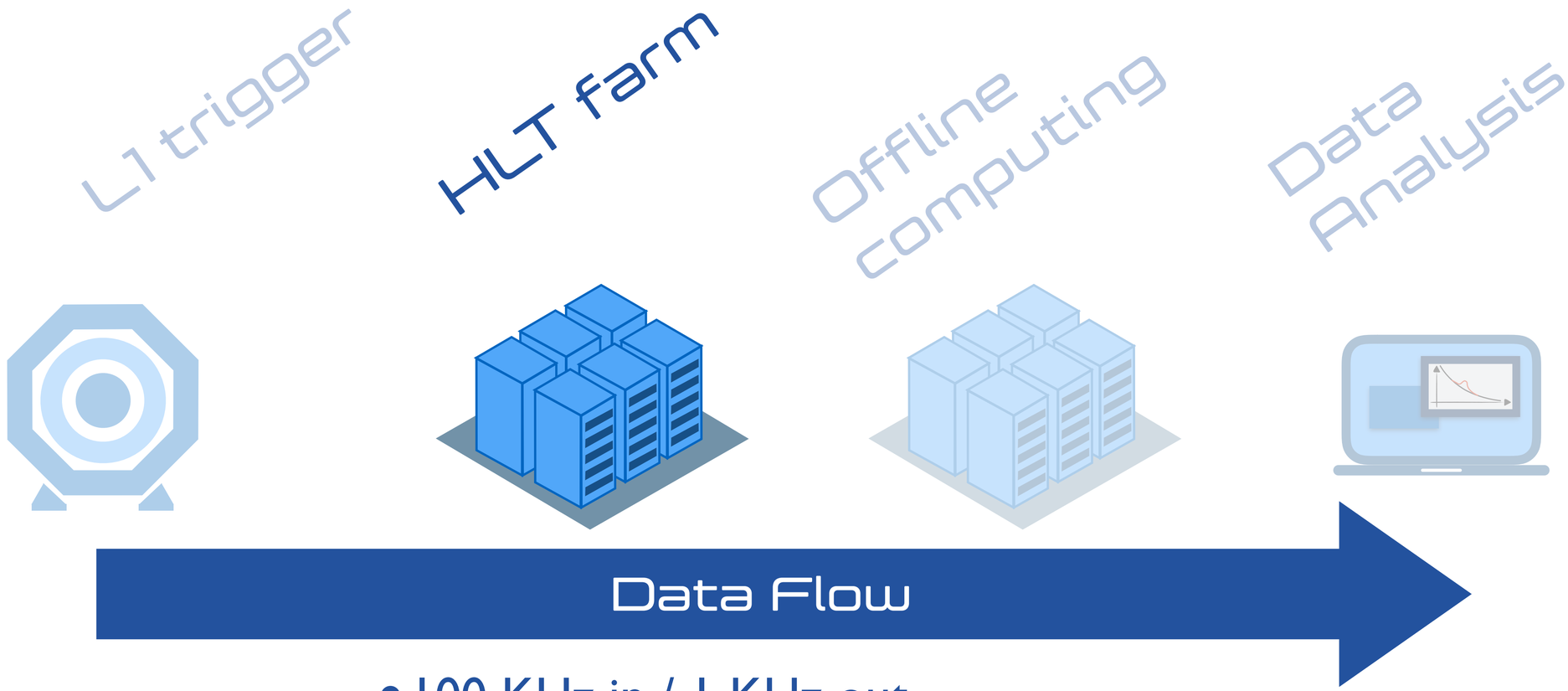
https://www.youtube.com/watch?v=jDC3-QSiLB4

The LHC Big Data problem



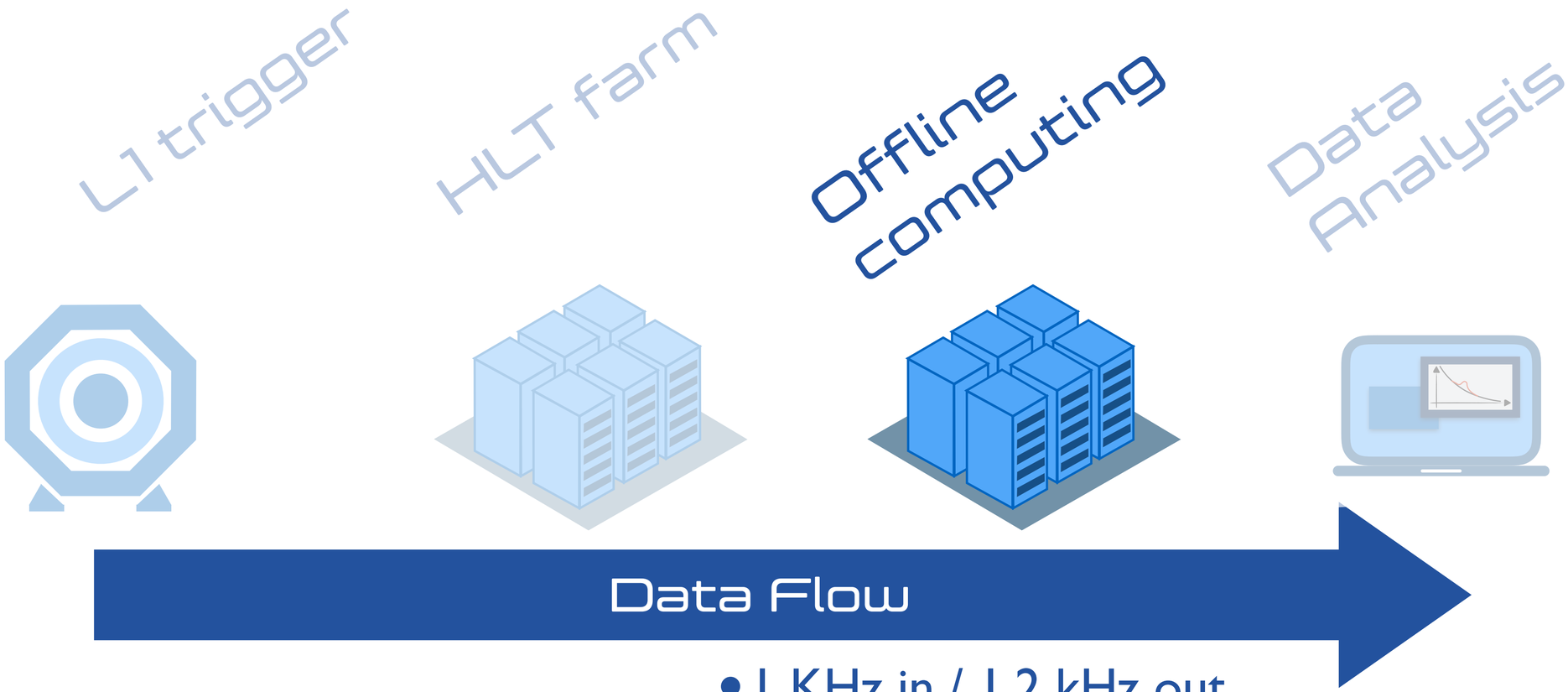
- 40 MHz in / 100 KHz out
- ~ 500 KB / event
- Processing time: ~10 µs
- Based on coarse local reconstructions
- FPGAs / Hardware implemented

The LHC Big Data problem



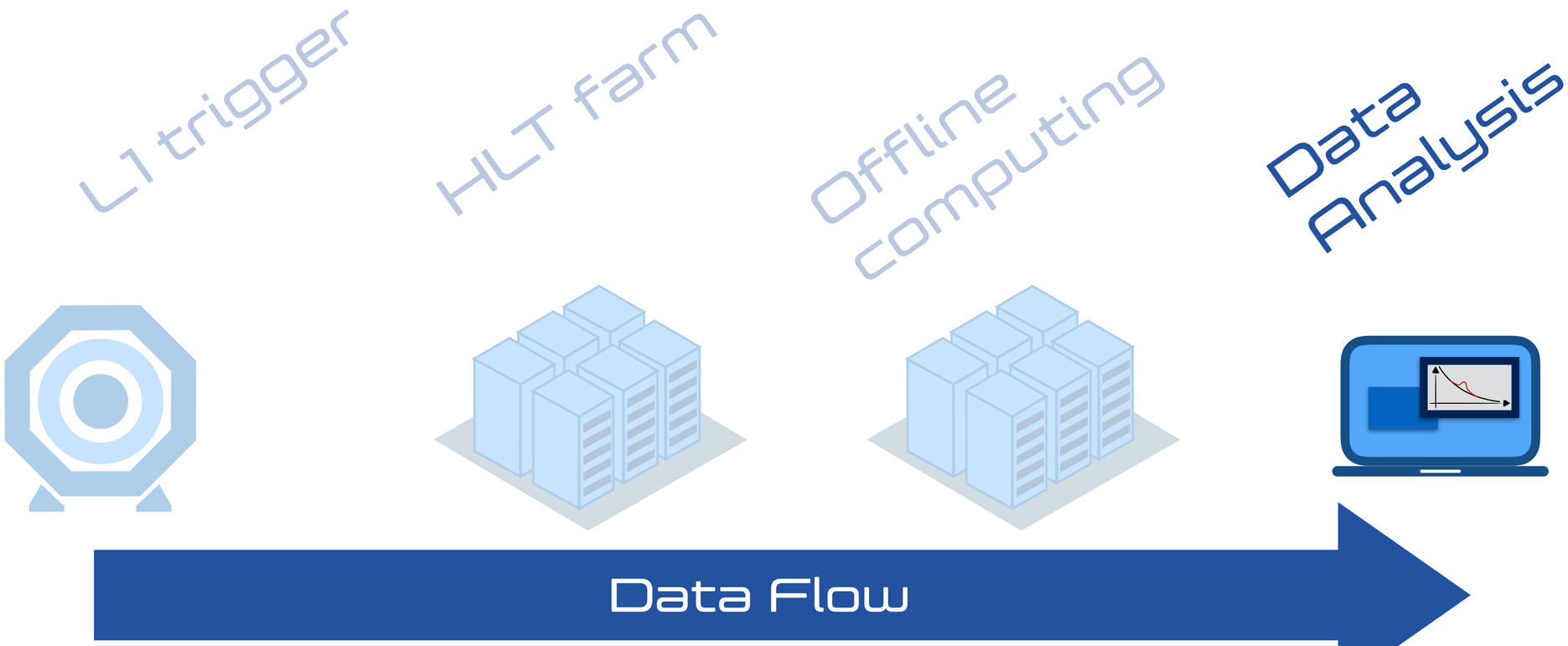
- 100 KHz in / 1 KHz out
- ~ 500 KB / event
- Processing time: ~100 ms
- Based on simplified global reconstructions
- Software implemented on CPUs

The LHC Big Data problem



- 1 KHz in / 1.2 kHz out
- ~ 1 MB / 200 kB / 30 kB per event
- Processing time: ~20 s
- Based on accurate global reconstructions
- Software implemented on CPUs

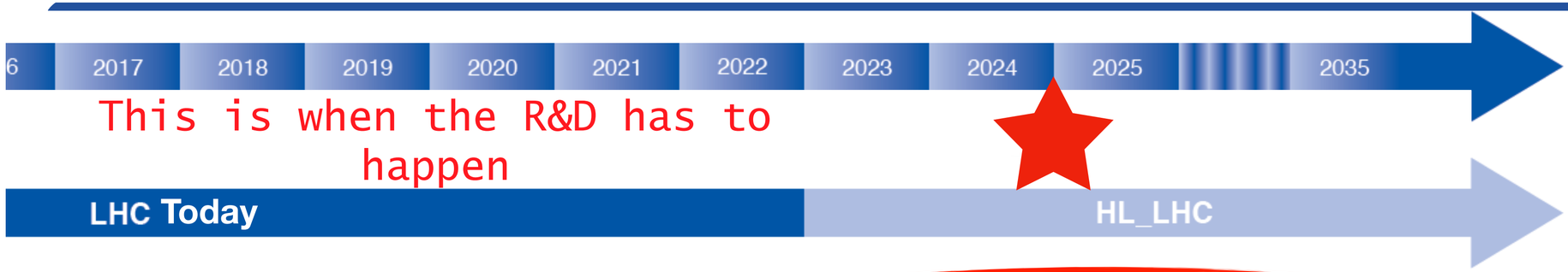
The LHC Big Data problem



- Up to ~ 500 Hz In / 100-1000 events out

- <30 KB per event
- Processing time irrelevant
- User-written code + centrally produced selection algorithms

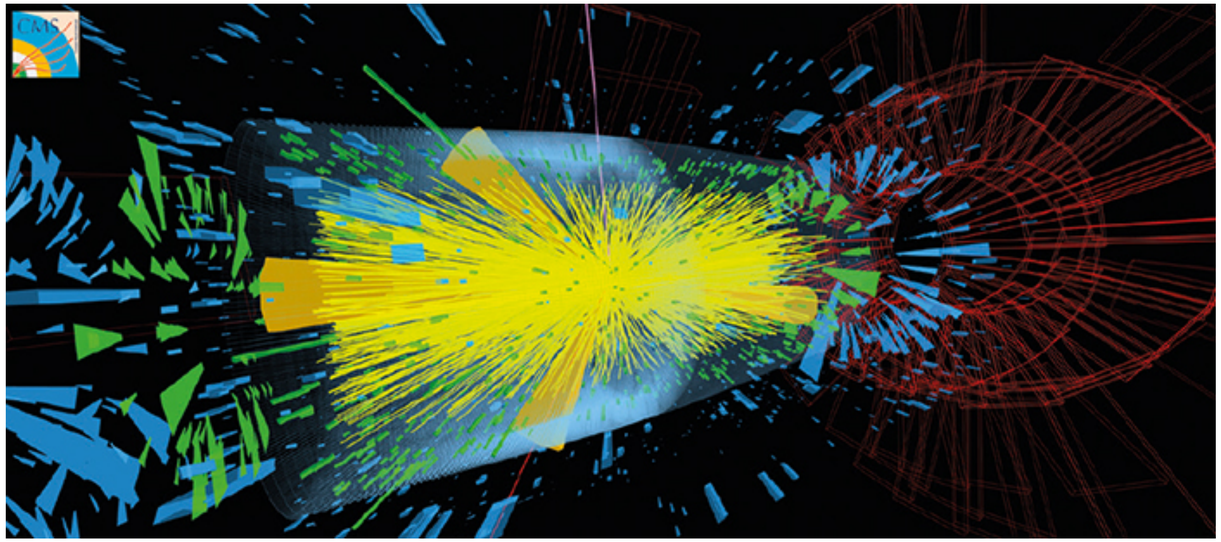
HL-LHC: elephant in the room



- ~40 collisions/event
- ~10 sec/event processing time
- (at best)Same computing resources as today

- ~200 collisions/event
- ~minute/event processing time(*)
- (at best)Same computing resources as today

- *Flat budget vs. more needs = **current rule-based reconstruction algorithms will not be sustainable***
- ***Adopted solution:*** *more granular and complex detectors → more computing resources needed → more problems*
- ***Modern Machine Learning might be the way out***



(*)With nowadays software development

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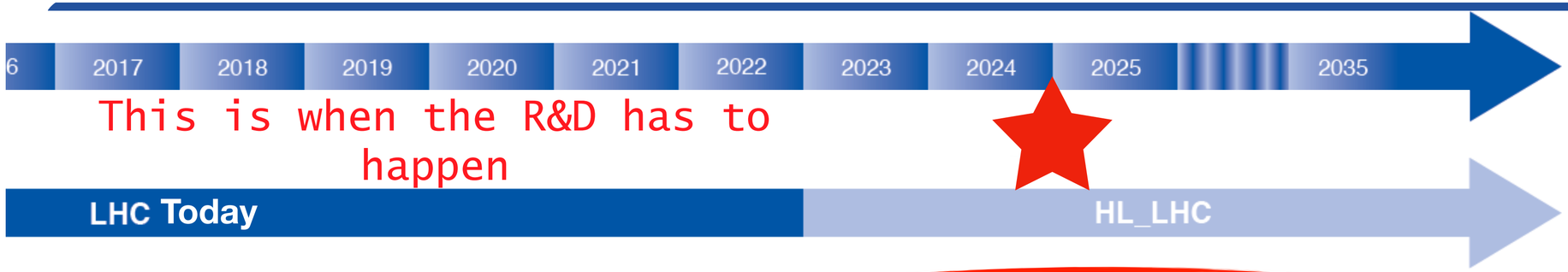

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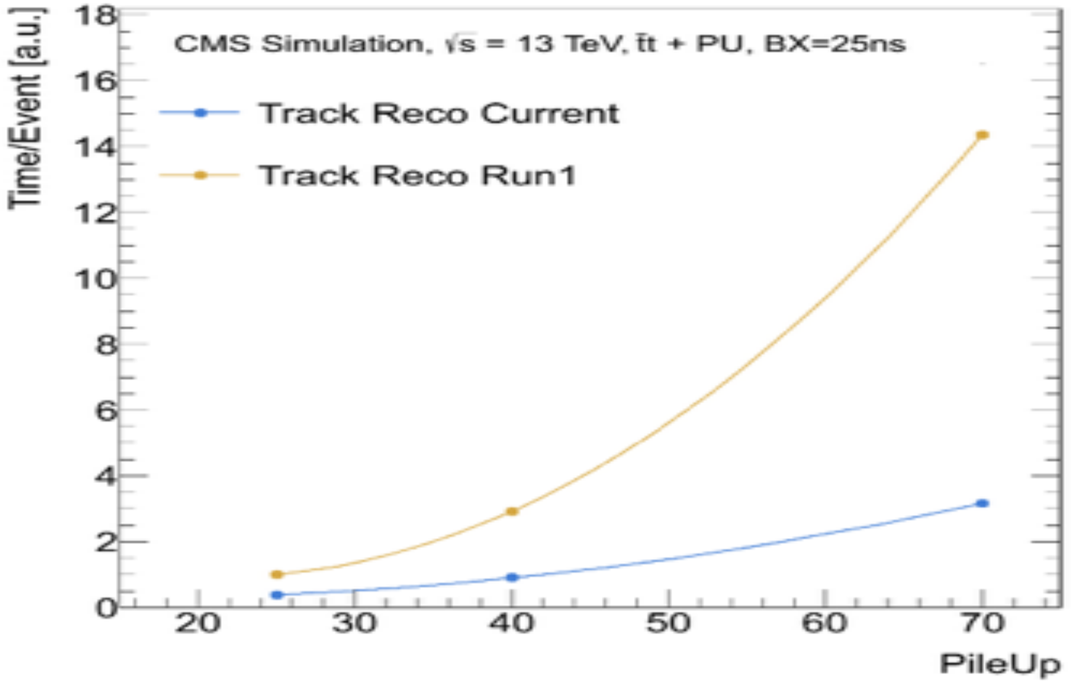

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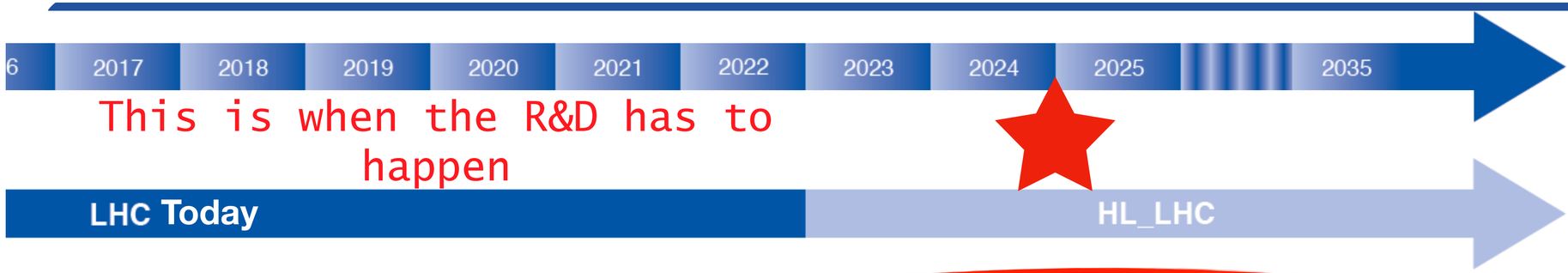

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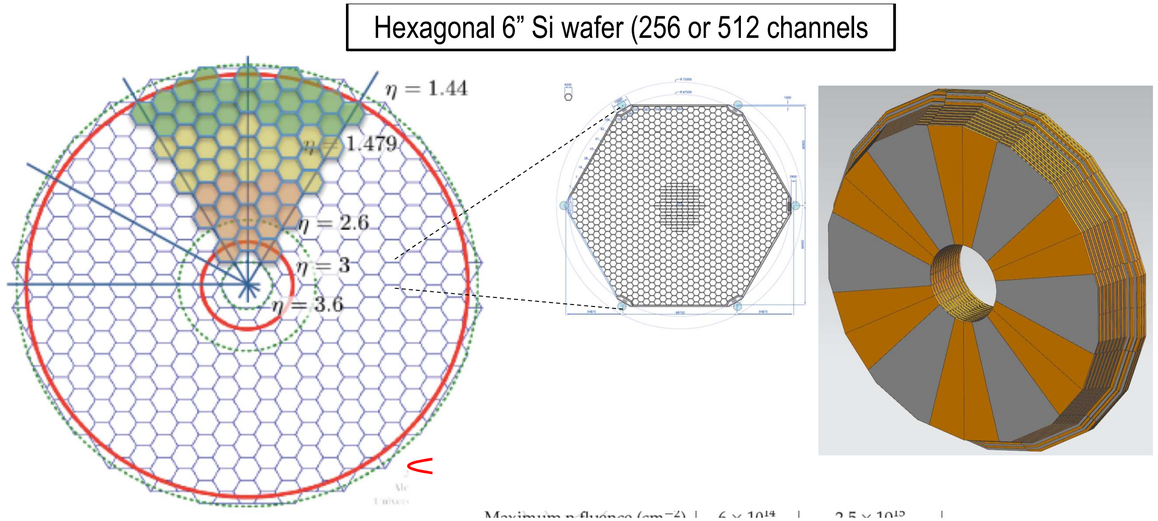
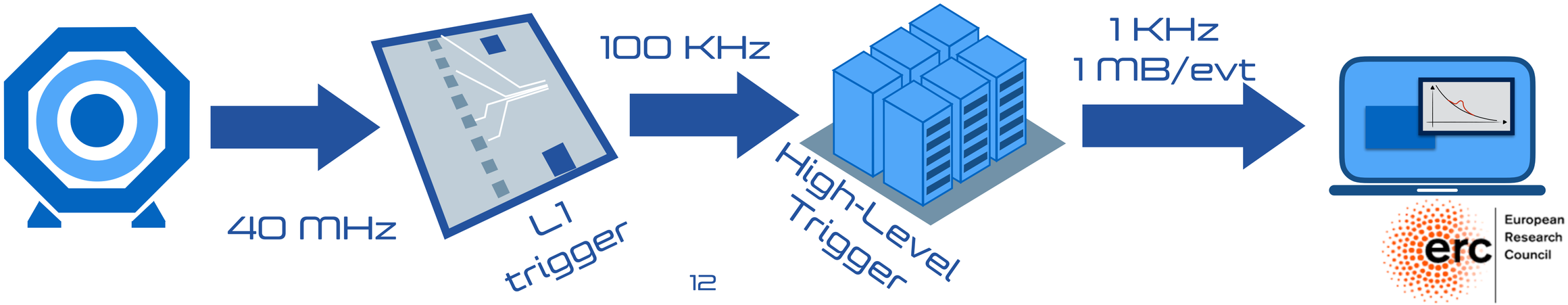


