

Super-resolution for calorimetry

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Learning to discover
27/04/22

[paper](#)



Intro

- Pflow algorithms exploit the different energy resolution measured in the tracker and calorimeter

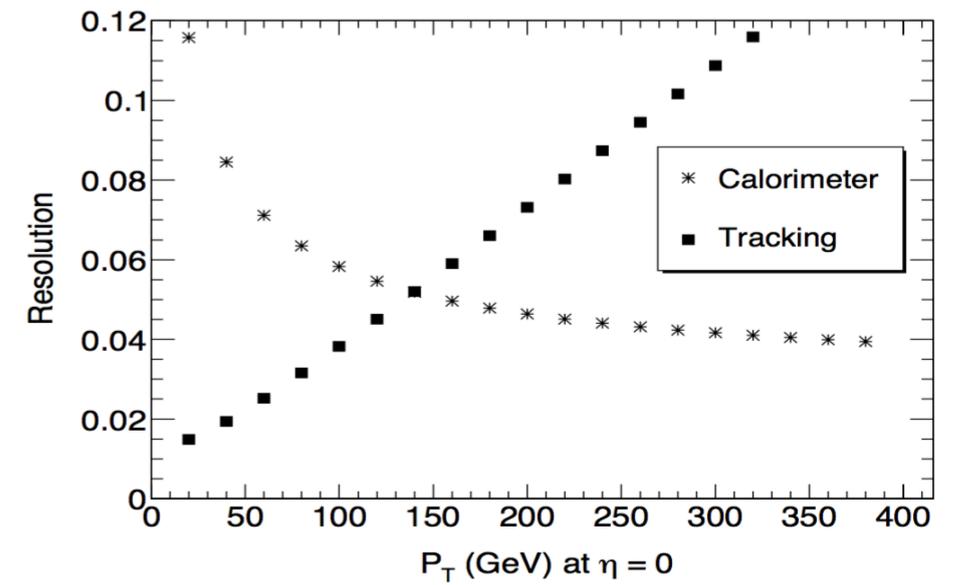
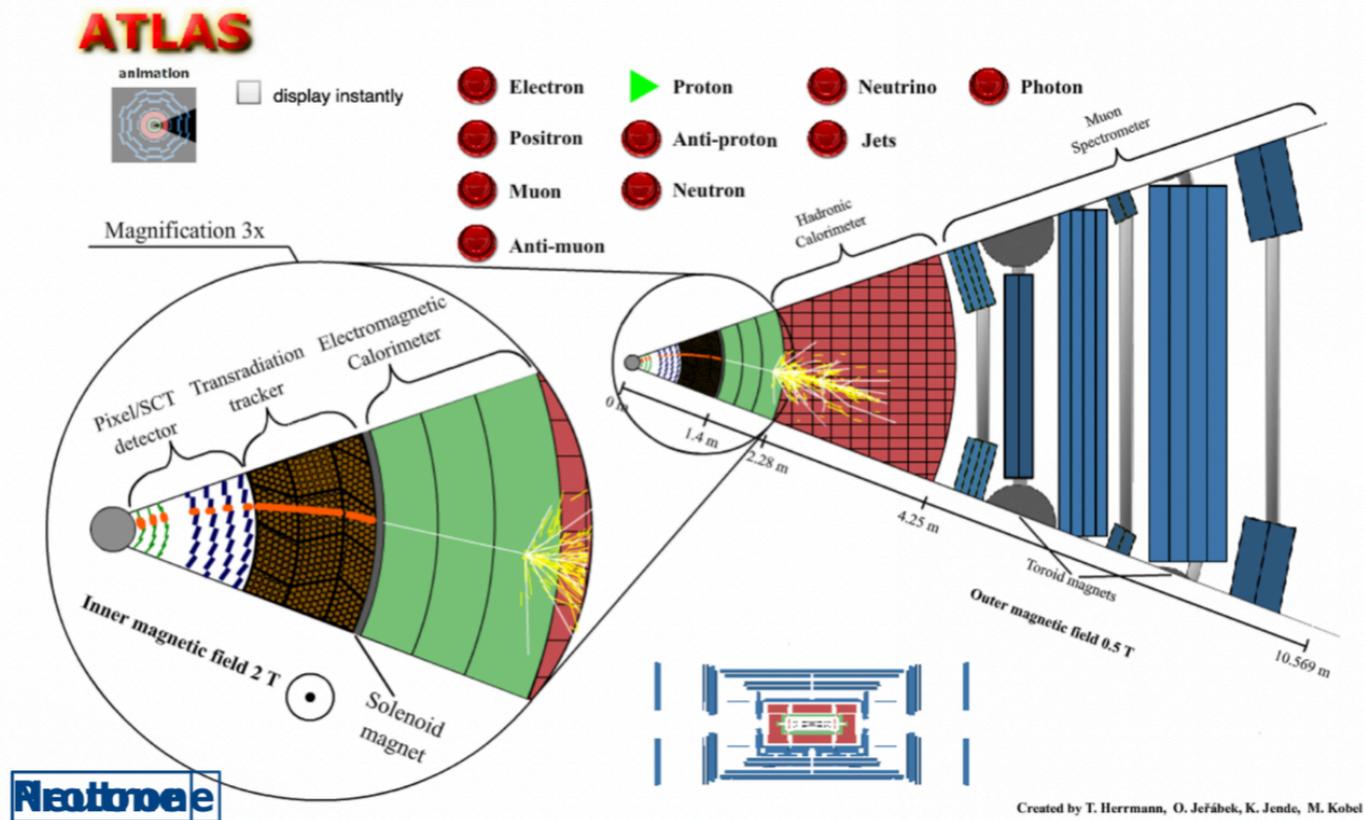
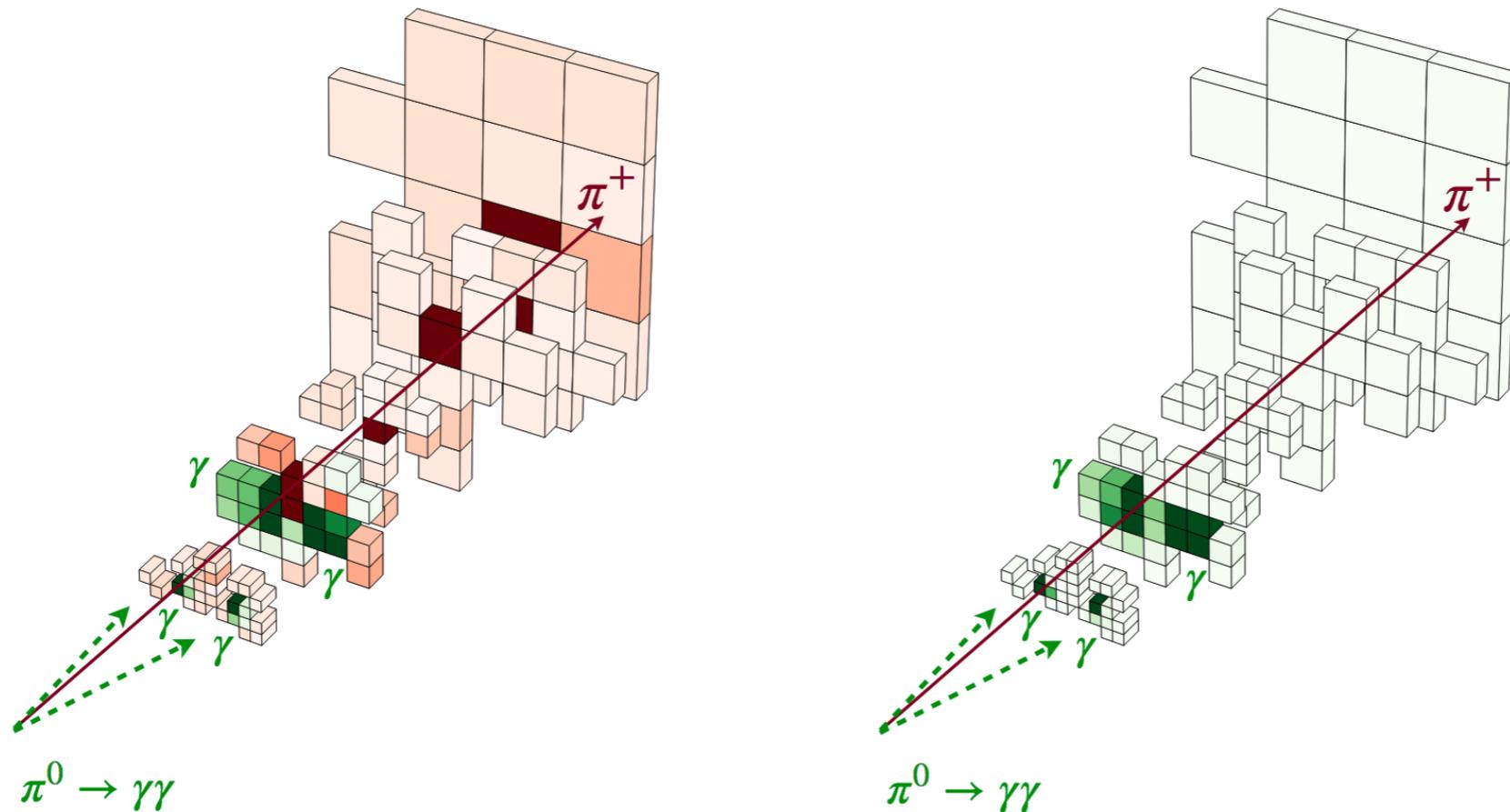


Figure 1: Resolution of Single Pions at $\eta = 0$ in Calorimeter and Charged Particle Tracking Detectors

The detector model



Pi+/p0 simulated with different energy ranges from 2 to 20 GeV

track pt obtained via smearing: $\frac{\sigma(p)}{p} = 5 \times 10^{-4} \times p [GeV],$

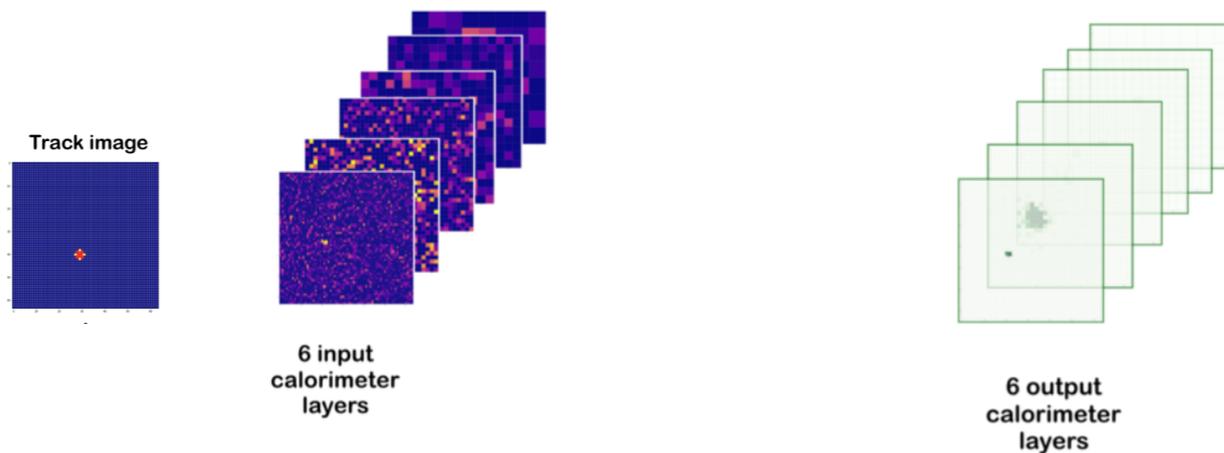
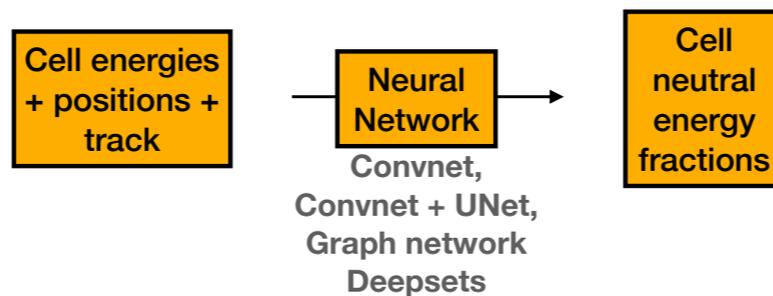
The ML task

