Particle Flow with deep learning (arXiv : 2003.08863)

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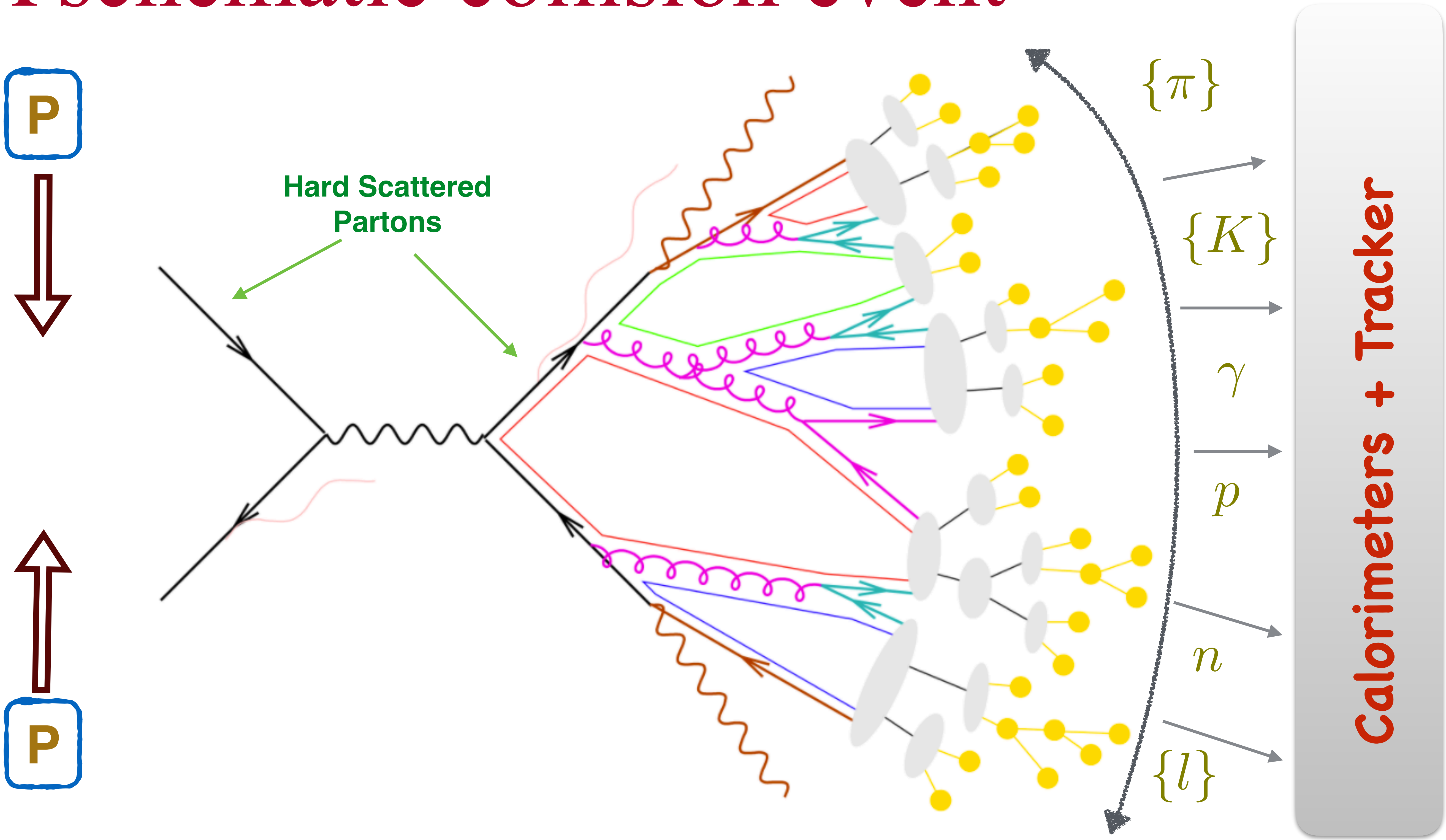
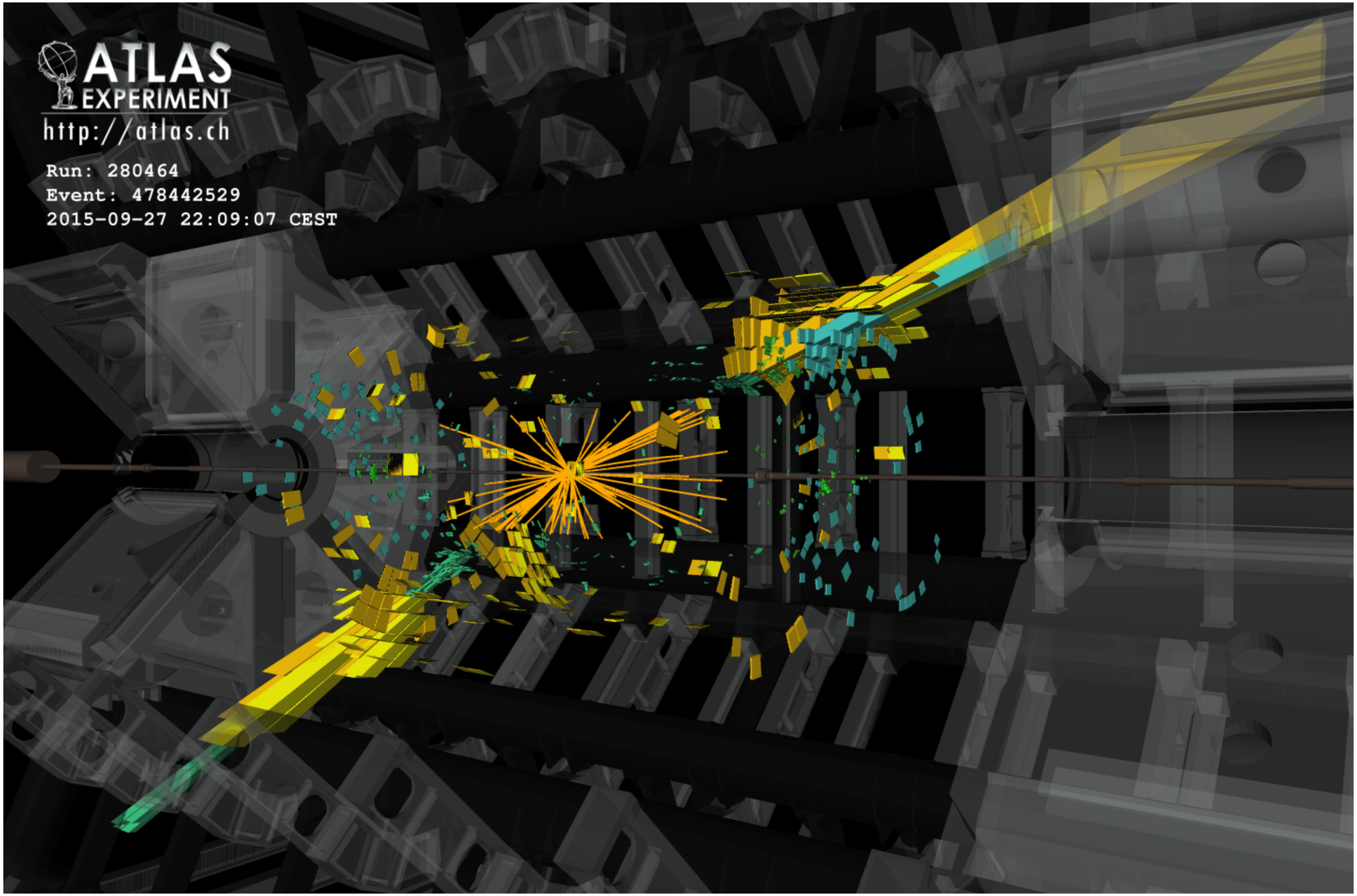
A schematic collision event



