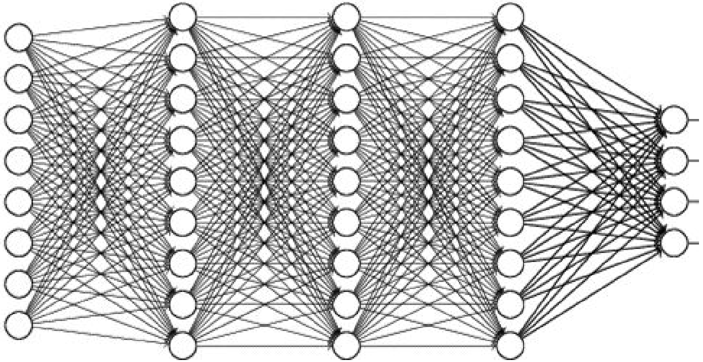
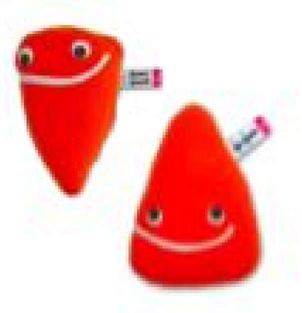
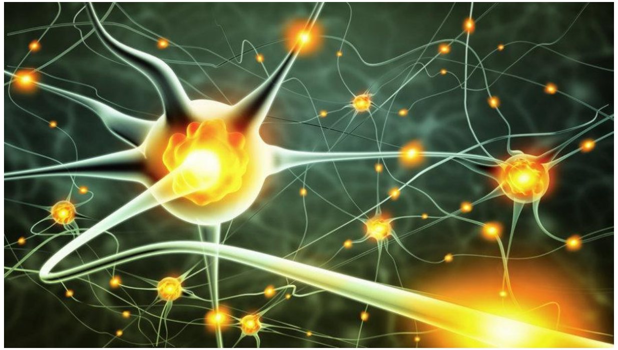




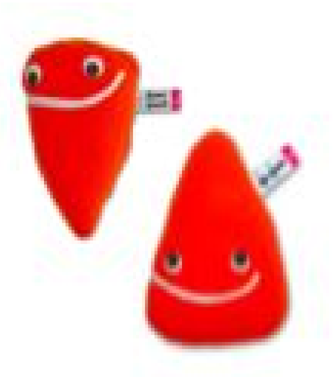
Deep Learning Photon Identification in a Super-Granular Calorimeter

Nikolaus Howe @ Williams College
Maurizio Pierini @ CERN
Jean-Roch Vlimant @ Caltech



Outline

- Introduction to the problem
- What is Machine Learning
- Our work so far
- Limitations and next steps

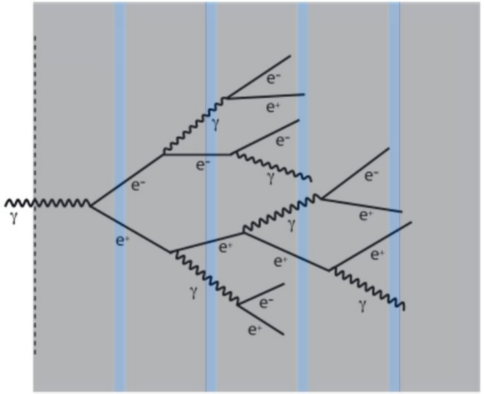


The Problem

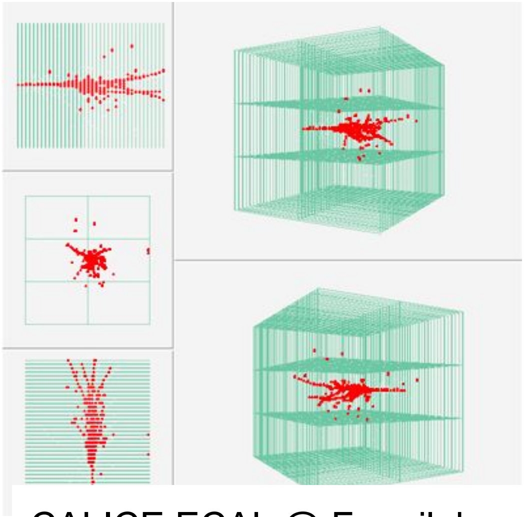
Introduction
- Problem -

Want to take advantage of high granularity of future HEP detectors...

...can contemporary Machine Learning (ML) techniques play a significant role?

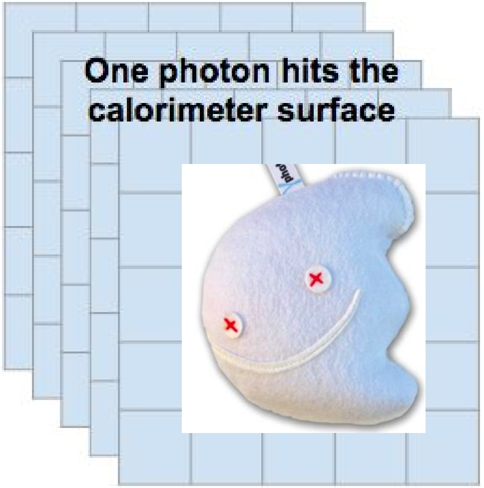


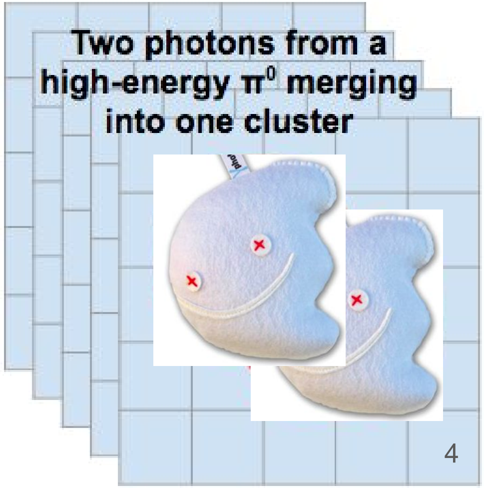
Photon shower



CALICE ECAL @ Fermilab

Define ideal problem:
Photon vs. Pi0
showers





Focus on current cutting edge:

- Super-granular detector geometry
- Deep Neural Networks

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- Problem -

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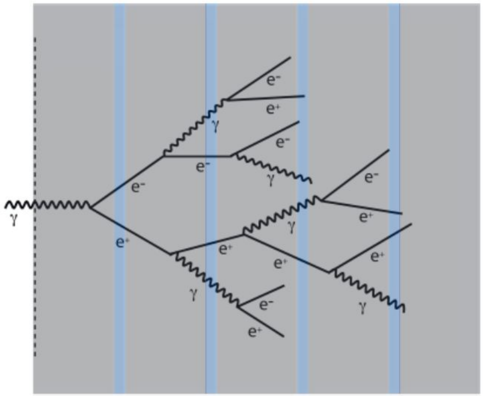
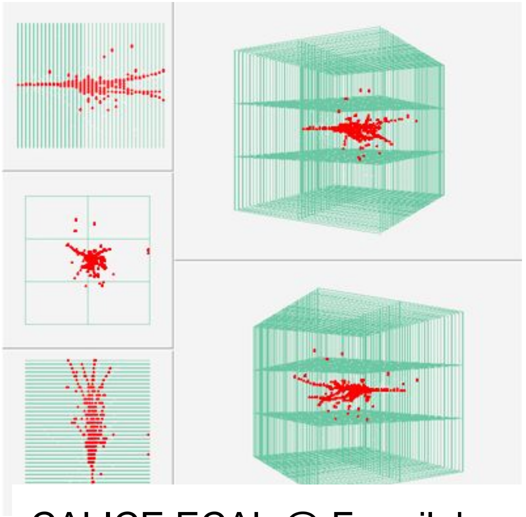


Photon shower



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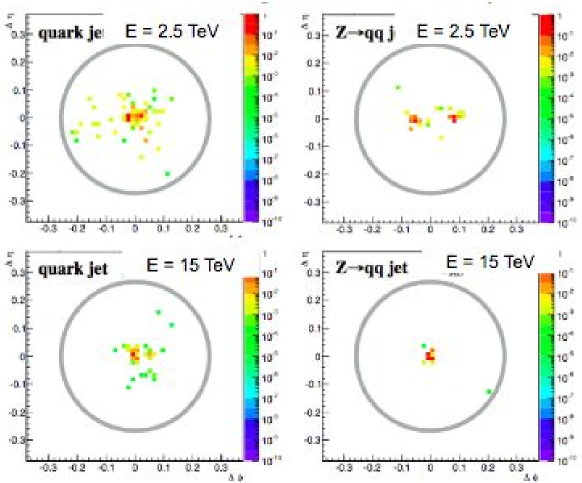


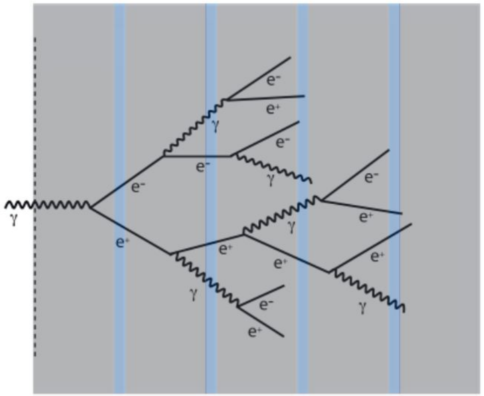
Focus on current cutting edge:

- Super-granular detector geometry
- Deep Neural Networks

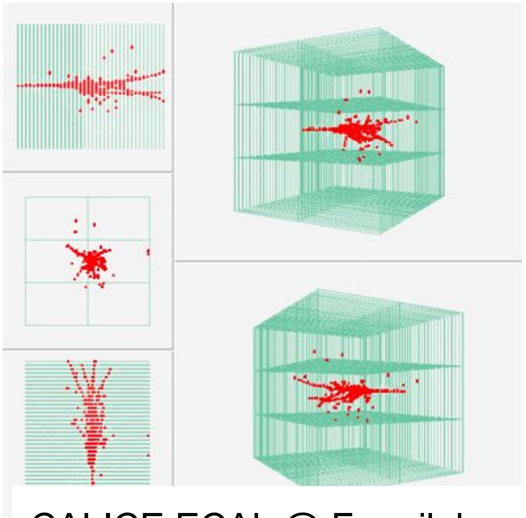
Introduction
- Detector -

Photon vs. **Pi0** showers
in LCD ECAL

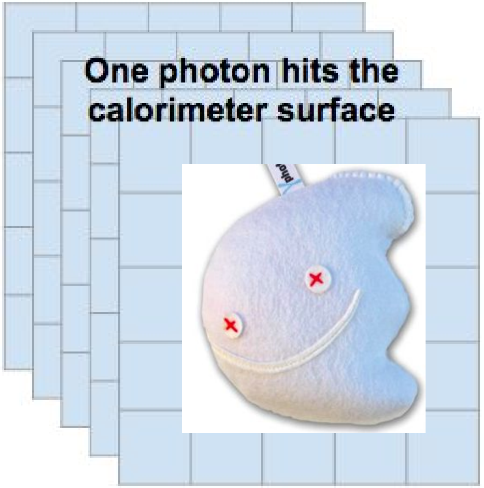
- Easy to simulate samples
- State of the art of the next-generation detector
- The ultimate granular calorimeter in (x,y) as well as z (3D problem)
- Very similar to classic ML problem (MNIST dataset, coming up later!)