Regress the neutral energy for each cell

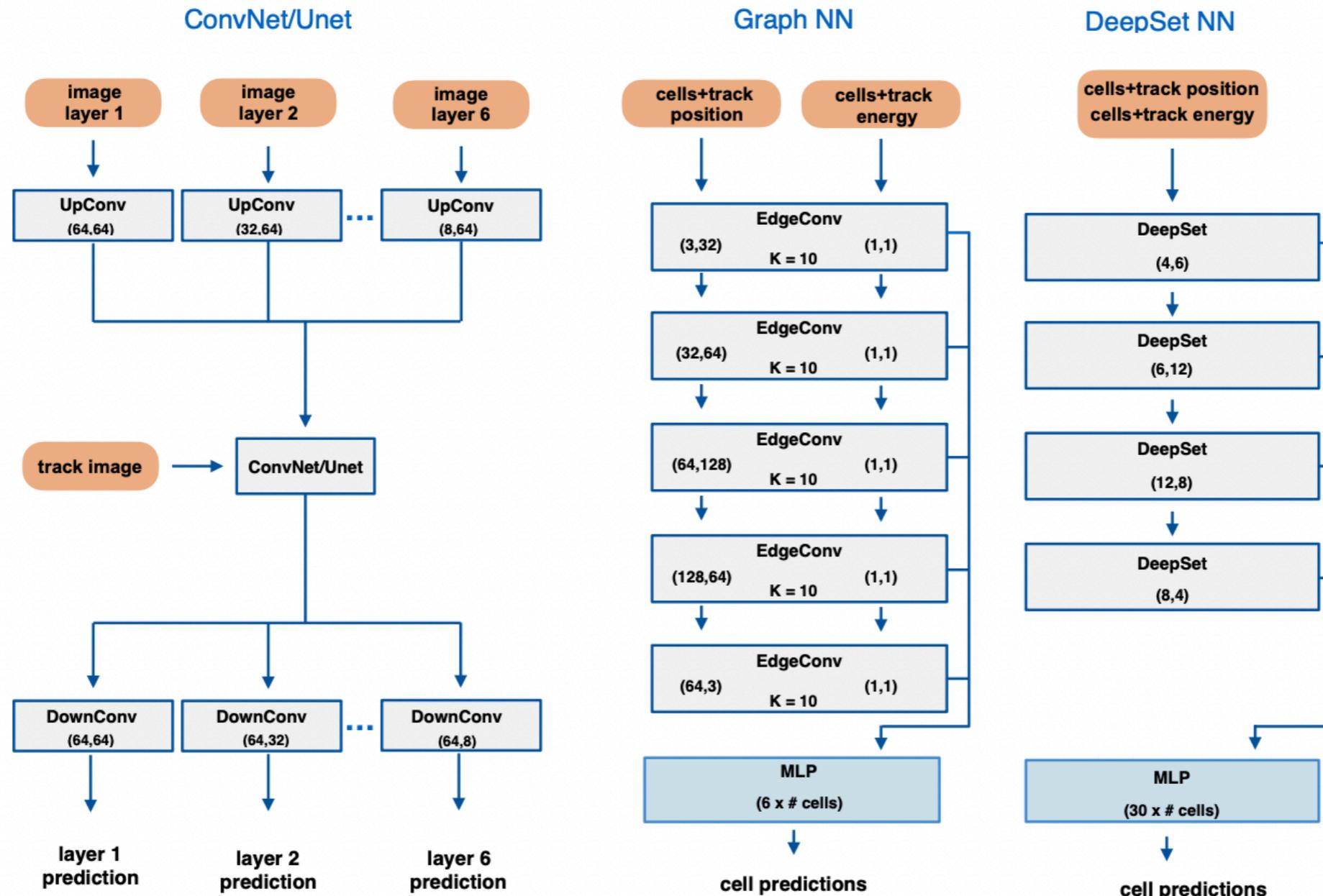
For CNNs the trick is to cope with images with different sizes, no such problems for graphs

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

Common network structure for energy overlap removal task



Some of the models

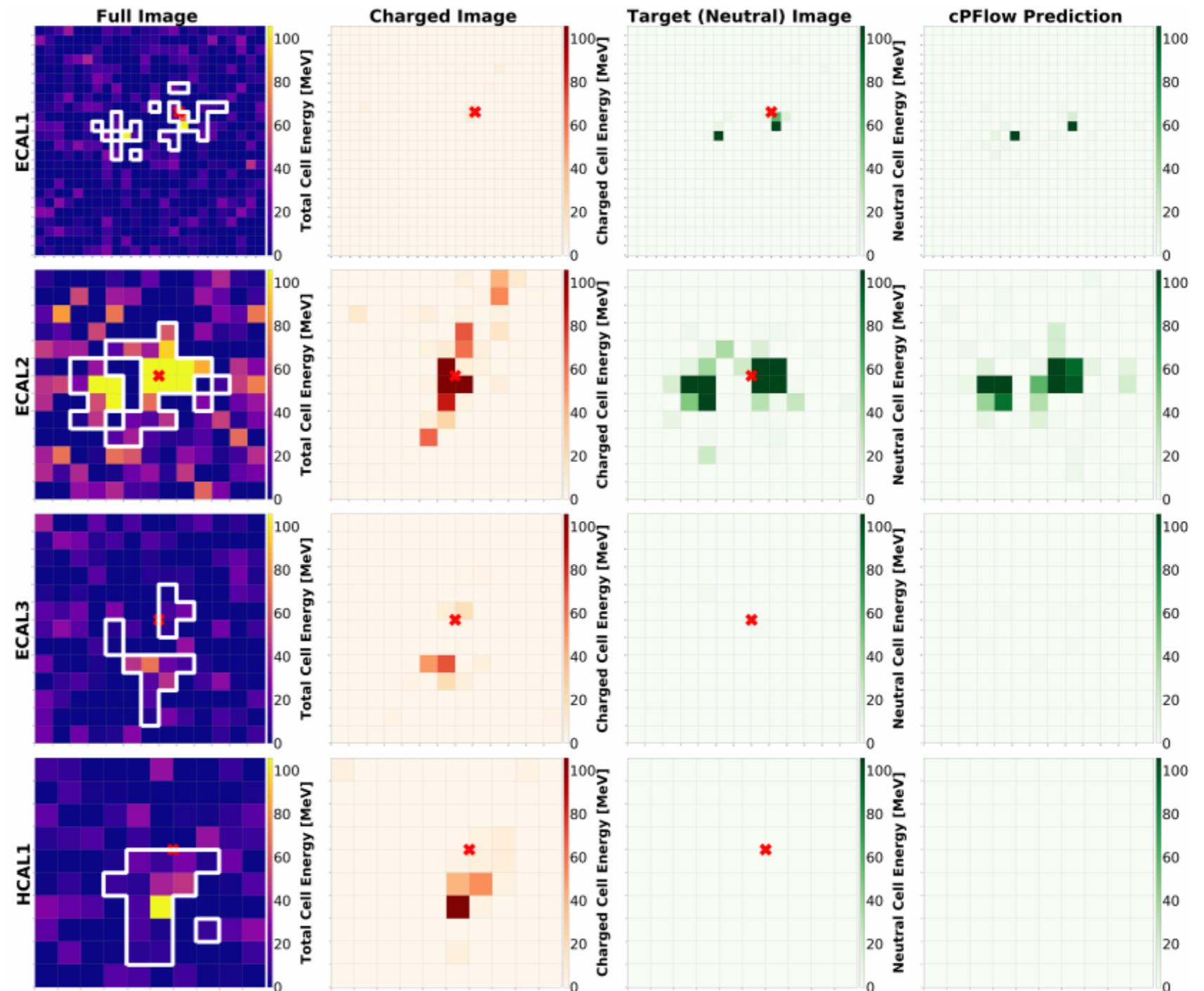


An event display

Topoclusters in white

Compare with traditional Pflow
and ML approaches.

Several tried out: CNNs, graph
networks & deep sets (more
suited to cope with cells+track).



Super-resolution

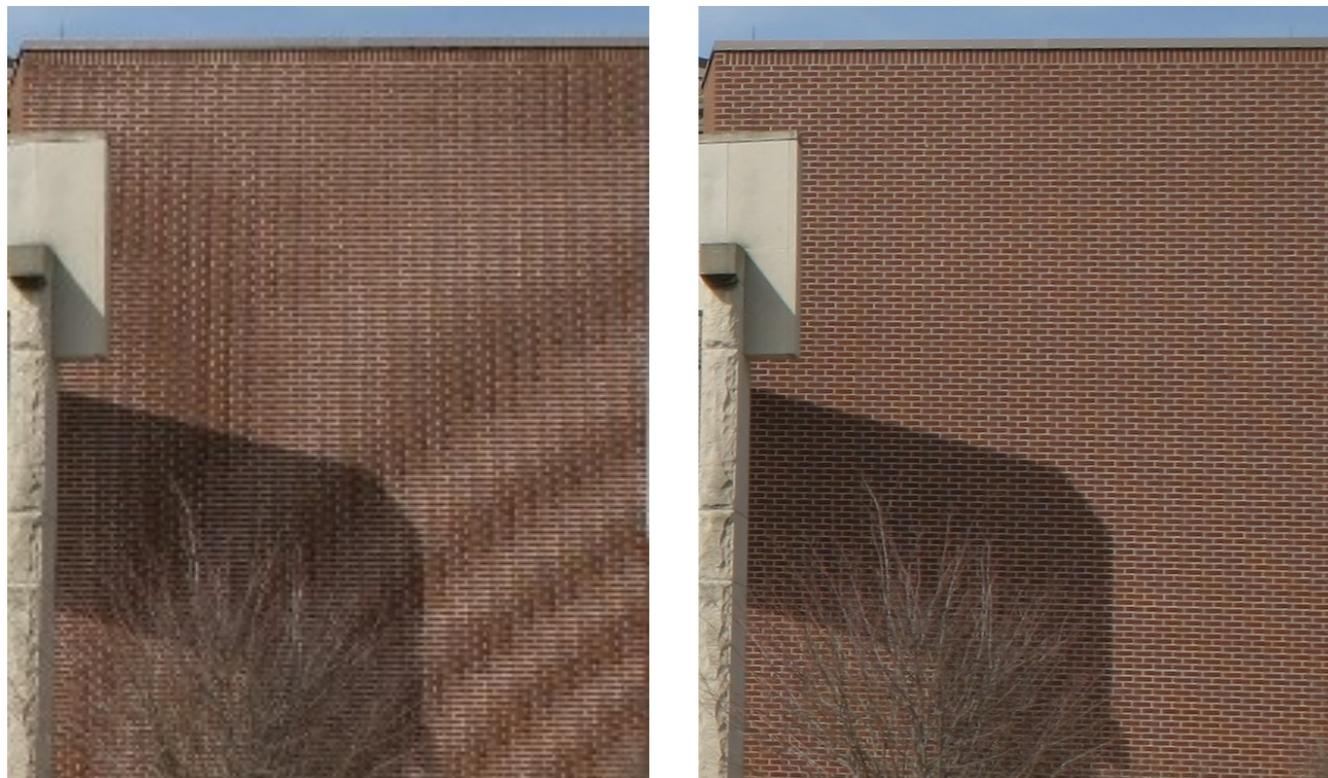
Introduction to super-resolution

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



google CNN (2017) for large up-scaling factor

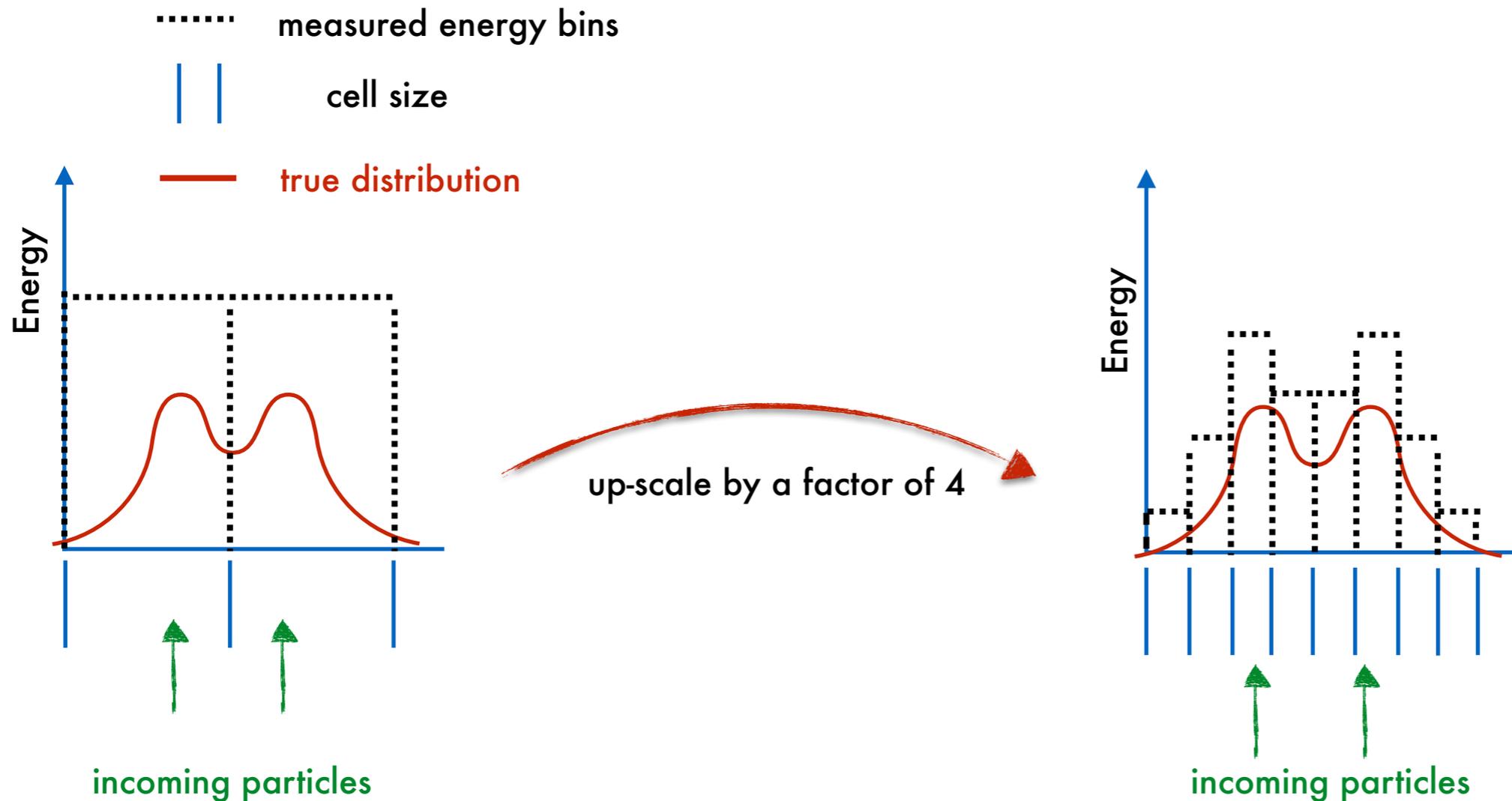
One of the main problem: how to get the HR target?



