Simulating Calorimeter Detector Signatures with the Lorenzetti Showers Framework for Electron Trigger Studies using Machine Learning

CHIPP 2024 Annual Meeting

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June 19th, 2024

Lorenzetti Showers

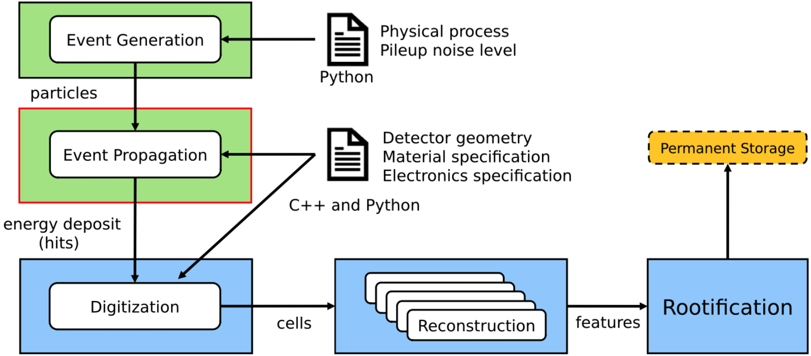
- A general-purpose framework for supporting signal reconstruction and triggering with calorimeters

Motivation for using Lorenzetti Showers

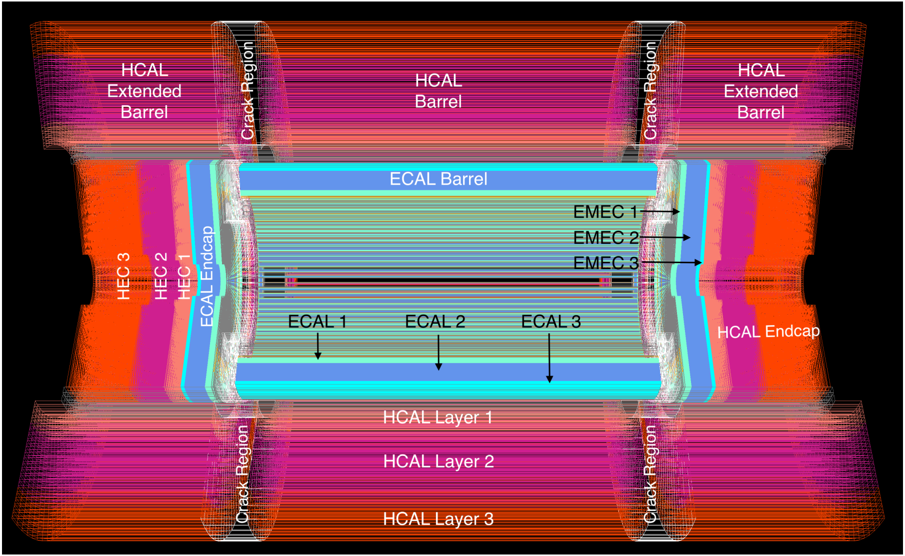
- Simulations are essential for preparing experiments, designing sub-detectors, interpreting results and for guiding upgrades in high energy physics.
- The high luminosity LHC upgrade will produce extreme signal pileup levels for which a fast and accurate simulation will become very important.
- The use of event simulation and reconstruction software is often restricted to one collaboration.
- Lorenzetti Showers provides a flexible general purpose framework for calorimetry which can be adapted for different detector specifications.
- https://github.com/lorenzetti-hep/lorenzetti