(*)With nowadays software development

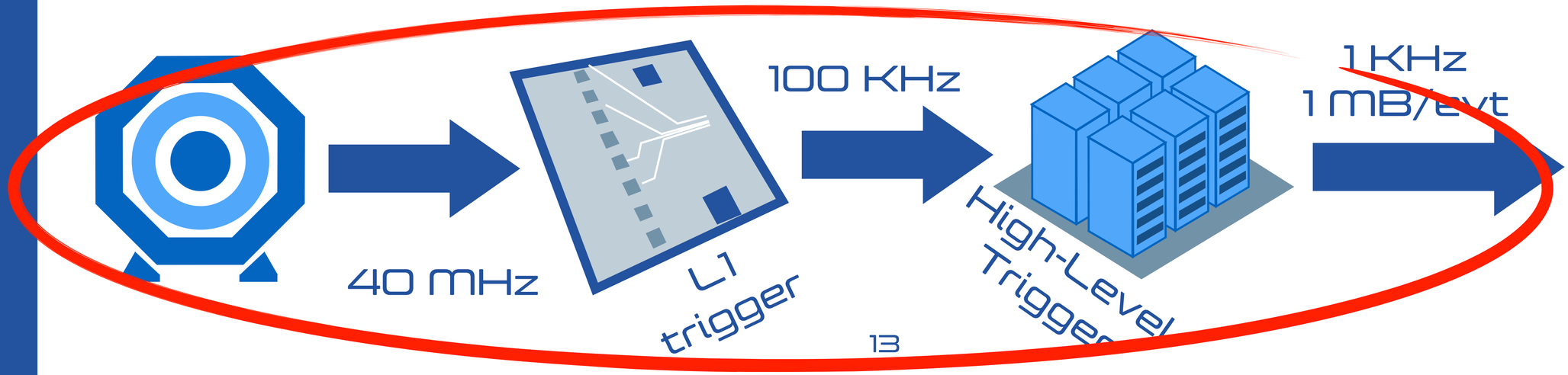
The LHC Big Data Problem

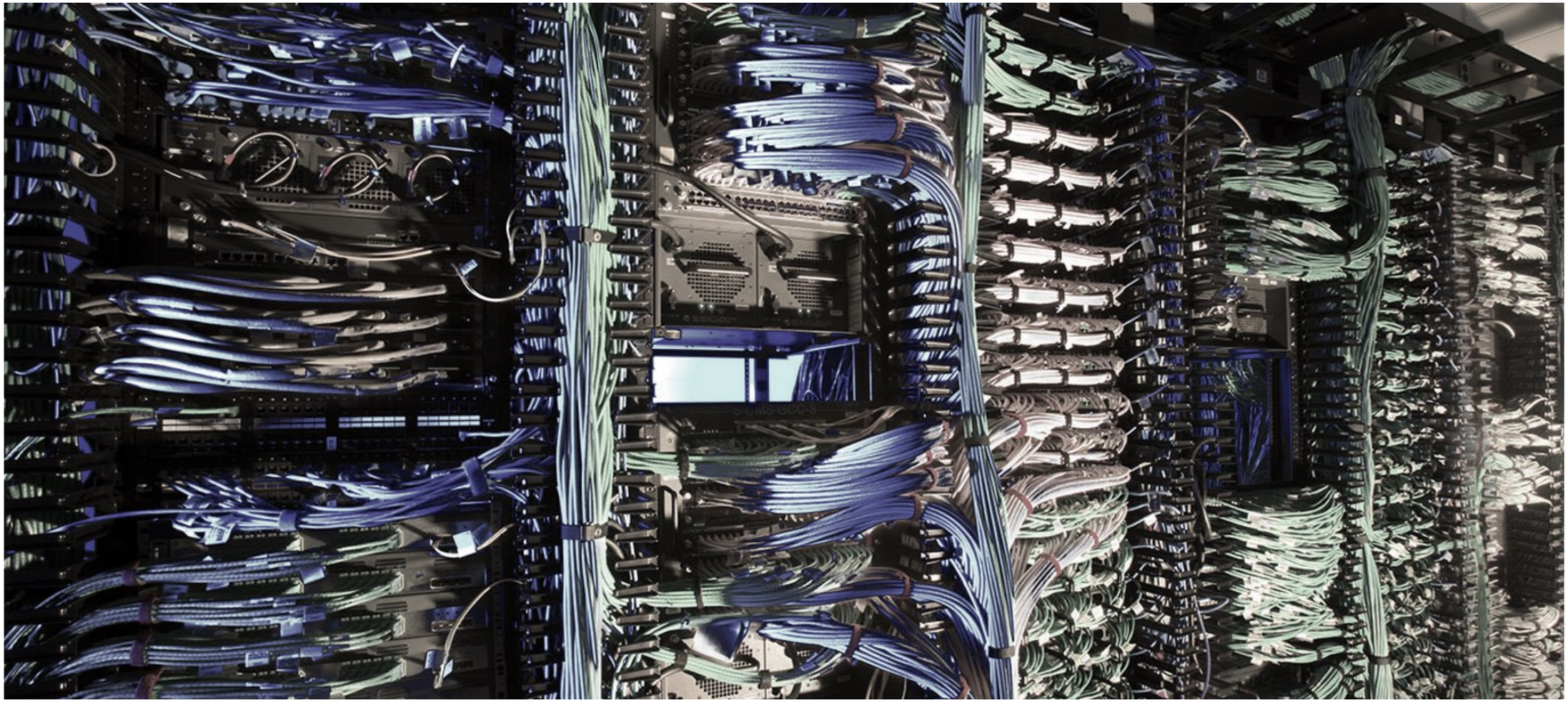
- *Too many data, too large data -> need to filter online*
- *Filters based on theoretical bias: **we might be loosing good events***
  - *L1 trigger: local, hardware based, on FPGA, @experiment site*
  - *HLT: local/global, software based, on CPU, @experiment site*
  - *Offline: global, software based, on CPU, @CERN T0*
  - *Analysis: user-specific applications running on the grid*



The LHC Big Data Problem

- *We are not seeing new physics: just re-doing what we do today with x10 more data WILL NOT be enough.*
- *The solution to the HL-LHC problem: modern Machine Learning as a fast shortcut between the data and the right answer (the outcome of our traditional & slow algorithms)*
- *This ML deployment need to happen in between collisions and data analysis (trigger, reconstruction, …), where freeing resources will make a difference*





Fast Decision Taking

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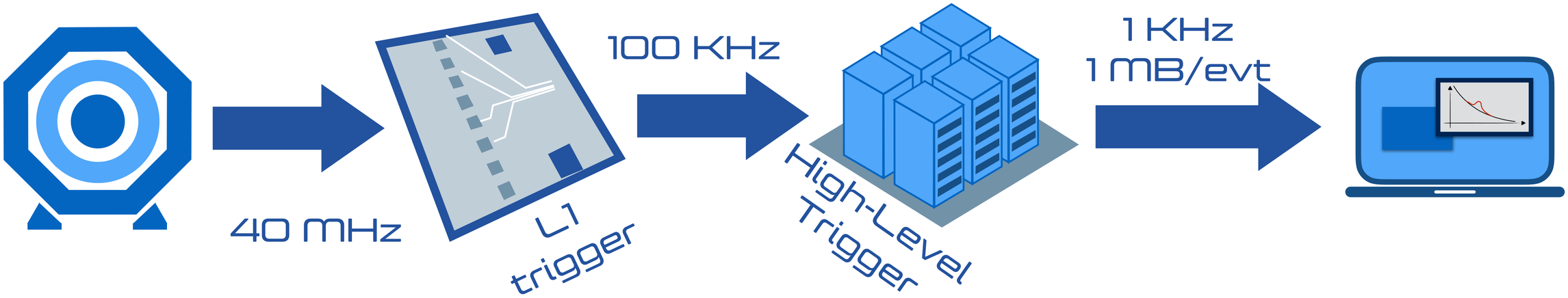
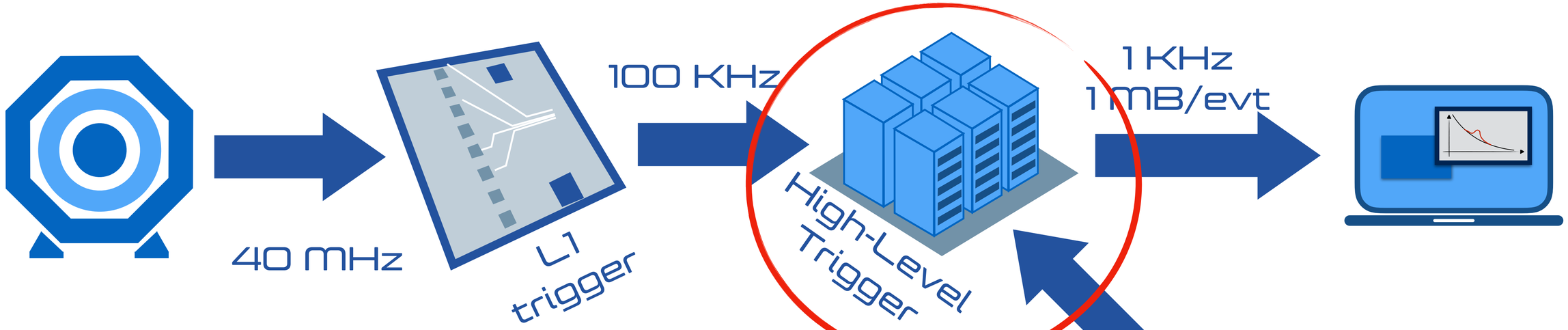
Future Architecture

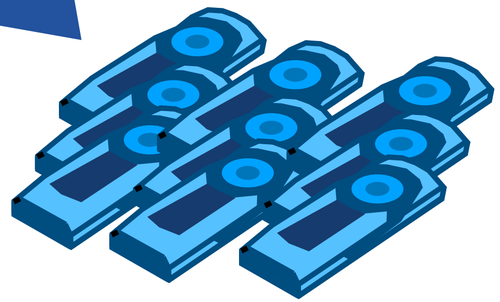


- *The more we use Machine Learning in our centralised reconstruction, the more we need to reconsider the design of our architecture*
  - *new performance/latency balance*
- *(to some extent) Not an issue after the event is written on disk (latency long enough that inference on CPU is OK*
- *This is not true for the trigger*

Not just a matter of training



- *Example: the seed-selection for tracking I showed you before*
  - *1 µsec to know if a seed is good or not*
  - *1M seeds/event -> 1sec to process an event serially*
- *This is why we are studying GPU clusters for our HLT farms*
  - *ML inference, tracking, etc delegated to GPUs as a service*



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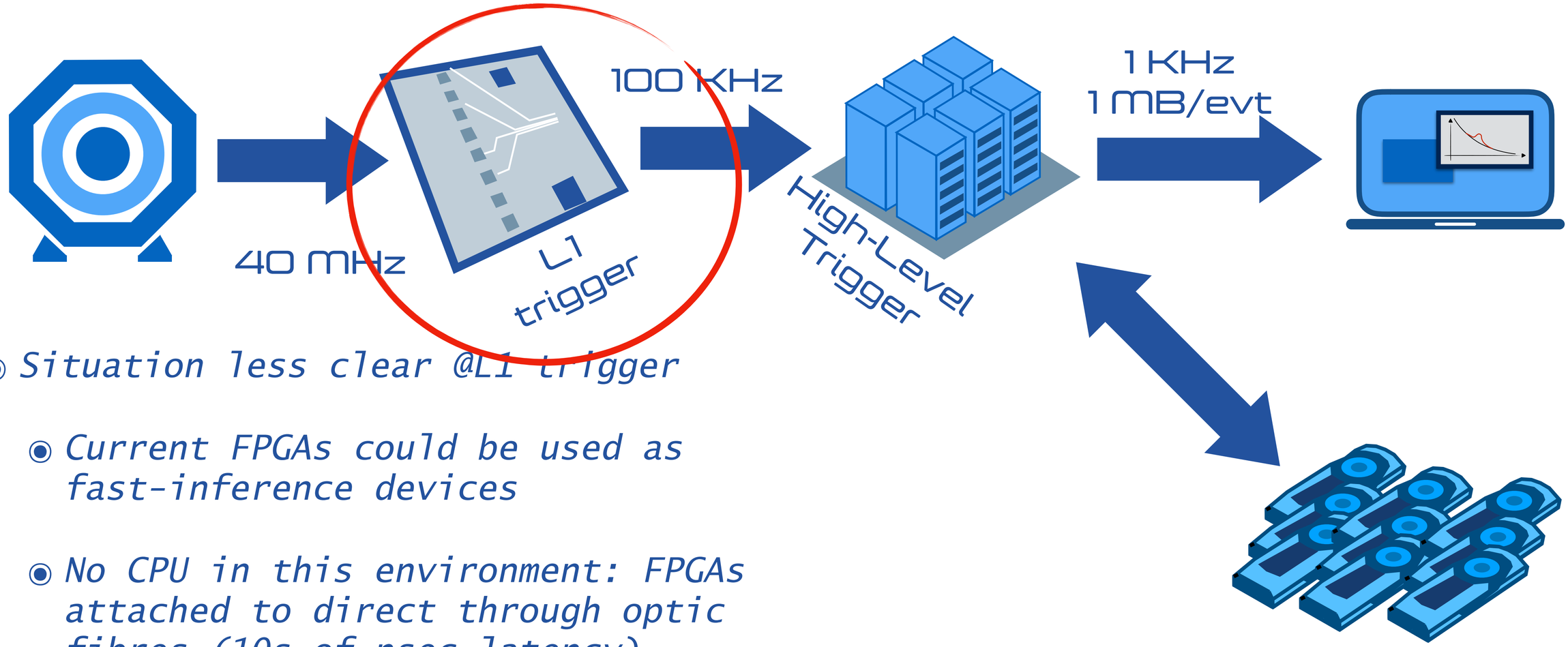
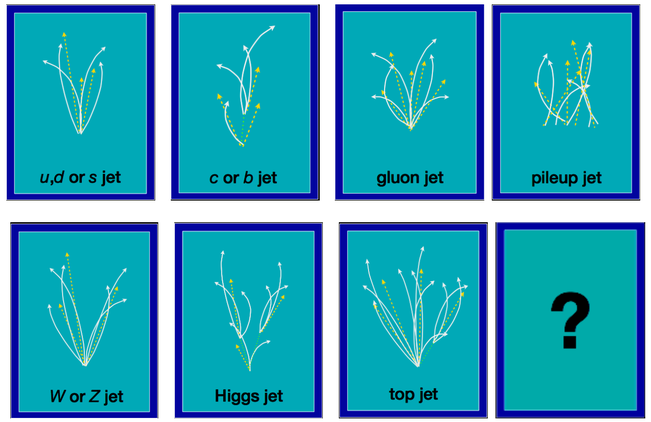


- *Situation less clear @L1 trigger*
  - *Current FPGAs could be used as fast-inference devices*
  - *No CPU in this environment: FPGAs attached to direct through optic fibres (10s of nsec latency)*