“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

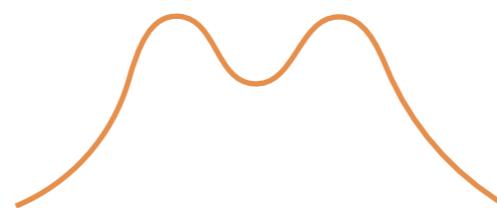
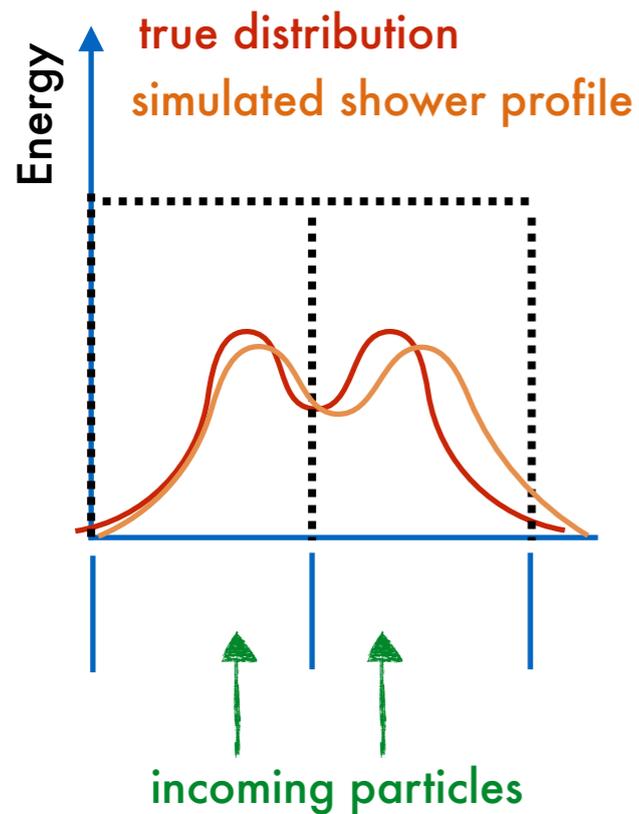
So far trivial statement:

“higher spatial resolution allows to resolve additional features”

but how to construct the high-resolution image?

