Neural Online Filtering Based on Preprocessed Calorimeter Data

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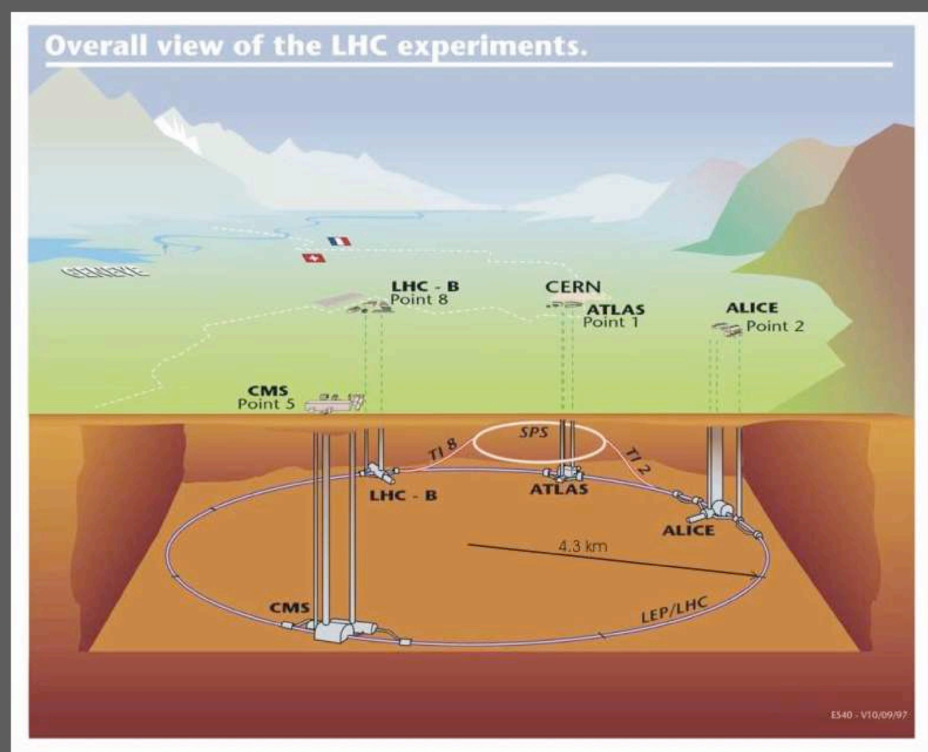
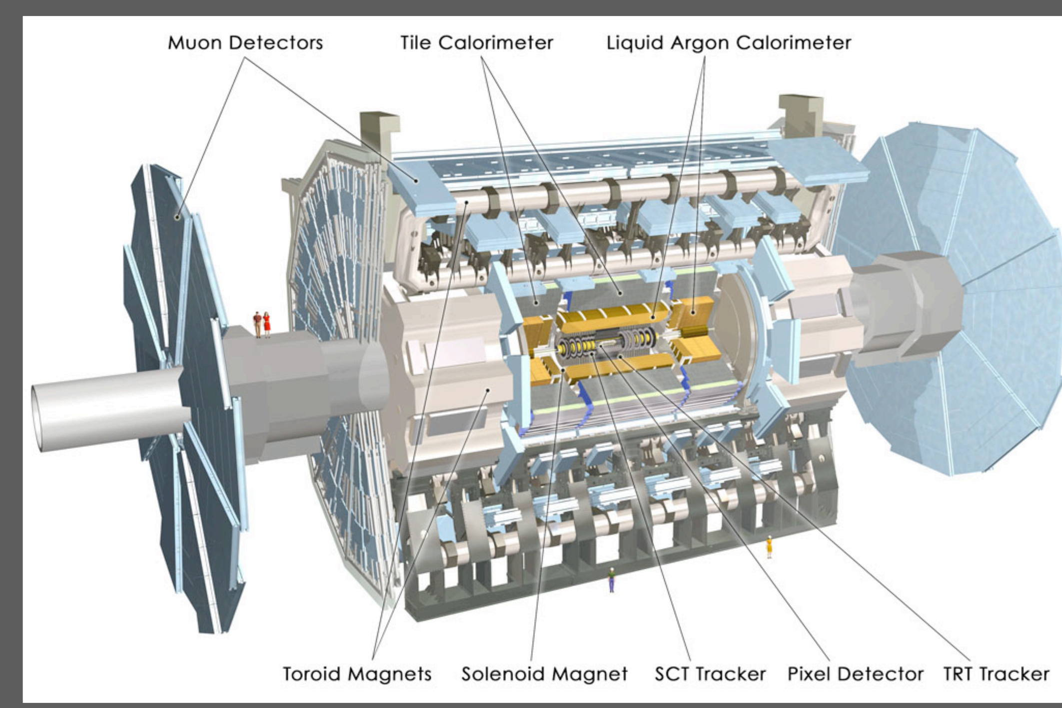
The LHC and the ATLAS Detector

