Machine Learning on FPGAs for Real-Time Processing for the ATLAS Liquid Argon Calorimeter

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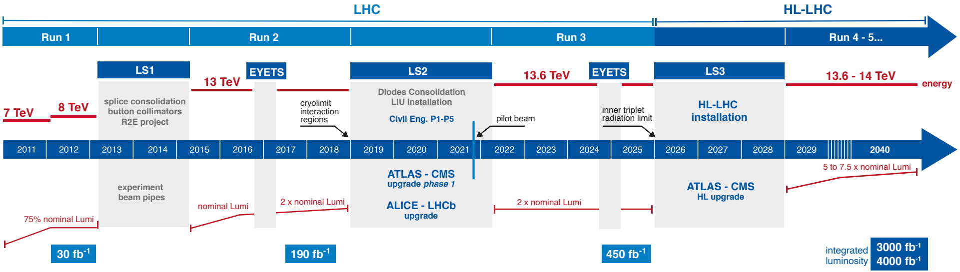
Content

The Phase-II Upgrade of the LHC

Upgrade of the ATLAS experiment

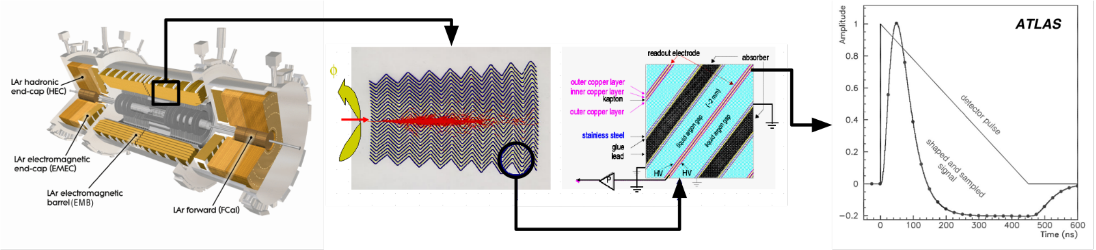


- The High Luminosity LHC (HL-LHC) is an important milestone for particle physics
  - To increase the luminosity to study rare processes
  - To increase the collision rate to up to 200 simultaneous p-p collisions (pileup) per bunch crossing
- The detectors will be upgraded to cope with the high collision rate at the HL-LHC
  - In particular the ATLAS calorimeter readout electronics will be completely replaced

ATLAS Liquid Argon Calorimeter

Energy reconstruction in the LAr calorimeter

- The Liquid Argon Calorimeter (LAr) mainly measures the energy deposited by electromagnetically interacting particles
  - Consisting of ≈ 182 000 calorimeter cells
- Passing particles ionize the material
  - Bipolar pulse shape with total length of up to 750 ns (30 BCs)
  - Pulse is sampled and digitized at 40MHz
- Energy reconstruction is done in real-time and used in triggering decision
  - Using the digitized samples from the pulse



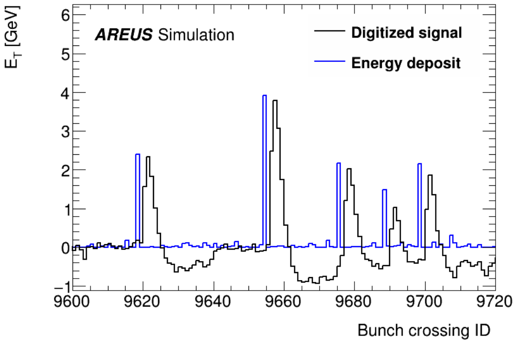
Energy Reconstruction

Energy reconstruction in the LAr calorimeter

- Current energy reconstruction uses the Optimal Filtering Algorithm with maximum finder (OFMax)

$$E(t) = \sum_{i=1}^{5} a_i \cdot s_i$$

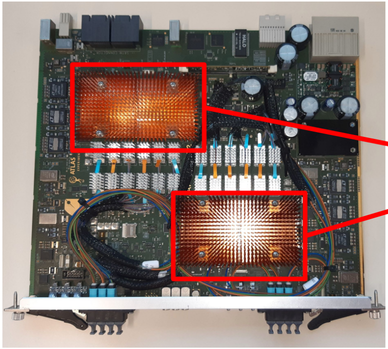
  - a_i - Predefined coefficients to fit the pulse
  - s_i - Sampled signal
- Distorted pulses result in significantly decreased performance of OFMax

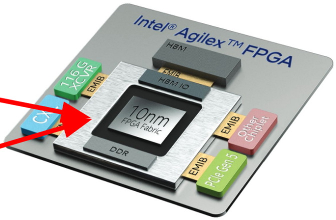


LAr Electronics Upgrade

Energy Reconstruction in Run-4

- LAr Signal Processor (LASP) board
  - For Phase-II one FPGA processes 384 channels and latency requirement of 125 ns
- Phase-II electronics with high-end FPGAs
  - Increased computing capacity
  - Improved online energy reconstruction using machine learning-based methods





