Online Particle Detection by Neural Networks Based on Topologic Calorimetry Information

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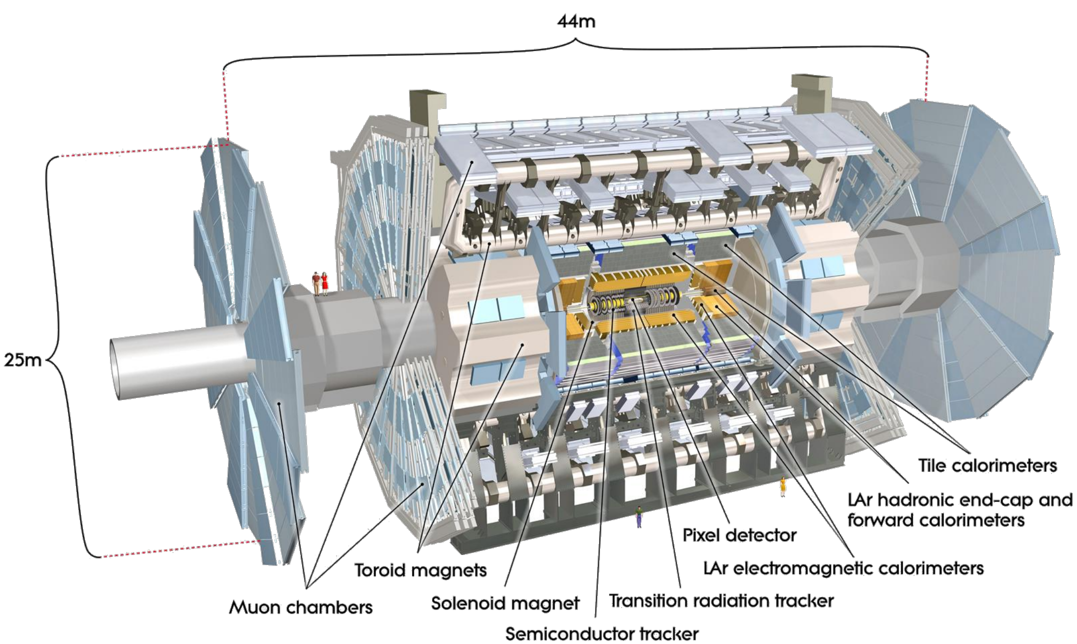
Agenda

- Introduction
- The Ringer algorithm
- Methodology
- Results
- Conclusions

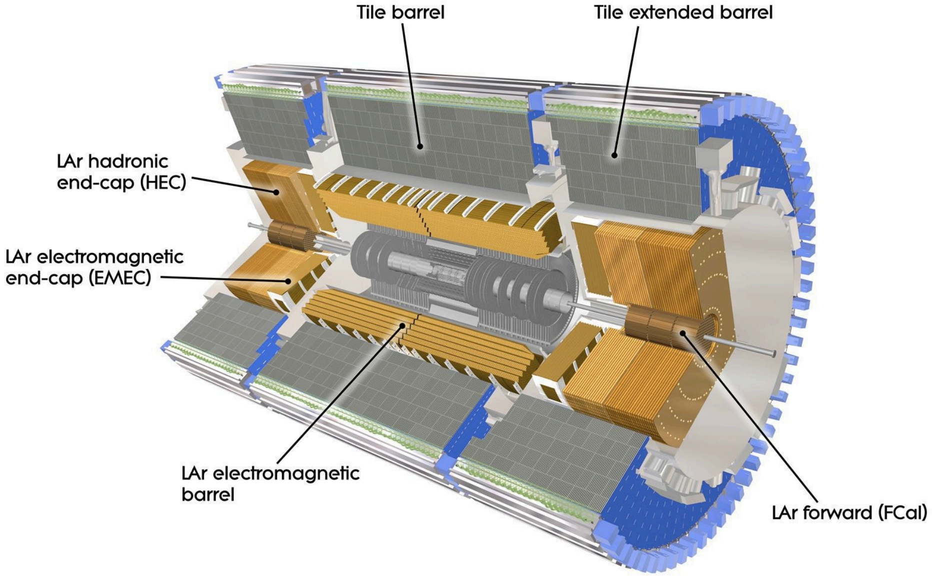
Introduction - ATLAS

- The ATLAS detector
  - Physics operation in the LHC beam line
  - Large amount of data from pp collisions
  - Currently, $\sqrt{s}$ = 7 TeV
  - Subdetectors
    - Inner tracker
    - Calorimeters
    - Muon detectors