Back to our first example



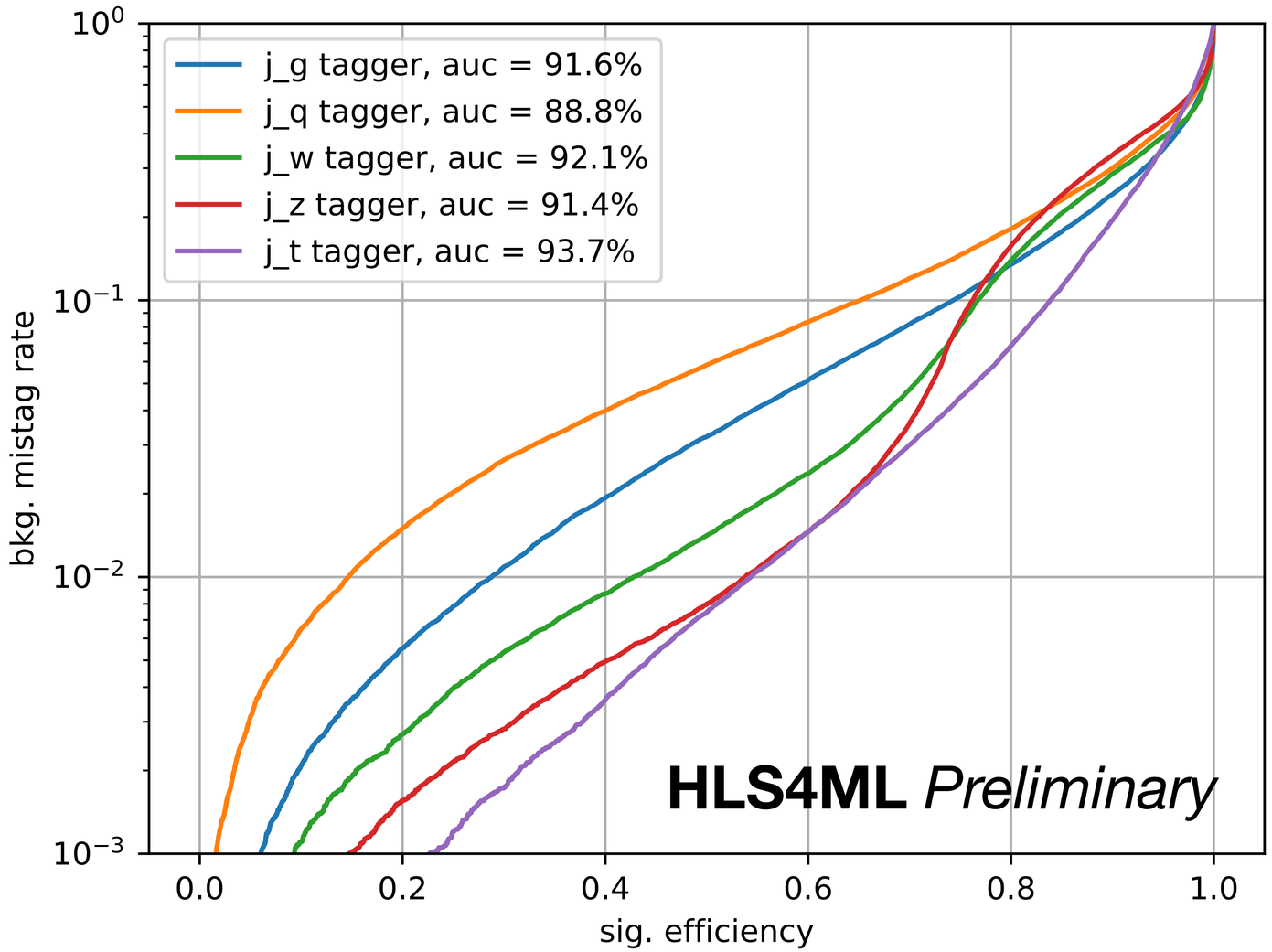
16 inputs

64 nodes
activation: ReLU

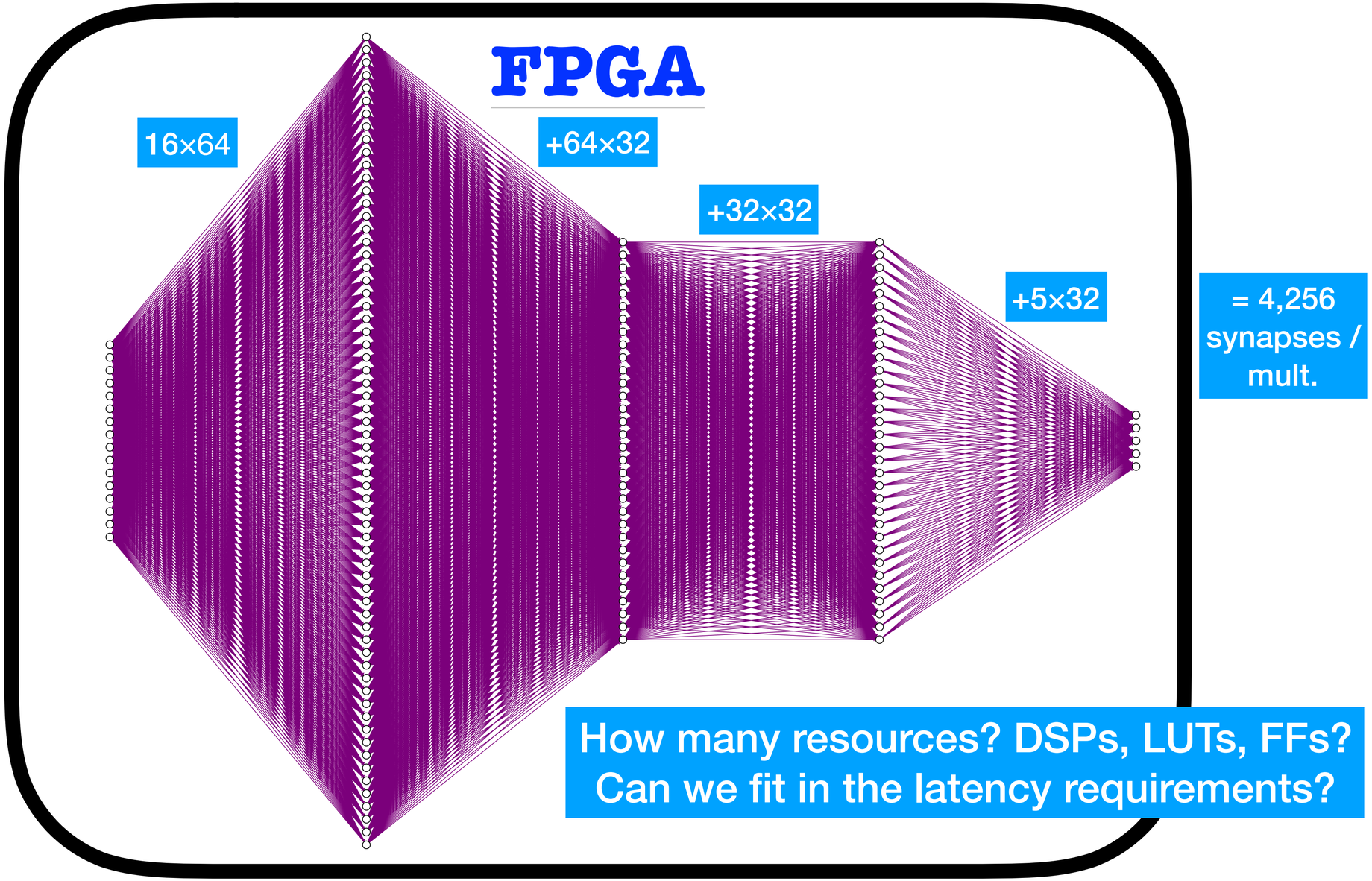
32 nodes
activation: ReLU

32 nodes
activation: ReLU

5 outputs
activation: SoftMax

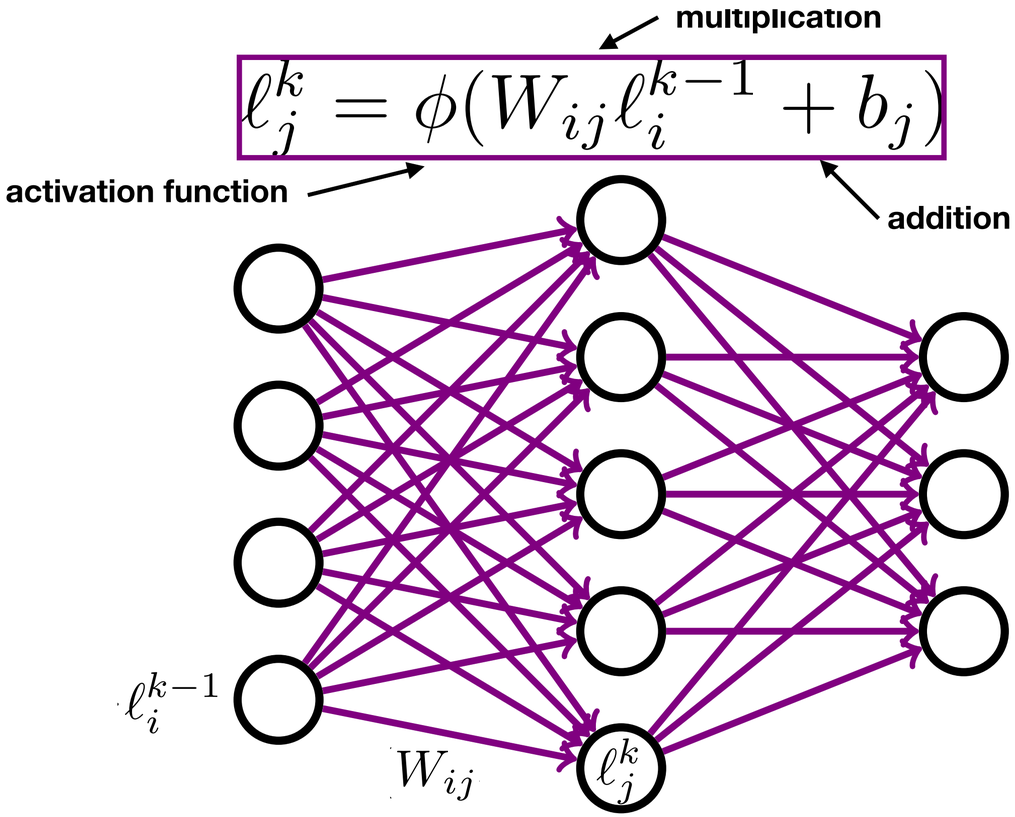


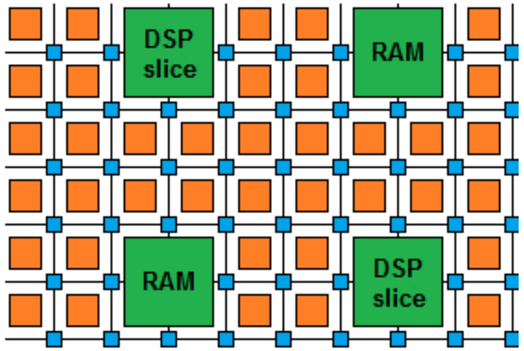
The full model



Network Operations

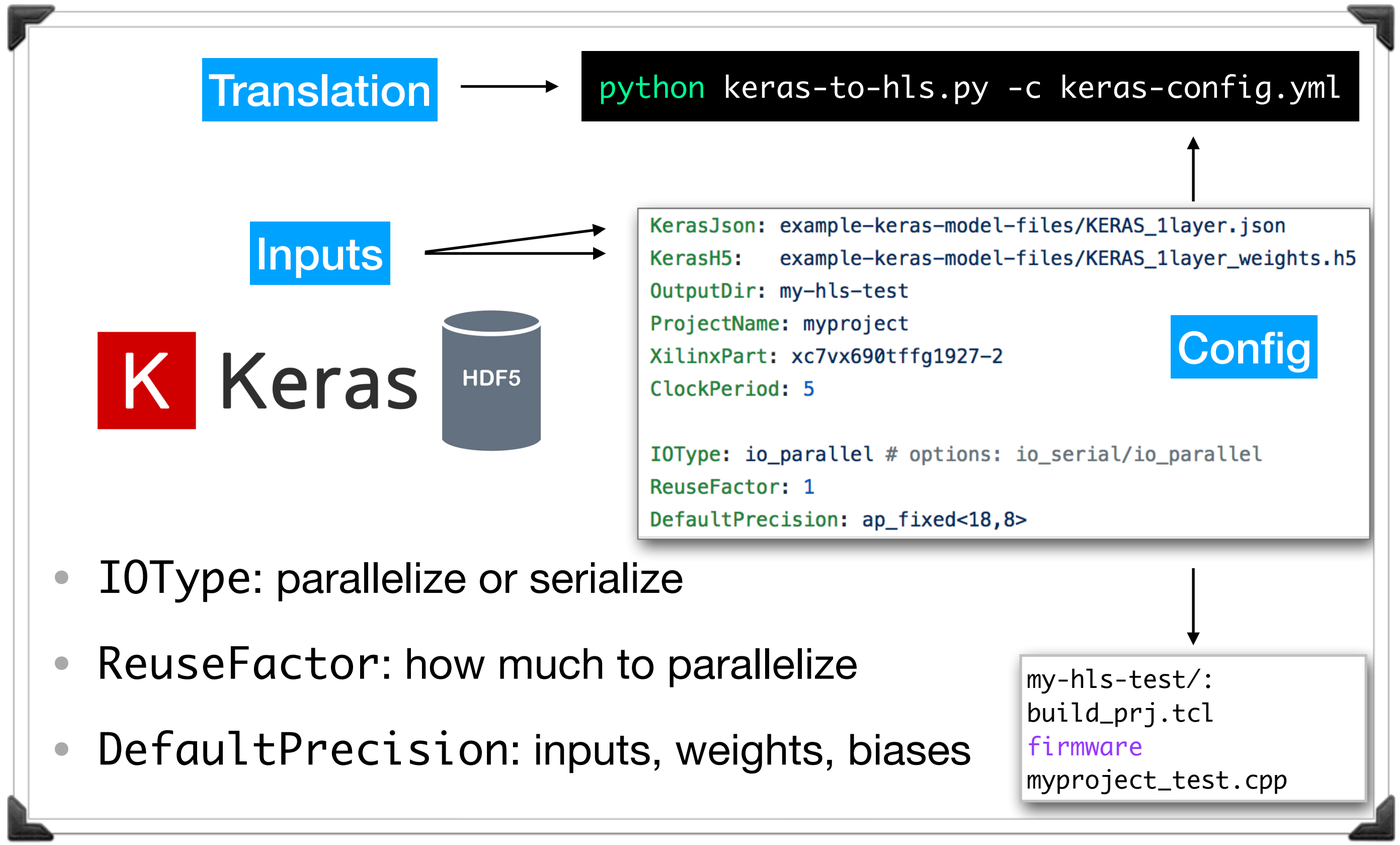
- A classic Dense NN manipulates the inputs in three ways
  - multiplying by weights
  - adding biases
  - applying activation functions
- All these operations map nicely into an FPGA
  - high IO, DSPs, LUTs, tunable precision





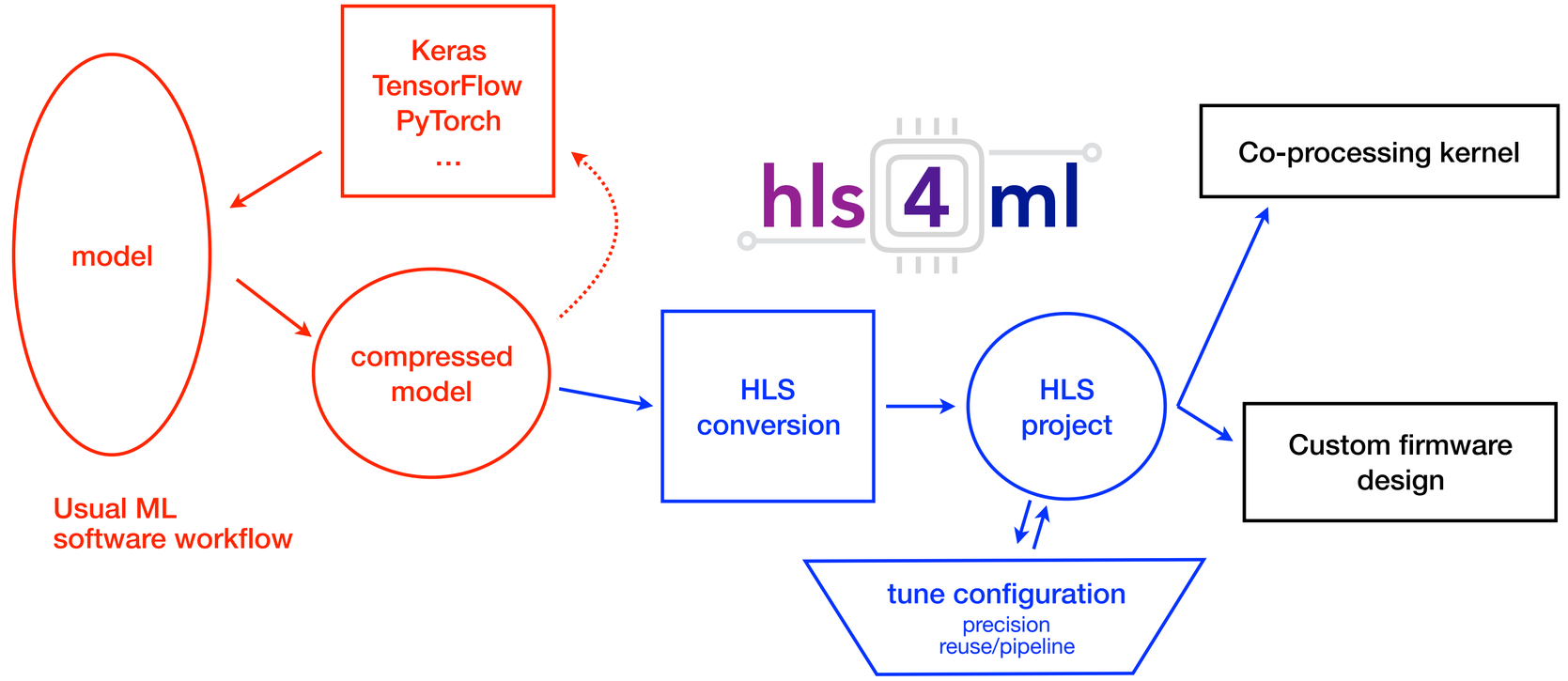
Bring the model to FPGA

- *How this works in practice*
  - *A python based library that takes inputs via a yam file*
  - *Model architecture with supported format*
  - *FPGA configuration parameters (reuse factor, FPGA model, Clock period, etc)*
- *The library provides inputs for Vivado HLS*



HLS4ML

- *HLS4ML aims to be this automatic tool*
  - *reads as input models trained on standard DeepLearning libraries*
  - *comes with implementation of common ingredients (layers, activation functions, etc)*
  - *Uses HLS softwares to provide a firmware implementation of a given network*
  - *Could also be used to create co-processing kernels for HLT environments*

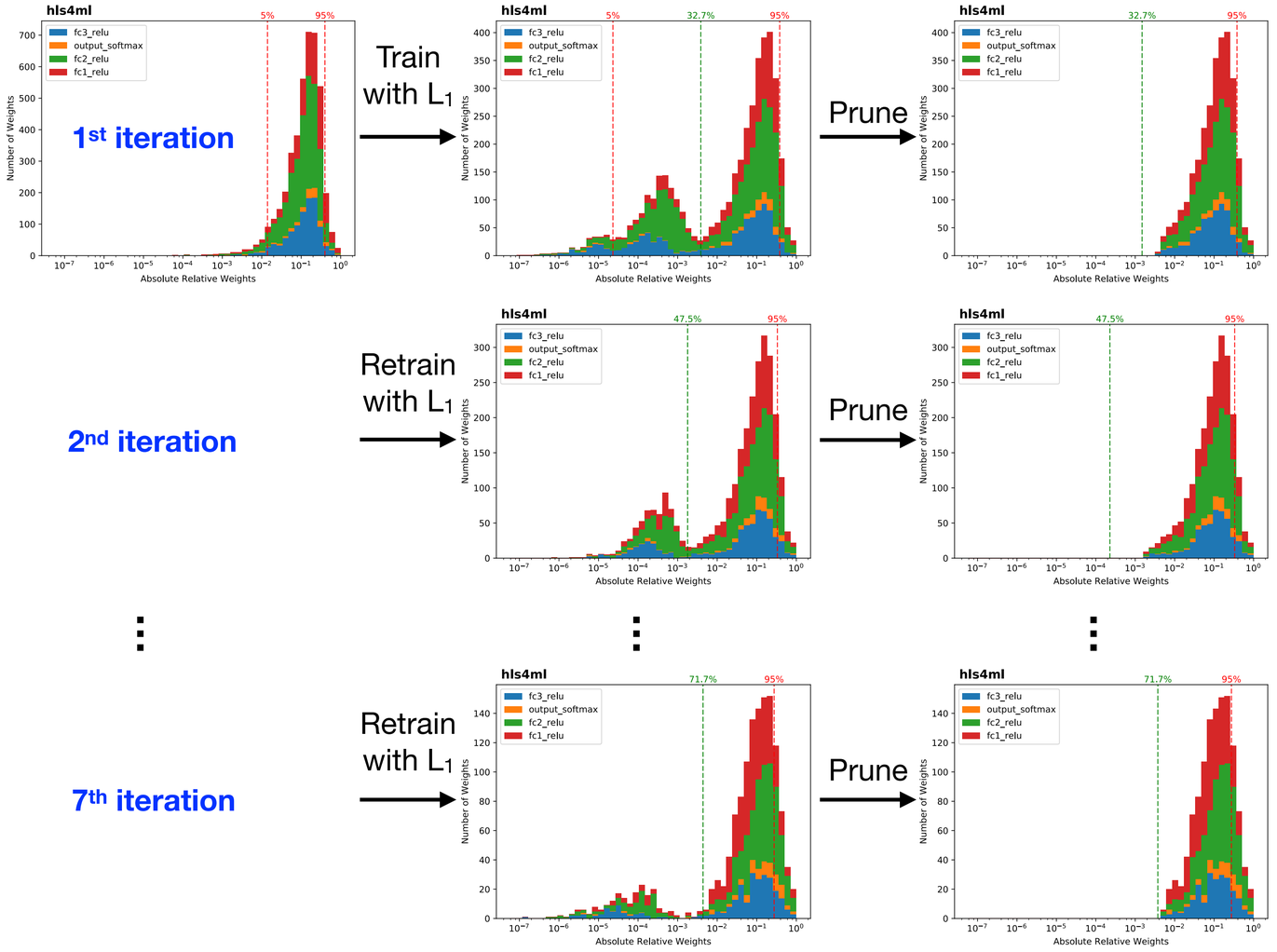


Make the model cheaper

- ***Pruning:*** *remove parameters that don't really contribute to performances*
  - *force parameters to be as small as possible (regularization)*

$$L_\lambda(\vec{w}) = L(\vec{w}) + \lambda||\vec{w}_1||$$

  - *Remove the small parameters*
  - *Retrain*



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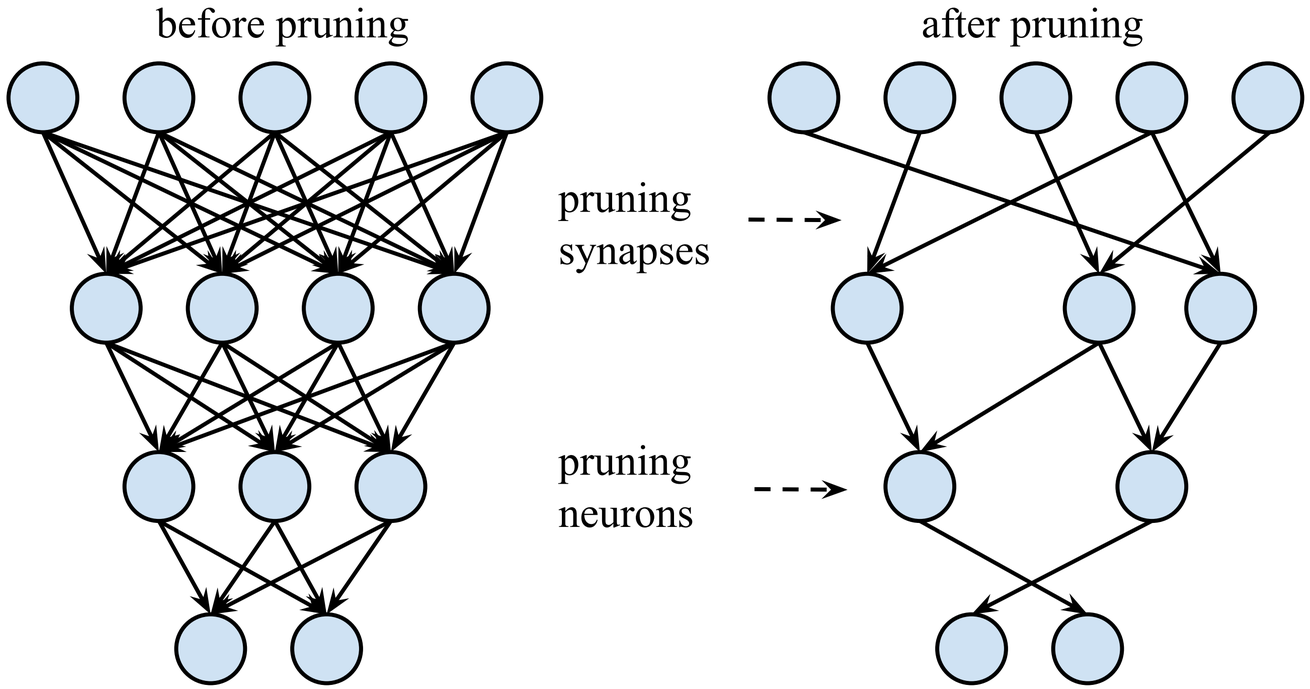
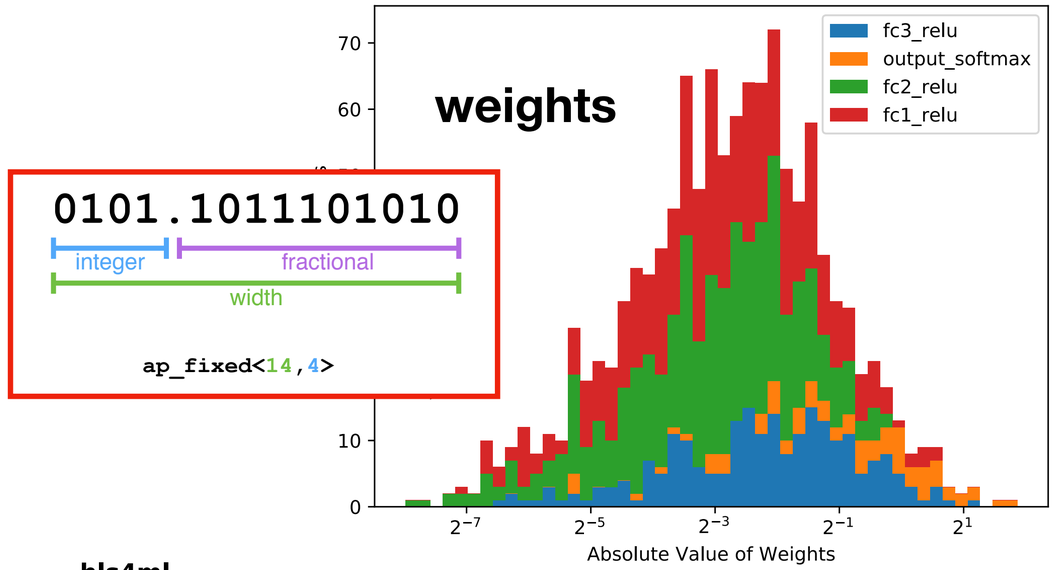
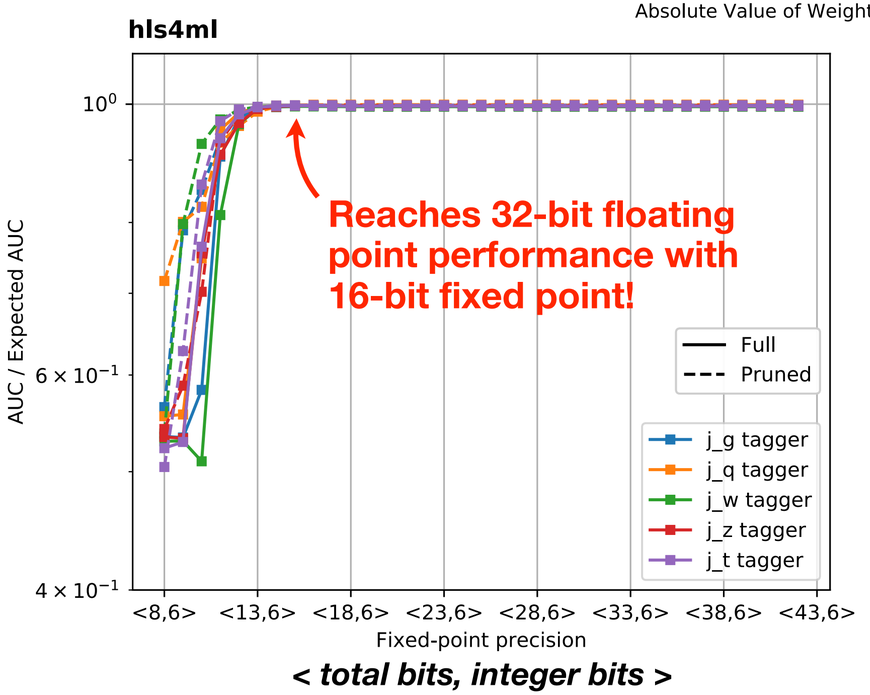


→ 70% reduction of weights and multiplications w/o performance loss

Make the model cheaper

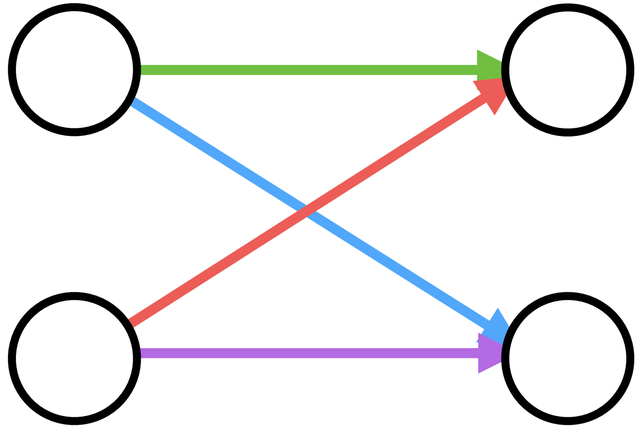
- ***Quantization***: *reduce the number of bits used to represent numbers (i.e., reduce used memory)*
  - *models are usually trained at 64 or 32 bits*
  - *this is not necessarily needed in real life*
- *In our case, we could reduce to 16 bits w/o loosing precision*
- *Beyond that, one would have to accept some performance loss*

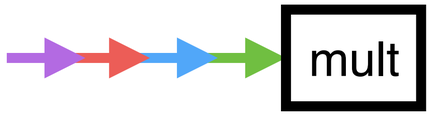




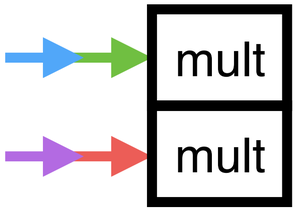
Parallelisation

- `ReuseFactor`: how much to parallelize

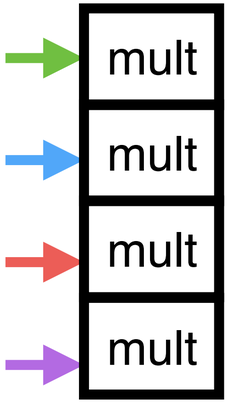




reuse = 4
use 1 multiplier 4 times



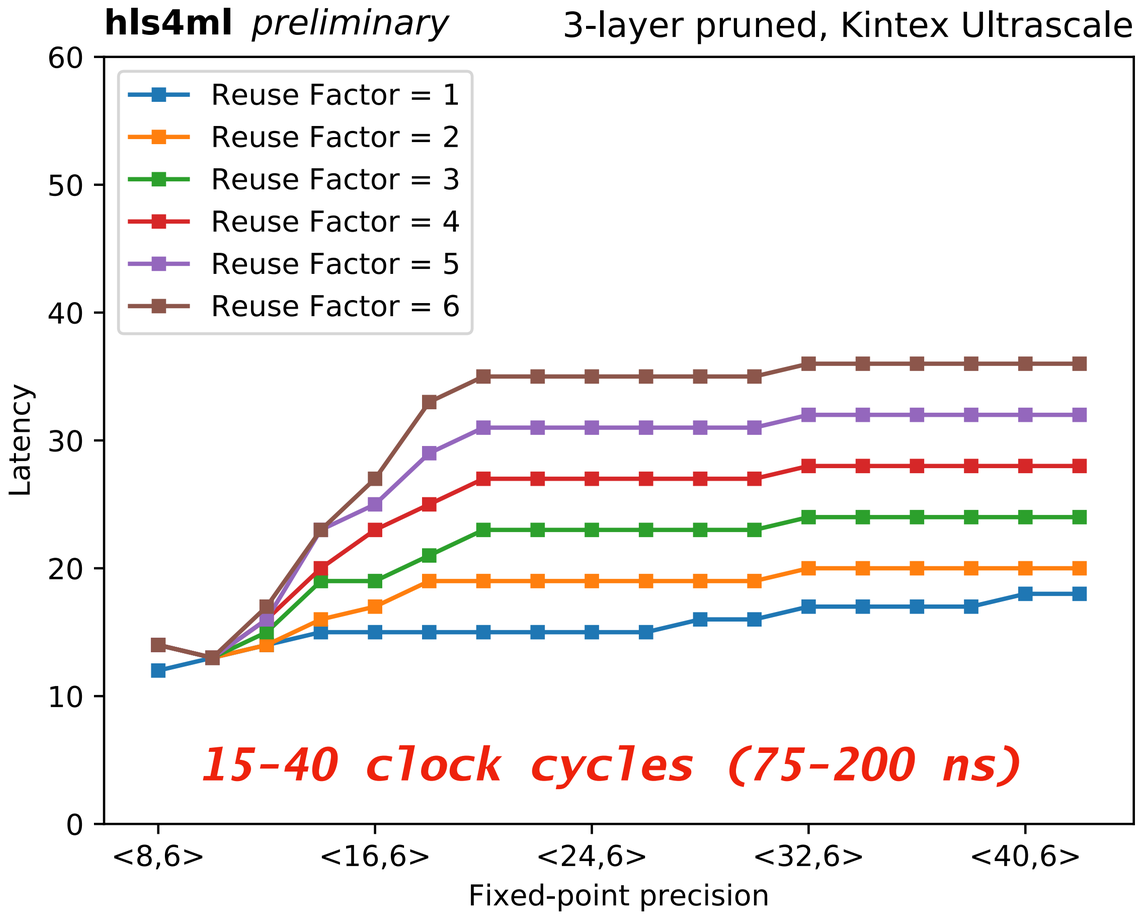
reuse = 2
use 2 multipliers 2 times each

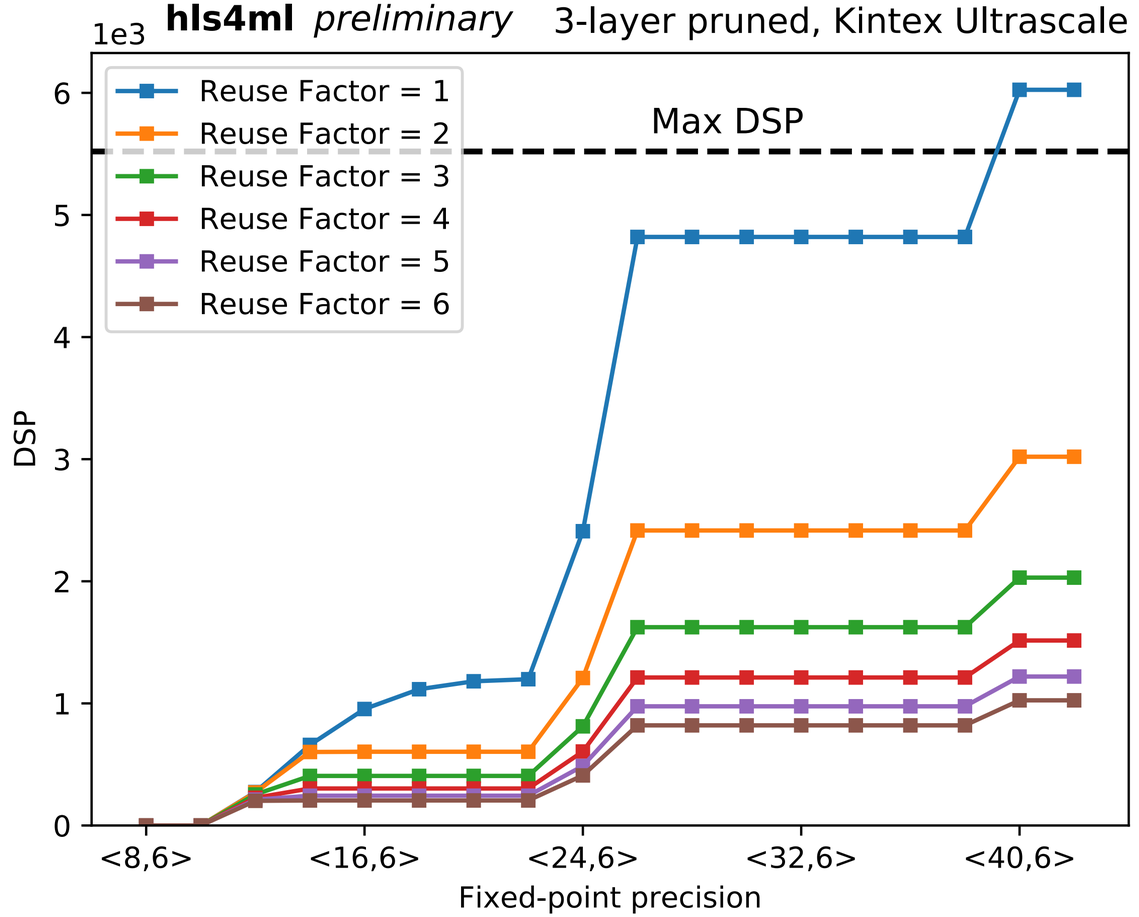


reuse = 1
use 4 multipliers 1 time each

related to the Initiation Interval = when new inputs are introduced to the algo.

