



MACHINE LEARNING TECHNIQUES FOR SELECTING FORWARD ELECTRONS WITH THE ATLAS HIGH LEVEL TRIGGER

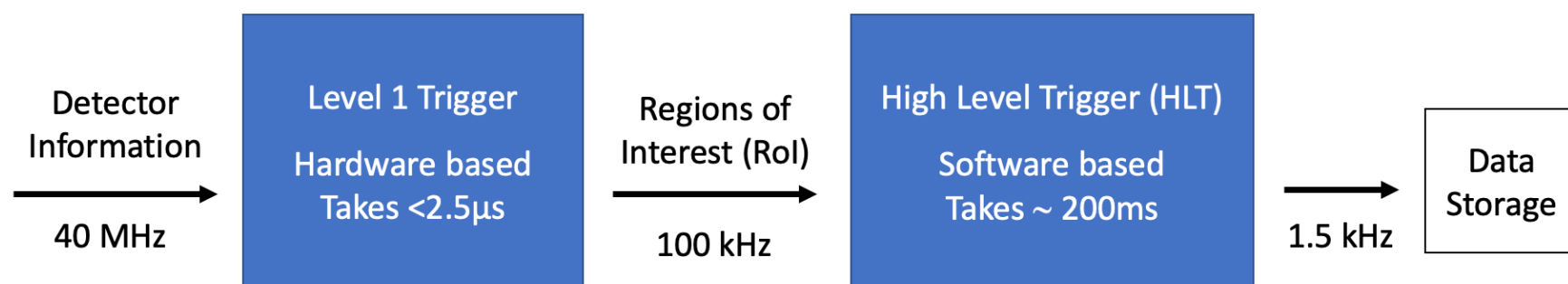
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ATLAS
EXPERIMENT

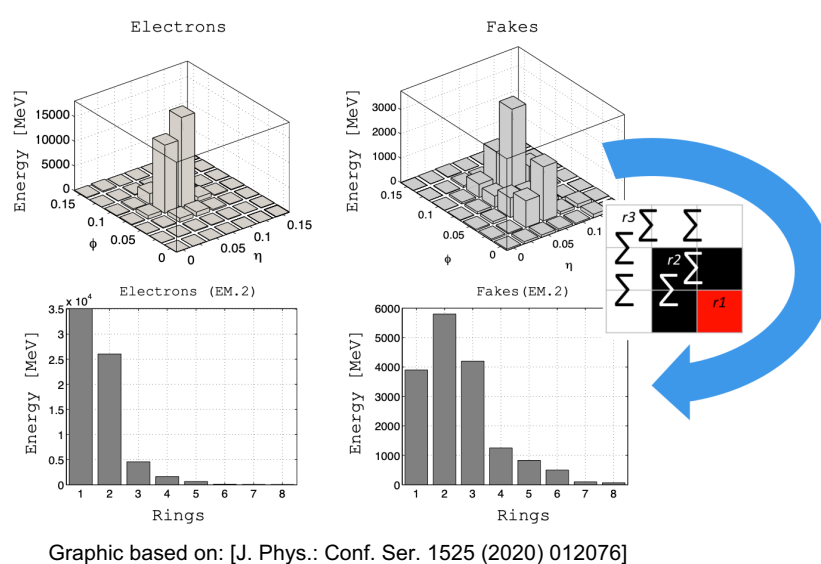
The ATLAS Trigger

- The ATLAS detector at the LHC measures proton-proton collisions during bunch crossings at a rate of 40 MHz.
- To store all this information would fill up data storages and overwhelm them with events irrelevant for analyses.
- A two level trigger system has been introduced to select events of interest.