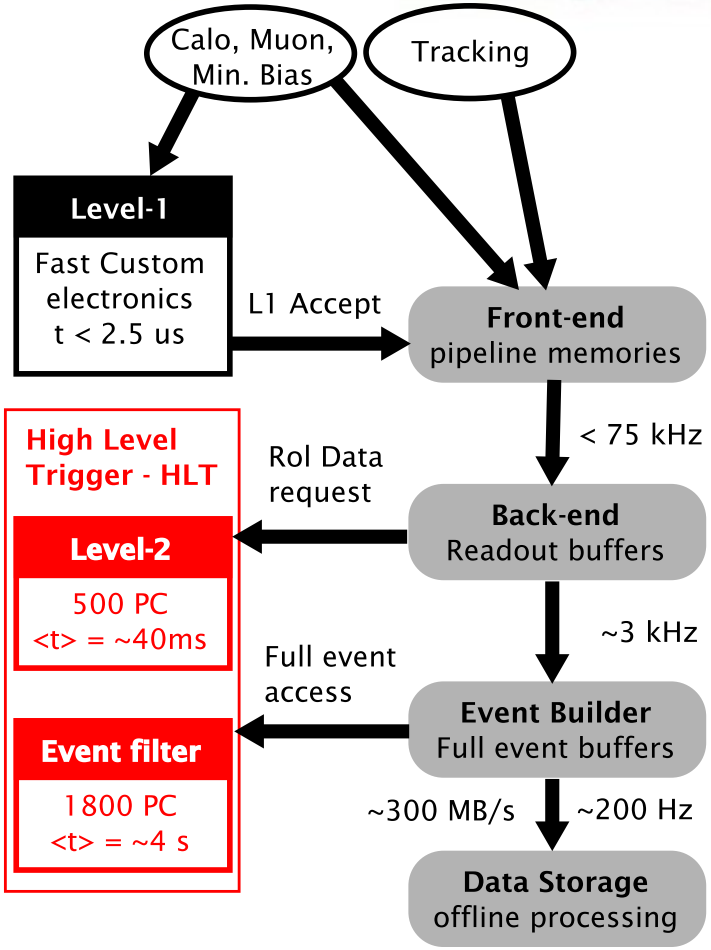
Introduction - Calorimeters

- Several technologies, multiple layers
- Lead / liquid argon electromagnetic (e.m.) calorimeters
  - 3 layers plus presampler
- Copper / liquid argon and iron scintillator hadronic calorimeters
  - 3 layers
- Tungsten rods / liquid argon as forward calorimeters to complete the detector
- Fine granularity for precise energy measurements
  - Improve particle identification
  - Heavy load for the data acquisition system



Introduction - Trigger System

- Level -1 (L1)
  - Based on hardware
  - Maximum of 2.5 us latency
  - Define Regions of Interest – RoI's
- Level - 2 (**HLT**)
  - Based on software (PC farm)
  - Mean processing time: 40 ms
  - Full granularity data within RoI
  - Specialized algorithms
- Event filter (**HLT**)
  - Based on software (PC farm)
  - Mean processing time: 4 s
  - Full event access
  - Adapted offline reconstruction algorithms