Event Generation and Processing

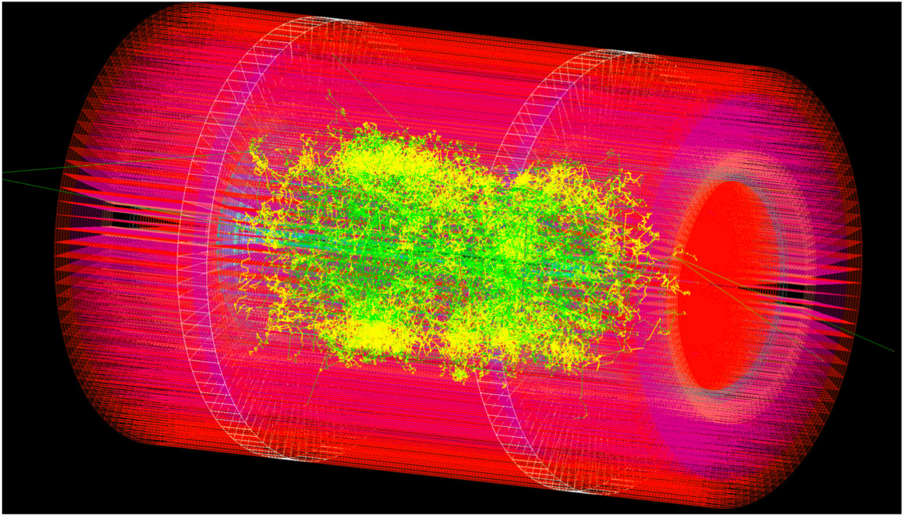
- Event generation based on Pythia 8
- Event propagation based on Geant4



Simulating the ATLAS Calorimeter System

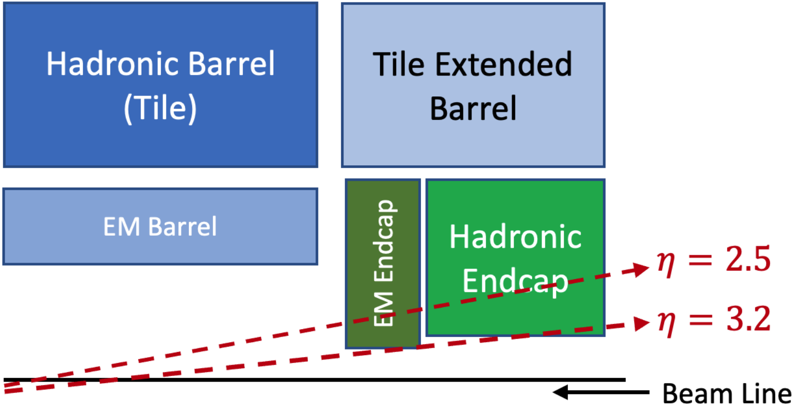


Showers with Lorenzetti



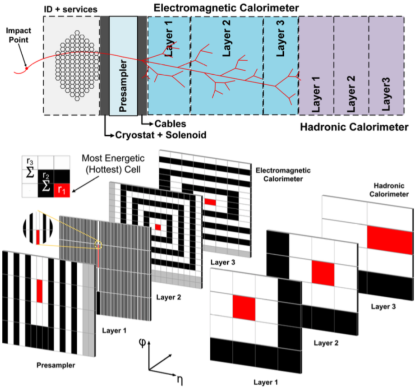
Forward Calorimeters in ATLAS

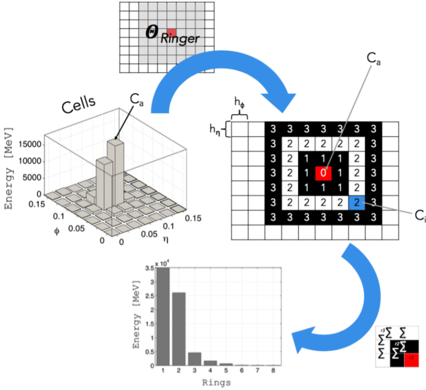
- ATLAS does not feature any tracking in the forward regions ($\eta > 2.5$).
- Therefore, calorimeter information becomes crucial for particle identification.
- Forward regions are more challenging due to reduced tracking information, lesser granularity and more inactive material.



