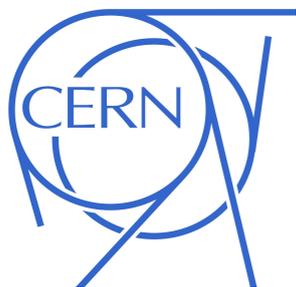


Super-resolution for calorimetry

F. A. Di Bello, S. Ganguly, E. Gross, M. Kado, M. Pitt, L. Santi, J. Shlomi,

IML WS
23/10/20

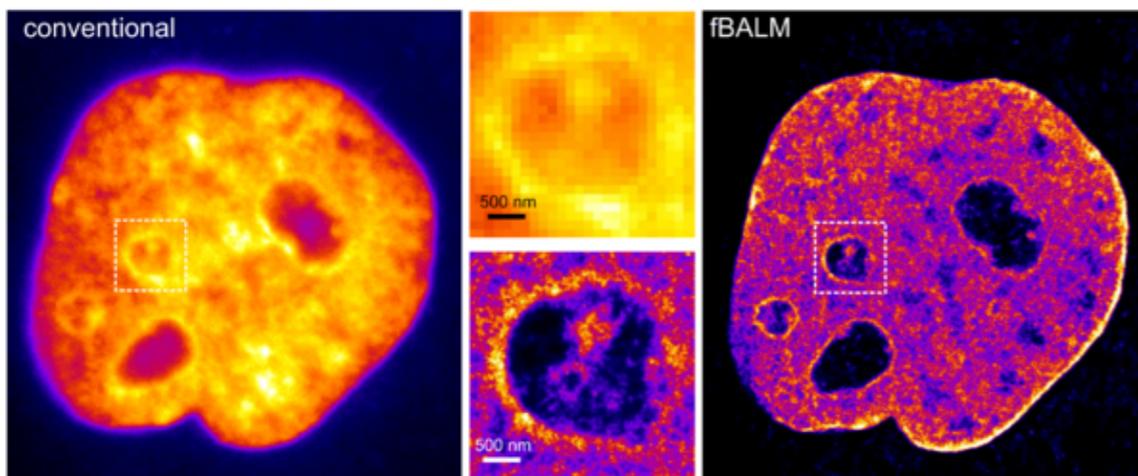
[arxiv pre-print](#)



Introduction

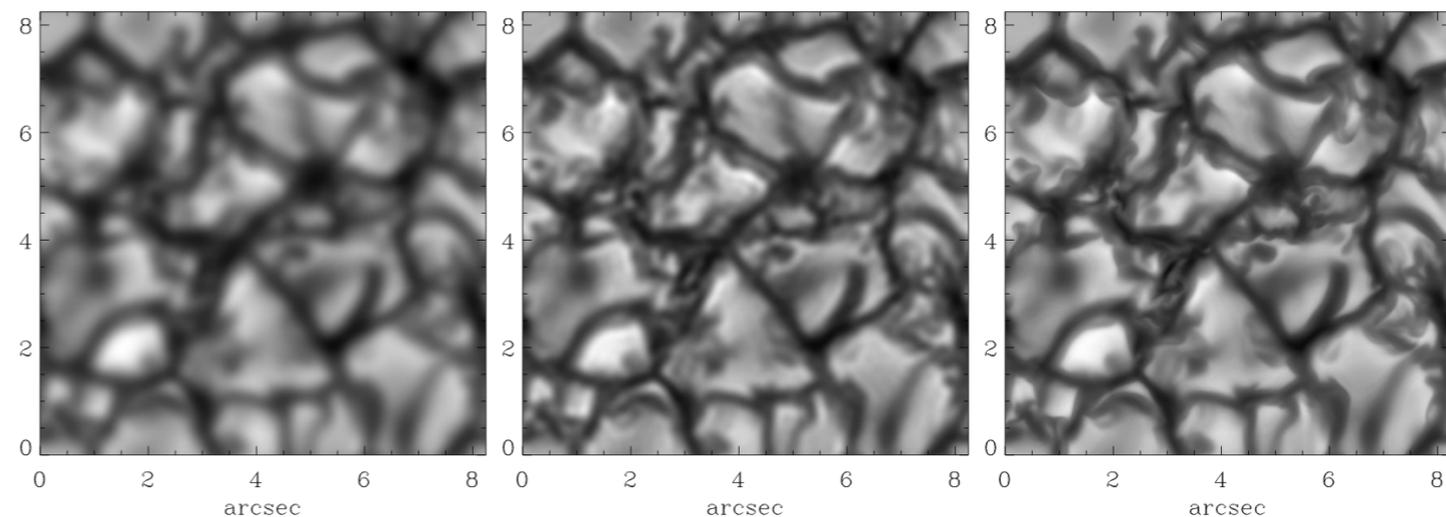
- Super-resolution is typically referred to as algorithms used to enhance the resolution of the measuring device
- Outside HEP, it has a large field of application (not a complete list):

- Super-Resolution microscopy [[Ref.](#)]
- Molecule -



[2014 chemistry nobel: "for the development of super-resolved fluorescence microscopy"](#)

- Astronomy [[Ref.](#)]
- solar granulation -



and industrial application....

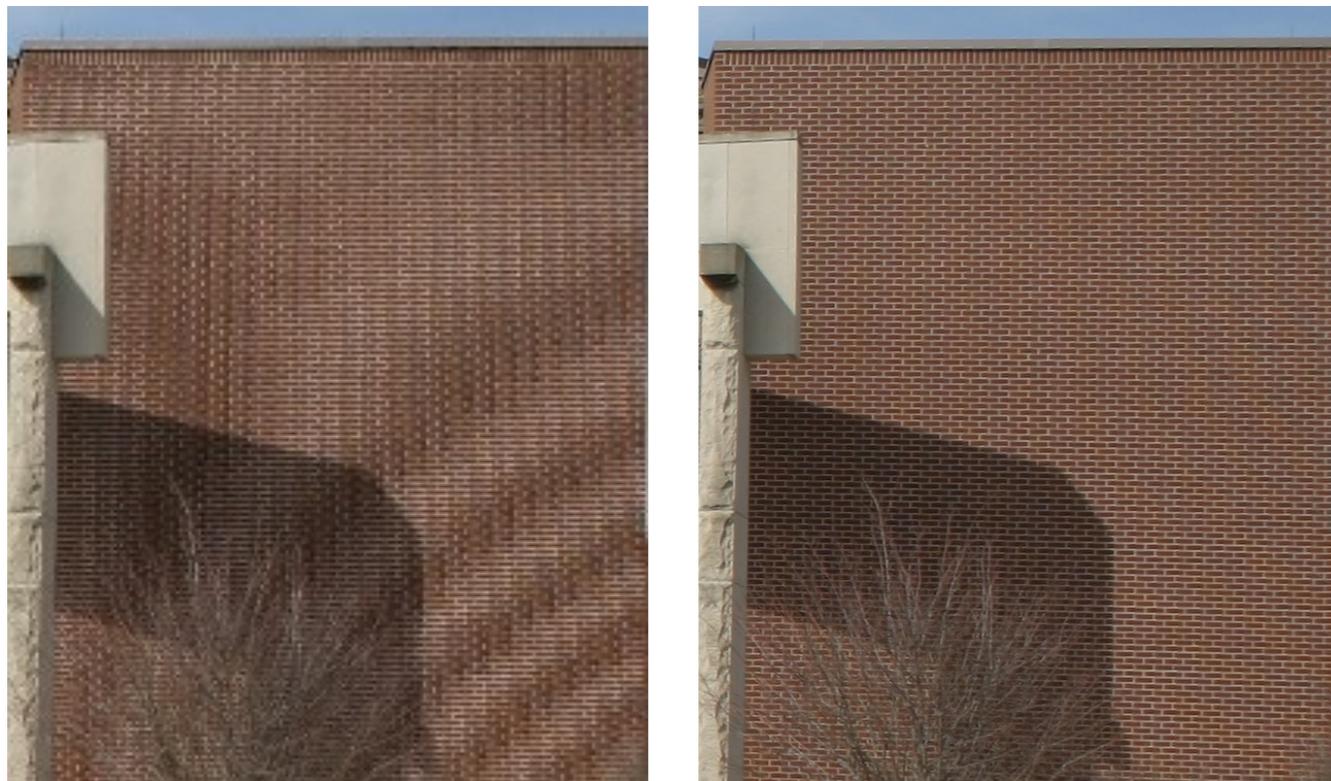
Introduction

- Imaging for camera etc [[Ref.](#), [Ref.](#)]



