

# Electron Identification with Deep Neural Networks

Dominique Godin  
Kazuya Mochizuki  
Emre Onur Kahya  
Arthur Boisvert

Jean-François Arguin  
Alain Tapp  
Otilia Ducu  
Julien Maurer  
Ioan-Mihail Dinu

# Electron Identification Motivation

- Though relatively rare, prompt electrons are very important for ATLAS experiment, Higgs' physics program and search for physics beyond Standard Model
- Example: 4 out of 5 Higgs' main signatures at LHC contain  $e^-$
- Electron classification is therefore crucial to discriminate prompt electrons from other electron-like signatures
- Machine learning could replace the more simple algorithms that are presently used in ATLAS for this identification
- The goal of this project is to use the best techniques available to eventually classify  $e^-$  as of many different types as we want (i.g. signal, charge-flipped, from b-jets,  $\gamma$ -conversion, fake)

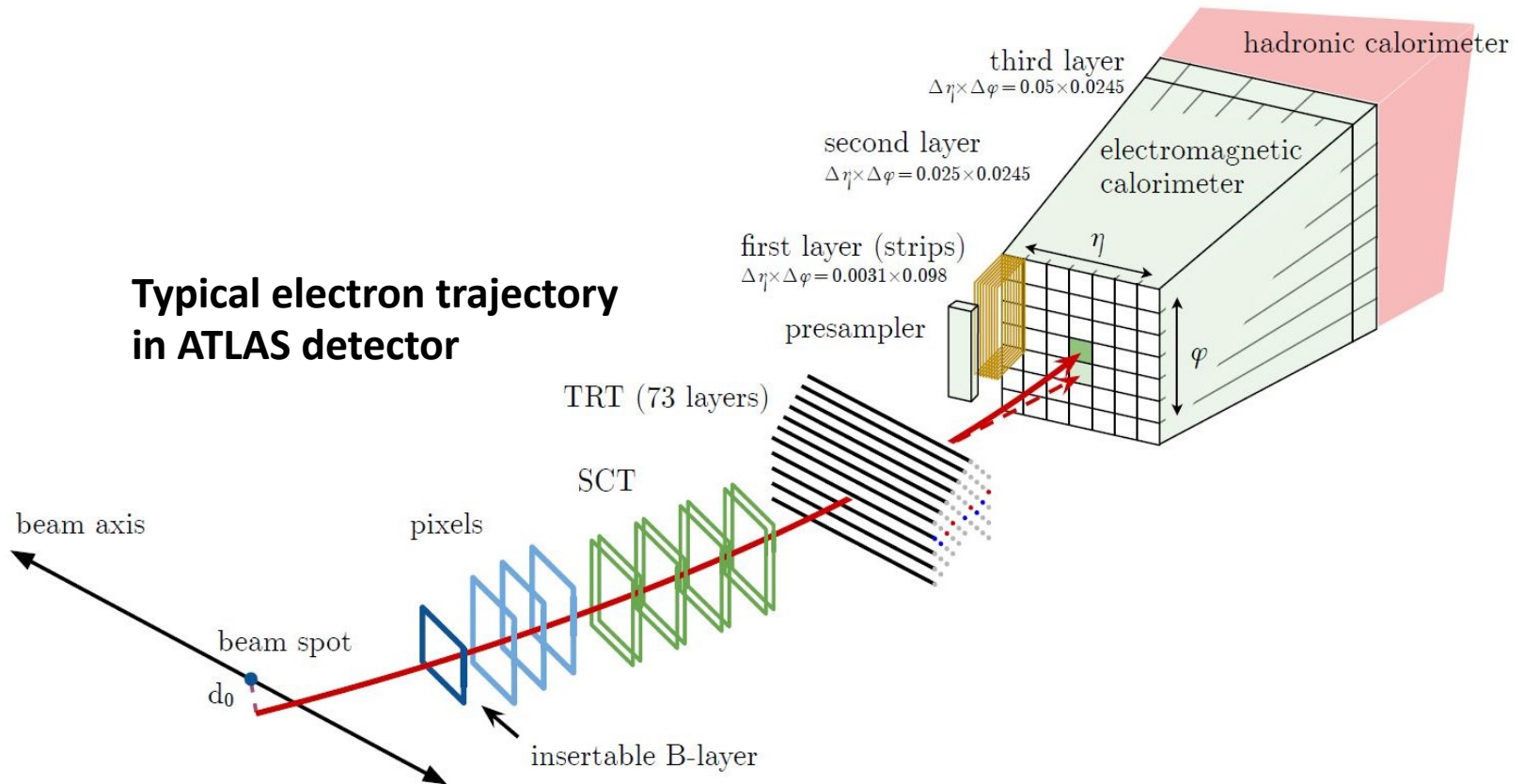
# Electron Data from ATLAS Detector

## Available MC data for each electron

- 15 track candidates ( $e\_frac, d\_eta, d\_phi, d\_0$ ) :
- 3 images from electromagnetic calorimeter:
- 2 images from hadronic calorimeter:

(15 x 4)  
3 x (56 x 11) in ( $\eta$  x  $\phi$ )  
2 x (7 x 11) in ( $\eta$  x  $\phi$ )

## Typical electron trajectory in ATLAS detector



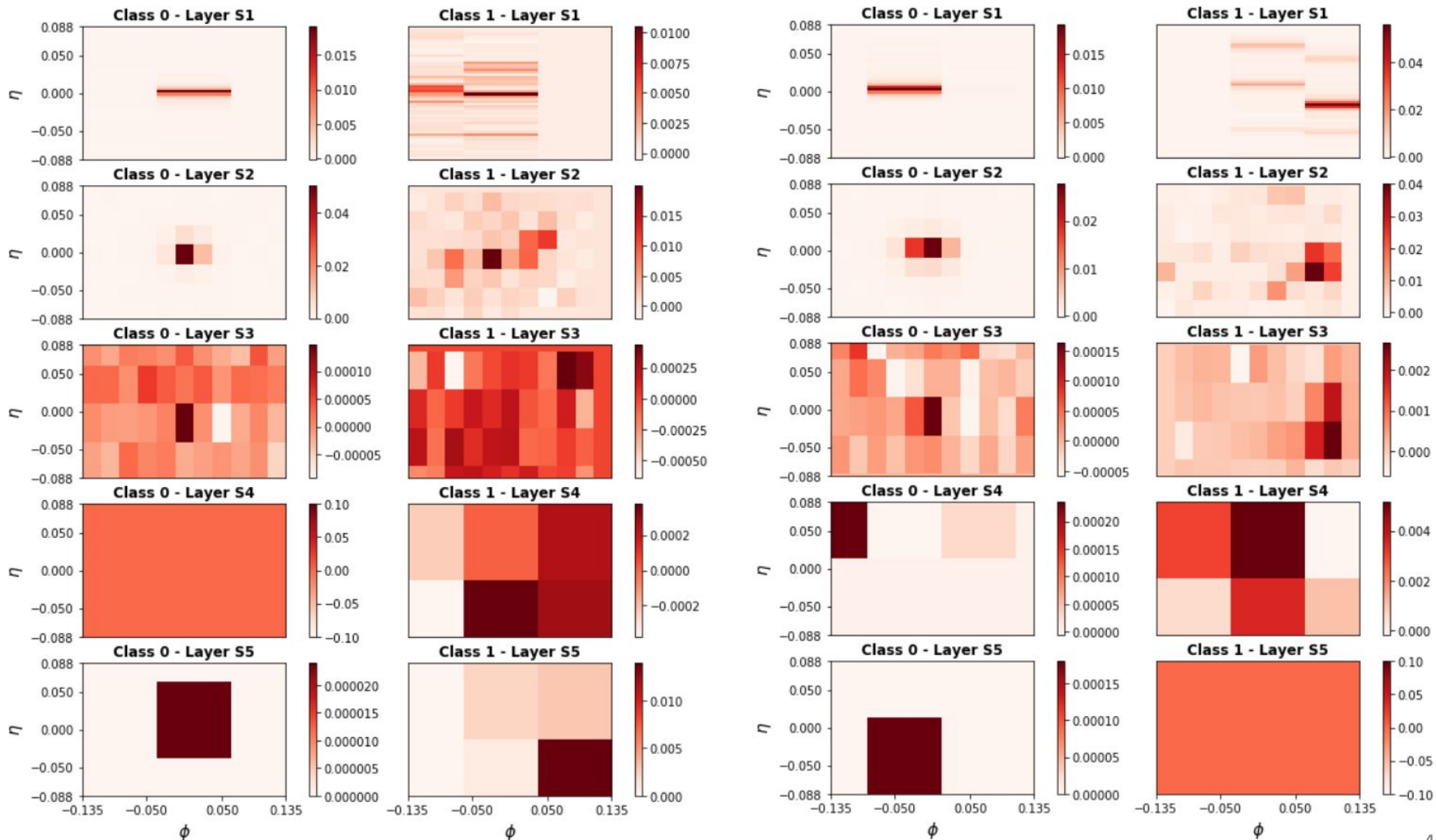
# Calorimeter Images MC Examples

Signal

Background

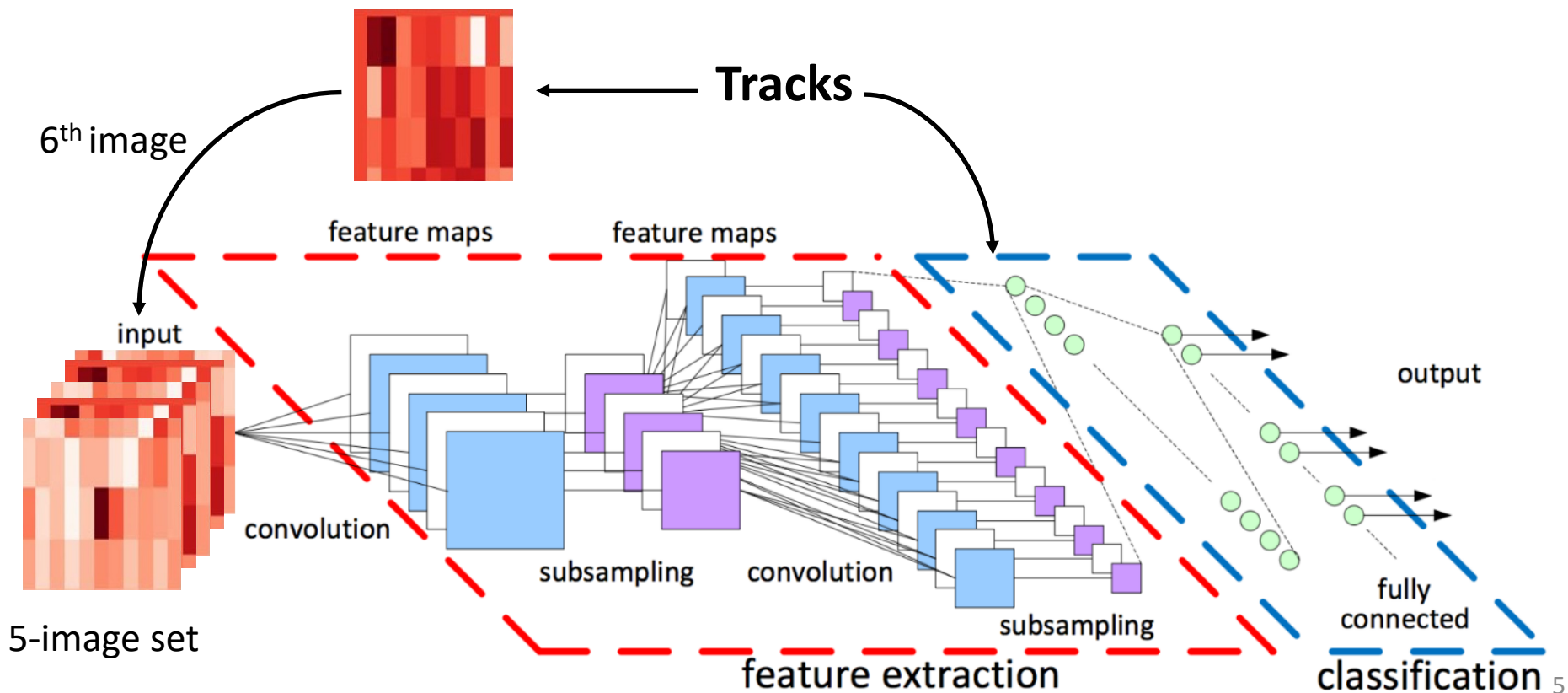
Signal

Background



# Preliminary NN Architecture

- Binary classification: 1) prompt  $e^-$  2) fake + non prompt  $e^-$
- Multi-channels CNN with calorimeter images + Tracks information
- The 5-image sets are concatenated in volume images (5-channel images)
- Tracks: either used as an image (6<sup>th</sup> channel) or concatenated in the FC layer
- Both methods seems to produce similar performance