The NeuralRinger Algorithm for Electron Identification

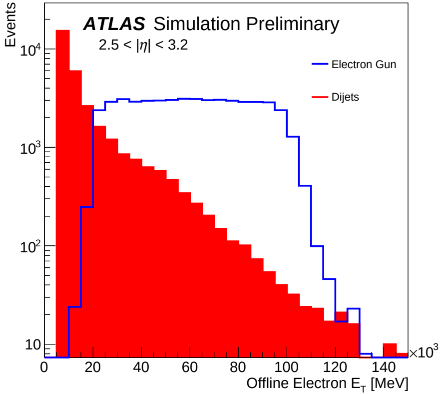
- The NeuralRinger is an algorithm using calorimetric data to identify electrons by building rings and calculating their energy sums.
- Training of neural networks (NN) on the ring sums provides selections to distinguish real from fake electrons

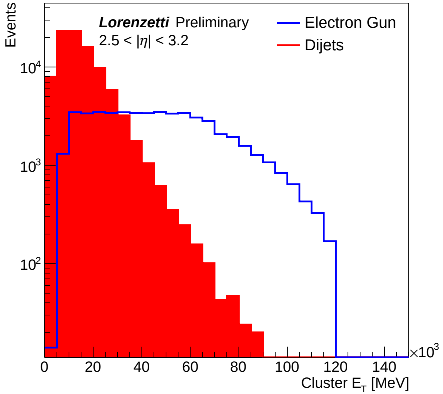




E_{T} Distributions

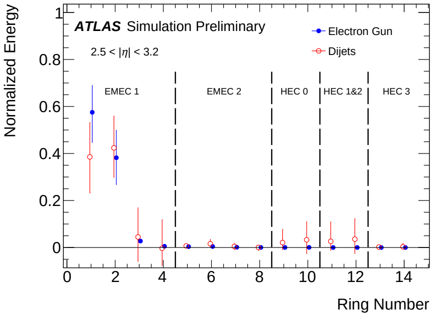
- ATLAS:
- Electron gun: 20 GeV $< E_{\mathrm{T}} <$ 100 GeV, Dijets: $E_{\mathrm{T}} >$ 50 GeV
- Lorenzetti:
- Electron gun: 100 GeV $< E <$ 1000 GeV, Dijets: $E_{\mathrm{T}} >$ 20 GeV

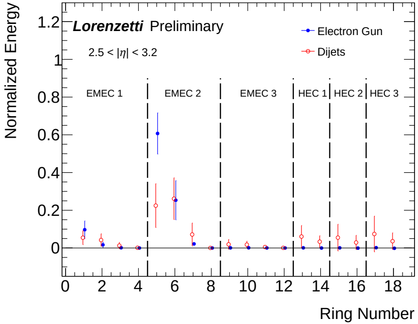




Normalized Ring Profiles

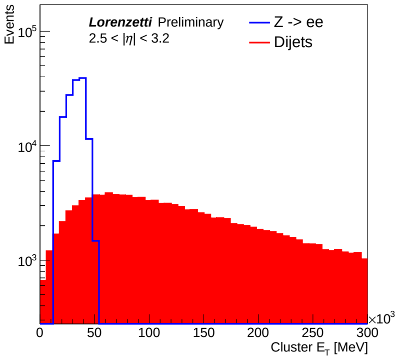
- Input variables for neural networks
- Lorenzetti simulation has an additional presampling layer in the EMEC
- Similar behaviour between ATLAS rings 1-14 and Lorenzetti rings 5-18
- Previous ATLAS studies were able to reduce fake acceptance by an order of magnitude

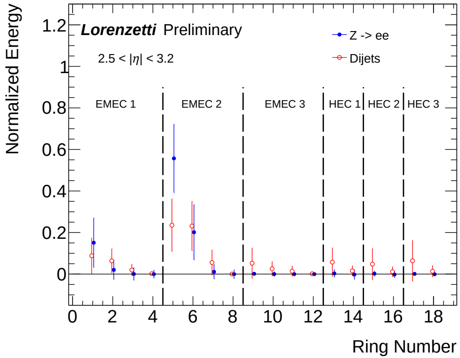




Using Z→ee Samples for Electron Candidates

- Z→ee samples required to have at least 1 electron going in $2.5 < |\eta| < 3.2$
- Dijets: $E_{\mathrm{T}} < 1$ TeV
- Still a clear difference between the ring profiles of both samples visible