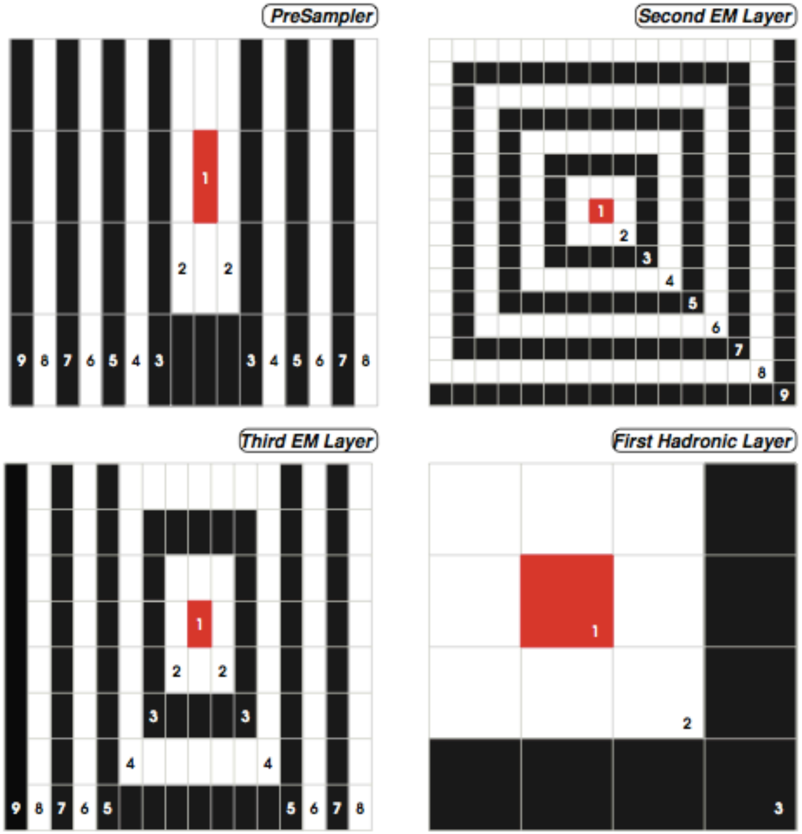


Introduction - Online Trigger

- Trigger Chain: sequence of reconstruction and selection algorithm
- Trigger Menu
  - Collection of trigger chains (and prescale factors)
  - Flexibility: menus and prescales evolve with LHC luminosity and physics requirements
- HLT Calo Algorithms
  - Set of algorithms running on HLT that use only calorimeter information
  - Common structures and designs (Feature Extraction - FeX - and Hypothesis test - hypo)
- Calorimetry plays an important role on electron identification
- L2 Neural Ringer alternative trigger algorithm
  - FeX by ring concentric sums
  - Artificial Neural Network for hypothesis testing

The Ringer Algorithm

- Operates over the RoI's identified by L1
- Feature extraction (FeX)
  - Rings built for each calorimeter layer
    - e.m. presampler + 3 e.m. layers + 3 hadronic layers
  - Forward calorimeter is not considered
  - Most energetic cell (layer based) is the first ring
  - Outer cells form the consecutive rings
- Hypothesis test (HYPO)
  - Feedforward MLP neural network



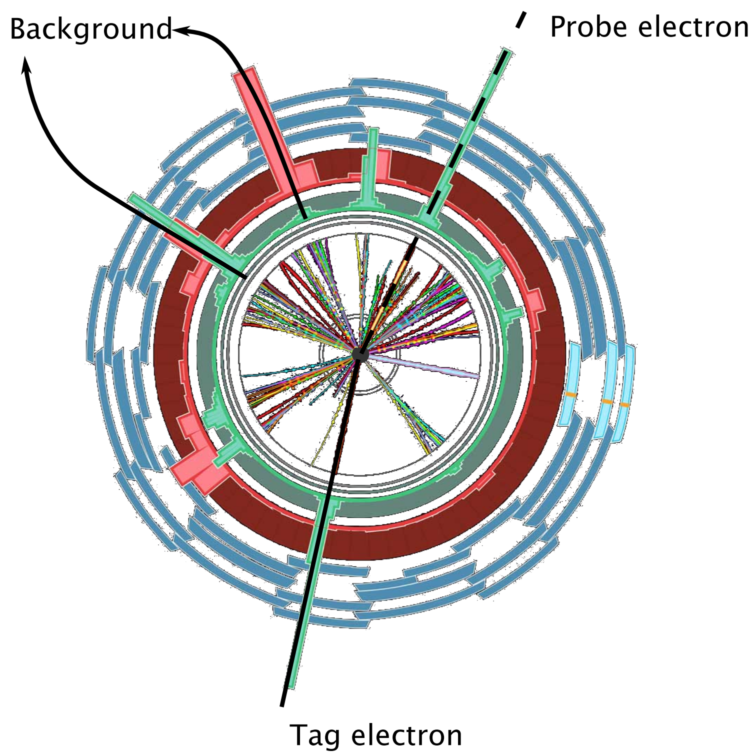
Methodology

- Simulated Monte Carlo data
  - Z->ee as signal
  - Jet as background
  - Pileup is also simulated
  - Nearly 10k events for each class

