

# Possible Architectures of Neural Networks for Particle Classification and Reconstruction in SPD ECAL

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# Motivation

The ECAL reconstruction algorithm must:

- be fast enough to be used in the online filter
- separate clusters from  $\pi^0/\gamma$  to reject background events
- be robust against ECAL miscalibrations
- (ideally) be interpretable

ECAL:  $\sim 25\text{k}$  cells  $\rightarrow$  need parallelizable algorithms  $\rightarrow$  convolutional neural networks (CNN) is a natural choice

# Convolutional neural networks

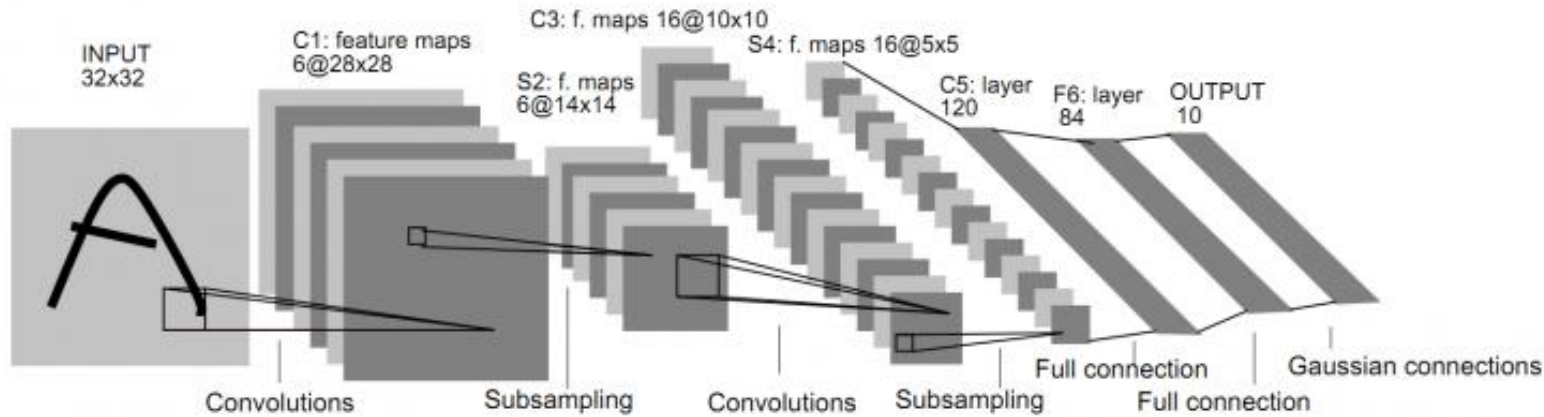
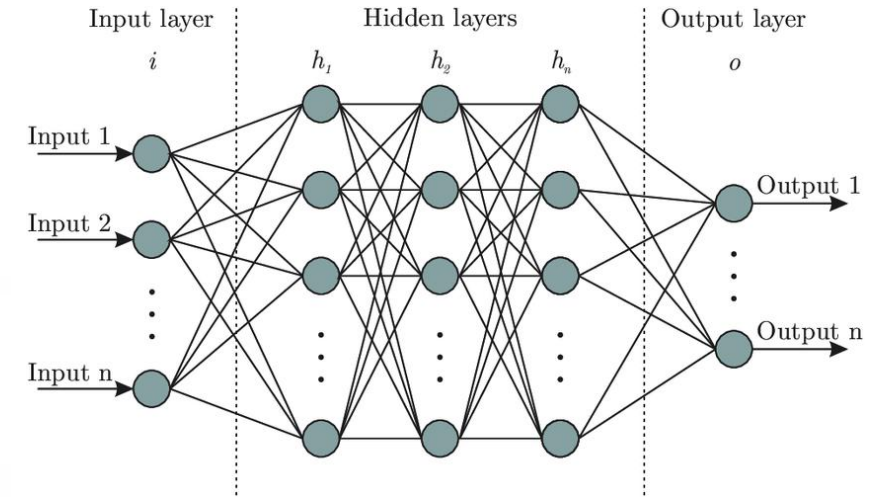


Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.



