GEFÖRDERT VOM

Convolutional Neural Networks on FPGAs for Processing of ATLAS Liquid Argon Calorimeter Signals

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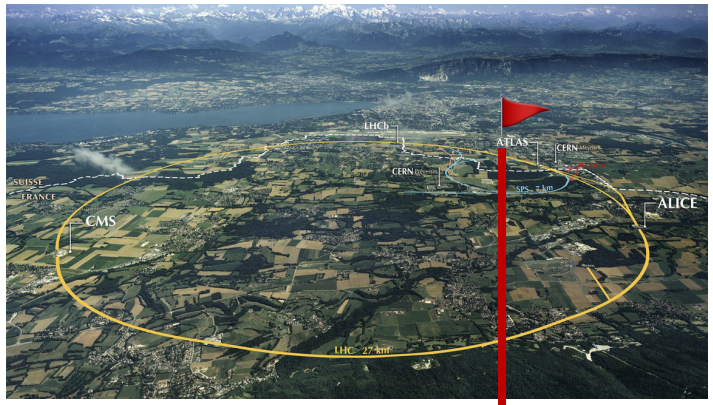
The ATLAS Detector at LHC



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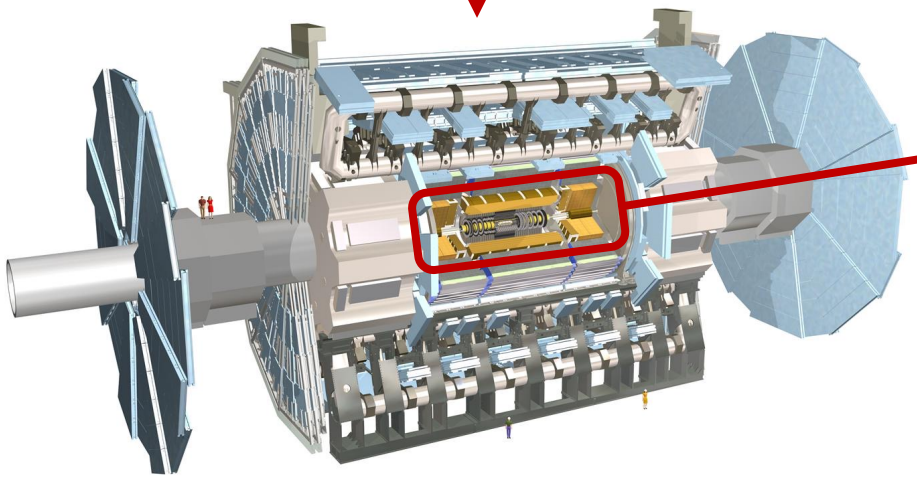

[2]

Large Hadron Collider (LHC)

- proton bunches collide with **25 ns** spacing (40 MHz)
- 2029: start of **High Luminosity LHC** (HL-LHC)

ATLAS detector

- HL-LHC: up to 200 collisions per bunch crossing (BC) (currently ~ 60), **pileup increases**
- modifications at **Liquid-Argon (LAr) calorimeter readout** necessary

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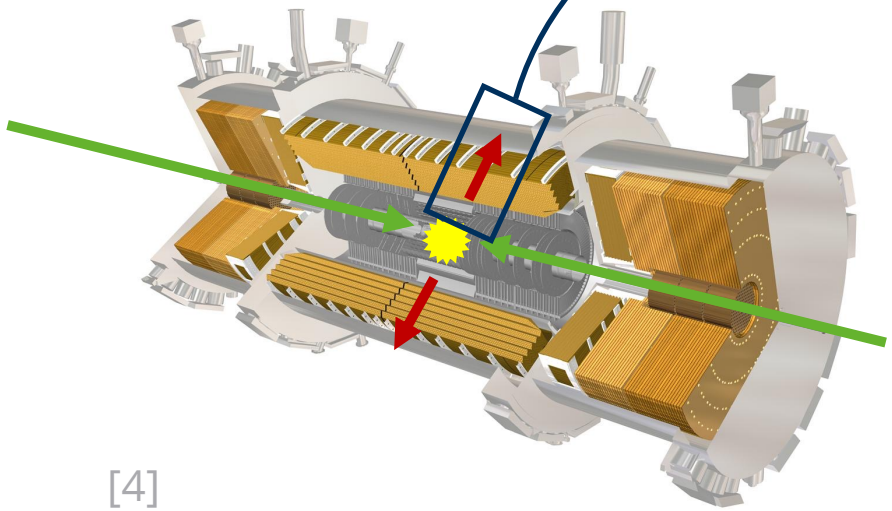
LAr Calorimeter Readout