- Ringer implementation on HLT for collision operation
  - Detailed Valgrind analysis
  - Increase algorithm speed
  - Reduce total amount of data

Methodology

- Tag-and-Probe
  - Data-driven method for efficiency estimation
  - **Performance**: “Probe-like” objects within a properly “tagged” sample of events
  - Suitable for physics processes characterized by a double-object final state signature
  - Electron pairs must be considered by offline algorithms and the reconstructed mass should match the Z boson’s



Methodology

- Neural Network design
  - EM RoI’s matched to simulated electrons from Z boson
  - Jet: all fake EM RoI’s (L1 approved as EM) considered as background
  - **Normalization**: total energy as the factor
  - **Two sets**: development (train) and generalization (test), 50%-50%
  - Architecture
    - One hidden layer with 10 neurons (from previous works)
    - Hyperbolic tangent as activation function
      - Training targets: electron (1), jets (-1)
  - **Training method**: resilient back-propagation
    - Considers only the variation of the gradient descent sign
    - 100 different initializations: avoid local minima

Methodology

- SP index
  - Balanced design with respect to electrons (P_e) and a jet (P_j) identification probabilities

$$SP = \sqrt{\sqrt{P_e \times P_j} \times \left(\frac{P_e + P_j}{2}\right)}$$

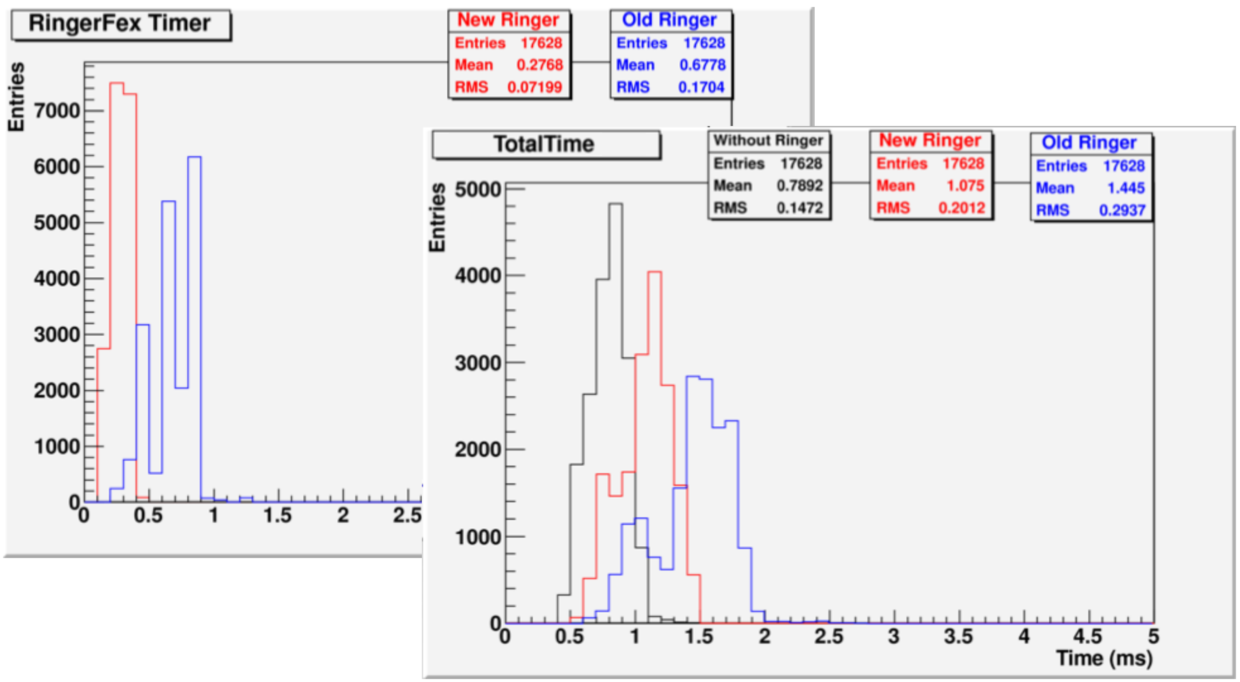
  - Discrimination threshold selected to maximize the SP index