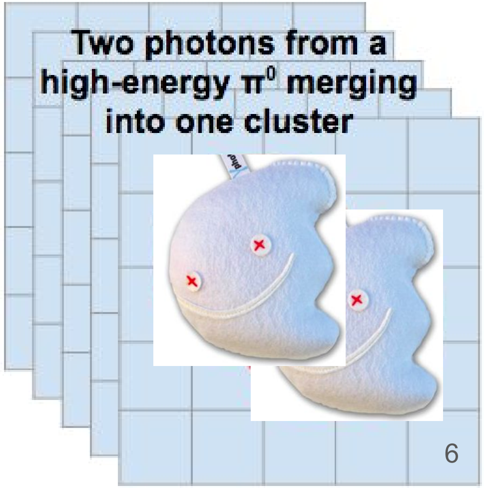


Photon shower



CALICE ECAL @ Fermilab

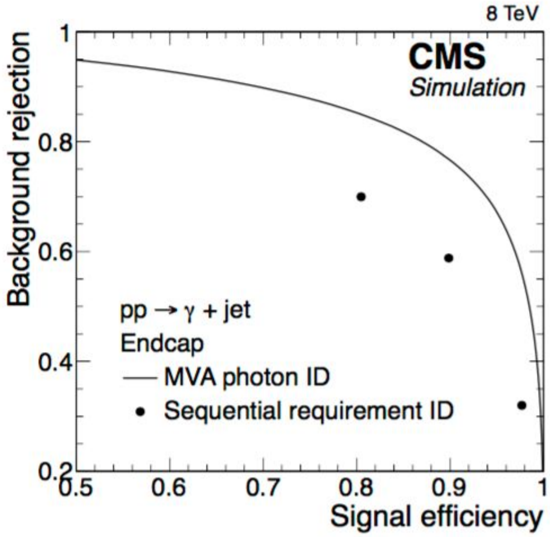




Introduction
- Particle ID -

ML in use in past & current experiments!

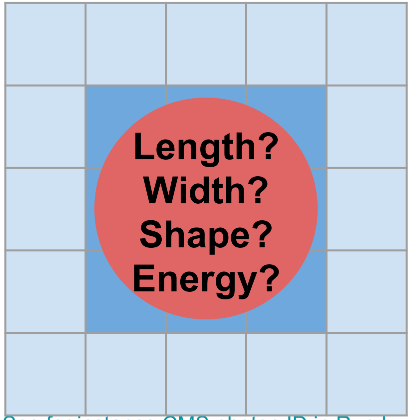
- Neural Networks @ LEP
- Boosted Decision Trees @ BaBar/Belle and the LHC



PID - *supervised classification problem:*

Current procedure:

- Get samples from simulation or detector
- Manually identify discriminating physics features (signal vs. background)
- Train algorithm (cut-based selection/BDT/NN/etc) to maximize separation
- Extract features and apply algorithm to classify new data



See for instance CMS photon ID in Run I

Introduction
- Particle ID -

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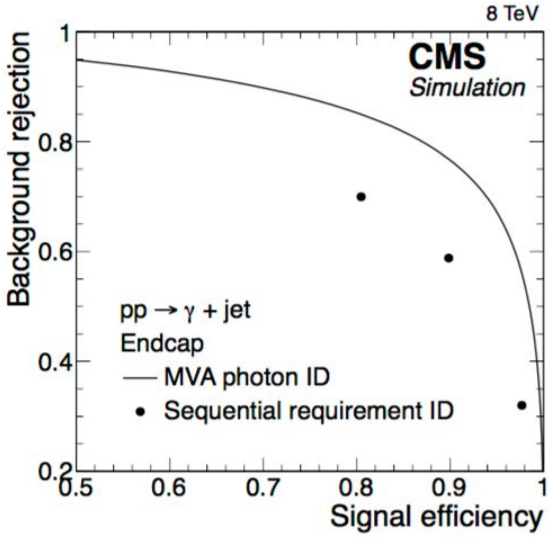
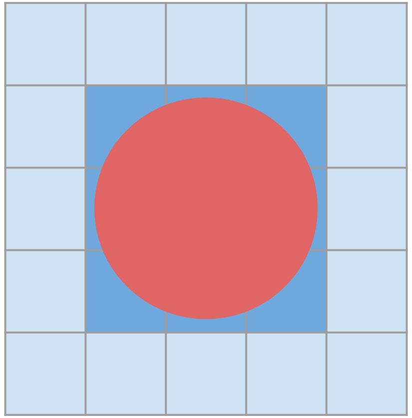


PID - *supervised classification problem:*

New Approach:

- Get samples from simulation or detector
- No feature identification—use only raw data
- Train DNN to *look at* clusters (imaging problem!) for PID
- Apply DNN to classify new data



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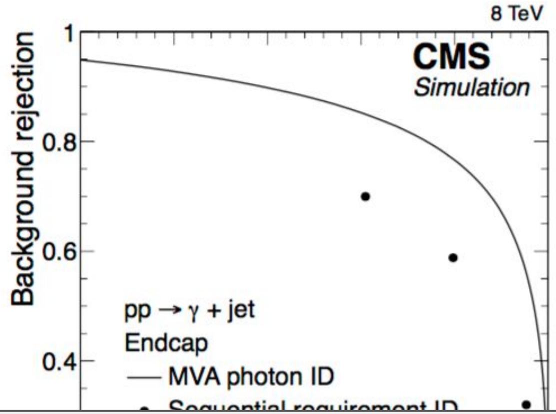
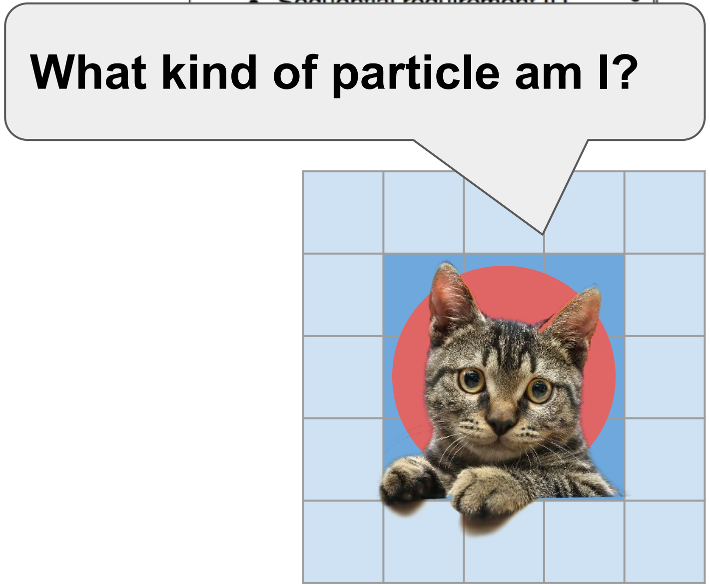
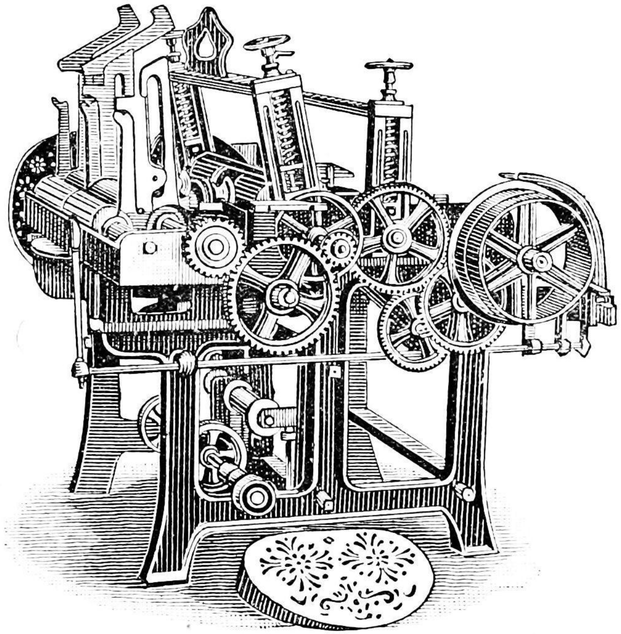




Machine Learning



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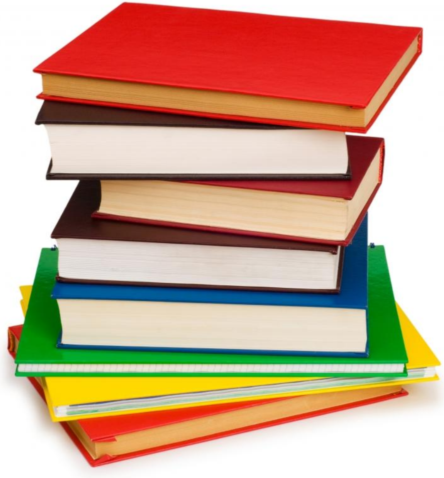


= ?

Machine Learning
- MNIST -

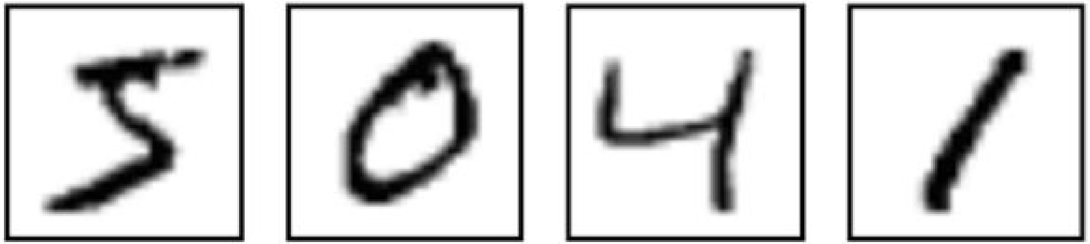
Machine Learning:

"teaching computers to classify data"

Classic Example:

MNIST handwritten digit dataset

70,000 28x28 centered arrays of labeled, handwritten digits



Machine Learning
- Procedure -

Collect tons of labeled data

↓

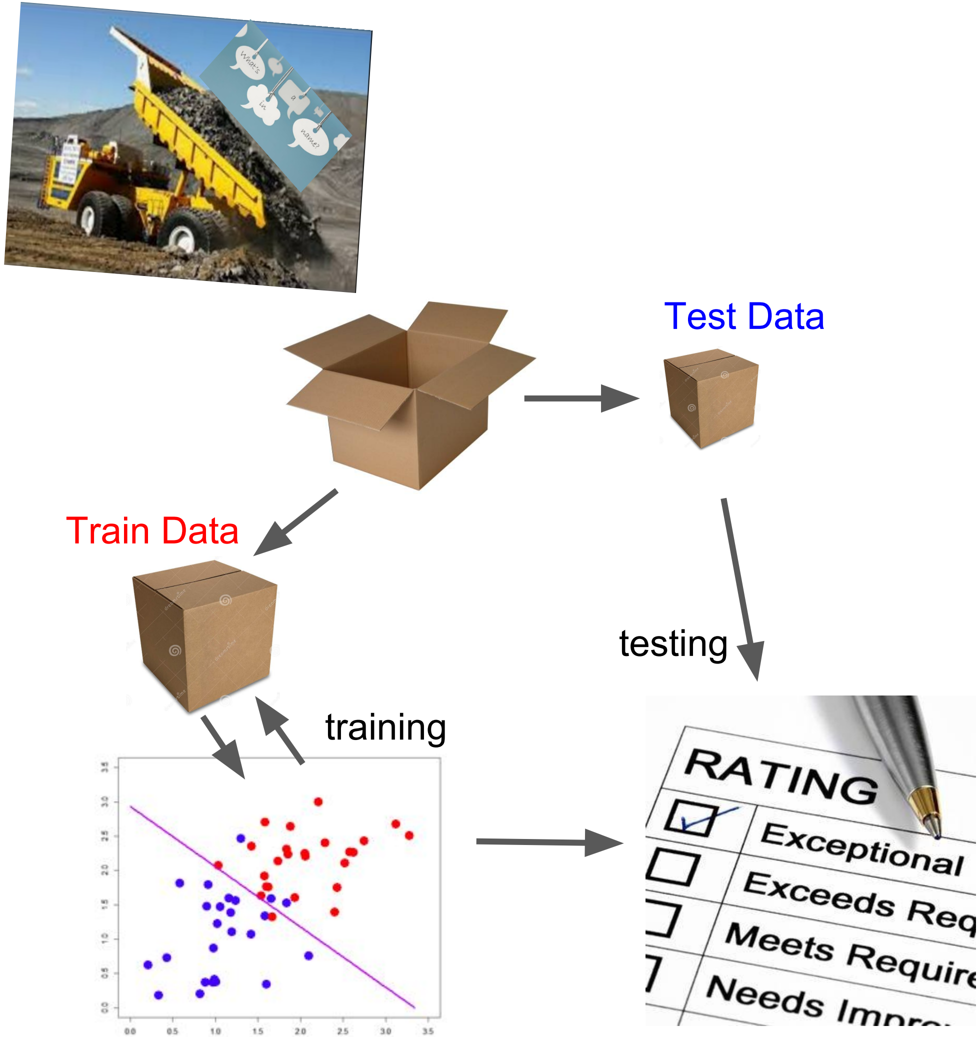
Divide into train and test sets

↓

Use train set to learn to separate classes based on attributes
(train for multiple ***epochs*** until ***loss*** is small)