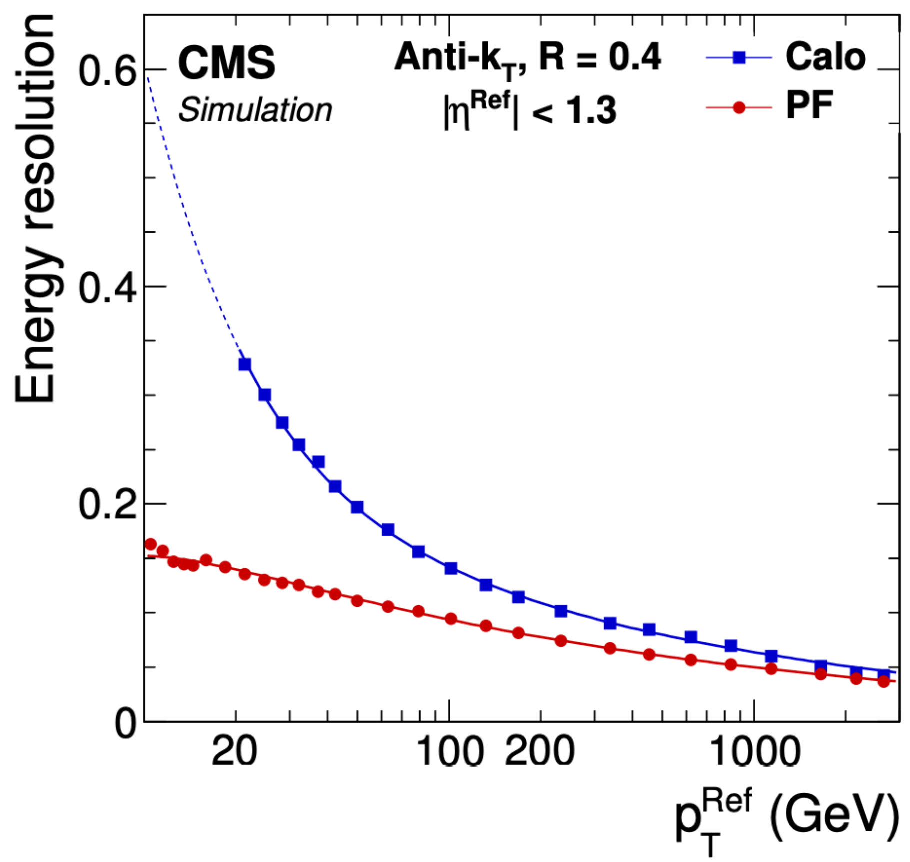
Dynamics at parton level has to be inferred from momentum distribution of stable particles.

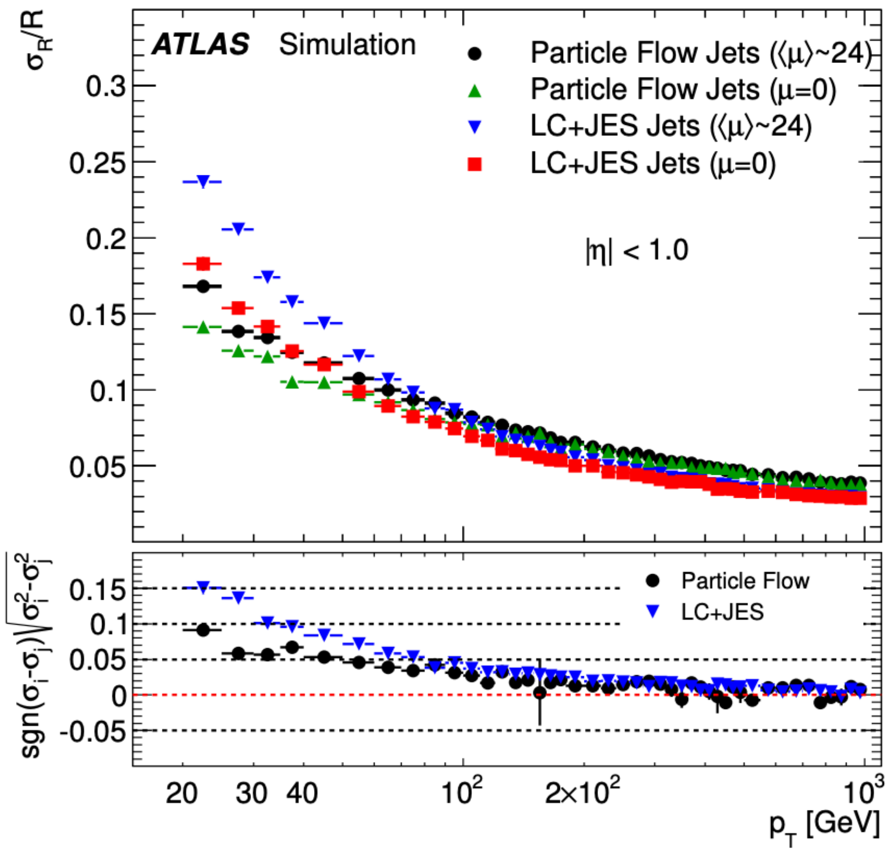
A real collision event at ATLAS



An accurate global event reconstruction (determining the 4-momenta of all the stable objects, combining the information from all sub-detector components) is crucial for understanding the underlying dynamics.

Difference between PFlow in ATLAS & CMS





	ATLAS	CMS
Tracking	arXiv : 1803.06991	
$1/p_T$ resolution	0.05% × p_T/ GeV ⊕ 1% [47]	0.02% × p_T/ GeV ⊕ 0.8% [48]
d_0 resolution (μm)	20 [49]	20 [48]
ECAL		
E resolution	$10\%/\sqrt{E} \oplus$ 0.2% [45]	$3\%/\sqrt{E} \oplus$ $12\%/E \oplus 0.3\%$ [46]
granularity	0.025 × 0.025	0.017 × 0.017
HCAL		
E resolution	$50\%/\sqrt{E} \oplus 5\%$ [45]	$100\%/\sqrt{E} \oplus$ 5% [50]
granularity	0.1 × 0.1	0.087 × 0.087

CMS combines the track & calorimeter information into unified PFlow object and forms PFlow jets. ATLAS used calojets by default until now.

For CMS, the gain from using PFlow is large.

- **CMS used PFlow from Run-1**

ATLAS benefits less from PFlow :

- **better HCAL resolution**
- **smaller magnetic field**
- **longitudinal segmentation of calorimeter**

