



Introduction

Clustering of signals in the ATLAS calorimeter is performed by the topocluster algorithm, where clusters develop iteratively according to geometric cell significance patterns. Topoclustering is among the slowest algorithms used in the ATLAS high-level trigger. This poster presents the application of a Convolutional Neural Network (CNN) to the identification of Regions of Interest in the calorimeter using topoclusters. The network architecture is also applied to the task of jet finding directly from the same cell images.

The SMARTHEP Network

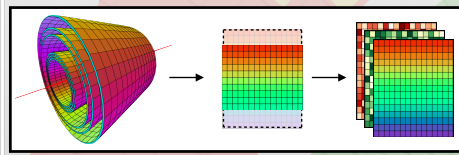
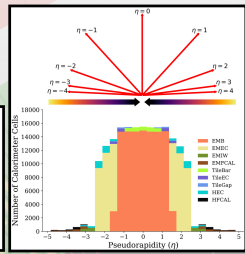
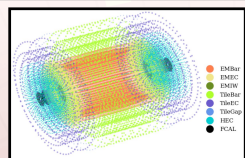
Synergies between MACHine learning, Real-Time analysis and Hybrid architectures for efficient Event Processing and decision-making (SMARTHEP) is a European Training Network with the aim of advancing real-time decision-making, driving data-collection and analysis towards synonymy.



1. Data Preparation

To interface with the CNN model the ATLAS calorimeter cell information was projected into a 2-dimensional $\eta \times \phi$ representation. The 187,000 cells are sorted into (125,96) pixels based on their position within the detector.

Each image contains 3 channels: one containing all of the calorimeter cells and two consisting of the cells from the electromagnetic and hadronic calorimeter layers exclusively.

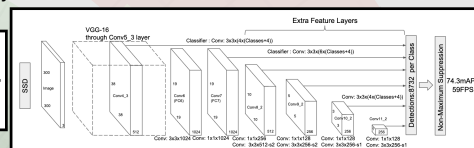


2. Model Architecture

The SSD [1] object detection architecture is used to predict a set of bounding boxes for each event. The model simultaneously evaluates each prediction with a confidence score, indicating the model's certainty in distinguishing signal from noise. The model performance was evaluated in two separate tasks, first using ATLAS topoclusters [2] as targets and then using Anti-kt jets [3].

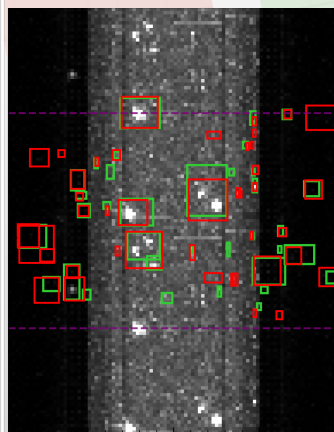
In both cases the Intersection over Union (IoU) with the target boxes was used to "match" or "unmatch" the model predictions to monitor the accuracy and efficiency of the model.

$$IoU = \frac{\text{Intersection}}{\text{Union}}$$

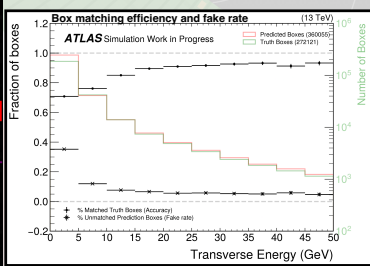


3. Cluster Identification

Using the topoclusters as targets, the model must locate the physically significant energy deposits in the calorimeter. Each cluster with raw energy $> 5\text{GeV}$ seeds a target box. The model was trained for 20 epochs over 50,000 simulated dijet events with pileup of $\langle \mu \rangle = 32$ interactions on average. The energy distribution of the target boxes is very broad, increasing from just a few GeV to $\sim 1\text{TeV}$.



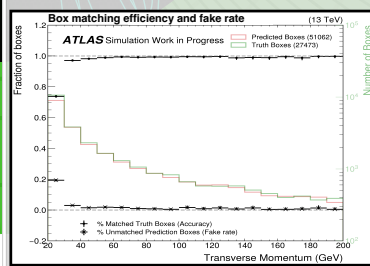
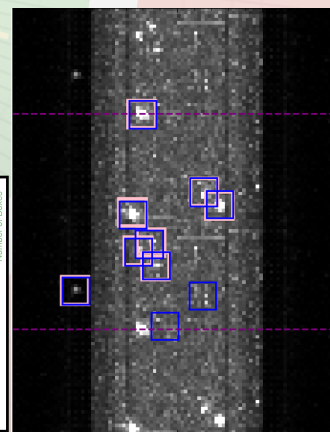
The model performance improves with increasing transverse energy. Here, 90% of target boxes are detected ("matched") with less than 5% fake predictions above 35GeV.



4. Jet Finding

A better performance is obtained when the same CNN architecture is used to find jets from the calorimeter cells. Jets are produced by sequentially combining constituents including topoclusters and their signatures are clearer with reduced multiplicity. The jets with transverse momentum $> 20\text{ GeV}$ seed a target box. The model was trained for 10 epochs over 50,000 simulated dijet events with $\langle \mu \rangle = 32$.

As before, a better performance is observed at higher transverse momenta. More than 99% of jets above 45GeV are "matched" with a fake prediction rate of $\sim 1\%$.



5. Timing Performance

All algorithms in the ATLAS trigger are subject to strict latency requirements. The current ATLAS topoclustering and Anti-kt jet finding take an average of 80ms and 15-25ms per event, respectively, on the current trigger CPU farm [4]. The CNN model strategy has not yet been optimised for inference speed. The post-processing step includes the cell retrieval and kinematics calculation.

	Inference (RTX 2080 Ti GPU)	Post-Processing (CPU)
Topocluster CNN (VGG16 backbone)	36 ms	10 ms
Jet CNN (VGG16 backbone)	35 ms	14 ms

Summary & Outlook

The application of object detection to locate topoclusters and jets in a 2-dimensional representation of the ATLAS calorimeter was demonstrated, building upon previous treatments of boxes as images. Next steps: Investigation of the model performance on a wider variety of event topologies and pileup conditions; verify the potential use of FPGA hardware to accelerate inference speed.

References:

- [1] SSD: Single Shot MultiBox Detector arxiv.org/abs/1512.02325
- [2] Topological cell clustering in the ATLAS calorimeters and its performance in LHC Run 1 arxiv.org/abs/1603.02934
- [3] The anti-k_t jet clustering algorithm arxiv.org/abs/0802.1189
- [4] The ATLAS Trigger System for LHC Run 3 and Trigger performance in 2022 arxiv.org/abs/2401.06630

