

# Deep Learning with JUNO

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Juno DFG Meeting  
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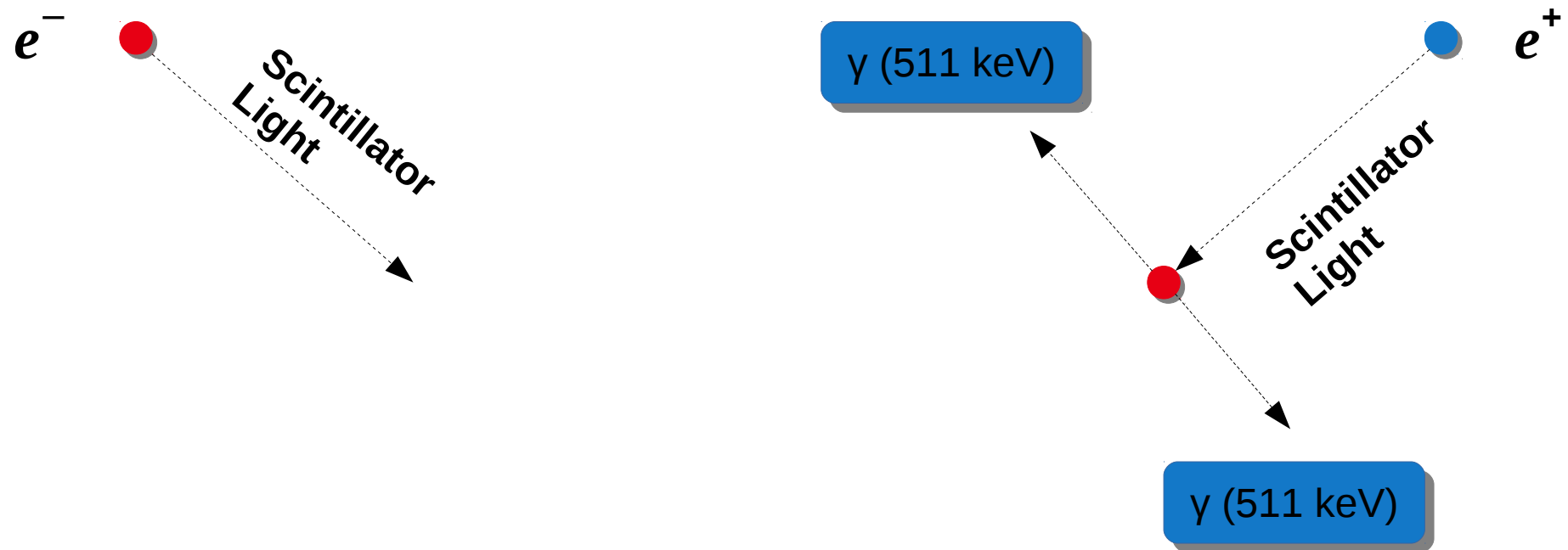
# Goals

- Deep Learning can be useful in many aspects of JUNO:
  - Classification (e.g. event types)
  - Reconstruction (e.g. tracking, energy, ...)
  - Many other tasks
- My studies focus on classification
  - Emphasize on  $e^+/e^-$  discrimination

# Outline

- Electron and Positron events
- Image Generation
  - Issues
  - Implementation
- Classification
  - Current state

# Electron and Positron events

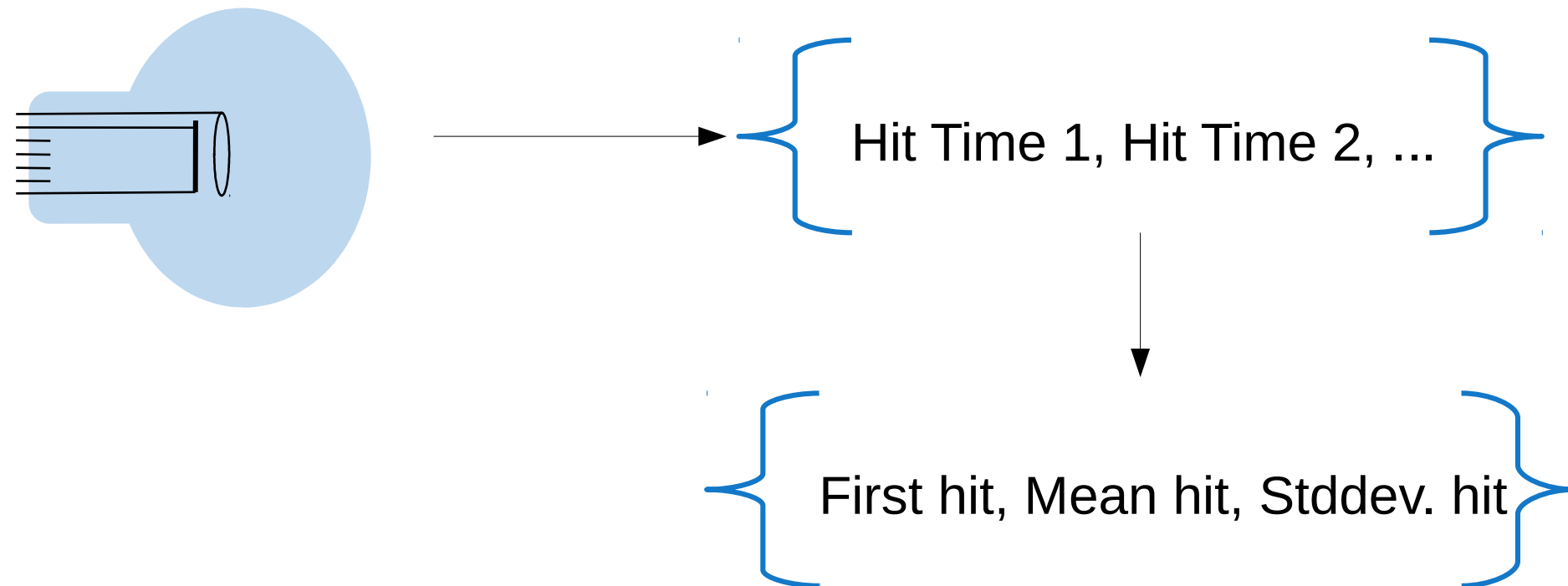


# Implementation

- State of the art classifications:
  - Neural Networks (NN) with image recognition
  - Usually realized as Convolutional Neural Networks (CNN)
- Need to produce images from events with spatial information of event
  - PMT hit times
  - Mean hit time
  - Charge