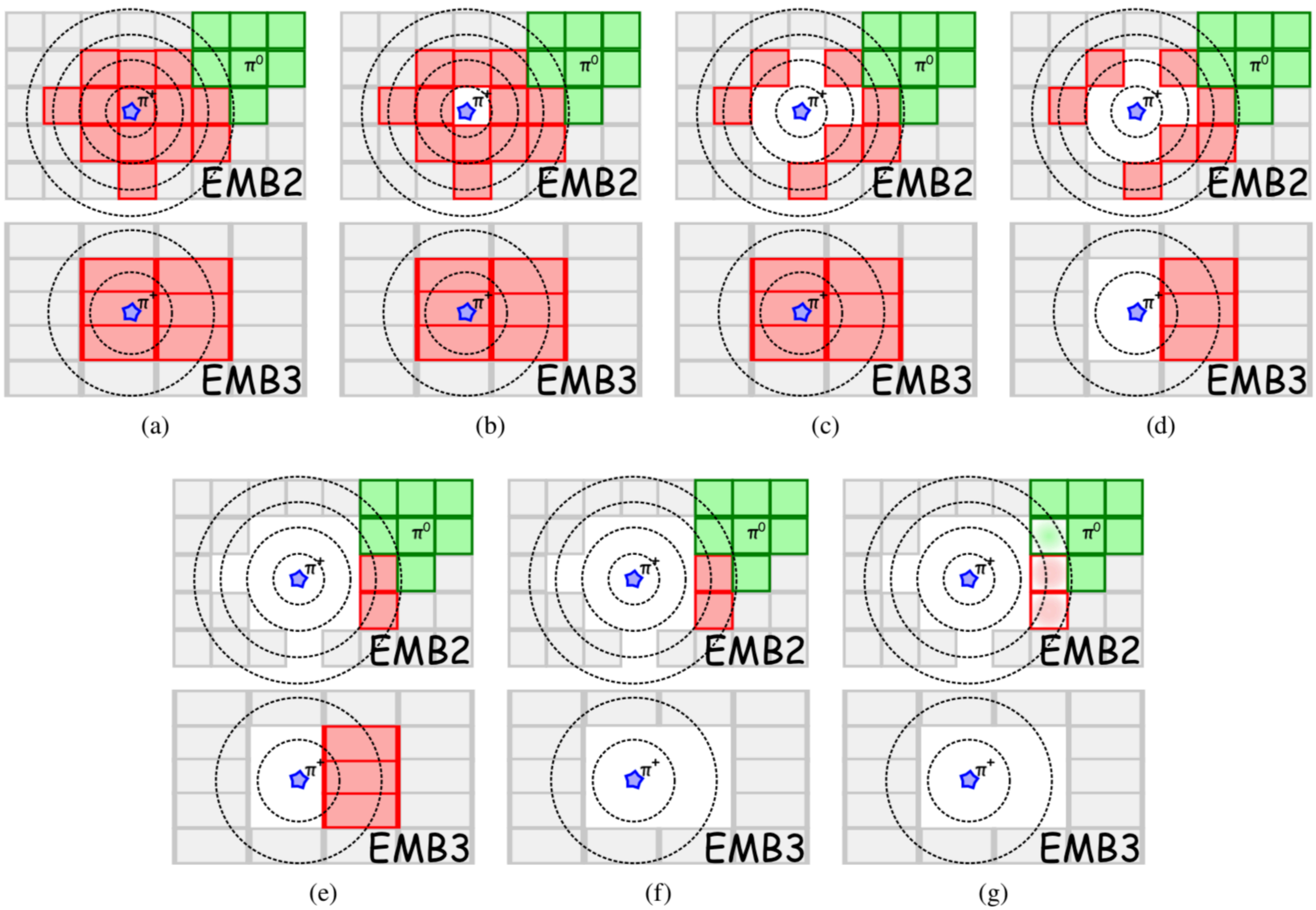
Motivation

Particle-flow algorithm is a generic event reconstruction technique. Its performance strongly depends on detector design

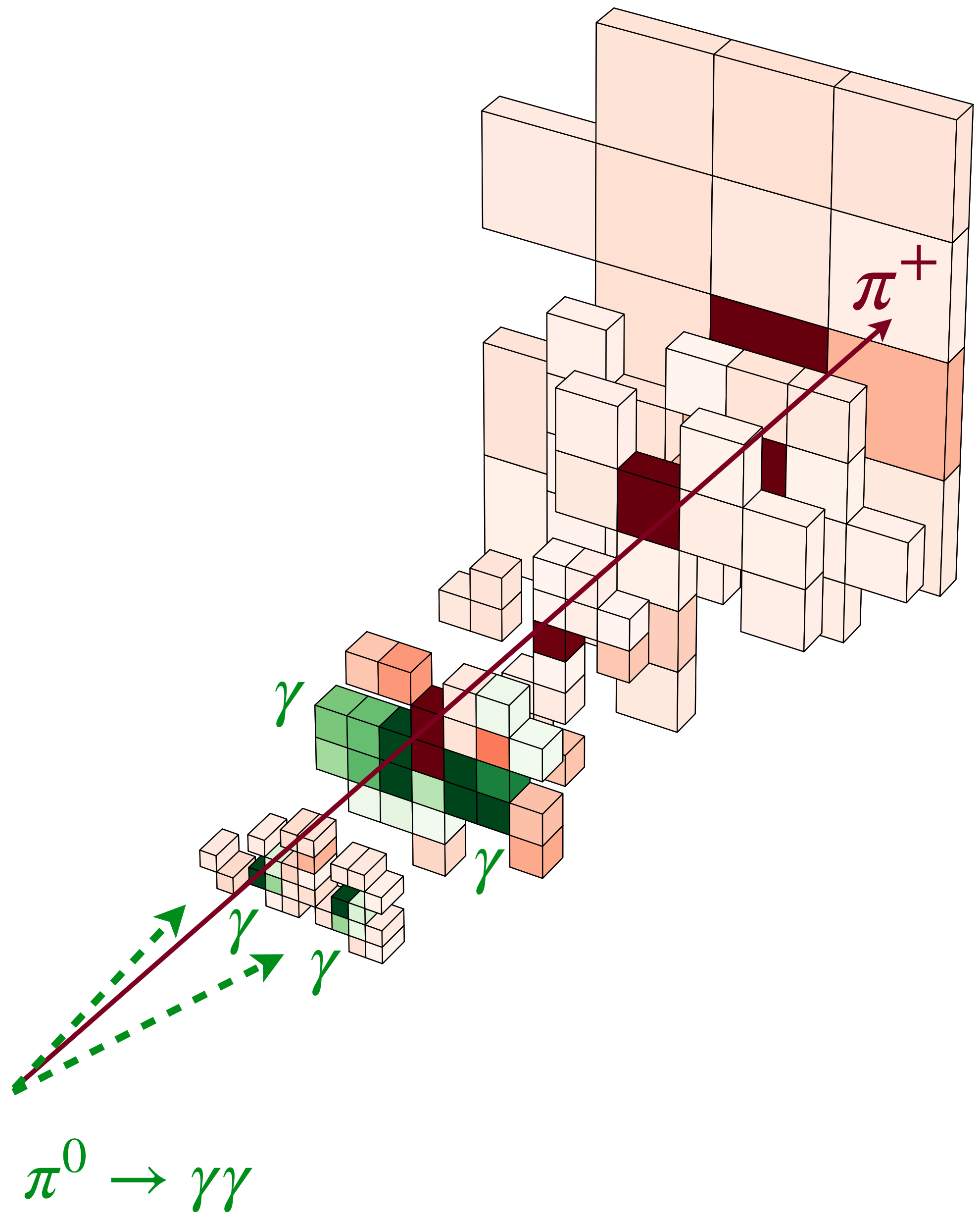
Our proposal :

