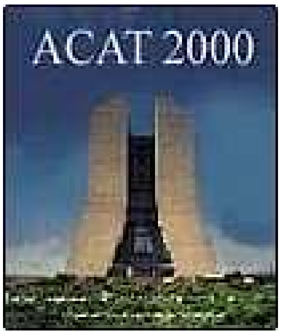

Principal Component Analysis for Neural Electron/Jet Discrimination on Highly Segmented Calorimeters

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SUMMARY

- Introduction
- Data Analysis
- Principal Component Analysis
- Results
- Conclusion

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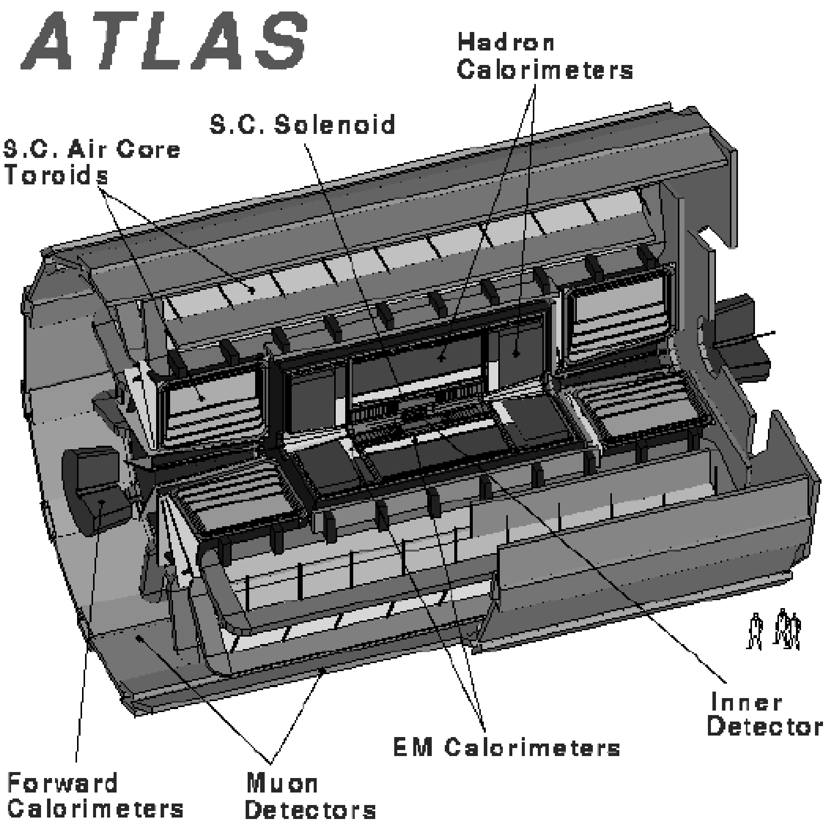
INTRODUCTION

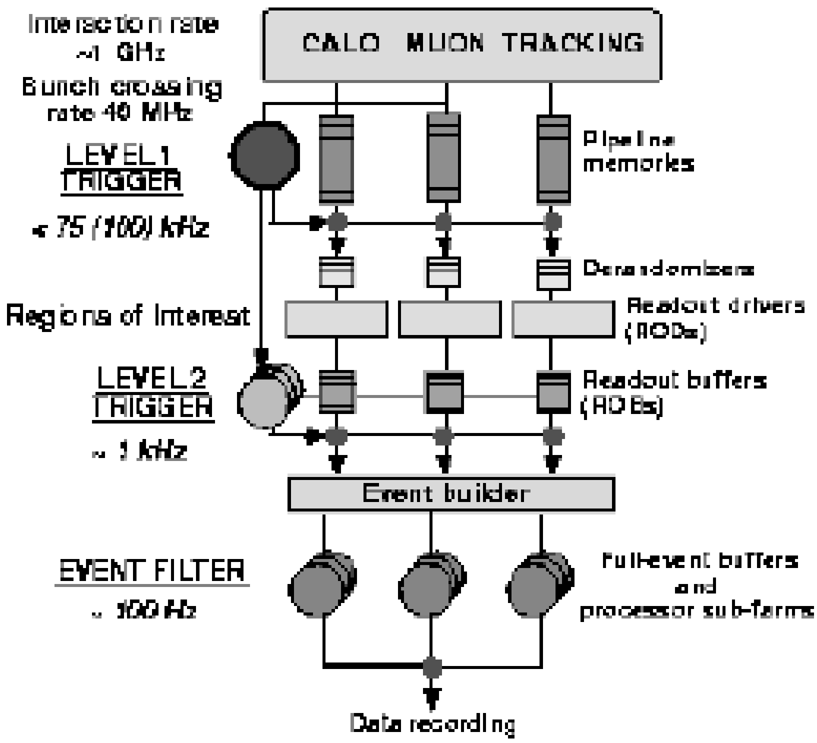
- By 2005, LHC (Large Hadron Collider) will be colliding protons of 14 TeV at periods of 25 nanoseconds;

- ATLAS is one of the detectors of LHC, and its triggering system is split into three levels $\longrightarrow$ high event rate;



INTRODUCTION

- Calorimetry is very important for the second-level triggering system of ATLAS detector, where the event rate amounts to 10^8 events/cycle (expected rejection factor of 100, for the level-two system);



INTRODUCTION

- The electromagnetic and hadronic calorimeters are highly segmented, providing a detailed information on the energy deposition profile;