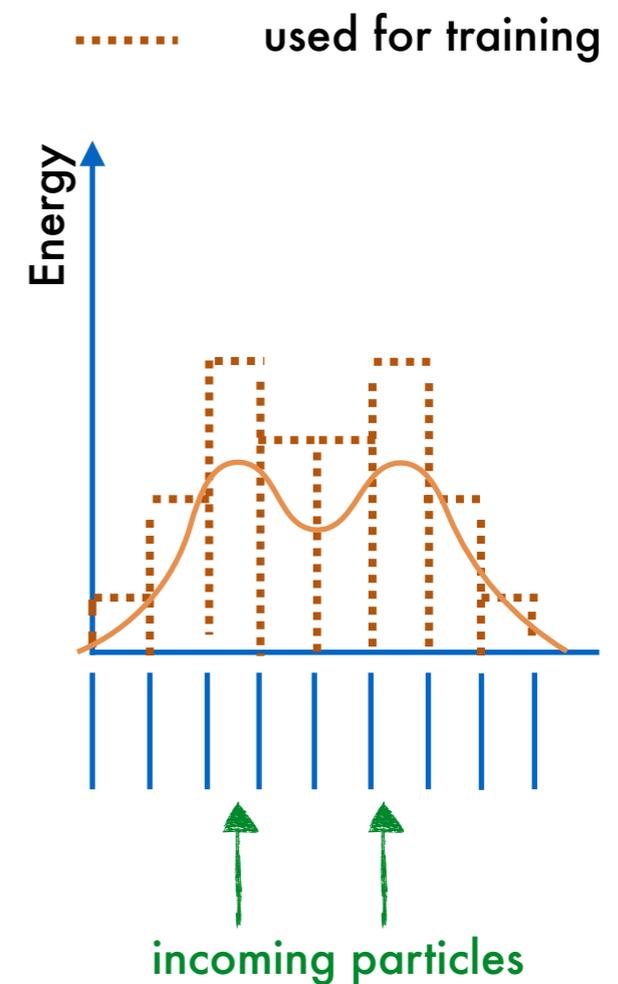
Application to HEP

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



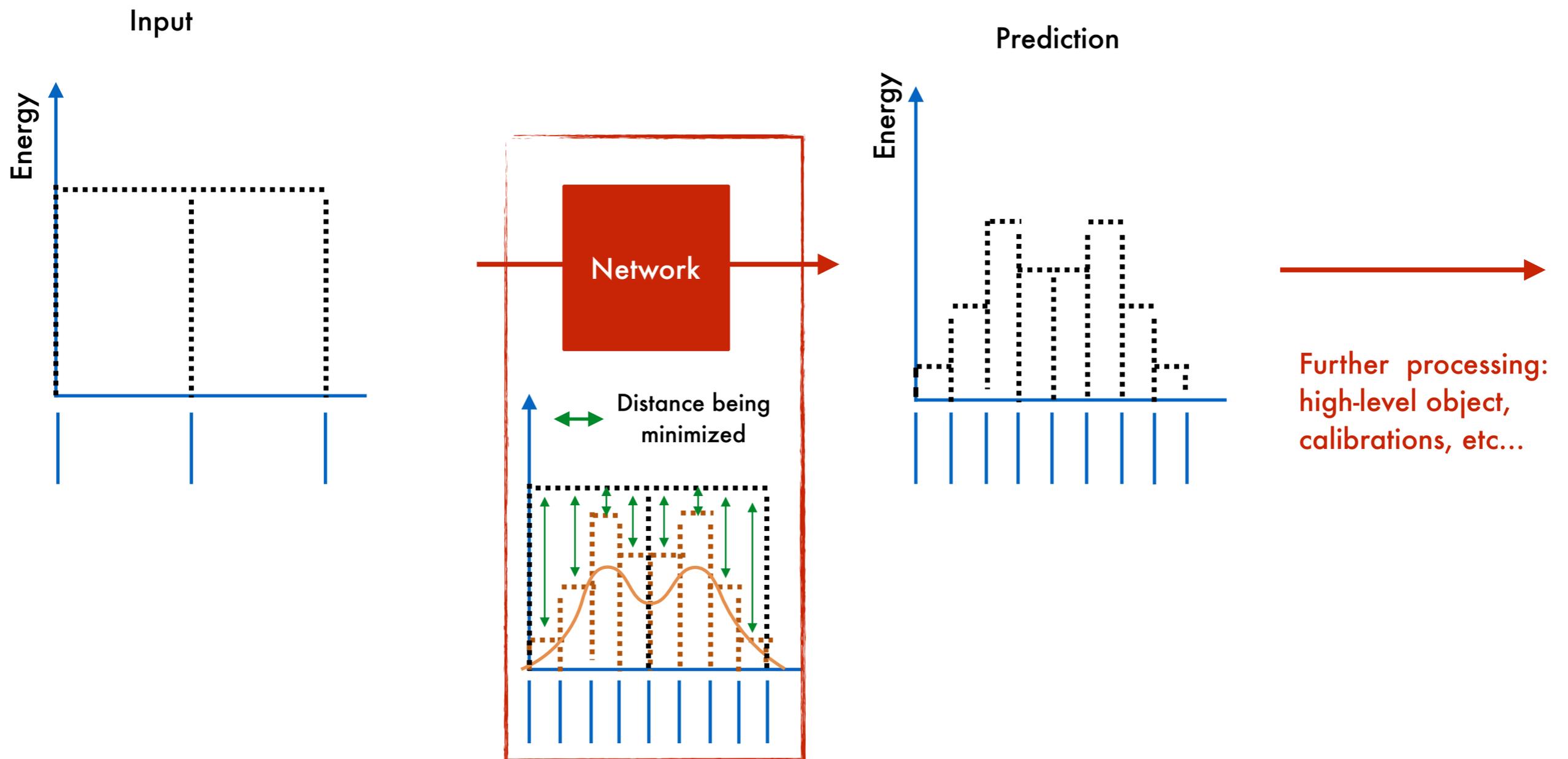
GEANT4 based simulation

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



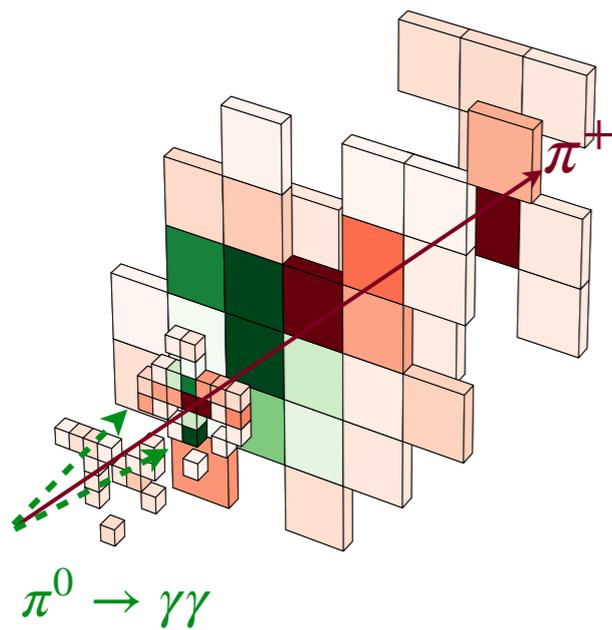
Application to HEP

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



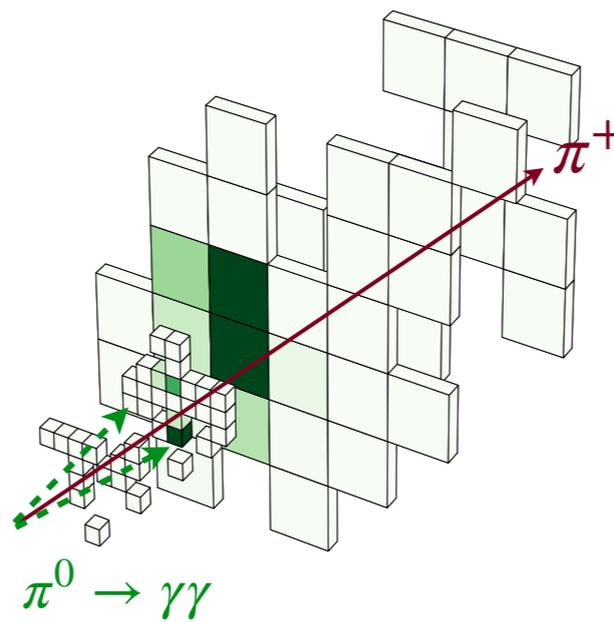
Experimental setup

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



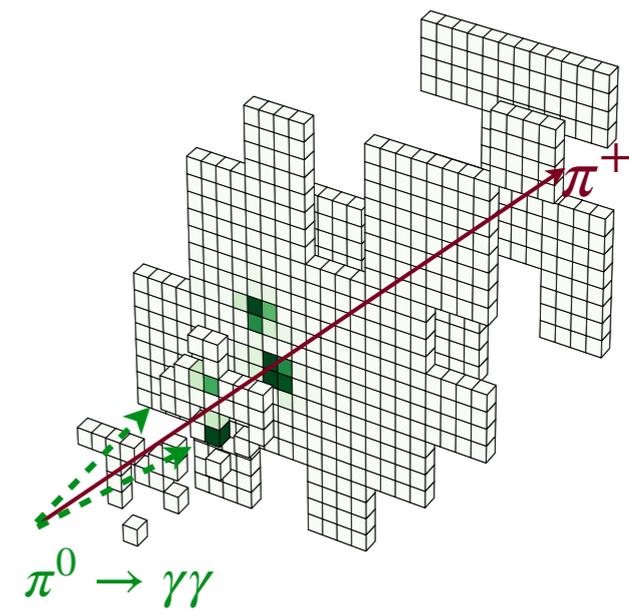
Low-Resolution

charged + neutral+noise



Low-Resolution - neutral only

second layer: 8x8



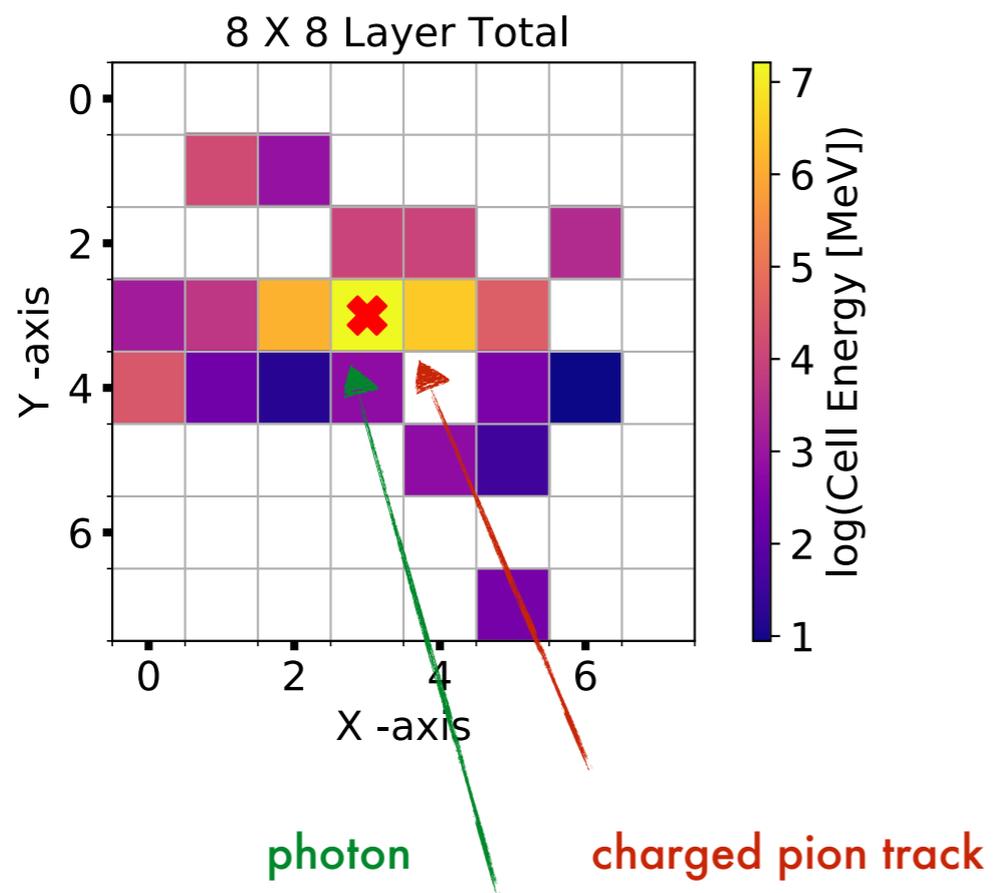
High-Resolution - neutral only

second layer: 32x32

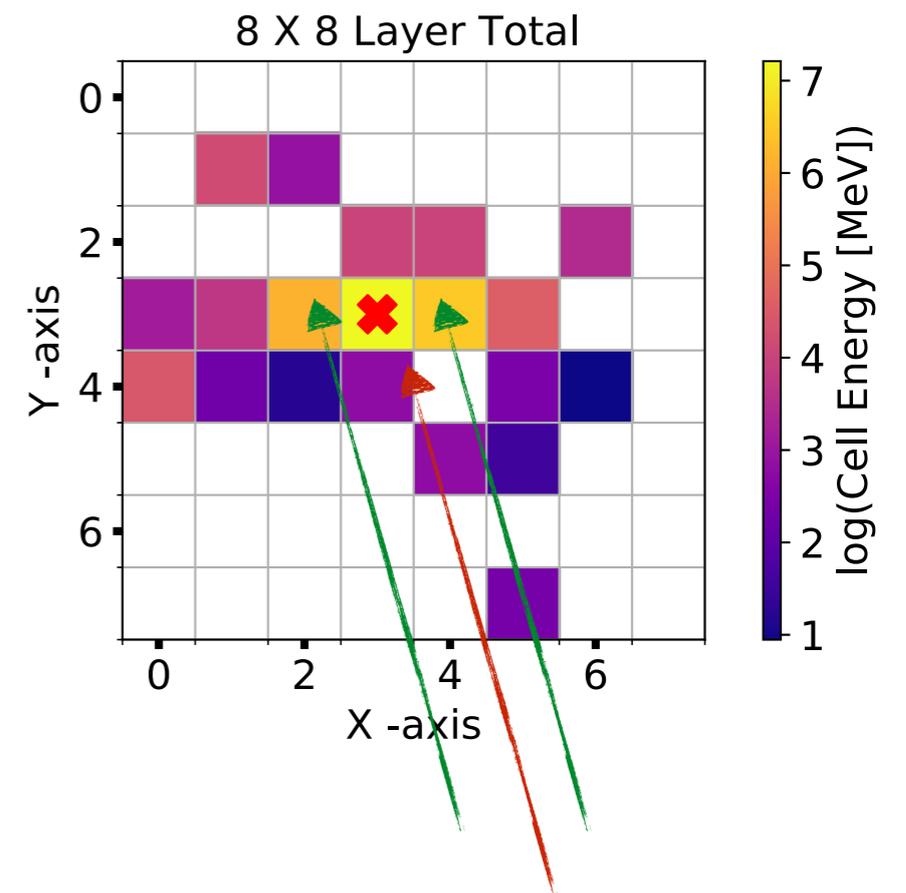
A quiz

- Which one is correct?

(A)

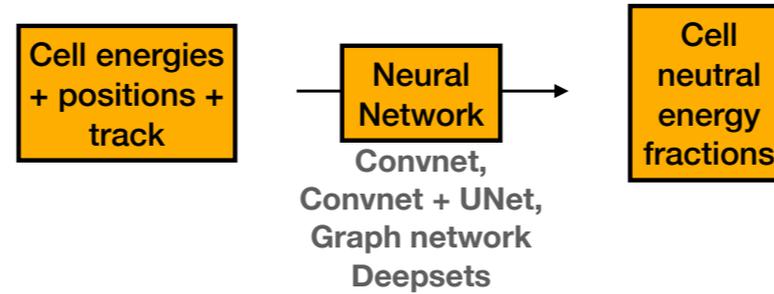


(B)



The model

Common network structure for energy overlap removal task



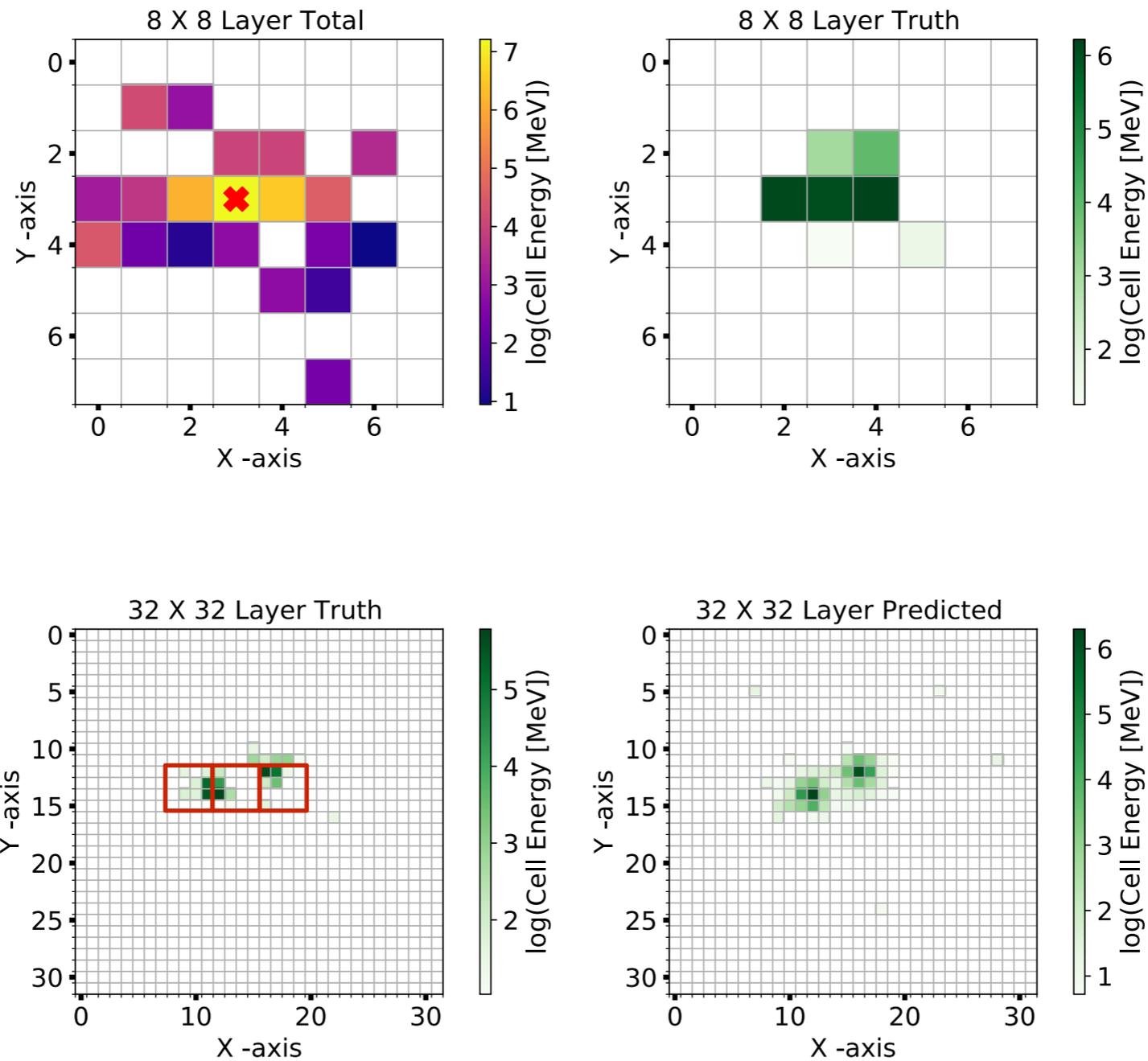
$$L_{event}^{super-res} = \frac{1}{E_{tot}} \sum_c E_c \sum_{s=0}^{us^2} (f_t^{sc} - f_d^{sc})^2$$



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

Results - quiz answer

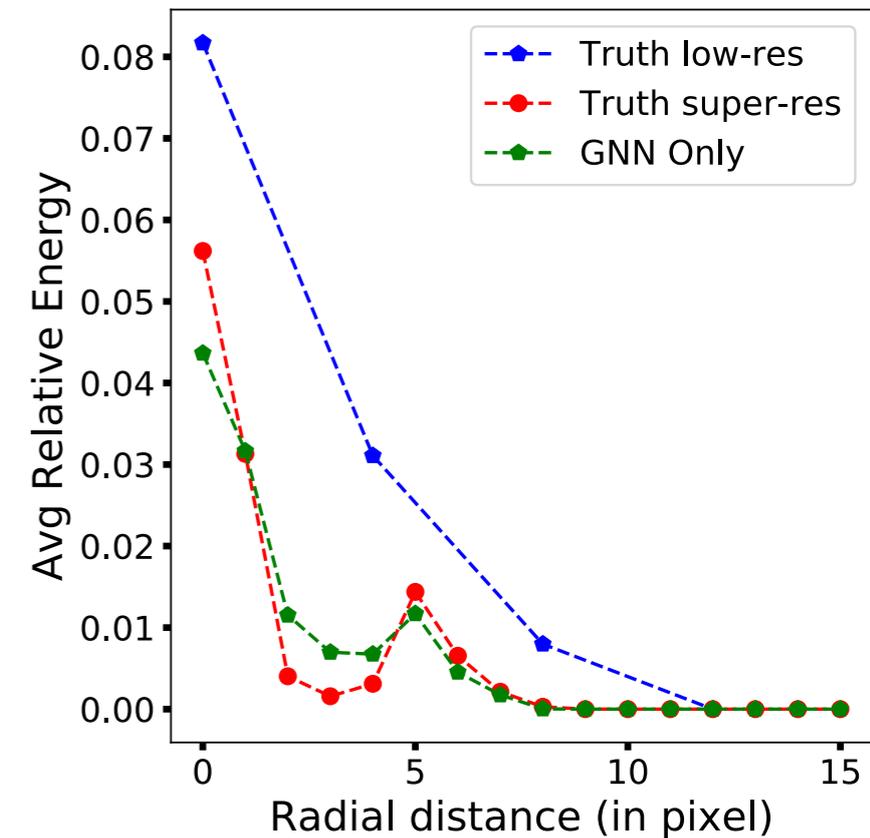
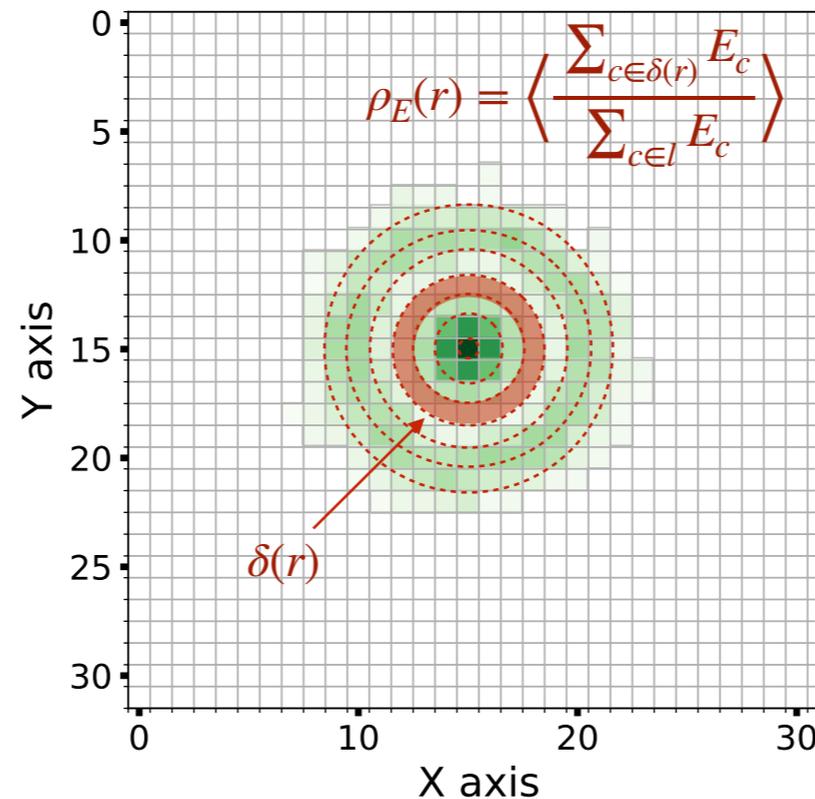
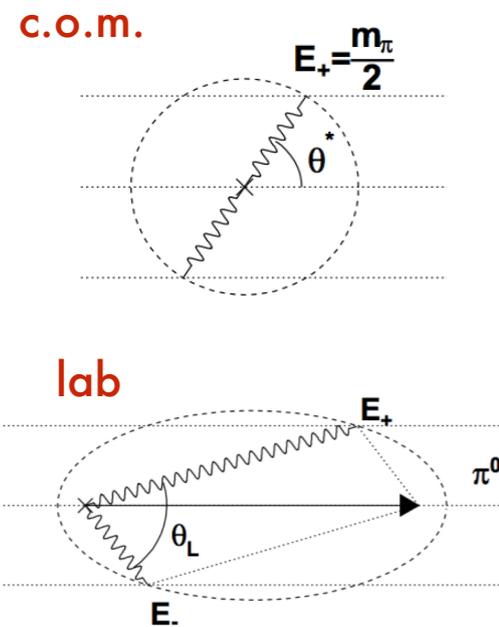
- Super-resolution at work