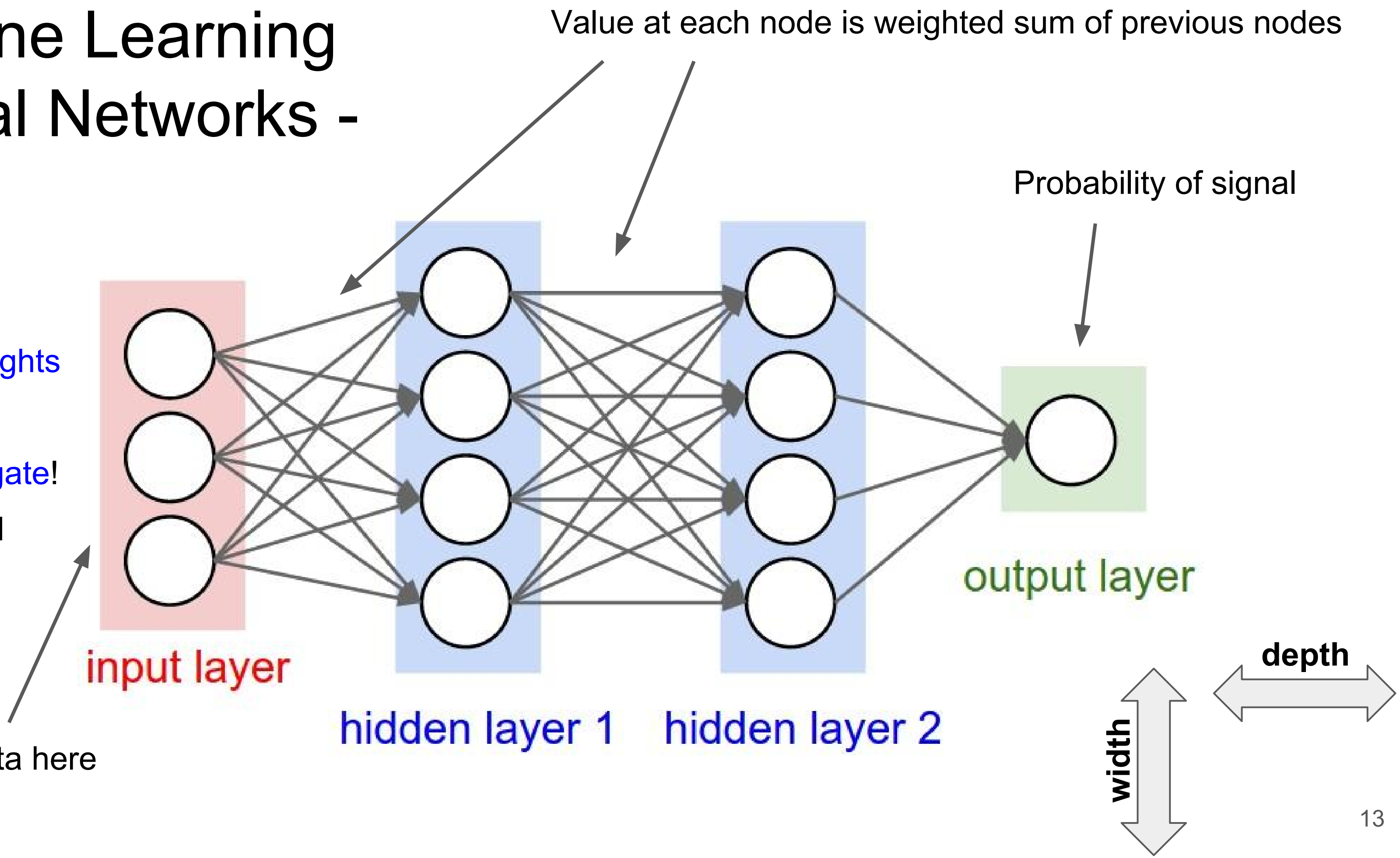
↓

Use test set to check model



Machine Learning
- Neural Networks -

- Start with random weights
- Get output
- Backpropagate!
- Repeat until small error



Machine Learning
- Hardware -

High dimensionality leads to highly parallelizable problem

↓

Use GPUs for training

Currently using two NVIDIA GTX TITANs @ Caltech...

...because CERN has no GPUs :(

Machine Learning
- Model Comparison -

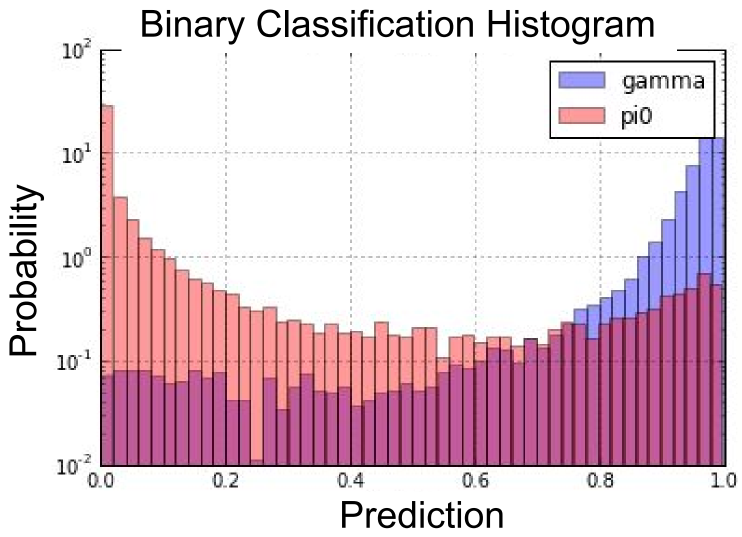
How to compare techniques?

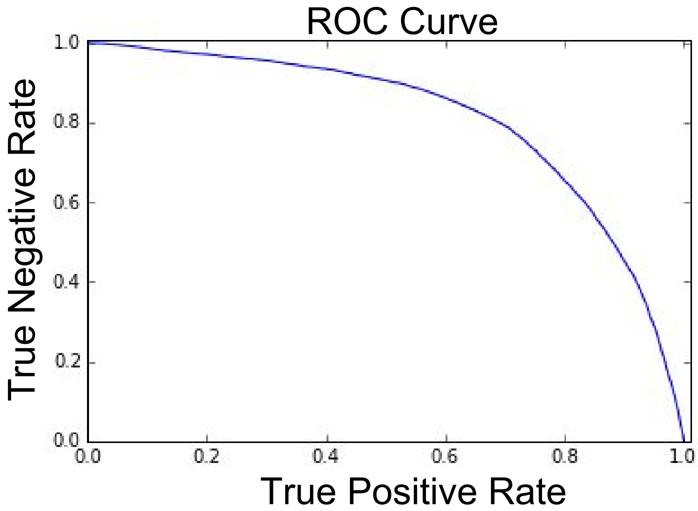
- Complexity / understandability
- Time to train
- Performance

ROC curves to compare performance

Give visual representation of Sensitivity vs. Specificity

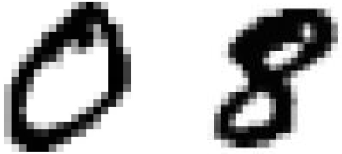
(aka True Positive Rate vs True Negative Rate)

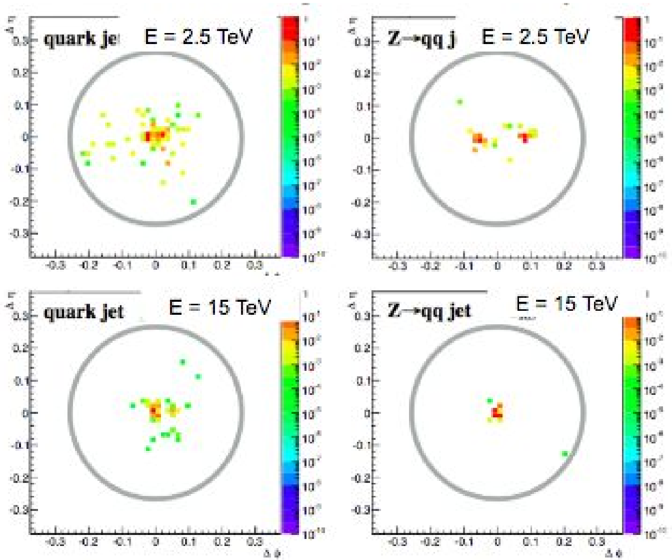


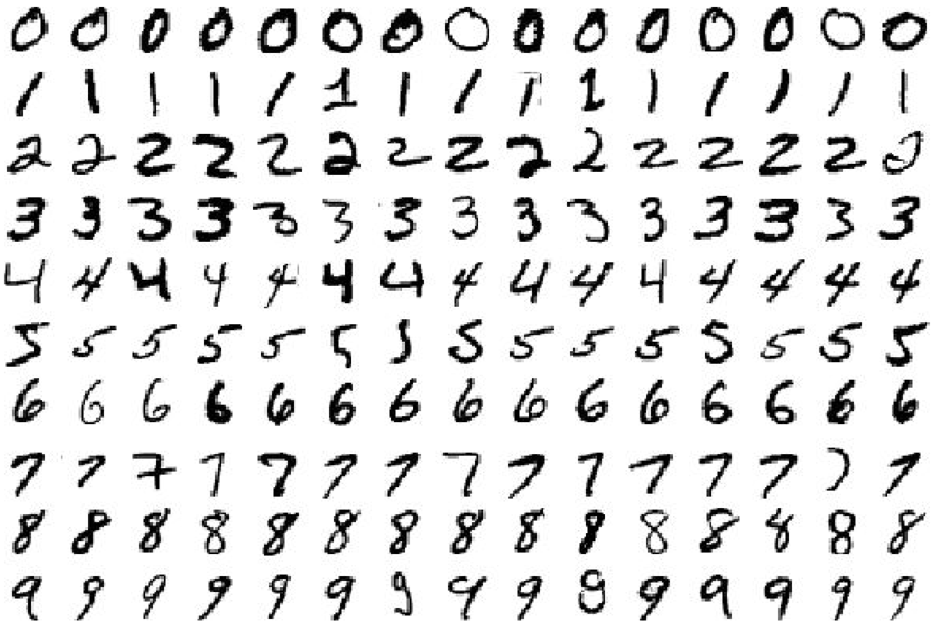


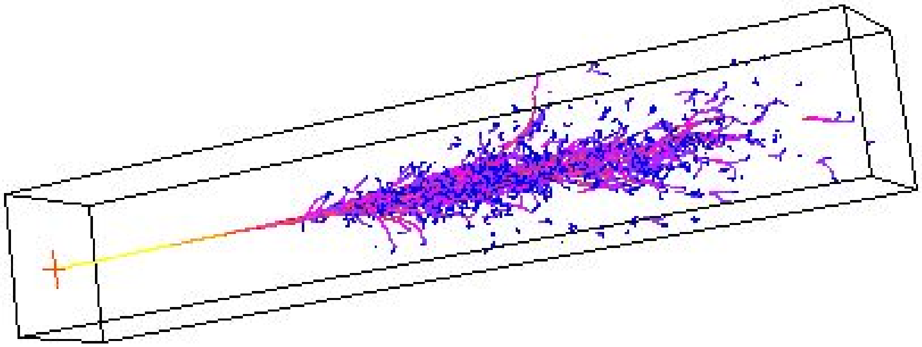
Particle ID
- // to MNIST -

- Imaging problem
- 2D vs 3D clusters
- “0” vs “8” analogy with “gamma” vs “pi0”









Our work

Project
- Tools -

python™

Software

jupyter

K

theano

Hardware

Project
- Data Preparation -

Use ROOT to generate 100-GeV single-particle events in Geant4 LCD calorimeter (@ CERN)

→

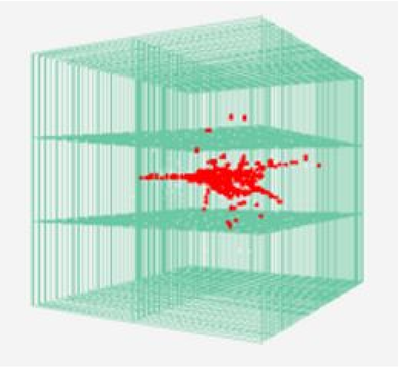
Extract ix, iy, iz, and E for each event; save in long python list (@ CERN)

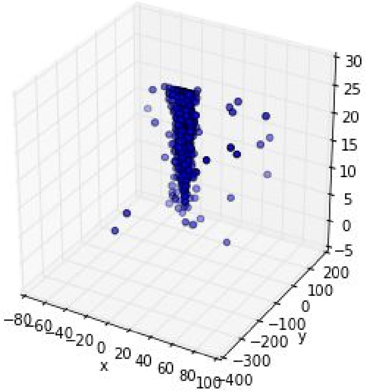
→ Send to Caltech!

