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Optimized Calorimeter Signal Compaction for an Independent Component based ATLAS Electron/Jet Second-level Trigger

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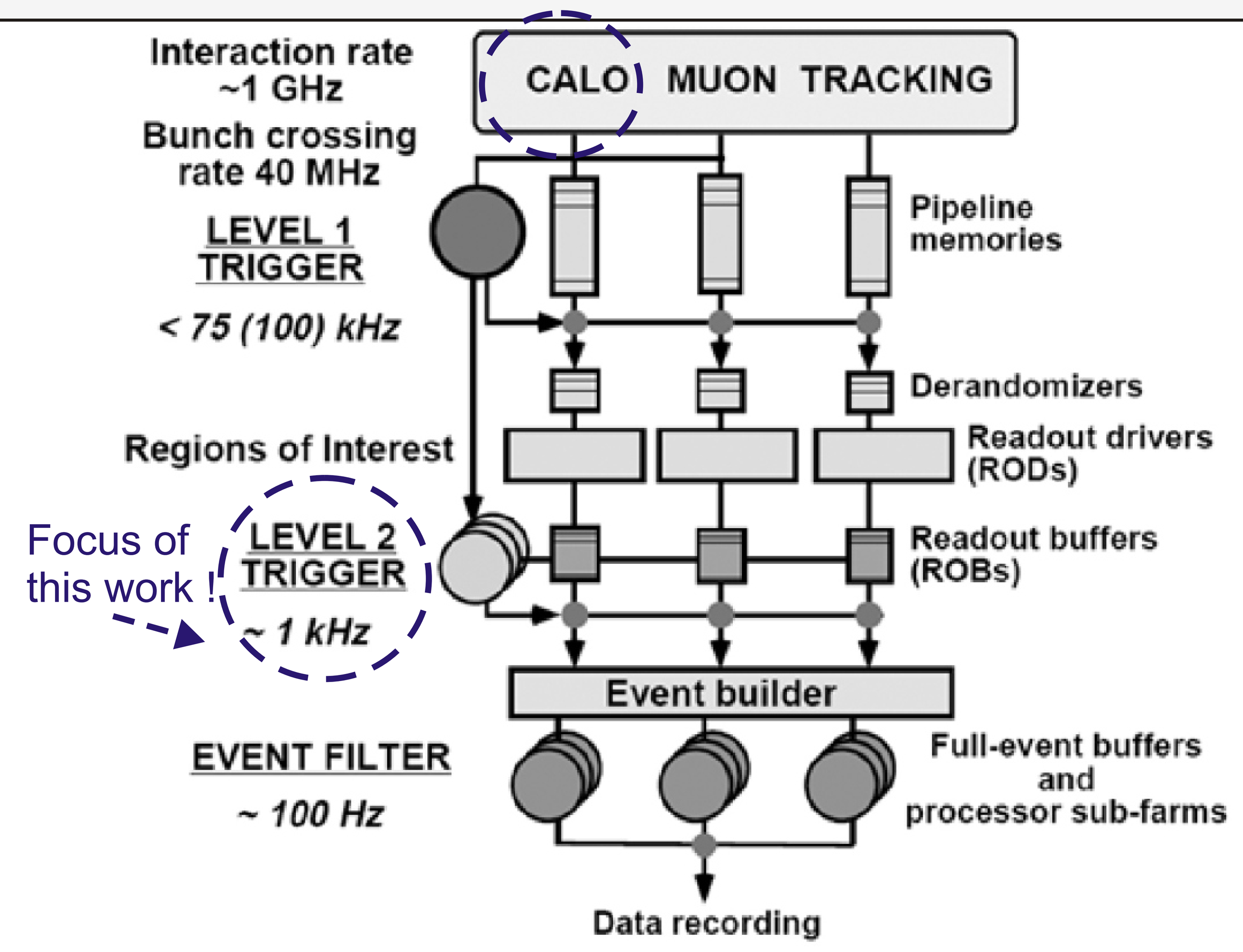
Introduction