google CNN (2017) for large up-scaling factor

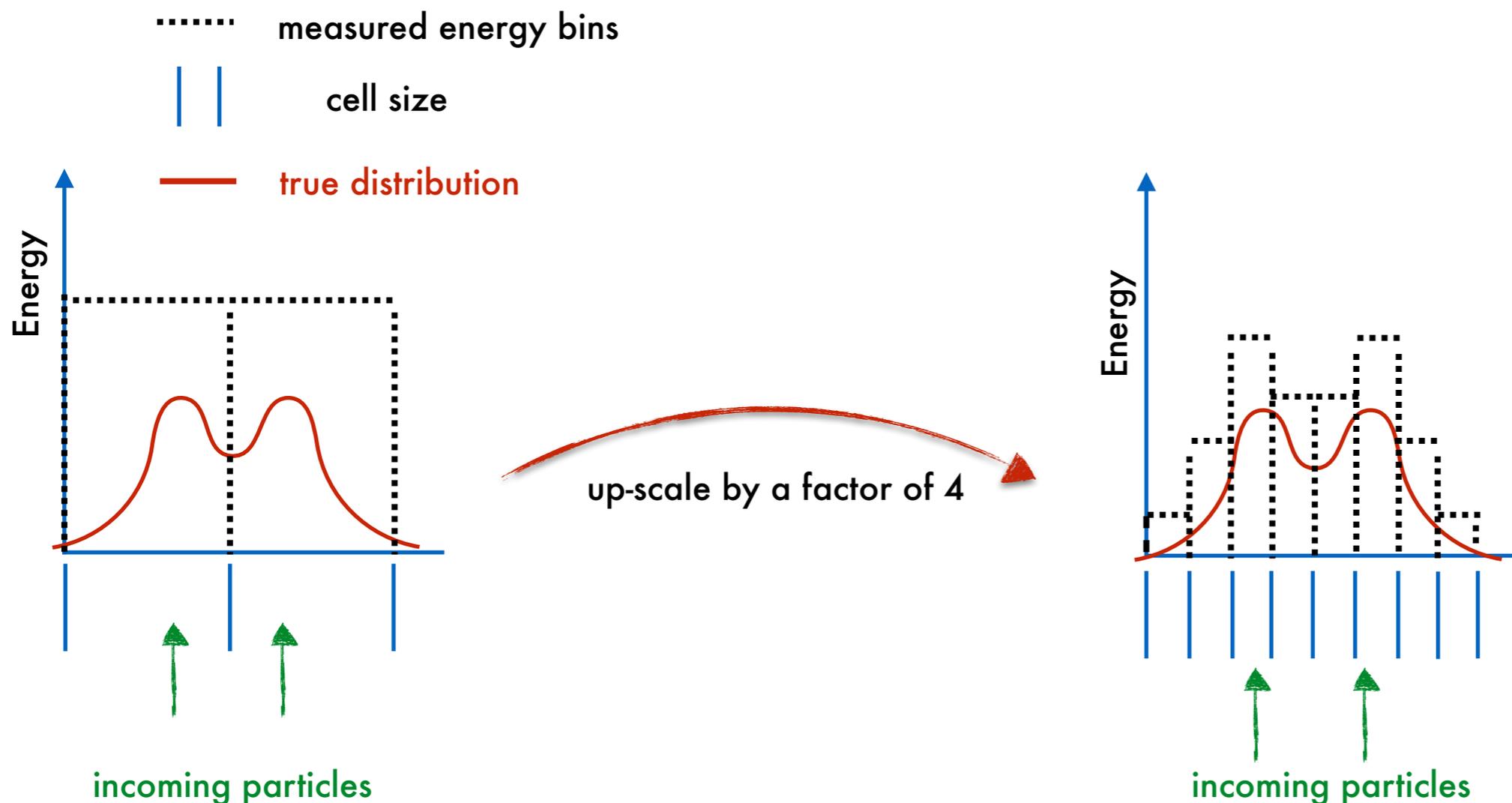
One of the main problem: how to get the HR target?



“Super-resolution usually involves applying prior knowledge about the object and the imaging process [...] in order to produce a single higher-resolution image”

Application to HEP

- The granularity of the measuring device is identified by the pixel/cells sizes (tracking/calorimetry)



Impossible to distinguish two particles or single particle hitting in between

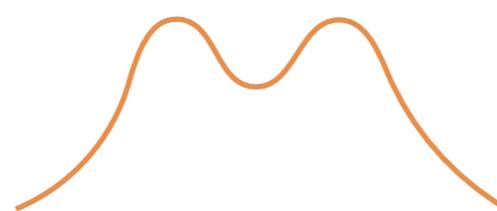
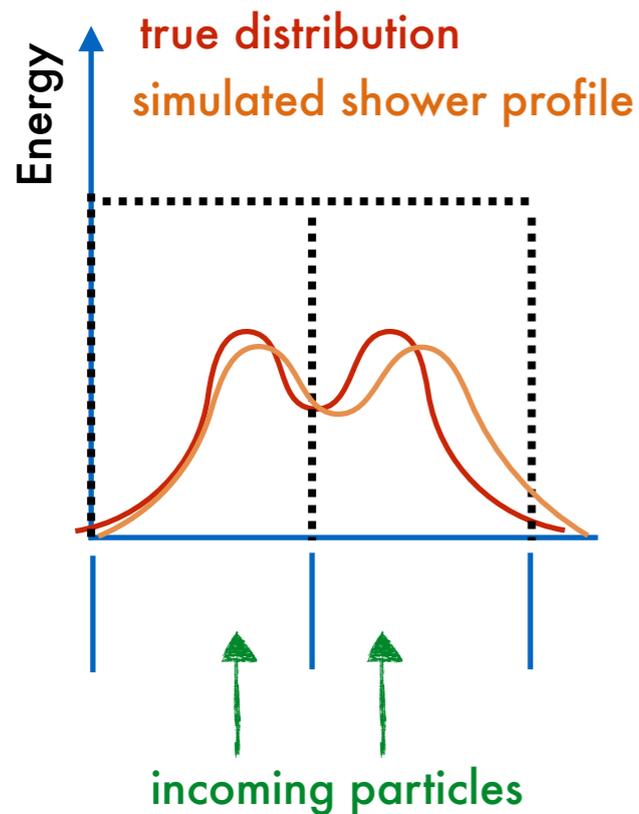
So far trivial statement:

“higher spatial resolution allows to resolve additional features”

but how to construct the high-resolution image?