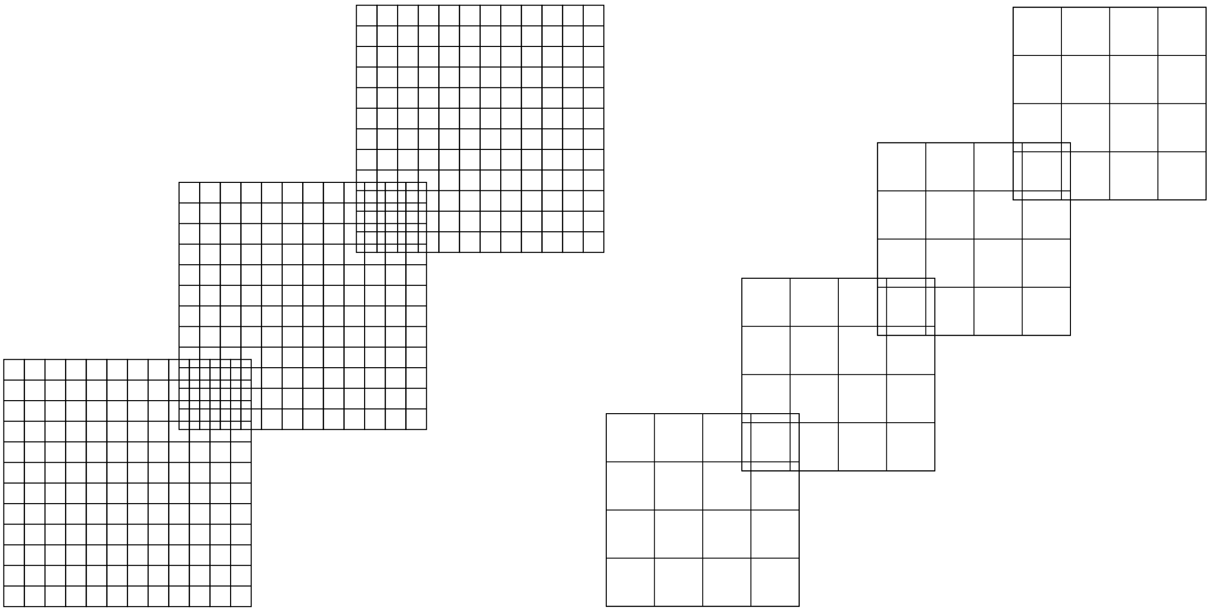
- The high dimensionality of the orignal data space (496) recquires preprocessing techniques for data compaction, able to retain the relevant information for the triggering task;

- The use of principal component analysis for data compaction and neural networks for electron/jet discrimination will prove to be a very attractive approach .

DATA ANALYSIS

The simulation data were based on the following configuration for the calorimeter system:

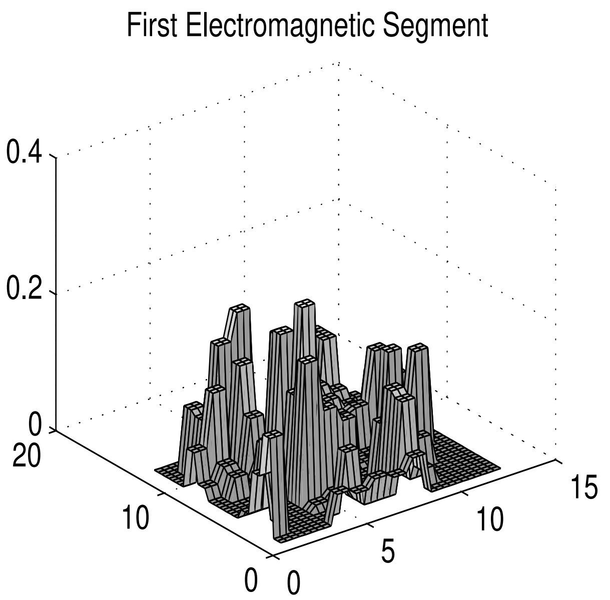
Electromagnetic $\longrightarrow$ 3 segments (144 cells each)
Hadronic $\longrightarrow$ 4 segments (16 cells each)

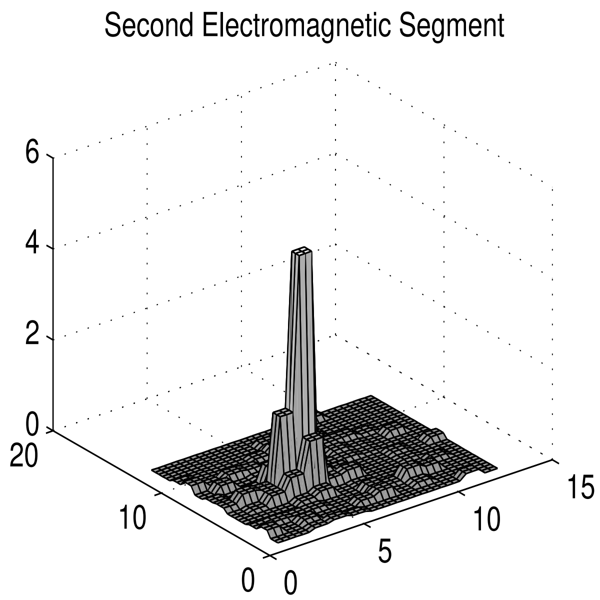


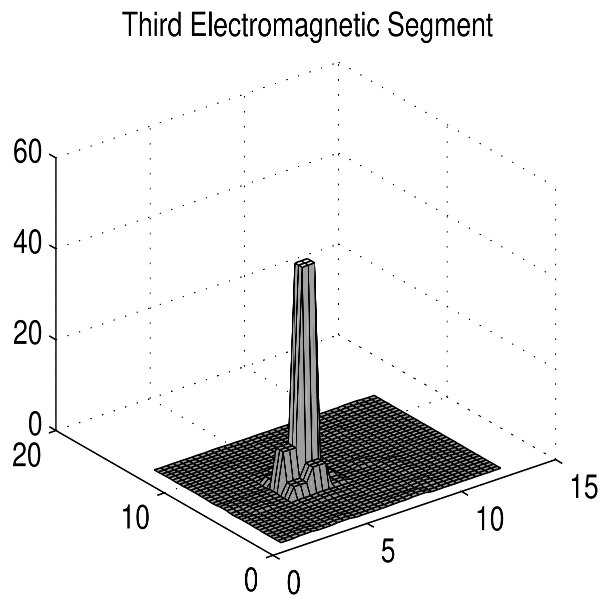
Total Dimension: 3x144 + 4x16 = 496.