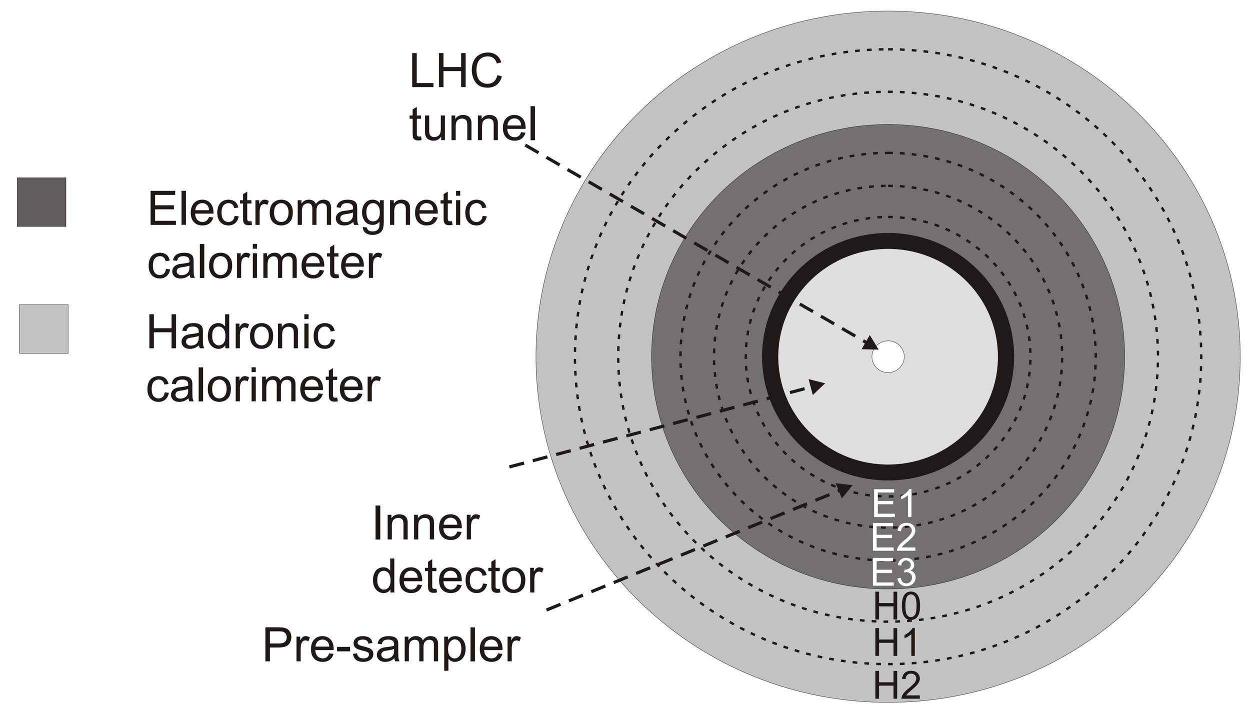
The ATLAS online trigger system:
- 60TB/s;
- three cascaded filtering levels;
- Jet rate at LVL2: ~25kHz

The Level two → two phases
- **feature extraction** - relevant information is extracted;
- **hypothesis testing** - particle discrimination performed over relevant variables.

Electron/jet separation relies very much on calorimeter information.

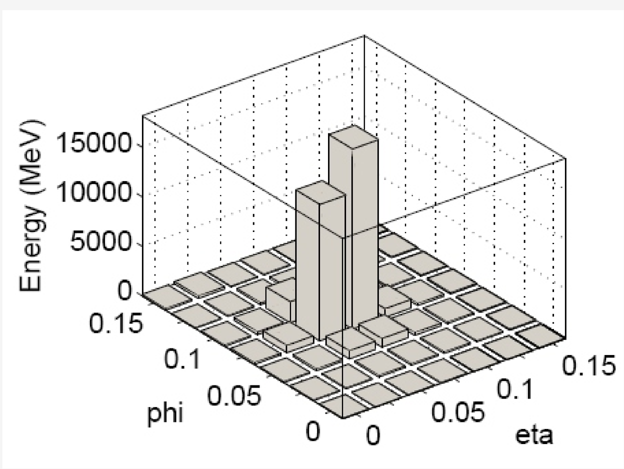


ATLAS calorimeter system:
- is segmented into seven layers;
- differences both in depth and cell granularity;