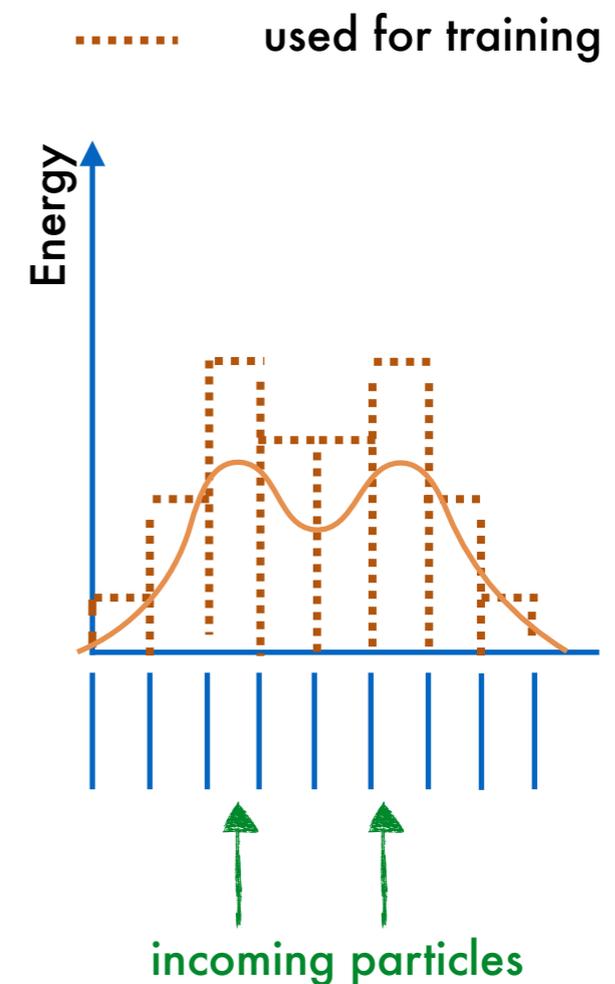
Application to HEP

- Profit from MC simulations to build the “super” detector used as the target for training



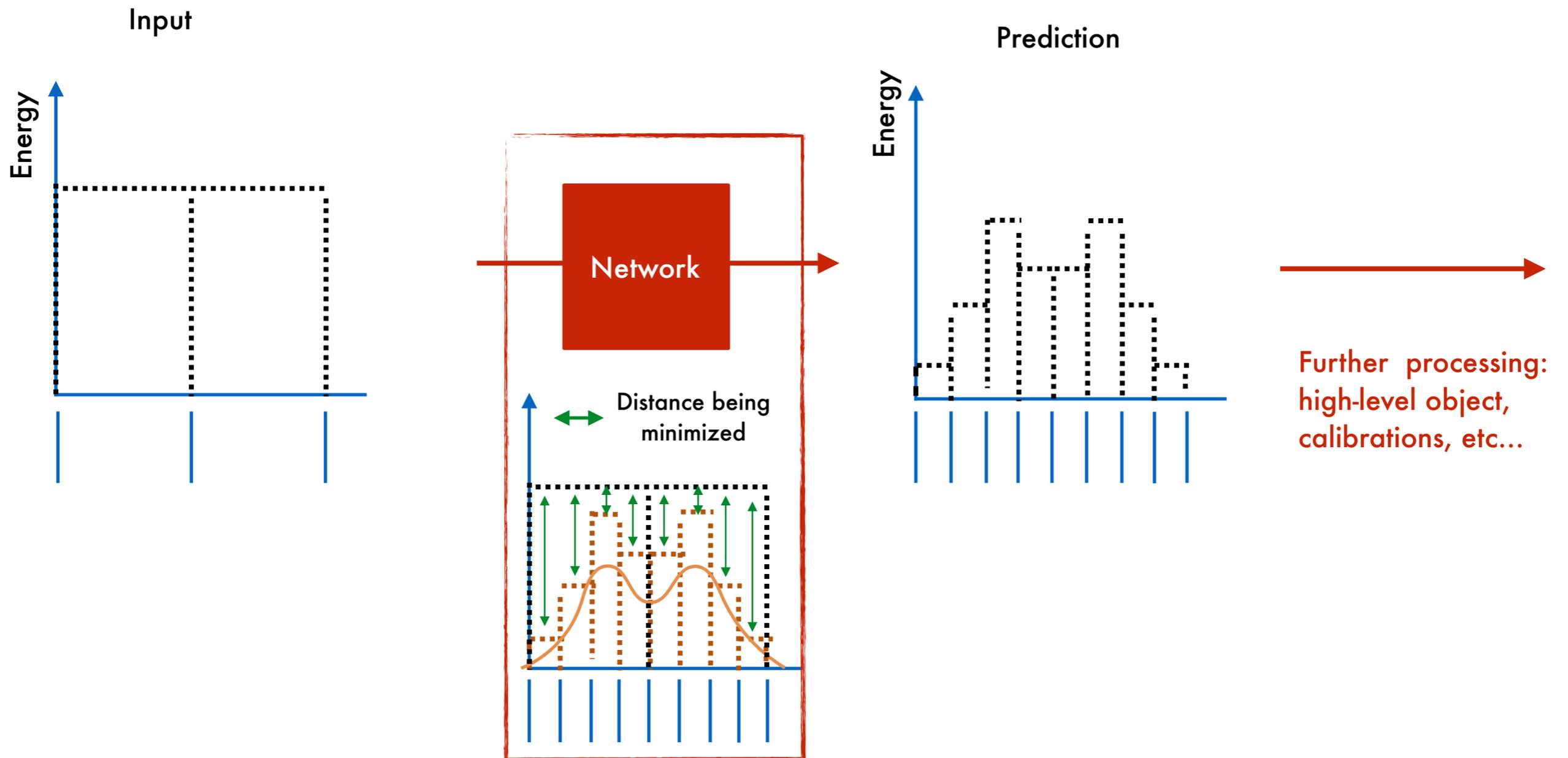
GEANT4 based simulation

for our purposes this is a continuous line that can be used to build high-resolution detector



Application to HEP

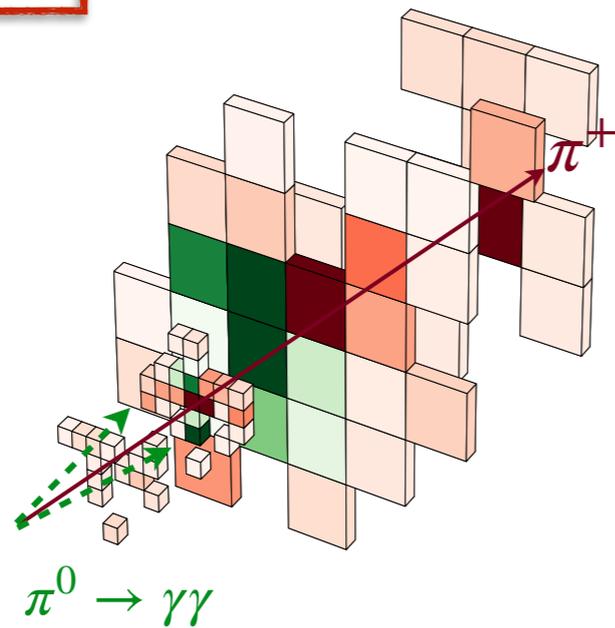
- The granularity of the measuring device is identified by the pixel/cells sizes (tracking/calorimetry)