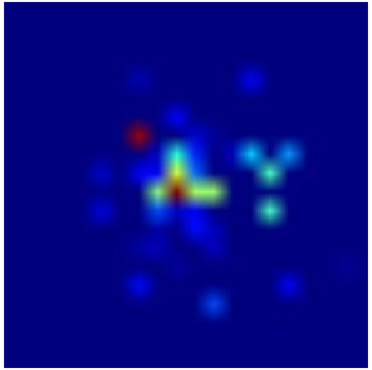
Parse into NumPy arrays; make 20x20x25 centered event arrays (@ Caltech)

→

Store ~40,000 event gamma and pi0 datasets (@ Caltech)





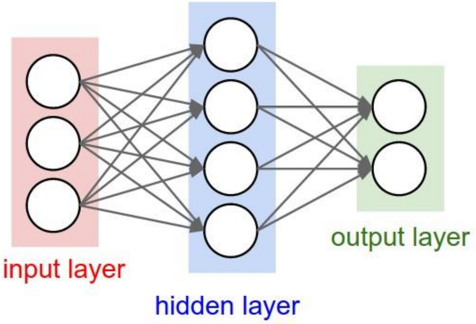


Project
- Network Topologies -

Three main types:

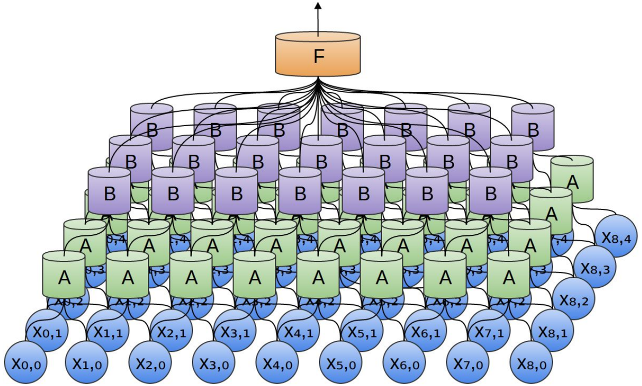
Fully connected

- Simple
- Generally fast
  (~1s per epoch)



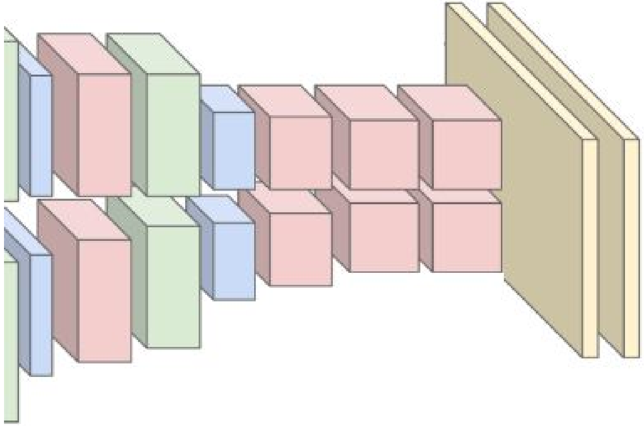
Convolutional

- Preserves Structure
- Slower
  (~60s per epoch)

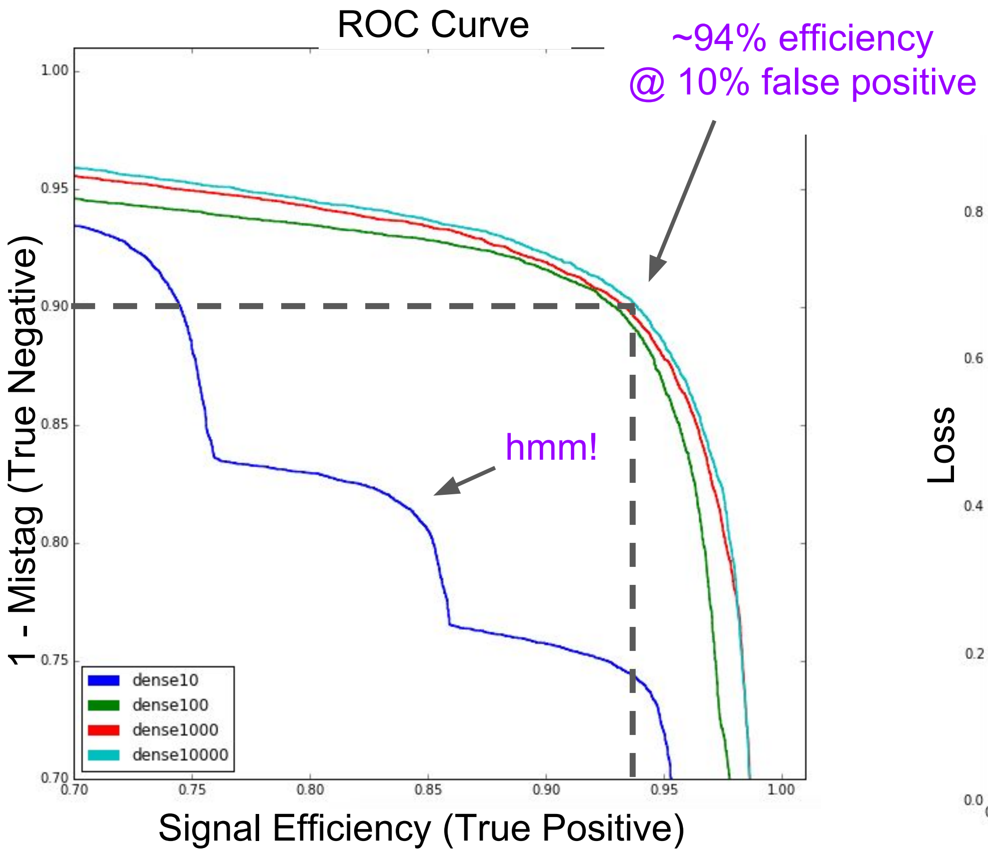


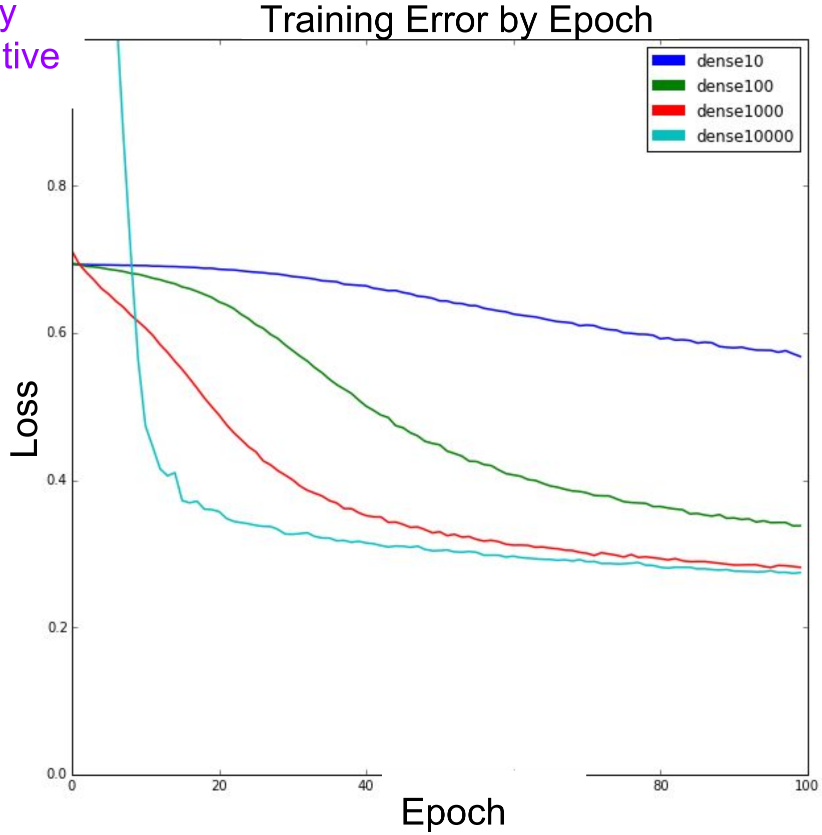
Branched and Multilayer Convolutional

- Even better feature recognition
- Takes long time to train
  (~180s per epoch)