Results 2

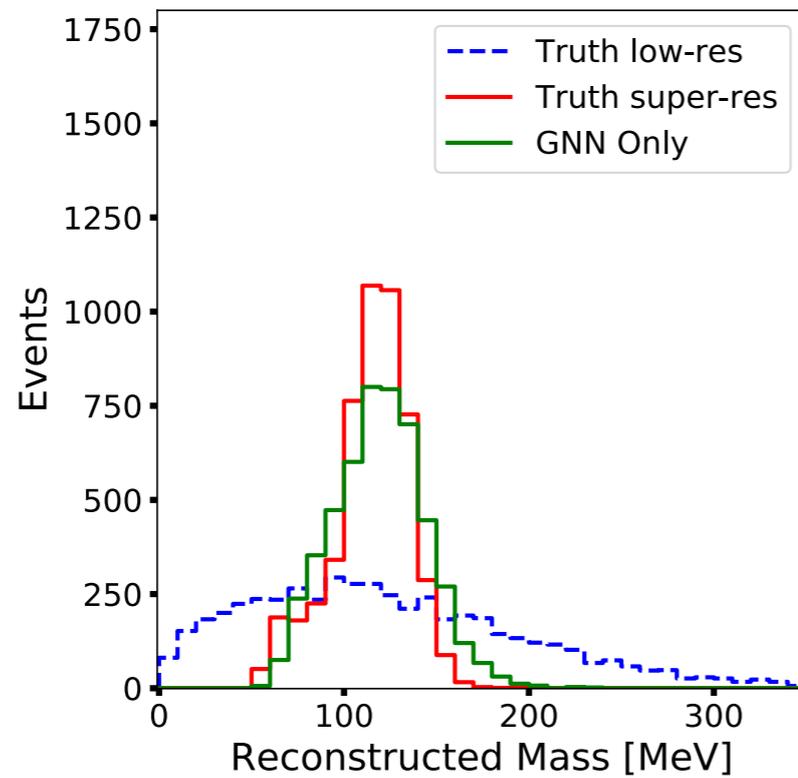
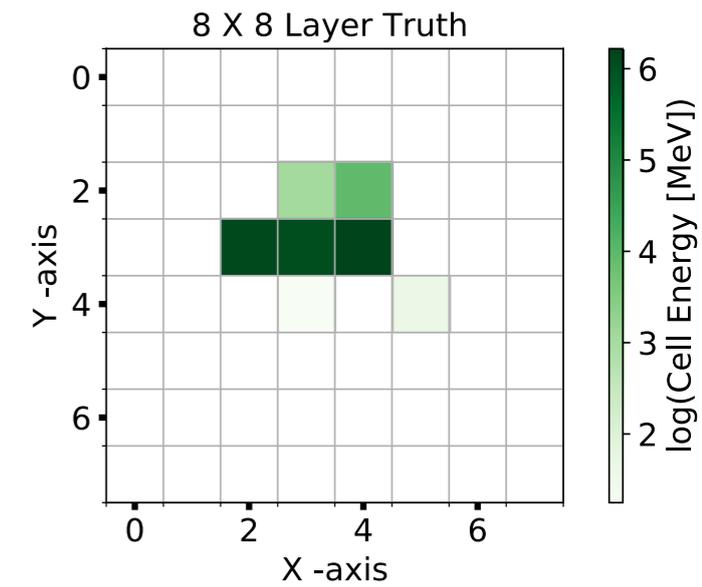
- Can we resolve the two photons from the decaying π^0 ?
- Check by centering the image for each event around the most energetic cell and averaging for all the events
- For a fixed momentum of the p_0 (and fiducial cuts to ask the two photons within detector acceptance), a circle representing the secondary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

truth average image

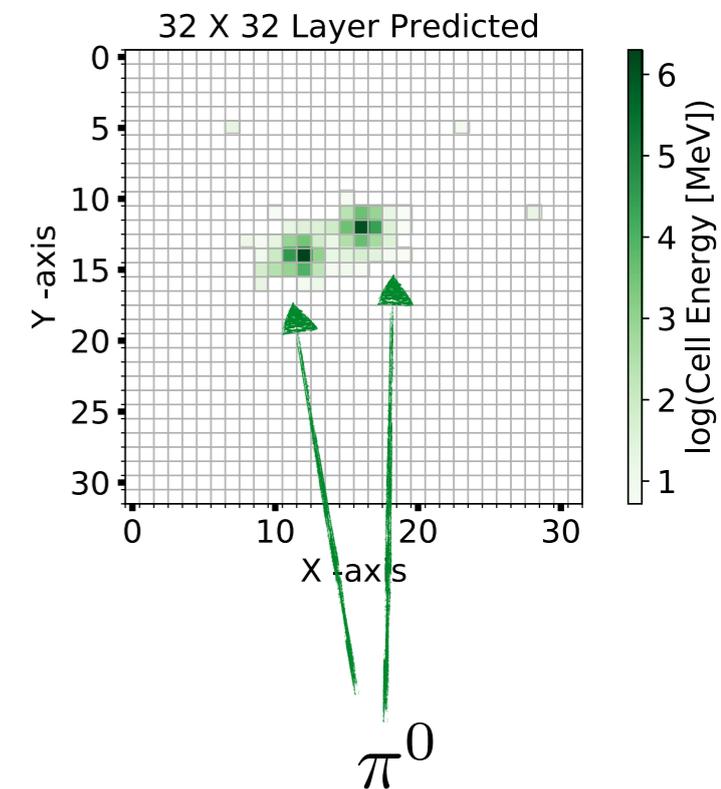


Results 3

- 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

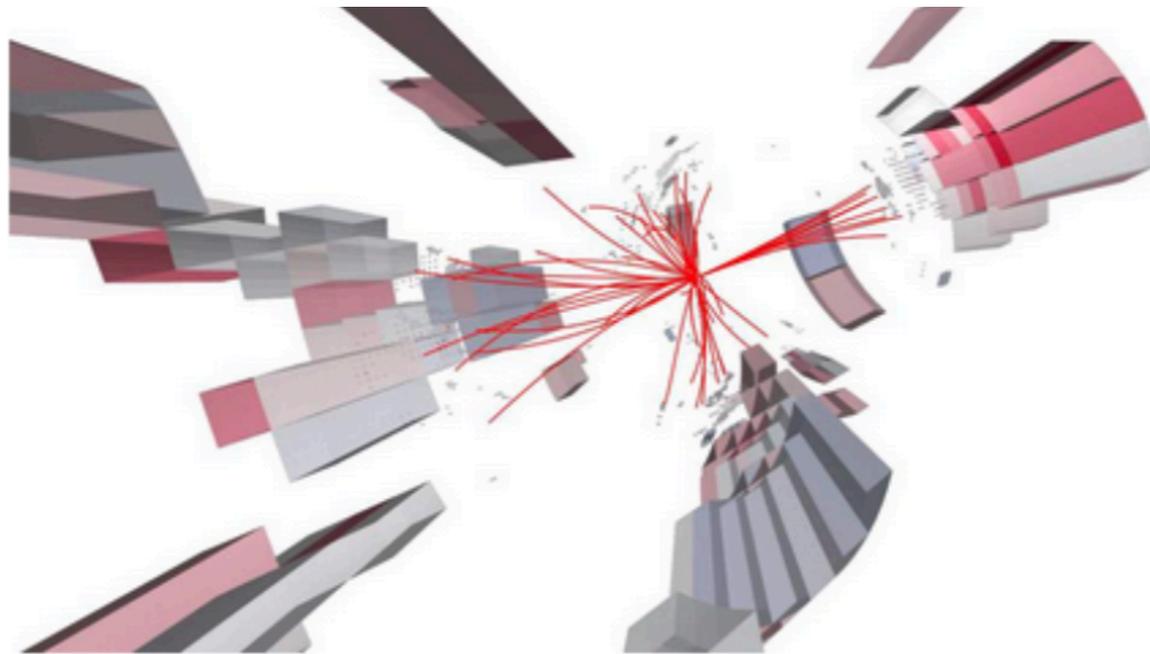


nice high-resolution peak



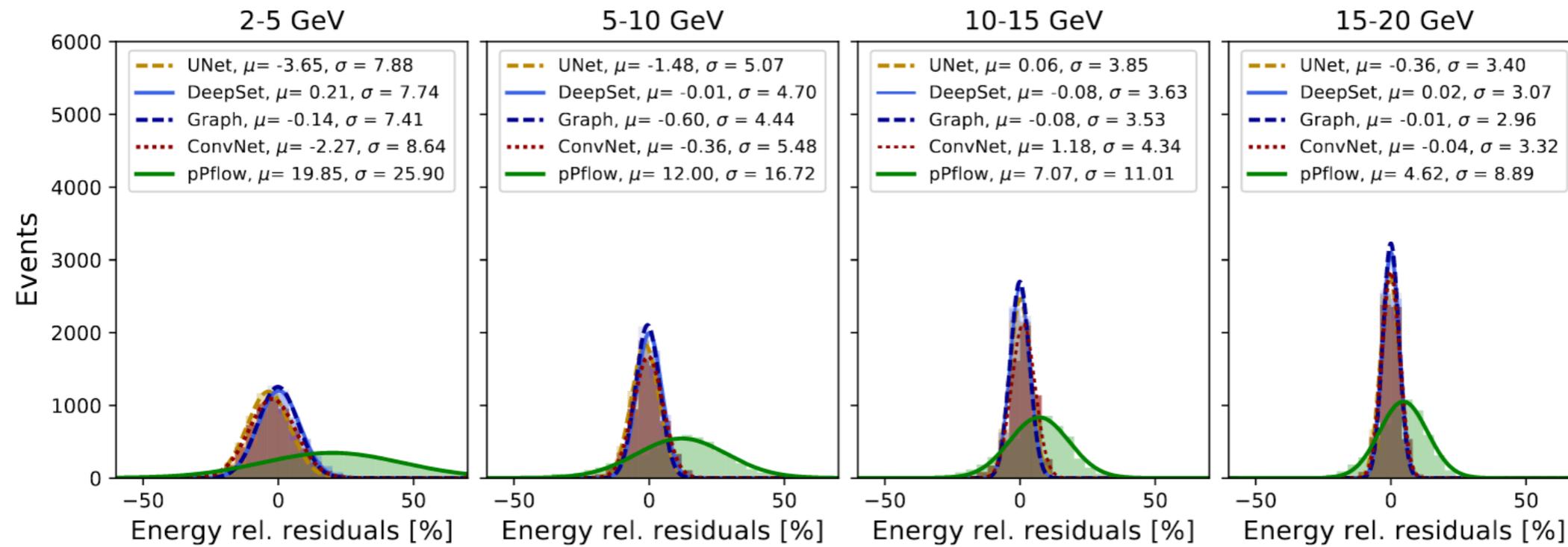
Conclusions

- Simple toy model developed
- Performance evaluated on a simplistic π^0/π^+ overlap
- Results show promising advantages: improving energy and spatial resolution (especially sup-res) of measuring systems
- Could be an interesting “intermediate” steps toward construction of more complete Pflow algorithms



Results

(1) Energy in topo clusters (also per cell in backup)