Experimental setup

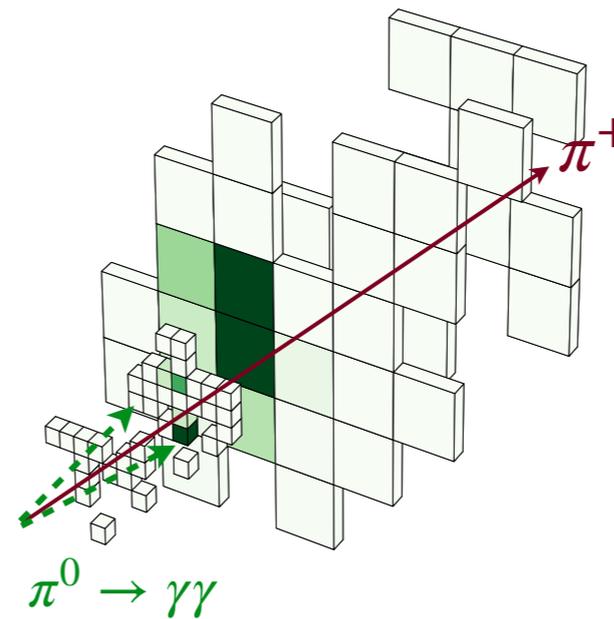
- Going back to 3D in a π^+ and π^0 environment - similar geometry to what presented by Sanmay

Detector Layer	Res. (HG)	Res. (LG)	Noise [MeV] (cf)
ECAL1	64×64	32×32	13 (4)
ECAL2	32×32	8×8	34 (16)
ECAL3	32×32	8×8	17 (16)
HCAL1	16×16	8×8	14 (4)
HCAL2	16×16	8×8	8 (4)
HCAL3	8×8	8×8	14 (1)



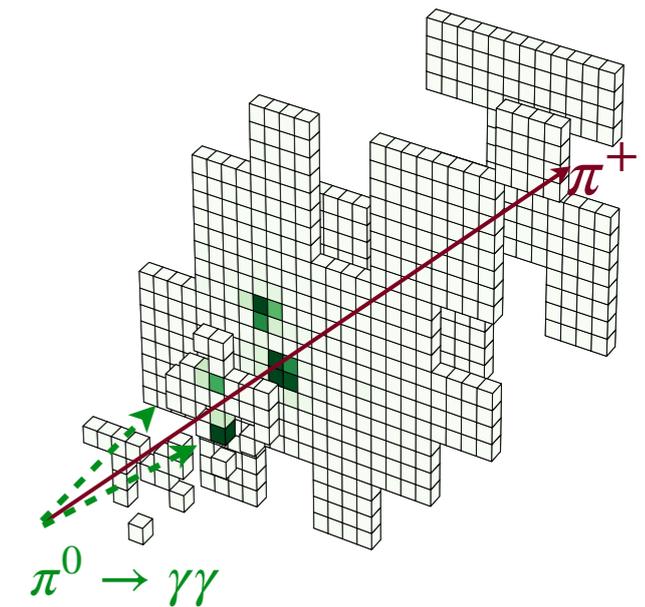
Low-Resolution

charged + neutral+noise



Low-Resolution - neutral only

second layer: 8×8



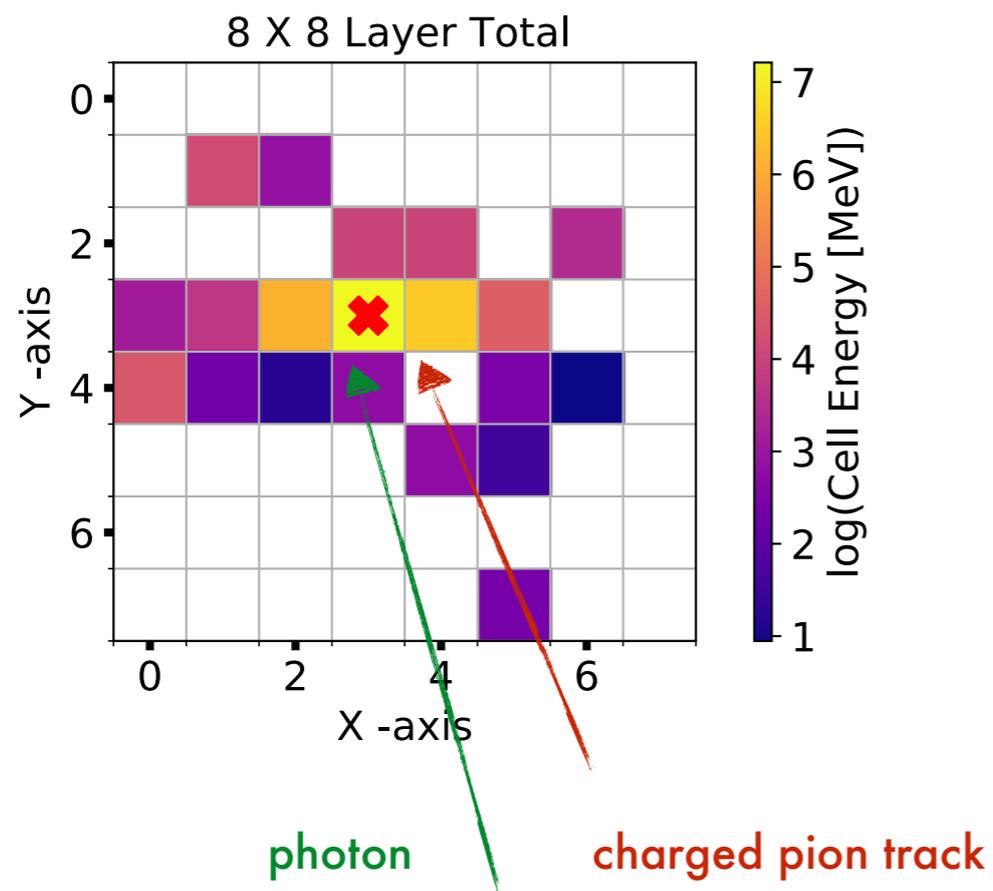
High-Resolution - neutral only

second layer: 32×32

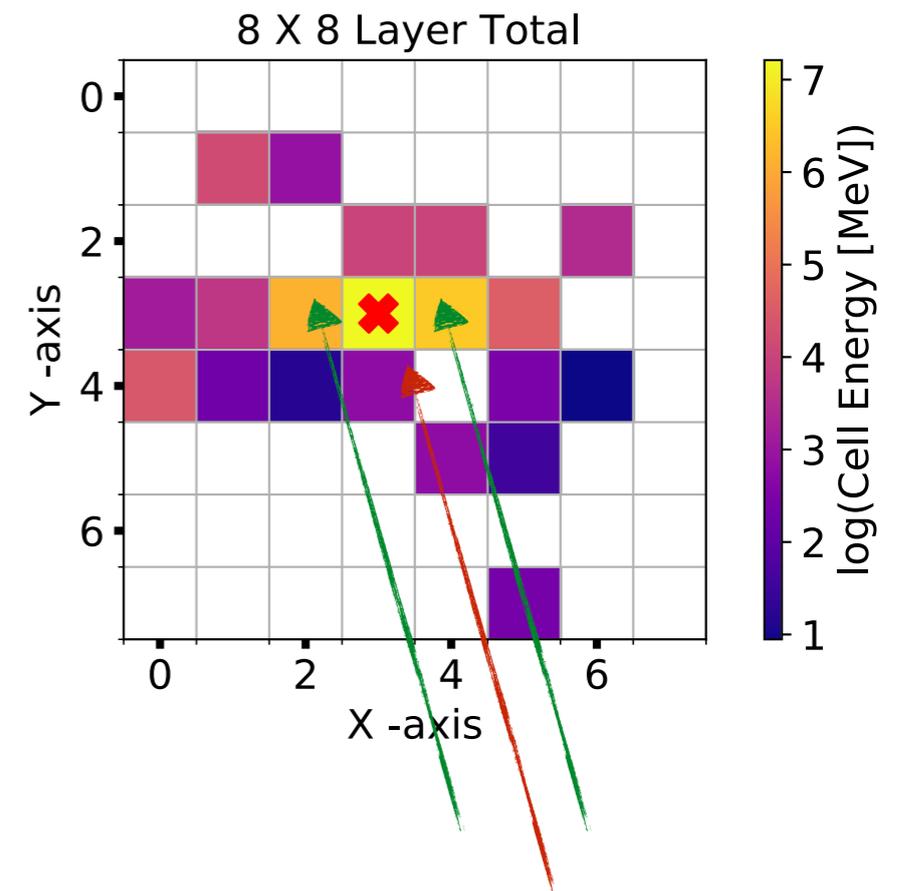
A quiz

- Which one is correct?