DATA ANALYSIS

Typical electron event readout by electromagnetic calorimeter segments

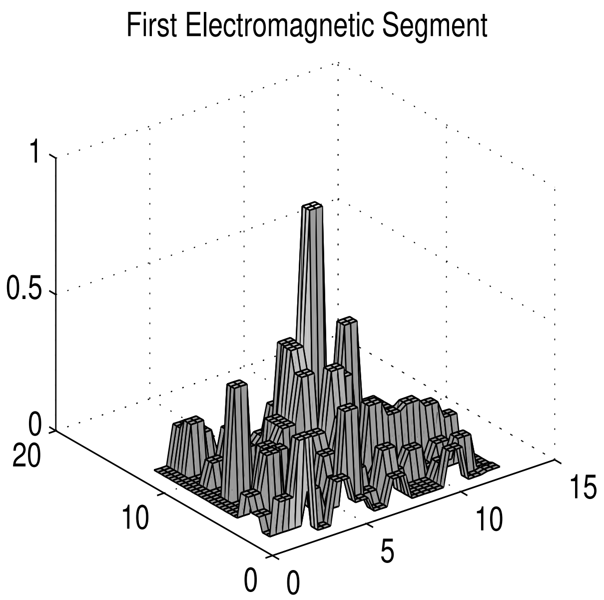


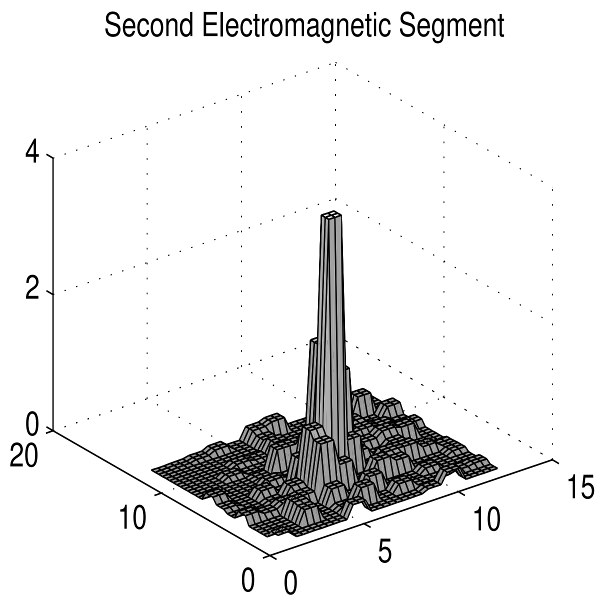


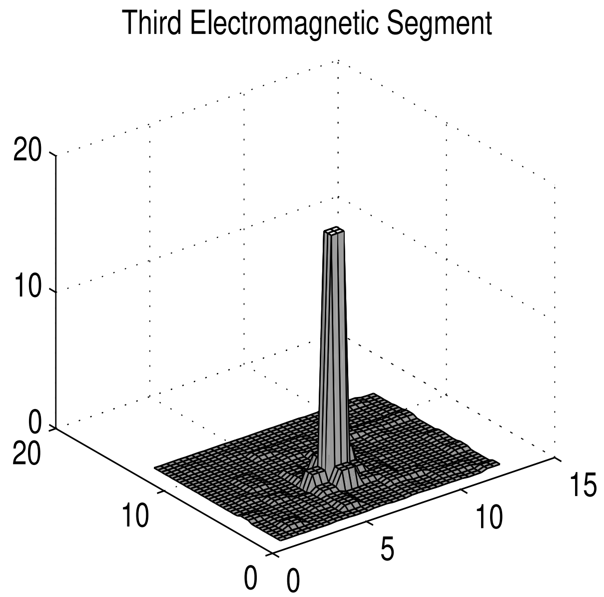


DATA ANALYSIS

Typical jet event readout by electromagnetic calorimeter segments







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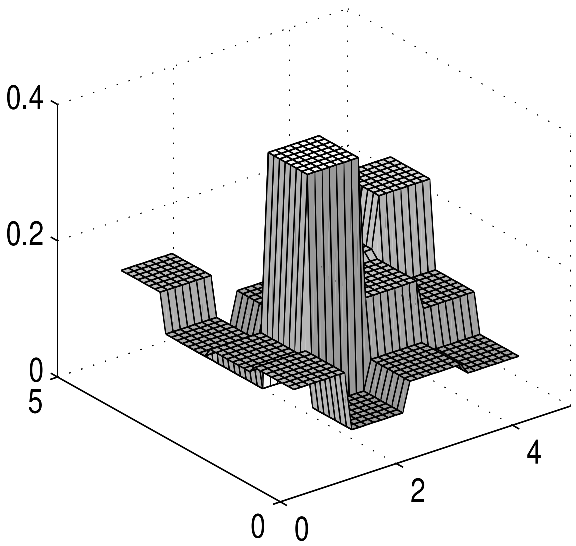
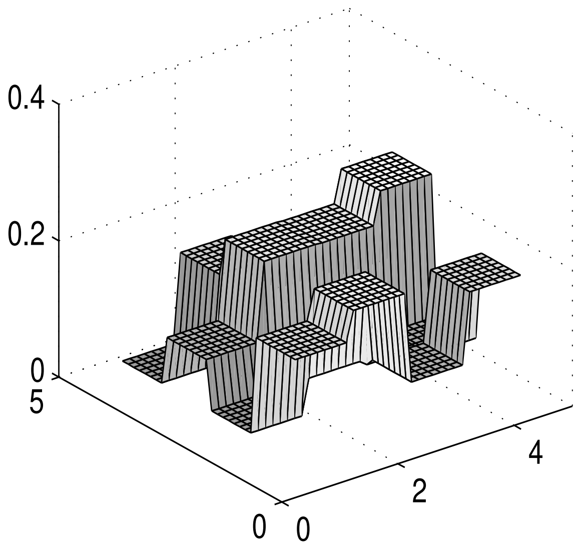
DATA ANALYSIS