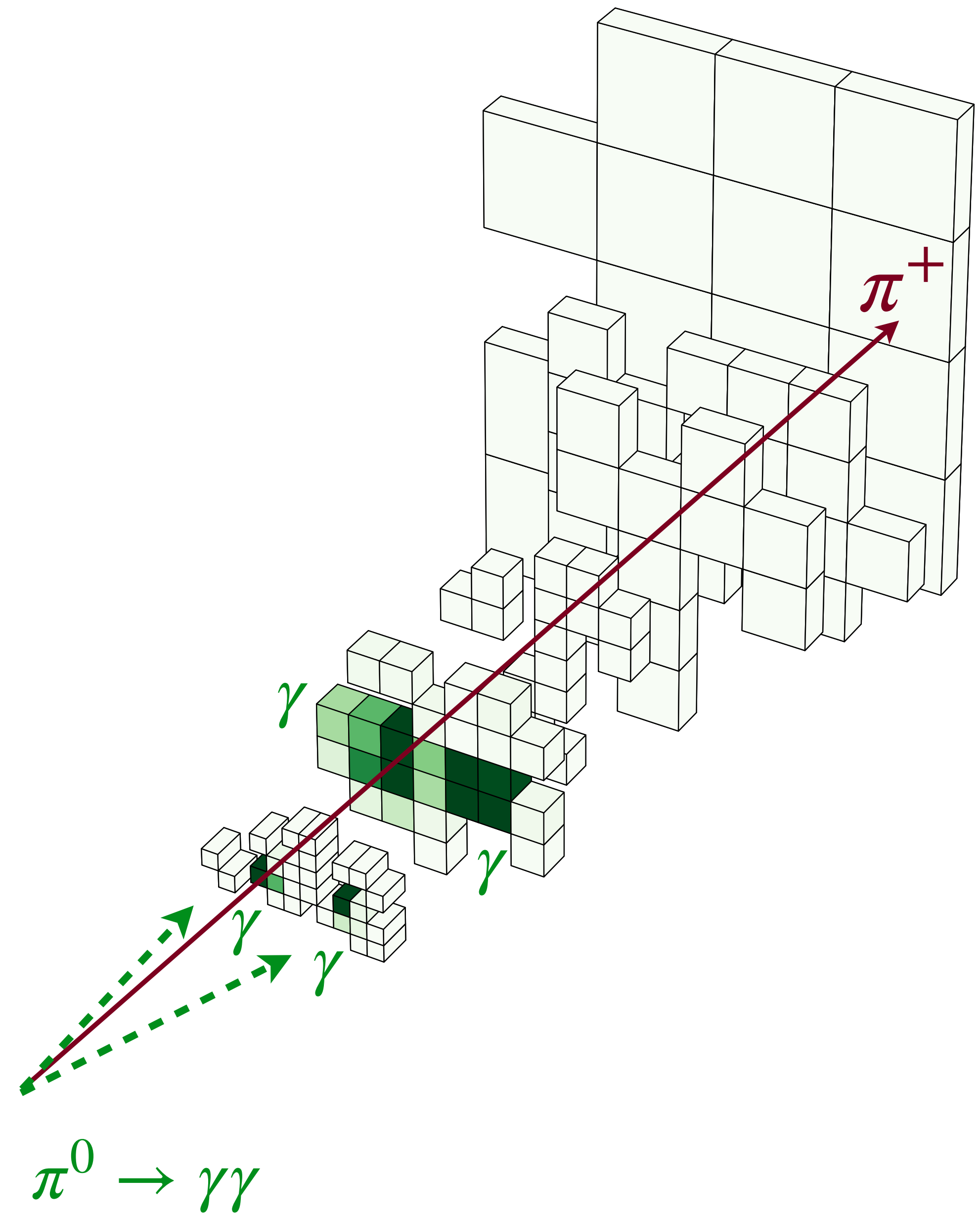
Implement a deep learning based method to extract the fraction of neutral energy for each cell in each layer of the ECAL and HCAL calorimeter layers.

The existing algorithm as of now :



A 3-D view for our datasets





Machine learning task

We want to regress the neutral energy per cell

Input :

6 channel image

(Signal + Noise)

Layer1 –> 64 X 64
Layer2 –> 32 X 32
Layer3 –> 32 X 32
Layer4 –> 16 X 16
Layer5 –> 16 X 16
Layer6 –> 8 X 8
+
Track Layer

→ **NN model** →

Output :

6 channel image

(neutral energy frac)

Layer1 –> 64 X 64
Layer2 –> 32 X 32
Layer3 –> 32 X 32
Layer4 –> 16 X 16
Layer5 –> 16 X 16
Layer6 –> 8 X 8

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

E_c : Energy of a cell, $E_{tot} = \sum E_c$

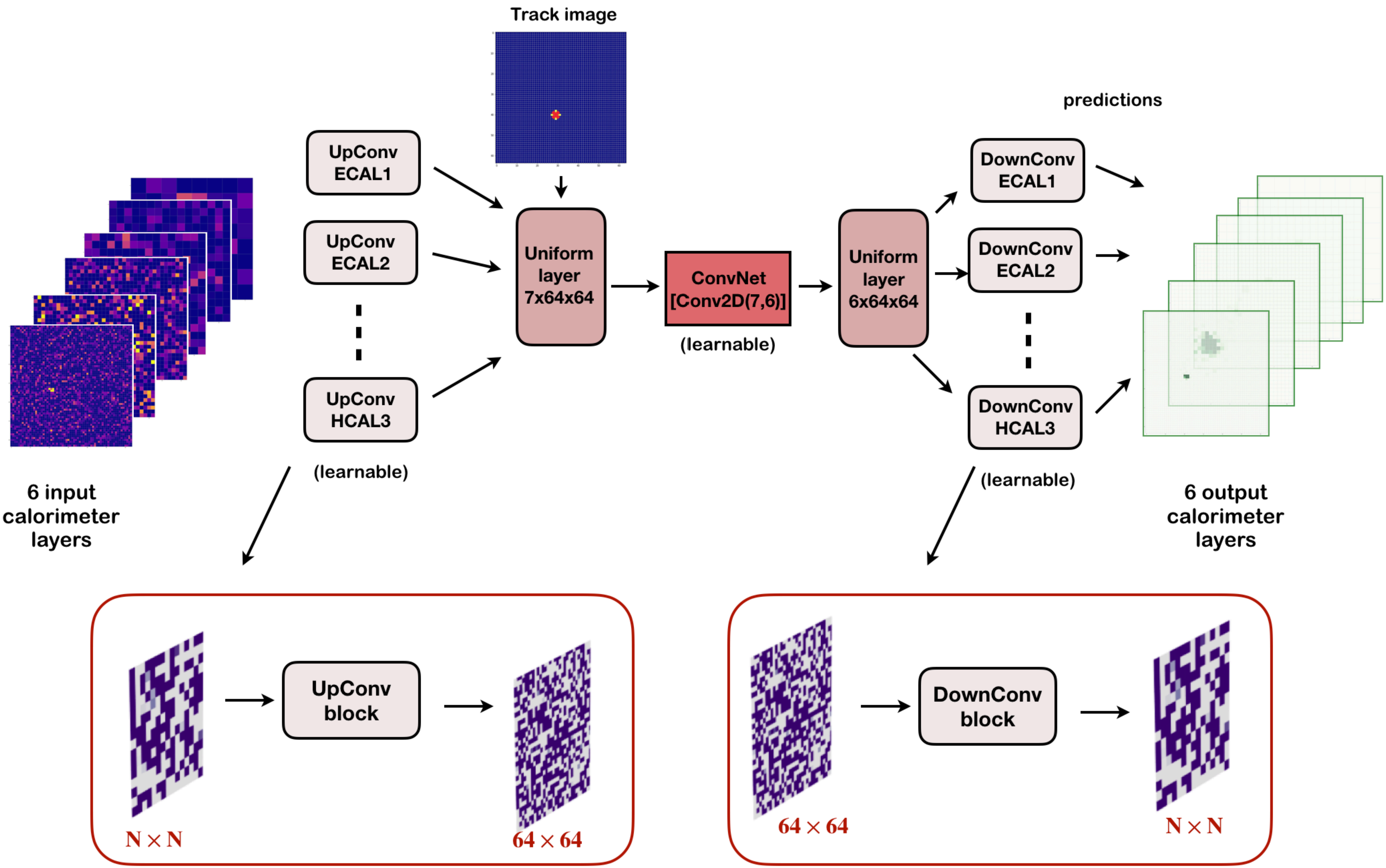
f_t^c : target neutral energy fraction

f_c^d : predicted neutral energy fraction

A simple L2 loss function doesn't serve the purpose, we need to put extra weights on highest seed cells inside a topocluster

A weight factor of $\sqrt{E}$ won't work either .