# PMT Data

Each PMT



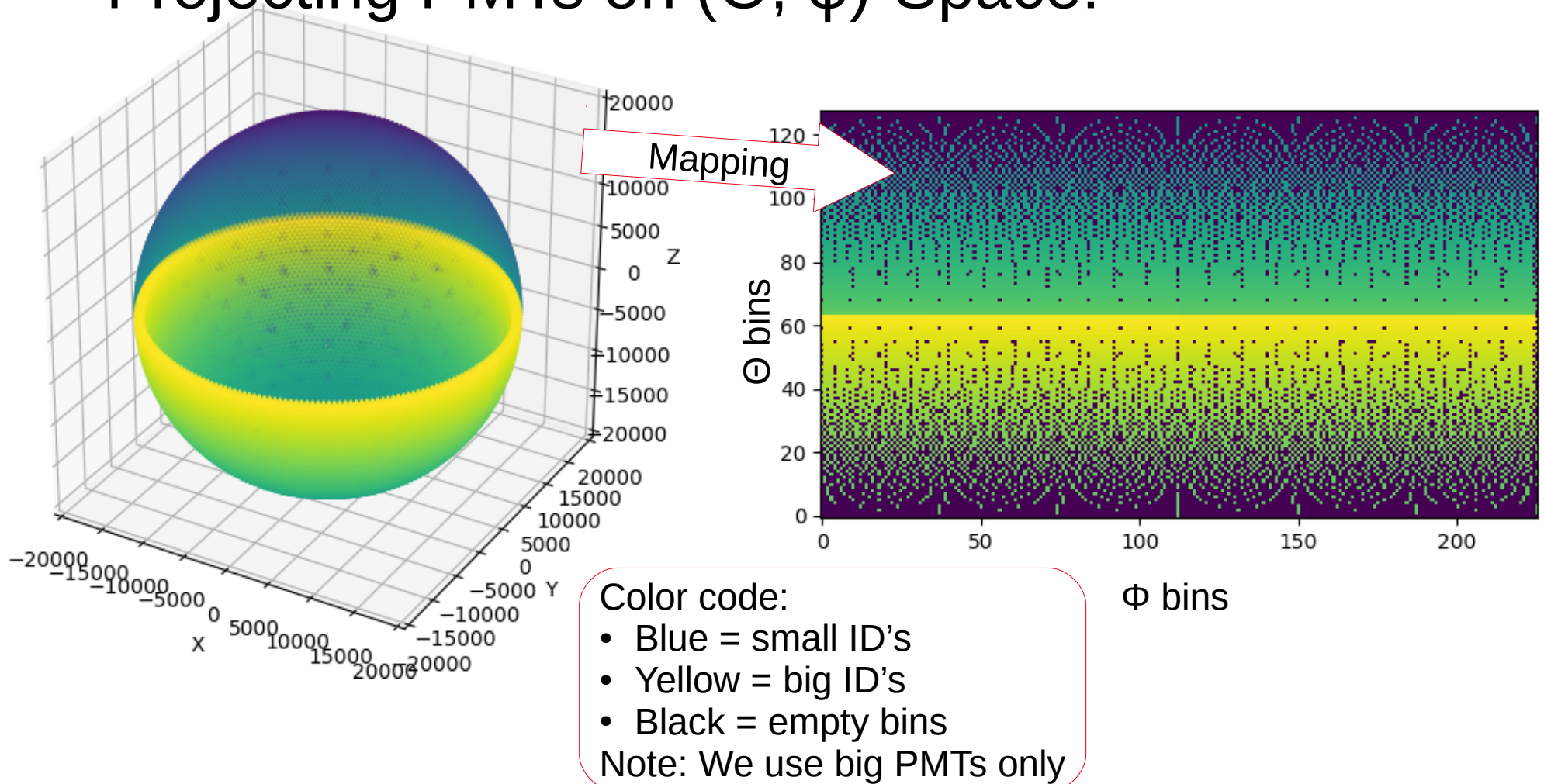
Gives us three channel with spatial information which can be interpreted as color channel for image.

# Image Generation - Issues

- NN's work with inputs of arrays/tensors of some shape (dim1, dim2, ...)
- How to get spherical distributed PMT pixels into array like shape?