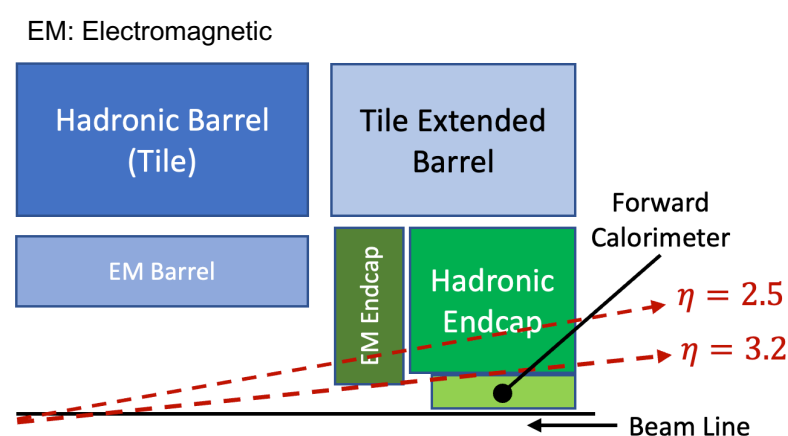


The Neural Ringer

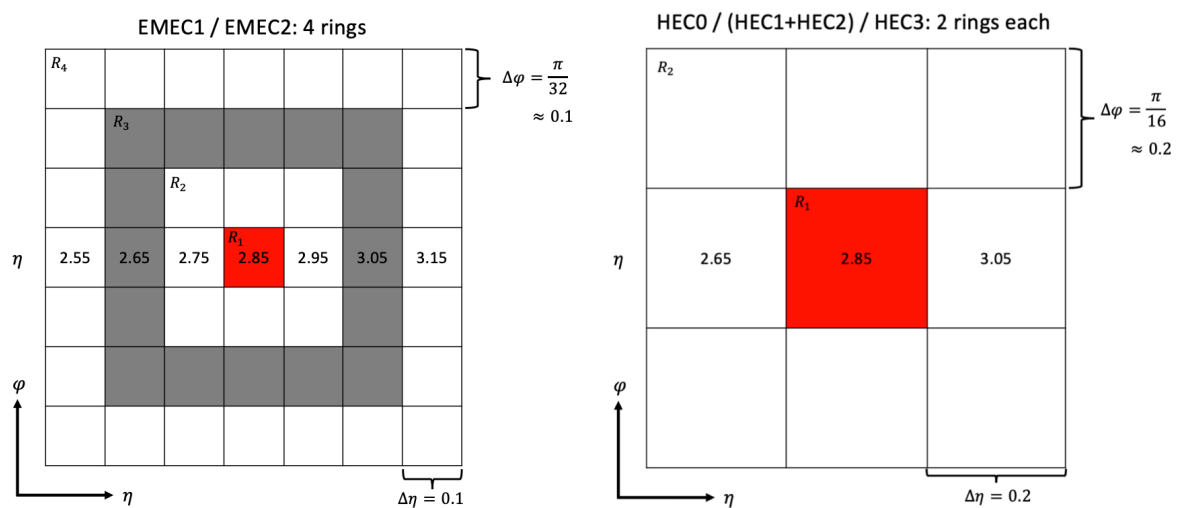
- With increasing performance of the LHC, more sophisticated trigger algorithms are necessary to maintain the efficiency
- In 2017, introduction of the Neural Ringer in the barrel region ($|\eta| < 2.5$) to reduce CPU demands
- Reduction of falsely identified electrons (fakes)
- Using calorimetric data in RoIs to build rings and calculate their energy sums
- Training of neural networks (NN) on the ring sums to distinguish real from fake electrons



Quarter section of the ATLAS calorimeter system



Implementing the Neural Ringer for Forward Electrons



- There are interesting physics processes going into more forward regions, however there is no specific HLT strategy for it
- More challenging regions due to reduced tracking information, lesser granularity and more inactive material
- Building rings in forward regions of $2.5 < |\eta| < 3.2$:
 - Electromagnetic and hadronic endcap calorimeters (EMEC & HEC)
 - 14 rings in total, 4 each in EMEC 1 & EMEC 2, 2 each in HEC 0, HEC 1&2 & HEC 3
 - 1st ring in each layer: highest energetic cell inside RoI
 - Further rings in same layer: Cells surrounding the previous ring

Forward Neural Ringer Tuning

Tuning specifications:

- Multilayer Perceptron (MLP)
- 1 hidden Layer (varying 2-10 neurons)
- 10 initializations
- 10 data folds (9 for training, 1 for test)
- Mean square error (MSE) loss function
- Stop after 25 successive failures of SP index validation improvement