Typical electron event readout by hadronic calorimeter segments

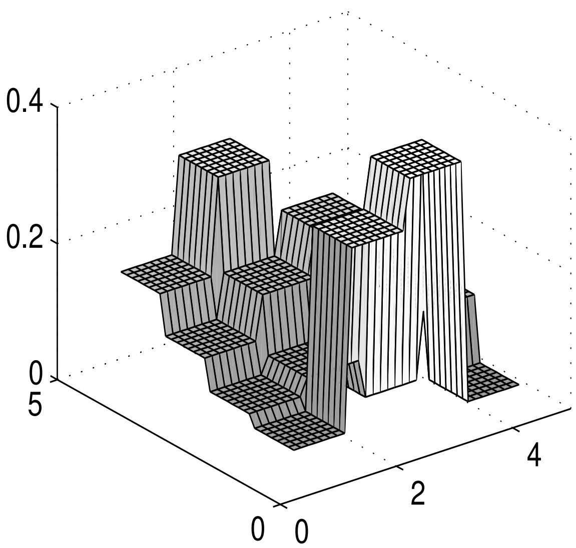
First Hadronic Segment



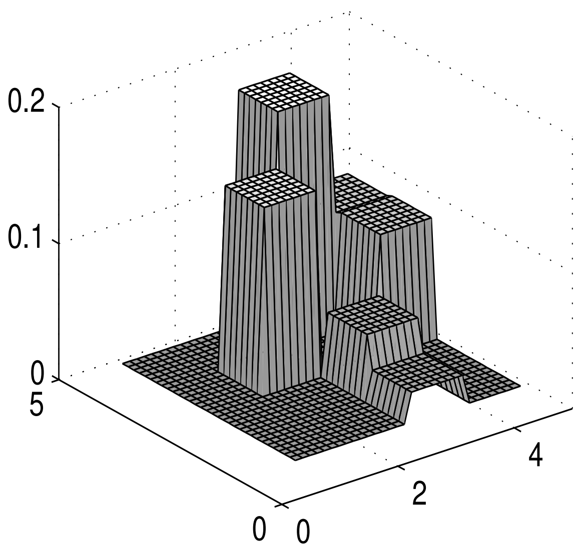
Second Hadronic Segment



Third Hadronic Segment

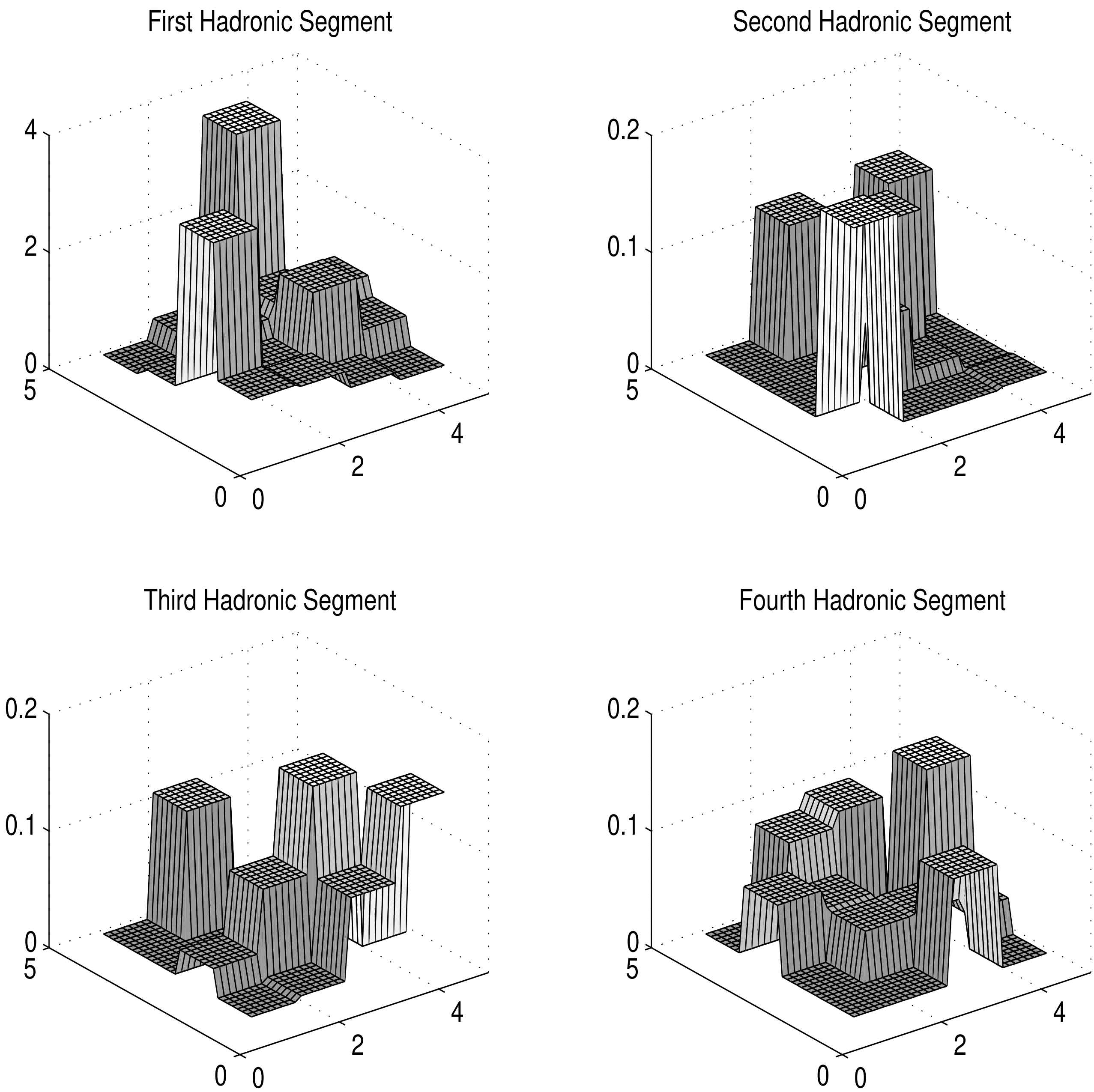


Fourth Hadronic Segment



DATA ANALYSIS

Typical jet event readout by hadronic calorimeter segments



PRINCIPAL COMPONENT ANALYSIS

$\Longrightarrow$ Based on KLT (Karhunen-Loève Transform) $\longrightarrow$ Data reconstruction from a basis of eigenvectors (data variance as figure of merit).