- **Relevance mapping**: how much a ring is relevant for discrimination
  - Measured from the relative variation of the maximum SP index achieved when a given input is fixed to its mean value

$$R_i = \frac{SP_{full} - SP_i}{SP_{full}}$$

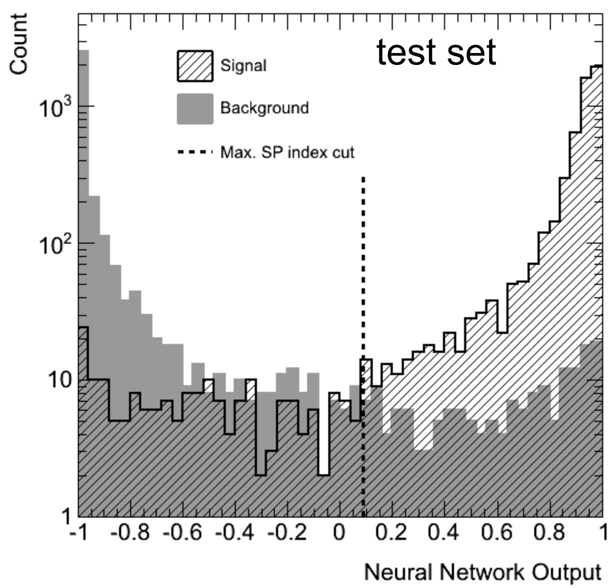
Algorithm Implementation

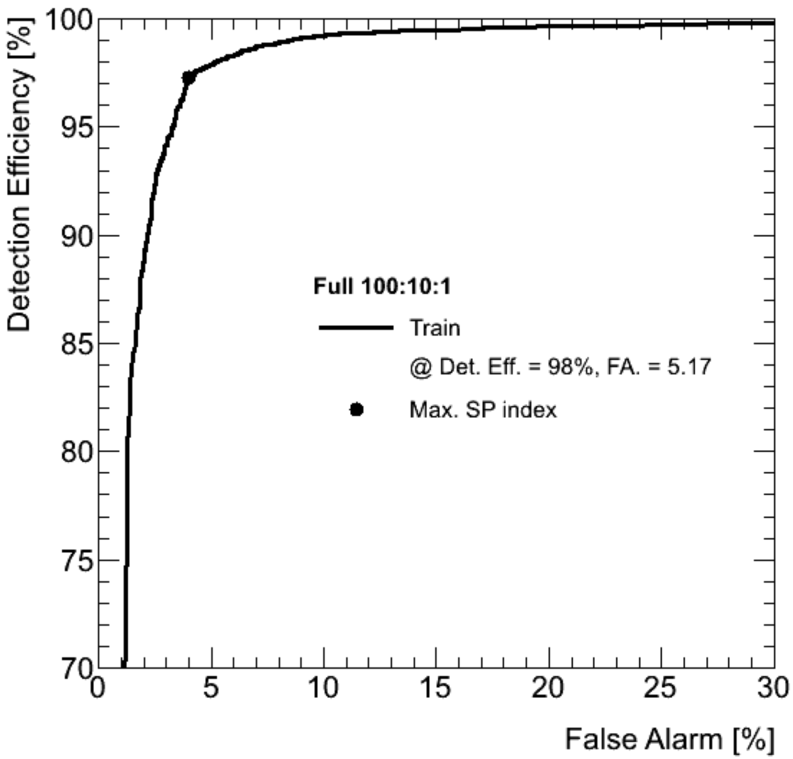
- Optimization led to a ~59% faster execution time (FeX)
  - Overhead of 0.3 ms/RoI
- Represents 6.2% of the total payload for electron/photon HLT algorithms