# Inside CNN Architecture

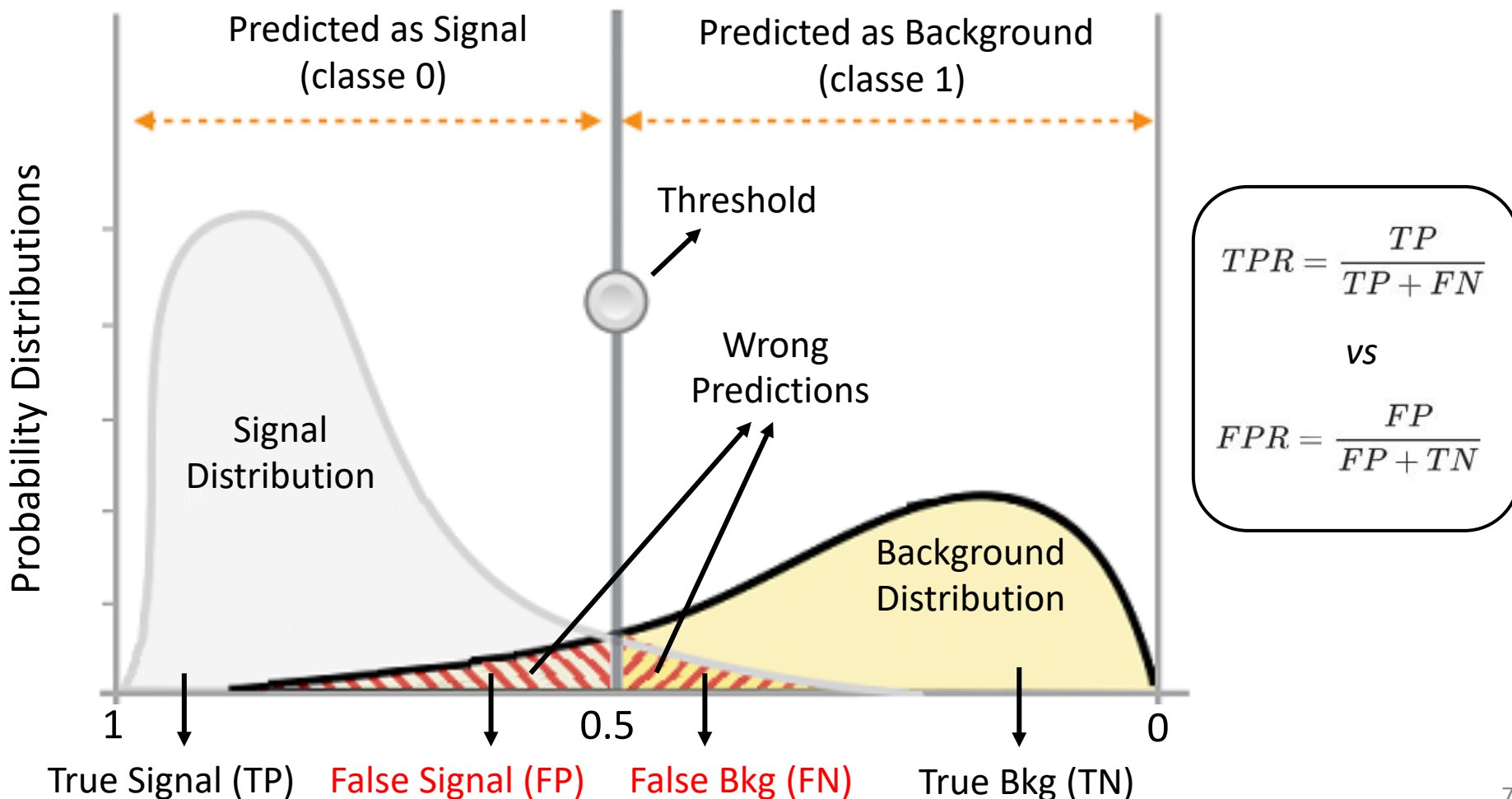
## Detailed Architecture

- Layer 1: 100 convolution maps with 3x3 filter
- Layer 2: 2x2 MaxPooling
- Layer 3: 50 convolution maps with 2x2 filter
- Layer 4: 2x2 MaxPooling
- Layer 5: maps vectorization tracks information concatenation
- Layer 6: 100-neuron fully connected
- Layer 7: binary Softmax layer (output probability-vector)