$\Longrightarrow$ Components were extracted from each segment, to take advantage from the segmented topology of the calorimeters.

$\Longrightarrow$ These components may be extracted by two methods: classical and neural.

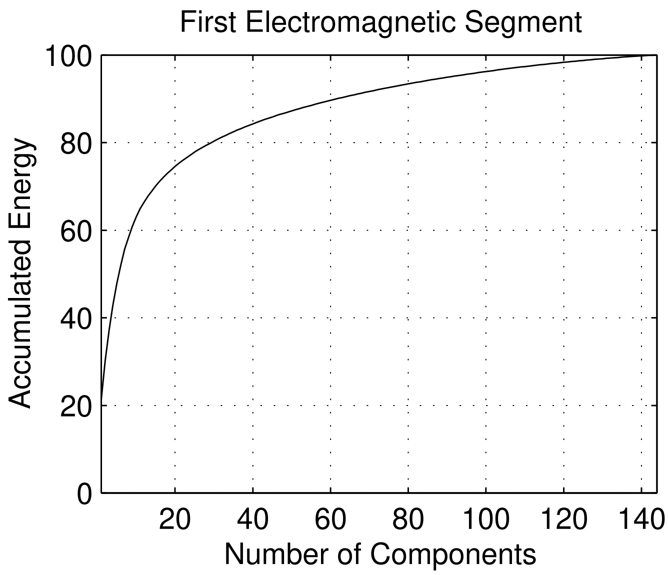
- Classical Method: eigenvectors of the autocorrelation matrix, ordered in decreasing order of the corresponding eigenvalues (data variance, energy).

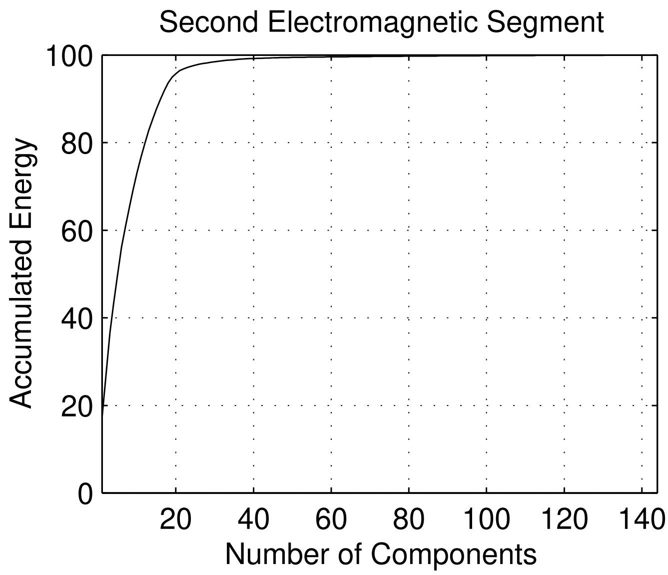
- Neural Method: Supervised or unsupervised training.

