Application of DeepSets Machine Learning in FPGA to Improve ATLAS L0 Global Trigger for HL-LHC

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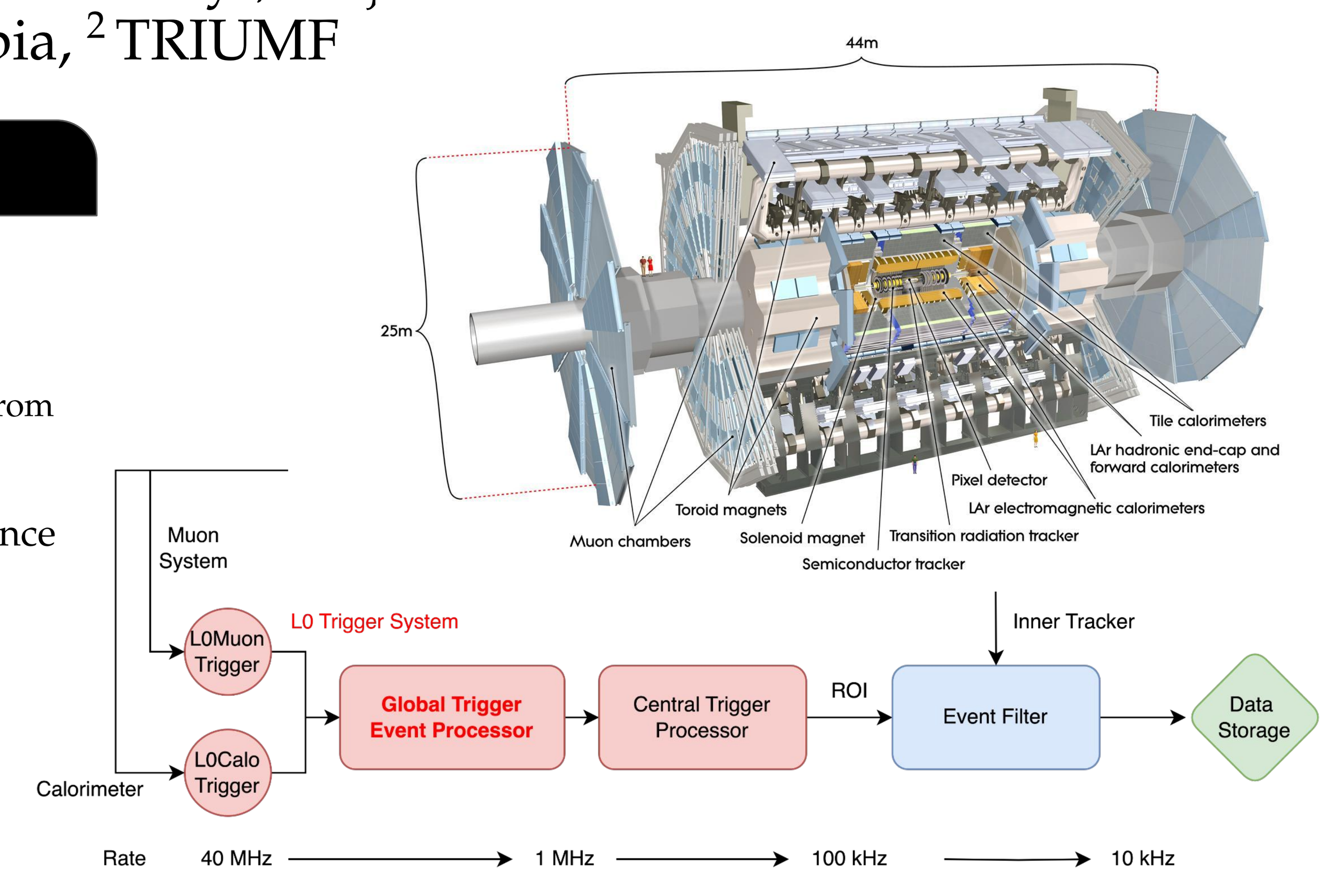
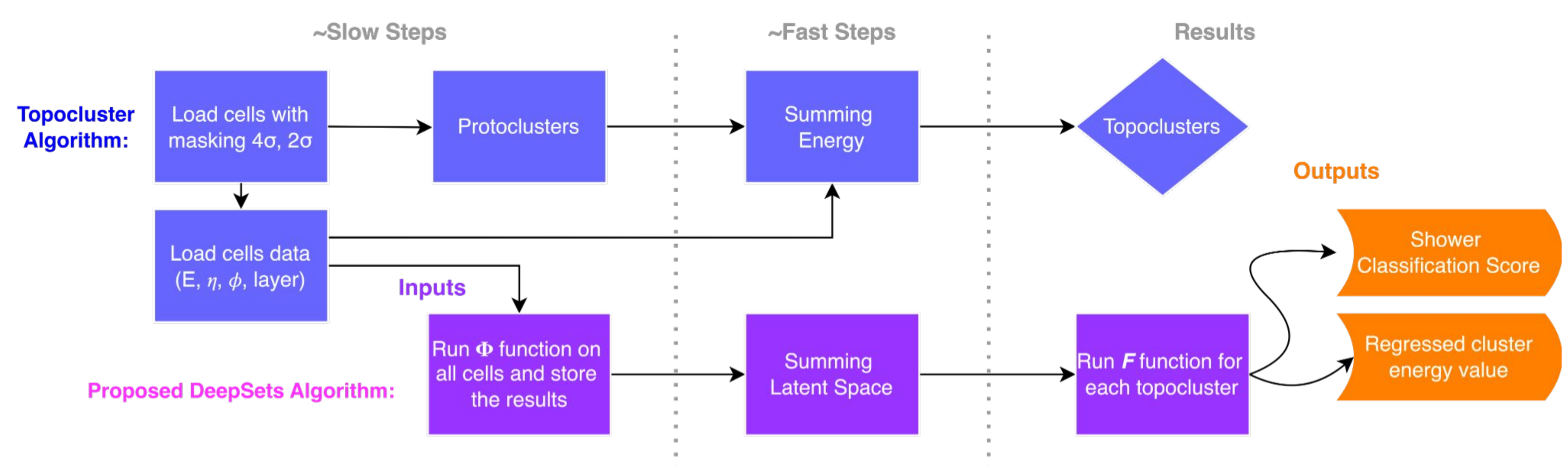
1.MOTIVATION