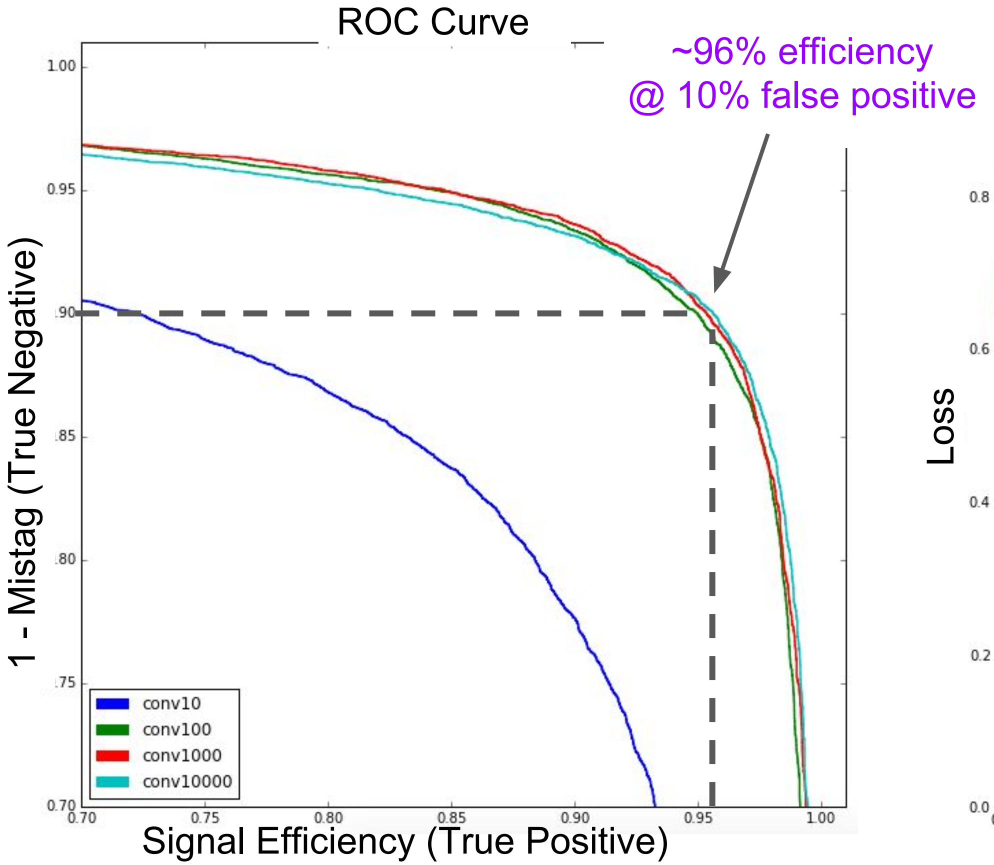


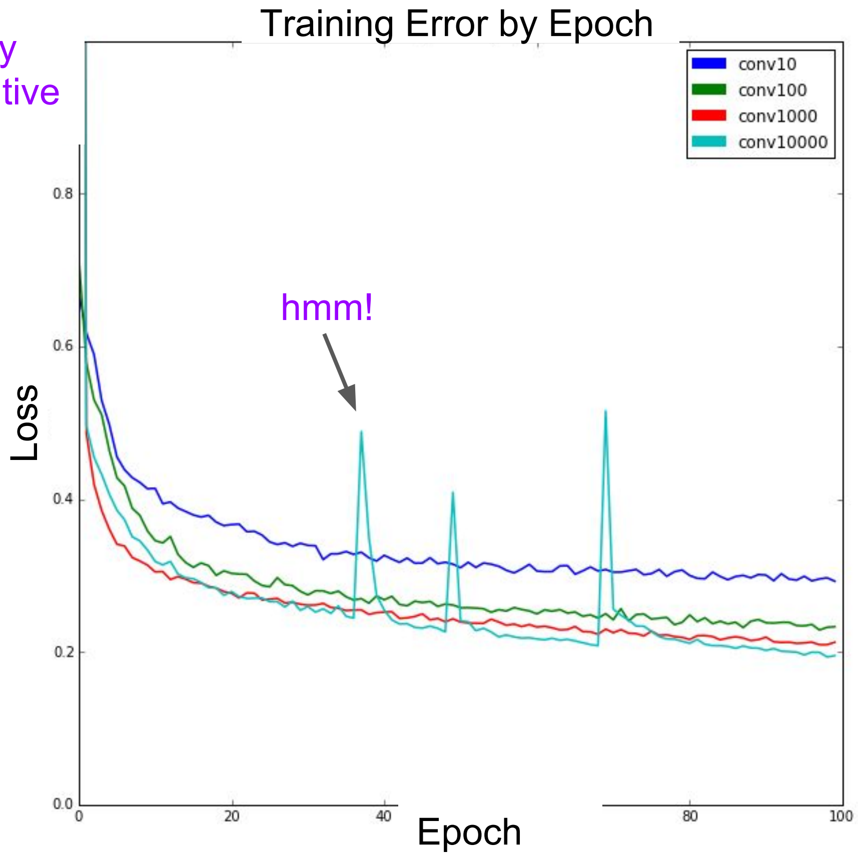
Project - Network Topologies - Fully Connected



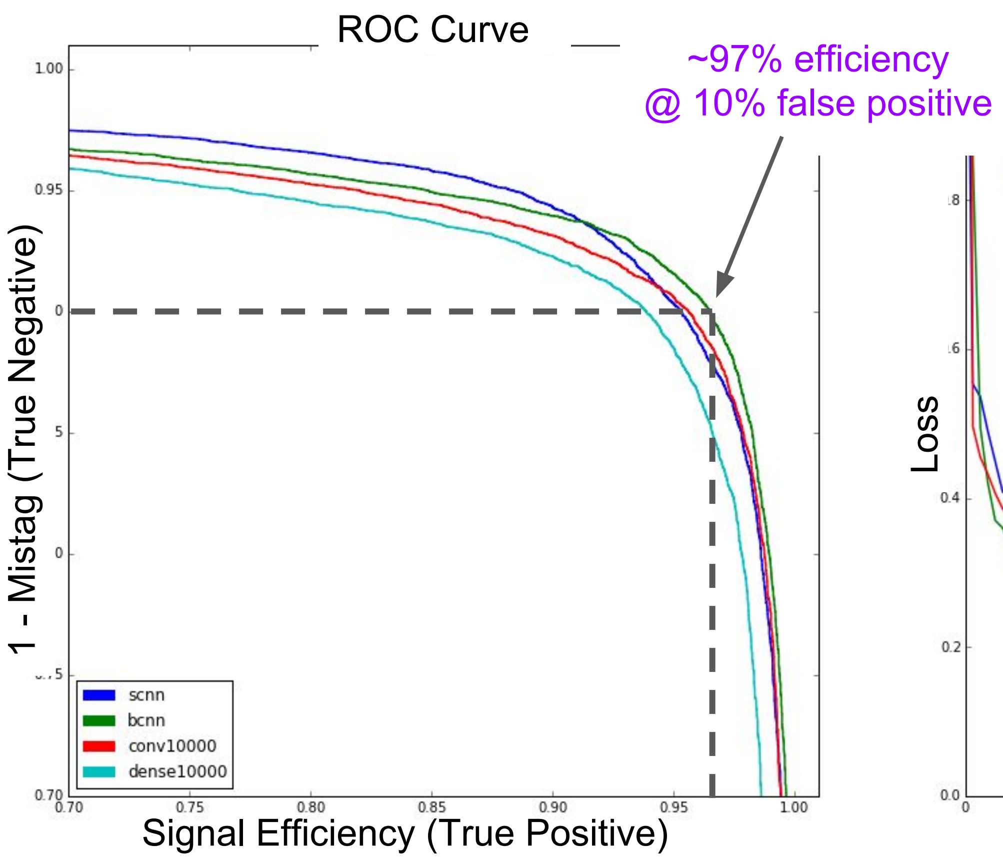


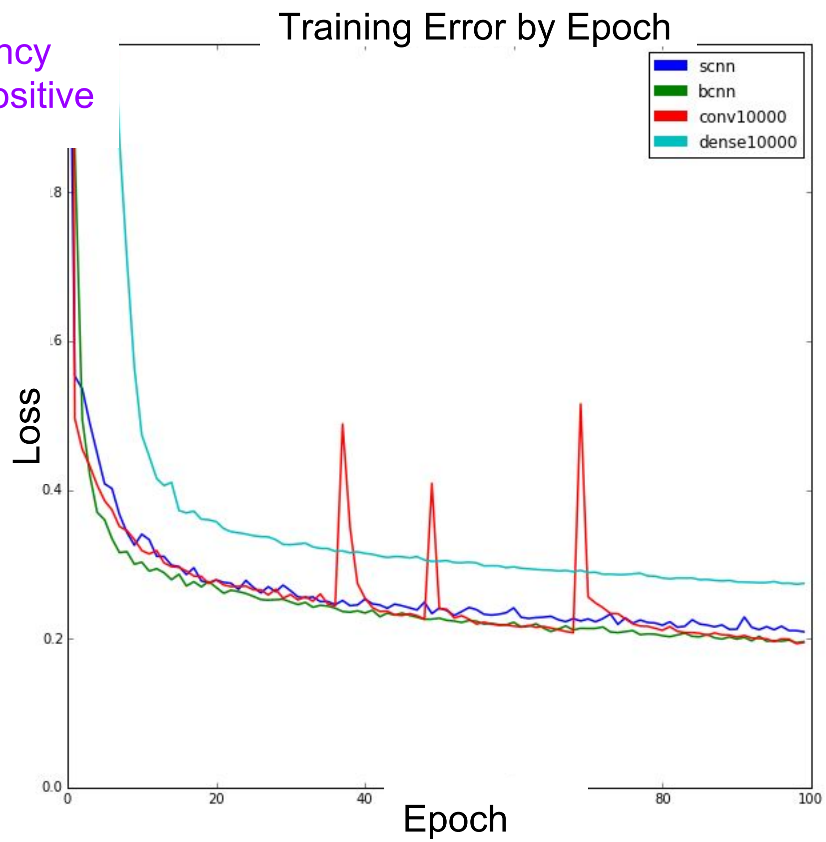
Project - Network Topologies - Convolutional



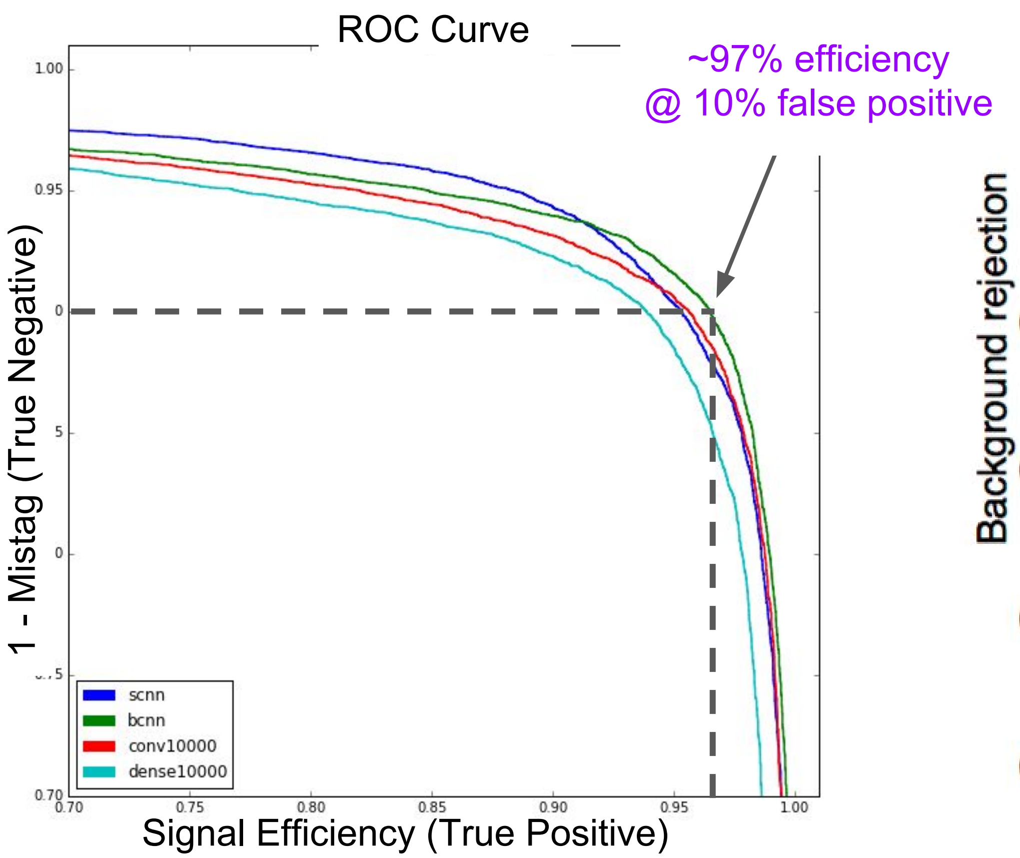


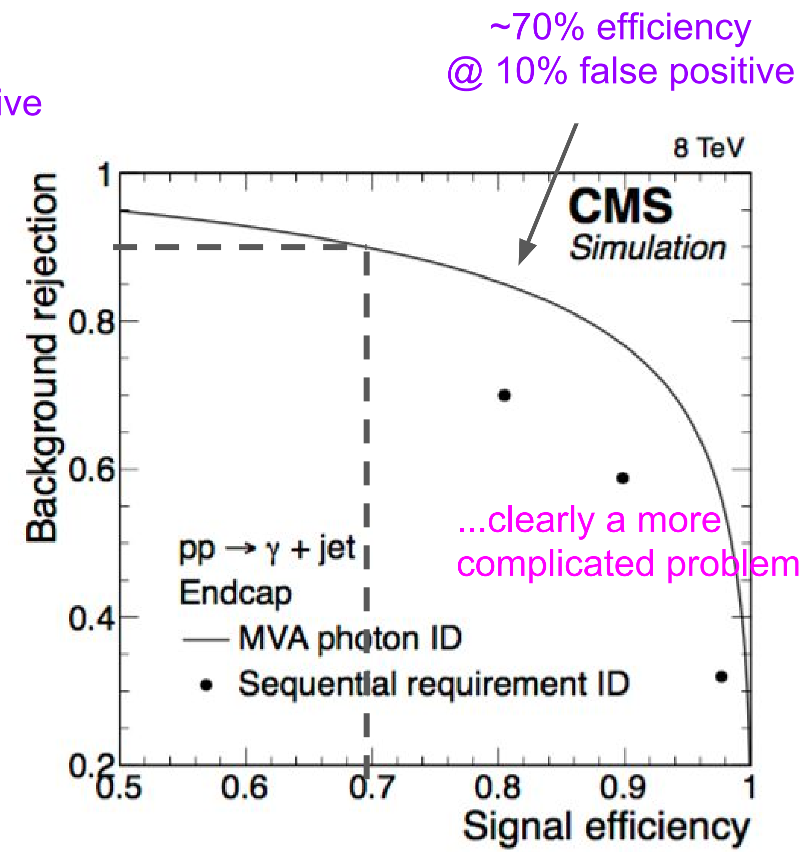
Project - Network Topologies - Convolutional II