Conclusions

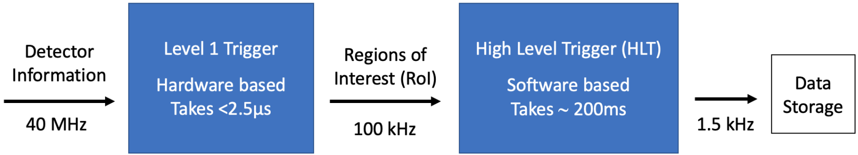
- As a general-purpose calorimetry framework Lorenzetti Showers provides a very useful tool for detector studies.
- It features an event generation and reconstruction chain which allows to provide samples based on calorimetry information.
- The same ring structures as the ones for ATLAS have been implemented in Lorenzetti.
- The ring energy distributions look quite similar for both.
- Comparisons are also being performed using shower moments which ATLAS uses for cutbased triggers.
- The studies are being extended by including different pileup scenarios.

Thank you!

Backup

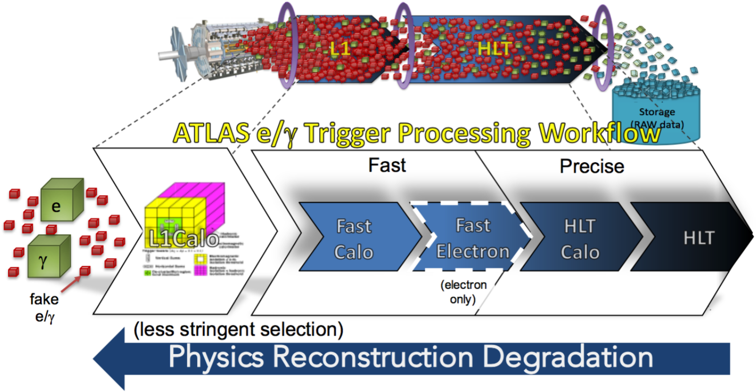
The ATLAS Trigger

- The LHC's beam luminosity of 10^{34} cm^{-2}s^{-1} results in 40 million bunch crossings with each about 20 collisions per second.
- To store all this information would fill up data storages and overwhelm them with events irrelevant for analyses.
- Therefore a trigger system is used to select events of interest.



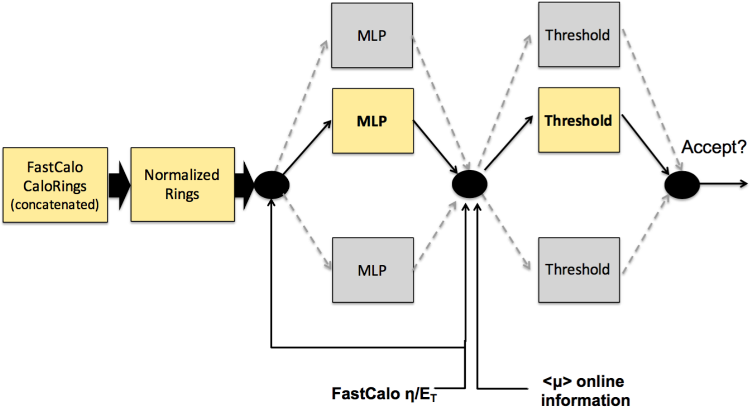
e/γ Trigger Processing Workflow

- The NeuralRinger algorithm has been introduced in 2017 in the Fast Calo step to reduce CPU demands.



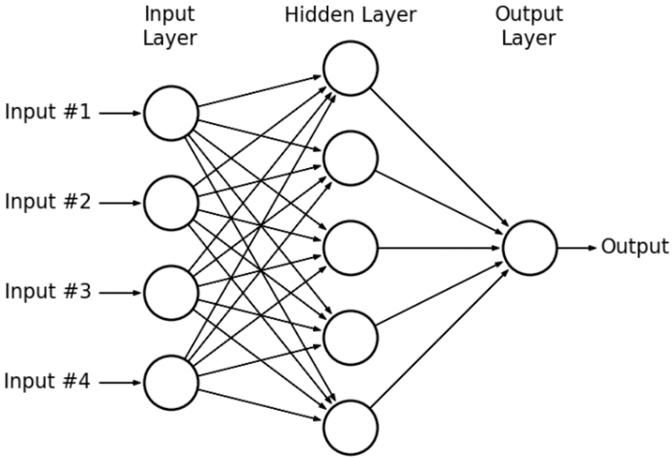
Processing Flow

- An ensemble of Multi Layer Perceptrons (MLPs) is trained with the informations from the rings to discriminate signal from background.
- The MLPs provide the discriminants for the trigger software.
- Using this technique it was possible to significantly reduce the CPU time and the rate of fake candidates that are passed on.