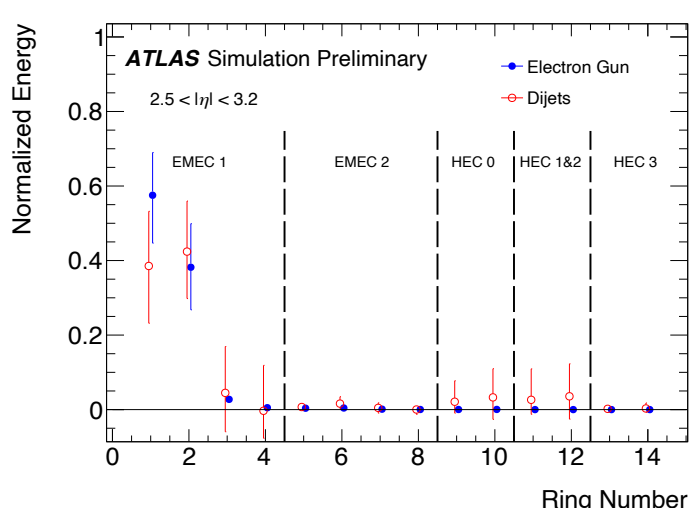
Results:

- Rejects much more background than by using the old cut-based approach (up to a factor 15)
- Similar performance for models with 3-10 neurons
- Worse performance with 2 neurons

Input data: ring sums normalized by the total energy sum of each candidate's 14 rings

Electron gun candidates: $E_T > 15$ GeV

Dijet electron candidates: $E_T > 5$ GeV



$$SP = \sqrt{P_D(1-F_R) \cdot 1/2 (P_D + (1-F_R))}$$

Detection Probability P_D : Probability for a signal candidate to be properly classified by the NN
Fake Rate F_R : Probability for a background candidate to be classified as signal

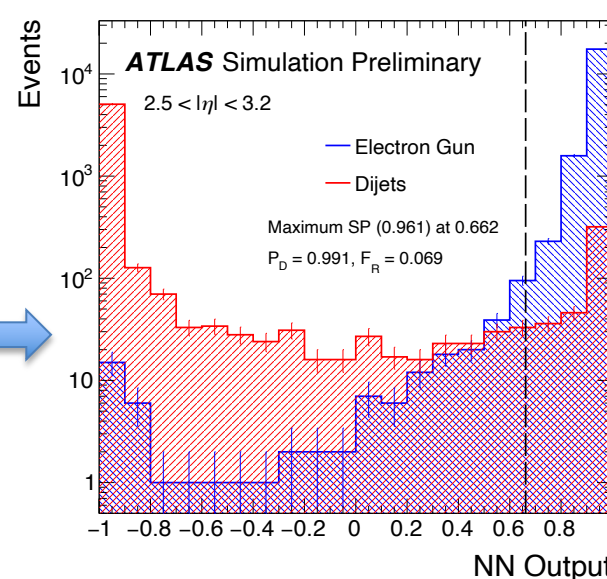
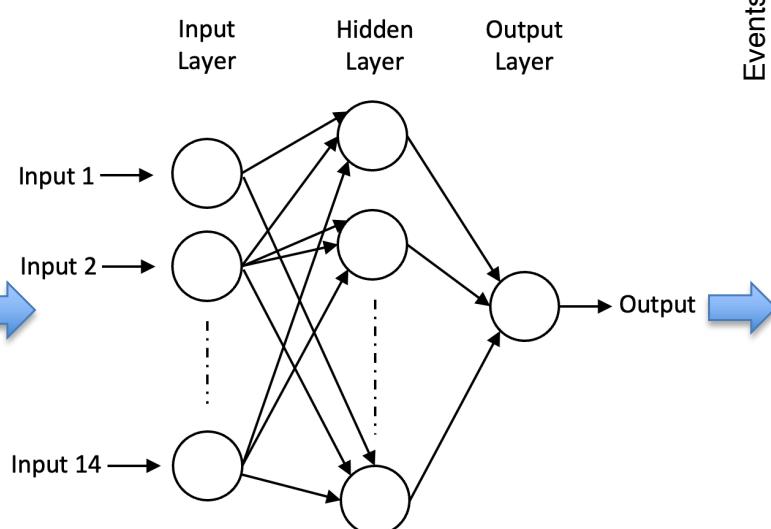


Table: Comparison of F_R for a fixed P_D of 94% corresponding to the medium working point of the old cut-based approach.
 $F_R(\text{cut})$: F_R by using the cut-based approach on the background sample
 $F_R(\text{NN})$: Average F_R of the NN models with more than 2 neurons

| $P_D(\text{fix})$ | $F_R(\text{cut})$ | $F_R(\text{NN})$ |
|-------------------|-------------------|-------------------|
| 94% | 9.14% | $0.58 \pm 0.05\%$ |

Reduction of a factor 15!