# Image Generation – Mapping to Array

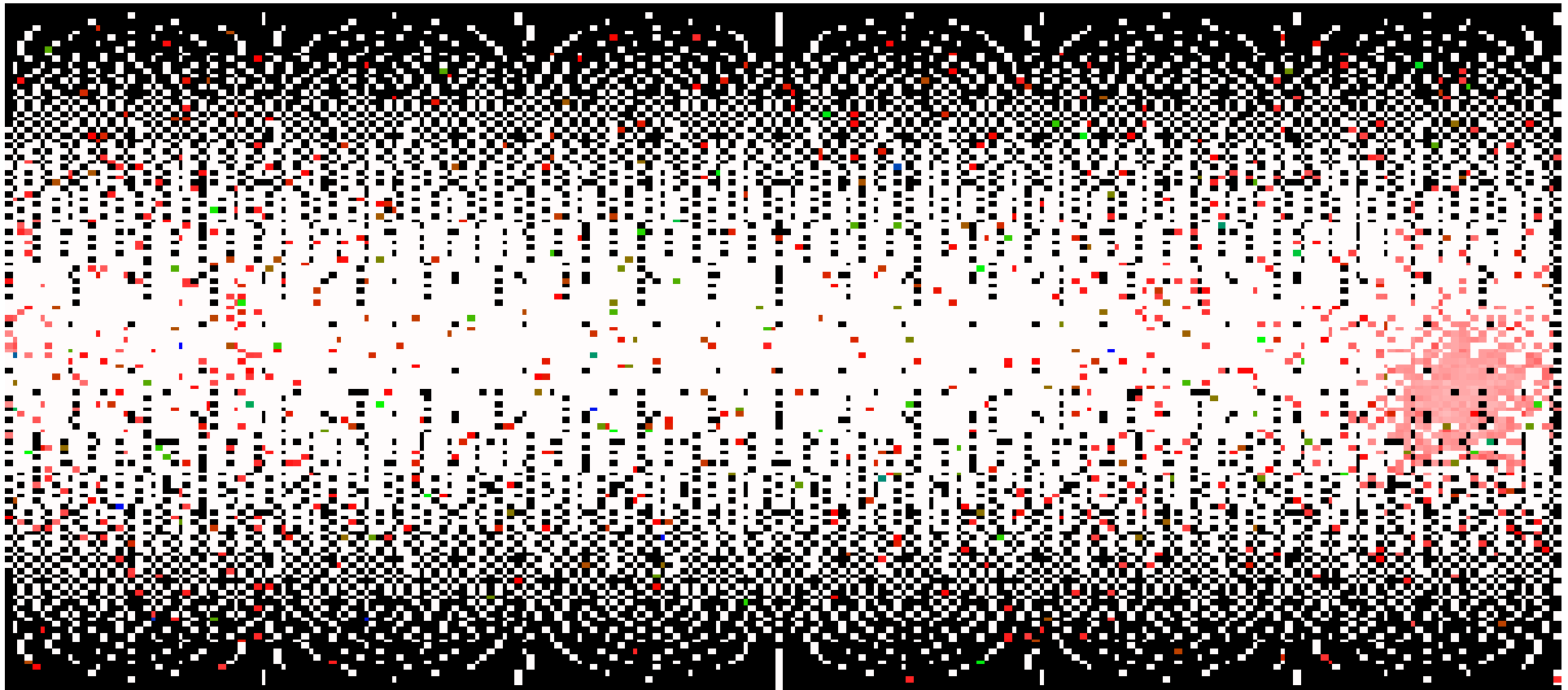
## Projecting PMTs on $(\Theta, \phi)$ -Space:





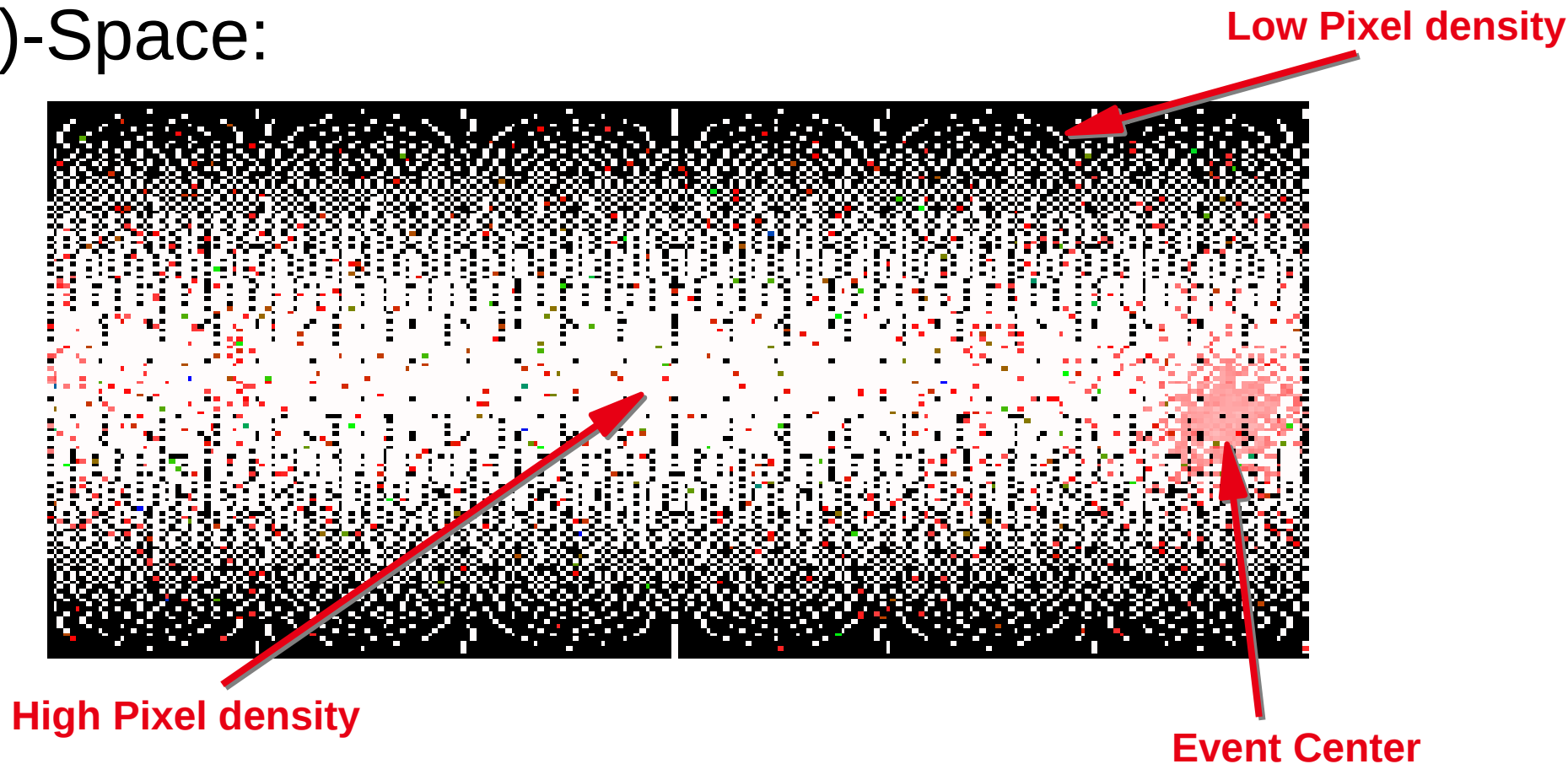
# Image Generation - Intermediate

- Simulated Electron event first hit times in  $(\Theta, \varphi)$ -Space:



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- Simulated Electron event first hit times in  $(\Theta, \varphi)$ -Space:

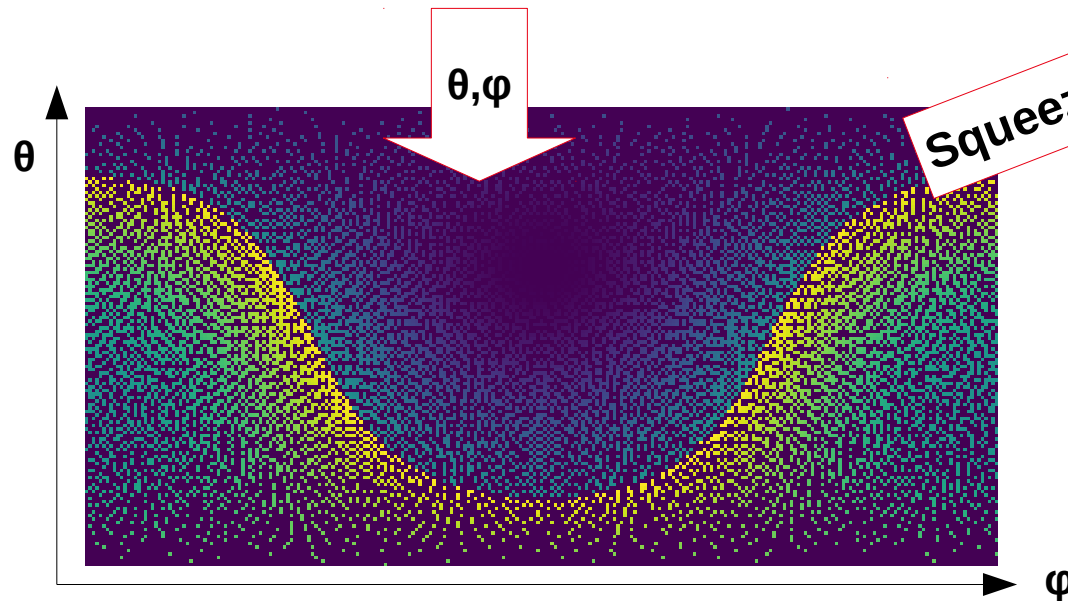
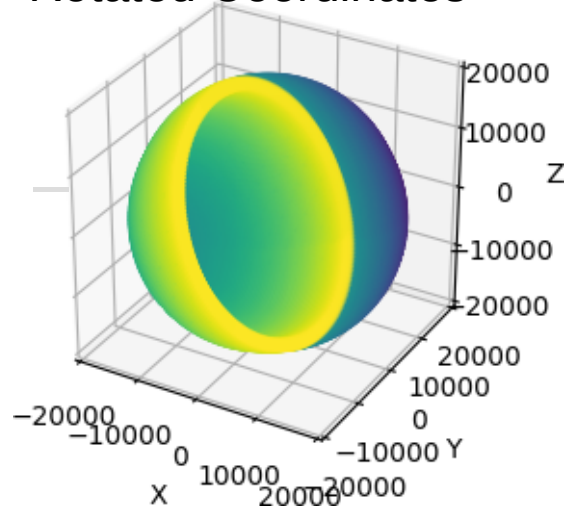


# Image Generation - Improvements

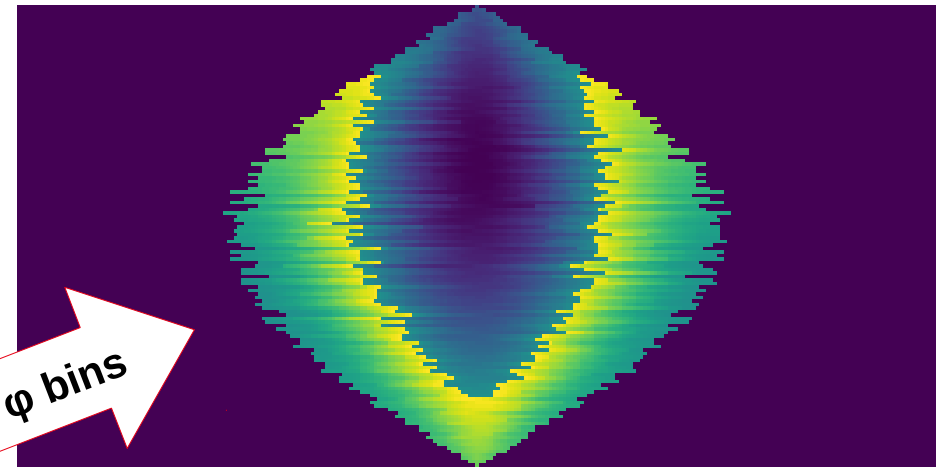
- Our approach to solve issues:
  - Rotate each image to its center of mass
    - No Image splitting
    - Reduce influence of event position to images
  - Shift pixel together
    - Constant pixel density