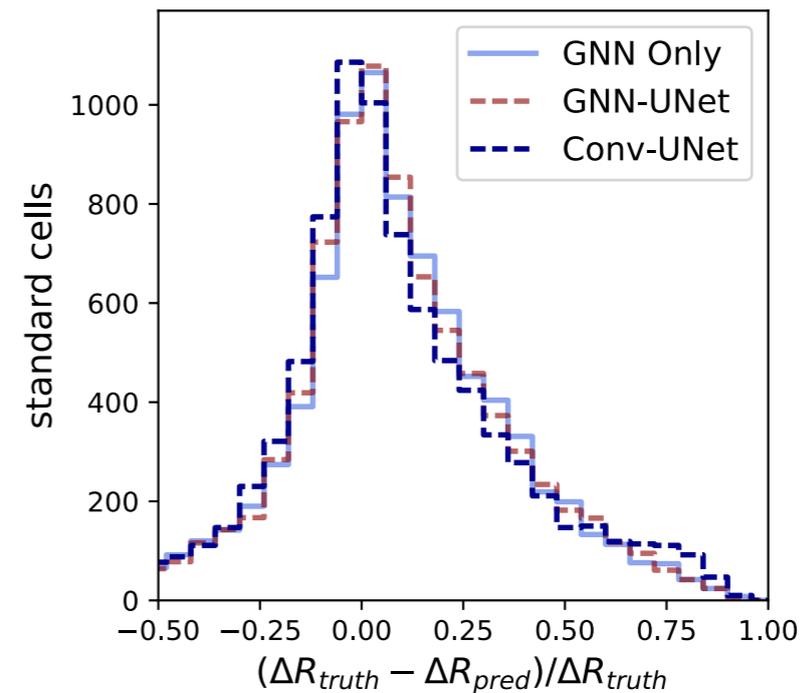
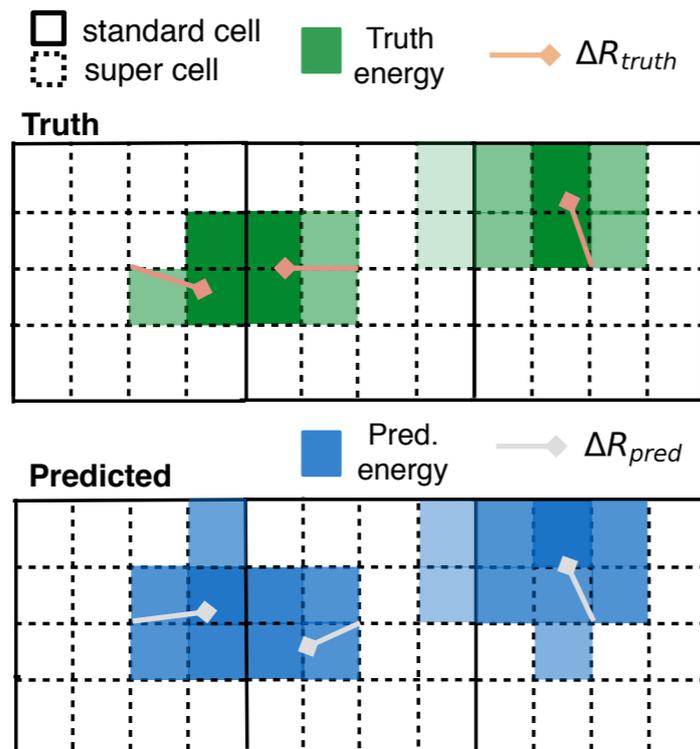
$$\frac{(E_{\text{predicted}} - E_{\text{Neutral}})}{(E_{\text{Neutral}})}$$

Less bias, much improved sigma for all models

Results 2

- Expect correlation between the radial distance of each standard cell

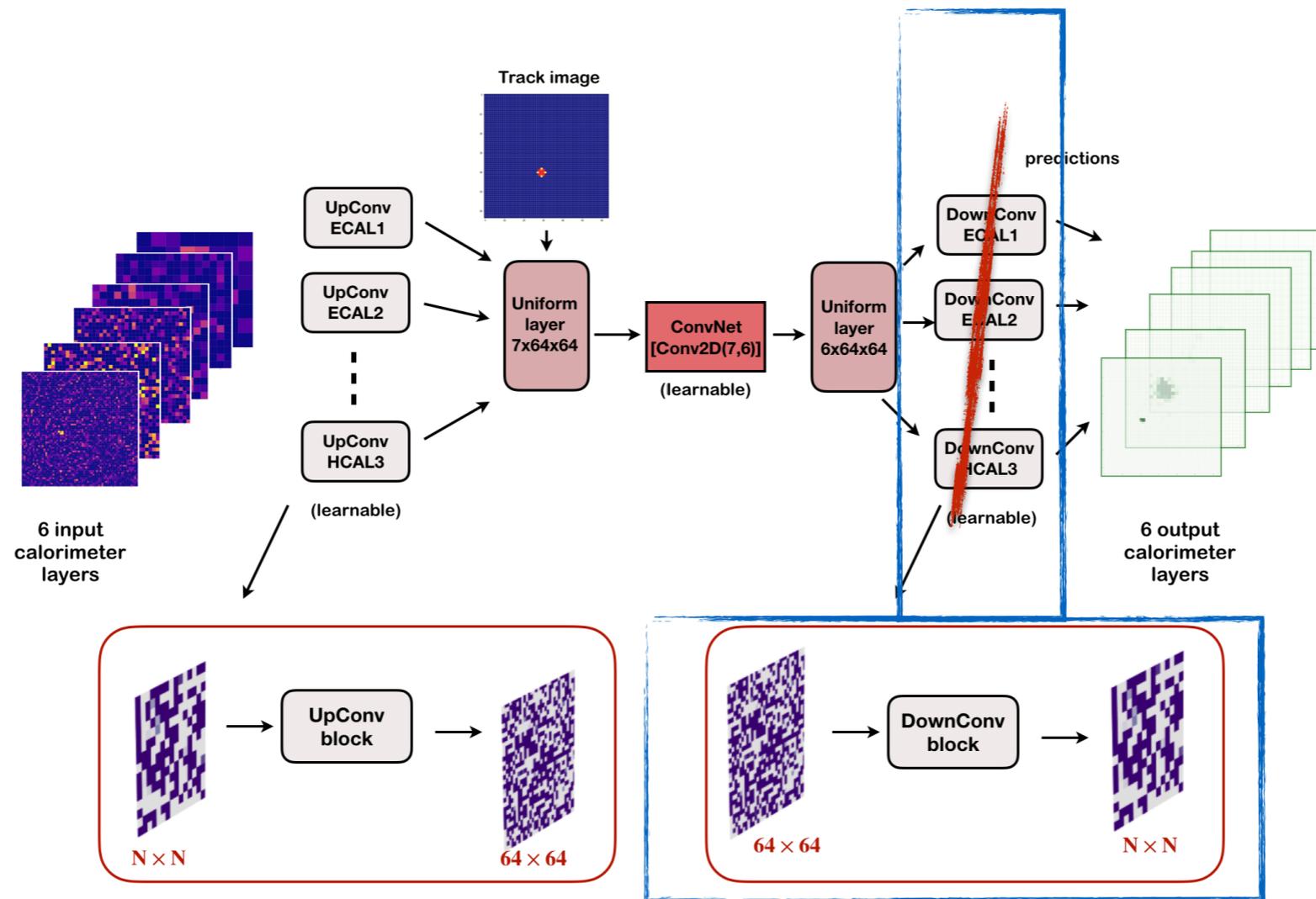
$$\Delta R = \frac{\sum_{sc}^{up^2} E_{sc} \sqrt{x_{sc}^2 + y_{sc}^2}}{\sum_{sc}^{up^2} E_{sc}}$$