Fast-inference





Foreseen architecture (FPGAs) will handle these networks
Inference-optimized GPUs could break the current paradigm
Looking forward to R&D projects with nVidia & E4 on this

Deep Learning on the Cloud

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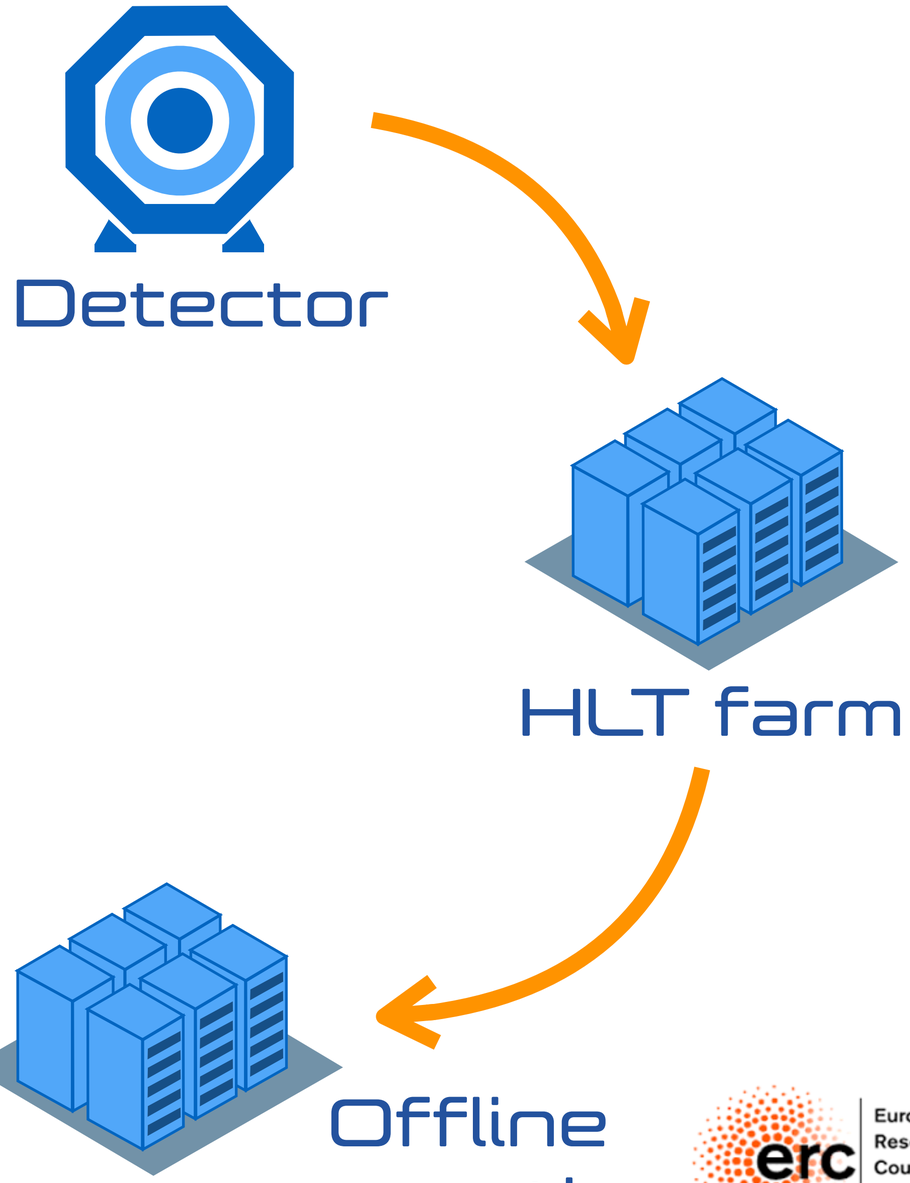
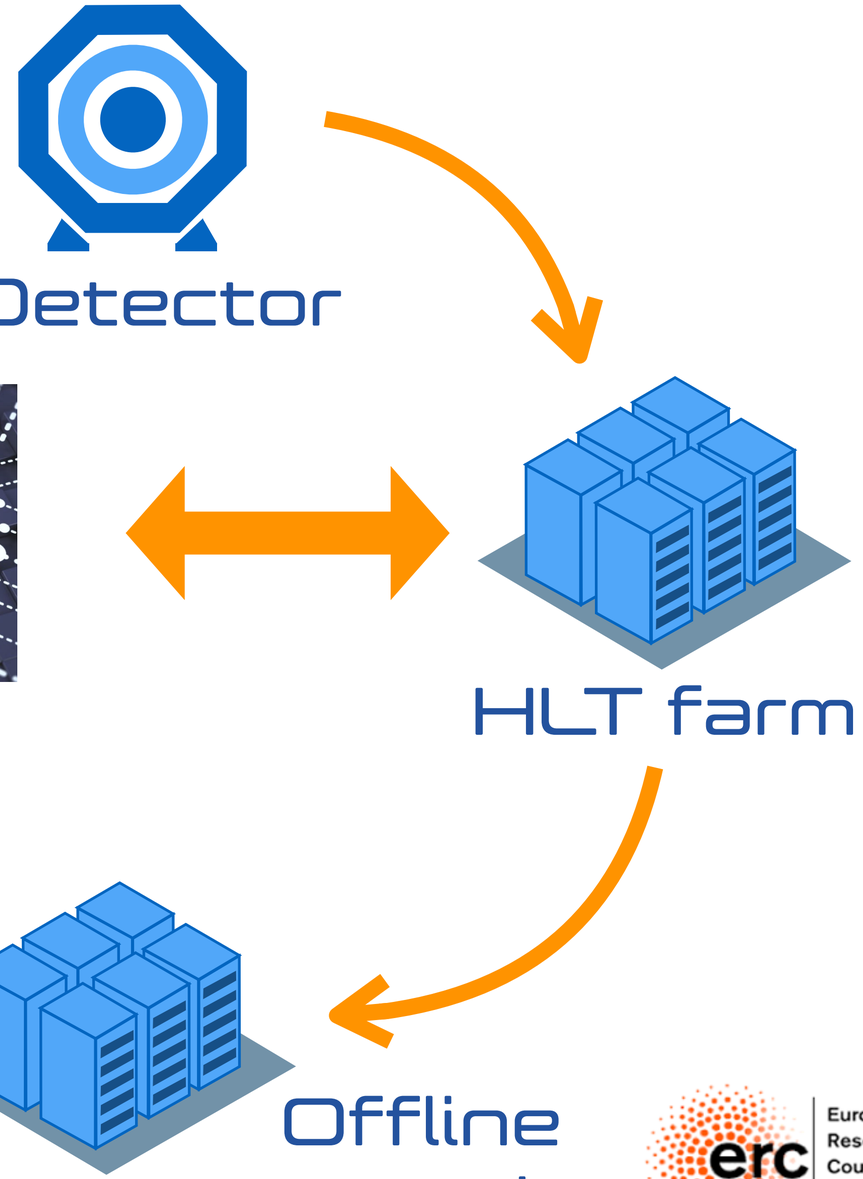
Heterogenous DAQ

- *In the (near) future, DAQ/HLT farms will be based on edge heterogenous computing*
  - *CPU+GPU / CPU+FPGA*
  - *Mainly to accelerate slow algorithms (e.g., tracking) through parallelisation*
  - *Also useful for ML inference*
- *Technology improving quickly*
  - *typically, our systems built ahead and old when operating (e.g., CMS FPGAs)*
  - *can we change the paradigm to take advantage of the improving technology?*



Heterogenous DAQ

- *One could instead use opportunistically cloud resources as part of the online processing system*
  - *price decreasing (could be competitive in the future)*
  - *always the best hardware at hand*



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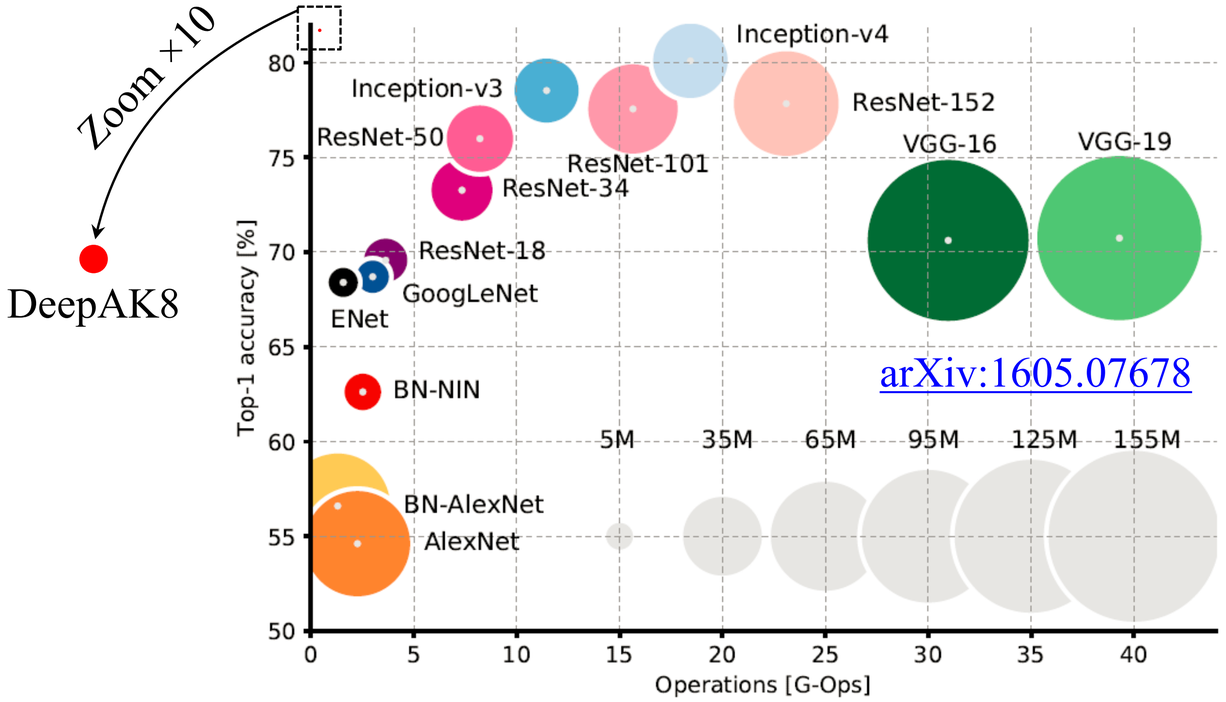
HEP & Modern Deep Learning

- *Deep Learning is becoming ubiquitous*
  - *used in many applications, mainly image recognition*
  - *large models deployed, reaching large accuracy on multiple tasks*
  - *optimized implementations of these models are deployed on commercial clouds*
- *Can we take advantage of that?*



arXiv:1605.07678

- ResNet50: 25M parameters, 7B operations
- Examples of large networks used in CMS:
  - DeepAK8, 500K parameters, 15M operations
  - DeepDoubleB, 40K parameters, 700K operations

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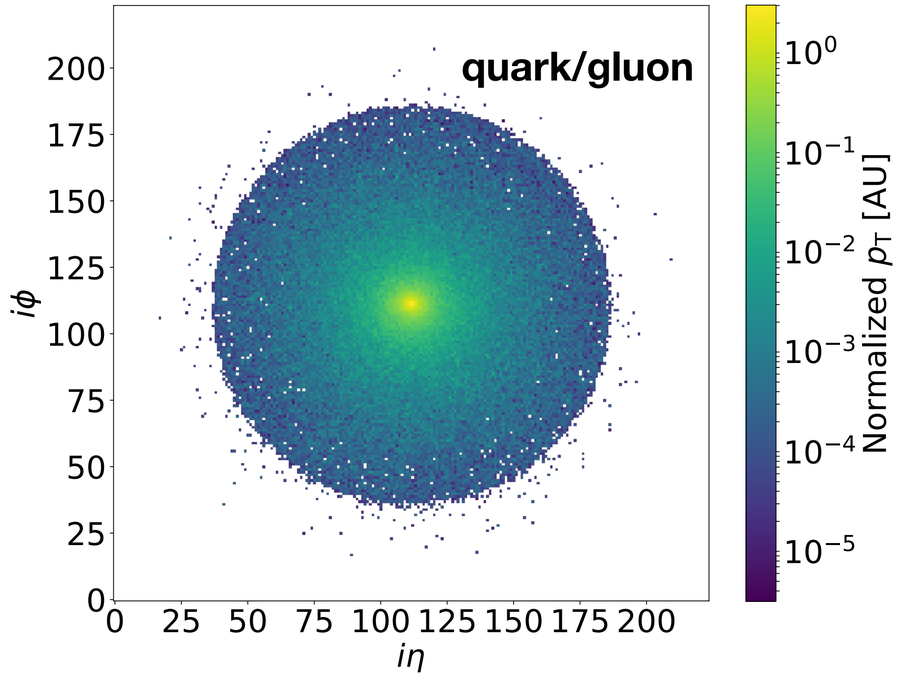
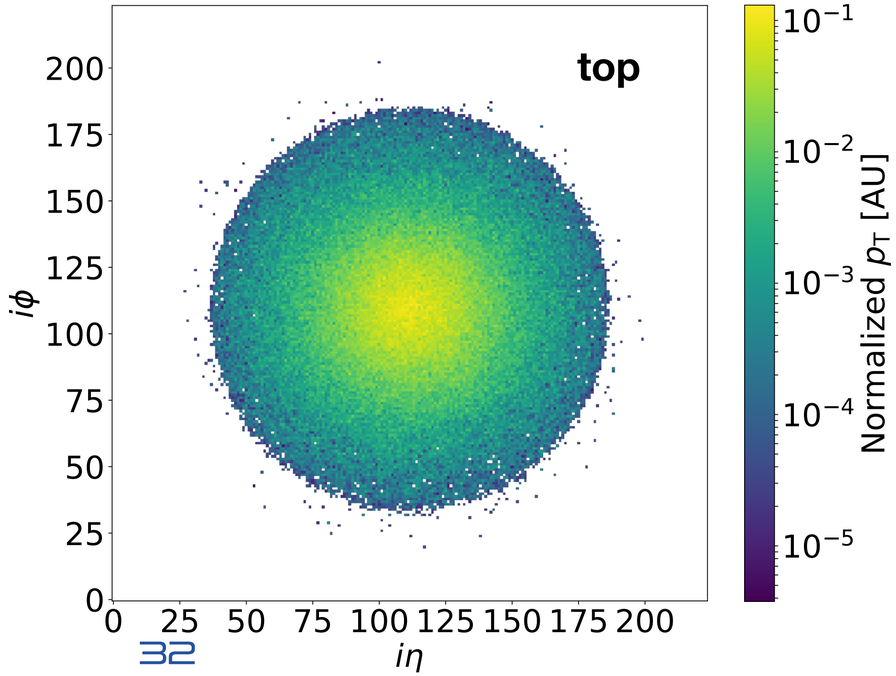
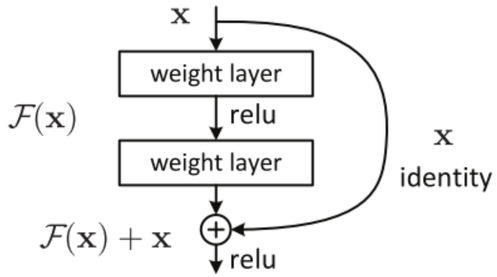
Jet Tagging with ResNet on Cloud

- *To exploit cloud services, we need to turn our problems in something similar to what is done there*
  - *mainly image identification*
  - *computing vision successfully exploited for jet tagging*
- *We investigated the use of a standard network (ResNet) for top tagging*



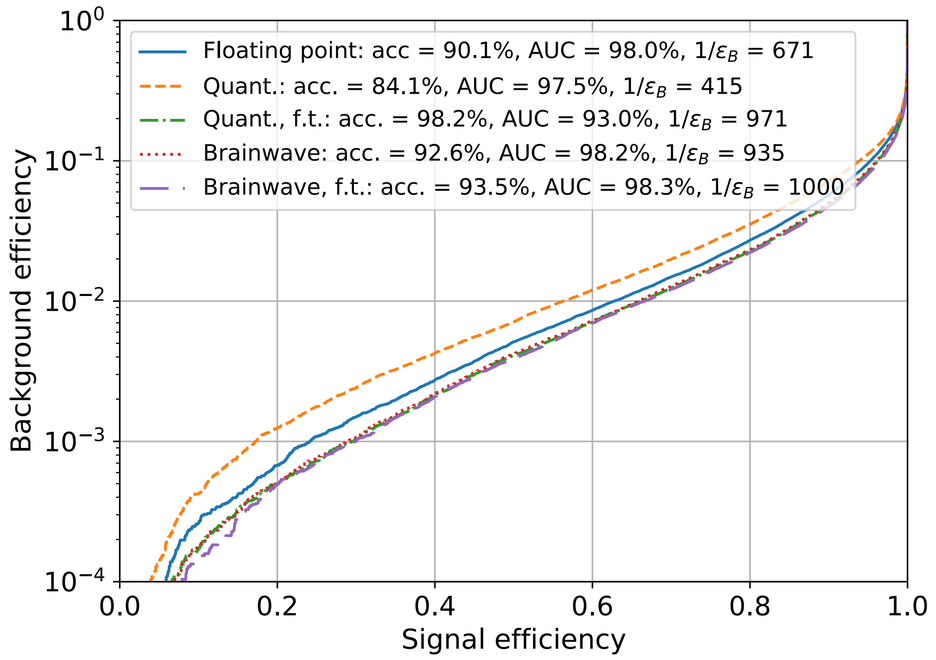




Jet Tagging with ResNet on Cloud

- *To exploit cloud services, we need to turn our problems in something similar to what is done there*
  - *mainly image identification*
  - *computing vision successfully exploited for jet tagging*
- *We investigated the use of a standard network (ResNet) for top tagging*

Model	Accuracy	AUC	$1/\varepsilon_B(\varepsilon_S = 30\%)$
Floating point	0.9009	0.9797	670.8
Quant.	0.8413	0.9754	414.6
Quant., f.t.	0.9296	0.9825	970.7
Brainwave	0.9257	0.9821	934.8
Brainwave, f.t.	0.9348	0.9830	999.6



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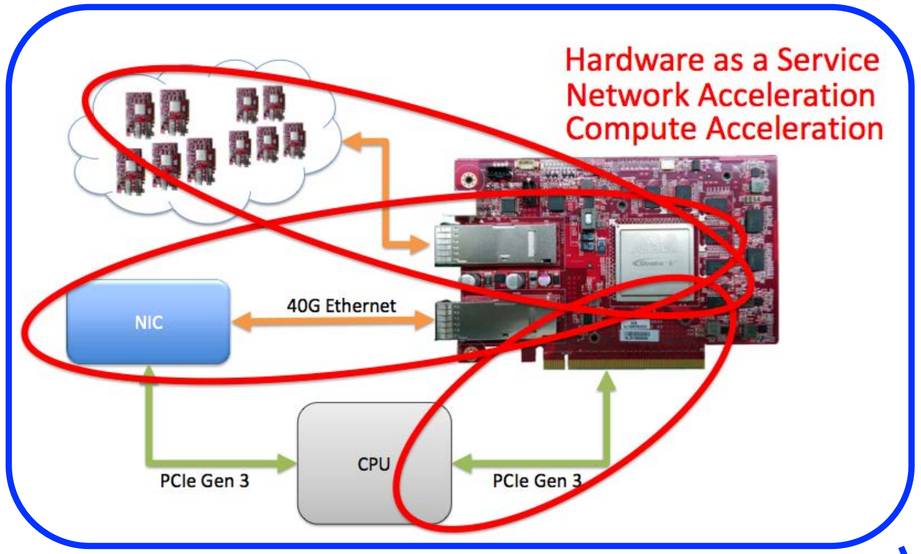
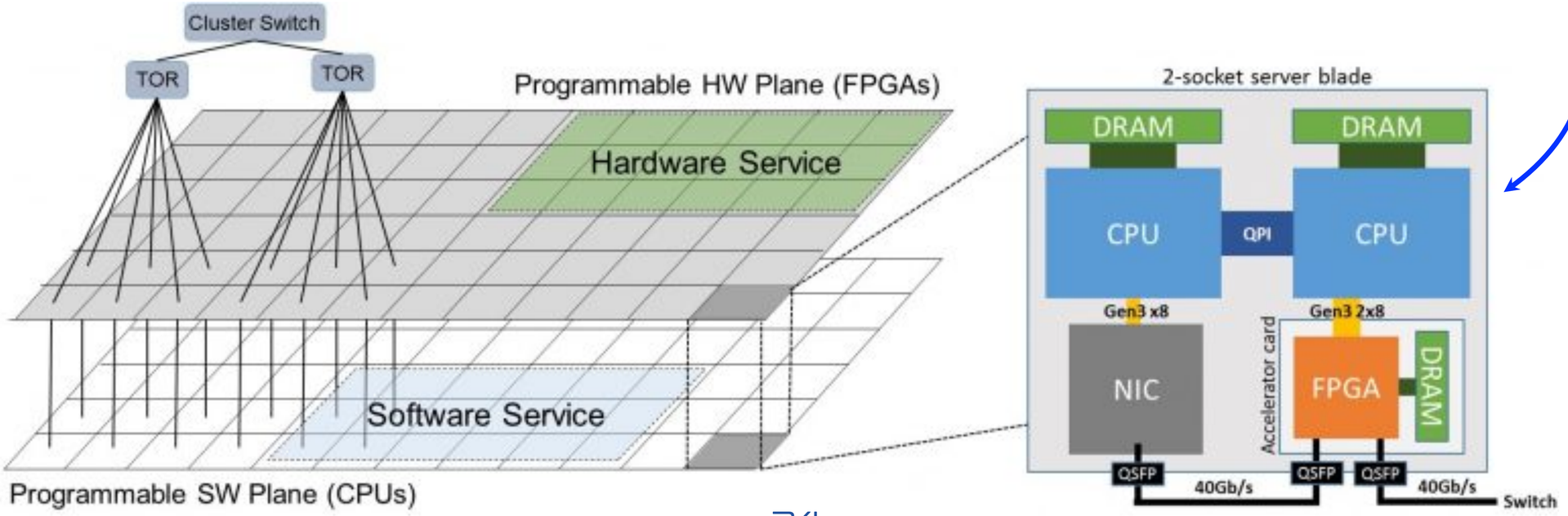
Brainwave at scale