Capacity: **118 652** trainable parameters (i.e. weights) altogether

# Classification vs ROC Curves

- NN with Softmax layers gives class probabilities for each sample (e.g. 0.43, 0.57)
- ROC curves are used in binary classification to study the output of a classifier
- Goal: maximize the true positive rate while minimizing the false positive rate

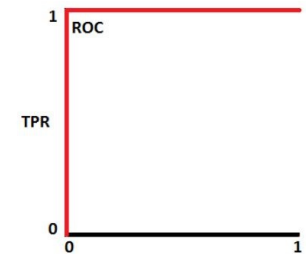
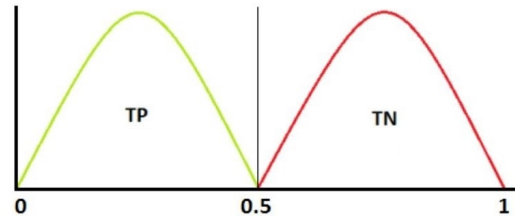


# More on ROC Curves

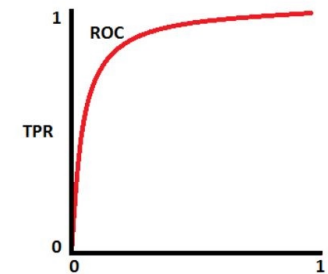
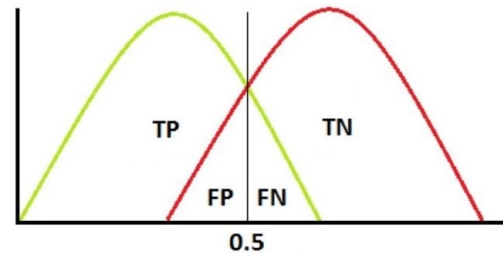
- **ROC curves:** better figure of merit than accuracy
- **AUC** (area under curve): also very useful to estimate overall performance

$$TPR = \frac{TP}{TP + FN}$$
$$FPR = \frac{FP}{FP + TN}$$

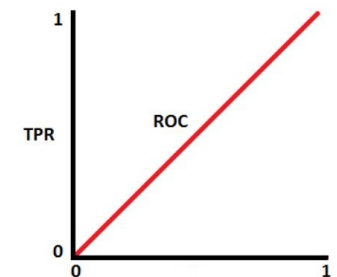
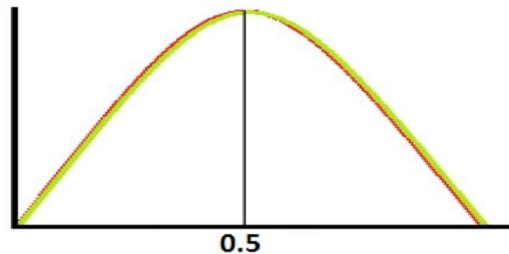
Separable Distributions



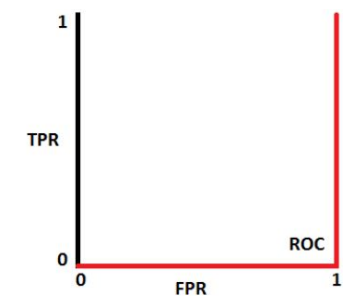
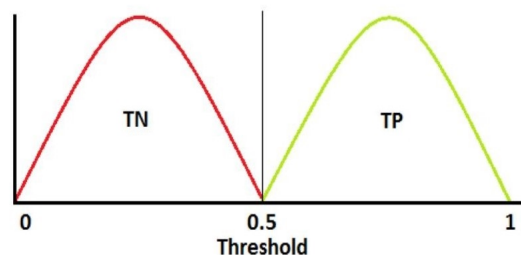
Overlapping Distributions