- In the ATLAS calorimeter, 2 primary types of particle shower are being observed:
  - EM showers: Originate from $e^{\pm}$, γ interactions and π^0 decays. These showers are all similar → Well-calibrated in the calorimeter.
  - Hadronic showers: Originate from $\pi^{\pm}$, p, n, … decays and interactions. Each of these showers is unique, i.e. huge resolution penalty from variations → Much more difficult to calibrate.
- Calorimeter is crucial for trigger system → Essential to accurately characterize the calorimeter response to both π^0 and $\pi^{\pm}$, since pions are the most abundant particle produced in collisions
- Previous studies [1-2] showed machine learning improves calorimeter calibration and classification
- Calibration also affect the online trigger → Many events recorded with <100% efficiency, difficult to be used in physics analysis
- **Can machine learning be applied in the L0 global trigger event processor for pions calibration?**



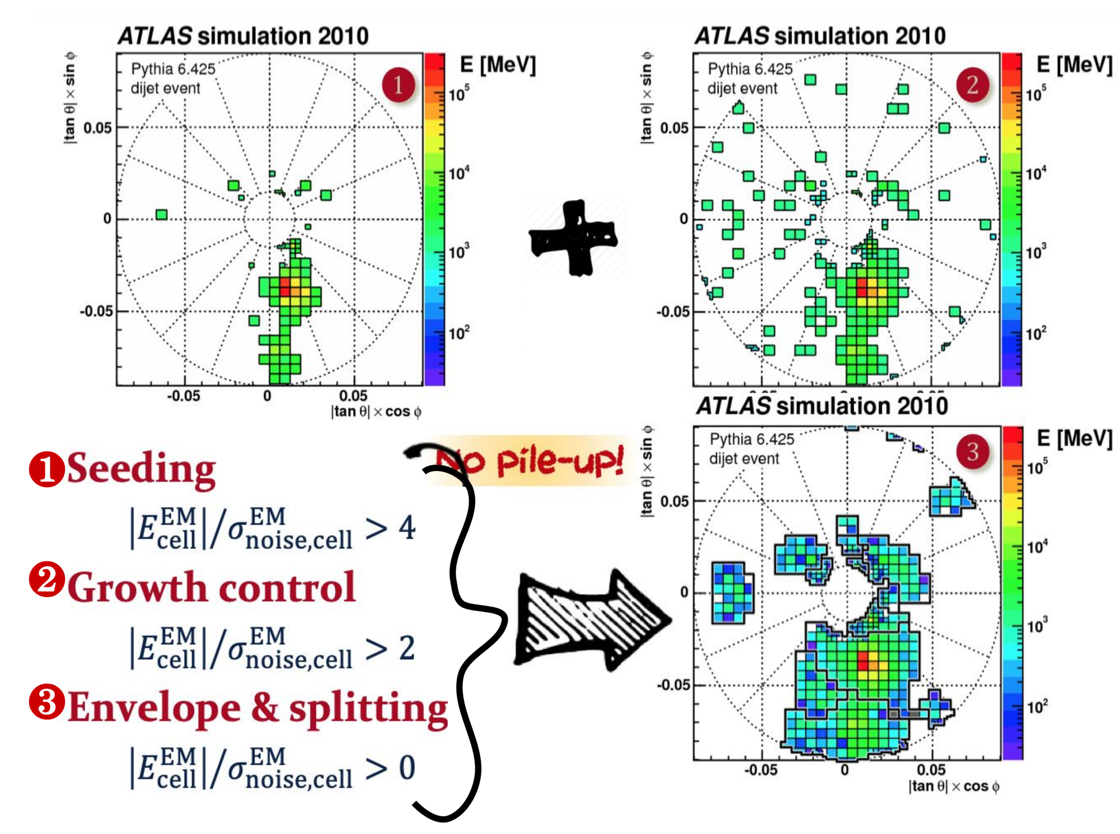
2.PROPOSAL

- Given only ~10 µs of latency in the L0 event processor, we propose to "hide" the DeepSets machine learning algorithm under the current topoclustering algorithm:



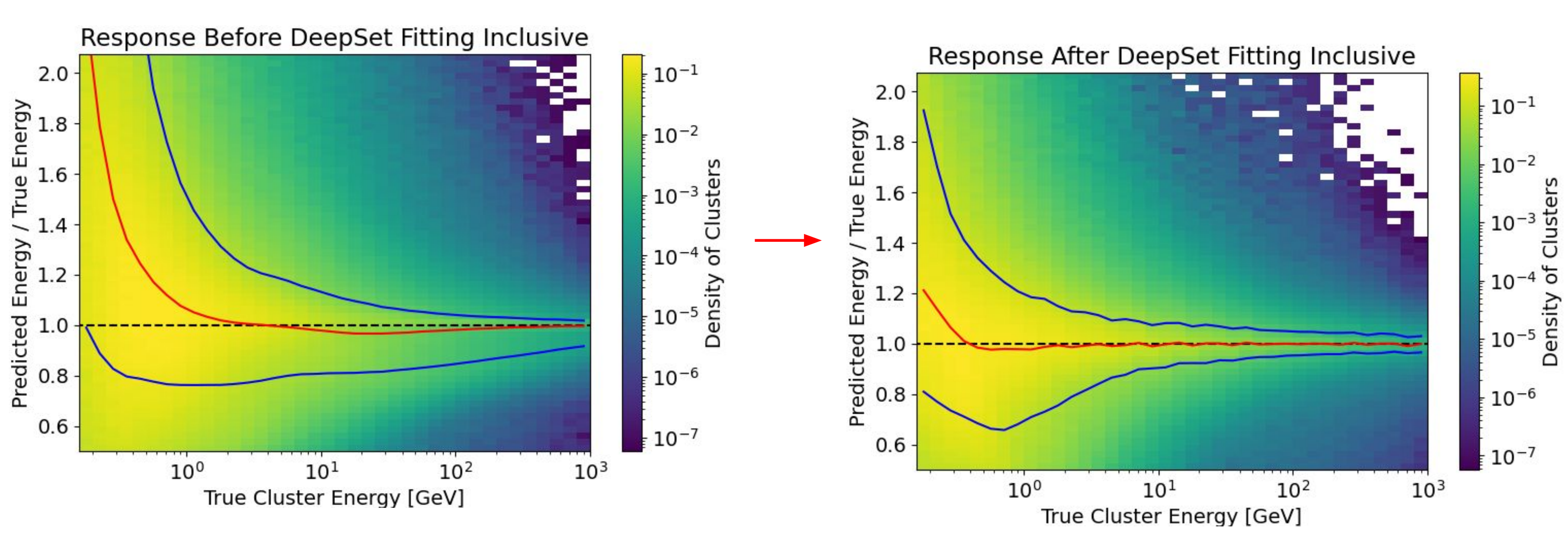
- Need to study exact latency and resource usage for each step on the FPGA in the event processor.