The LHC is the largest particle accelerator in the world. With a circumference of 27 km, it will be capable of colliding protons with 14 TeV in their center of mass, with a total luminosity of 10^{34} $cm^{-2}s^{-1}$. By their collision, studies of the structure of matter can be performed. During nominal operation, LHC collisions will happen at a rate of 40 MHz.





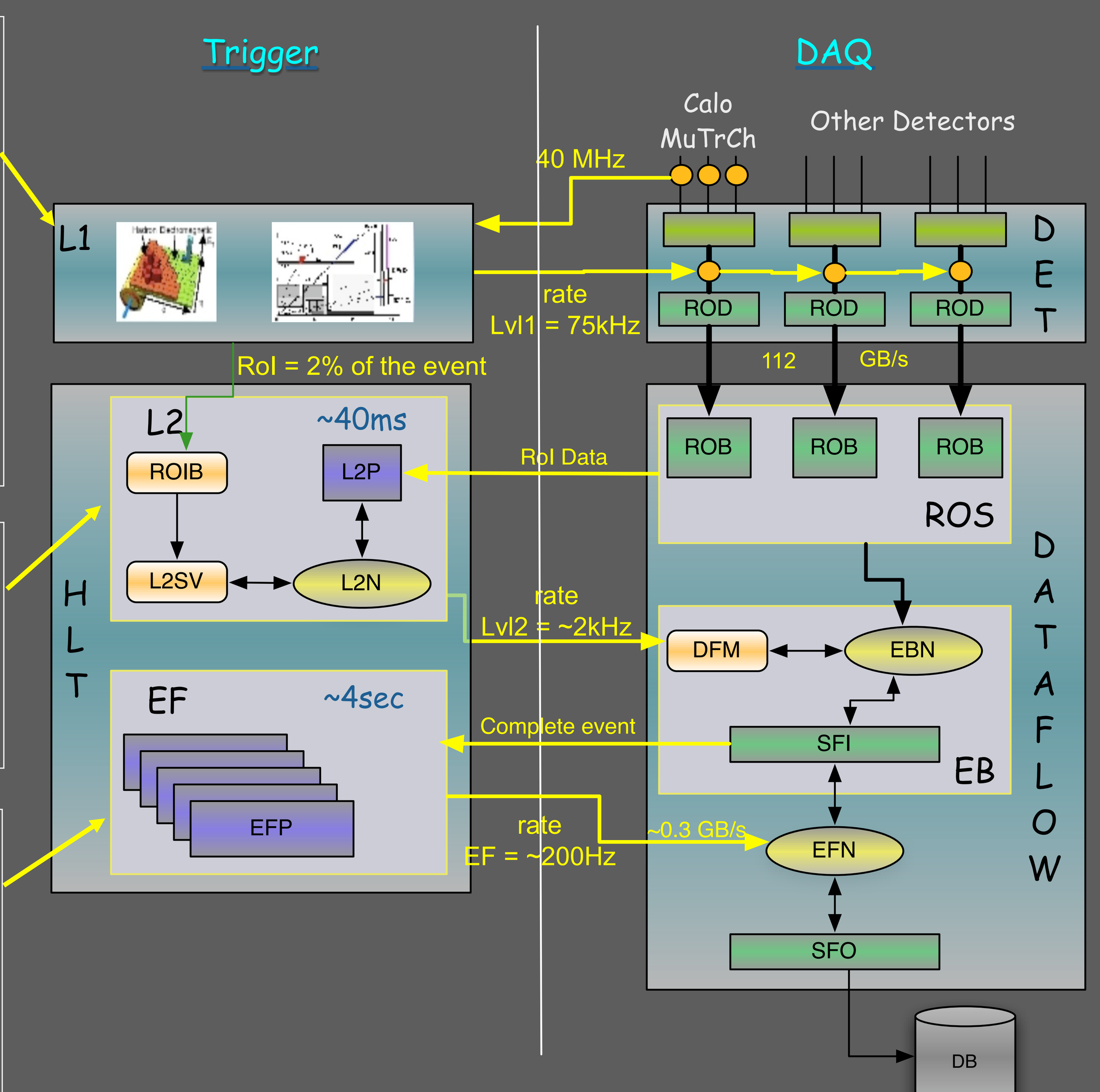
- General purpose detector comprising
  - Tracking
  - EM calorimeter (pre-sampler + 3 layers)
  - HAD calorimeter (3 layers)
  - Muon chamber
- Input data rate of ~60 TBytes/sec
- Rate has to be reduced to ~300 MBytes/s
- Online, three-level triggering system was developed.