(A)



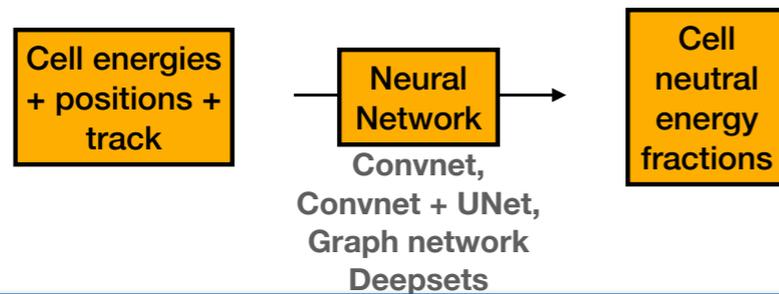
(B)



The model

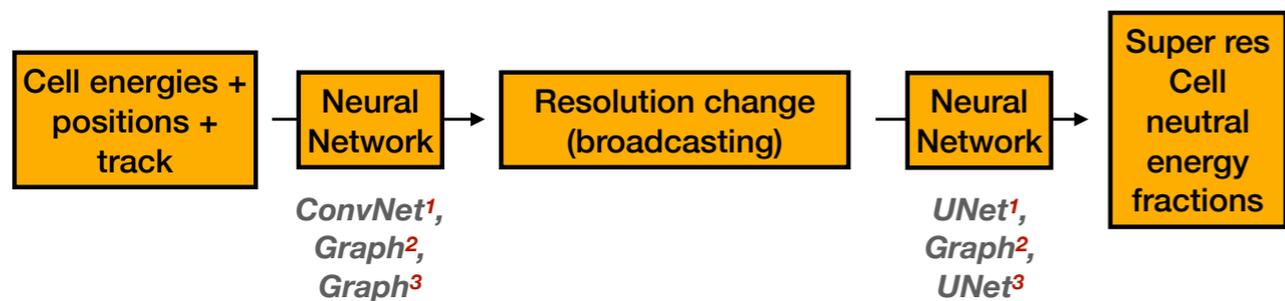
This is what Sanmay discussed in the previous talk

Common network structure for energy overlap removal task



This is what we discuss now

Common network structure for super-resolution task



1. Transpose convolution,
2. Low res cell to high res cell clone
3. Transpose convolution

Track traded as point in an image for CNN and as a global graph feature for the GNN

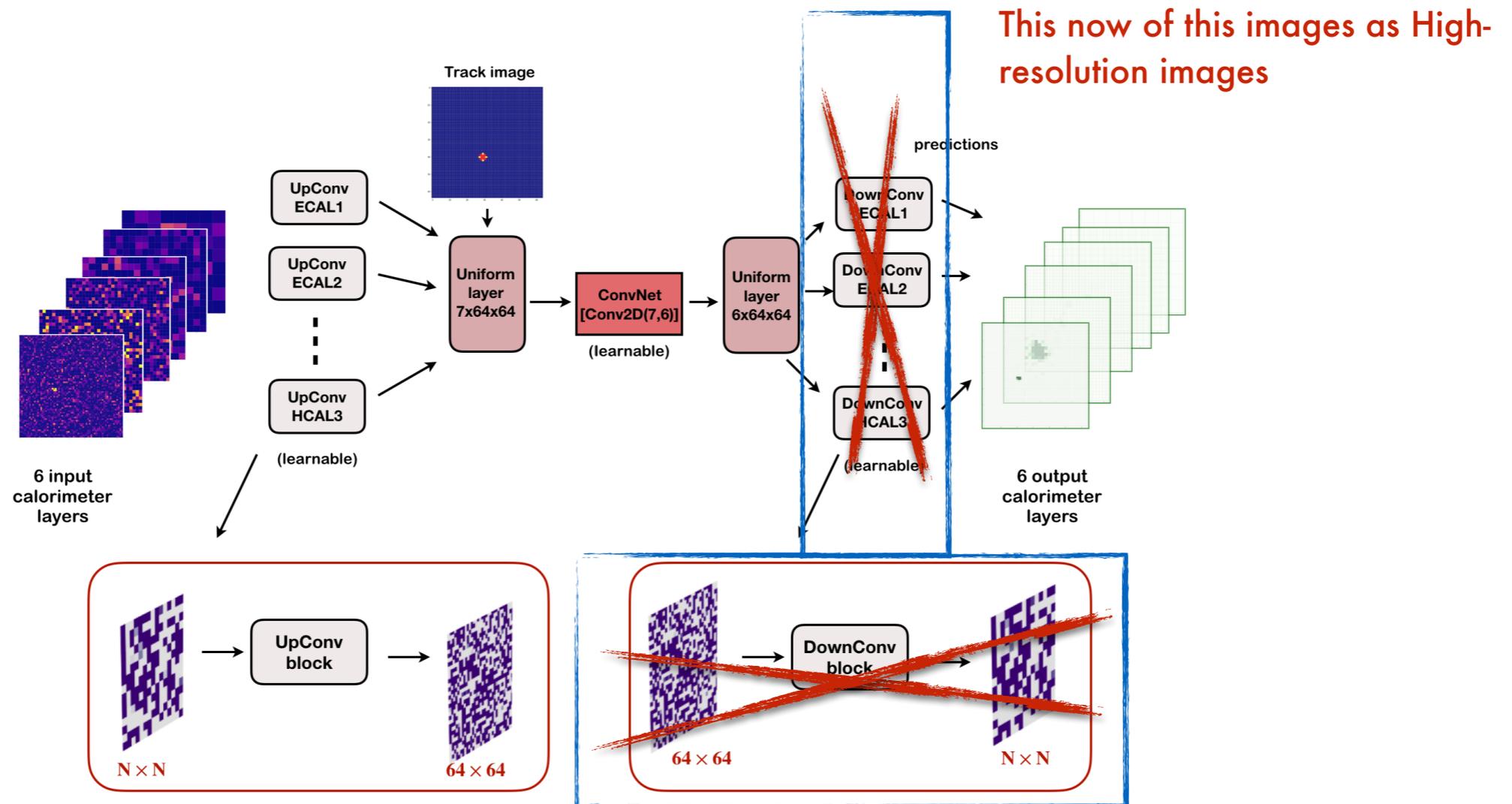
$$L_{event} = \frac{1}{E_{tot}} \sum_c E_c (f_t^c - f_d^c)^2$$

$$L_{event}^{super-res} = \frac{1}{E_{tot}} \sum_c E_c \sum_{s=0}^{us^2} (f_t^{sc} - f_d^{sc})^2$$

now we minimize each HR cell (s) in a given standard cell (c)