Neural Network Training

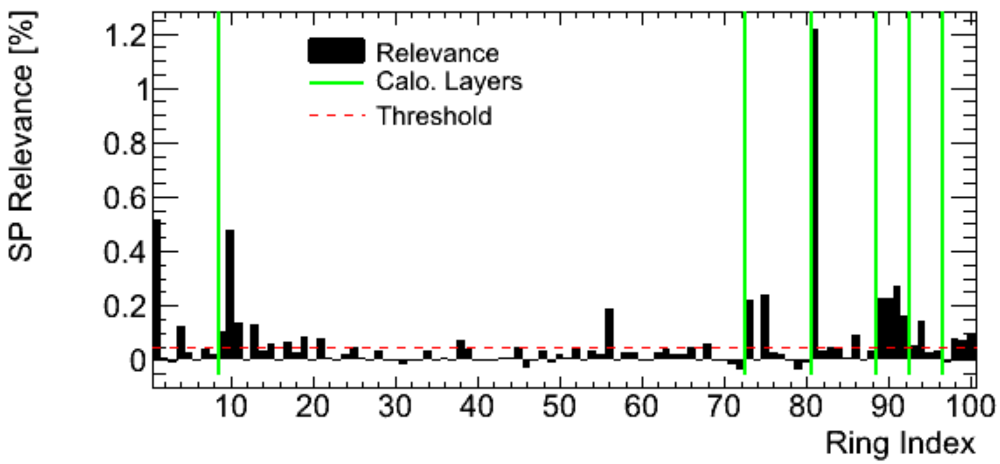
- ROC: receiver operating characteristic
  - Electron detection efficiency and jet false alarm (jet misclassified as electron) behavior as a function of the discrimination threshold, for all RoI's

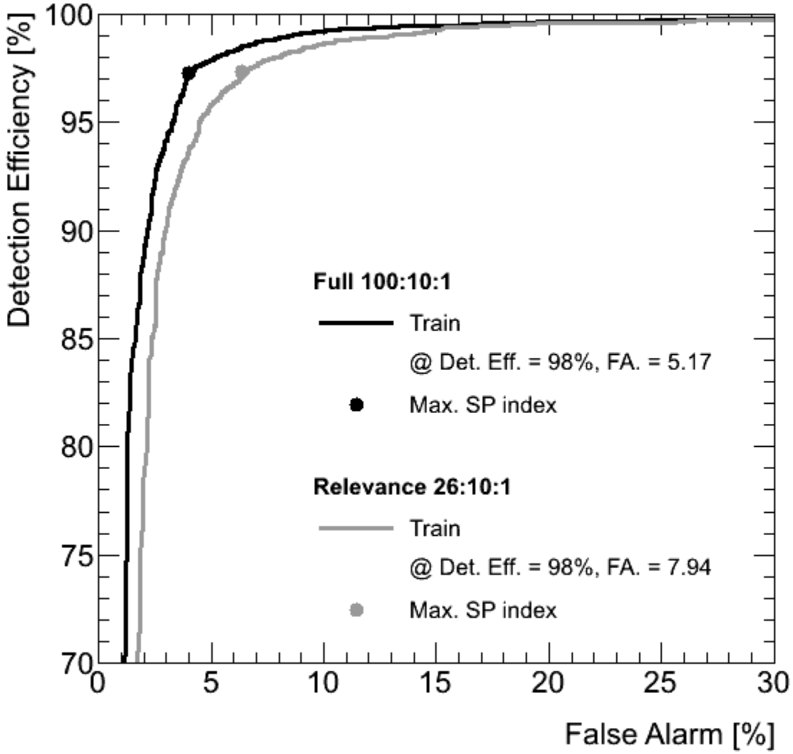




Neural Network Training

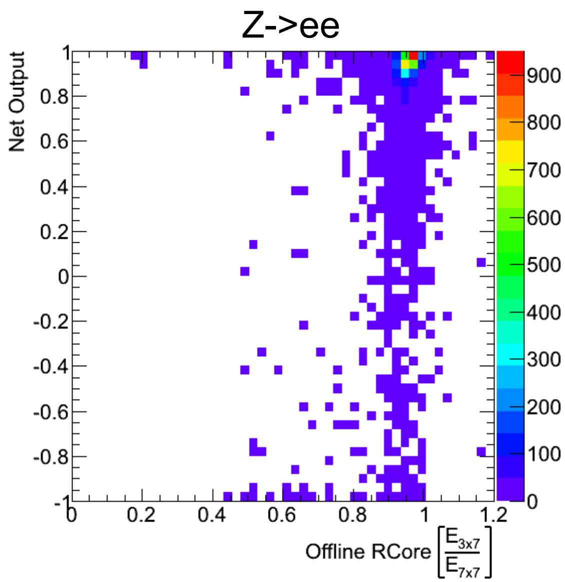
- Relevance
  - Considering the train set
    - 26 selected rings