- Provides a full service at scale (more than just a single co-processor)
- Multi-FPGA/CPU fabric, accelerating both compute and network

➢ Demonstrated large improvements in processing time for Bing searches

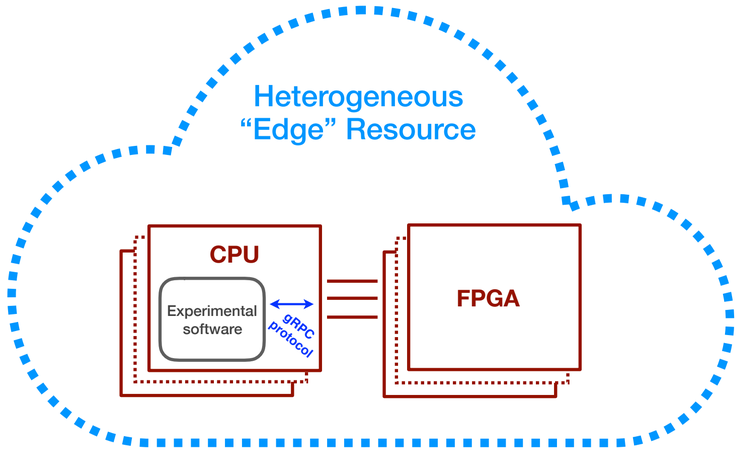
- Caveat: only selected pre-trained DNN models currently available

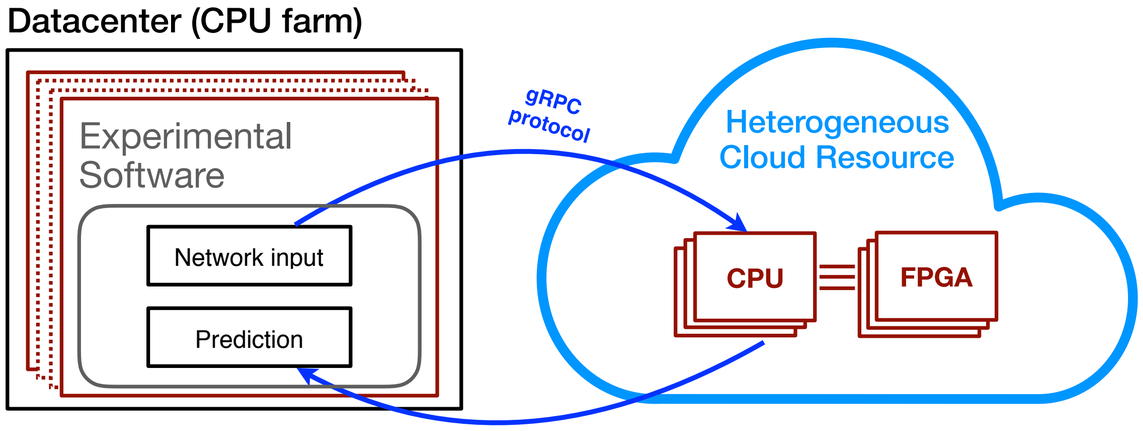




Edge vs Cloud

- *On Brainwave, we emulated the edge and the cloud options on the same hardware*
  - ***edge (on prem):*** *there, we emulated a CPU+FPGA infrastructure*
  - ***cloud (remote):*** *at FNAL, we emulated a CPU-only infrastructure, communicated to Brainwave (in Virginia)*
  - *communication via gRPC protocol (driven by Microsoft infrastructure boundaries)*
- *We then compared these two solutions against alternative options (e.g., GPU acceleration)*





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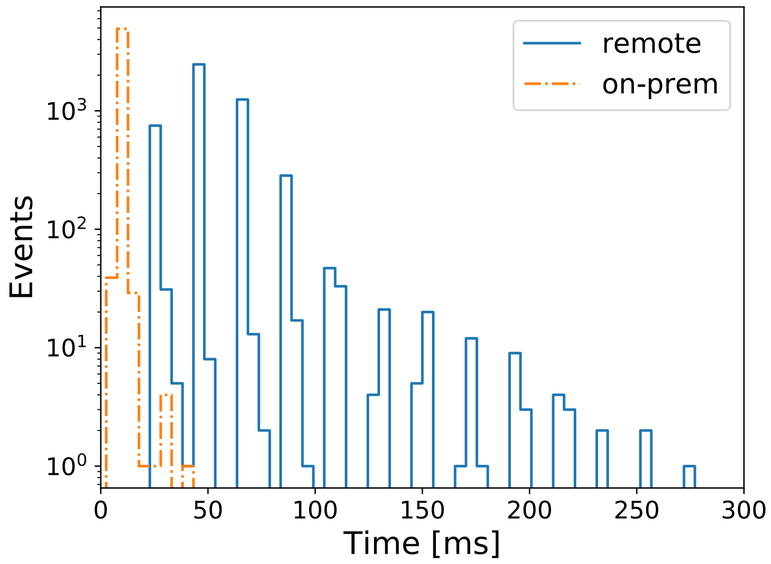
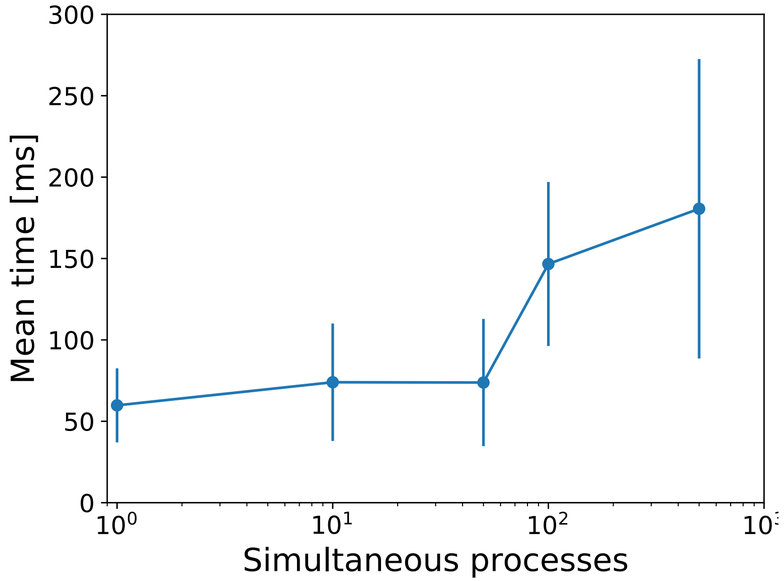
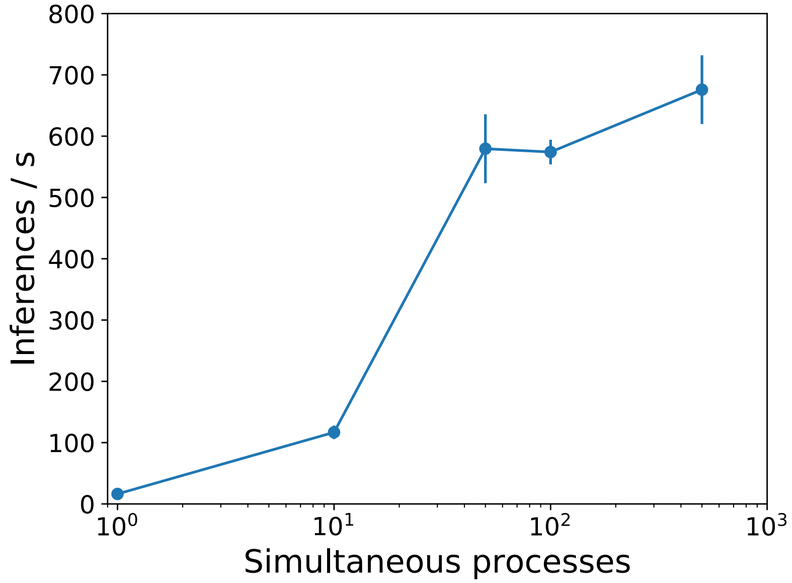
Performance of Remote Solution



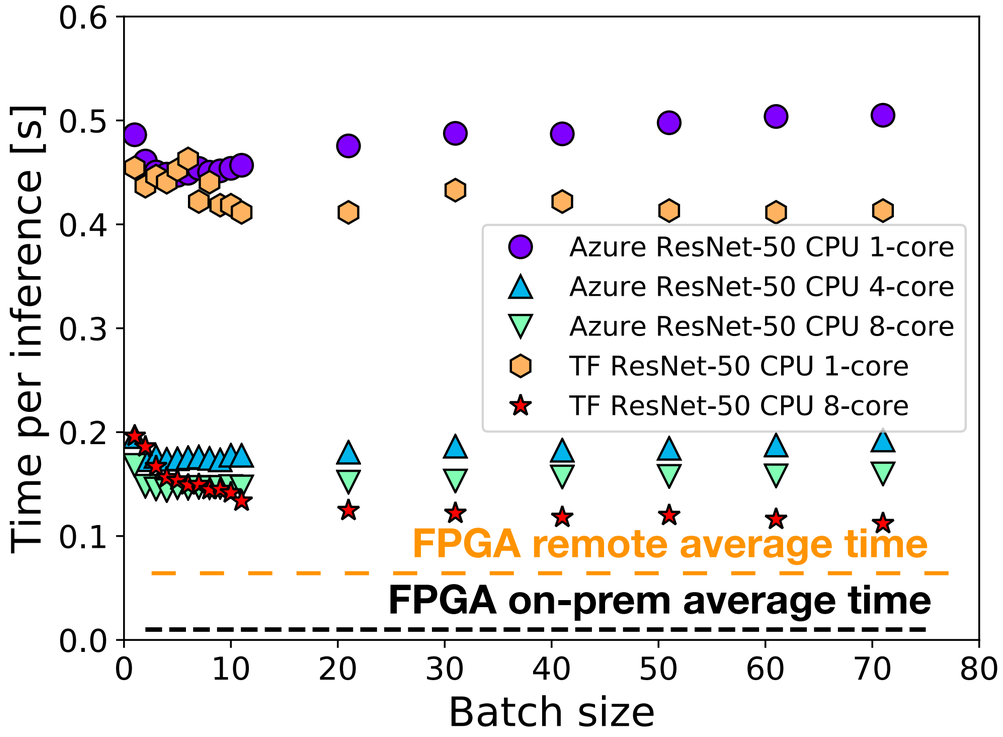


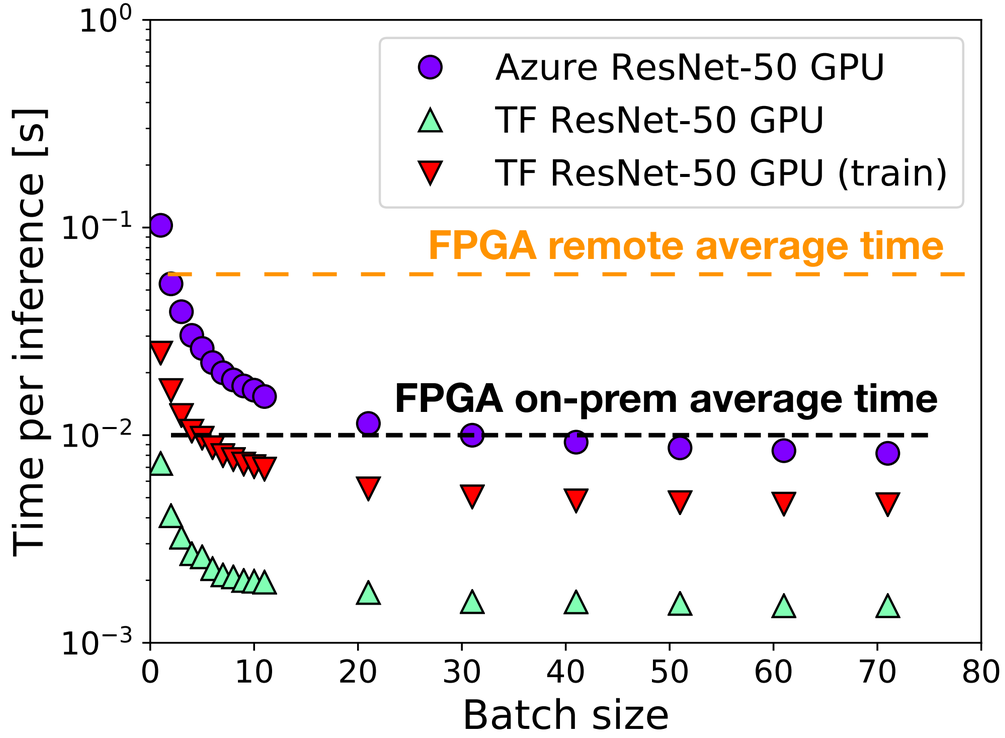


- Good performance in initial tests
  - “remote”: cmslpc @ FNAL to Azure (VA), ‹time› = 56 ms
  - “onprem”: run CMSSW on Azure VM, ‹time› = 10 ms
    (~2 ms on FPGA, rest is classifying and I/O)
  - CPU (cmslpc): 1.75 sec
    (6 min to load ResNet50 session)

➢ More than order of magnitude improvement!

Comparison to CPU/GPU





- *Worse performance with CPUs, partially recovered when increasing #cores*
- *GPUs become competitive when running simultaneously on batches (GPU more efficiently occupied)*
- *Optimal solution depends on use case (batches vs no batches)*

Comparison to CPU/GPU

Type	Hardware	⟨Inference time⟩	Max throughput	Setup
CPU	Xeon 2.6 GHz, 1 core	1.75 seconds	0.6 img/s	`CMSSW`, `TF v1.06`
CPU	i7 3.6 GHz, 1 core	500 ms	2 img/s	python, `TF v1.10`
CPU	i7 3.6 GHz, 8 core	200 ms	5 img/s	python, `TF v1.10`
GPU (batch=1)	NVidia GTX 1080	100 ms	10 img/s	python, `TF v1.10`
GPU (batch=32)	NVidia GTX 1080	9 ms	111 img/s	python, `TF v1.10`
GPU (batch=1)	NVidia GTX 1080	7 ms	143 img/s	TF internal, `TF v1.10`
GPU (batch=32)	NVidia GTX 1080	1.5 ms	667 img/s	TF internal, `TF v1.10`
Brainwave	Altera Artix	10 ms	660 img/s	`CMSSW`, *on-prem*
Brainwave	Altera Artix	60 ms	660 img/s	`CMSSW`, *remote*

- *Worse performance with CPUs, partially recovered when increasing #cores*
- *GPUs become competitive when running simultaneously on batches (GPU more efficiently occupied)*
- *Optimal solution depends on use case (batches vs no batches)*

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https://github.com/hls-fpga-machine-learning/hls4ml

https://github.com/hls-fpga-machine-learning/SonicCMS

https://hls-fpga-machine-learning.github.io/hls4ml/

arXiv.org

https://arxiv.org/pdf/1804.06913.pdf

https://arxiv.org/pdf/1904.08986.pdf

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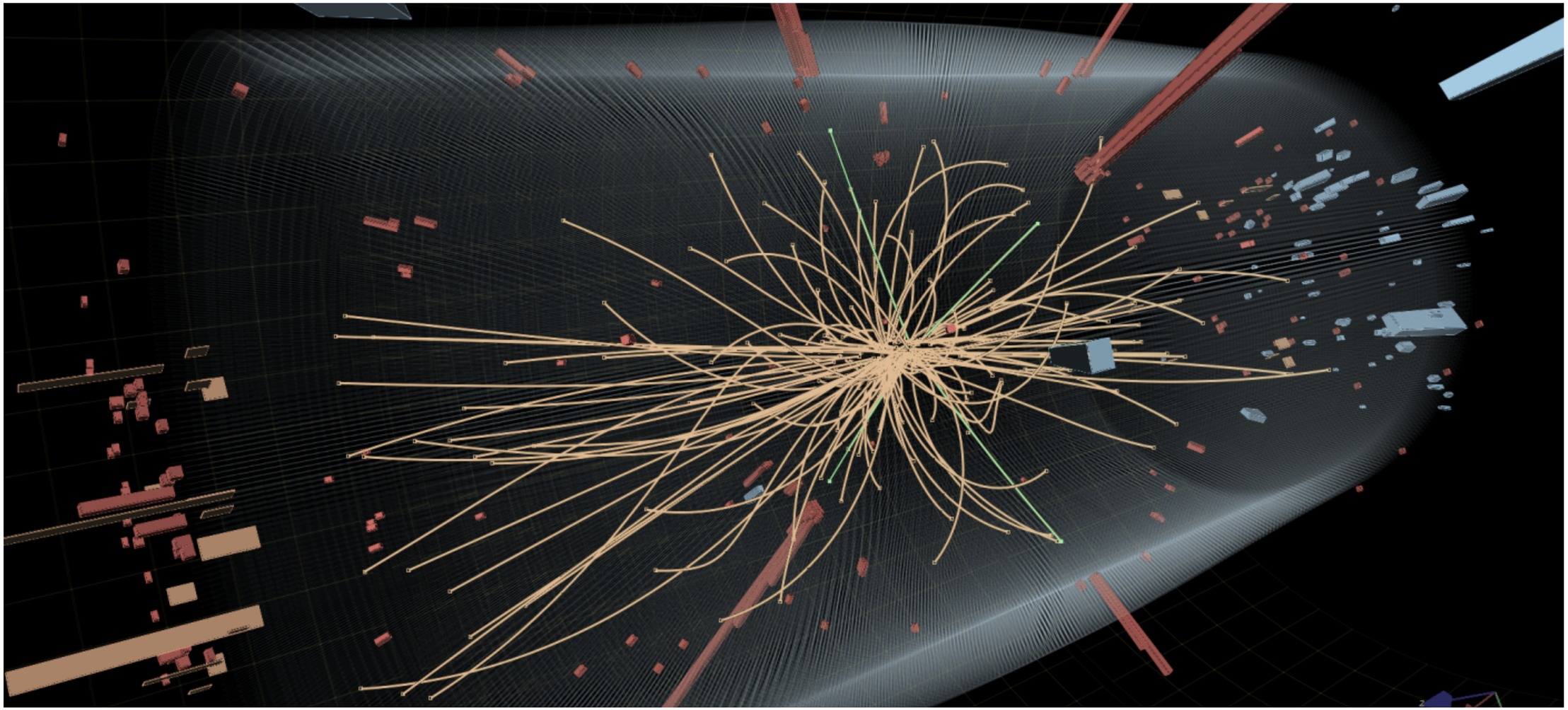

Language processing for particle physics

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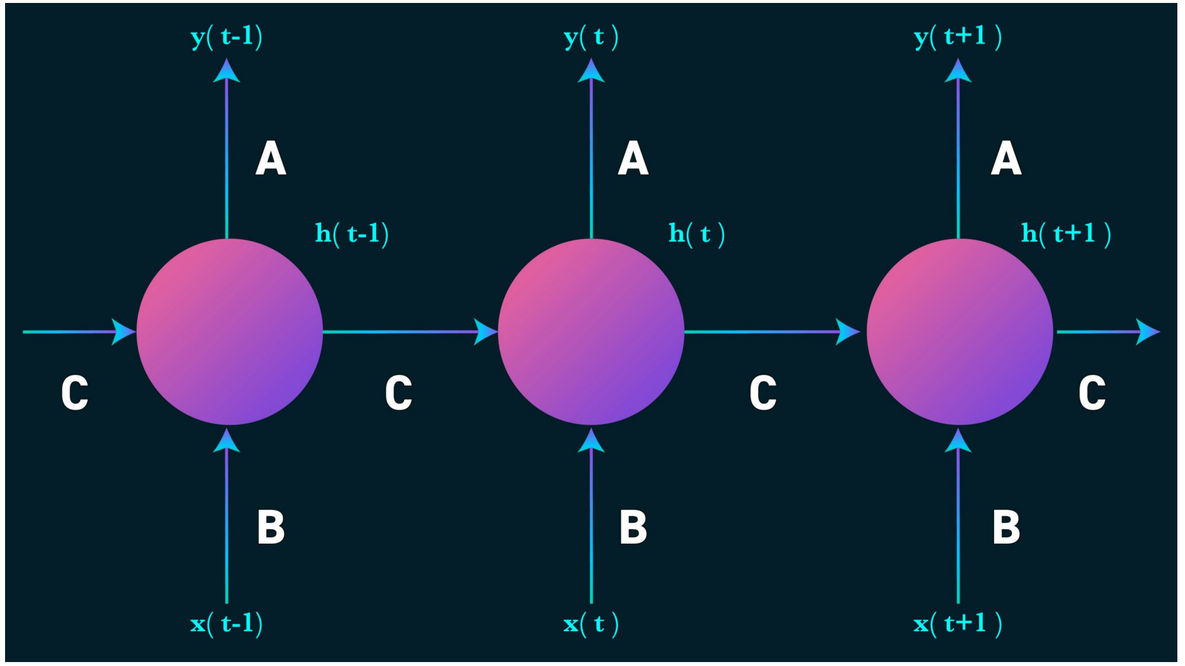
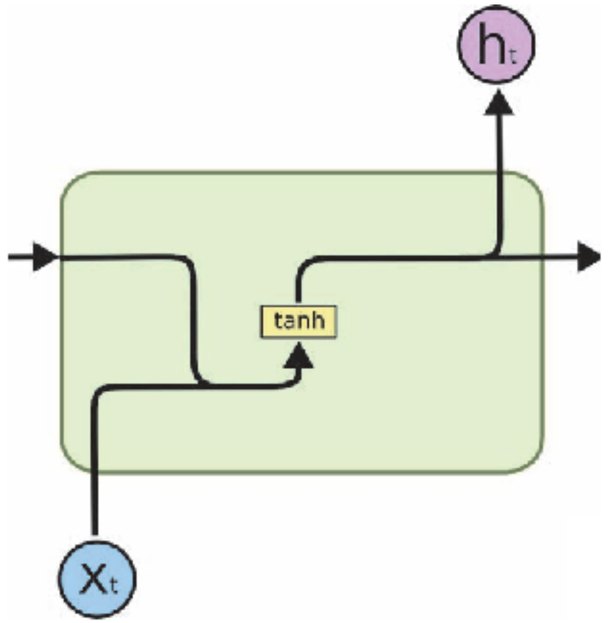
Recurrent betworks

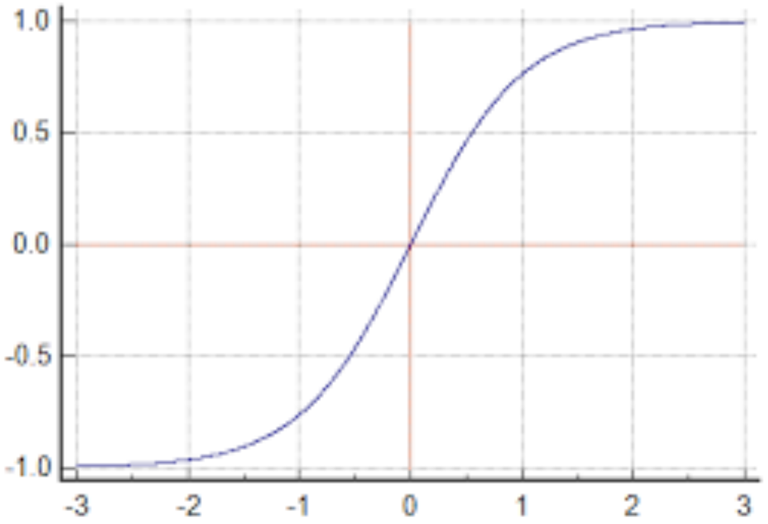
- *Recurrent architectures are designed to process sequences of data*
- *Then idea is to have information flowing in the network while the sequence is sequentially processed*
- *Through this idea, recurrent networks mimic memory persistence*
- *Advantages*
  - *the input is not fixed-sized*