Project - Network Topologies - Convolutional II





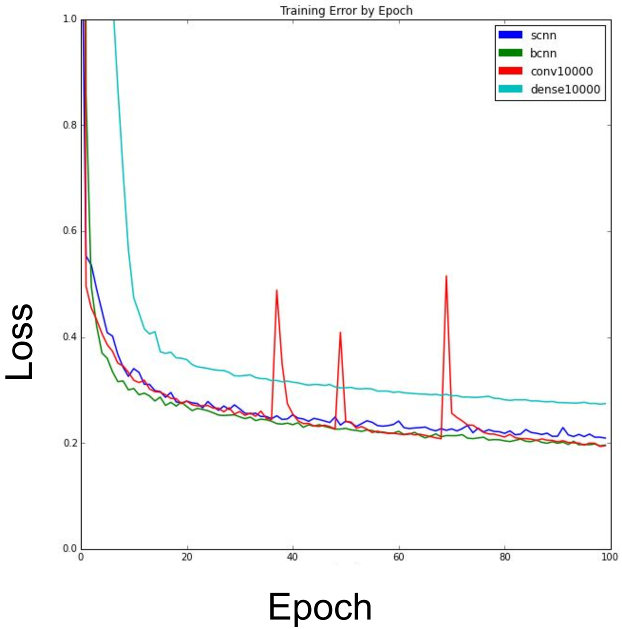
Limitations and Moving On

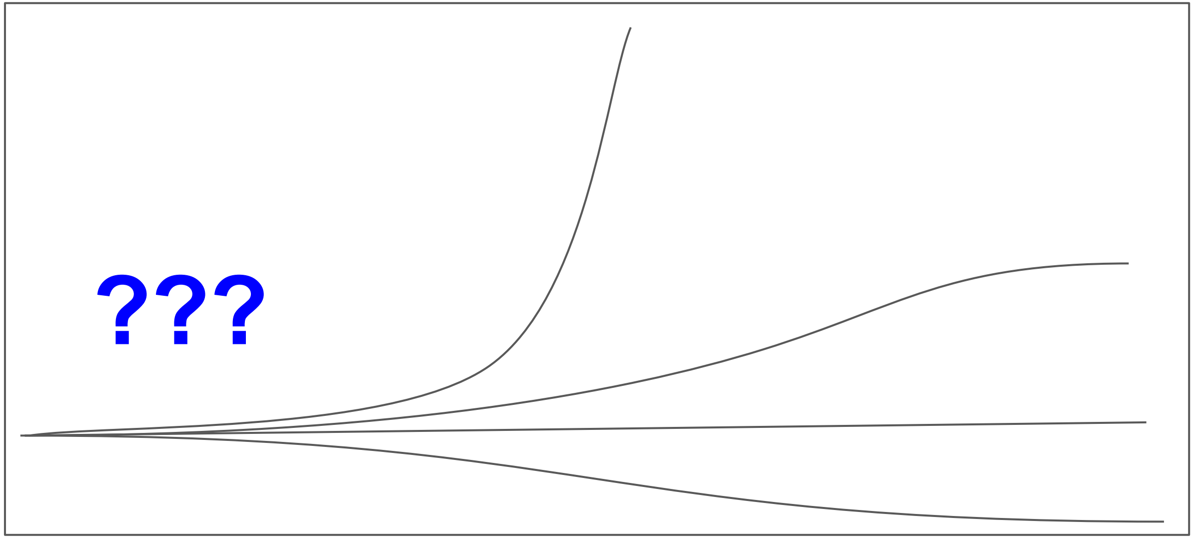
Project - Current Limitations

How long to train?

“Best” model?

- Loss keeps decreasing well after 100 epochs
- Don’t have enough GPUs for quick training!
    - Looking to get time on CSCS GPU cluster





Project - Current Limitations

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“Best” model?

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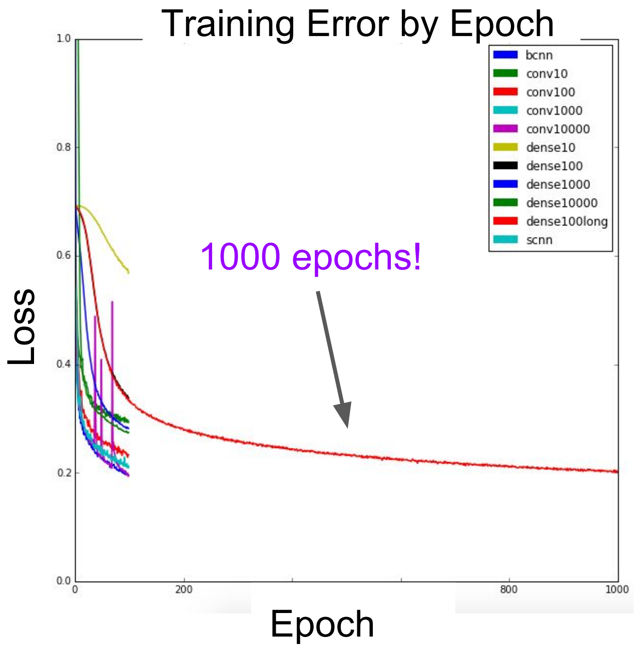
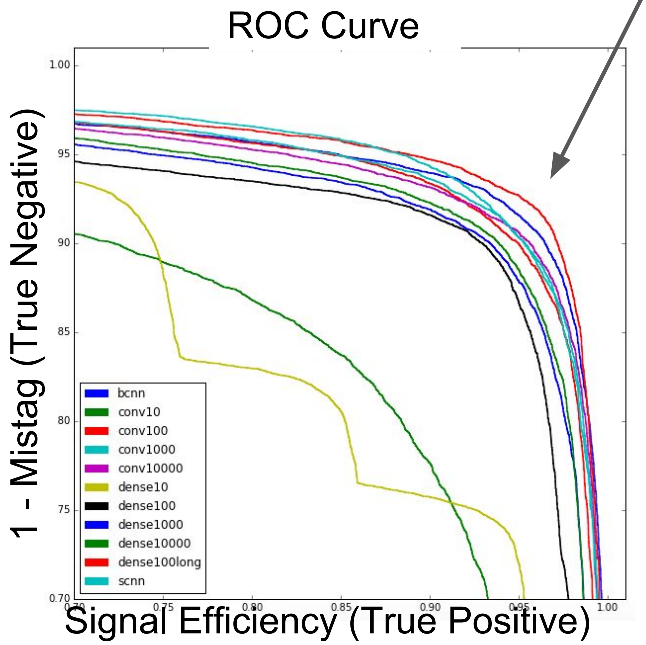
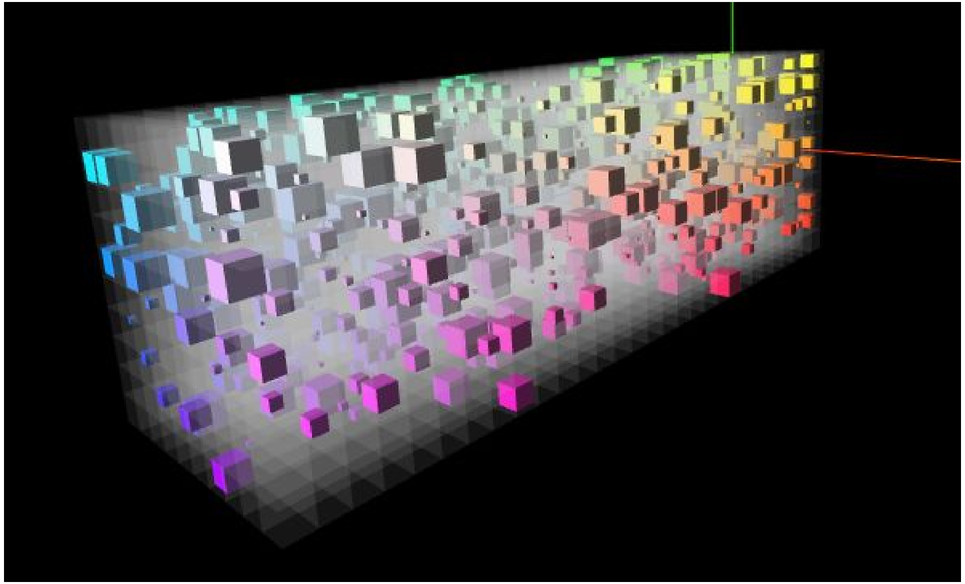
~98% efficiency
@ 10% false positive





Project
- Next weeks -

- Identify 'ideal' network topology for binary classification
  - Scan over hyperparameters
- Regression on energy