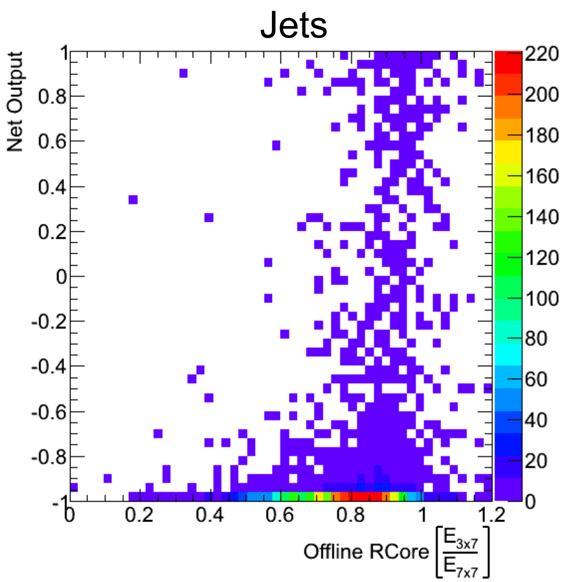




Neural Network Training

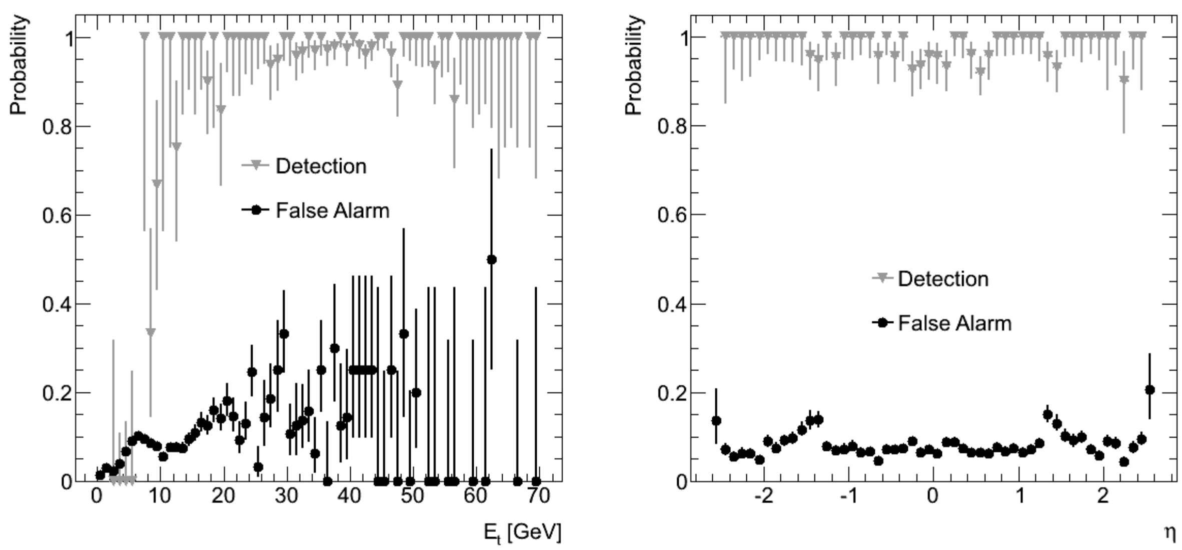
- Network output against one of the offline discriminant variable (test set)
  - Energy ratio (RCore): energy sum, at the second e.m. layer, in a 3x7 window on the ηxφ plane, divided by energy sum in a 7x7 window (both centered at the most energetic cell)
    - Close to unity for electrons (narrow electronic cascade)





Tag-and-Probe Evaluation

- Z->ee detection
  - Tag is the standard algorithm with strong criteria for electron selection
  - Probe is the neural network and its threshold maximizes SP index
- Jet false alarm: EM RoI's which have passed the neural network threshold



Conclusions

- Ringer implementation
  - Code optimization and architecture remodeling reduced the total algorithm execution time to 59% faster
  - Data payload represents 6% of total used by electron/photon algorithms at L2

- Algorithm performance with Monte Carlo simulations and pileup
  - Ringer is able to identify electrons with high performance
  - Trained neural networks could be used with collision data
    - Tag-and-Probe over the test set showed good performance
  - Relevance study reduced in 74% the neural network input dimension, with small impact on detection performance

- Guidance from offline quantity RCore shows good agreement with the neural network response for electrons and jets