❖ TopoClustering algorithm [3] in global trigger splits between local signal maxima in calorimeter



3.OPTIMIZATION

- Trade-off study with MC simulation shows using small # of nodes (especially in Φ function) while allowing more hidden layers in the DeepSets can still on average give better prediction and achieve better resolution

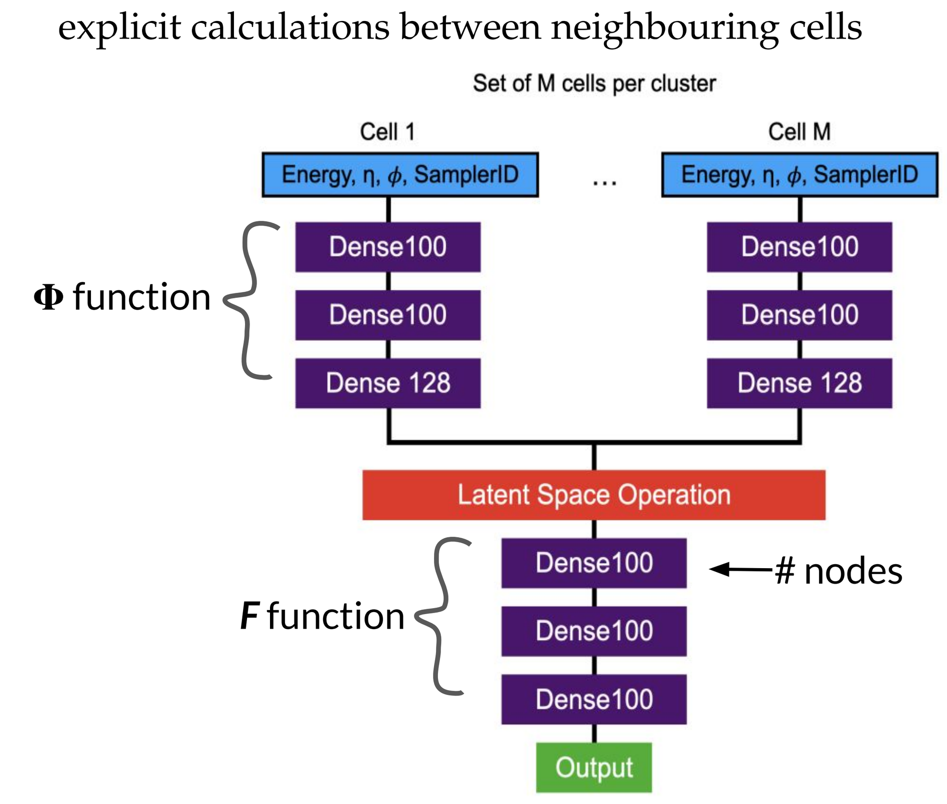


❖ Training details:
  ➢ ~18M clusters of both π^0 & $\pi^{\pm}$ labels
  ➢ Epochs: 100
  ➢ Learning rate: 0.001 (min: 0.00001)
  ➢ Batch size: 4096

❖ Model details:
  ➢ Φ nodes: 64
  ➢ Φ layers: 5
  ➢ F nodes: 64
  ➢ F layers: 5

Fig 1: Prediction vs true cluster energy in MC using (left) the default energy; (right) the DeepSets neural network. Red and blue line indicate median and 1σ response of test data.