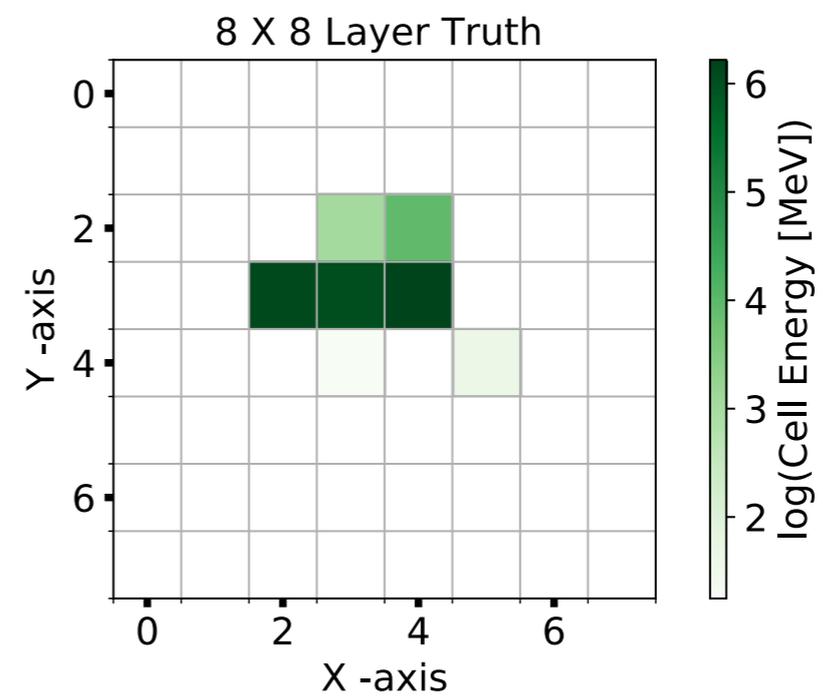
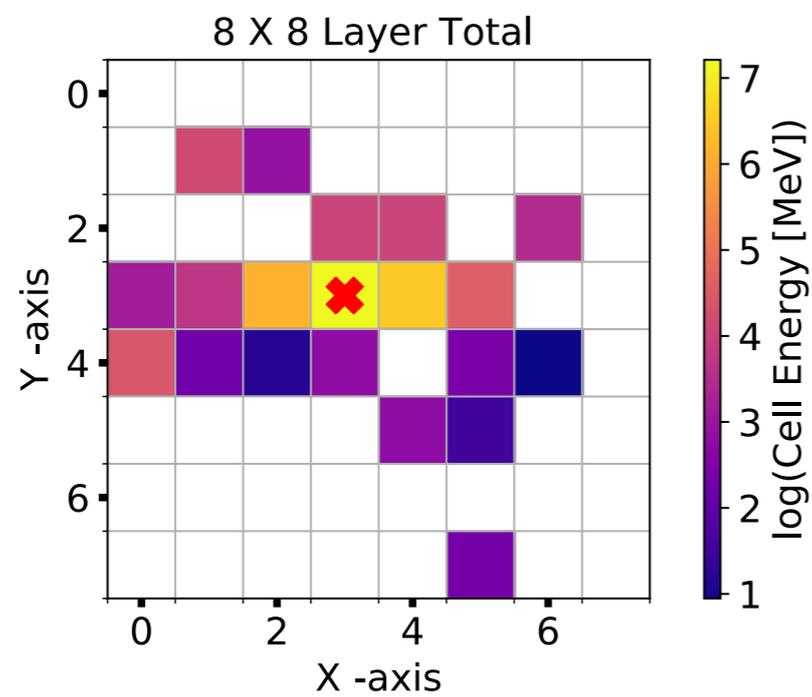
The model

- For CNN, the same model with minor modifications can be used
- Similarly for the graphs, even if not shown in an image



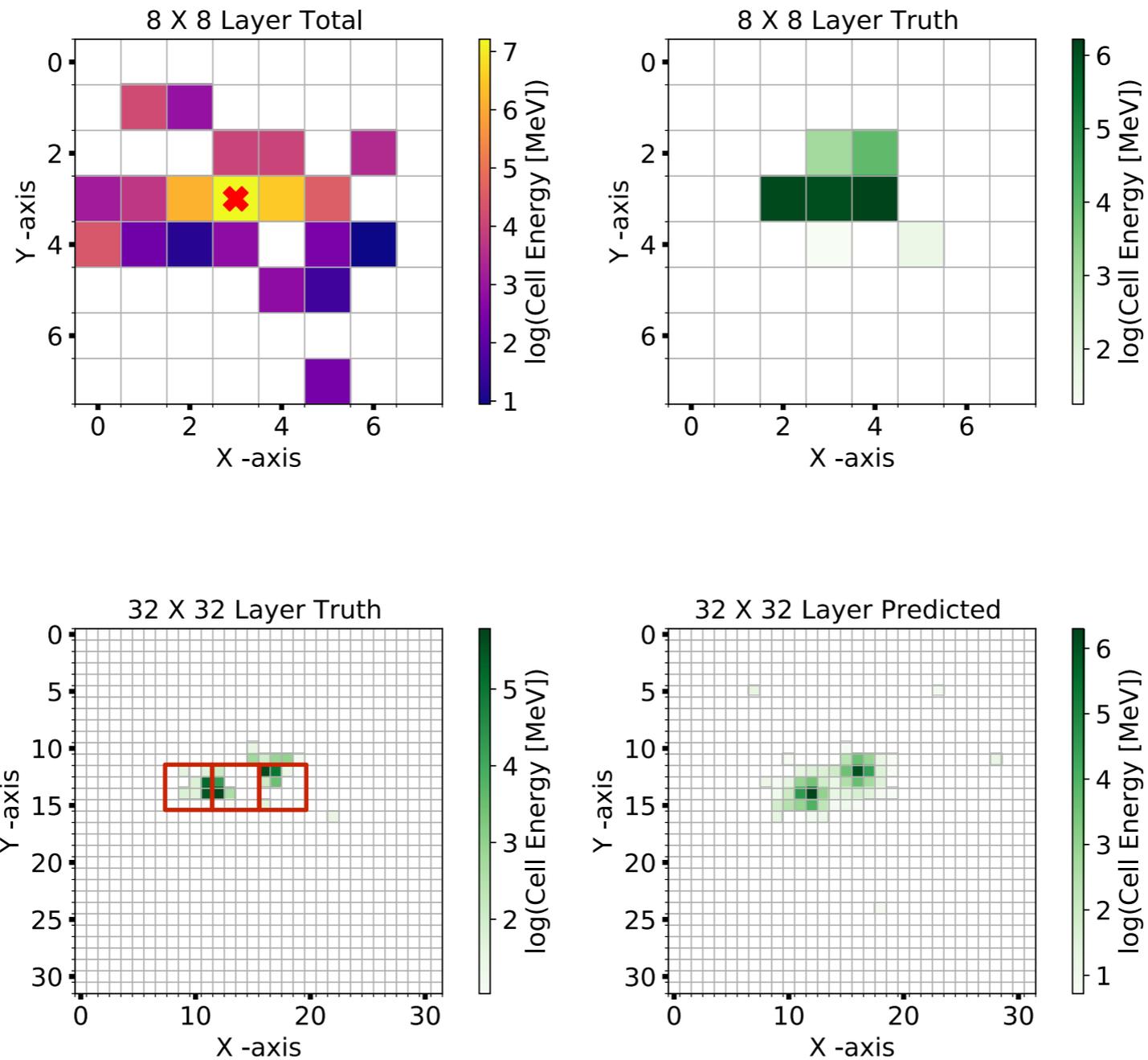
Results 1 - quiz answer

- Let's first divide charged and neutral (similar to what shown in the previous talk)