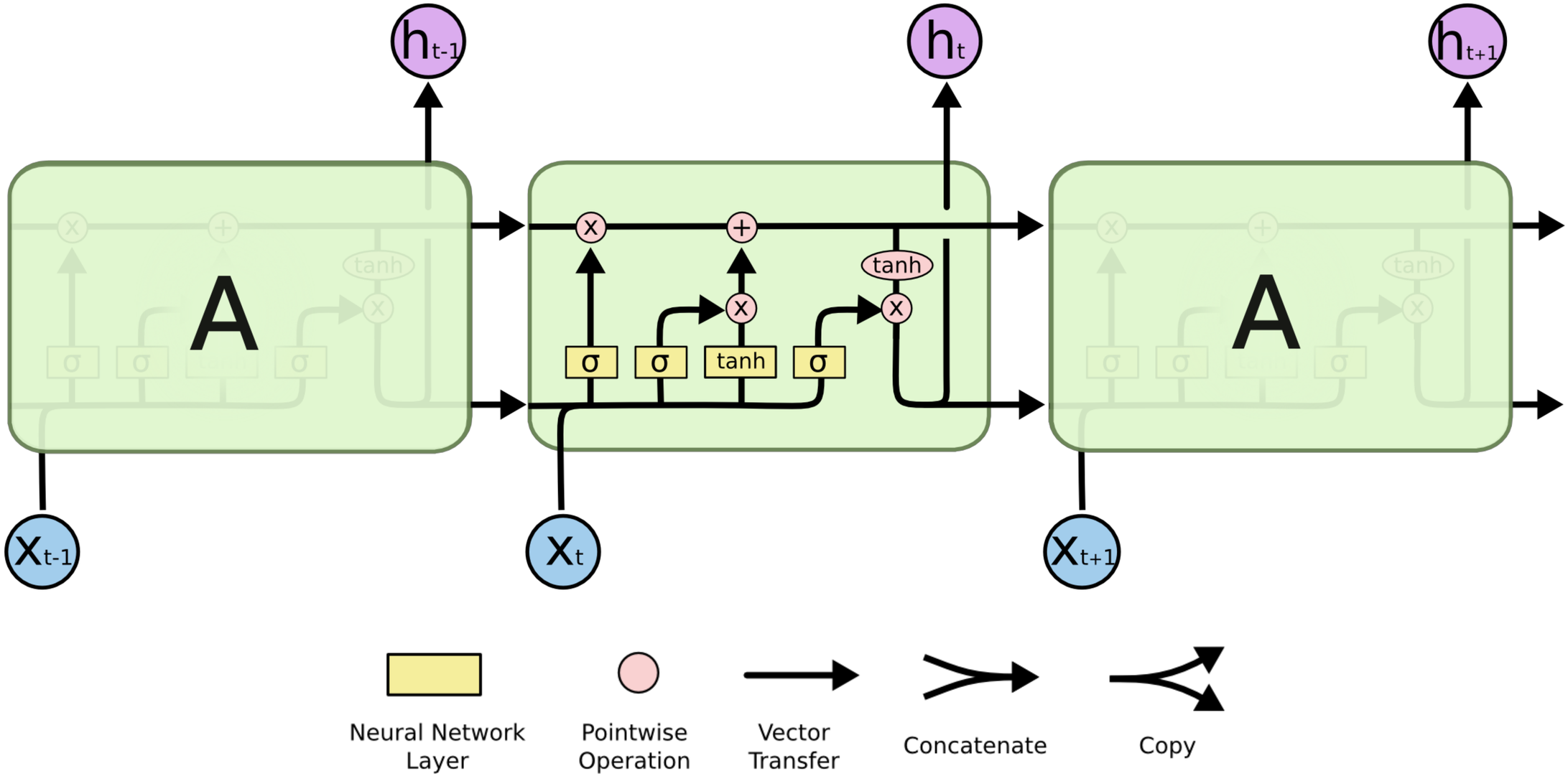
RNN

- *The simplest recurrent architecture*
  - *The processing unit receives an input x and the output of the previous-particle processing h (the context)*
  - *The product of the two is activated by a tank function*
  - *the result can be used as it is and/or passed to the next processing*

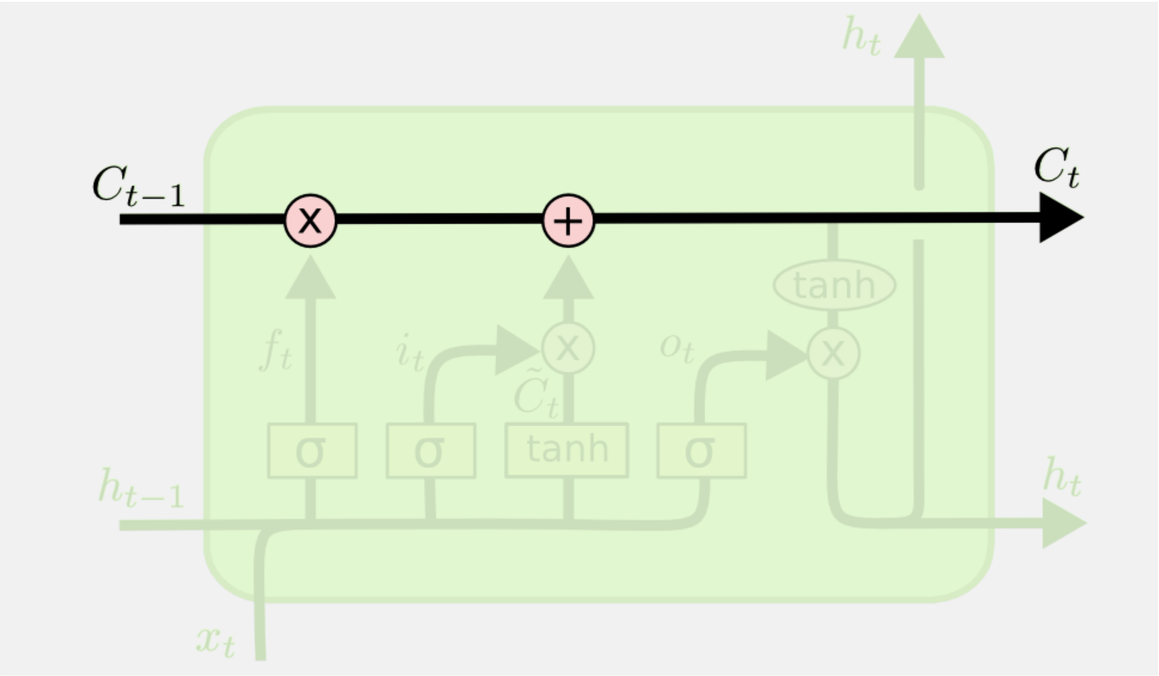


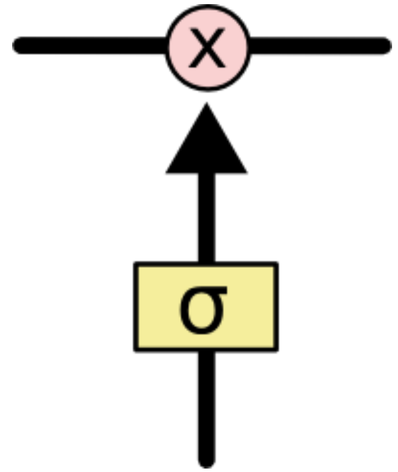


LSTM


h_{t-1}
h_t
h_{t+1}
A
A
tanh
σ
σ
tanh
σ
tanh
X_{t-1}
X_t
X_{t+1}
Neural Network Layer
Pointwise Operation
Vector Transfer
Concatenate
Copy

LSTM's memory cell

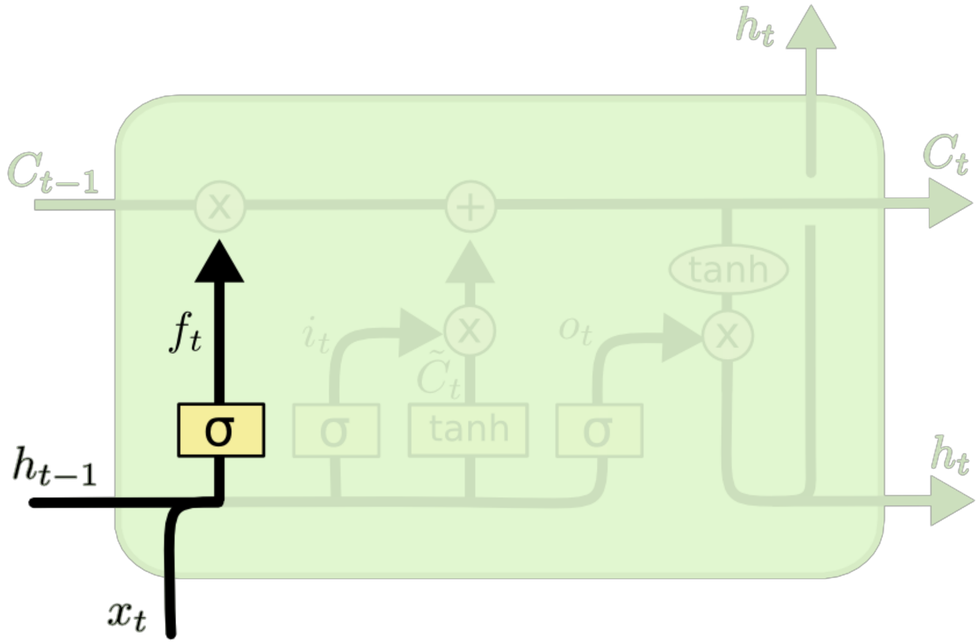




- *Information in the network flows through the memory cell*
  - *simple operations on it (to make the flow easy)*
  - *capability to reset the information, whit the next input acting as a gate*

LSTM processing

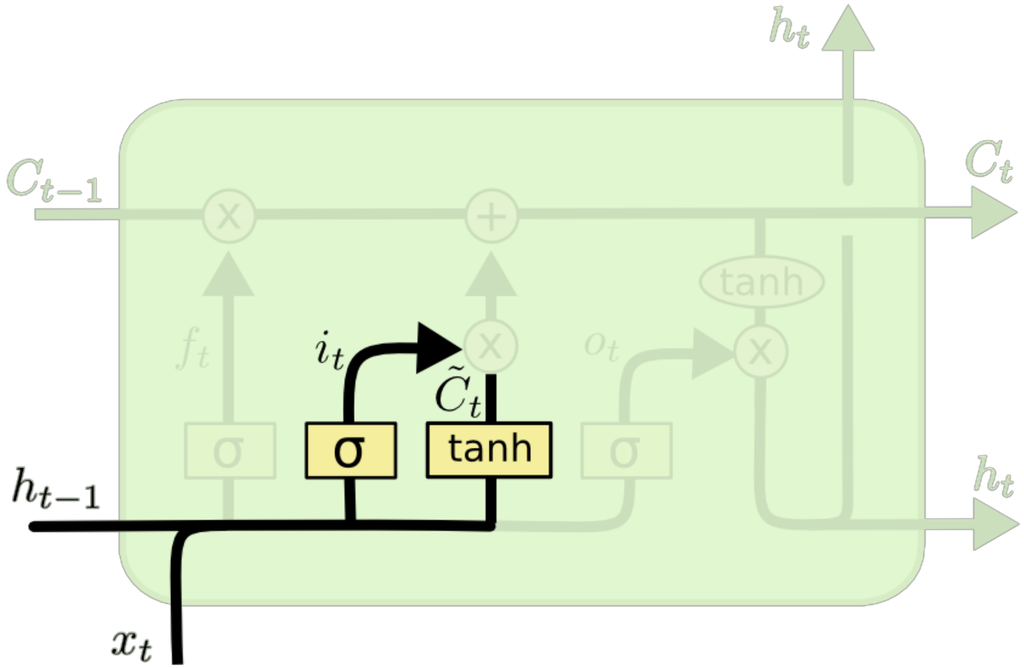
- ***Layer1:*** *decide if the context stored in the memory cell is to be forgotten or not*
  - *yes/no question -> sigmoid function*
  - *decision taken based on context and input*



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

LSTM processing

- ***Layer2:*** *two networks act to update the memory cell*
  - *a sigmoid (as in layer 1) decides which values to pass through (0/1)*
  - *a tanh function assigns a weight in [-1,1] to it*

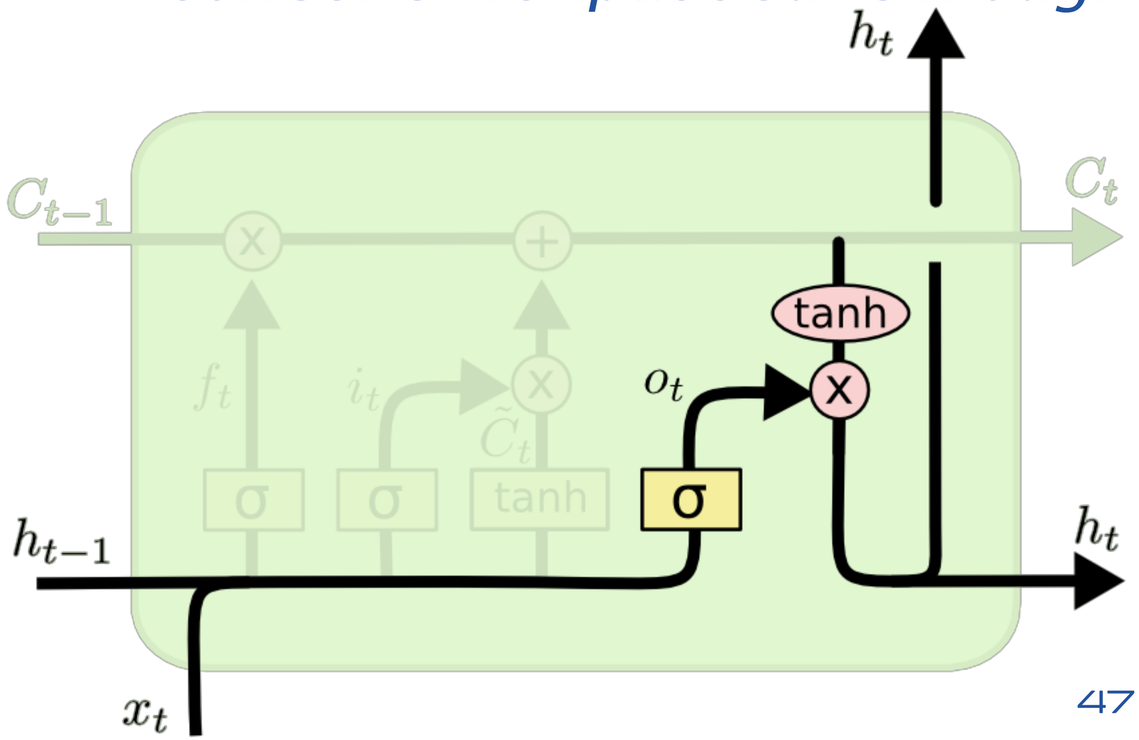


$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

LSTM processing

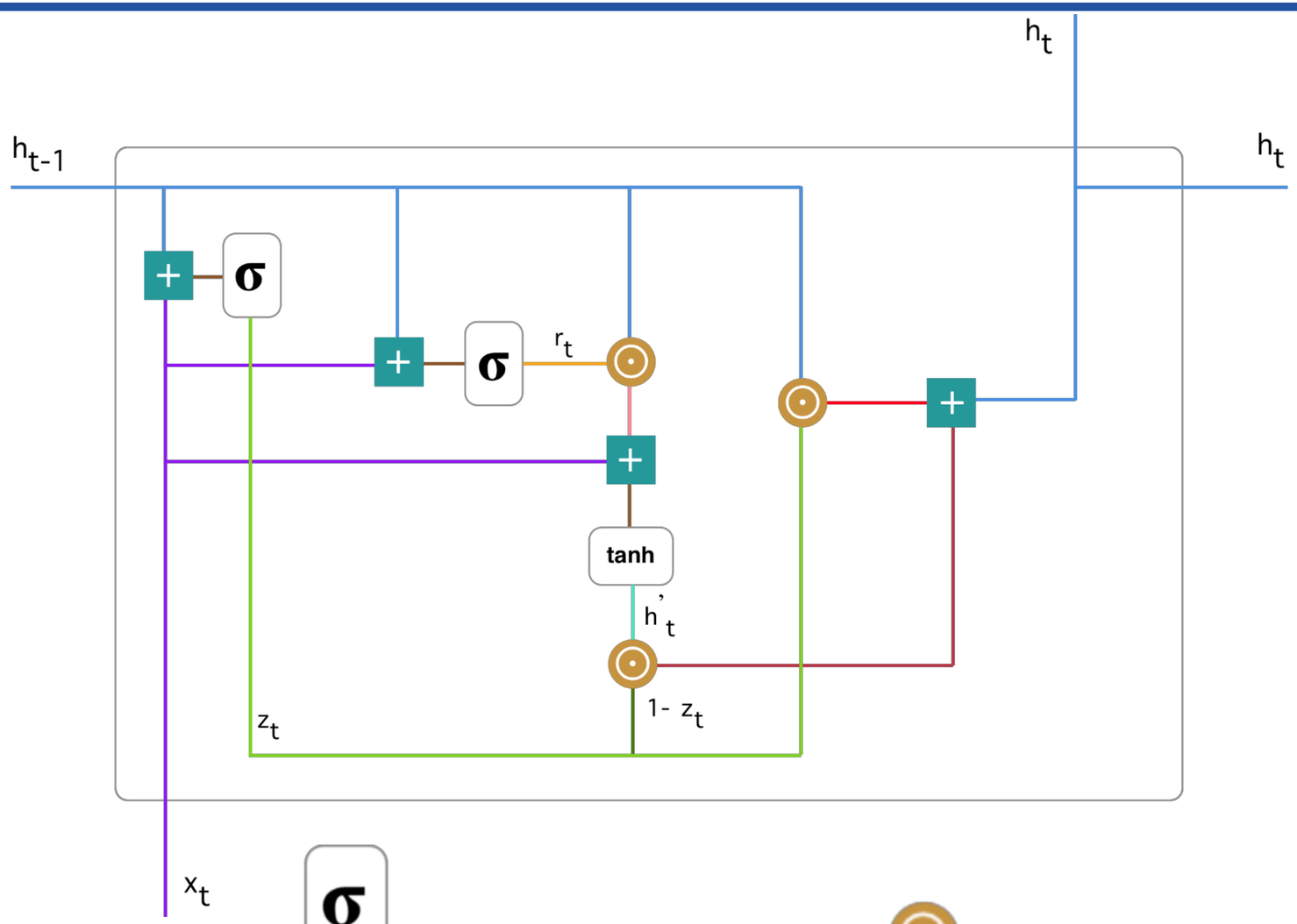
- ***Layer3:*** *fixes the output value to be passed next*
  - *the cell content is pushed in [-1,1] by a tan*
  - *a gate function (sigmoid) sets which fraction of the cell content is passed through*



$$o_t = \sigma\left(W_o\left[h_{t-1}, x_t\right] + b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

Gated Recurrent Unit



"plus" operation

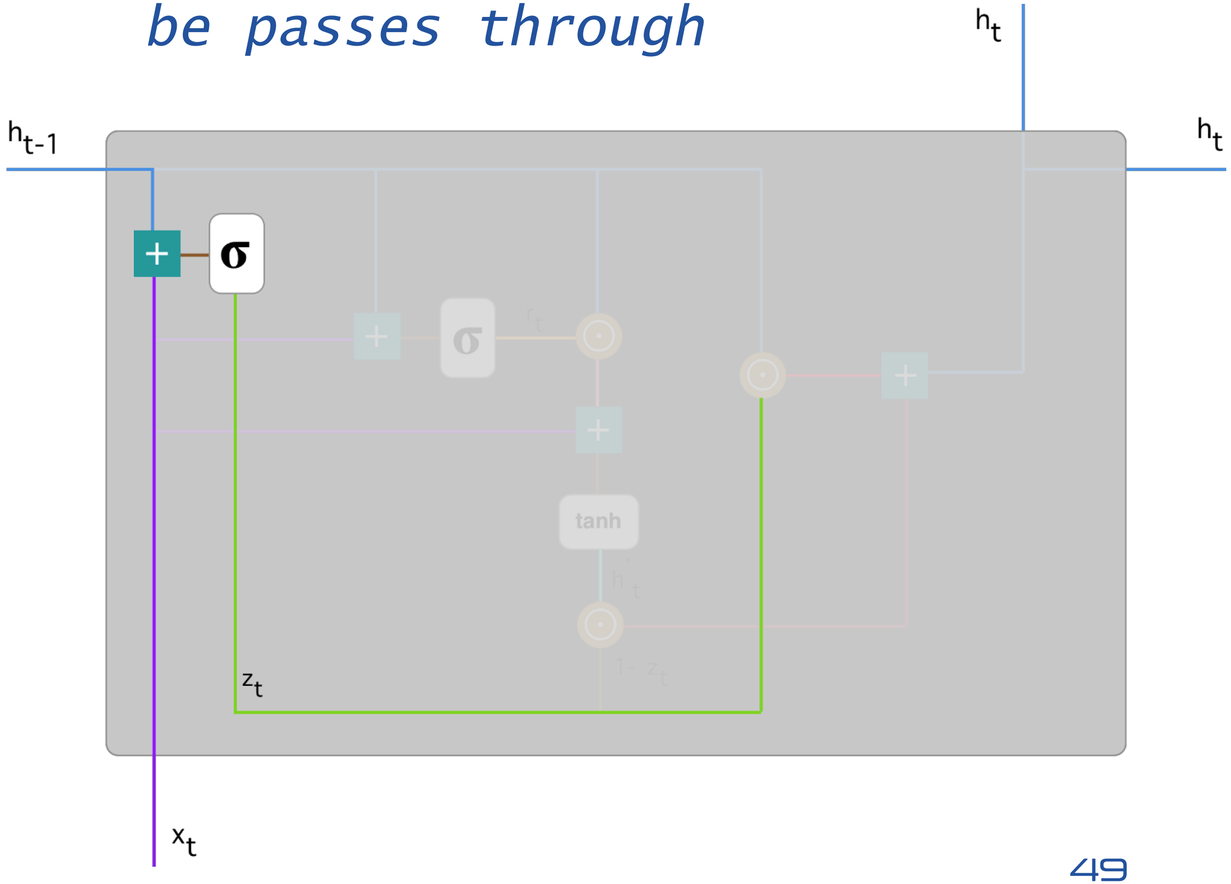
"sigmoid" function

"Hadamard product" operation

"tanh" function

GRU processing

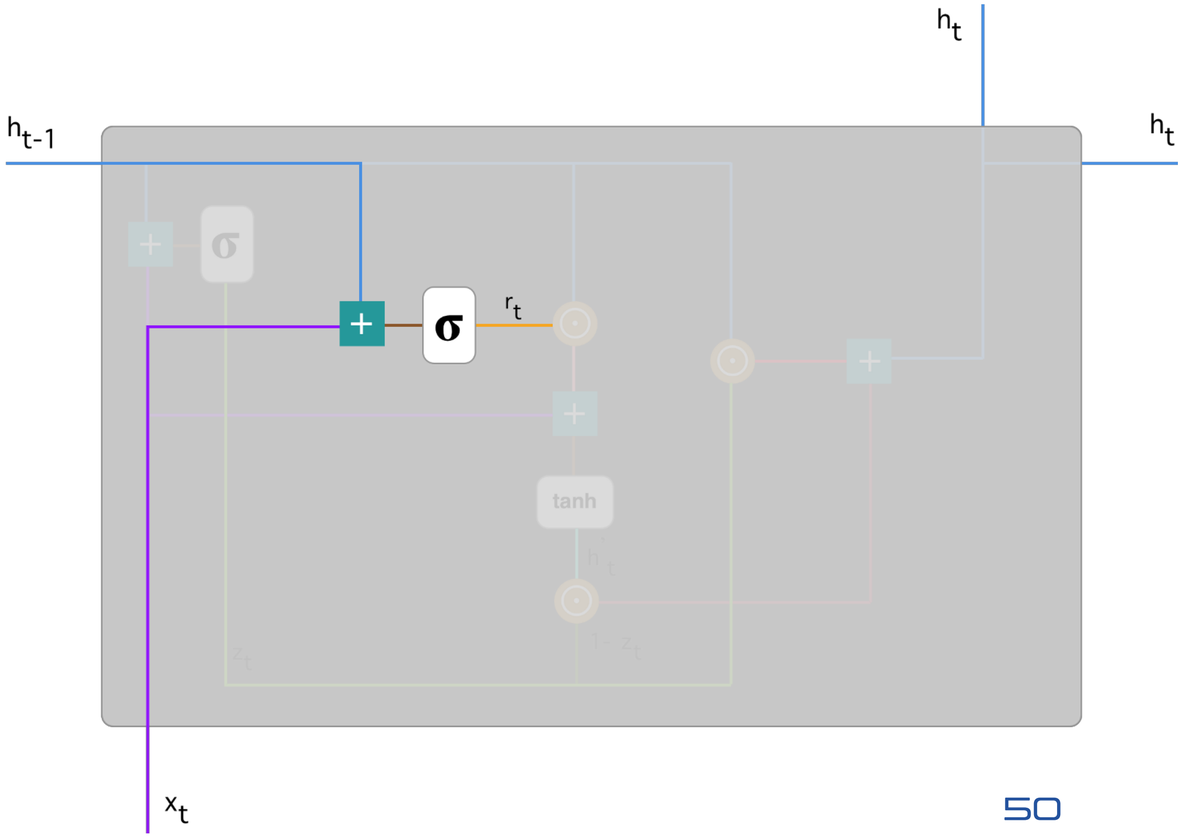
- ***Layer1:*** *update gate*
  - *multiply input and context by update weights*
  - *based on that, decide how much of the previous information should be passes through*