- Future -

Beyond 1-1 classification

- Jet ID
- Gluon vs quark vs boosted Higgs vs boosted Z vs boosted top

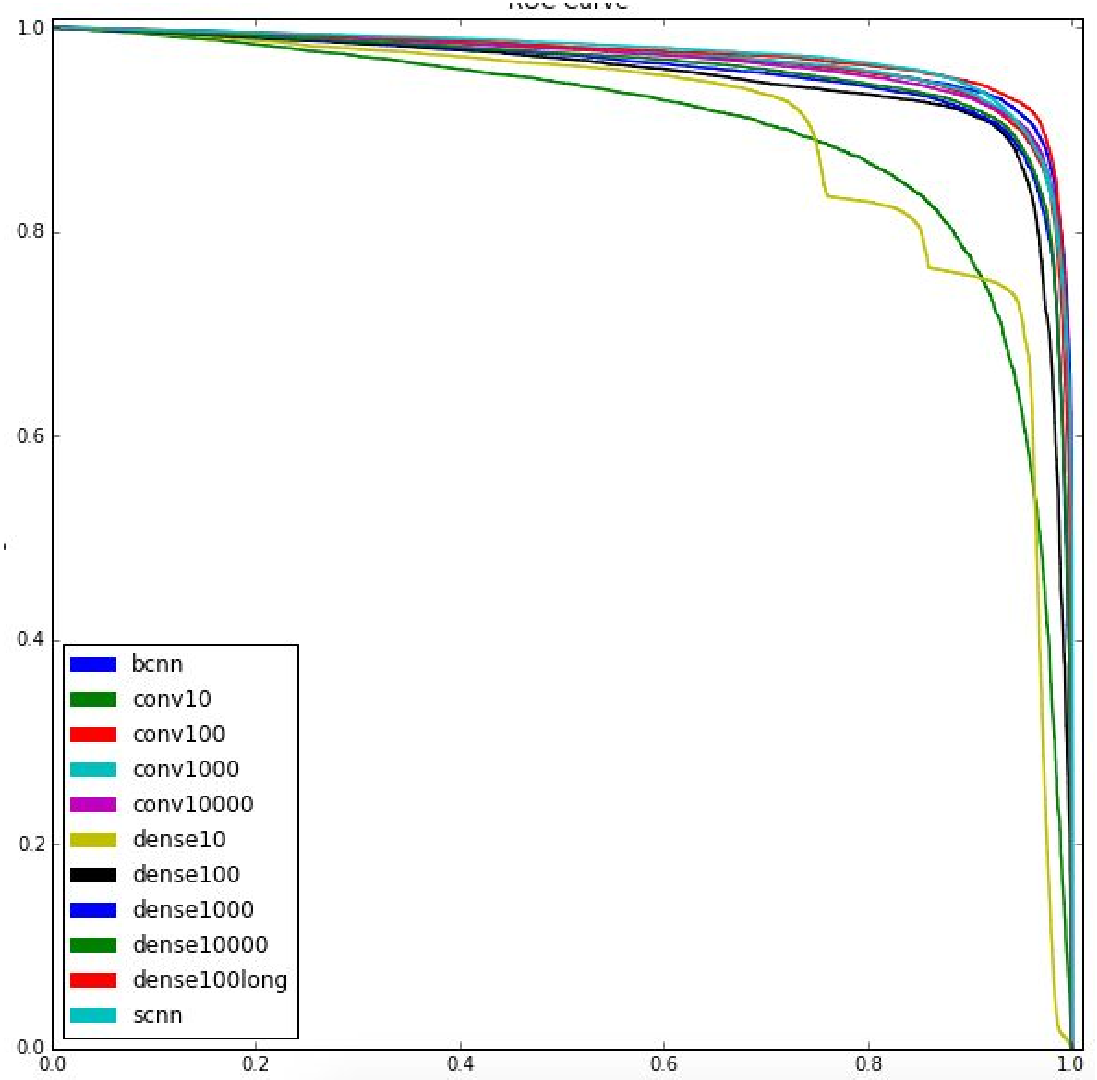
Provide general resource

- Benchmark for professionals
- Publish on Open data as a ML standard (the MNIST of Particle Physics)

Big thank you to BU, Augusto, Maurizio & Jean-Roch!

...any questions?

Backup Slides


1.0
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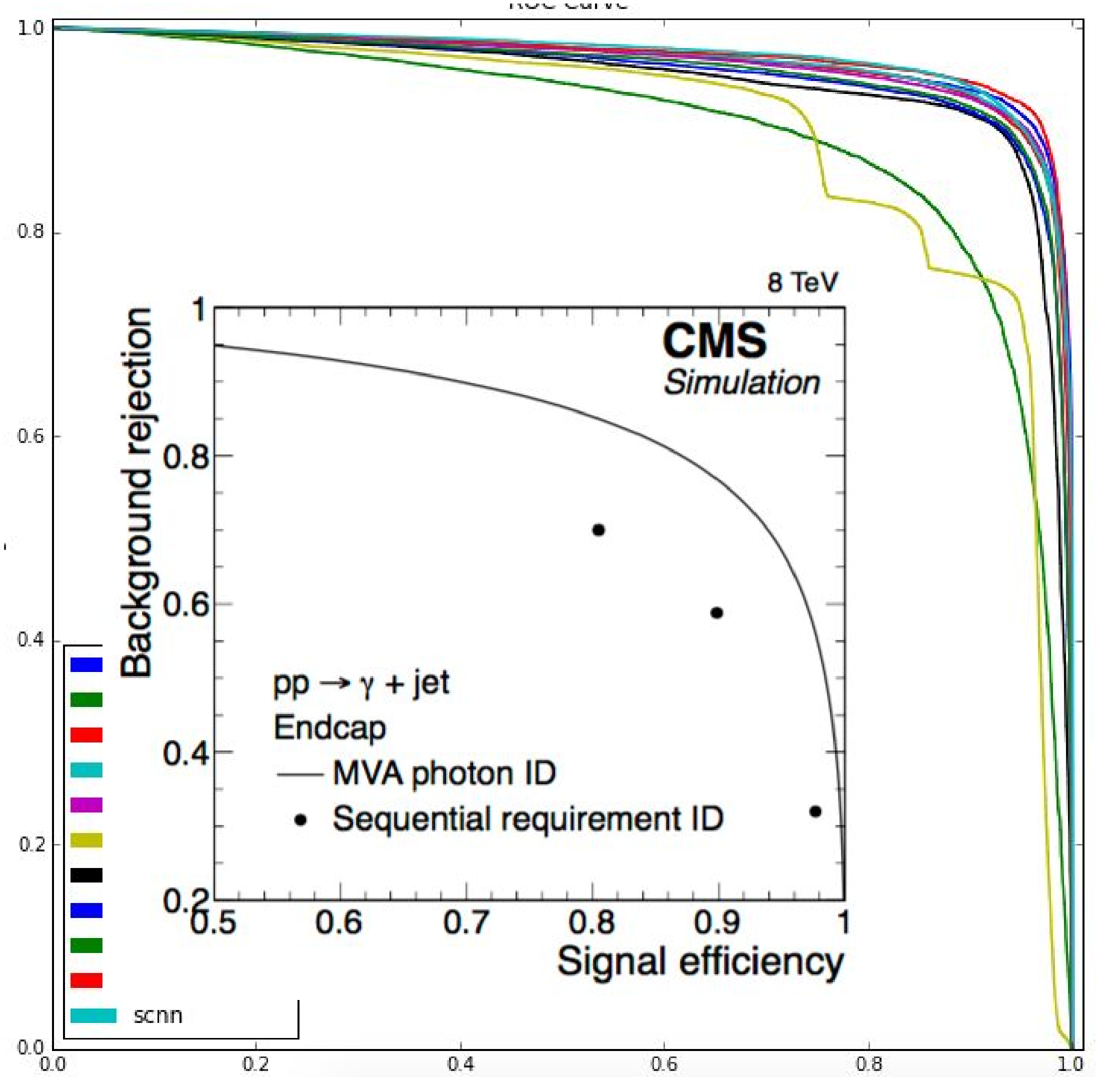
bcnn
conv10
conv100
conv1000
conv10000
dense10
dense100
dense1000
dense10000
dense100long
scnn



1.0
0.8
0.6
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0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
scnn
8 TeV
CMS
Simulation
Background rejection
Signal efficiency
pp → γ + jet
Endcap
MVA photon ID
Sequential requirement ID
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0.7
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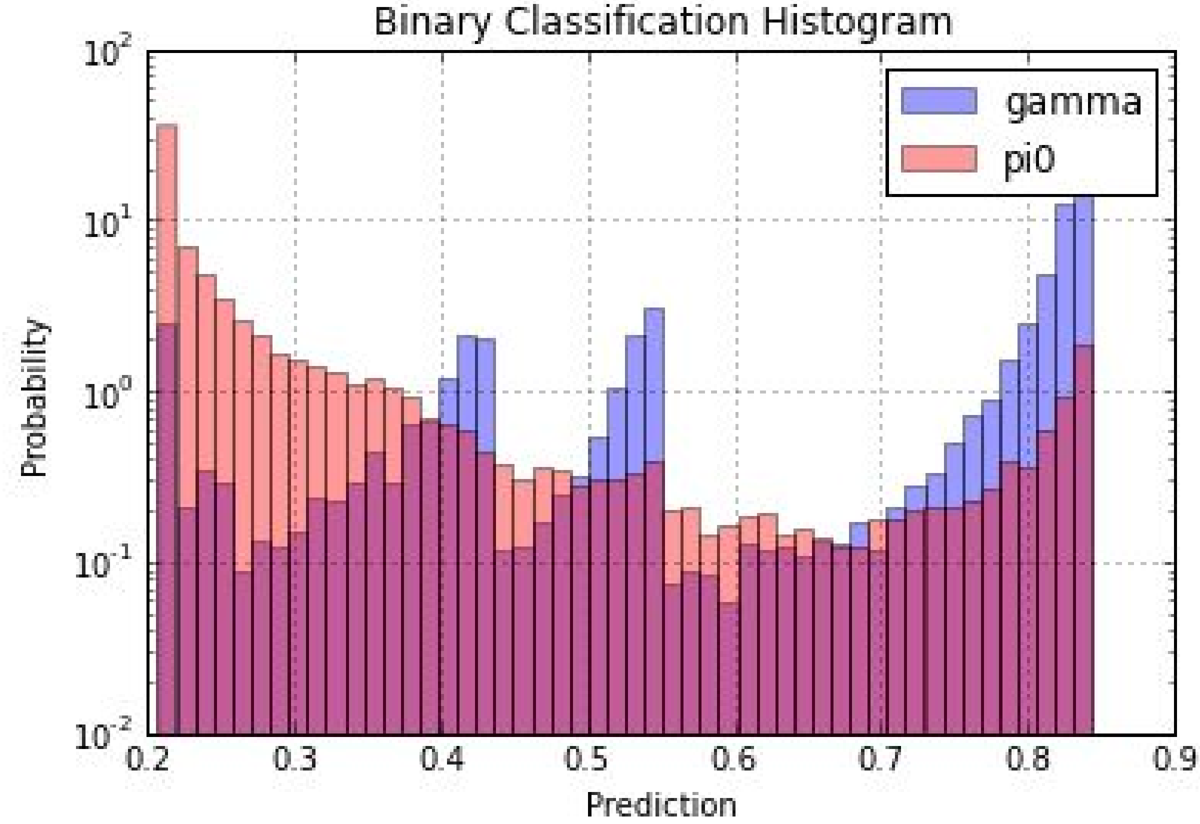
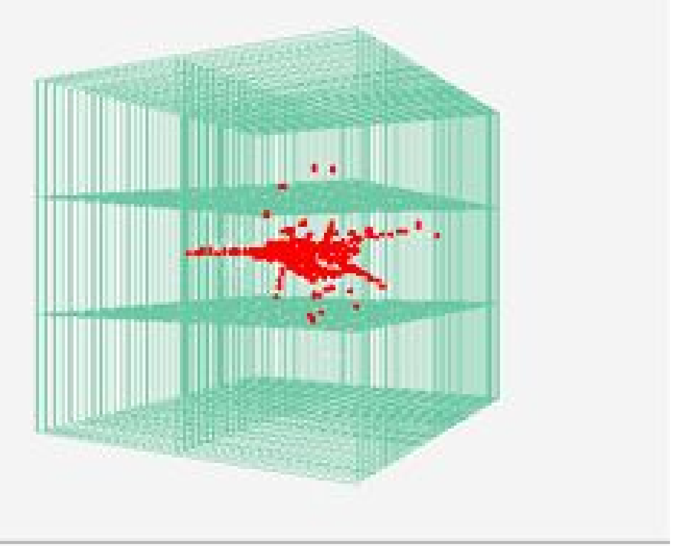
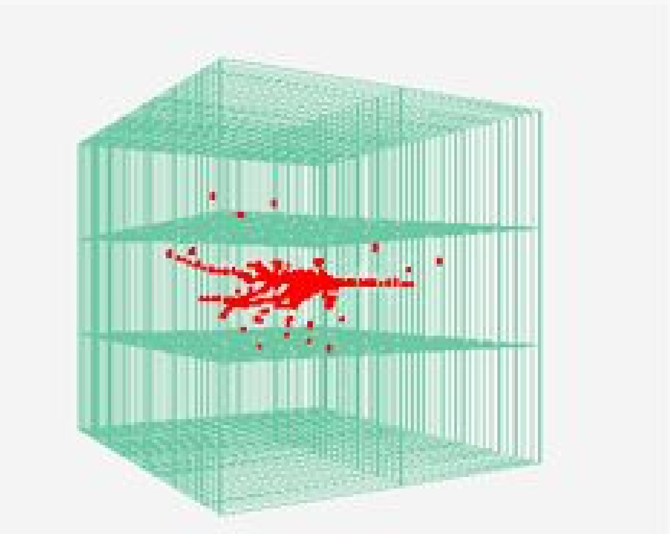
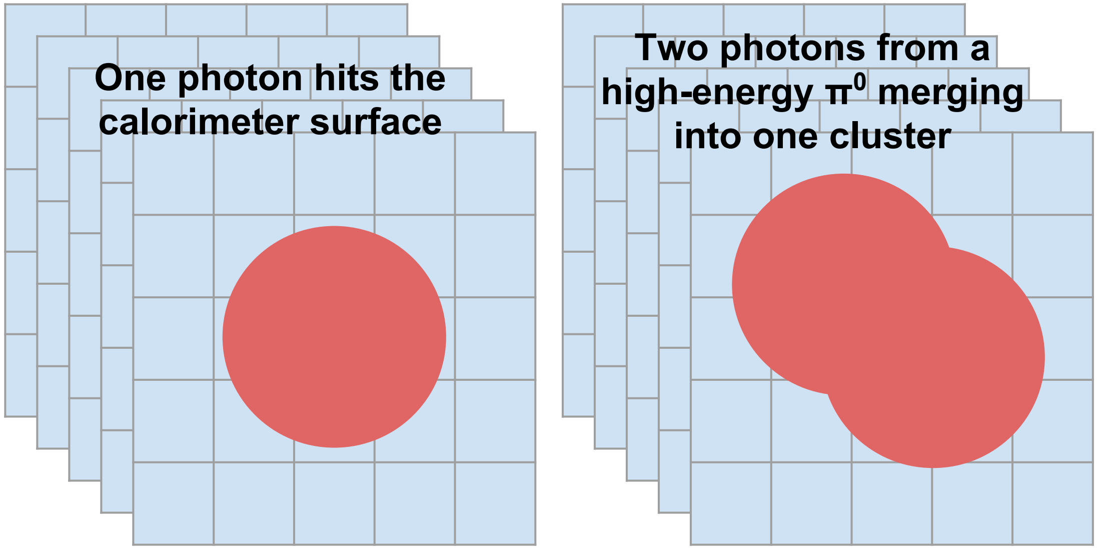
1