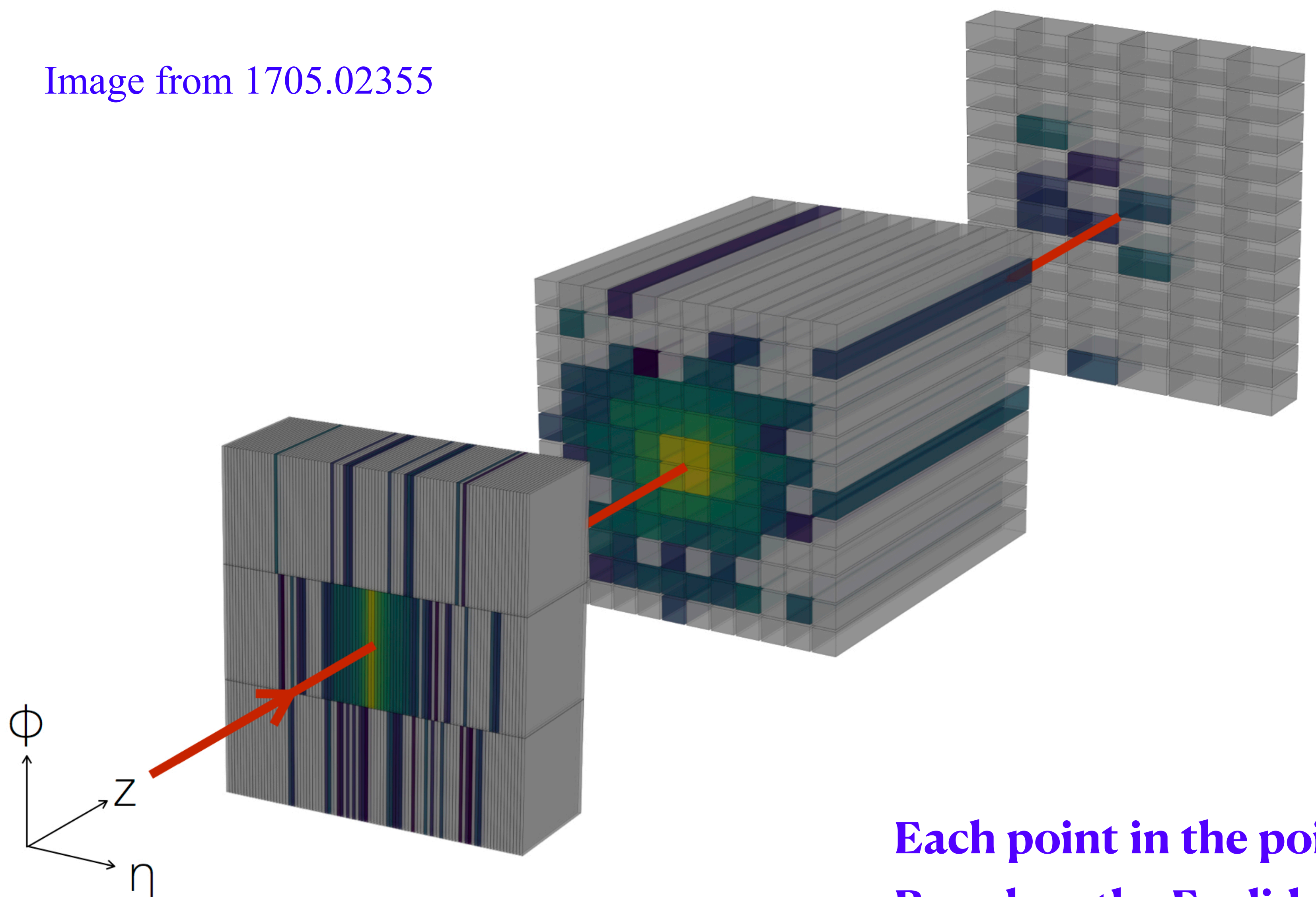
The neural network architecture (cPFlow)

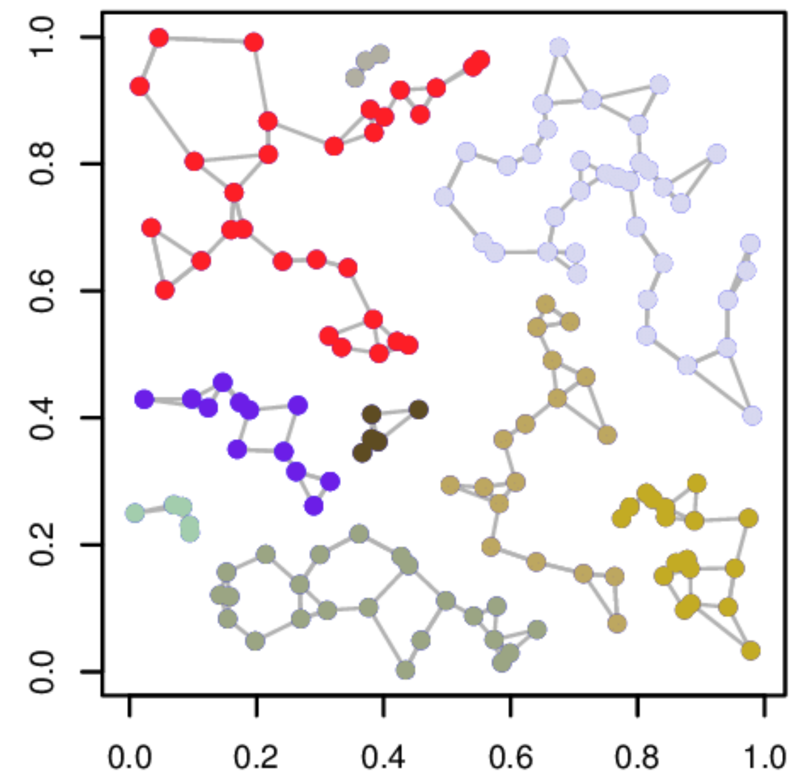


The graph network

Calorimeter showers have natural representation of a point cloud.

Image from 1705.02355





Each point in the point-cloud has 4 features (x, y, z, E).
Based on the Euclidean distance among the points, one can form a K-nearest-neighbor graph