[Gradient-based learning applied to document recognition, Y.Lecun et al.](#)

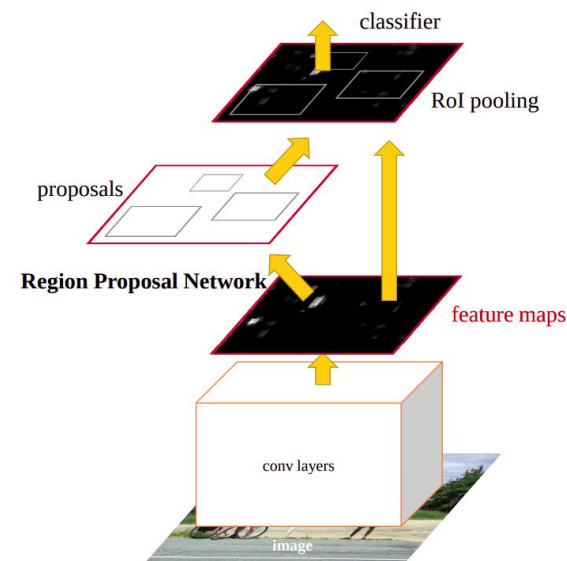
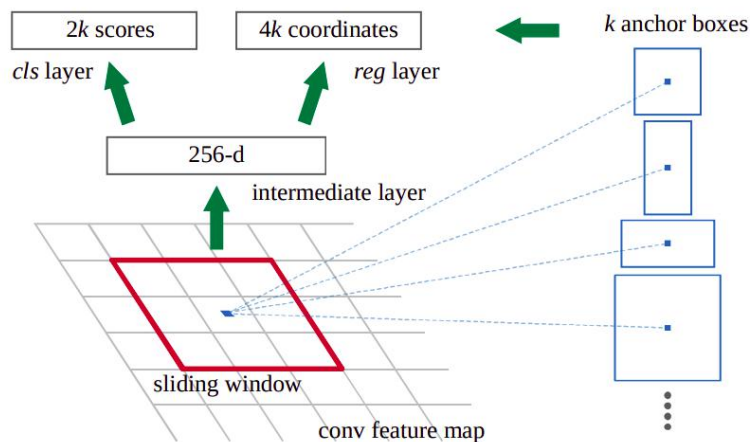
[Facundo Bre et al.](#)

- “Sliding” window (kernel), here  $5 \times 5$  pixels; multiple kernels correspond to multiple features
- basic features in the first layers, more complex features in the latter layers
- for regression (continuous output)/classification (discrete output), the final layer is flattened and fed as input to multi-layer perceptron or more complicated networks
- optimizing weights in kernels through training and backpropagation

Understandable how to process one image. But how to select multiple images (clusters) in e.g. ECAL?

# Reconstruction network

Idea inspired by [Faster R-CNN](#):  
two networks:



1) Region proposal network:

for each region, predict:

- rough bounding box (could be omitted)
- whether it's an object

originally, "anchors" of different aspect ratio were used, but could be omitted

2) Object detection network:

proposals → RoI pooling (could be omitted?)

predicts:

- precise bounding box → energy, position
- object class → PID

postprocessing: non maximum suppression  
(to remove duplicate objects)

As a first step, try to use only PRN, but with PID and energy/position as outputs

# Tests of the reconstruction layers

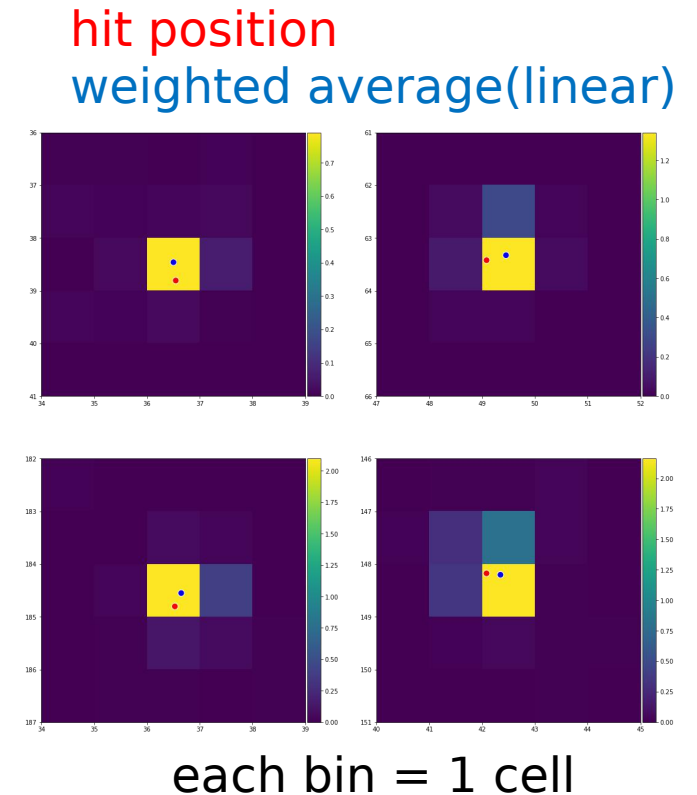
Convolutional layers and region selection replaced by simple search of local maxima