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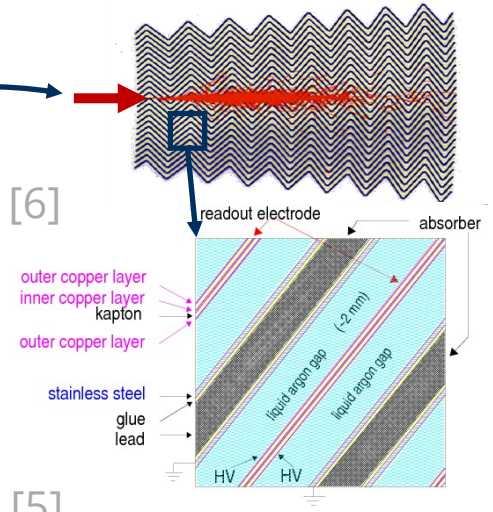

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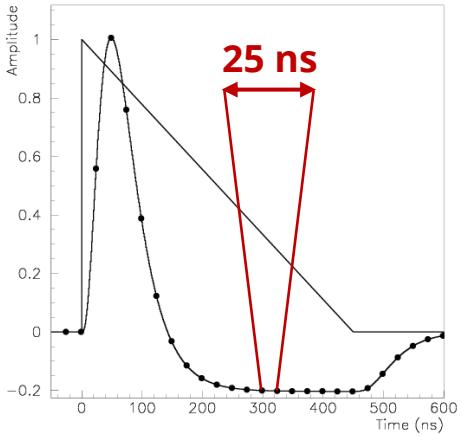

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real time signal processing

Save ADC-values?

(32 bit per BC and 182468 cells)

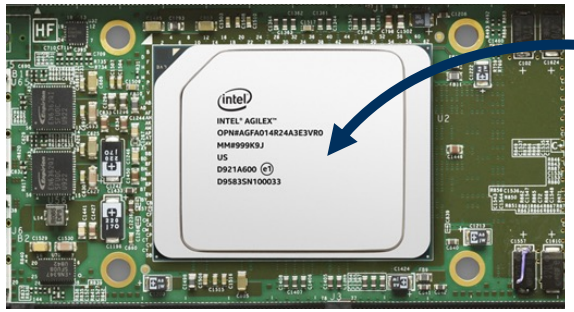
~ 1.7 PB for just one minute of runtime of LHC!

- absorber (Pb, Cu, W) and electrodes in accordion geometry
- liquid Argon **(LAr)** as active medium

- drifting ionisation electrons from electromagnetic shower raise **triangular pulse**
- shaped into **bipolar pulse**
- parameter of interest: **amplitude ~ deposited energy**

LAr Calorimeter Readout

FPGA - field programmable gate array



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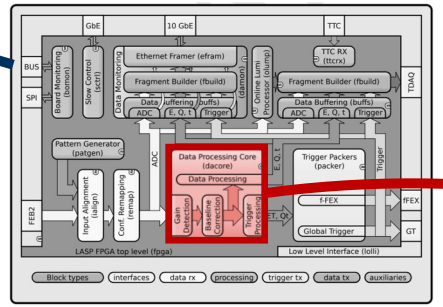
- Intel Agilex 7
- real time signal processing

LASP (liquid Argon signal processor) **- firmware**



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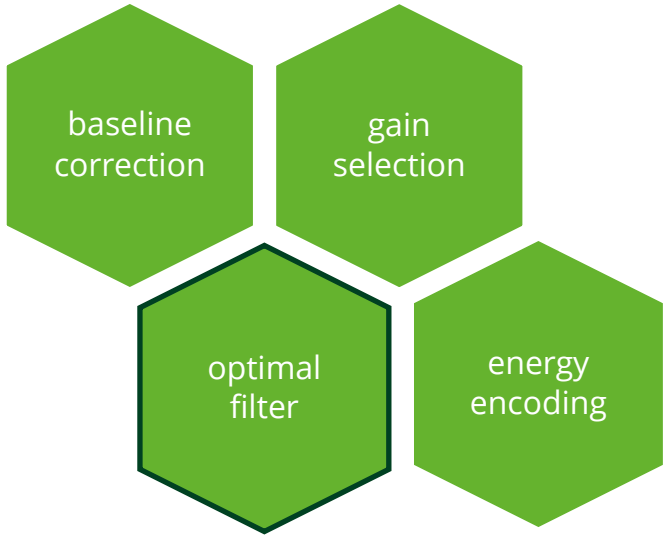
- Implemented in VHDL targeting
- energy reconstruction in **da**ta processing **core (dacore)**

reconstructed energy of an event

(using optimal filter)