# Image Generation - Complete

Rotated Coordinates

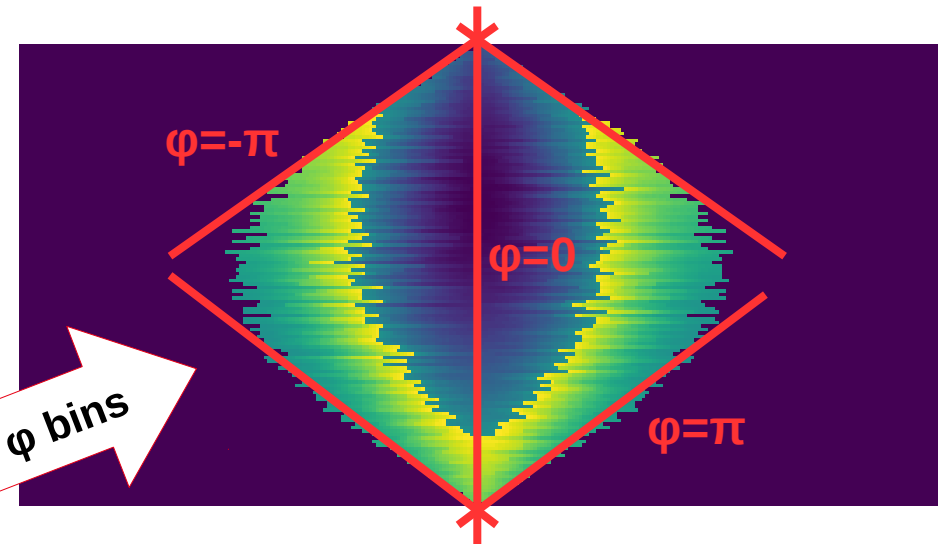
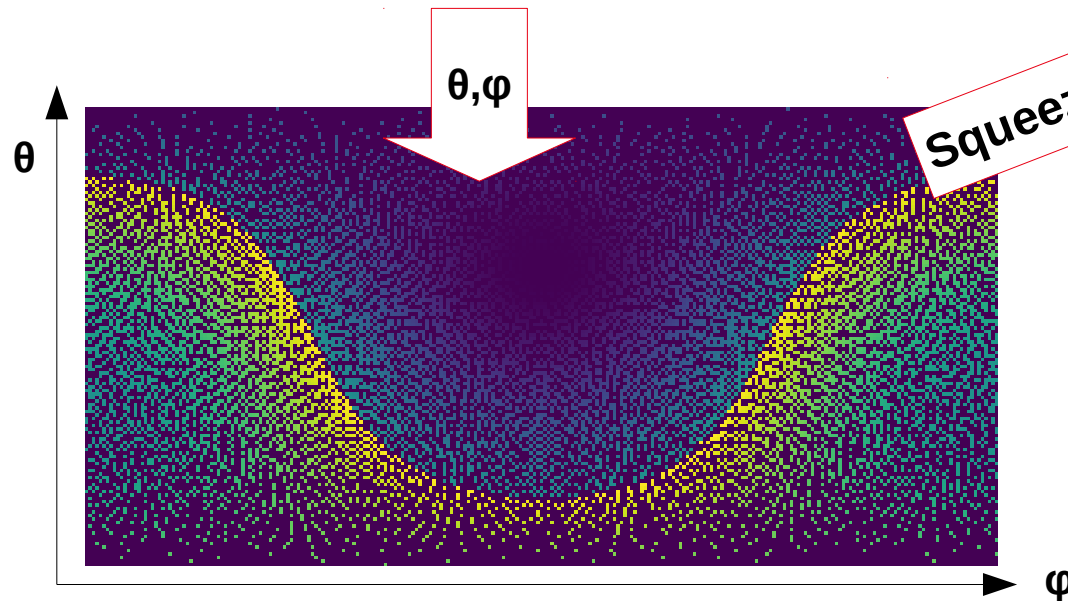
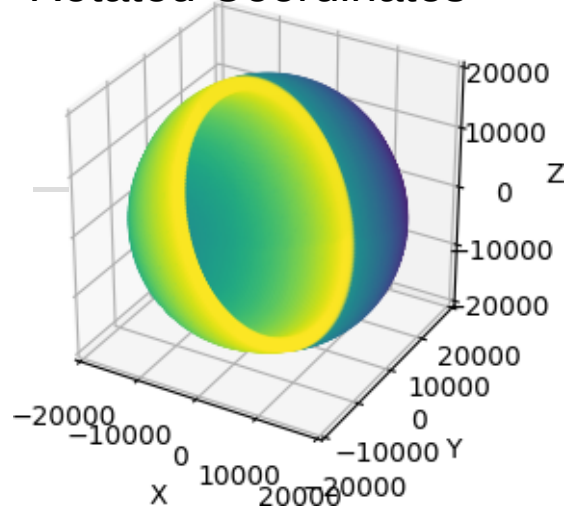