$$z_t = \sigma(W^{(z)}x_t + U^{(z)}h_{t-1})$$

GRU processing

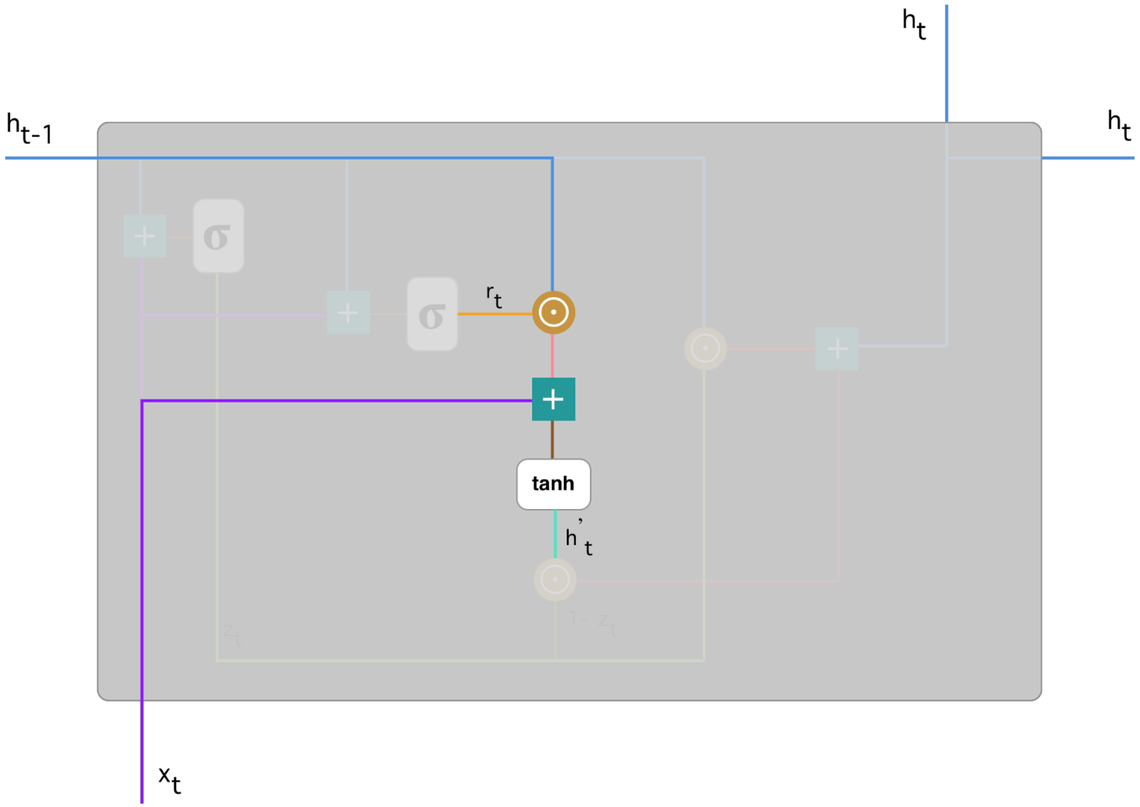
- ***Layer2:*** *reset gate*
  - *multiply input and context by reset weights*
  - *decide how much of the previous information is to be forgotten*



$$r_t = \sigma(W^{(r)}x_t + U^{(r)}h_{t-1})$$

GRU processing

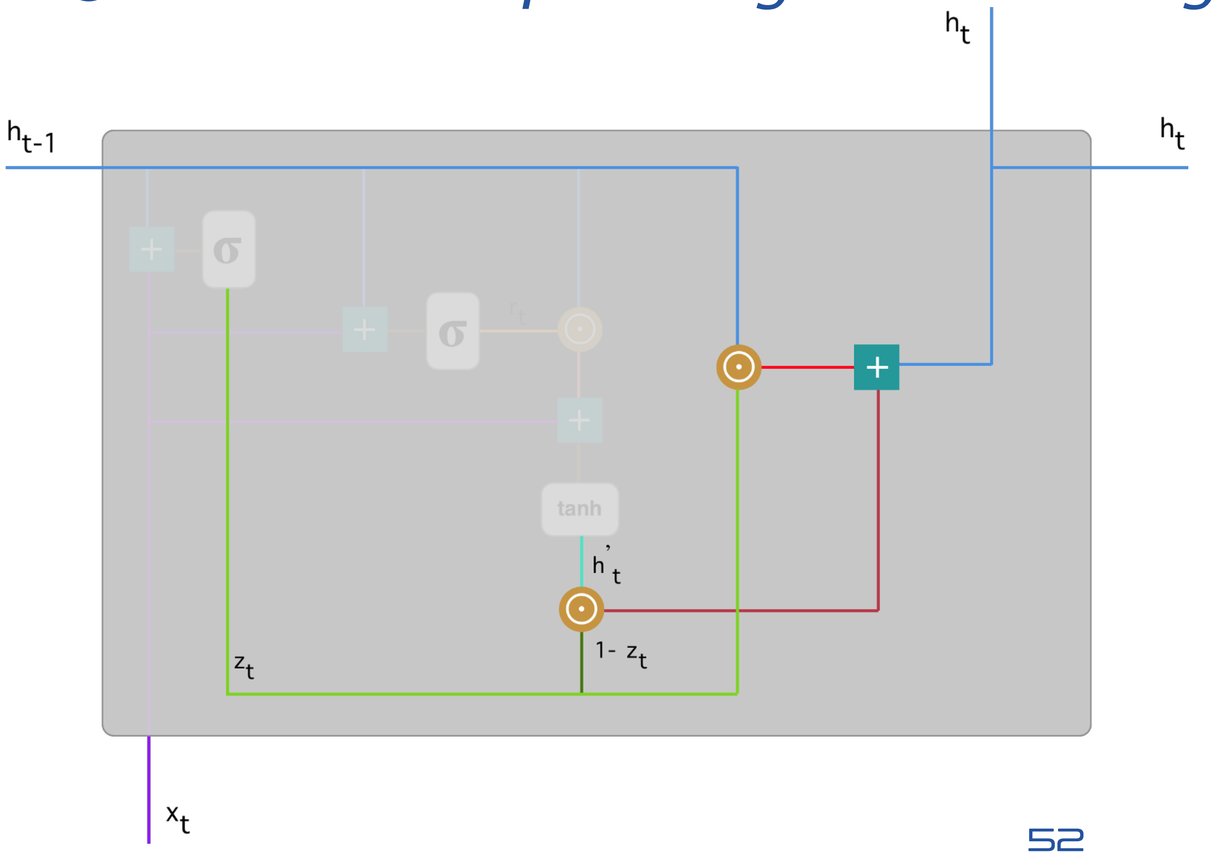
- ***Layer3:*** *determine the current memory content*
  - *the context information is partially removed to an element-by-element product with the reset gate*
  - *the result is summed to the (weighted) input and passed through a tank activation function*



$$h_t' = \tanh(Wx_t + r_t \odot Uh_{t-1})$$

GRU processing

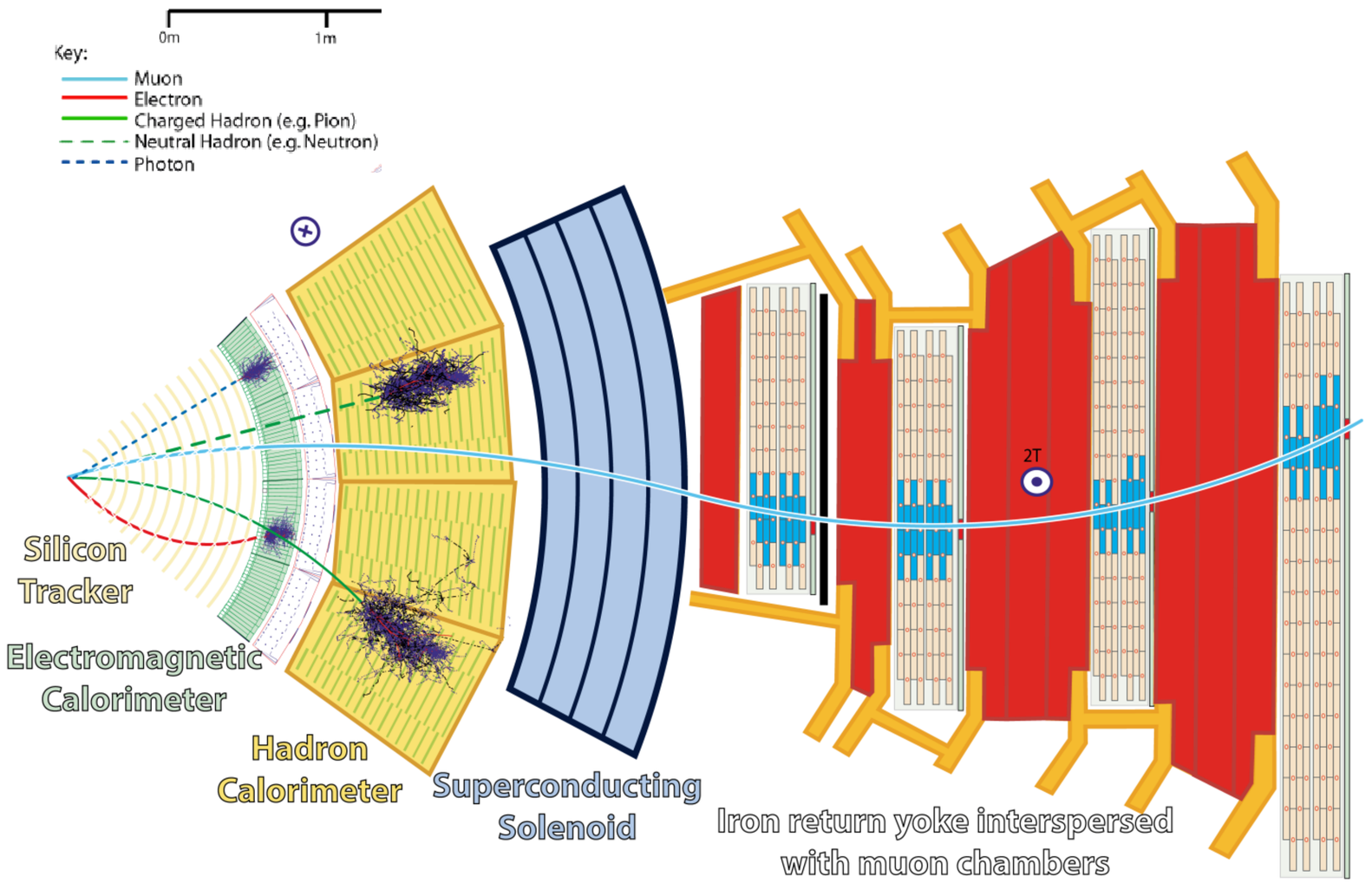
- ***Layer4:*** *compute the new memory state, to pass through*
  - *mixes the current memory state with the input one*
  - *uses the update gate to weight the two contributions*



$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot h'_t$$

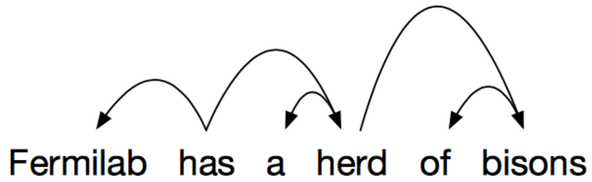
RNNs for particle physics

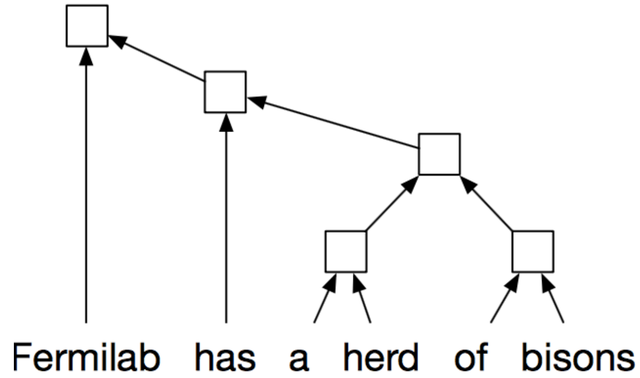
- *RNN can be used to deal with list of reconstructed particles*
- *Their architecture better fits our needs*
  - *No underlying assumption on the detector geometry*
- *This comes at two costs*
  - *Some ordering principle needs to be specified*
  - *Inference is sequential (not ideal for L1 real time)*

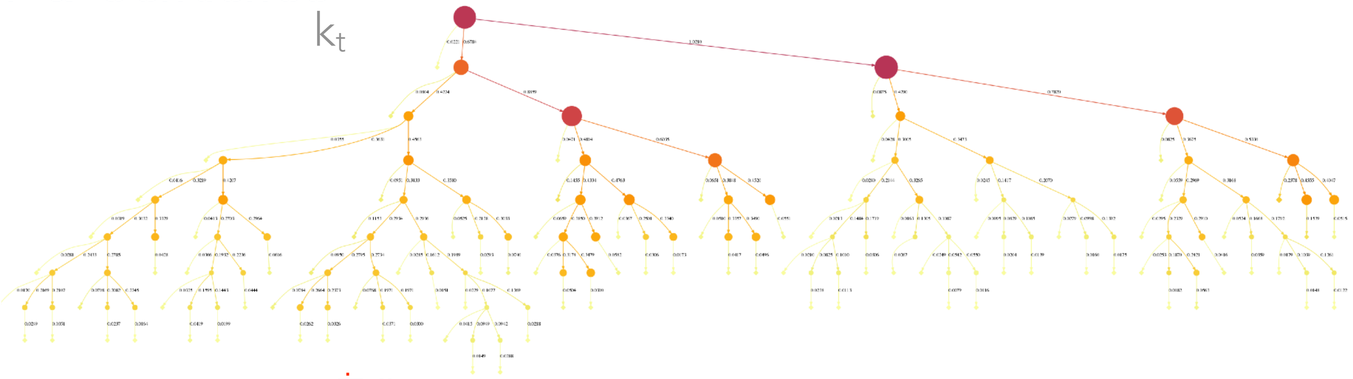


LHC events & language processing

- *PF reco is not the best match for computing vision techniques (e.g., convolutional neural networks) don't work*
  - *one would have to convert the particles to a pixelated images, loosing resolution*
- *Instead, list of particles can be processed by Deep Learning architectures designed for natural language processing (RNN, LSTMs, GRUs, …)*
  - *particles as words in a sentence*
  - *QCD is the grammar*

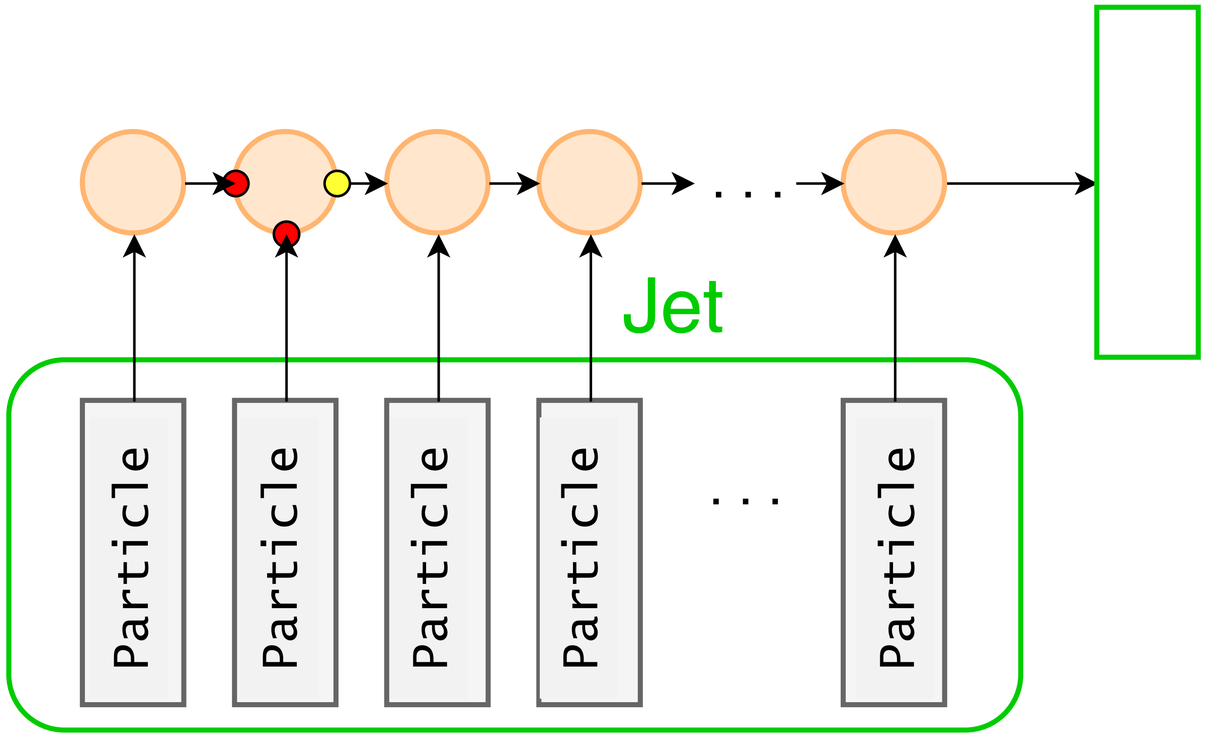






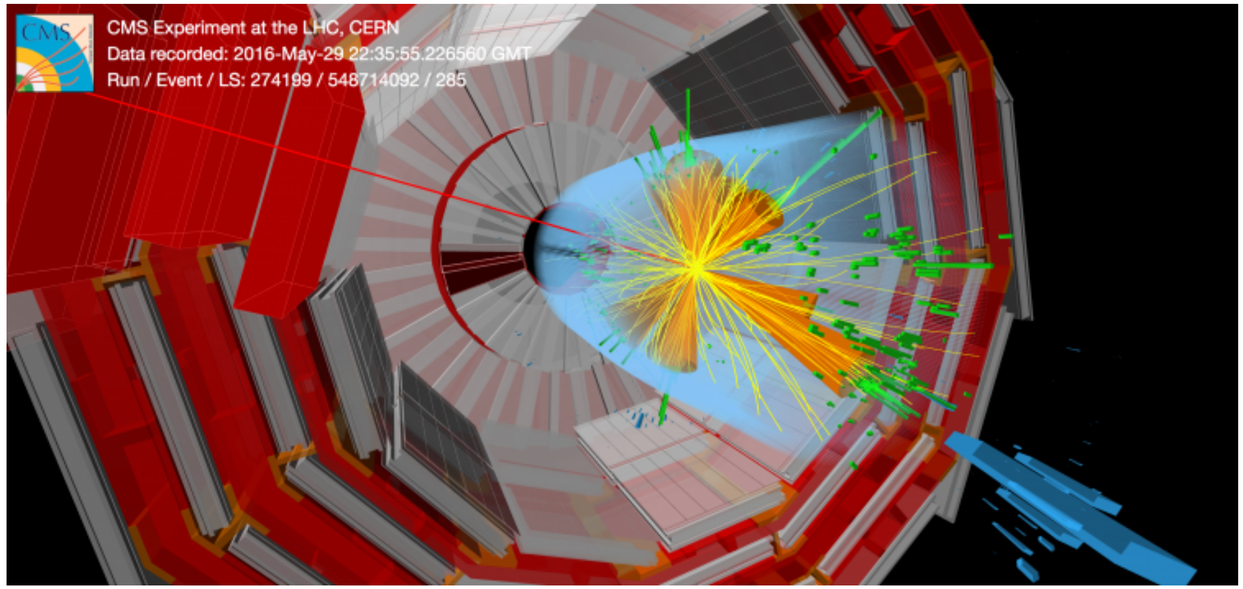
Recurrent Neural Networks

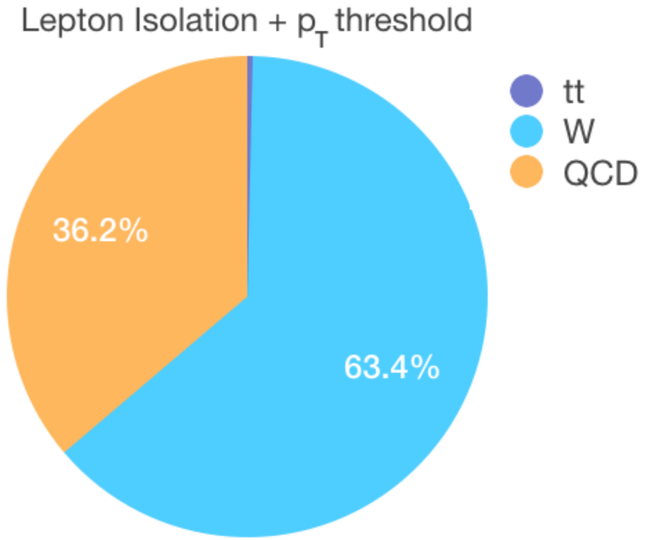
- A network architecture suitable to process an ordered sequence of inputs
  - words in text processing
  - a time series
  - particles in a list
- Could be used for a single jet or the full event
- Next step: graph networks (active research direction)



Example: topology classification @LHC

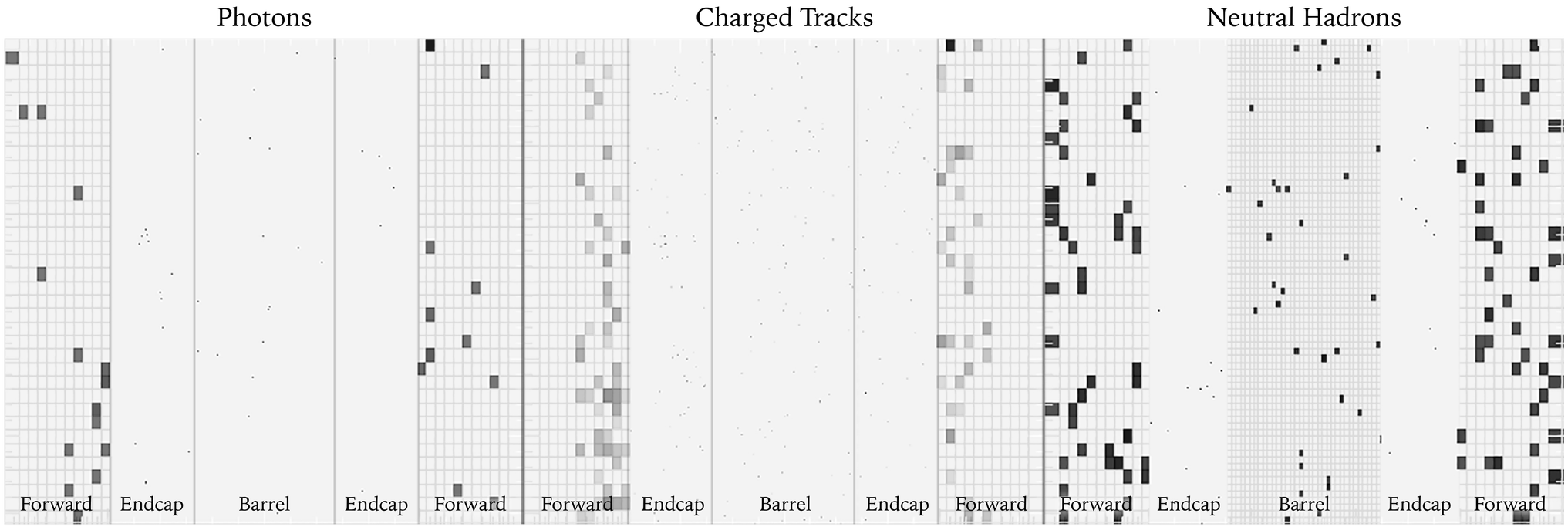
- *Finding which process generated an event is a typical task @LHC experiments*
- *Let's take as input the events with one energetic electron or muon (lepton)*
  - *After some loose selection, mainly three processes left: jet production (QCD, the background) + W or tt productions (the signals)*
  - *We want to separate the three components*