For testing purposes: mirroring LASP dacore in **Python model**



Reconstruction of Energy

current way for energy reconstruction (OF)

$$y_t = \sum_{n}^{M-1} x_{t-n} \cdot a_n$$

y_t ... OF output for bunch crossing (BC) t

$\vec{x}$ ... input ADC samples

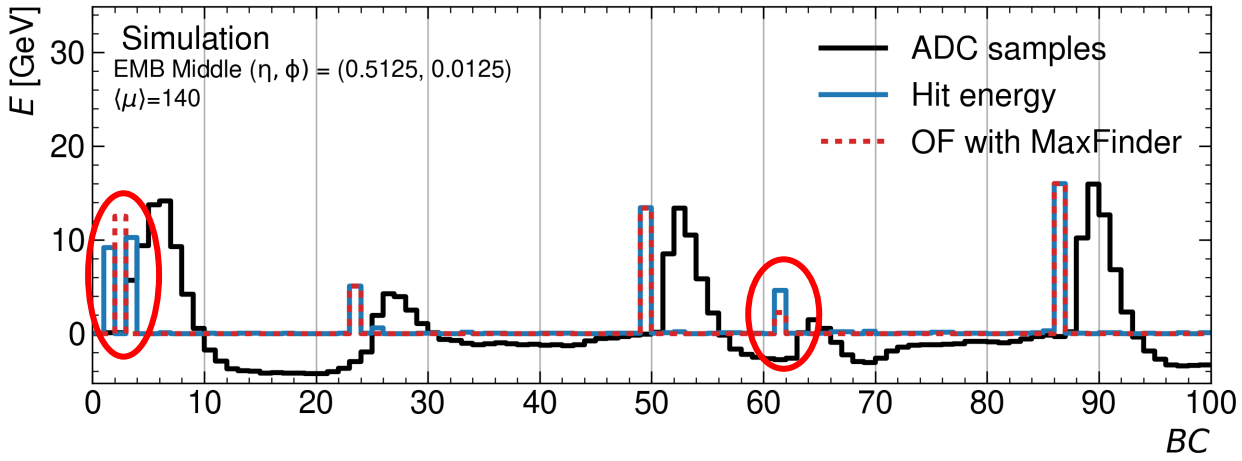
a_n ... OF coefficients

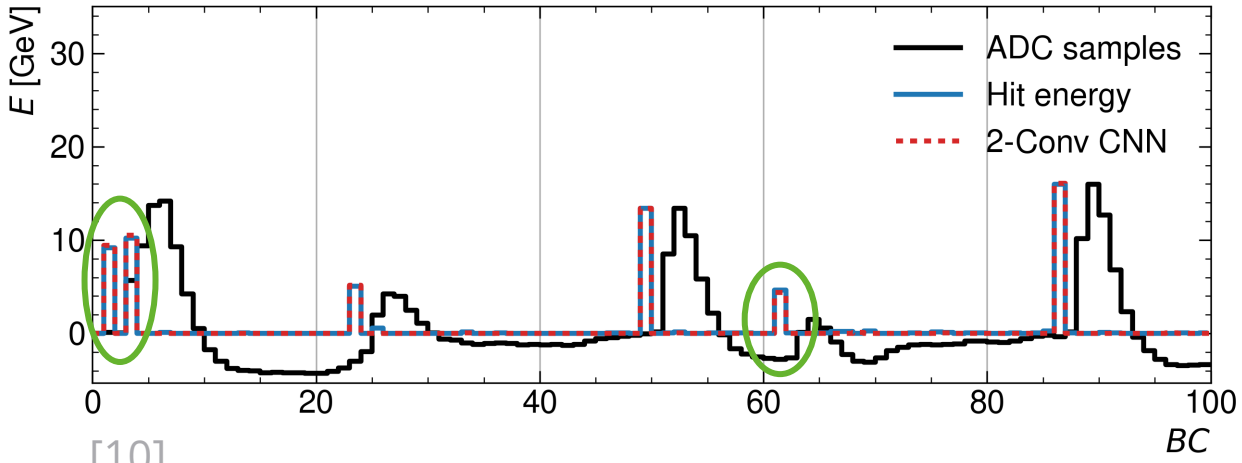
M ... OF filter depth

- close signals cannot be resolved
- signals within undershoot underestimated

Convolutional Neural Networks (CNNs)