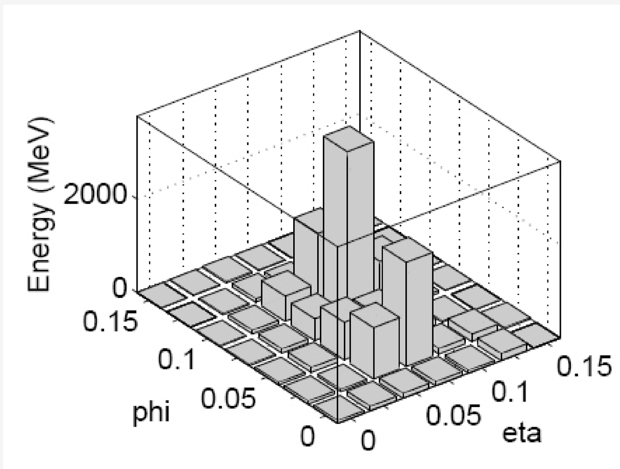


Proposed Method

Data Pre-processing: ➡ **ring formatting**

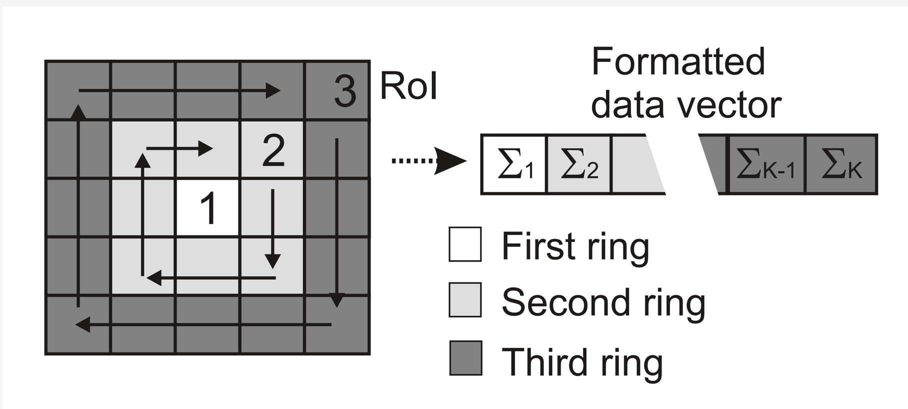


Typical electron - E2



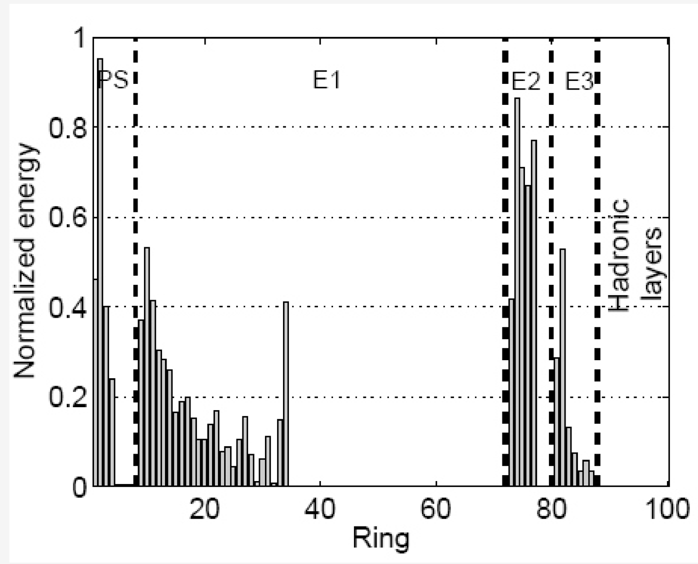
Typical jet - E2

Here, Region of Interest (RoI) data are formatted into concentric ring sums:

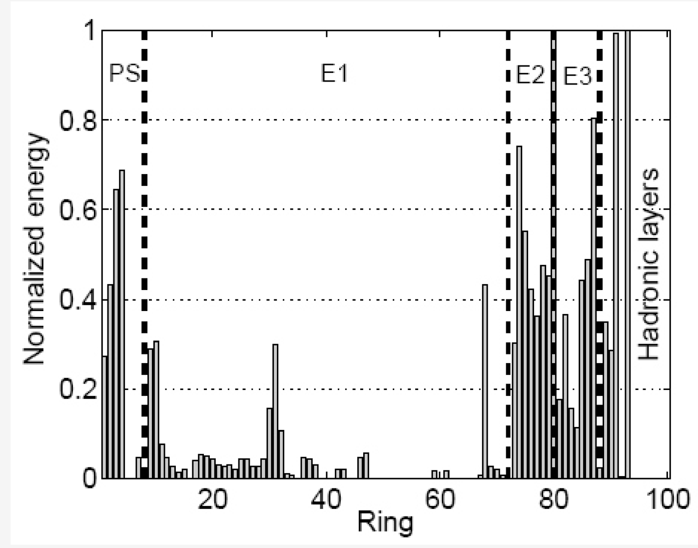


Ring Sums

Typical electron



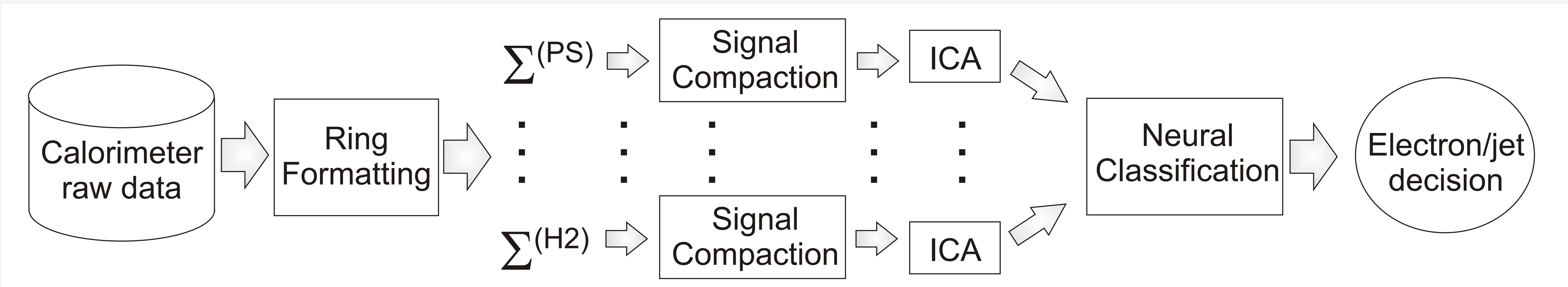
Typical jet



Proposed Discriminator: ➡ **Segmented (layer level) feature extraction - Compaction + ICA**

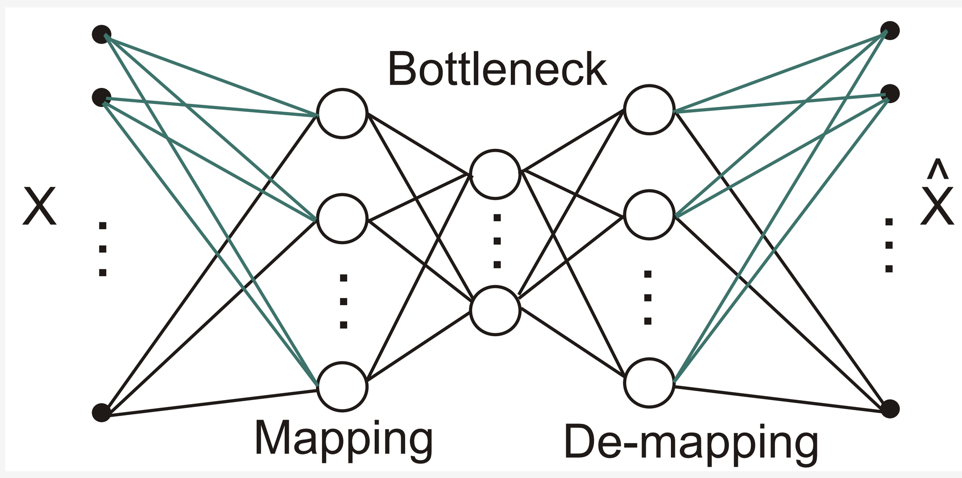
Independent Component Analysis (ICA) is a linear technique which projects the observed multidimensional data $\mathbf{x}=[x1, ..., xn]^T$ into a set of statistically independent features $\mathbf{s}=[s1, ..., Sn]^T$ ➡ $\mathbf{s=Wx}$

The number of components to be extracted from a RoI is estimated through different signal compaction strategies,such as Principal Component Analysis (PCA), Nonlinear Principal Component Analysis (NLPCA) and Principal Components for Discrimination (PCD).

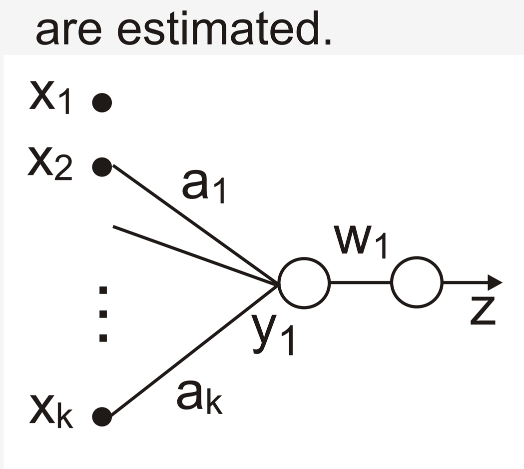


PCA:
- uses second order statistics;
- the projections are non-correlated and have maximum variance;
- may be performed through eigenvalue decomposition of data covariance matrix;