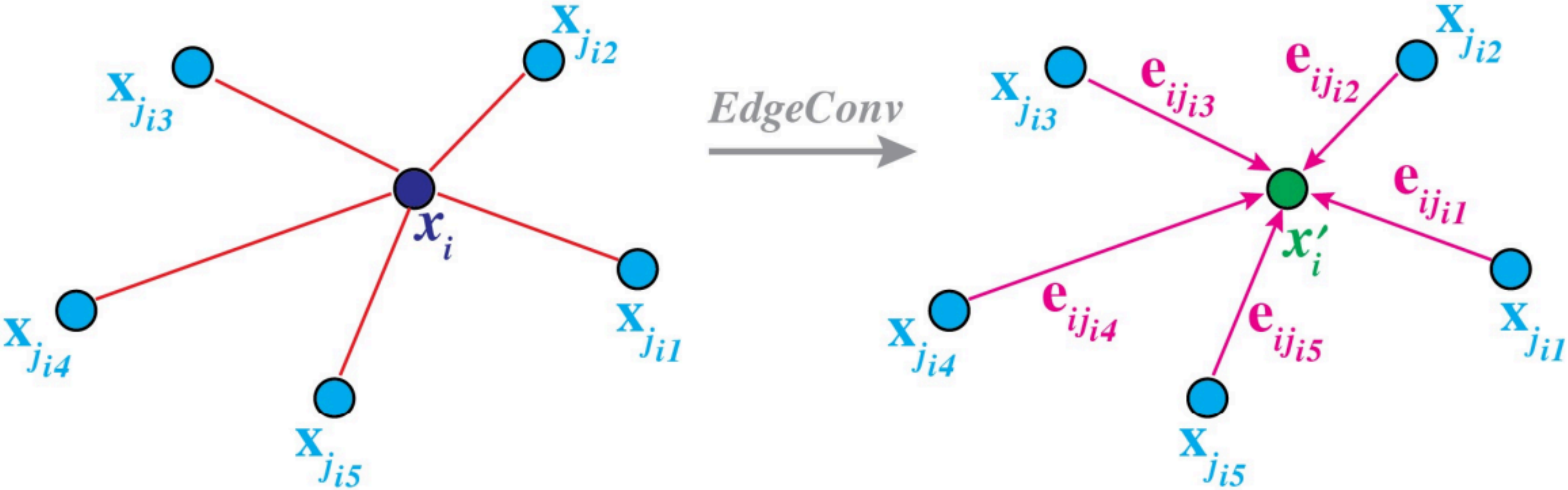
The graph network

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

In a graph, each node can "learn" about the state of neighboring node through message passing operation

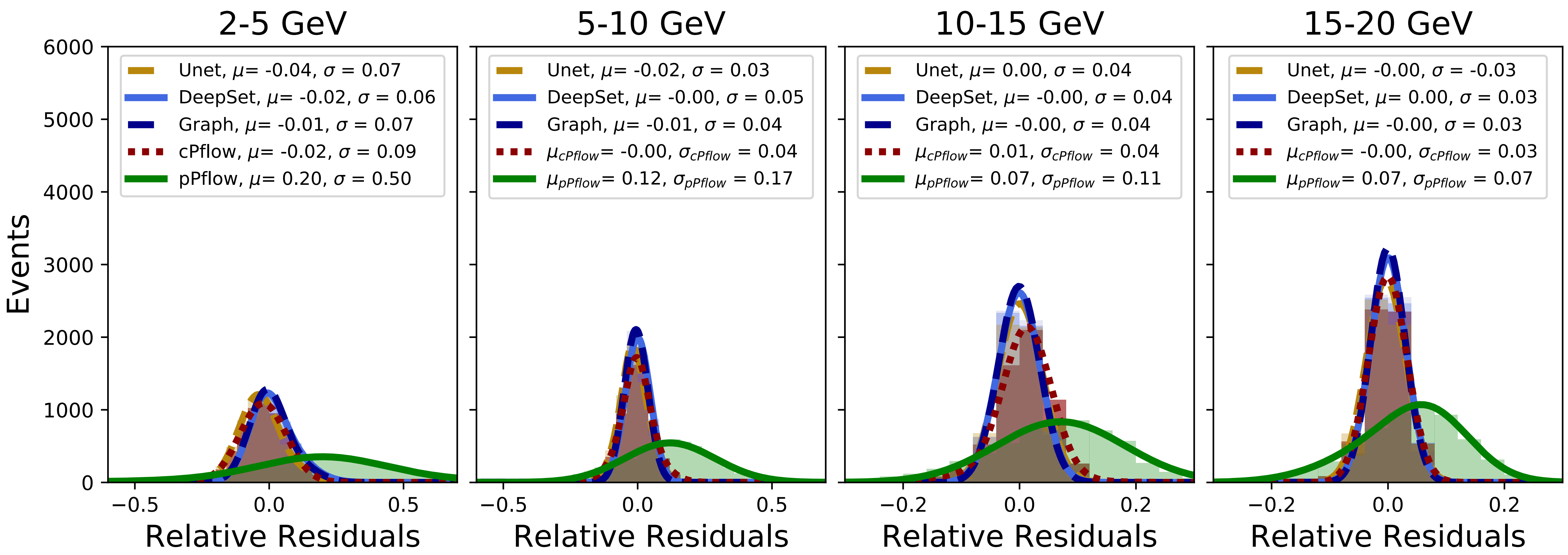
$$(x')_i^{l+1} = max_{j \in \mathcal{N}(i)} \, \Theta_x(x_j^l - x_i^l) + \Phi_x(x_i^l)$$

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



Energy response comparison

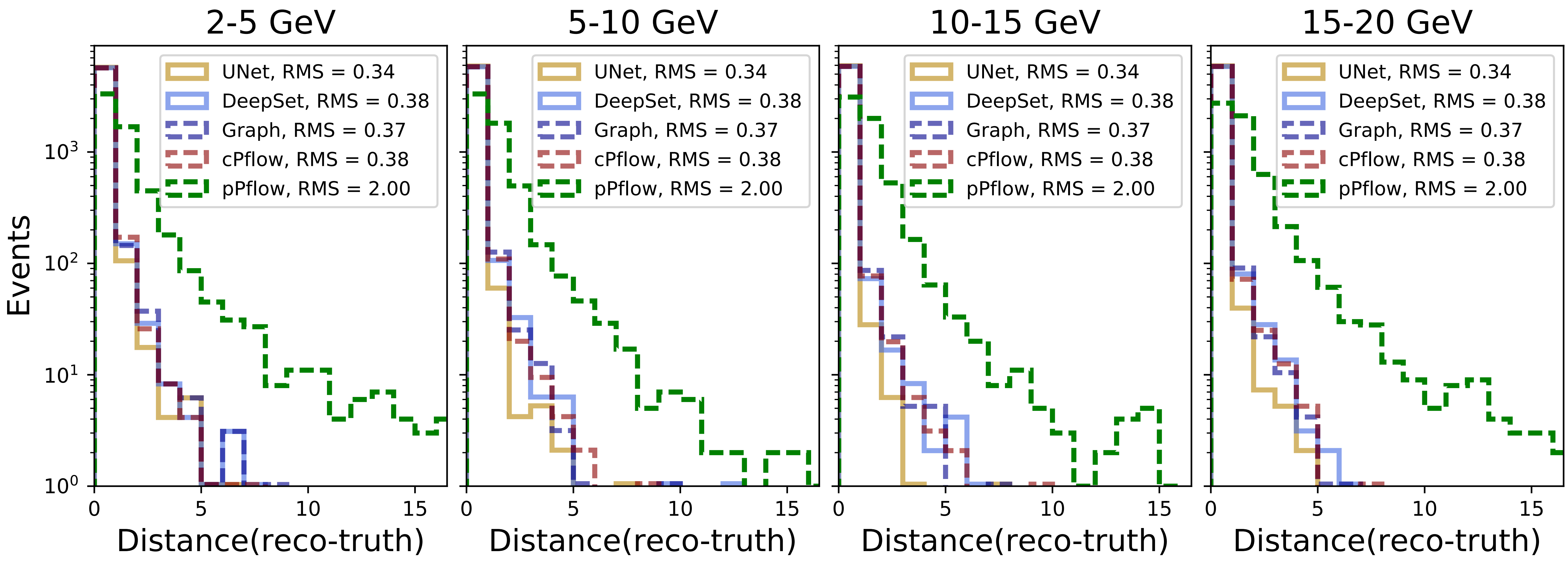
At low energy the cPFlow has 7X better resolution than traditional PFlow



$$\textbf{Relative Residual} = \left(\frac{E_{predicted} - E_{neutral}}{E_{neutral}}\right)$$