- optimized to reconstruct overlapping signals





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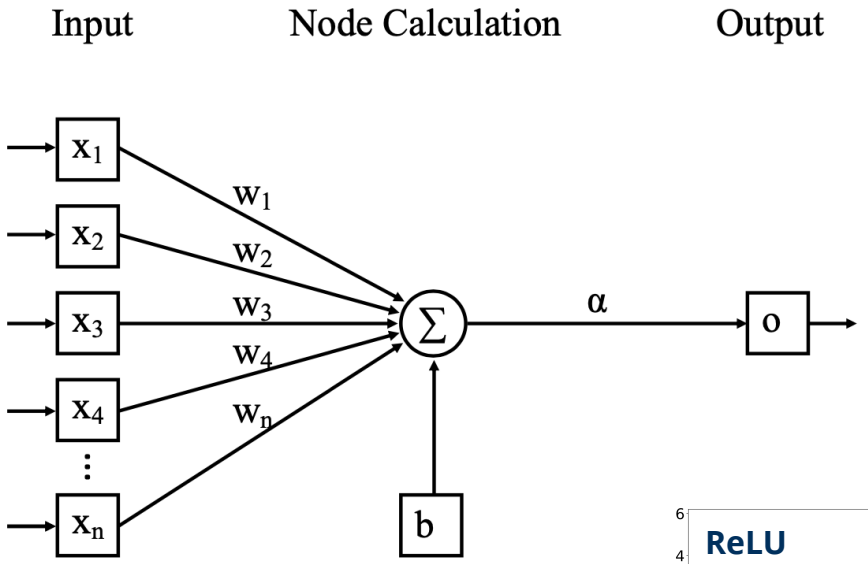
Artificial Neural Network (ANN)

single node



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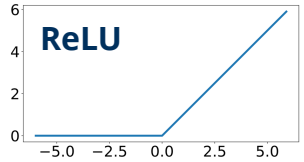
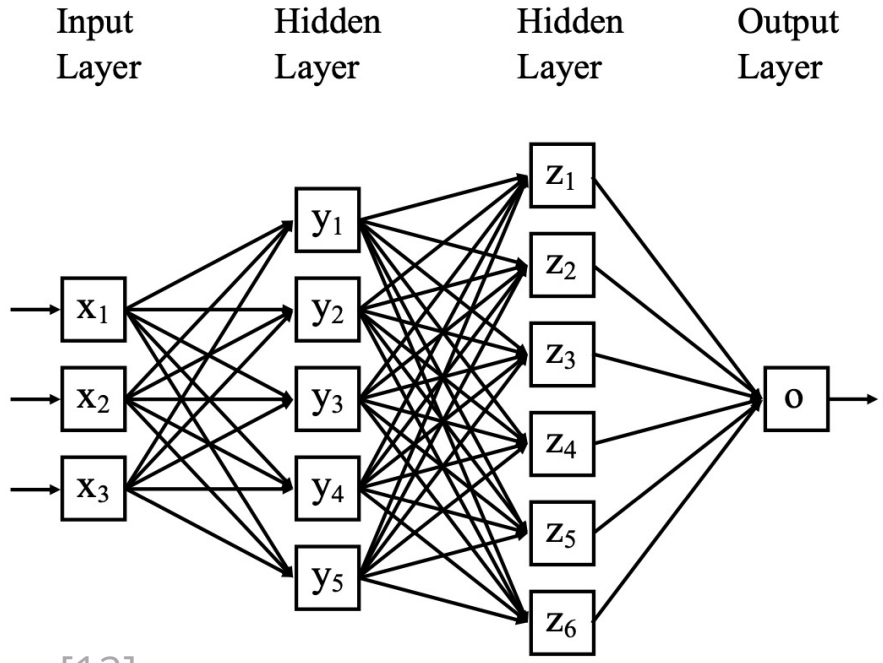