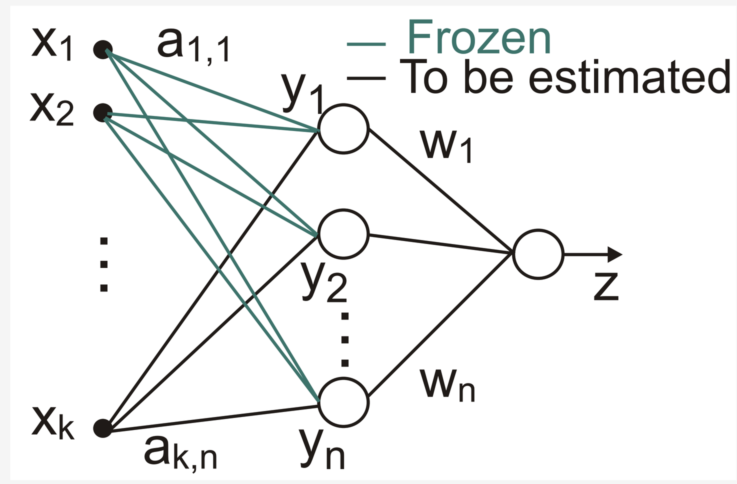
NLPCA:
- nonlinear signal compaction through auto-associative neural networks: ➡
- After convergence, the NLPCs are the bottleneck layer outputs.



PCD:
- linear transformation that maximizes class separation and data compaction rate simultaneously;
- extracted by a neural network;
- first component: single hidden neuron;
- by sequentially adding neurons to the hidden layer and restarting the training procedure, the following components are estimated.



First component



N-th component

Results

For performance comparison ROC curve and SP were used:

- ROC curve: Probability of Detection x False Alarm as decision threshold changes
- SP:

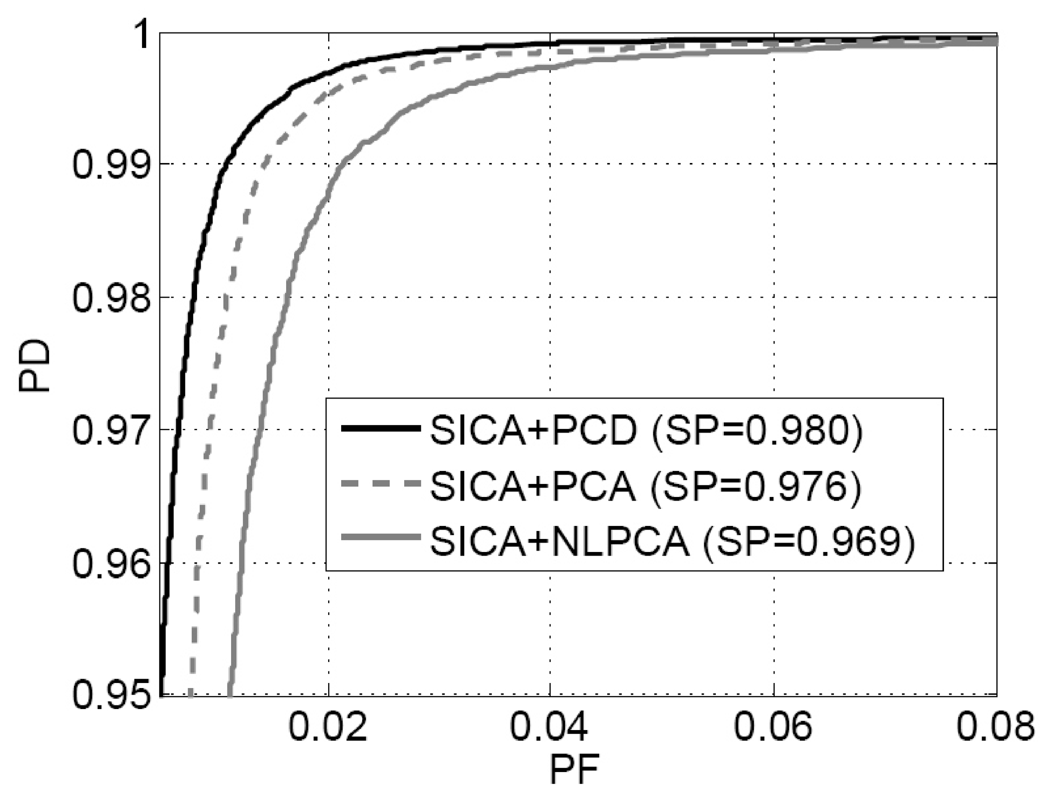
$$SP = \frac{Ef_e + Ef_j}{2} \times \sqrt{(Ef_e \times Ef_j)}$$