The board is being tested with Intel Stratix 10 FPGAs but will be upgraded to Agilex

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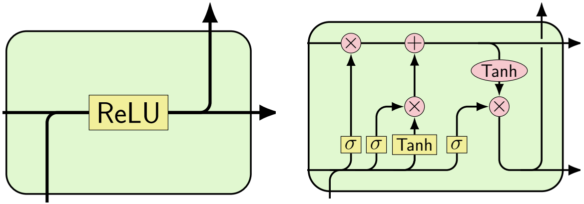
RNN Architecture

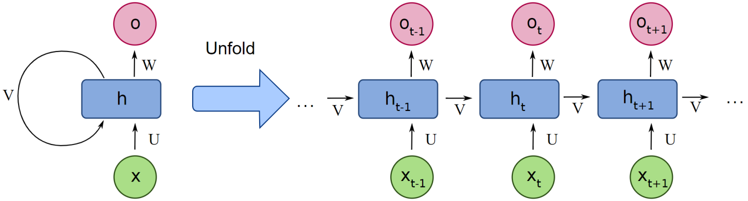
Time series processing with Recurrent Neural Networks (RNNs)

- Recurrent Neural Networks (RNNs) are designed to process time series data
- RNNs consist of neural network layers that process by combining new time input with past processed state
- Vanilla RNN is the smallest RNN structure
- Long Short-Term Memory (LSTM) network for efficiently handling past information

Vanilla

LSTM

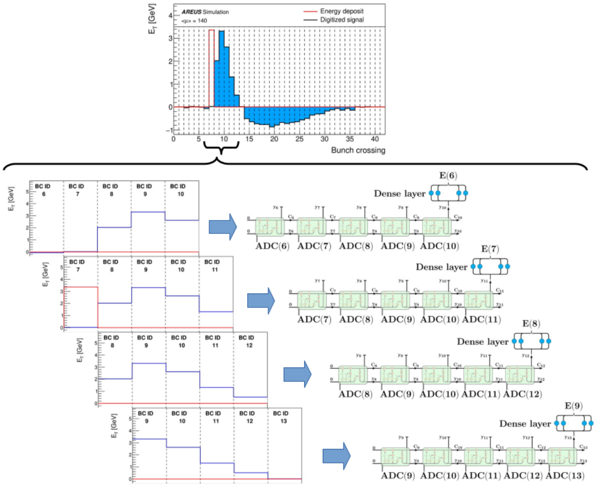




RNNs for Energy Reconstruction

Using many-to-one and many-to-many networks for energy reconstruction

- Use digitized samples as inputs for the recurrent network
- Sliding window
  - Full sequence split into overlapping subsequences with a sliding window
  - One energy prediction per subsequence
  - Four samples in the peak, one in the past
  - Possible for Vanilla RNN and LSTM
- Single cell
  - Use the LSTM cell to process all digitized samples in one continuous chain instead of a sliding window
  - Full history of events available
  - Possible only for LSTM



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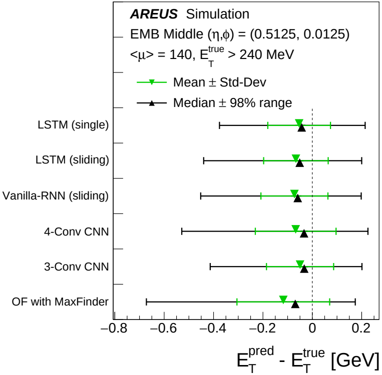
NN Performance

Resolution and network size

- Overall better energy resolution than OFMax
  - Smaller tails and mean closer to zero
- Best performance with LSTM
  - Too large to fit on the FPGA
- CNNs and Vanilla RNN perform well with fewer parameters

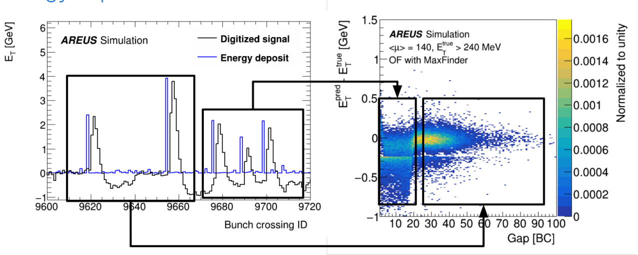


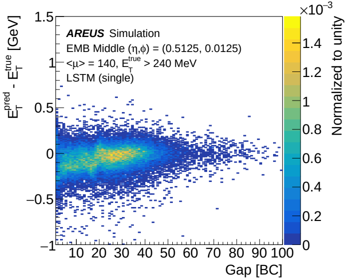
Algorithm	LSTM (single)	LSTM (sliding)	Vanilla (sliding)	CNN (3-conv)	CNN (4-conv)	Optimal filtering
Number of parameters	491	491	89	94	88	5
MAC units	480	2360	368	87	78	5