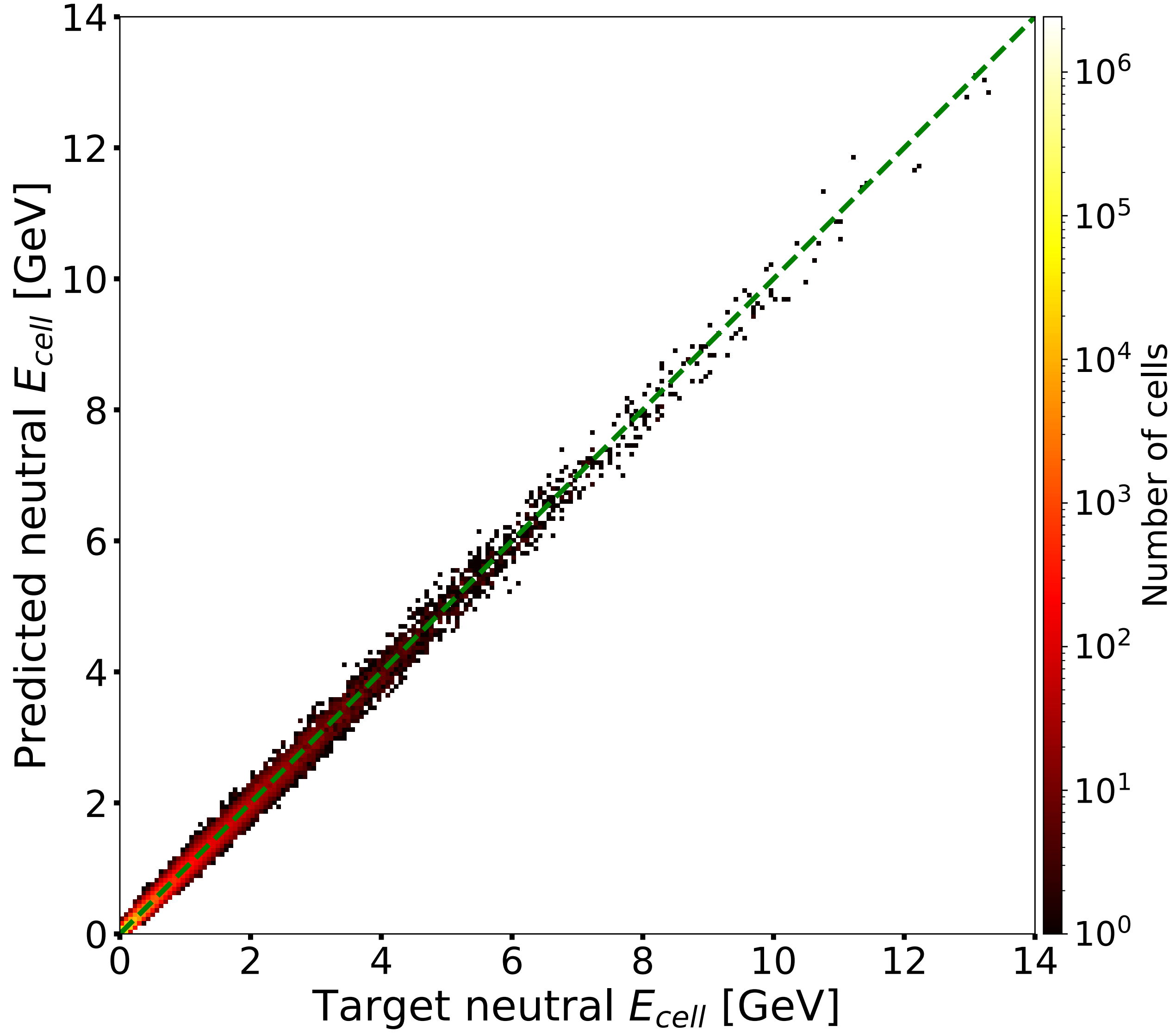
Direction response comparison

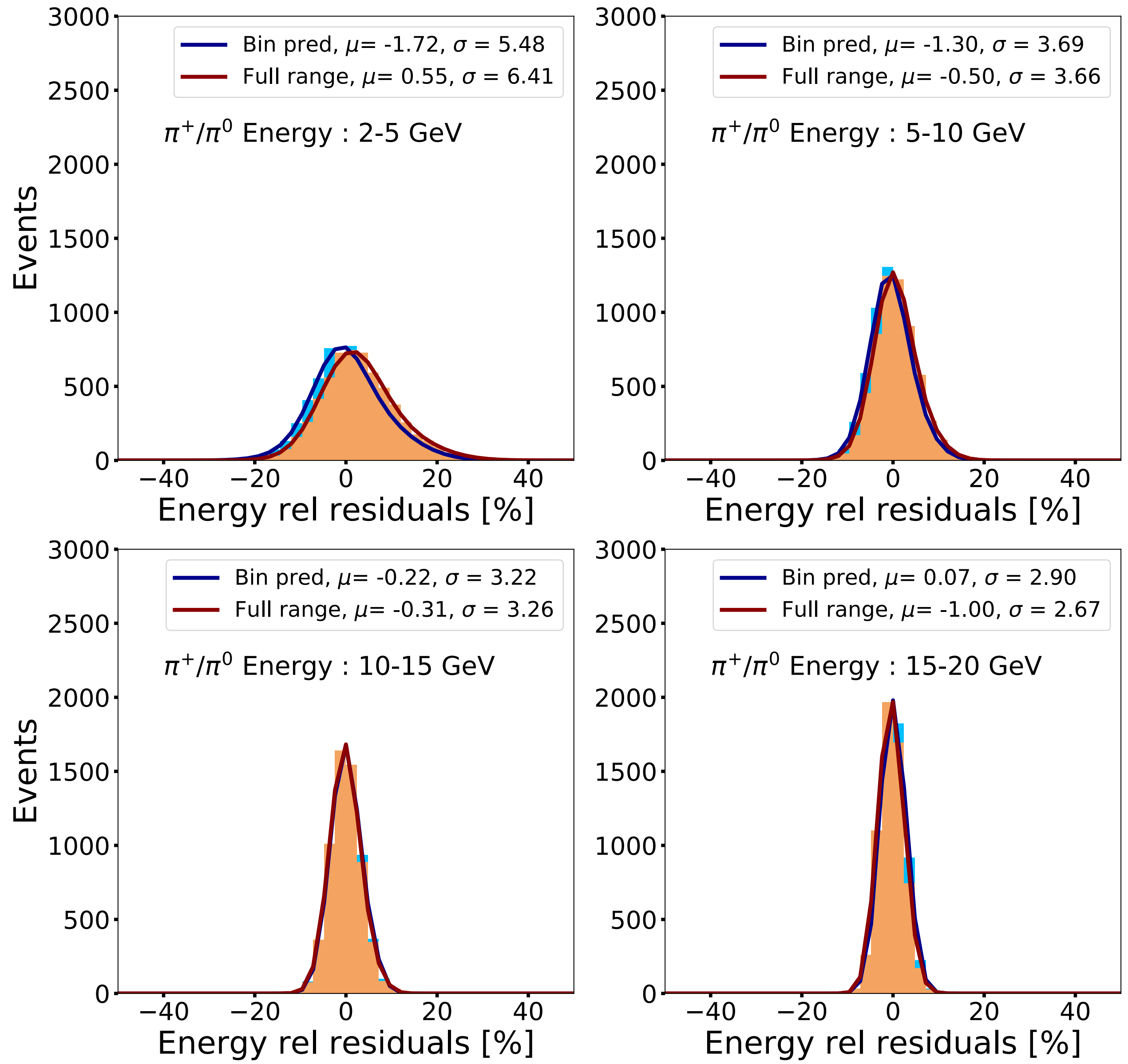
The distance computed in number of cells between the barycenter of the predicted and truth neutral energy in the ECAL2 layer.