Results 1.1 - quiz answer

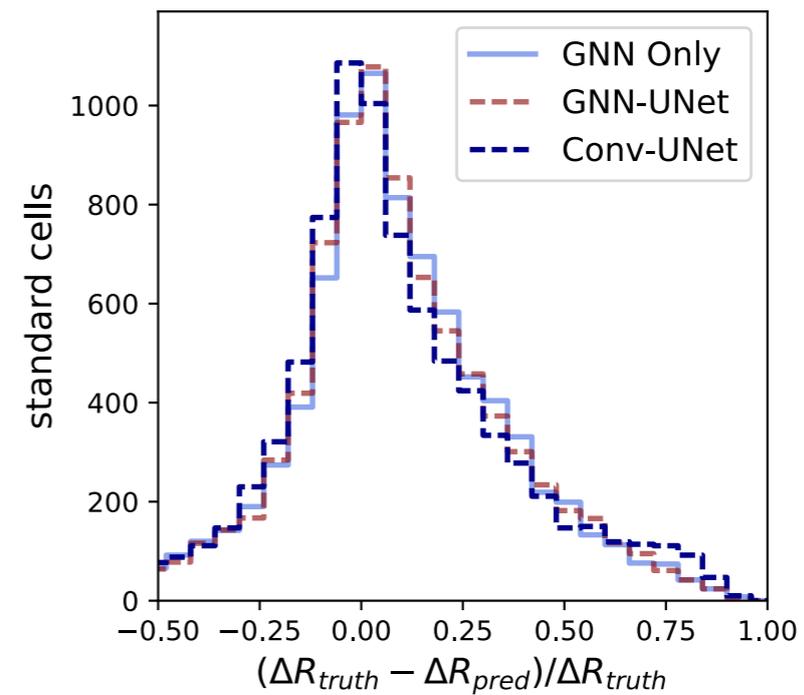
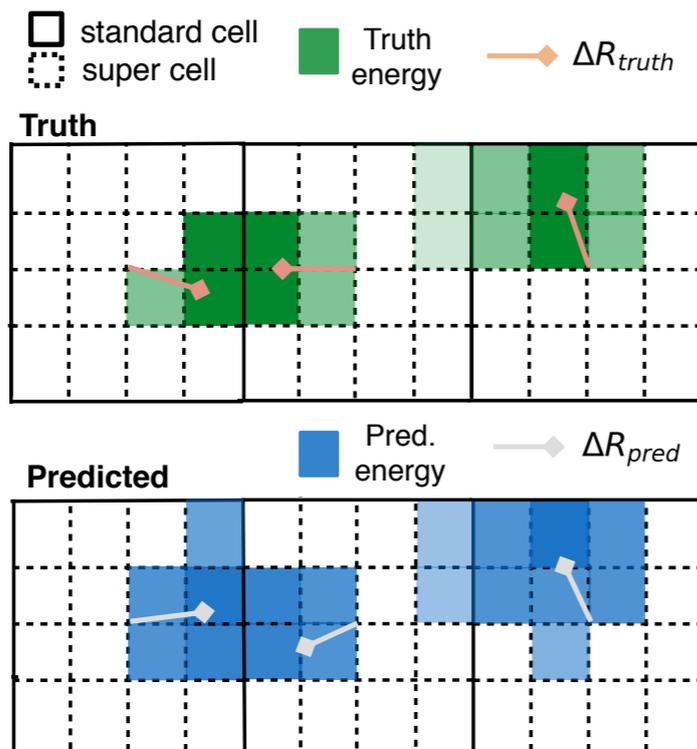
- And now super-resolution at work



Results 2

- Expect correlation between the radial distance of each standard cell

$$\Delta R = \frac{\sum_{sc}^{up^2} E_{sc} \sqrt{x_{sc}^2 + y_{sc}^2}}{\sum_{sc}^{up^2} E_{sc}}$$



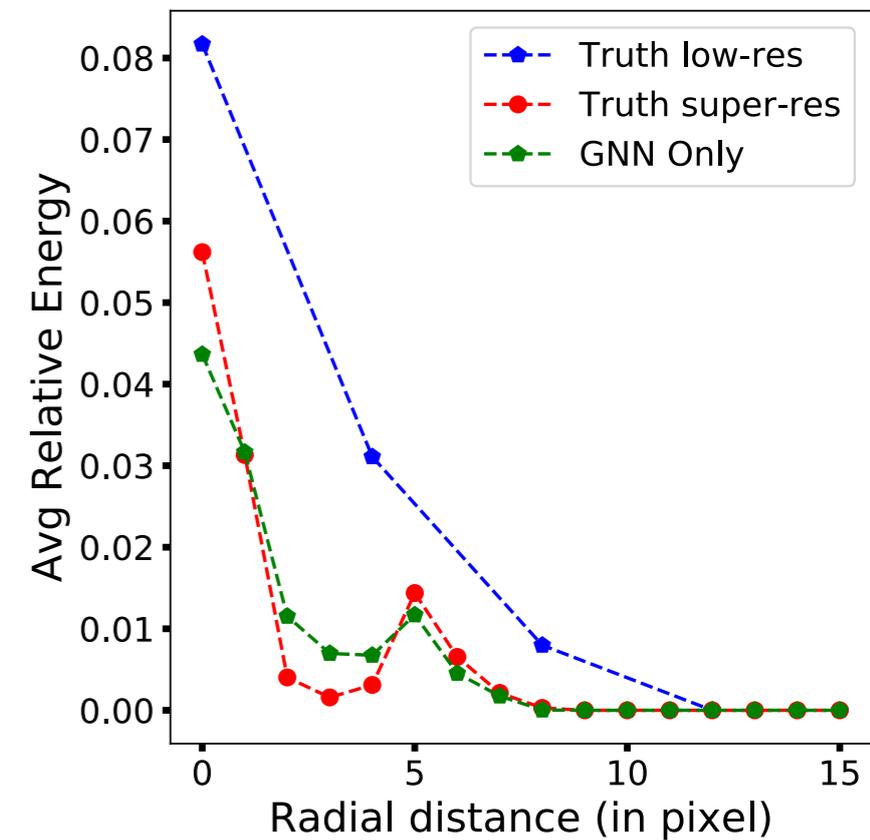
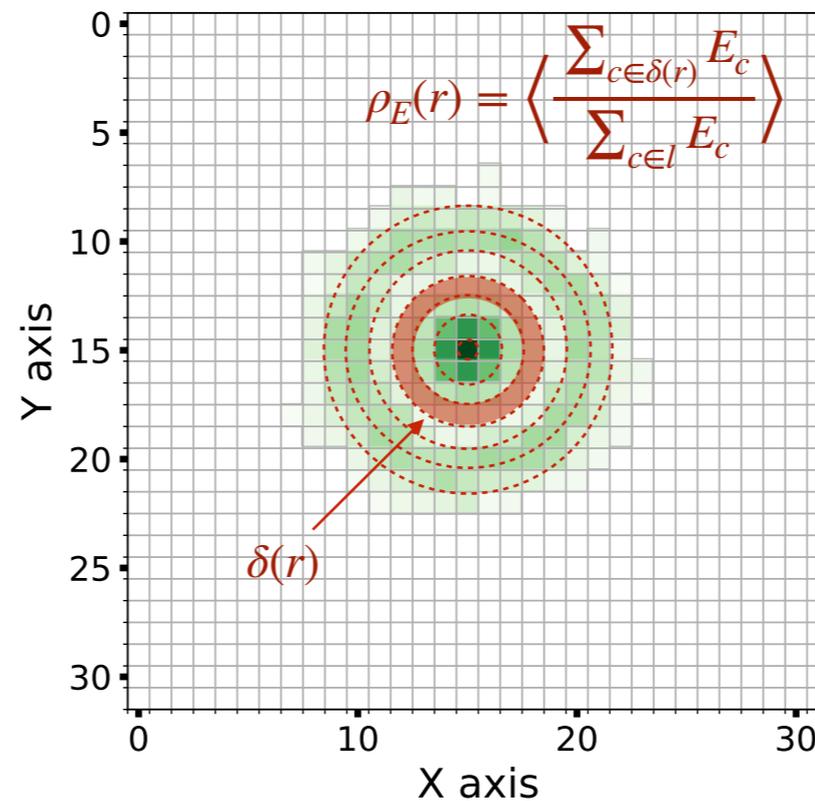
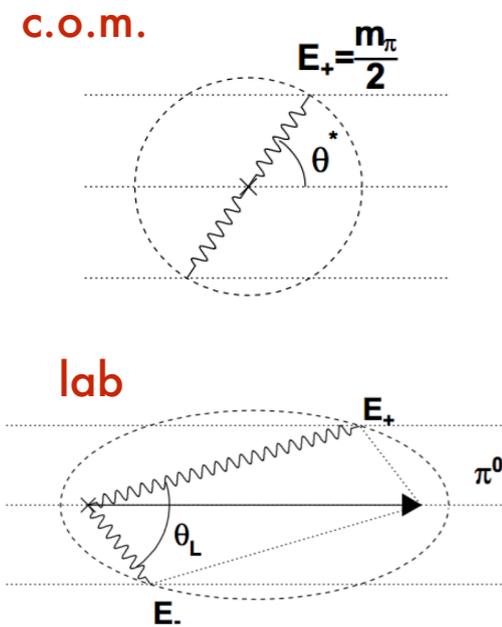
Learning high-resolution patterns