Network setup:

$N_{\text{neurons}} = [25(\text{input}), 50, 30, 10, 3/1(\text{output: } x/y/e)]$

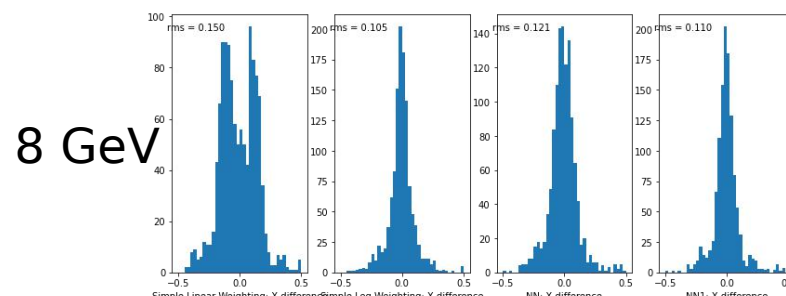
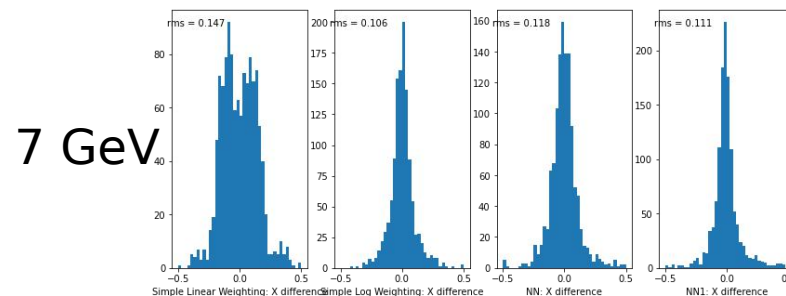
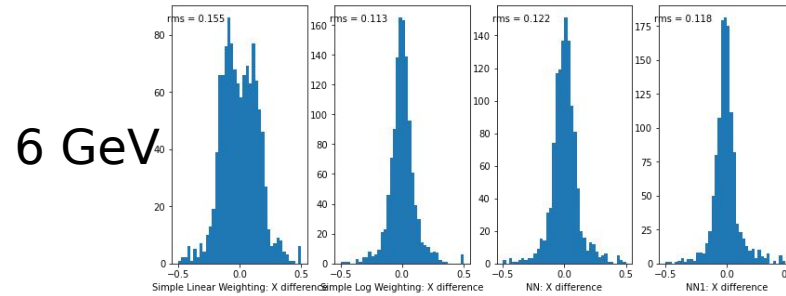
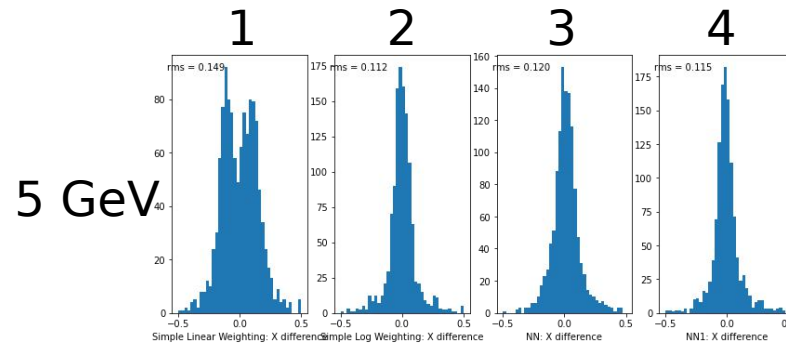
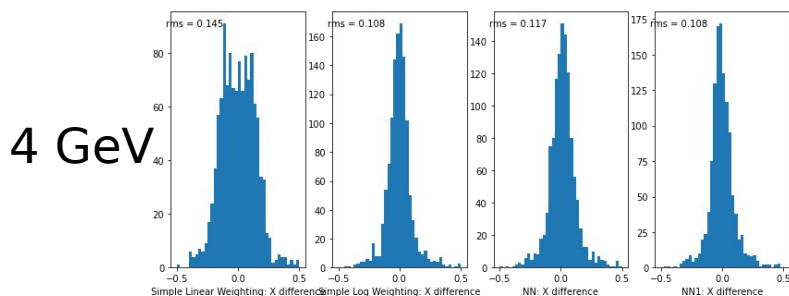
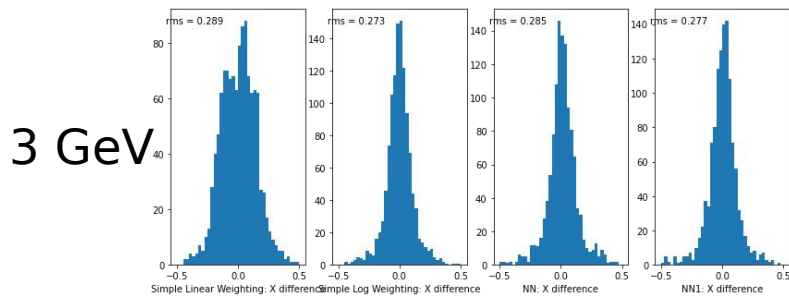
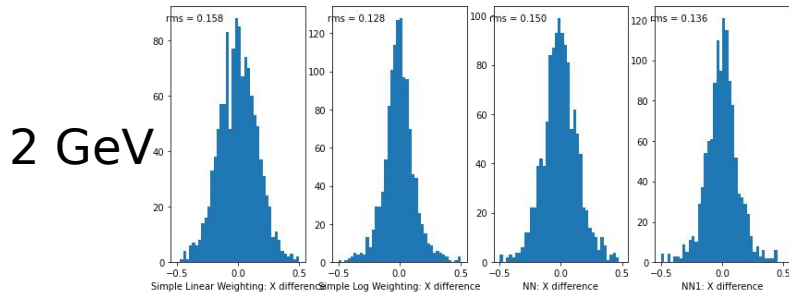
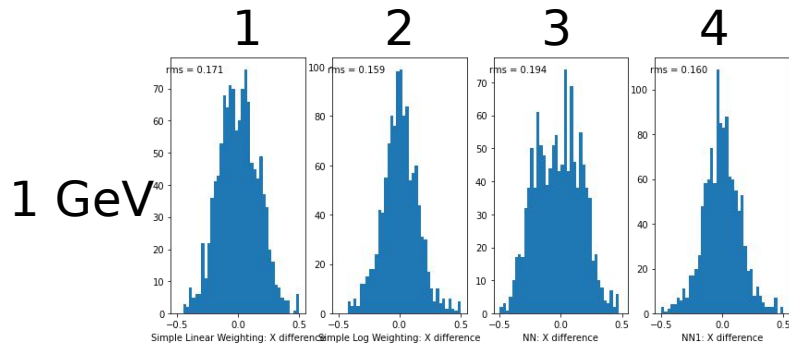
- Adam, lr = 0.01,  $\beta=(0.9, 0.999)$ , 1400 iterations
- ~17k input 5x5 images, energies: 1,2,3,...,8 GeV, angles:  $[0,20]^\circ$
- MSELoss for position, modified loss function for energy resolution: taking into account energy resolution  $4\% \oplus 6\%/\sqrt{E}$
- two options: 3 outputs (x/y/e) or 3 separate networks for x/y/e

Performance compared to weighted average with linear or log. weights (cutoff parameter for log. weighting optimized for each energy)