❖ DeepSets neural network consists of 3 stages and requires no explicit calculations between neighbouring cells



4.NEURAL NETWORK BEHAVIOUR

- Probe neural network behaviour by studying 1-cell cluster inputs with model above
- Implication:
  - Latent space dimension are not fully utilized. Information are encoded in length of a few vector components.
    → Possible to further reduce # nodes in DeepSets and reduce resource usage
  - Plateau in low energy in full network energy output coincides with electronic noise level in sub-detectors.
    → Possible explanation for over-prediction for <200 MeV in Fig 1 after fitting

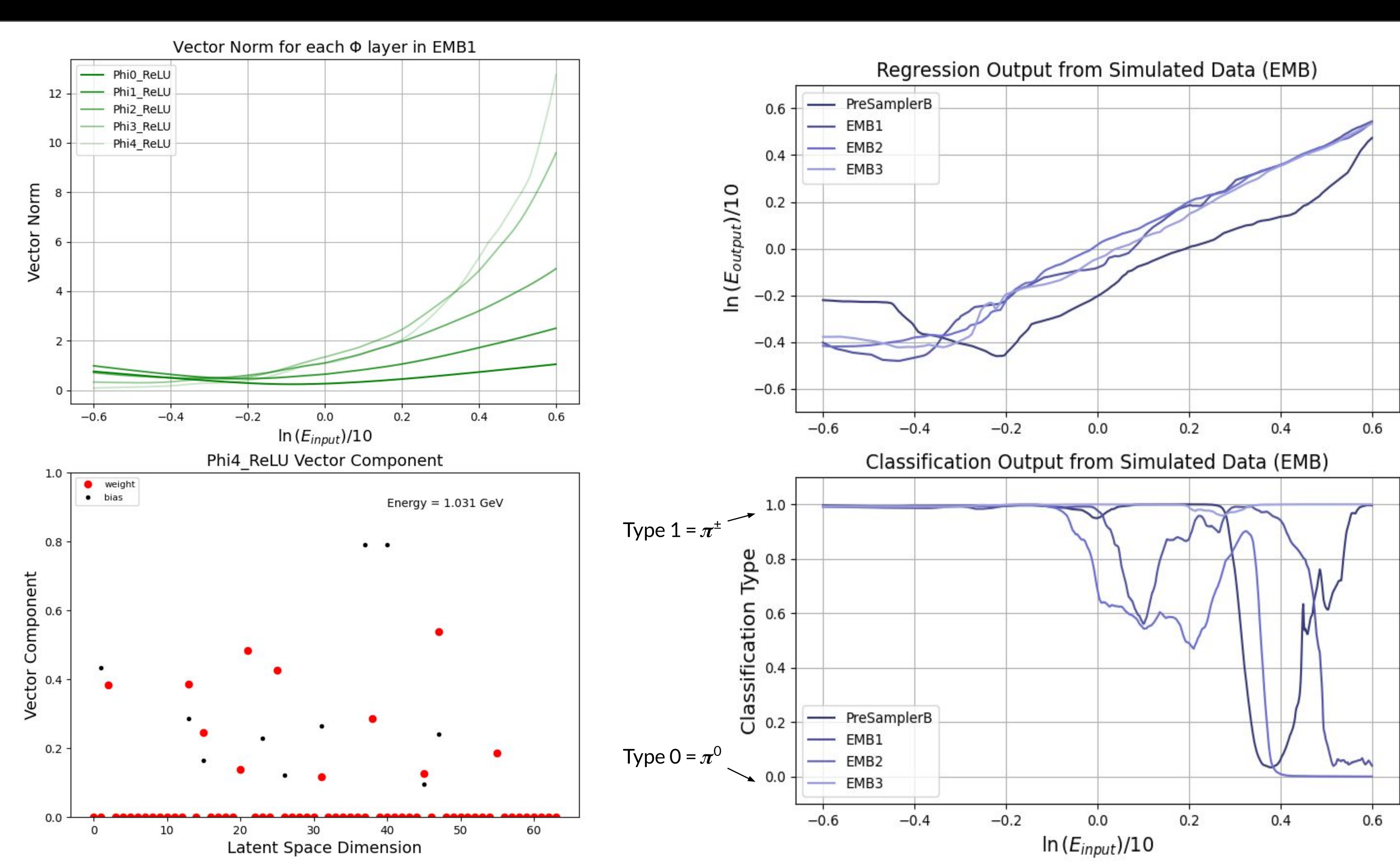
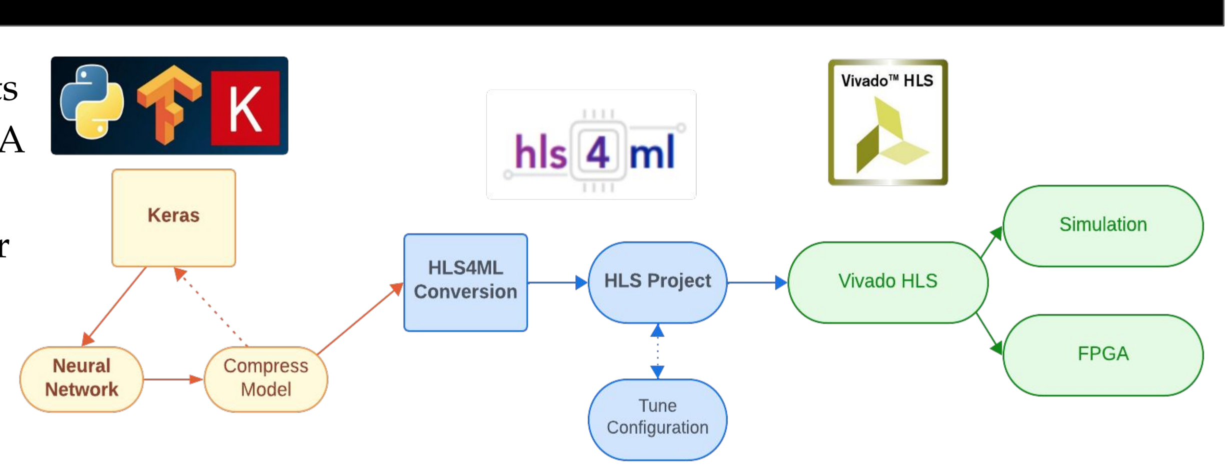


Fig 2: Input energy of the 1-cell cluster vs regressed energy, classification prediction from the trained model, (unnormalized) vector norm in hidden layers, and length of vector component.

5.NEXT STEPS

- Convert trained DeepSets model to VHDL for FPGA
- Study precision and quantization in FPGA for DeepSets



6.CONCLUSION

- **Problem trying to solve:**
  - Improve calorimeter calibration for online trigger during the High-Luminosity LHC
- **Why ML?**
  - ML methods performs better than current algorithms in pion classification and energy calibration
- **Challenges ahead:**
  - To be run in FPGA in the L0 global trigger under the shadow of the current topocluster algorithm
  - Strict requirement on latency and limitation of resource to implement the DeepSets neural network, requiring to minimize the size of latent space
  - Need neural network to recognize electronic noise to prevent over-prediction at low energy

REFERENCES

[1] "Deep Learning for Pion Identification and Energy Calibration with the ATLAS Detector," 7 2020.
[2] "Point Cloud Deep Learning Methods for Pion Reconstruction in the ATLAS Experiment," 2022.
[3] "Topological cell clustering in the ATLAS calorimeters and its performance in LHC Run 1,"Eur. Phys. J. C, vol. 77, p. 490, 2017.