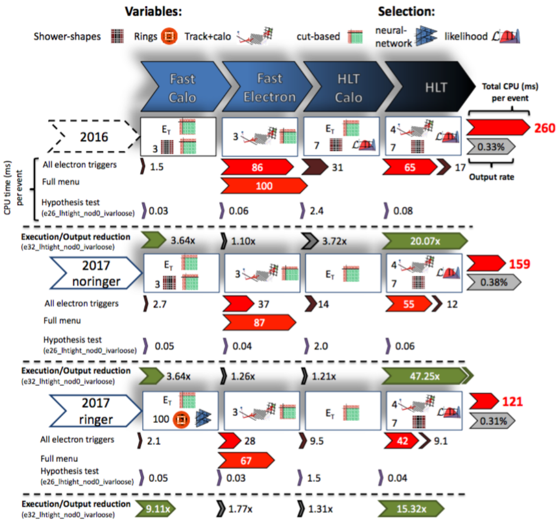
Multi Layer Perceptrons (MLPs)

- MLPs are a class of feedforward artificial neural networks.
- Each node except the input has a nonlinear activation function which allows MLPs to distinguish data which are not linearly separable.



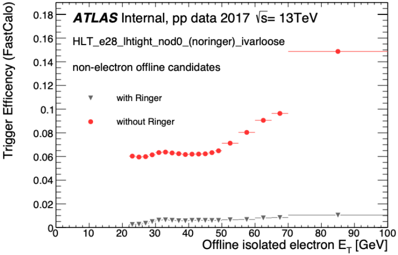
NeuralRinger CPU Reduction

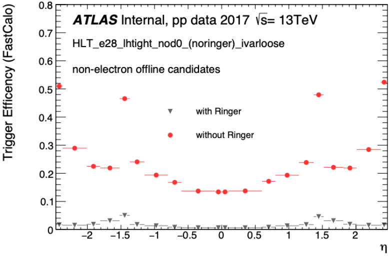
- Using the NeuralRinger it was possible to reduce the electron trigger CPU time by 38 ms per event.



NeuralRinger fake rate Reduction

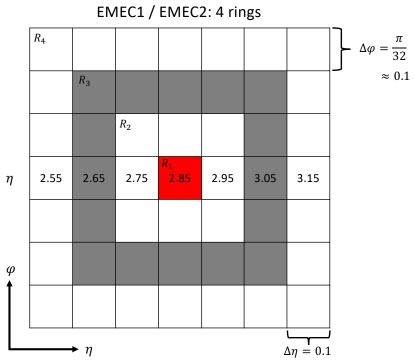
- Using the NeuralRinger it was possible to reduce the fake electron rates in the FastCalo step by an order of magnitude.