Asymmetric tails, the NN tend to smooth a bit the output image

Results 3

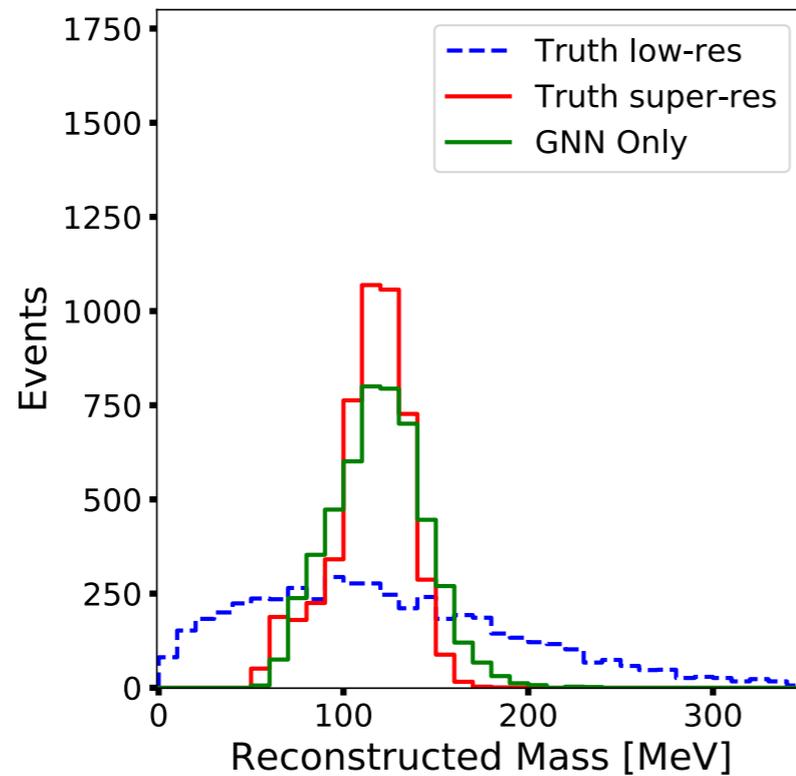
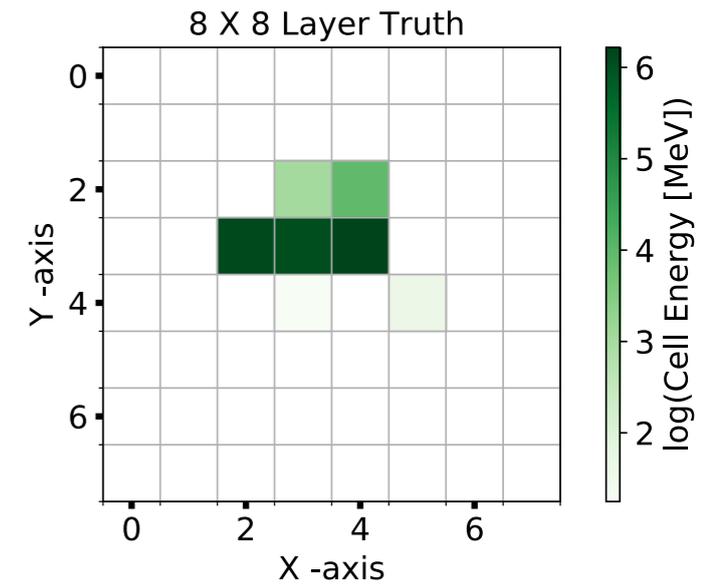
- Can we resolve the two photons from the decaying π^0 ?
- Check by centering the image for each event around the most energetic cell and averaging for all the events
- For a fixed momentum of the p_0 (and fiducial cuts to ask the two photons within detector acceptance), a circle representing the secondary photon is expected

truth average image

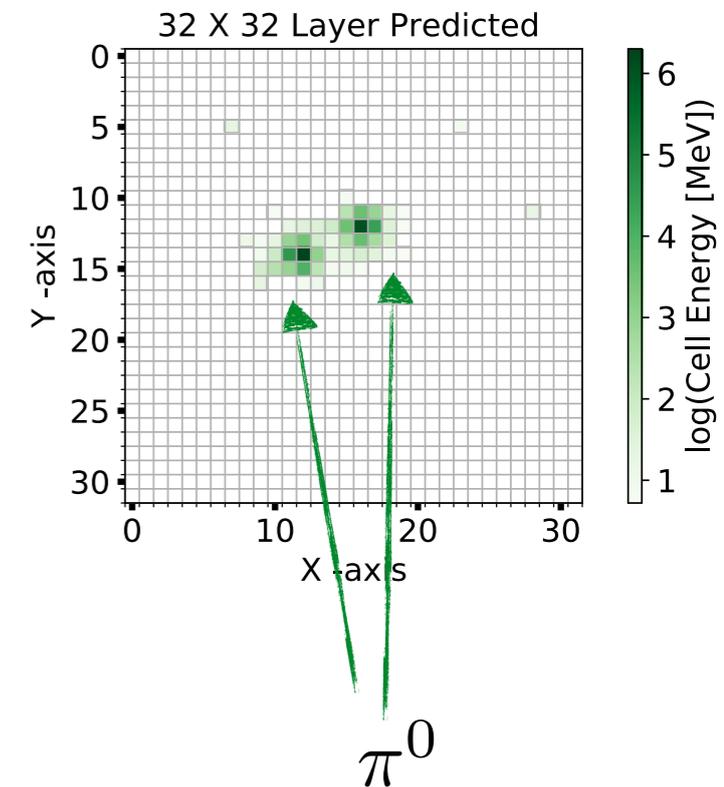


Results 4

- Can we reconstruct the mass of the π^0 ?
- K-mean clustering algorithm min n-cluster = 2 was used to cluster HR image
- Four-momenta of the photons computed from the production location of π^0
- SF applied to “calibrate” the truth as well as predicted to the π^0 mass



nice high-resolution peak



Conclusions

- Proposed super-resolution algorithms
- Performance evaluated on a simplistic π^0/π^+ overlap
- Results show promising advantages: improving spatial resolution of measuring systems
- Could be an interesting “intermediate” steps toward construction of more complete Pflow algorithms

Graph model