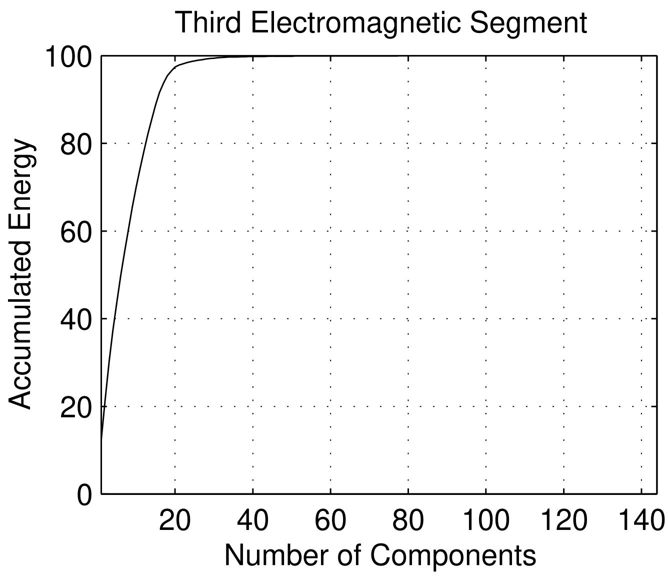
PRINCIPAL COMPONENT ANALYSIS

Reconstruction

Electromagnetic Calorimeter



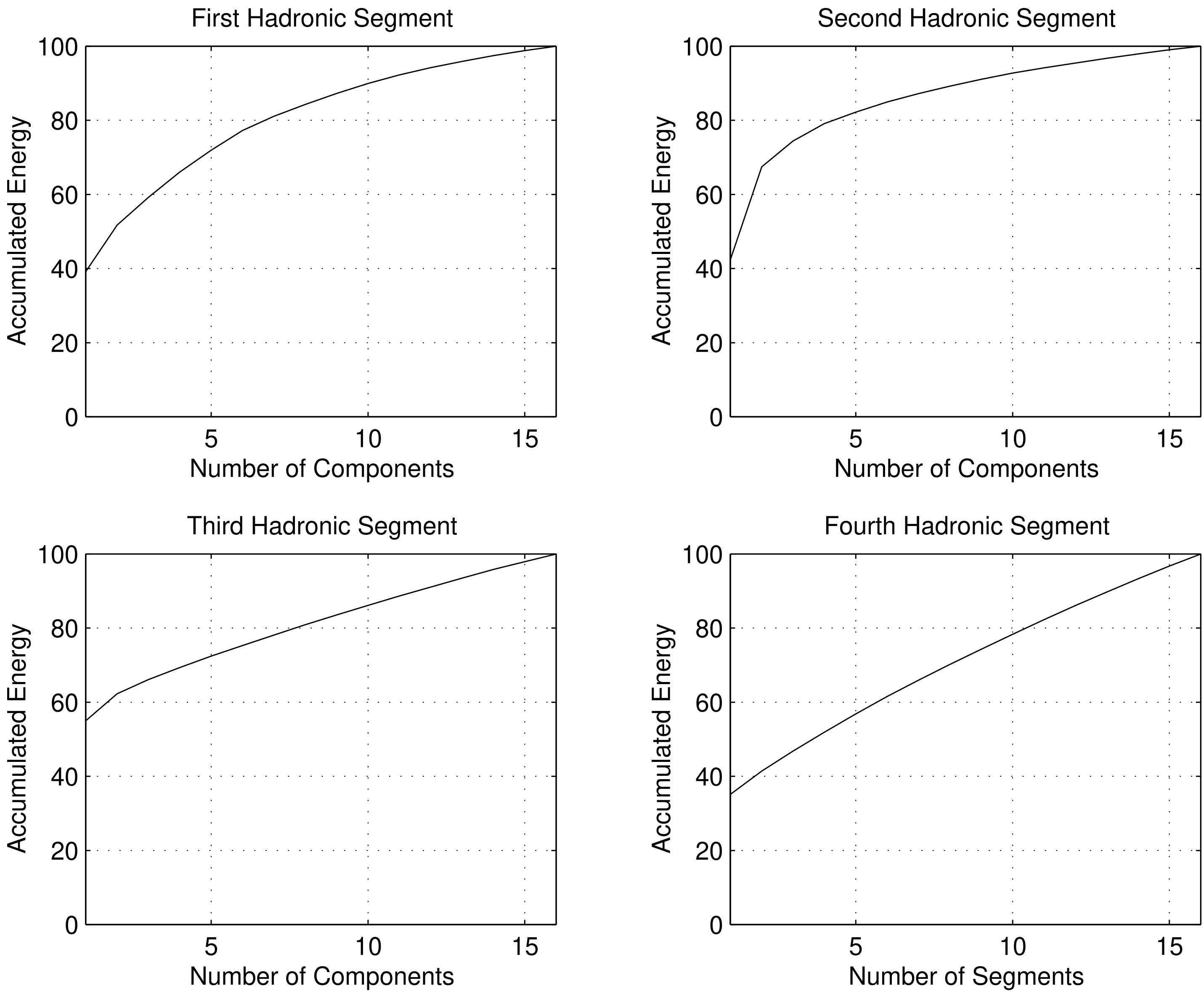




PRINCIPAL COMPONENT ANALYSIS

Reconstruction

Hadronic Calorimeter



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RESULTS - NN Topology

The projections of the events onto the selected components compose the input data for the neural discriminator.

NEURAL DISCRIMINATOR:

- Three-layer Neural Network (MLP $\longrightarrow$ Multilayer Perceptron);
- No. of input nodes $\longrightarrow$ No. of components selected;
- 33 neurons in hidden layer and 1 neuron for the output layer;
- The hyperbolic tangent was selected as the activation function for all neurons;
- Backpropagation method was used to train the network;
- Results are shown for the test set.

RESULTS

Data Set

Data Sets	Number of Events	
	Electrons	Jets
Training Set	1264	343
Testing Set	1264	342
TOTAL	2528	685

Normalization

$\longrightarrow$ Electromagnetic Calorimeter: the projections of each event have their elements divided by the total amount of energy deposited on the electromagnetic calorimeter for that event.