Squeeze  $\phi$  bins



# Image Generation - Complete

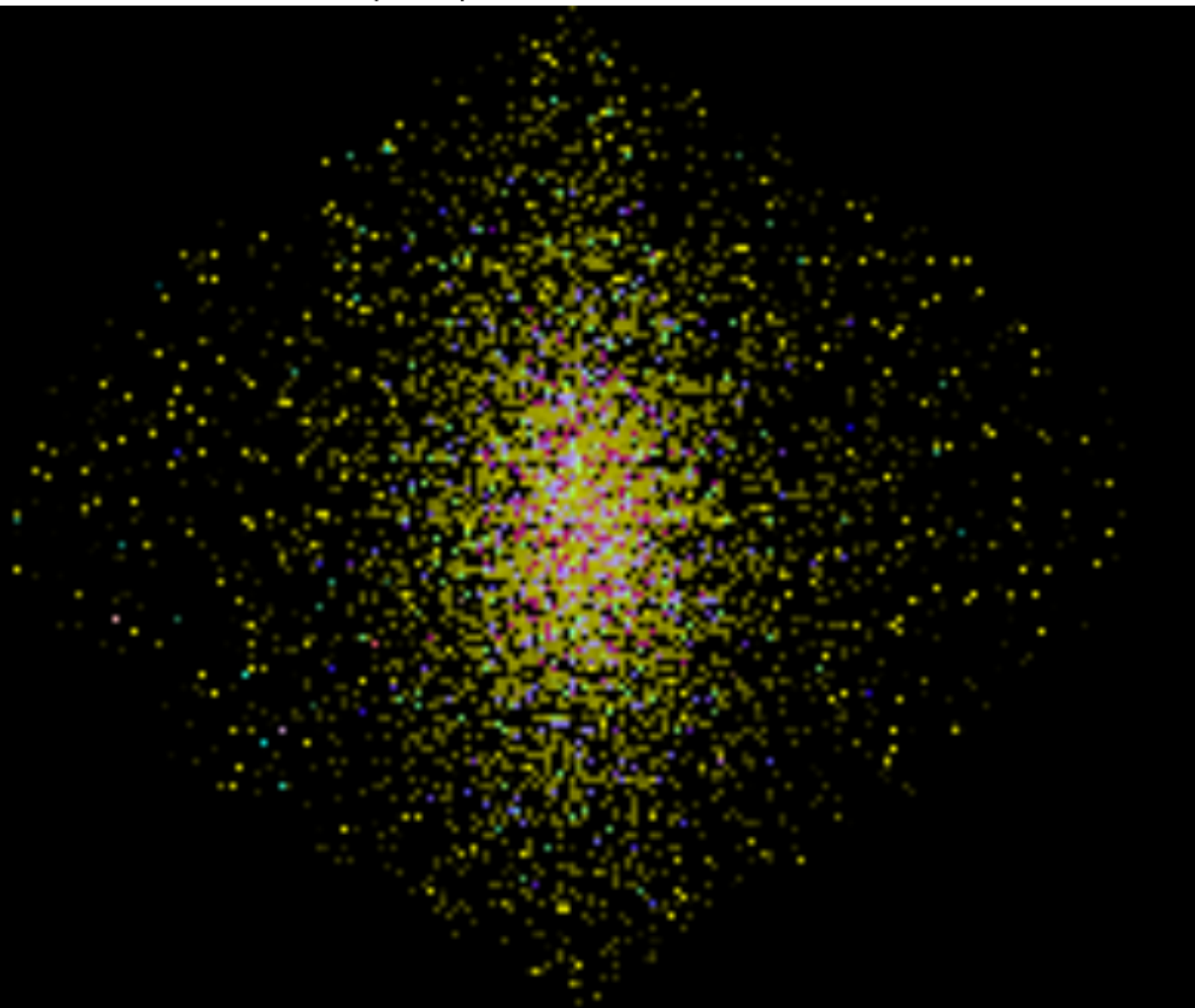
Rotated Coordinates



- Event always in the center of image
- No empty bins between pixel

# Image Generation – Example Event

Complete processed Electron Event 5 MeV

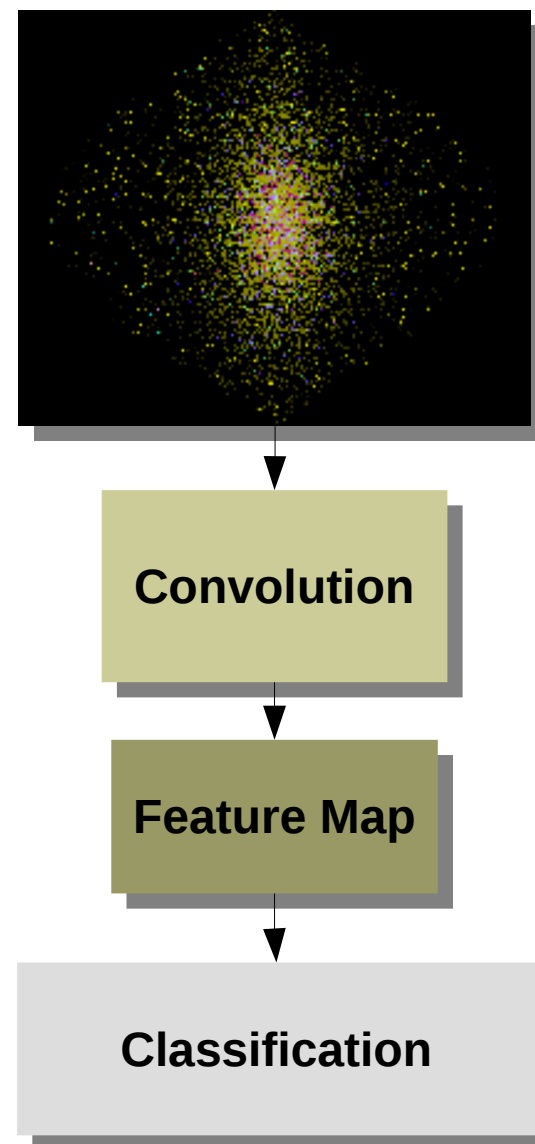


**RGB Color Channel:**  
**Red** = first hit time  
**Green** = mean hit time  
**Blue** = stddev hit times

# Classification

- Training Convolution Layers of deep networks is costly
- Especial with lots of data (3.6 million uniform distributed electron+positron events)
- Try using a high performing pretrained net as base
  - ResNet 50 for example