$$y_t = A\left(\sum_{i=0}^{n} x_i \cdot w_i + b\right)$$

- y_t … node output for time t
- $\vec{x}$ … input samples
- $\vec{w}$ … weights
- b … bias term
- A … activation function **(ReLU)**

full network



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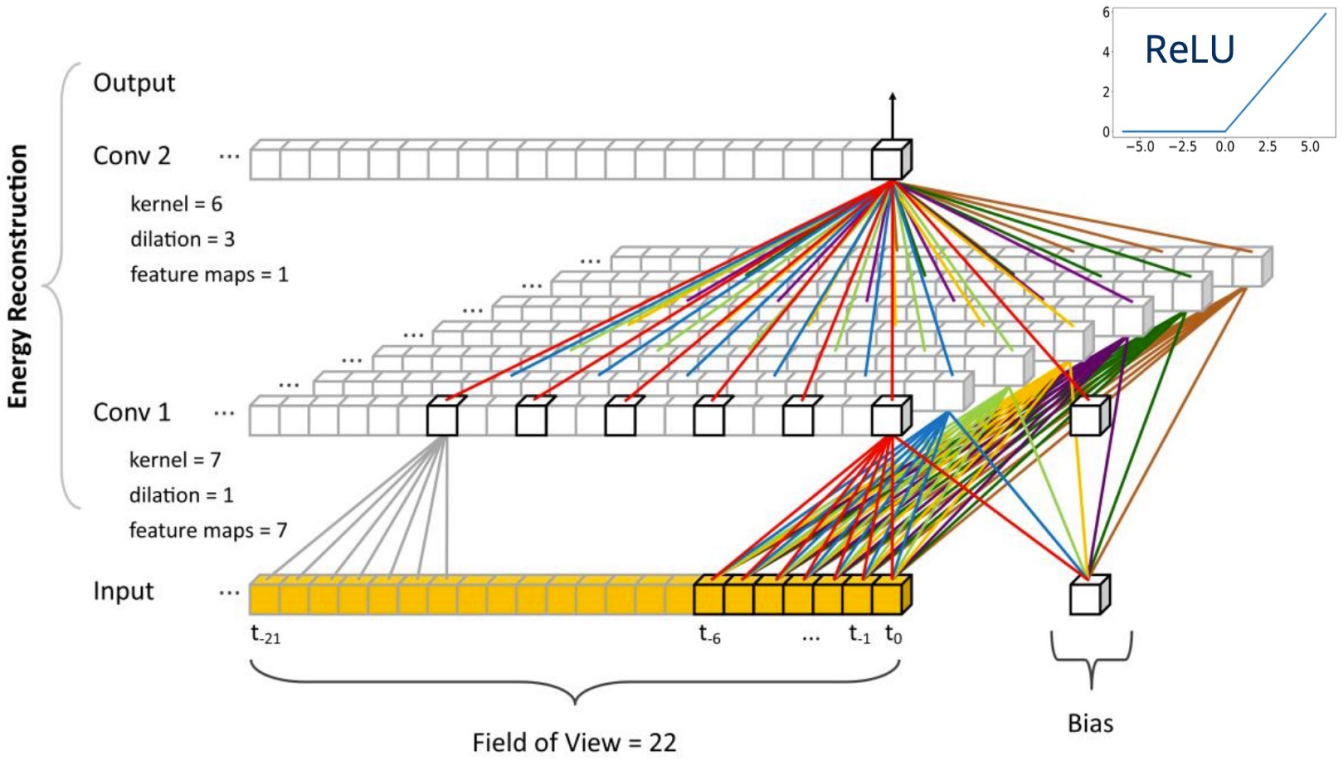
$$\mathbf{x} = (x_1, x_2, x_3) \quad \mathbf{y} = \mathbf{W}_x \mathbf{x} + b_x \quad \mathbf{z} = \mathbf{W}_y \mathbf{y} + b_y \quad o = \mathbf{W}_z \mathbf{z} + b_z$$

- interconnections between **several nodes**, within layers
- during **training** output tuned to fit target