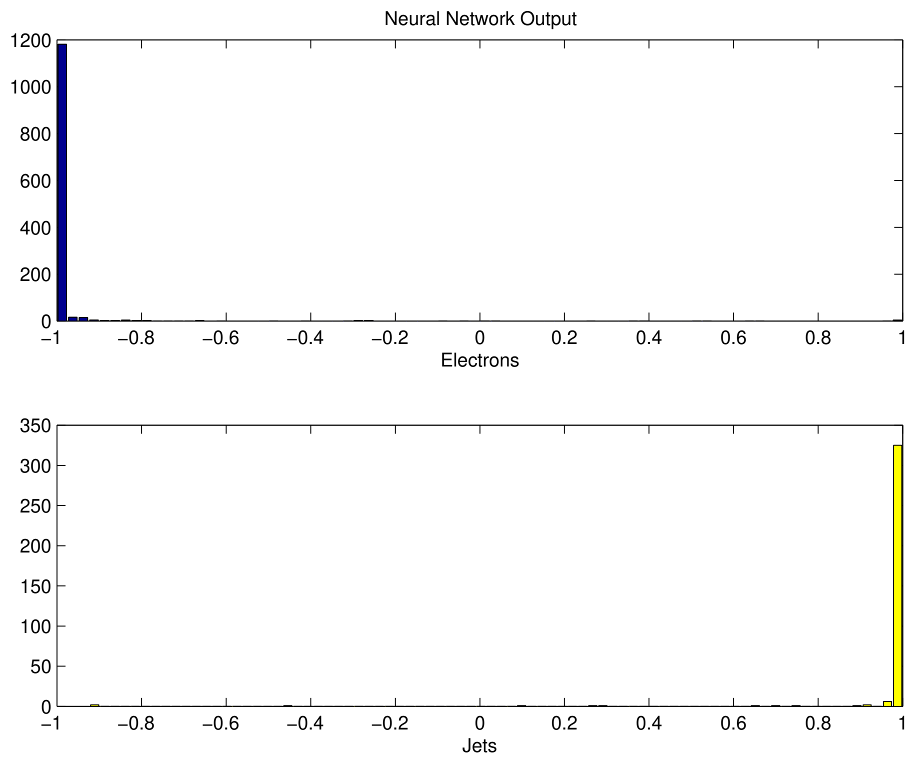
$\longrightarrow$ Hadronic Calorimeter: there is no normalization procedure. The projections of the events are directly fed into the neural discriminator.

RESULTS - Component Selection

Best efficiency (33 components):

Segment	Electromagnetic Calorimeter	Hadronic Calorimeter
	No. of Extracted Components	No. of Extracted Components
First	2	7
Second	4	7
Third	4	7
Fourth	-	2

With just 33 components, the electron efficiency was 98.9% with a false alarm probability (jets misclassified as electrons) smaller than 1%.



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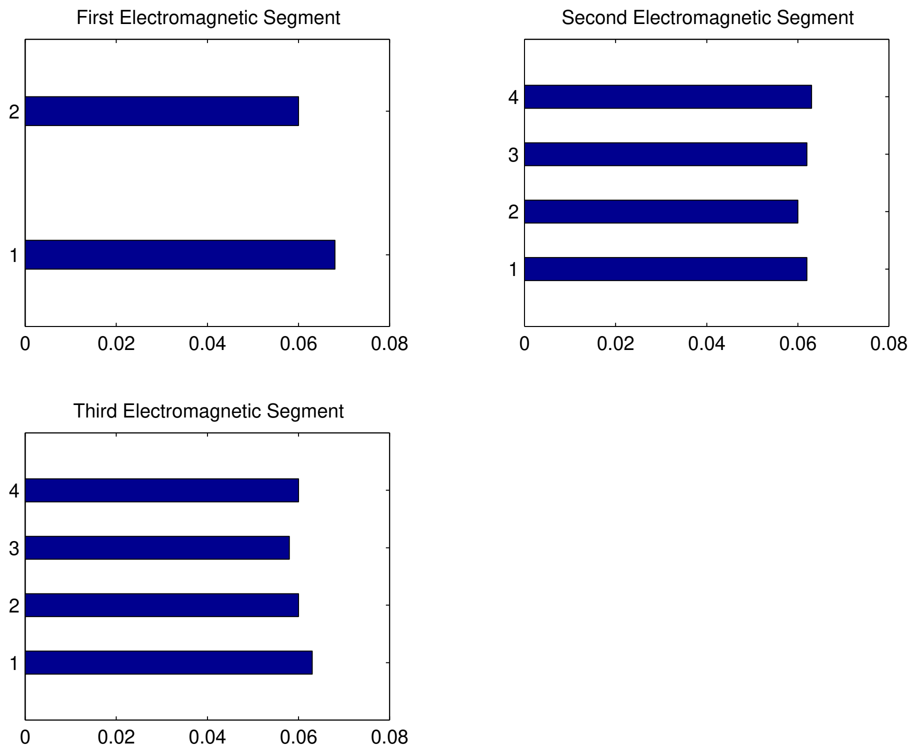
RESULTS - Relevance

Relevance for the i-th Component

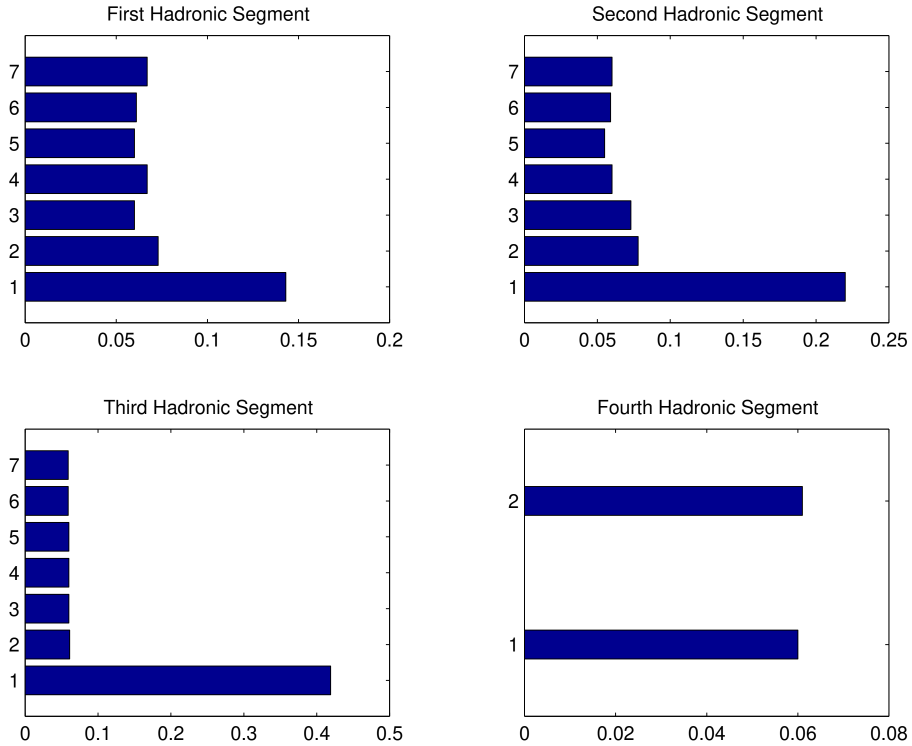
$$R_i = \frac{1}{N_{pattern}} \sum_{j}^{N_{pattern}} \left(out(\overrightarrow{x_j}) - out(\overrightarrow{x_j}|_{x_{j,i}=\bar{x_i}}) \right)^2$$