The ATLAS Trigger and Data Acquisition

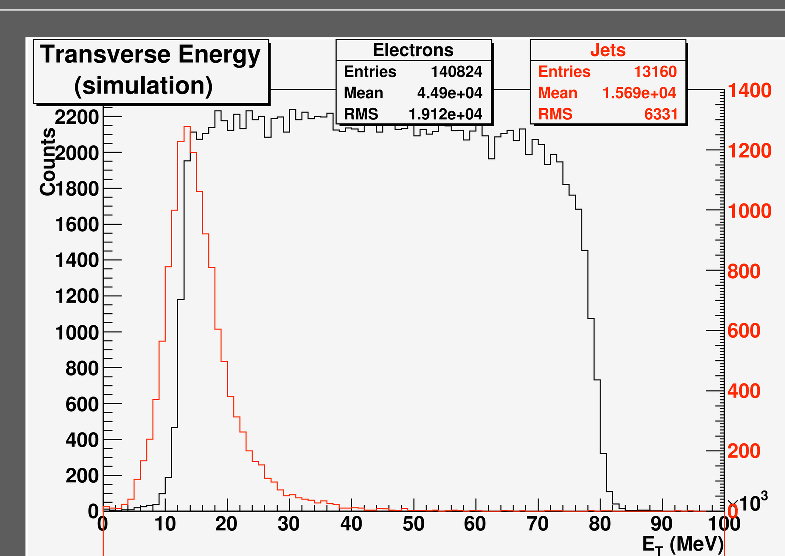
The hardware based first-level trigger (L1) performs a preliminary rejection using data from calorimeters and muon system. For a maximum latency of 2.5 µs, L1 operates with reduced detector granularity. Also, L1 marks the so-called Regions of Interest (RoI), which contain the η and ϕ directions of the identified L1 objects, as well as the transverse momentum thresholds that have been passed.