# Performance of reconstruction network

## Resolution in X(Y/Z/ $\phi$ ) variable in terms of cell size

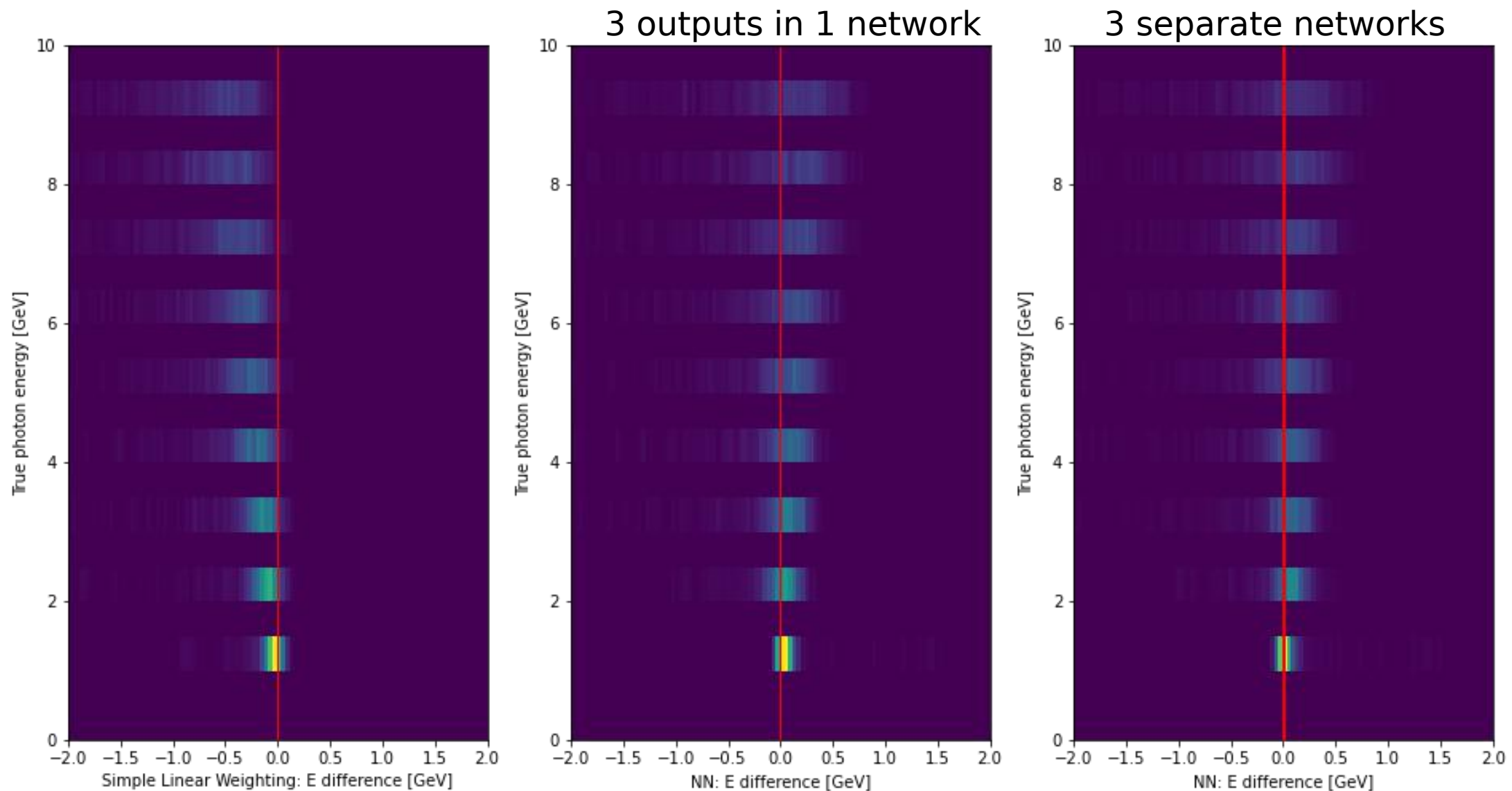


Columns:

- 1) linear weighting
- 2) log.weighting
- 3) one network with 3 outputs
- 4) 3 separate networks

# Performance of reconstruction network

## Energy resolution



# Conclusions and outlook

- Script to produce calorimeter array from SPDROOT output was set up
- Training of a simple network works for photons under small angles — the procedure works in general
- Next step: try implementing the CNN with common conv layers and separate layers for PID and position determination