Components of the Electromagnetic Calorimeter



RESULTS - Relevance

Components of the Hadronic Calorimeter

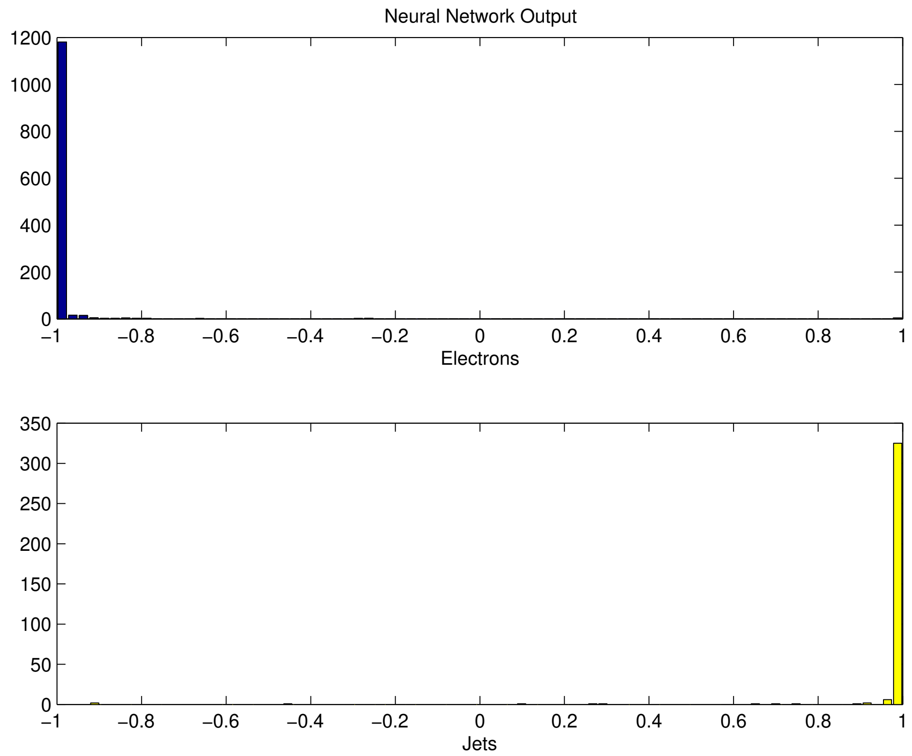


RESULTS - Relevance

From the relevance analysis, just nine components were selected:

Segment	Electromagnetic Calorimeter Components (first)	Hadronic Calorimeter Components (first)
First	1	2
Second	1	2
Third	1	1
Fourth	-	1

The electron efficiency decreased to 97.9% with 2% of false alarm.
ADVANTAGE: Faster!



RESULTS

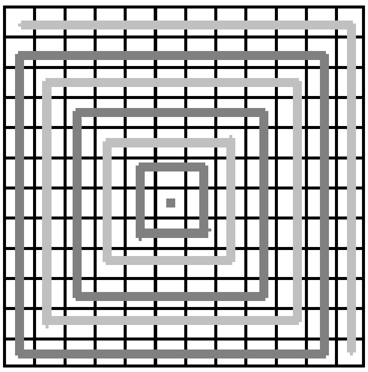
Comparison with other methods:

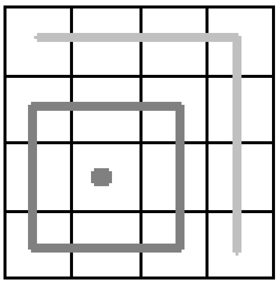
Method used for discrimination	**Electron Efficiency (%)**	**Misclassified Jets (%)**
Neural Network using 33 Non-segmented principal components	72.4	39
Matched Filters (approximation)	76.0	32
Neural Network directly on energy cells (496)	97.9	10
Neural Network using 9 principal components	99.1	3
Neural Network with topological mapping (Rp) and rings	98.7	2
Neural Network using 33 principal components	98.9	1

R_p Mapping:

$$(E_i, r_i) \longrightarrow \frac{E_i^\alpha r_i^\beta}{\sum E_i^\alpha}$$

Rings:





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CONCLUSION

- Segmented principal component analysis was developed envisaging to perform neural calorimetry trigger for the second-level triggering system of ATLAS at LHC conditions;

- High detection efficiency (98.0%) for low false alarm rate (1%) was achieved using only 33 components;

- Faster high-efficiency pre-trigger is possible using only 9 components;

- The neural discrimination using the compaction provided by segmented PCA is better than that obtained with unsegmented data analysis;

  PRINCIPAL COMPONENTS $\longrightarrow$ Data Compaction + Improved Neural Discrimination Efficiency

- It is possible to combine PCA with topological mapping methods;

- On going hardware implementation (DSP multiprocessing).

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