CNNs for LAr Readout



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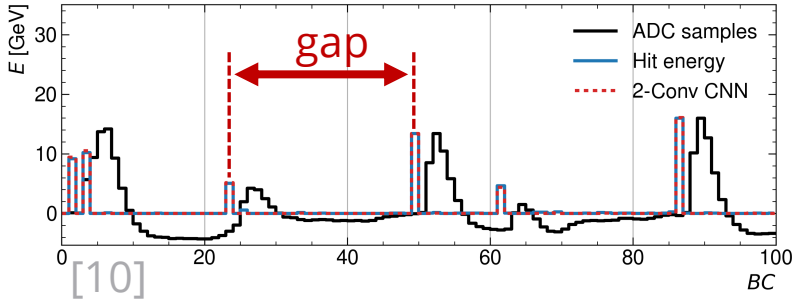
- **CNN** as ANNs which are specialized to **identify structures** (e.g. pulses from LAr calorimeter)
- network size **restricted by # of parameter** (so far ~100) available on the FPGA
- more resources on Agilex FPGA: **up to ~400 parameter possible**
- architecture of CNN optimized by **Hyperparameter search**

Energy Reconstruction on CNN

comparison of a well-trained 2-layer CNN (100 parameter) with 3- and 4-layer CNN **only trained during hyperparameter search**



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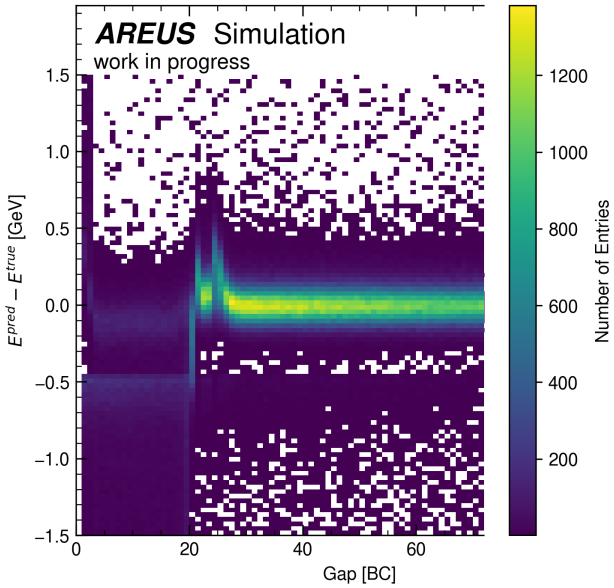
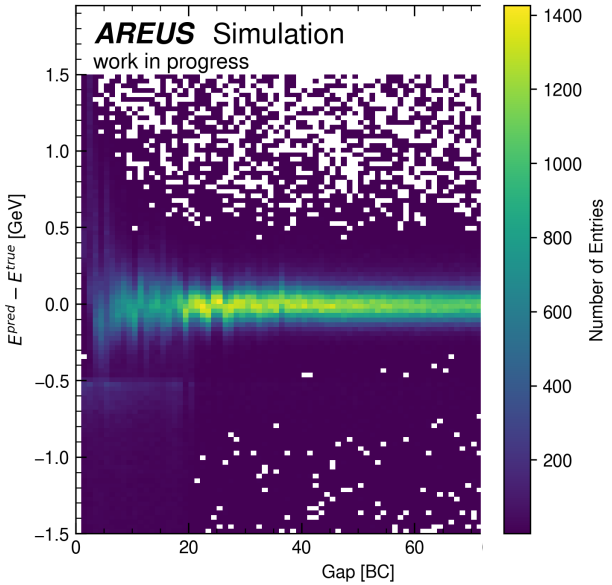
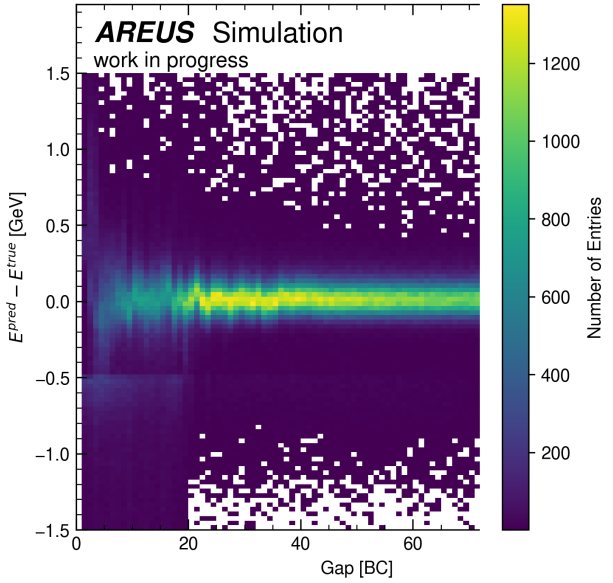