https://titans.hep.caltech.edu:8182/notebooks/Niki/Plot_Models.ipynb



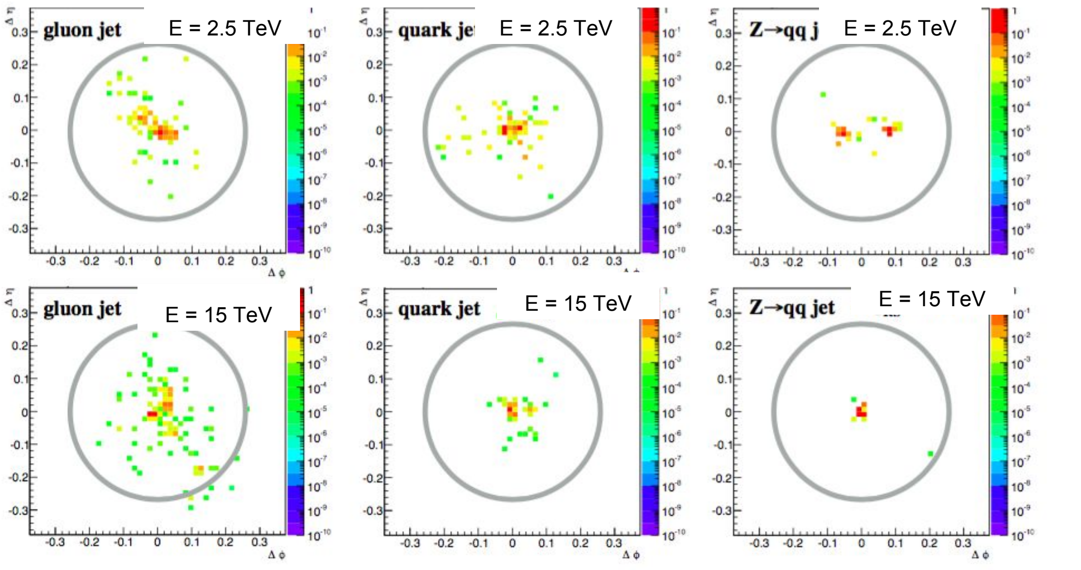


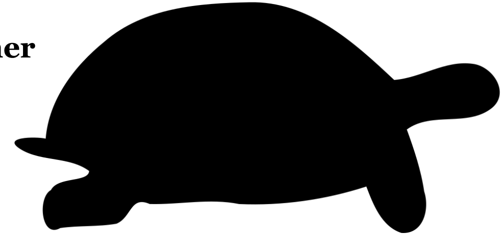

One photon hits the calorimeter surface
Two photons from a high-energy π^0 merging into one cluster

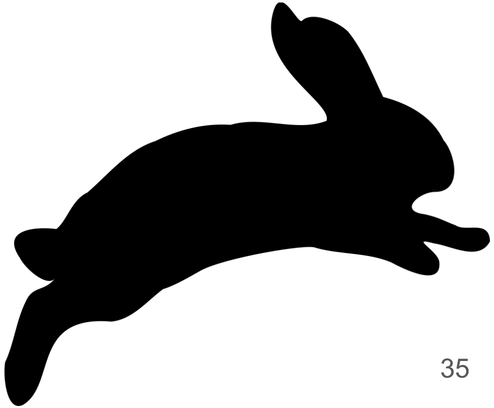
Particle ID
- Importance -

1) Fast yes/No answer based on what a cluster look like
   a) Problem reduced to reading the detector and evaluating the function
   b) No complex reconstruction involved
   c) Faster than actual reconstruction good for granular-calorimeter triggers at future colliders? (e.g. FCC, High-Luminosity LHC, etc)
2) Potentially, could reach similar performances as traditional techniques
   a) Energy reconstruction from regression (already done offline with BDTs @LHC)
   b) Particle identification from classification
3) **Could be extended to more complex problems (identify jets of particles, rather than single particles)**

Jet-constituent energy fraction as a function of the angular distance from the jet axis







Introduction
- ML for Particle ID -

Machine learning successfully used for Particle Identification in HEP

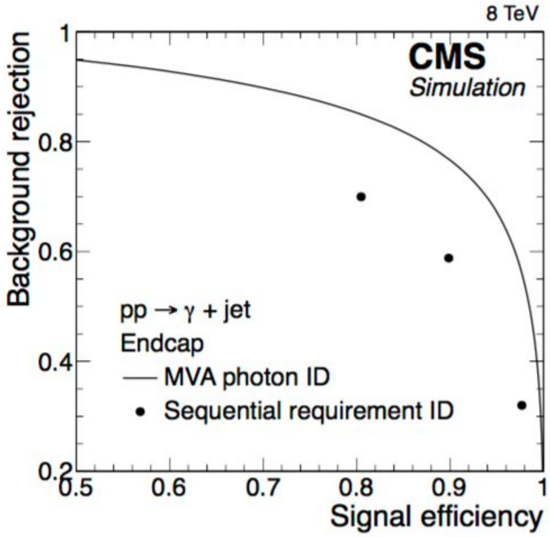
- Neural Networks @ LEP
- Boosted Decision Trees @ BaBar/Belle and the LHC

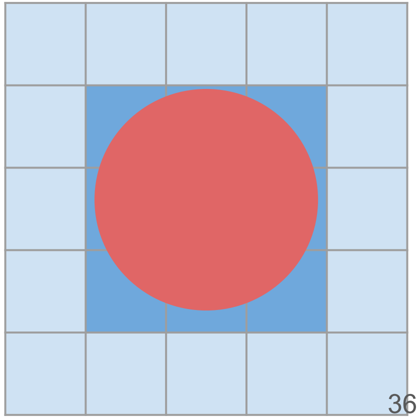
Particle Identification is a classical *supervised classification problem:*

- A training sample for signal and background available from real collisions and/or simulation
- A set of features identified, having discriminating power between signal and background. RAW data already “manipulated” to select an optimal set of physics-motivated variables. Good for the physicist, but potentially limiting for the algorithm.
- A selection algorith (cut-based selection/BDT/NN/etc) trained to maximize the separation

As a next step in this development line, we try to apply Deep Neural Networks

- Go back to RAW data
- Train a convolutional Neural Network to LOOK AT the clusters and see the pions [THE IMAGING CALORIMETRY]





An example of “high-level” feature (i.e., not RAW data)
R9 = (energy 3x3 cluster)/(energy 5x5 cluster)

See for instance CMS photon ID in Run I

Moving on...

1) In this study:
   a) Regression on energy as well as pid
2) Potentially:
   a) Beyond 1-to-1 classification: Jet ID
      i) Gluon vs quark vs boosted Higgs vs boosted Z vs boosted top
3) In the future:
   a) More complex algorithms: provide a benchmark for professionals
      i) Publish dataset on Open data as a standard (the MNIST of Particle Physics) ← how exactly does this work?

Show the event display they made for us

Particle ID
- Importance -

- Yes/No answer based on what a cluster looks like - no complex reconstruction
- Faster than actual reconstruction in triggers at future colliders? (e.g. FCC, High-Luminosity LHC, etc)
- Similar performance to traditional techniques for particle ID?
  - Energy reconstruction from regression (already done offline with BDTs @LHC)
- More complex problems?
  - Jet ID?

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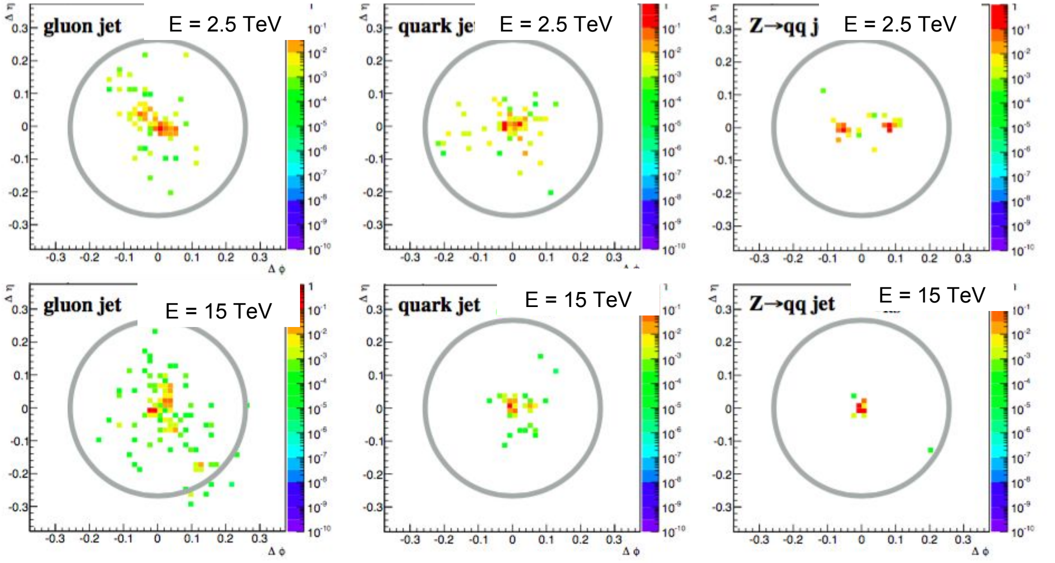

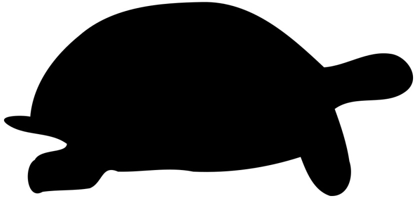

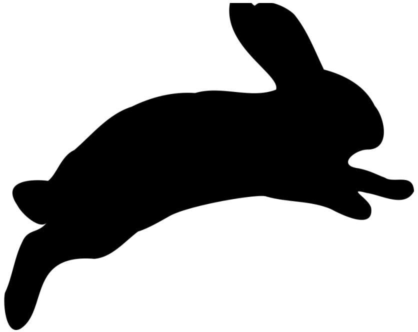

Ok, so what have we done so far?