Identical Distributions

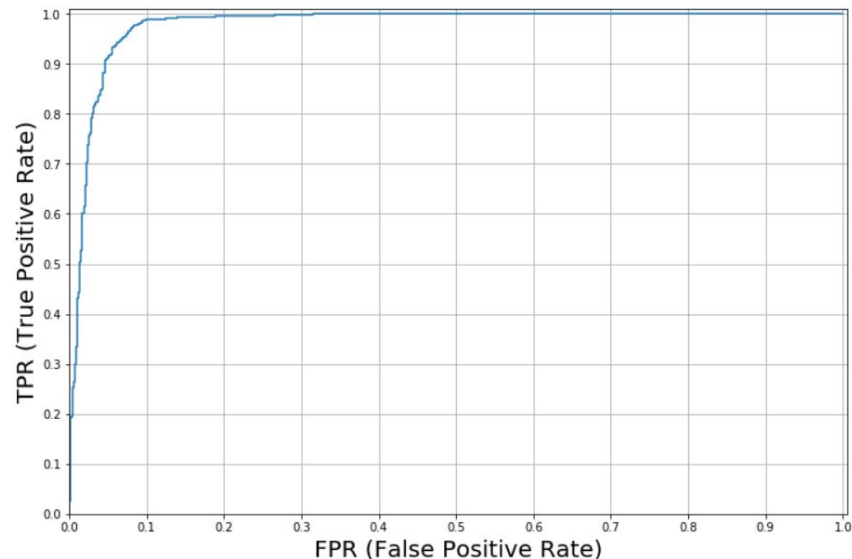
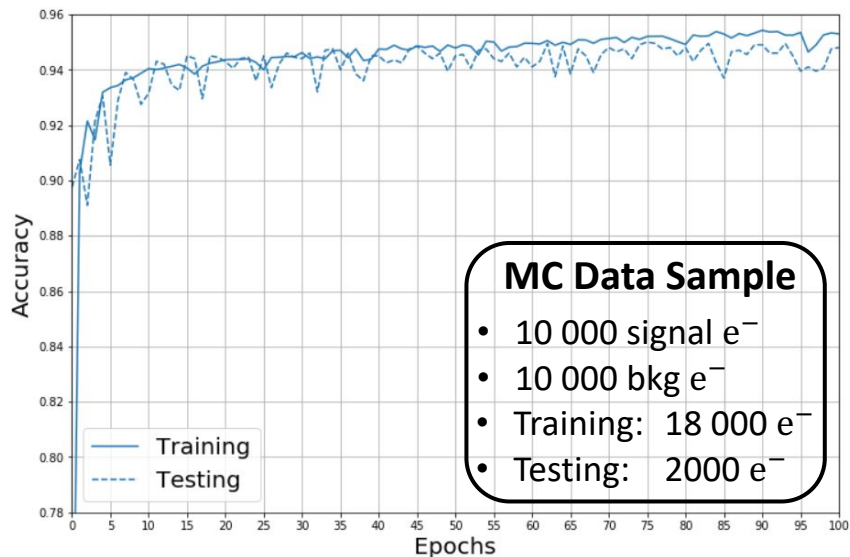