Compaction rates

from 100 rings to:

- PCA: 53 components
- NLPCA: 44 components
- PCD: 28 components

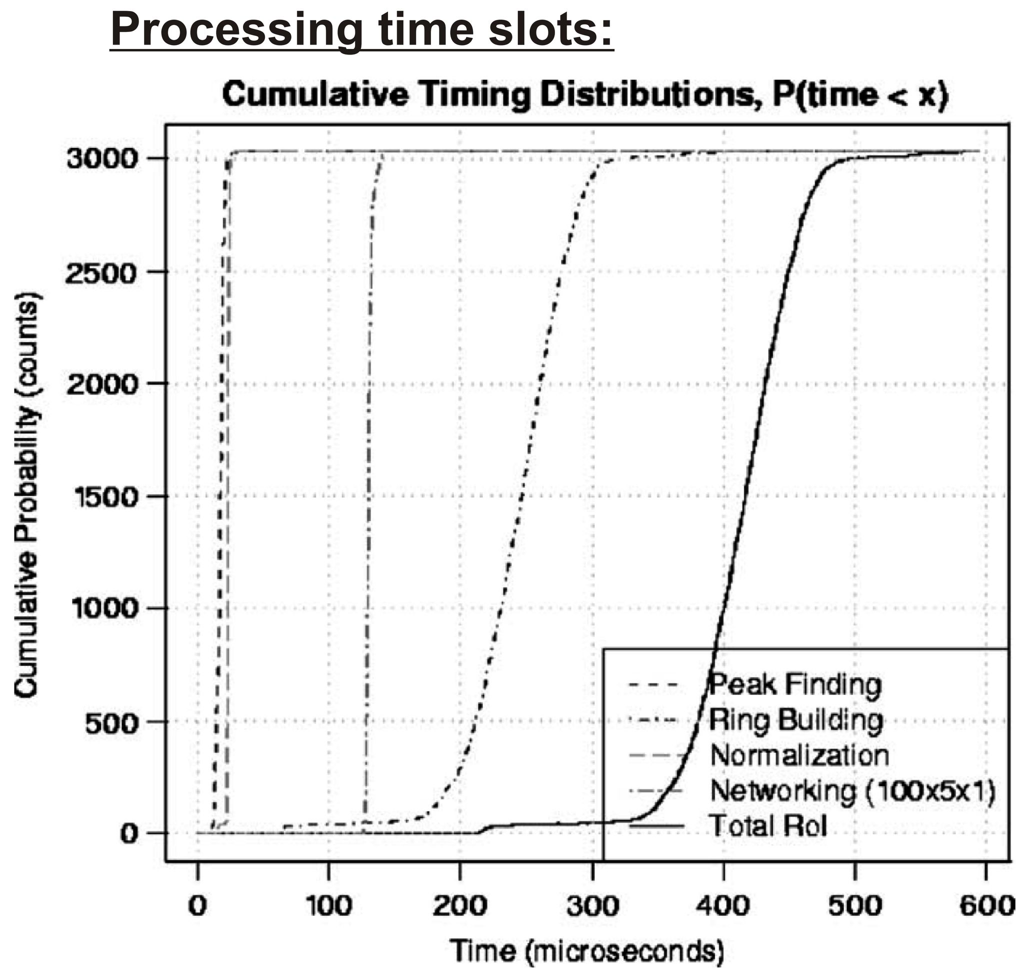
ROC for the proposed discriminators



Comparison with other discriminators:

- ATLAS baseline discriminator (T2Calo): SP=0.853.
- Neural Ringer (neural classifier operating over ring sums, implemented in ATHENA): SP=0.870.

Processing time slots:



- Only a matricial multiplication is added.
- The number of classifier inputs is reduced.
- No increase in the time slots is expected

Conclusions

- LVL2 based on Independent Components.

- Components extracted from ring described RoI.

- Efficient data compaction.

- Outperforms the baseline discriminator.

- Easily implemented in ATHENA (ring formatting and neural classification already opperational).

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