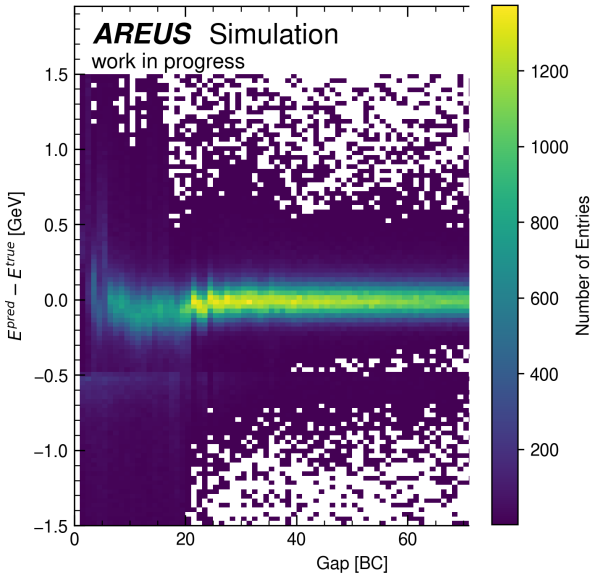
Optimal filter



2-layer CNN (~100 param.)



3-layer CNN (~400 param.)



4-layer CNN (~400 param.)

Summary

- upgrade of LHC to HL-LHC increases pile up of LAr calorimeter signal
- CNN suitable replacement for optimal filter for energy reconstruction in LASP Firmware
- larger number of parameters for CNN enables networks with more layers
- CNNs with 400 parameter show comparable or better energy resolution after hyperparameter search compared to trained network with 100 parameter

Outlook:

- Quantized training of 400 parameter CNN

Sources I

Slide 2:

[1] URL: https://static1.bmbfcluster.de/3/4/3/8_ef6a5eef8f44963/3438meg_22ce2885dae52af.jpg

[2] Joao Pequenao. Computer generated image of the whole ATLAS detector. CERN. Mar. 27, 2008. URL: https://cds.cern.ch/record/1095924(visited on 20/02/2024).

[3] Peter Vankov, ATLAS Upgrade for the HL_LHC: meeting the chalenges of a five-fold increase in collision rate.
CERN. Jan. 25, 2012. URL: https://cds.cern.ch/record/1419213/ (visited on 20/02/2024).

Slide 3:

[4] Joao Pequenao. Computer generated image of the ATLAS Liquid Argon. CERN. Mar. 27, 2008. URL: https://cds.cern.ch/record/1095928 (visited on 20/02/2024).

[5] Nikiforou, Nikiforos, Performance of the ATLAS Liquid Argon Calorimeter after three years of LHC operation and plans for a future upgrade.
CERN. Jun. 28, 2013. URL: https://cds.cern.ch/record/1558820/ (visited on 20/02/2024)

[6] Karl Jakobs. Lecture Material. CERN. 2015.
URL: https://www.particles.uni-freiburg.de/dateien/vorlesungsdateien/particledetectors/kap8

[7] ATLAS Collaboration. Monitoring and data quality assessment of the ATLAS liquid argon calorimeter. CERN. May 13, 2014. URL: https://cds.cern.ch/record/1701107 (visited on 05/24/2023).

Sources II

Slide 4:

[8] URL: https://www.terasic.com.tw/cgi-bin/page/archive.pl?Language=English&CategoryNo=142&No=1262 (visited on 20/02/2024).

[9] Ma, Xiangyuan, Vachon, Brigitte. Developing Firmware and Algorithms for the Liquid Argon Signal Processor
CERN. 18 Aug, 2023. URL: https://cds.cern.ch/record/2875234 (visited on 20/02/2024).

Slide 5 and 8:

[10] Berthold, Anne-Sophie. ML for Processing of ATLAS LAr Calorimeter Signals with FPGAs. CERN. 14 June 2023. URL: https://cds.cern.ch/record/2863770 (visited on 20/02/2024).

Slide 6 and 7:

[11]–[13] Berthold, Anne-Sophie. Simulation Studies of Convolutional Neural Networks for the Real-Time Energy Reconstruction of ATLAS Liquid-Argon Calorimeter Signals at the High-Luminosity LHC. CERN. 21 Dec. 2023. In publication.