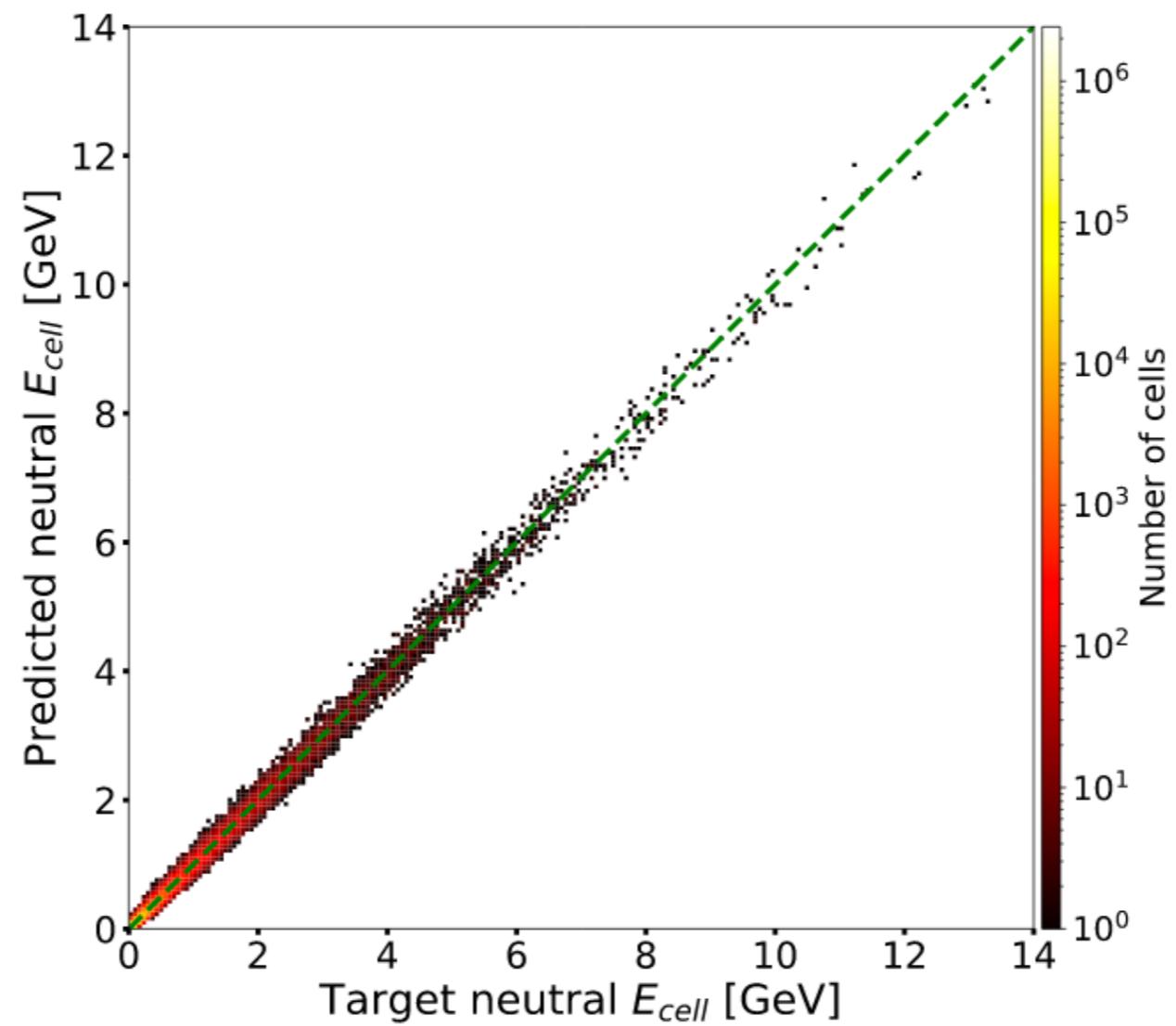
Learning high-resolution patterns

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

The model

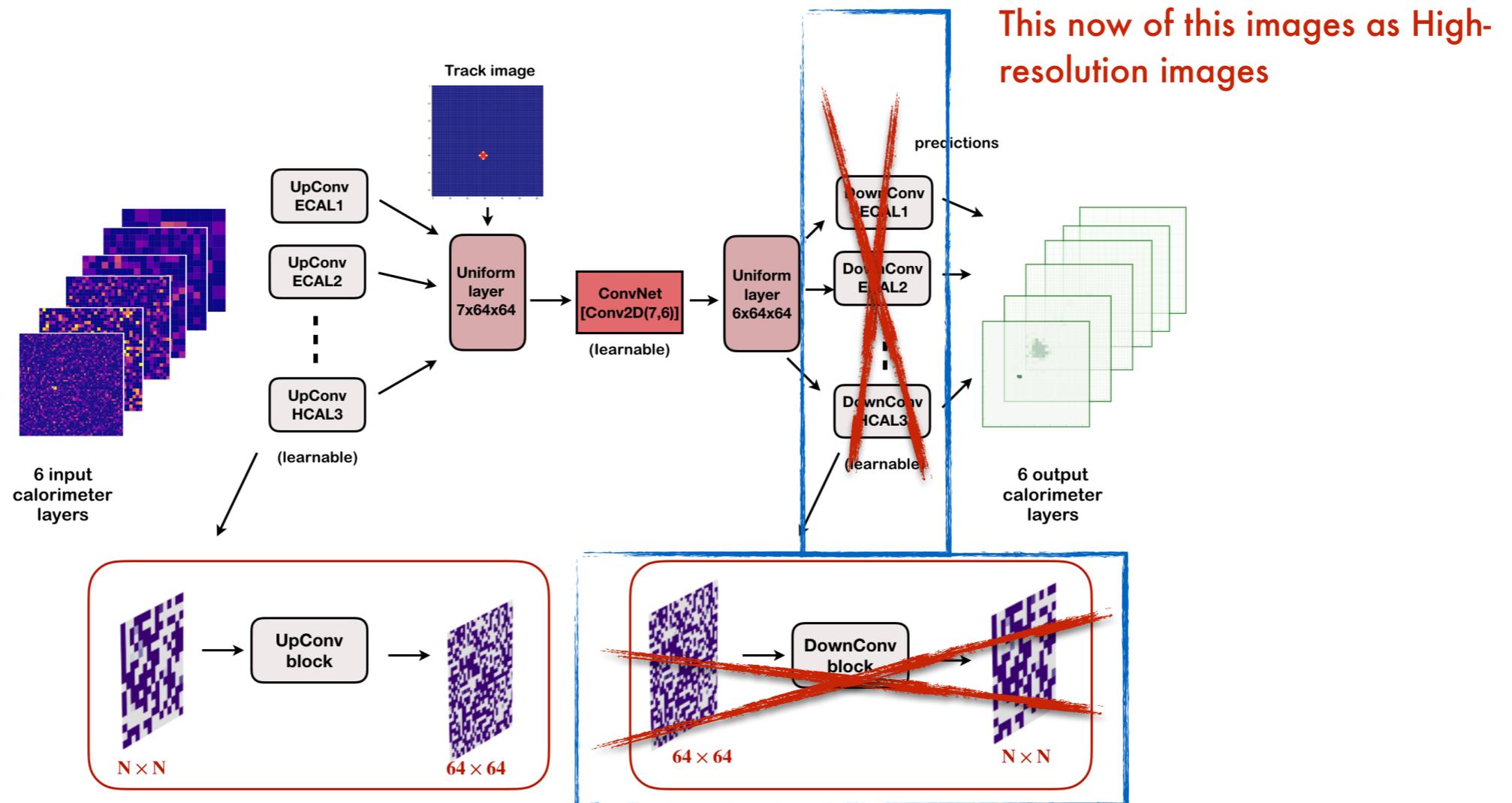


The model

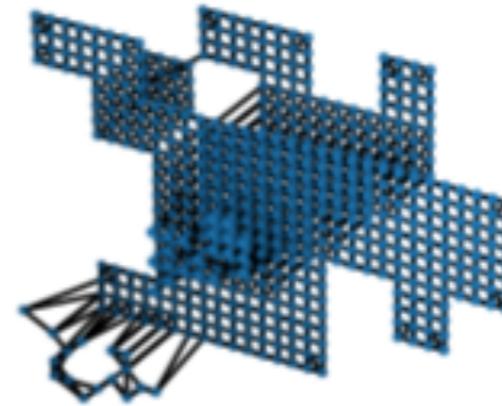
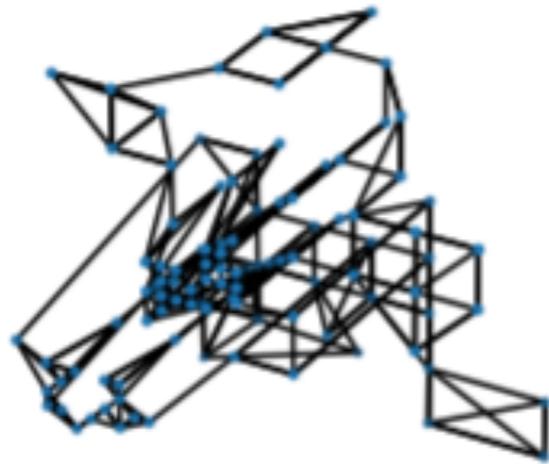


The model

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



Graph model

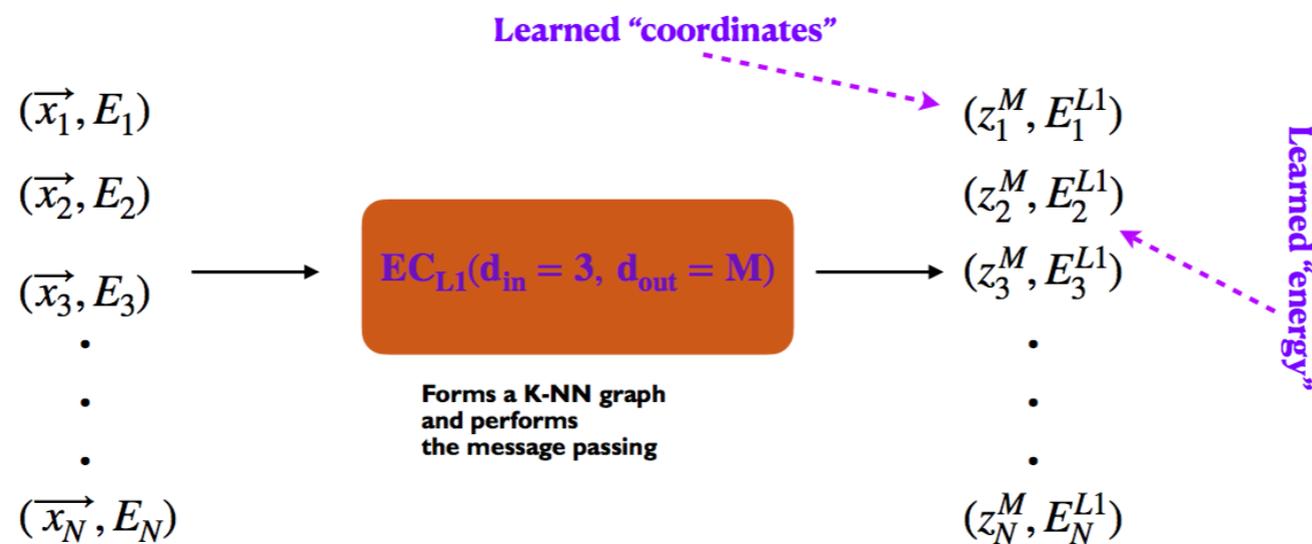


Graph model

<https://arxiv.org/pdf/1801.07829.pdf>

$$(x')_i^{l+1} = \max_{j \in \mathcal{N}(i)} \Theta_x(x_j^l - x_i^l) + \Phi_x(x_i^l)$$

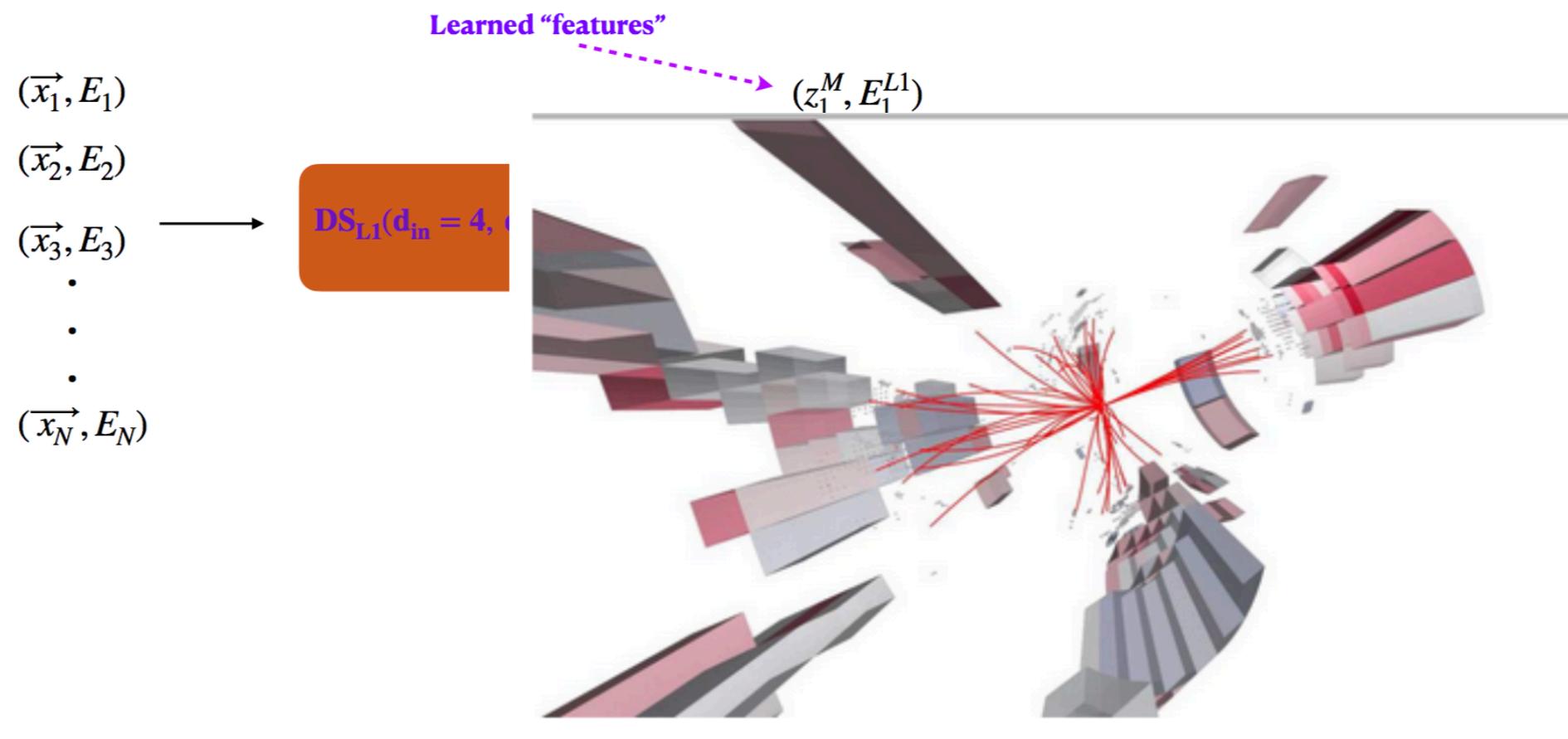
$$(e')_i^{l+1} = \text{mean}_{j \in \mathcal{N}(i)} \Theta_e(e_j^l - e_i^l) + \Phi_e(e_i^l)$$



Deep sets

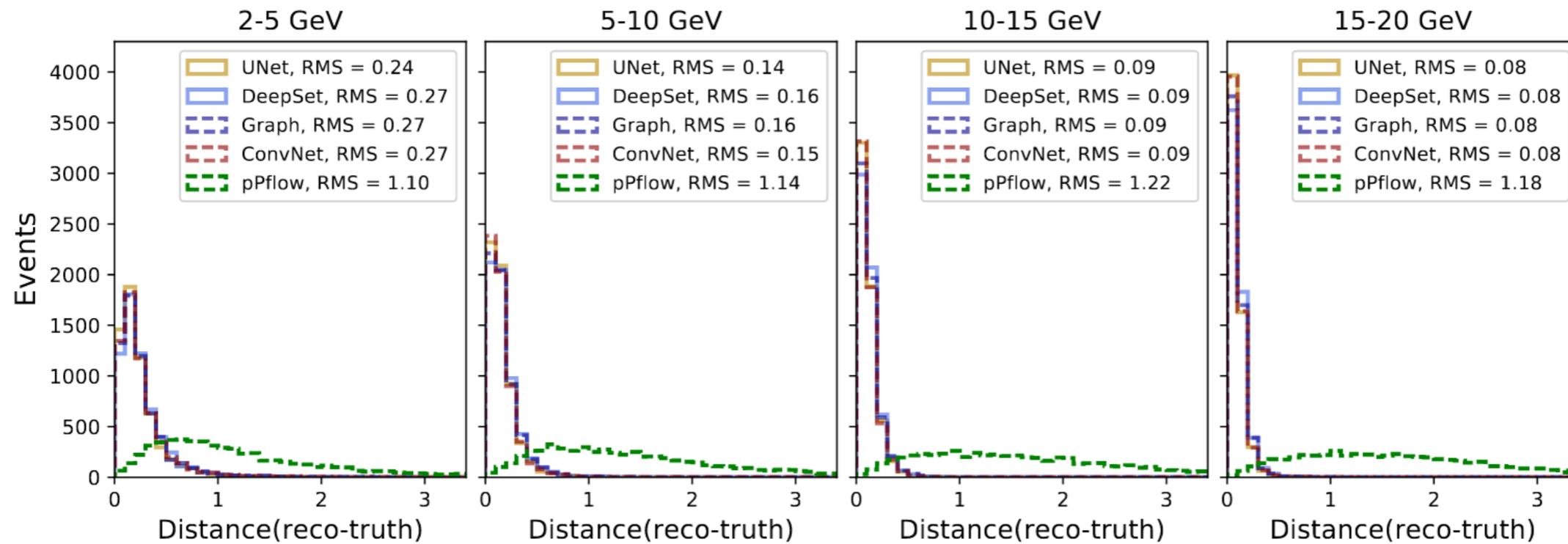
<https://arxiv.org/pdf/1703.06114.pdf>

$$O(\{p_1, \dots, p_n\}) = F\left(\sum_{i=1}^n \Phi(p_i)\right),$$



Results

(2) Position



distance in number of cells for ECAL layer 2

Introduction to Super-resolution

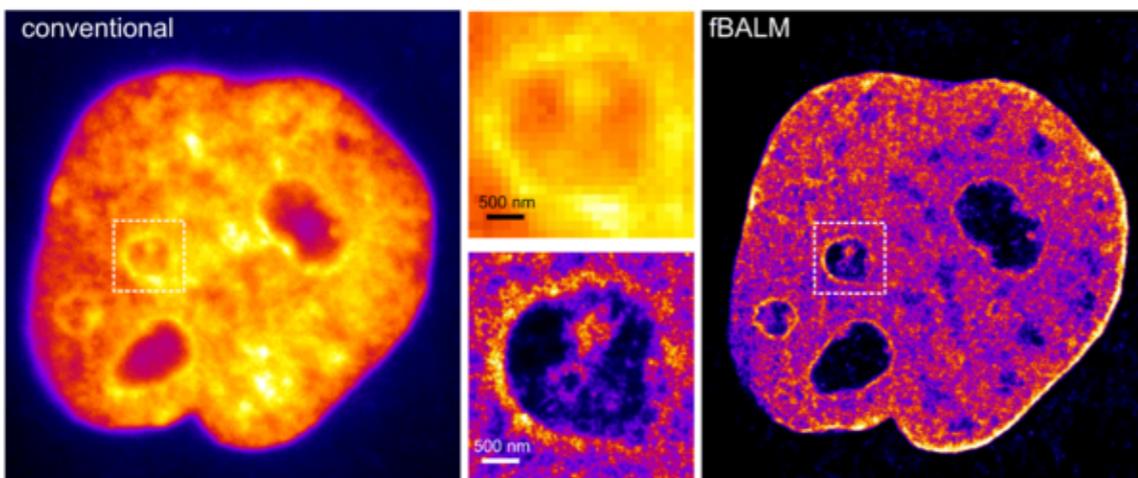
- **Lorenzo's master thesis!**

- 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.](#)]