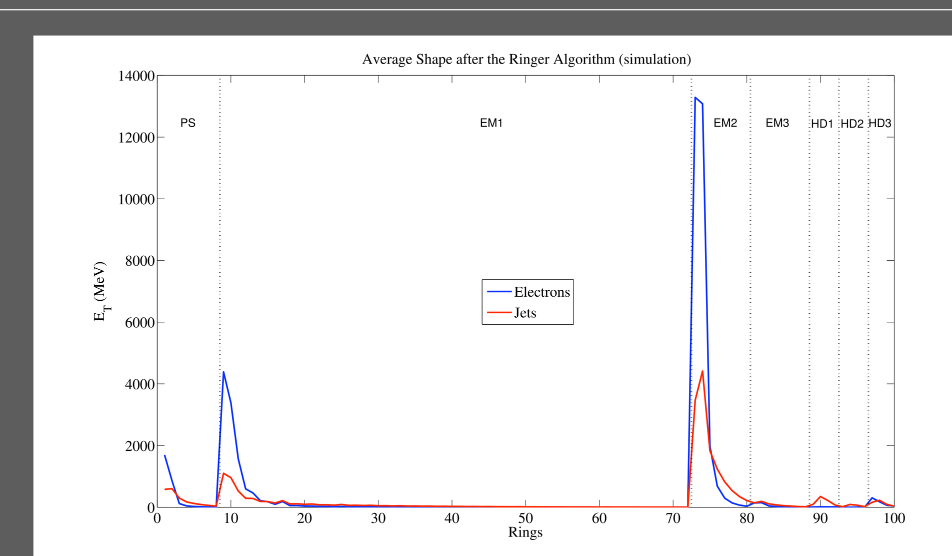
The second level (L2) will validate L1 decision by using full detector granularity, but focusing its analysis to the RoI received from L1. A mean processing time of 40 ms is expected for this level.

The event filter will look at the event's full information, in order to provide the final trigger decision. An average processing time of 4 sec is expected. Events passing this level are propagated to mass storage devices for further offline analysis.



Here, the NeuralRinger algorithm is developed as a candidate to perform L2 electron/jet separation based on calorimetry. Simulation data produced ~160k single electrons between 7 and 80 GeV in E_T and ~100k QCD dijets events, which contain at least one e/ɣ candidate with E_T > 17 GeV. Both datasets were initially pre-filtered by L1, considering energy, EM and HAD isolation. A total of ~140k electron and ~13k fake electron (jets) RoI reached L2 system.



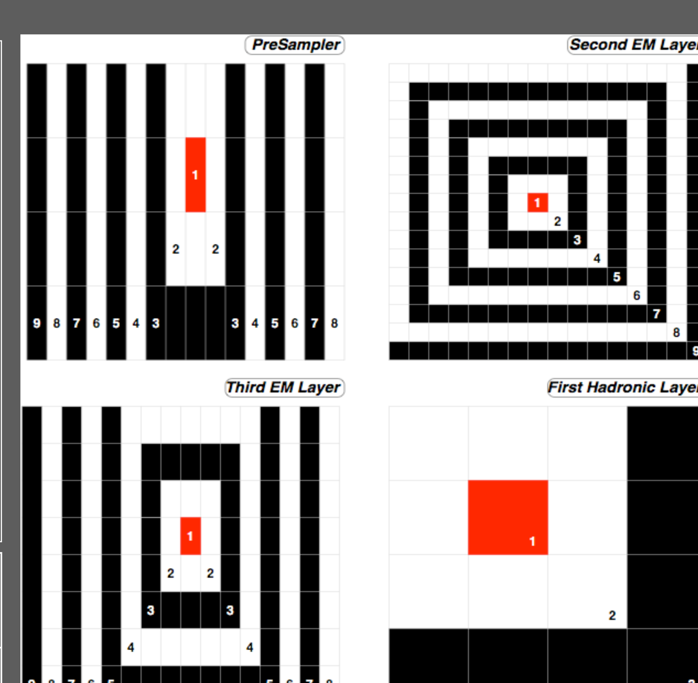


The Ringer Algorithm

Is responsible for extracting intelligent information from incoming particles, while maintaining their physics interpretation. For each calorimeter layer, a set of concentric rings, over a 0.4 x 0.4 (η,ϕ) window and centered at the hottest cell is generated. The cells belonging to a given ring are summed up, generating a single value. A total of 100 rings sum is produced. Finally, the rings sum are normalized by their total energy by computing:

$$r_i = \frac{r_i}{\sum_{j=1}^{100} r_j}$$

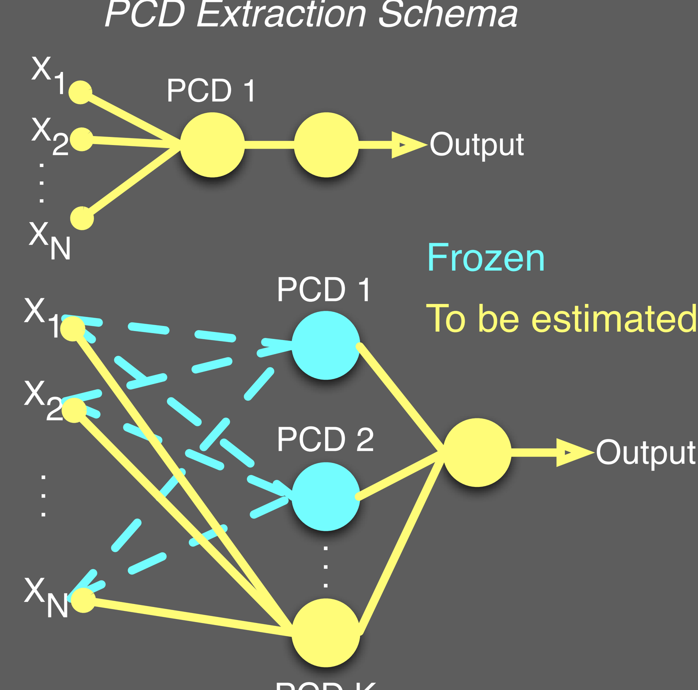
Calorimeter Section	Electromagnetic				Hadronic		
Calorimeter Layer	PS	EM1	EM2	EM3	HD1	HD2	HD3
# Rings	8	64	8	8	4	4	4



PCA / PCD Extraction

- **Principal Component Analysis (PCA)**
  - Data representation
  - Extracted by computing the eigenvectors of the covariance matrix
  - Ranked by reconstructed data variance
  - Drawback: minor components might be important for classification
- **Principal Component of Discrimination (PCD)**
  - Data discrimination
  - Extracted by finding the directions where the differences between classes are maximized
  - Ranked by their discriminating power
  - Employs an artificial neural network

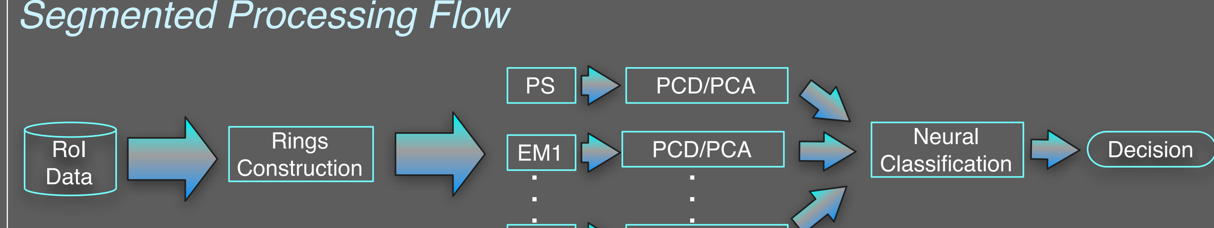
PCD Extraction Schema



Trigger e/ɣ Identification Step via Artificial Neural Networks

By applying non-linear cuts, the neural network is capable of better defining the boundaries of each class, resulting in higher detection efficiencies for equivalent rates, when compared to linear cuts. The neural network is fed from the concatenation of the PCA/PCD projection extracted on a per-layer (segmented) basis or from the 100 rings as a whole (non-segmented approach).

Segmented Processing Flow



Non-segmented Processing Flow

Results

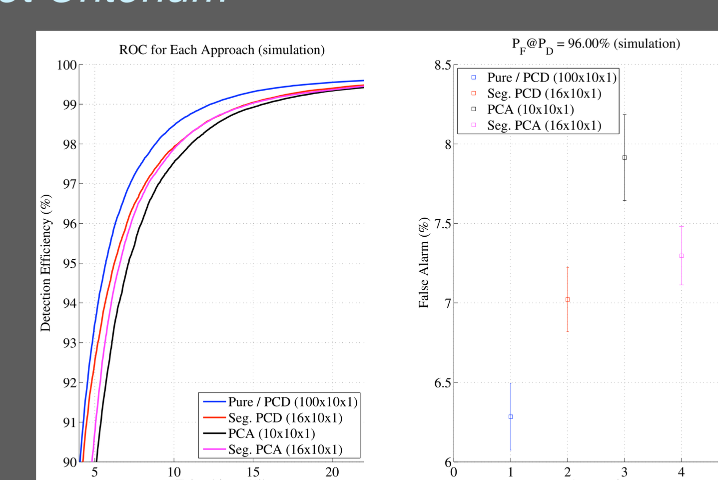
Component Selection: PCA Rank Based on Average Root Criterium