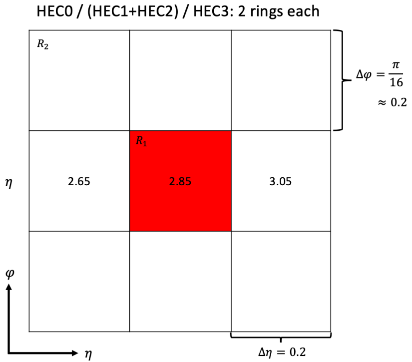




Forward Ring Shapes

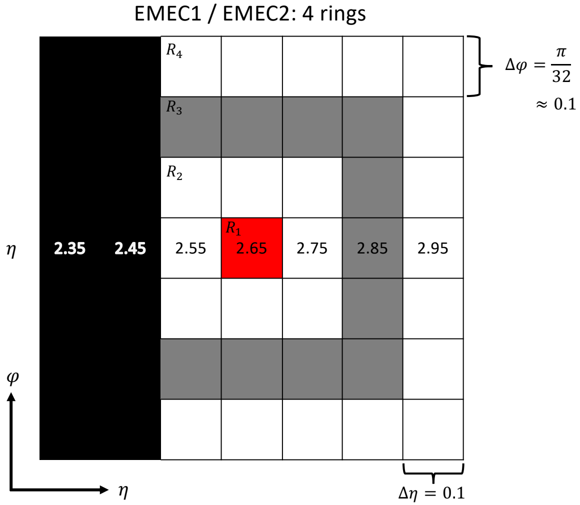
- According to detector granularities only 4 rings are built in the EMEC layers and only 2 rings in the HEC layers.
- The Lorenzetti simulation has 3 EMEC layer, whereas ATLAS only has 2, both have 3 HEC layers.
- Rings reaching into regions of different granularity are cut at $\eta < 2.5$ and $\eta > 3.2$.





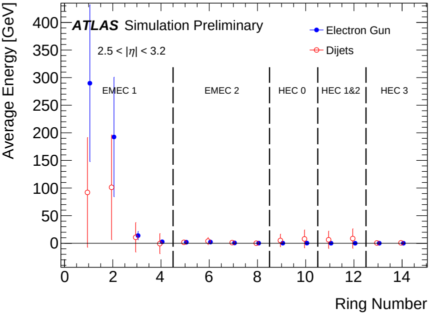
Example of Rings that are Cut

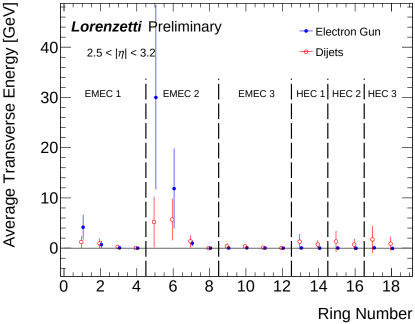
- If the hottest cell is for example at $\eta = 2.65$, the cells with $\eta < 2.5$ are cut from the 3rd and 4th ring.



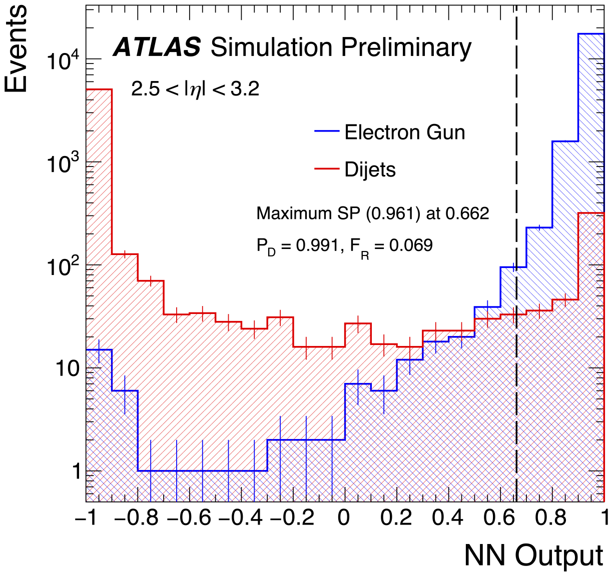
Ring Energies

- ATLAS (total Energy) vs Lorenzetti (E_{T})
- Standard deviation error bars; large energy range (see Slide 9) -> large deviation in the highest energetic cell
- ATLAS rings 1-14 very comparable to Lorenzetti rings 5-18





NN Output Distribution (ATLAS)



Sum Product (SP) Index

- $SP = \sqrt{\sqrt{P_D(1 - F_a)} \cdot \frac{1}{2}(P_D + 1 - F_a)}$.

- P_D: Probability of detection $(\frac{N_{signal}(passed)}{N_{signal}(total)})$.
- F_a: False alarm $(\frac{N_{bkg}(passed)}{N_{bkg}(total)})$.
- (passed = identified as signal)