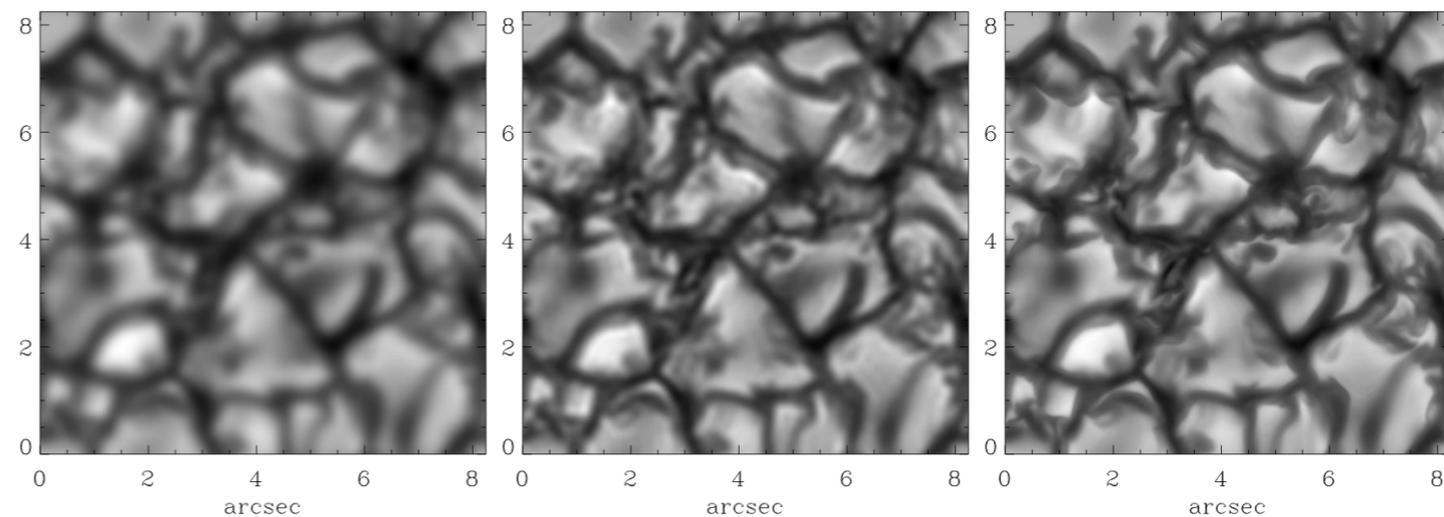
- Molecule -



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

- Astronomy [[Ref.](#)]

- solar granulation -



and industrial application....

The Geant model

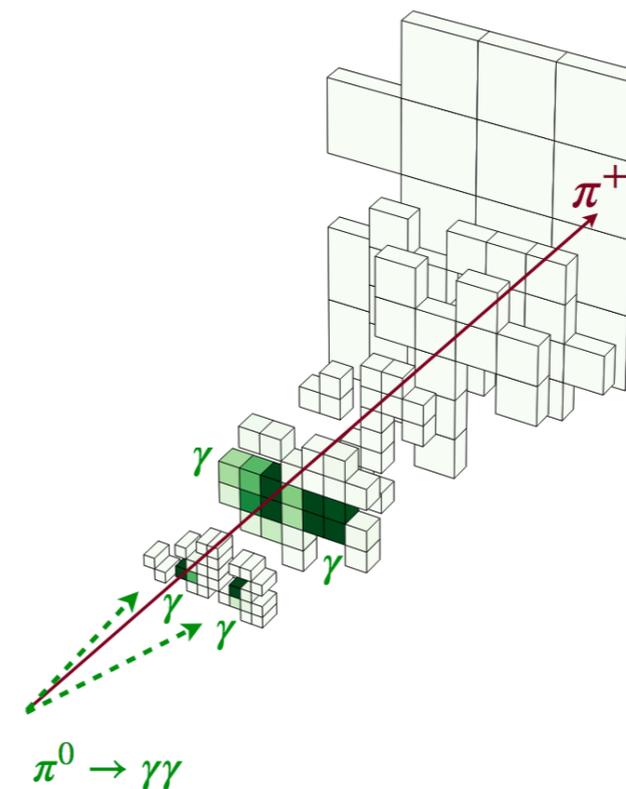
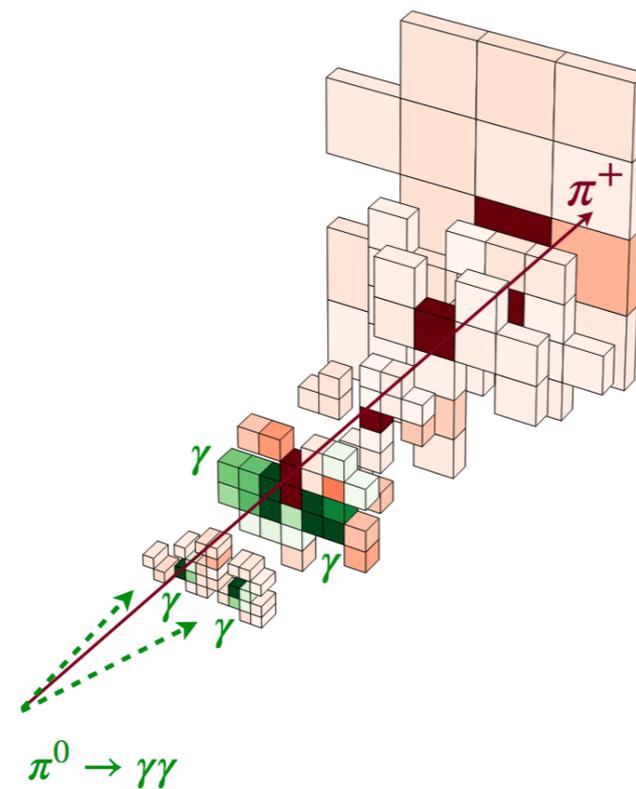
Detector	Absorber	Scintillator	Subdetector (Legth)
ECAL	Lead 1.2	Liquid Argon 4.5	ECAL1 ($3 X_0$)
			ECAL2 ($16 X_0$)
			ECAL3 ($6 X_0$)
HCAL	Iron 4.7	Plastic organic 1.0	HCAL1 ($1.5 \lambda_{\text{int}}$)
			HCAL2 ($4.1 \lambda_{\text{int}}$)
			HCAL3 ($1.8 \lambda_{\text{int}}$)

$$X_0 = 3.9 \text{ cm}$$

$$\lambda_{\text{int}} = 17.4 \text{ cm}$$

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)

random noise added per cell with gaussian shapes



π^+/p^0 simulated with different energy ranges from 2 to 20 GeV

track pt obtained via smearing: $\frac{\sigma(p)}{p} = 5 \times 10^{-4} \times p [GeV]$,

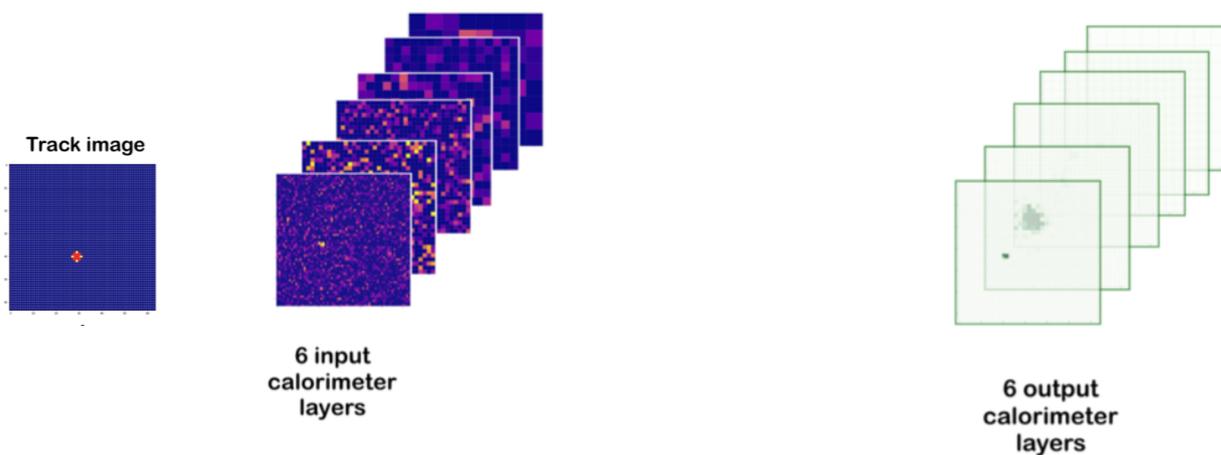
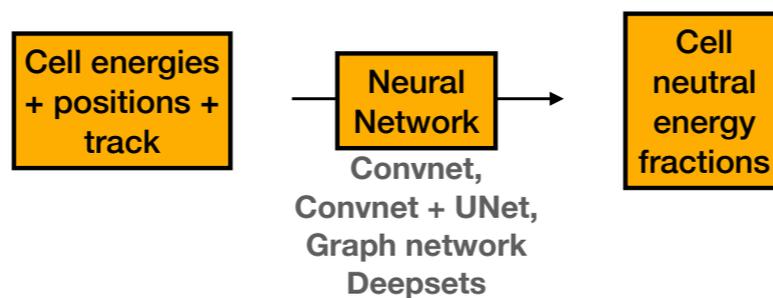
The ML tasks

Regress the neutral energy for each cell

For CNNs the trick is to cope with images with different sizes, no such problems for graphs

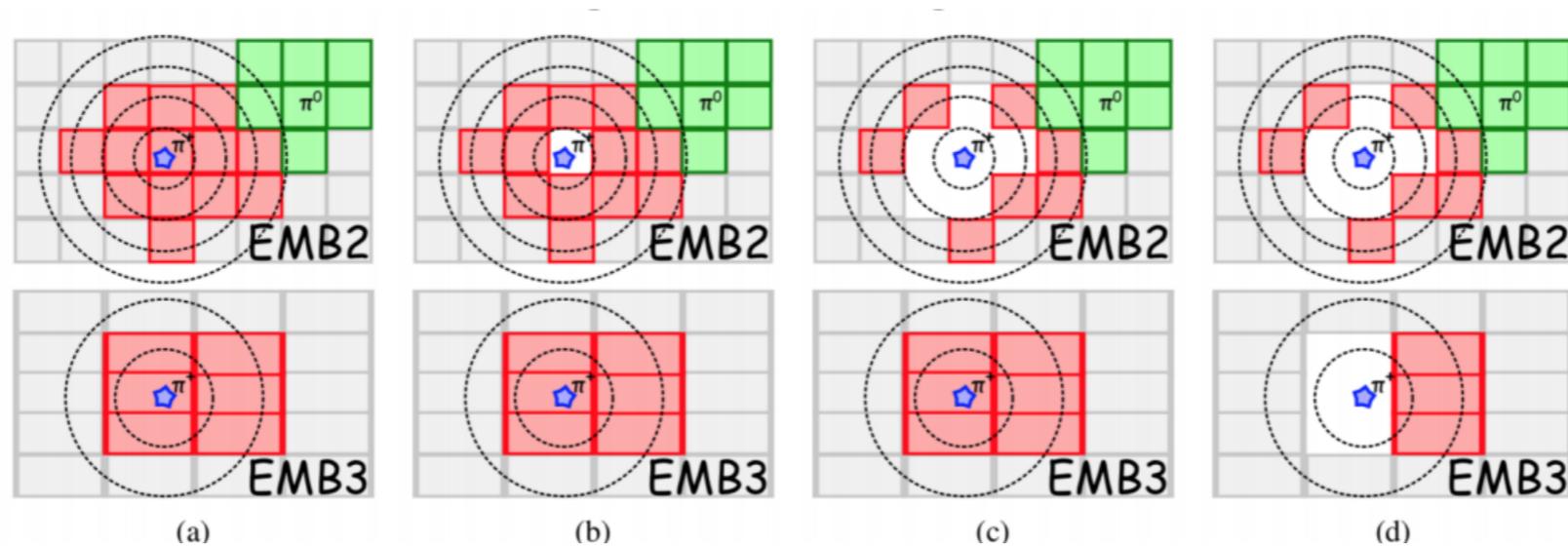
$$L_{event} = \frac{1}{E_{tot}} \sum_c E_c (f_t^c - f_d^c)^2$$

Common network structure for energy overlap removal task



Atlas Pflow

- Particle flow algorithm (ATLAS like):



- ... what if the two pion energies overlap? Parametric form not really suited to cope with overlapping scenarios