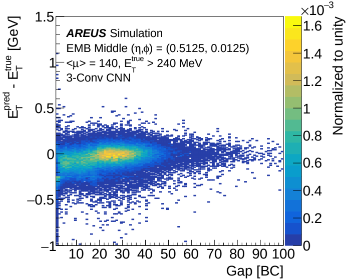
NN Performance

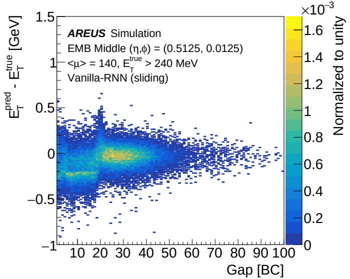
Resolution as a function of gap to previous energy deposit in BCs

- Clear performance decrease with OFMax at low gap
- All NNs perform better with overlapping events
  - More past samples allows for better correction of overlapping events





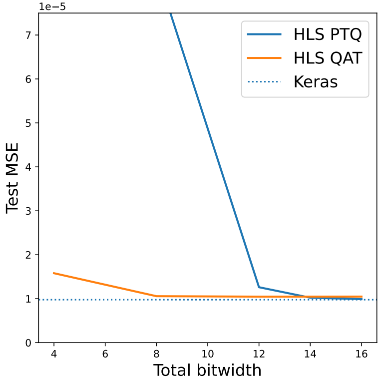




Quantization Aware Training

Optimizing NNs for firmware

- Math operations in firmware are done using fixed-point arithmetic
- Quantizing NNs after training known as post-training quantization (PTQ) with decreases the accuracy
- It is possible to mitigate this effect with quantization aware training (QAT)
    - Training using math operations as if they were quantized
- Simulation results from High Level Synthesis (HLS) implementation of RNNs show that the required bitwidth can be halved by using QAT



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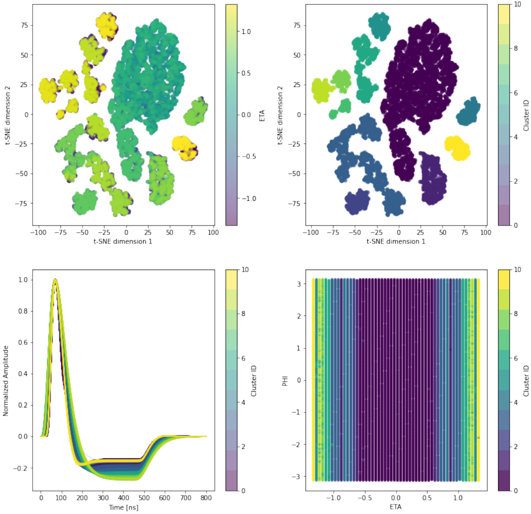
Reconstruction for Full Detector

Pulse Clustering

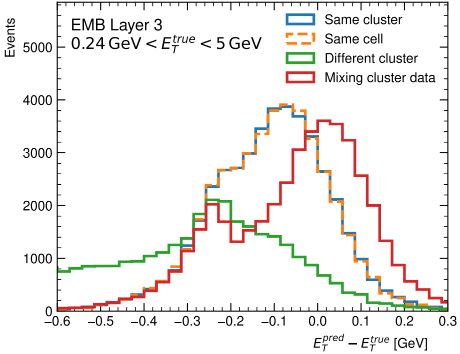
- Pulse shape differs in the detector
  - Reduced performance with differing pulse shapes
  - One NN training will not perform well for the full detector, nor is 182k NNs feasible
  - Need to reduce the number of NNs trained while maintaining accuracy
- Clustering method used to group detector regions
  - t-SNE from calibration pulses to acquire clustering
  - DBSCAN to automatically classify cluster
  - Separation correlates with η according to pulse shape differences



Pulse Clustering

Reconstruction in different regions

- Evaluate inside same cluster
  - Train with one cell, test with another
  - Same performance as with training and testing with the same cell
- Large performance drop when training with one cluster and testing with another
- Train with mixed data from all clusters, test with single cluster
  - Mixing data across clusters slightly restores performance



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Conclusion

Energy reconstruction using recurrent neural networks

- Energy reconstruction with RNNs overperforms legacy algorithms in Phase-II conditions
  - Better energy resolution overall
  - Better recovery of energy resolution with overlapping signals
- Implemented and validated in firmware and the implementations mostly fulfill the LAr real-time processing requirements
  - Testing on DevKits started and is showing good results
- Next step is to quantify the effect on object (electrons, photons) reconstruction and physics performance
- Paper published available Here