The cPFlow algorithm has much better (upto 6 X) spatial resolution than traditional PFlow

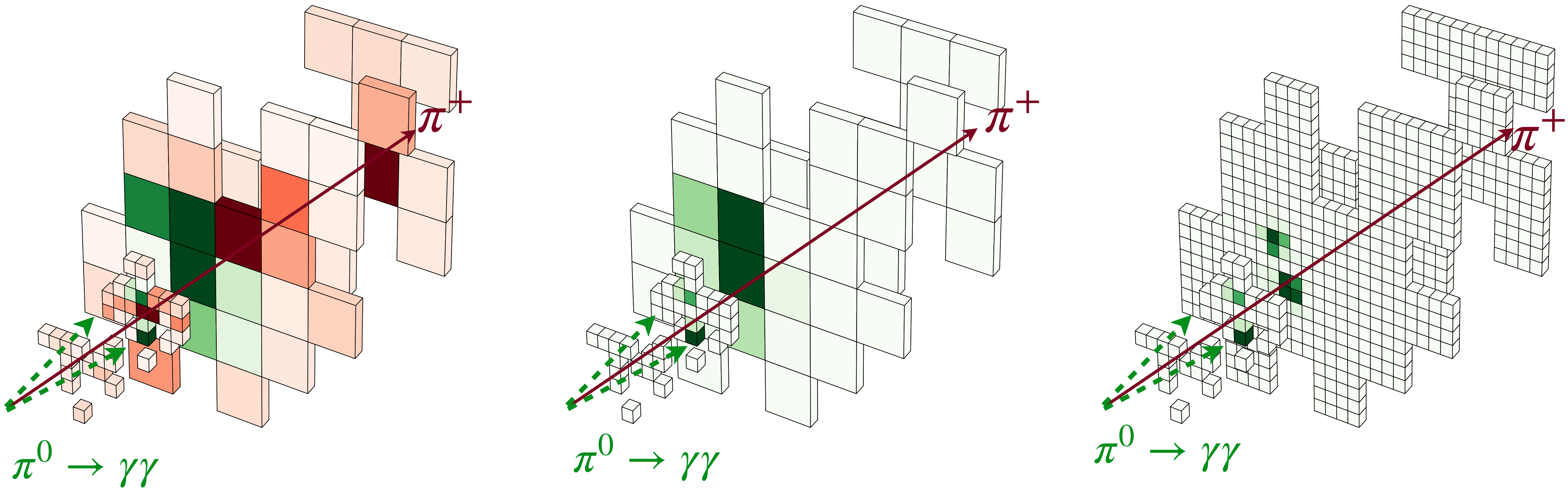
Per cell level performance





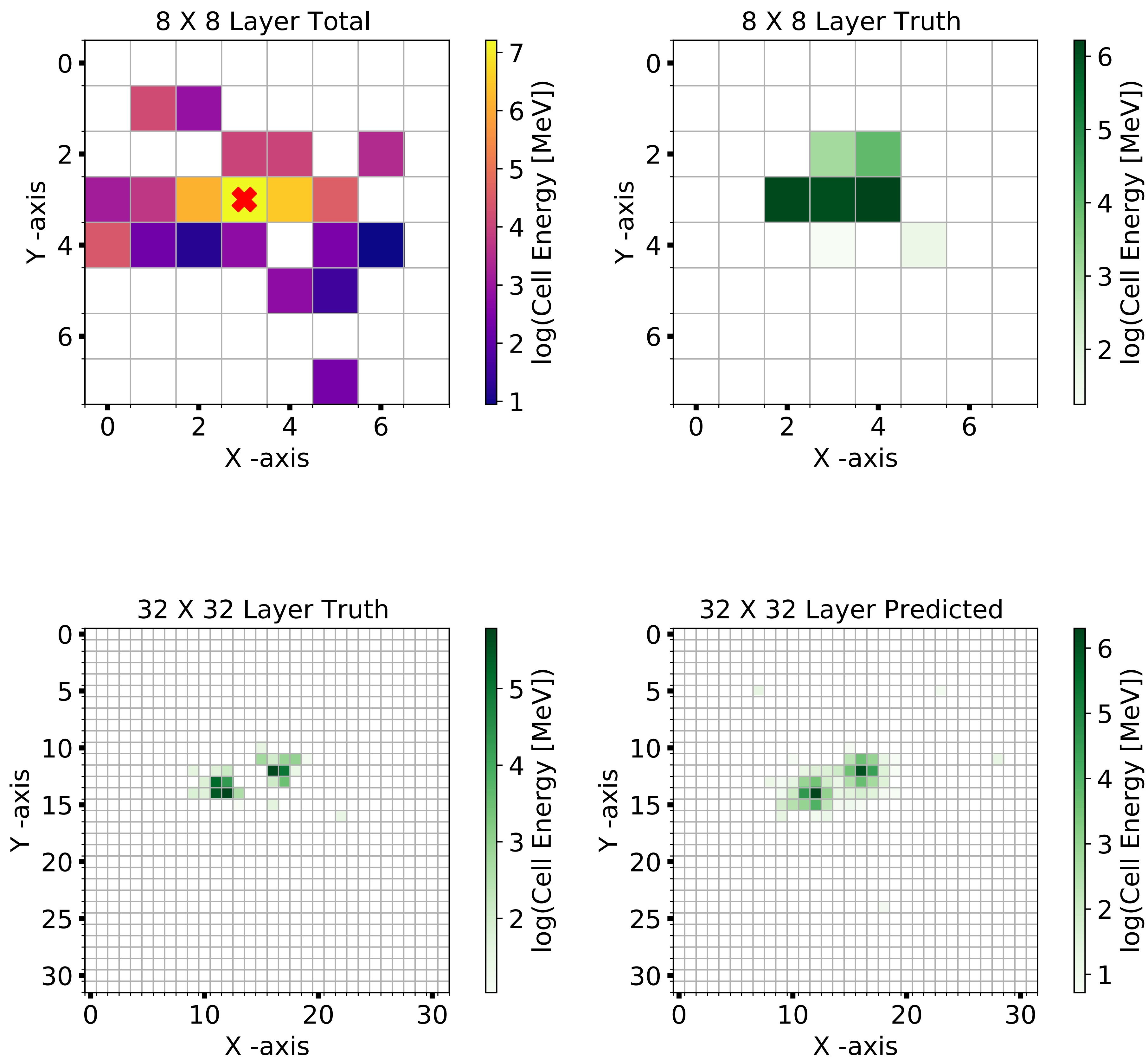
The networks in general have good noise removal abilities.

A case for calorimeter super-resolution



A higher resolution calorimeter has the ability to capture multi-prong decay pattern in showers.

An event display for super-res prediction



Summary

- ☑ We have demonstrated that a suitable ConvNet, Graph, Deepset architecture gives descent energyfraction estimation for the generalized case :
  Input —> Variable Resolution + Noise + Track, Output —> Real resolution.

- ☑ The algorithm actually succeeds in yielding a complete image of neutral energy profile of the layers.

- ☑ The trained NN is able to learn and predict the noise pattern.
  A network trained on topoclusters has better performance on the topoclusters.

- ☑ These ML based algorithms are shown to improve the energy and direction estimation over existing PFlow algorithm, in case of overlapping charged and neutral pions.
  3 to 5 times resolution improvement obtained at low energy regime.

- ☑ Demonstrated the applicability of super-resolution techniques for calorimetric study.