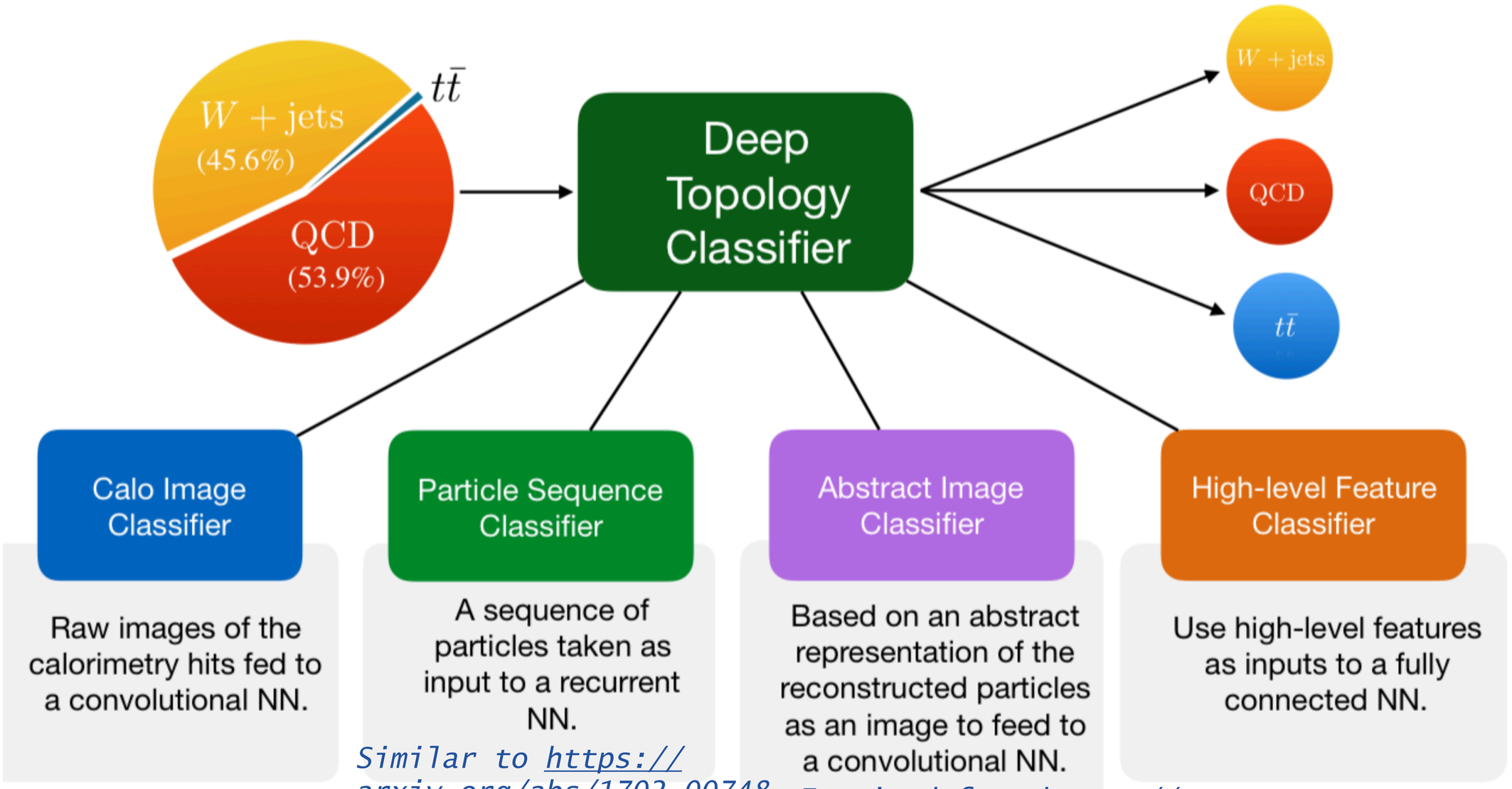


What the event looks like

- *sparse image with many pixels*
  - *not the kind of image that CNNs usually deal with*
  - *still, reasonable performances (AUC~90%) can be obtained*



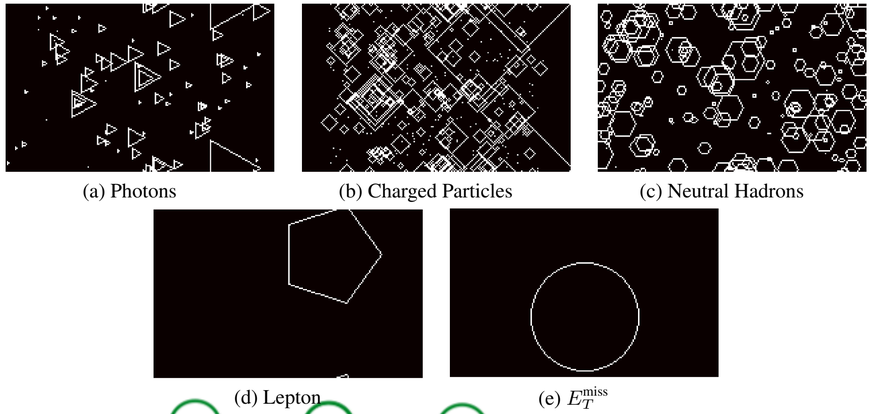
Event Representations

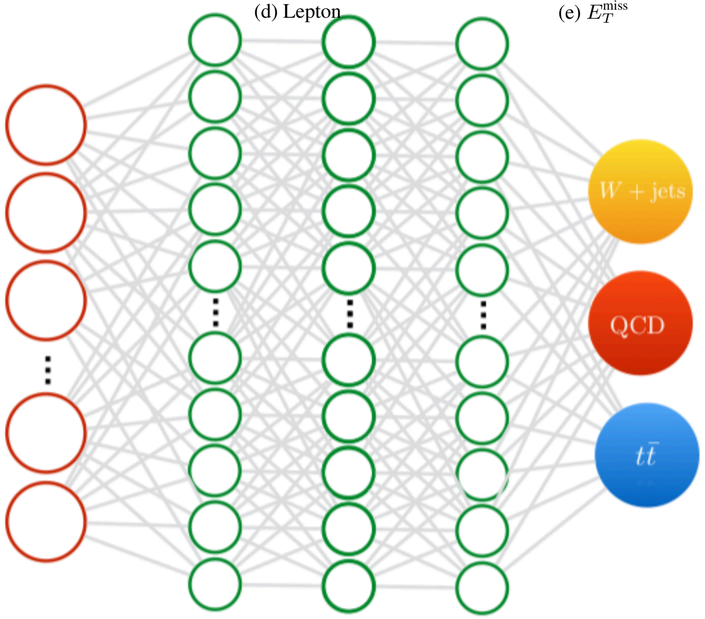


Similar to https://arxiv.org/abs/1702.00748

Inspired from https://arxiv.org/abs/1708.07034

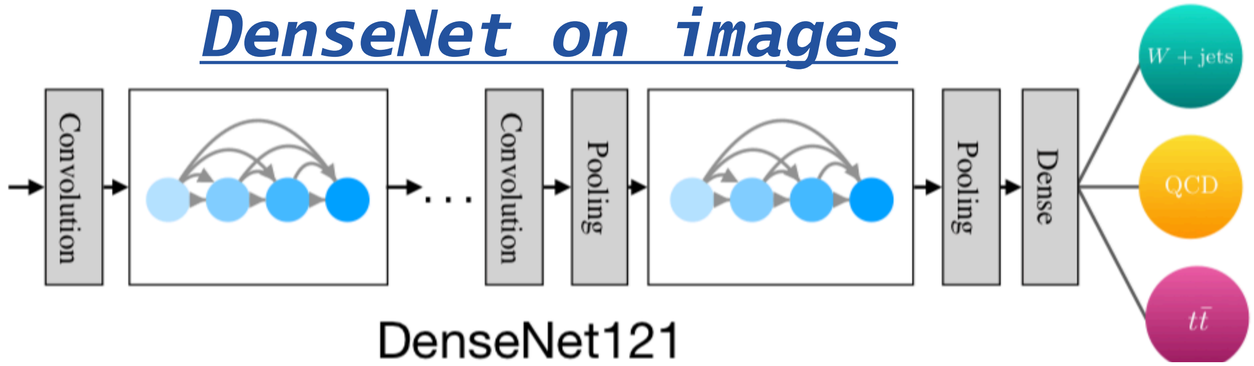
Event Representations



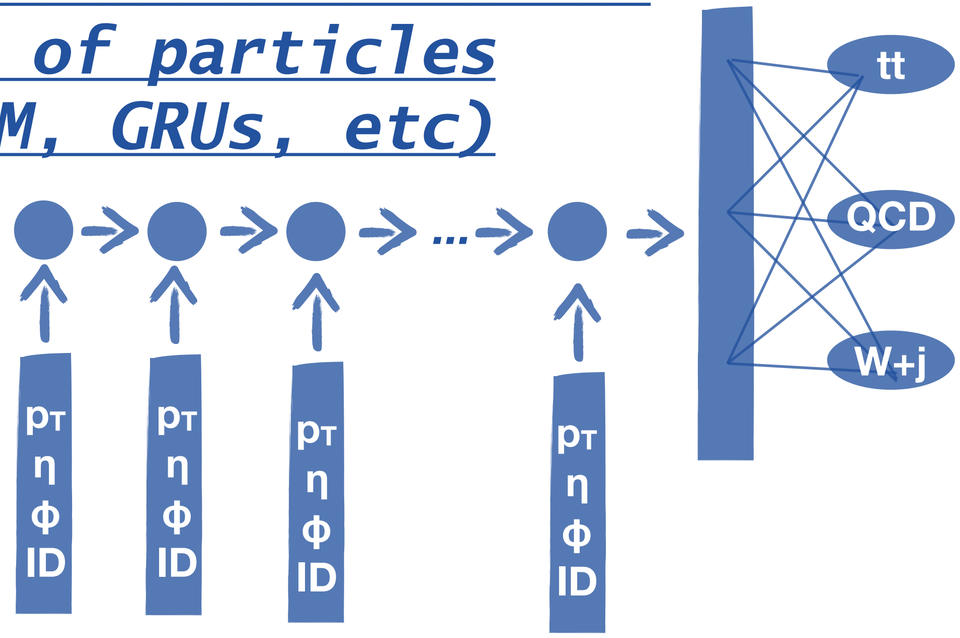


Fully-Connected classifier on physics-motivated features

DenseNet on images

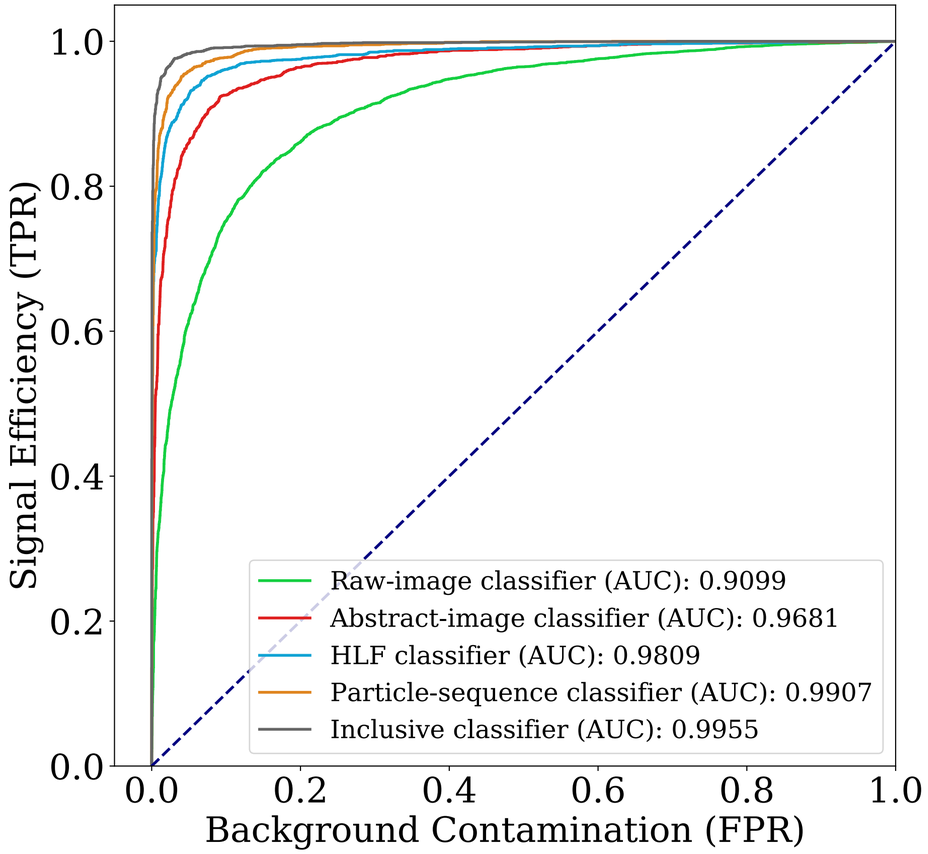


Recurrent nets on the list of particles (LSTM, GRUs, etc)

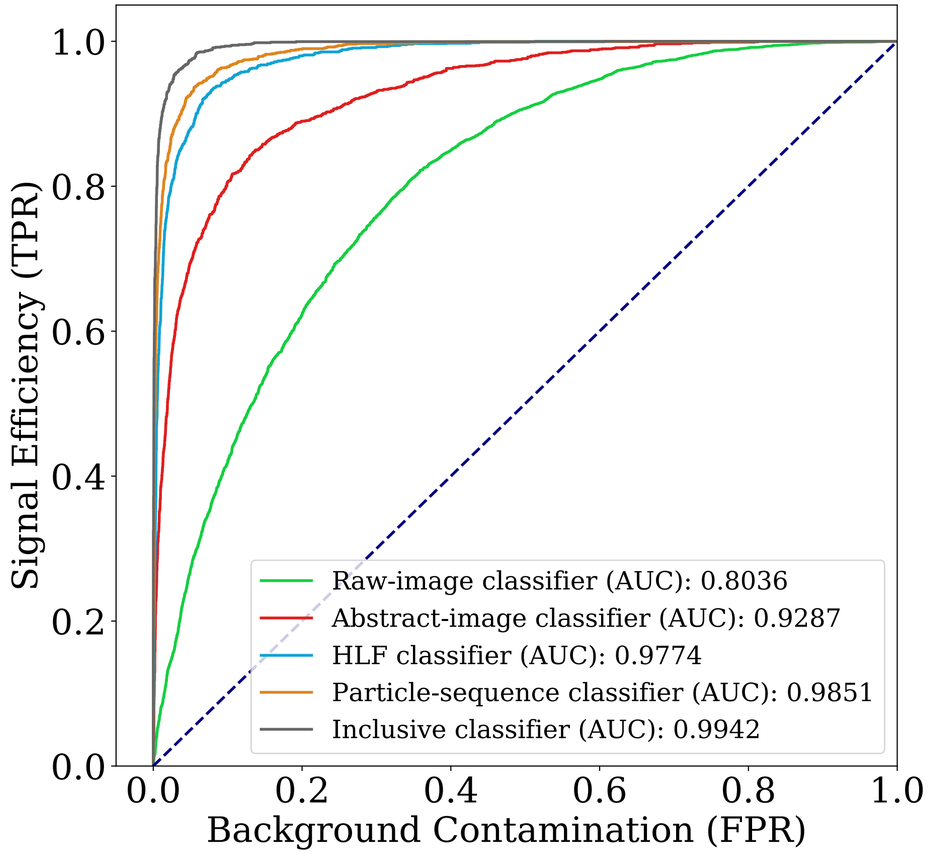


Performance

- *The GRU provides the best discrimination power*
- *The HLFs come second*
- *The combination of the two further improve*

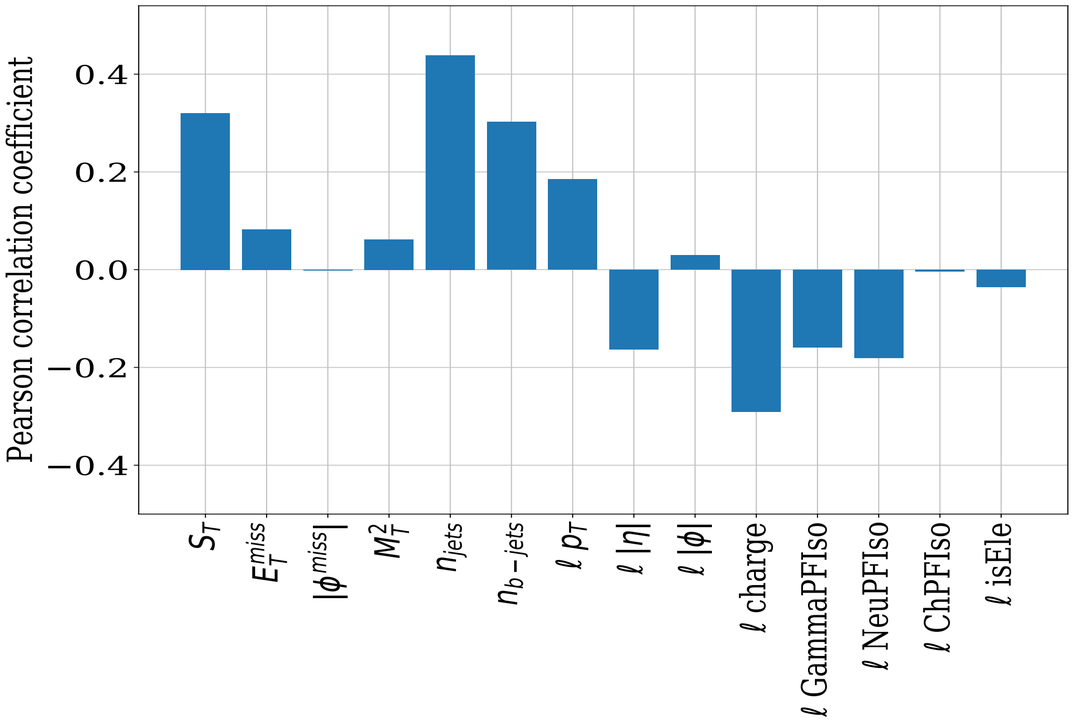


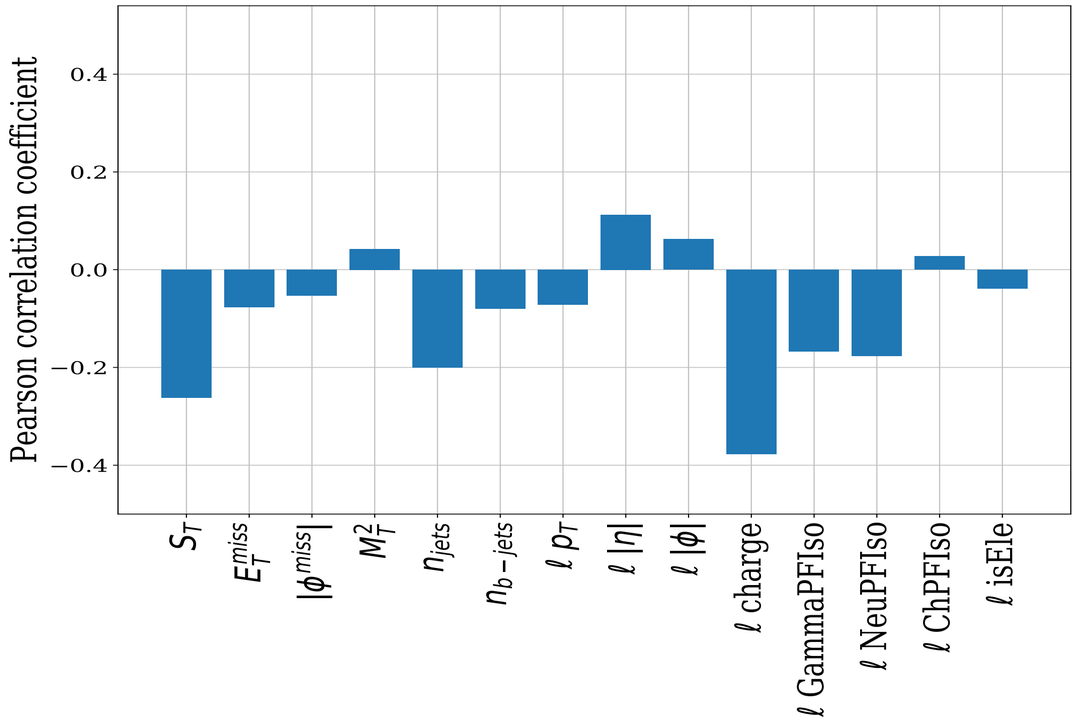
(a) $t\bar{t}$ selector



(b) W selector

Selection performances





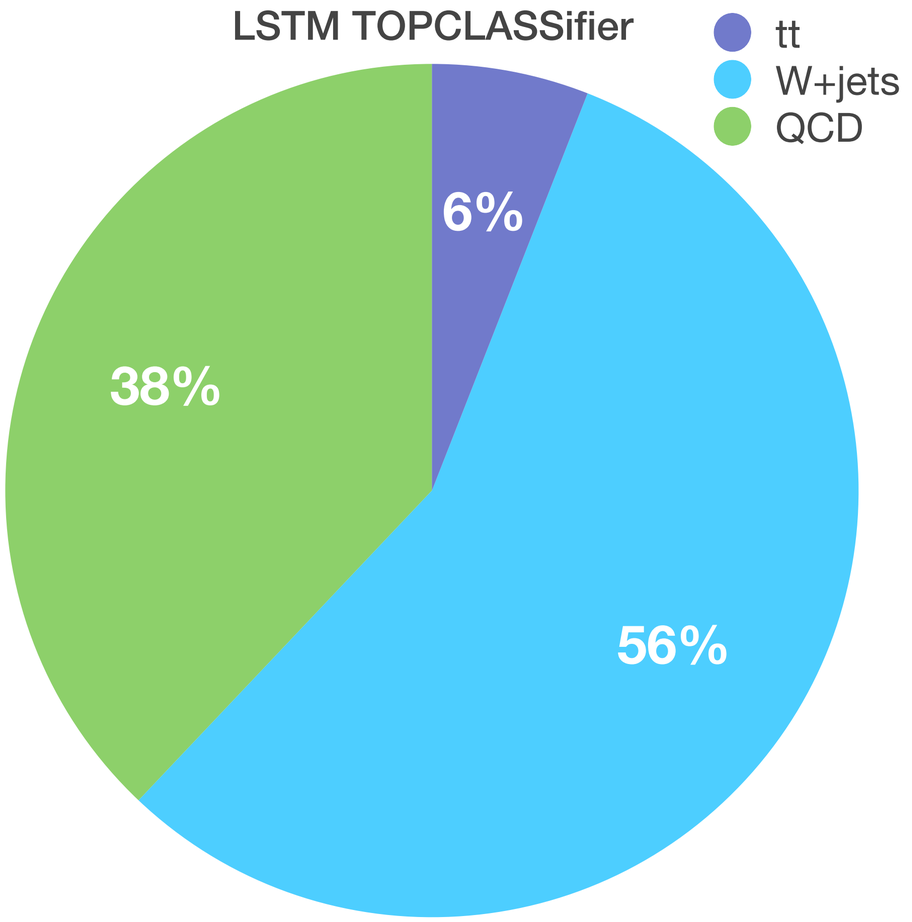
What is the network learning?

- tt events are more crowded that W events
- leptons in W and tt events are isolated from other particles

Cleaning up selected sample

A typical example: leptonic triggers

- *at the LHC, producing an isolated electron or muon is very rare. Typical smoking gun that something interesting happened (Z,W,top,H production)*
- *Triggers like those are very central to ATLAS/CMS physics*
- *The sample selected is enriched in interesting events, but still contaminated by non-interesting ones*
- *Contamination can be reduced with a DL classifier that rejects obvious false positives looking at the full event, not just at the lepton*



Summary

- *We discussed the importance of fast inference for future LHC upgrade*
- *We saw how NNs could be ported on FPGAs (translation to electronic circuit)*
- *We saw how cloud solution could be explored for on-line big-data processing*
- *We discuss recurrent NNs and their potential usage to save processing resources @LHC*

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