- *i-th* PCA retained if its eigenvalue (λ_i) satisfies the condition

$$\lambda_i > 0.7 \times \bar{\lambda}$$

- #PCD = #PCA

Approach	Segmented								Non-Segmented
Layer	PS	EM1	EM2	EM3	HD1	HD2	HD3	TOTAL	TOTAL
Number of Components	2	5	2	2	2	2	1	16	10
% Variance	95.1	96.6	93.2	68.9	79.2	79.2	72.1	N/A	95.3

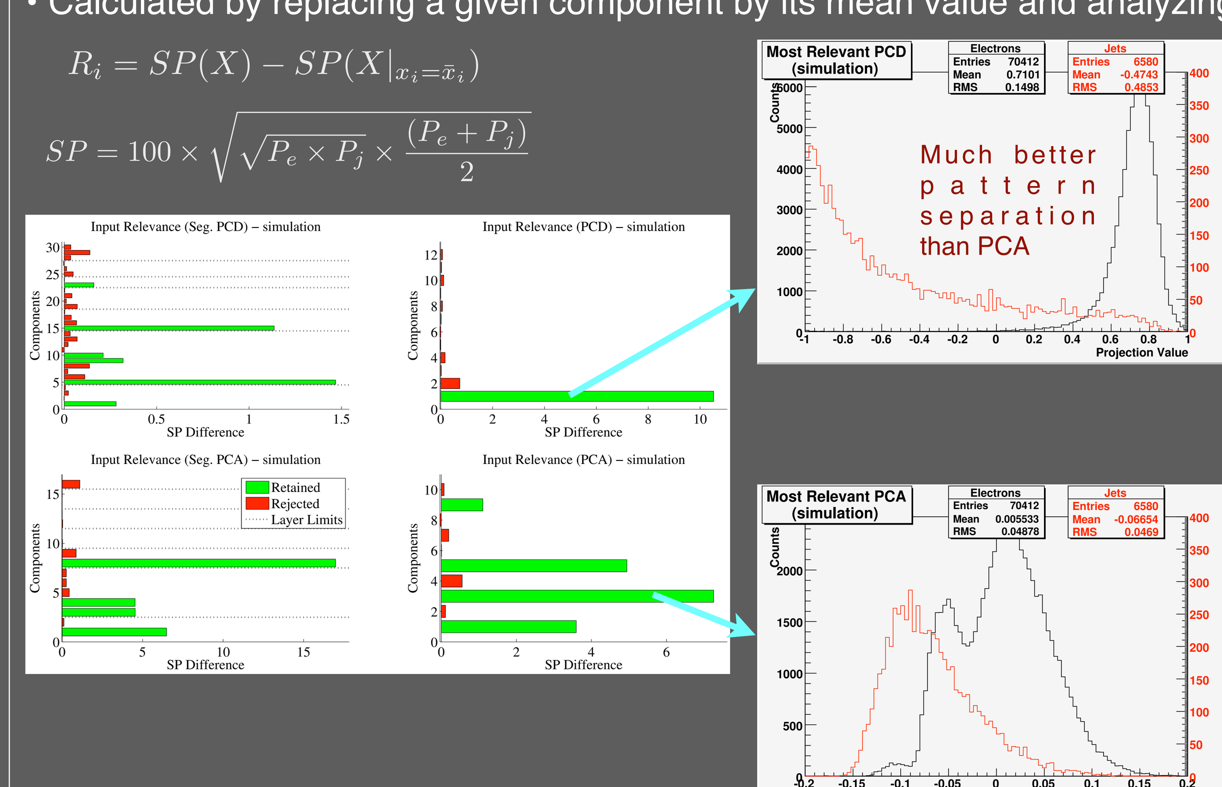


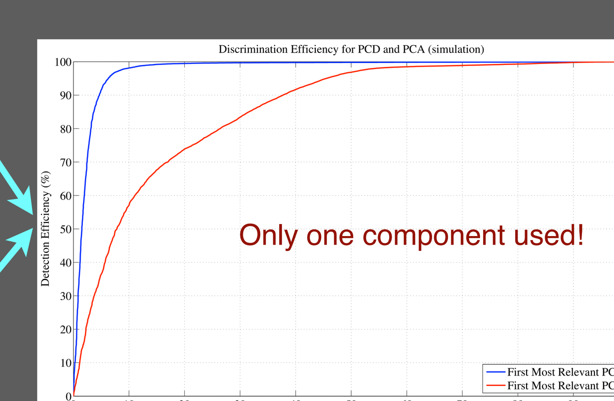
Component Selection: Relevance Mapping

- Points to the best components for classification
- Calculated by replacing a given component by its mean value and analyzing the classification performance

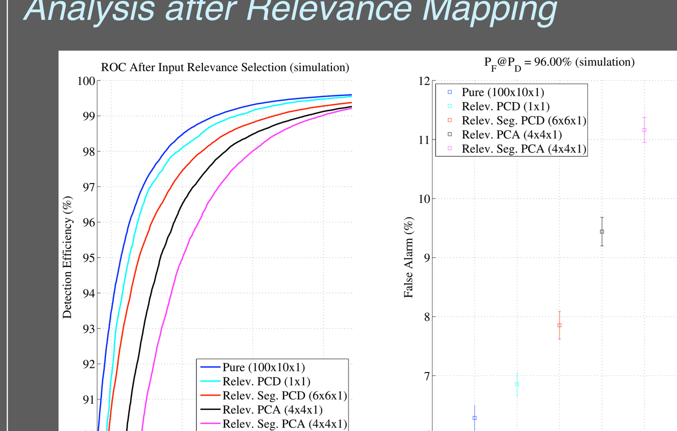
$$R_i = SP(X) - SP(X|_{x_i = \bar{x}_i})$$

$$SP = 100 \times \sqrt{\sqrt{P_e \times P_j} \times \frac{(P_e + P_j)}{2}}$$

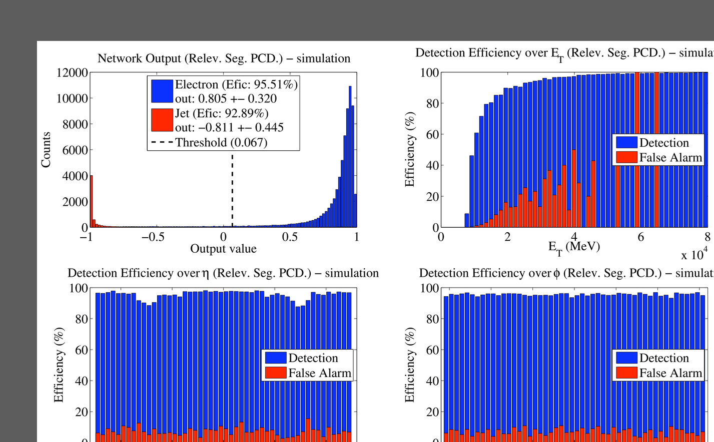




Analysis after Relevance Mapping



Validation studies considering the Segmented PCD case after relevance cut



Conclusions

- Good compaction levels achieved either by PCA and PCD
- PCD achieved better detection efficiencies than PCA, for the same number of components
- Segmented approach allows better interpretation on how each layer contributes to the discrimination result
- Relevance analysis pointed that only one PCD for the non-segmented case suffices, showing that a linear discriminant might be already a reasonable candidate for the pattern recognition section
- Relevance works like a knob for detection efficiency x processing speed trade off.

Acknowledgment

The authors would like to express their gratitude to CNPq, FINEP, CAPES, FAPERJ (Brazil) and CERN (Switzerland) for the support. We also thank the ATLAS collaboration at CERN for providing the simulated calorimeter data and for fruitful discussions concerning this work.