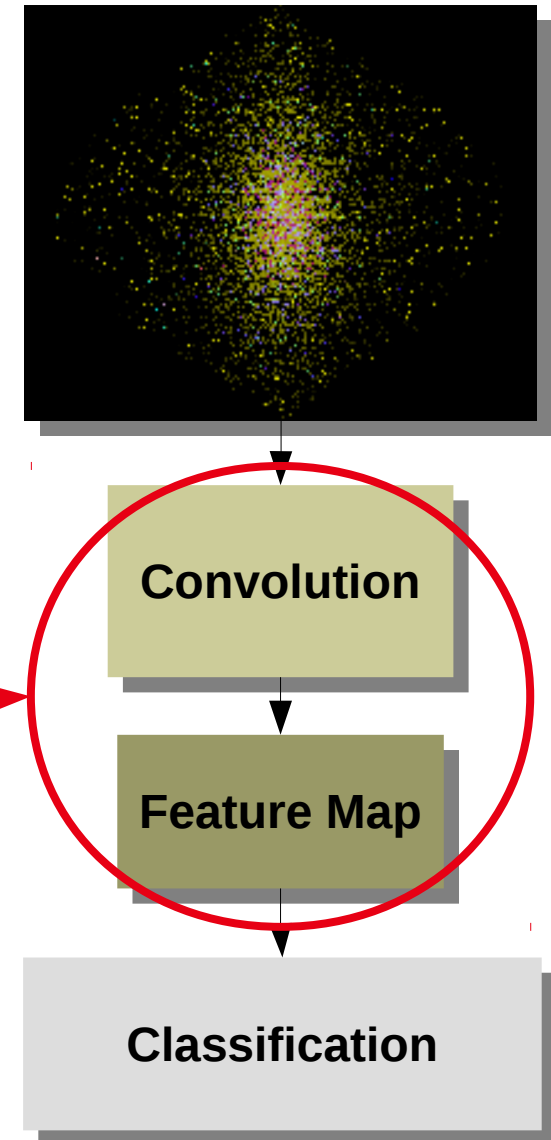
Typical CNN:



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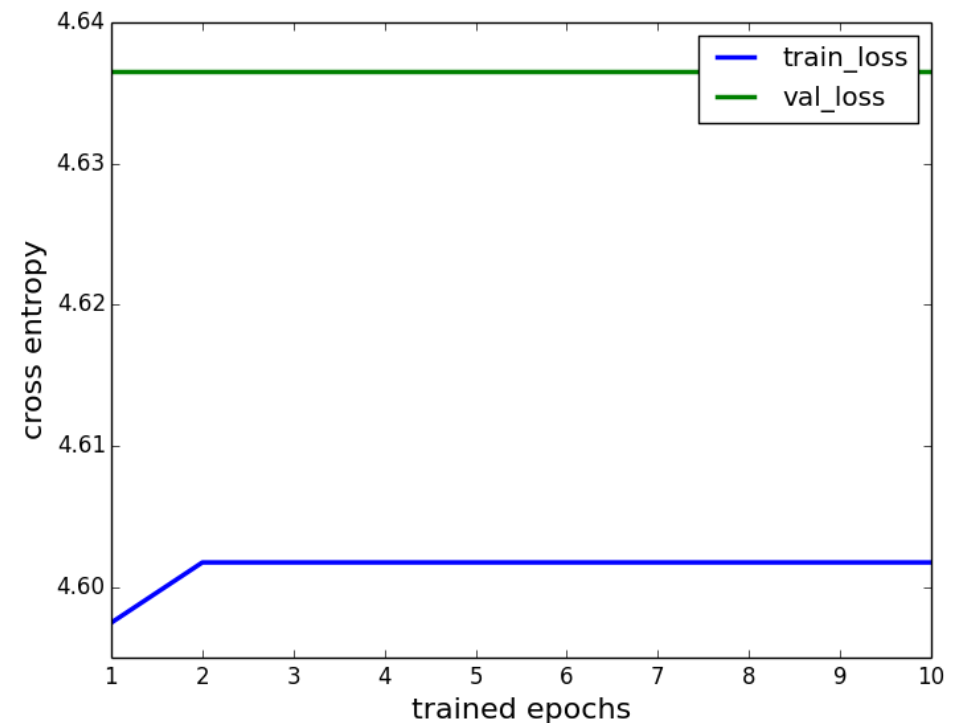
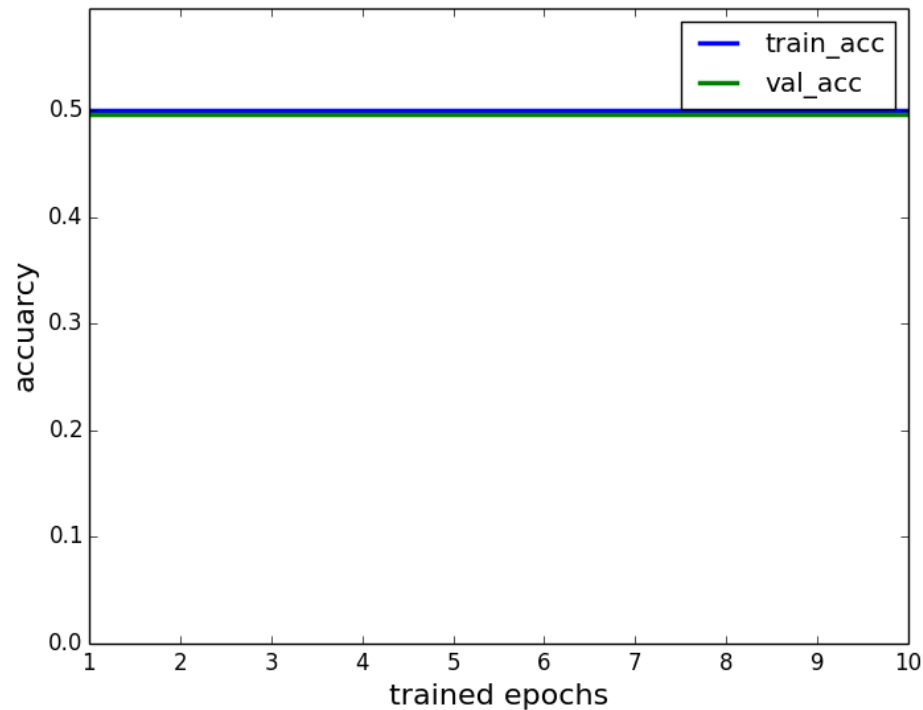
Typical CNN:



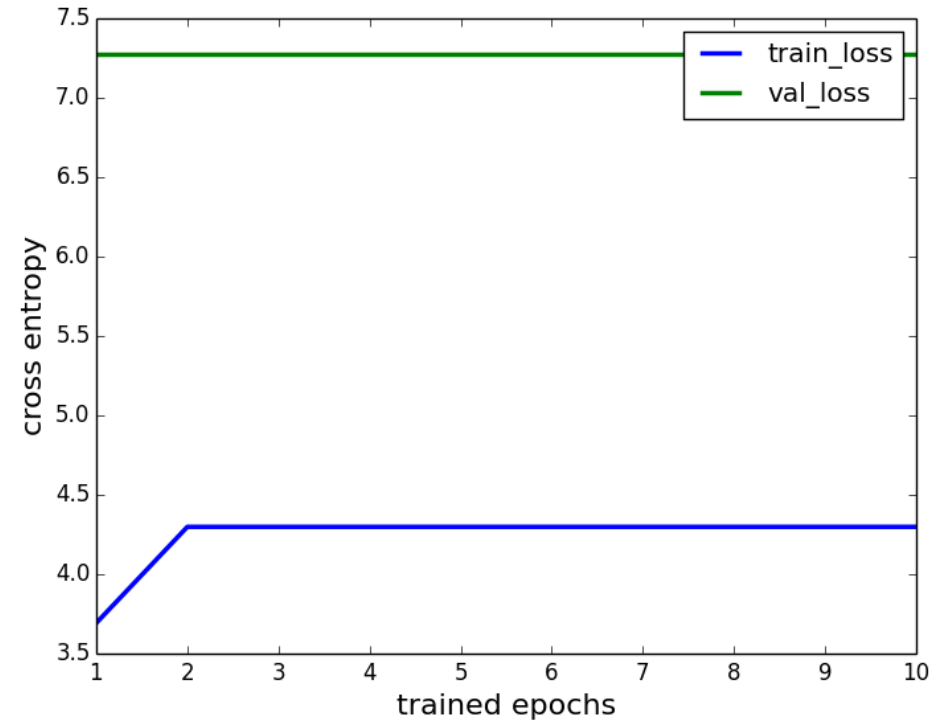
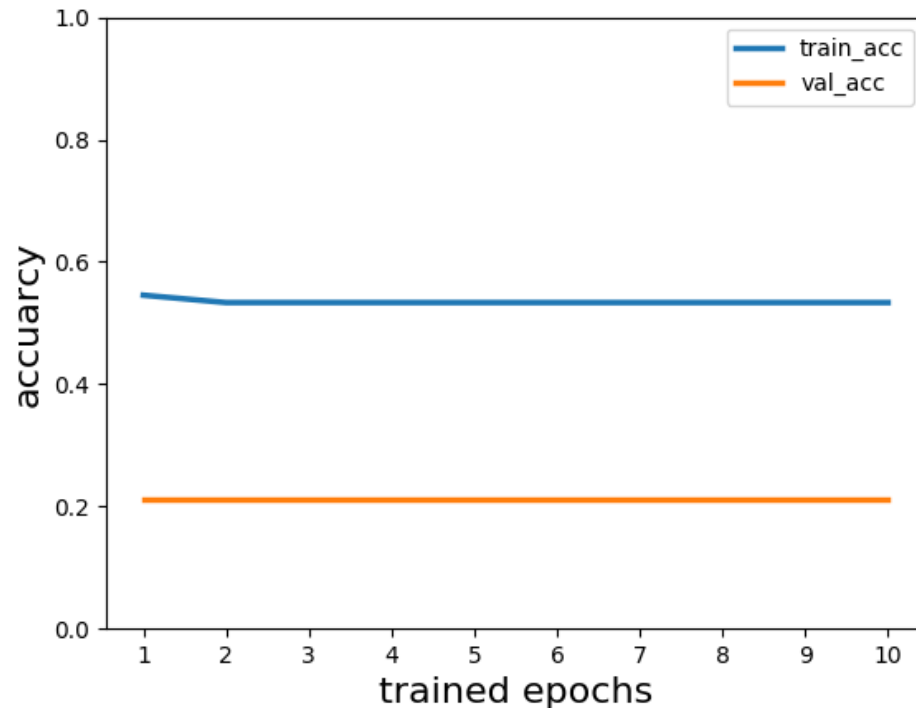


# Positrons vs. Electrons

Training results with sample of 100k events



# Muons vs. Electrons



- Bug in the program
- ResNet 50 not able to distinguish shape differences

# Thank you for your attention!

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# Categorical Cross Entropy

- Categorical Cross Entropy is minimized for training

$$J(\theta) = -\frac{1}{n} \sum_i \sum_j \mathbf{y}^i \log (\mathbf{y}_{\text{model}}(\mathbf{x}^i | \theta))$$

- $\mathbf{y}_{\text{model}}(\mathbf{x}^i | \theta)$  is probability for class as predicted by NN
- $\mathbf{y}^i = 1$  for true class, 0 else