Reciprocating Distributions

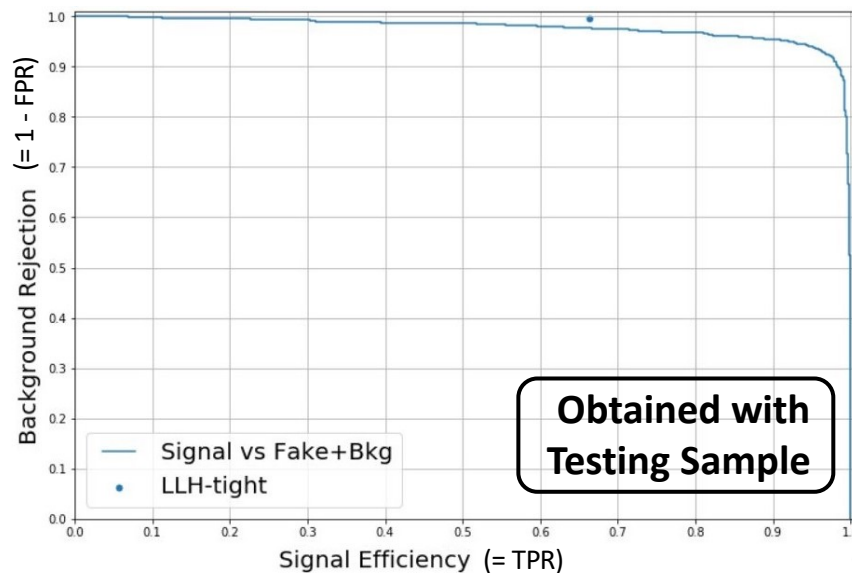




# CNN Results: Accuracy and ROC Curve

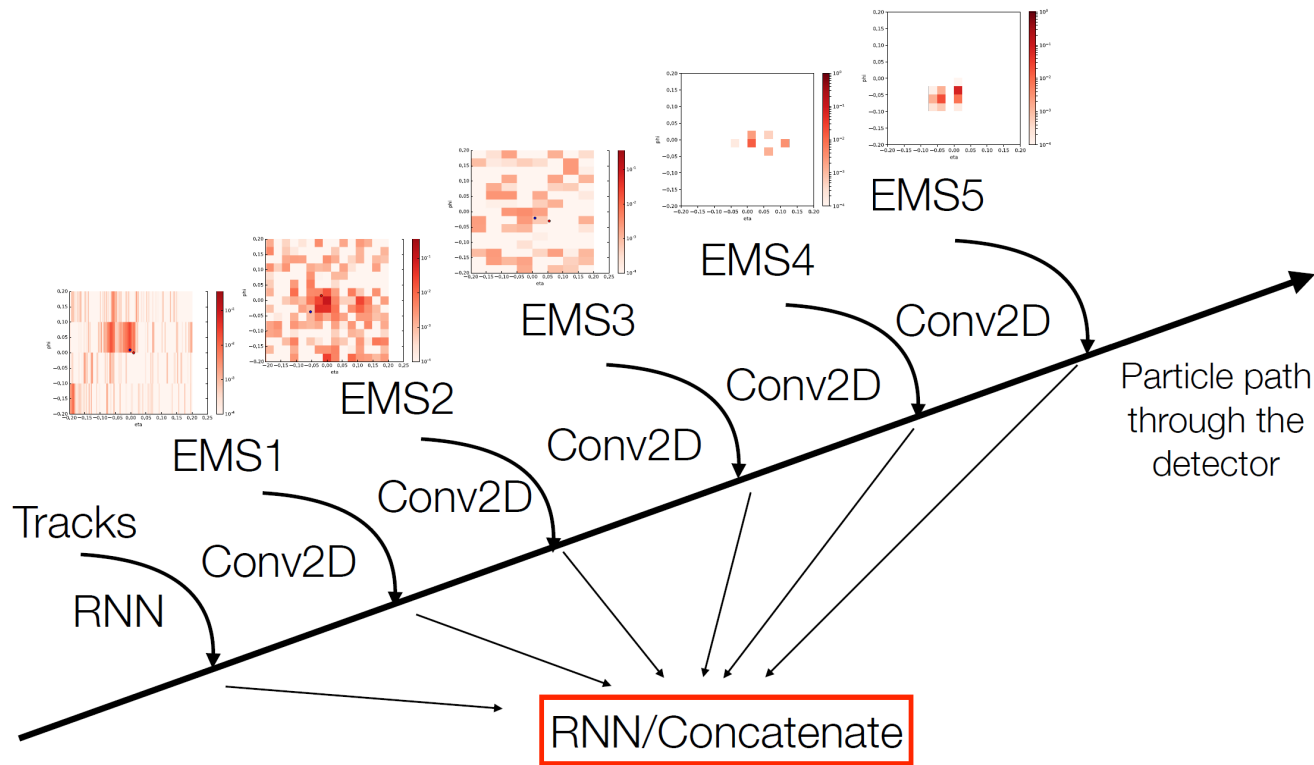


- Maximum accuracy is achieved rapidly
- 4s/epoch (generator + 4 CPU's + RTX 1080Ti )
- Batch size of 500  $e^-$  was used
- No sign of serious overfitting
- Bkg vs Signal ROC curve is obtained by switching axis, expressing 1- FPR vs TPR
- LLH-tight is still performing better but NN might outperform loose and medium LLH
- Future: deeper architectures and 5-class NN



# Future: RNN and 5-class Identification

- 5-class  $e^-$  identification: 1) signal 2) charge-flipped 3) from b-jets 4)  $\gamma$ -conversion 5) fake
- More advanced architecture: RNN made up of 6 sub-networks (1 RNN + 5 CNN's)



- Such an architecture already showed promising results for leptons  $\tau$  classification

# Conclusion and Future Developments

- Electron identification is of great importance for the Atlas experiment
- The electron classification into different classes is a challenging problem
- CNN's and RNN's showed to be effective for  $\tau$  and jets classification

## Long-term possible developments

- Transition from RNN to LSTM for longer tracks or images sequences
- Training with low-level variables available from the ATLAS detector
- Eventually performing 5-class identification with real data instead of MC
- Adapt architectures to regression for estimation of variables (e.g.  $E$  ou  $P$ )
- Explore pre-processing methods for better image information extraction