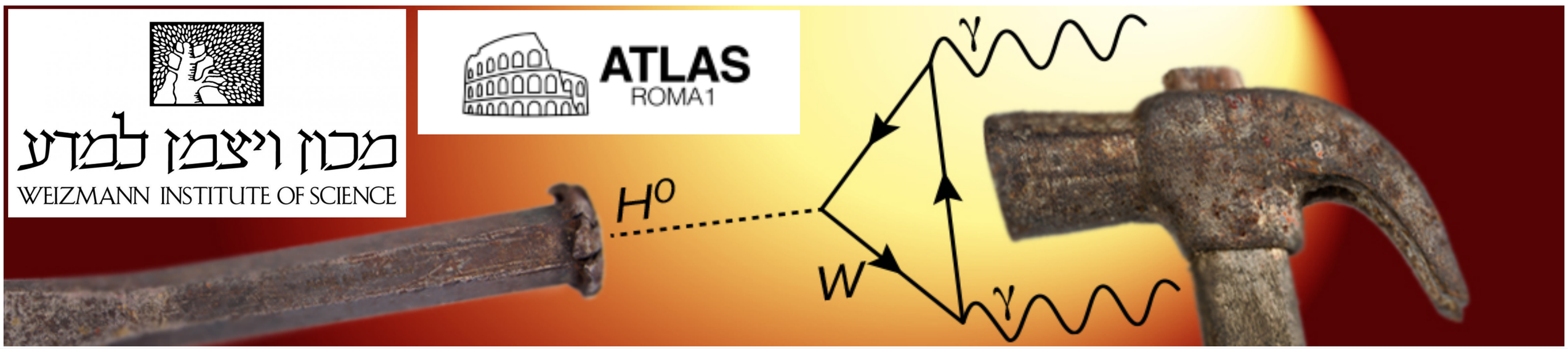
Energy flow regression using deep learning

Sanmay Ganguly, Michael Pitt, Jonathan Shlomi, Eilam Gross
Weizmann Institute Of Science

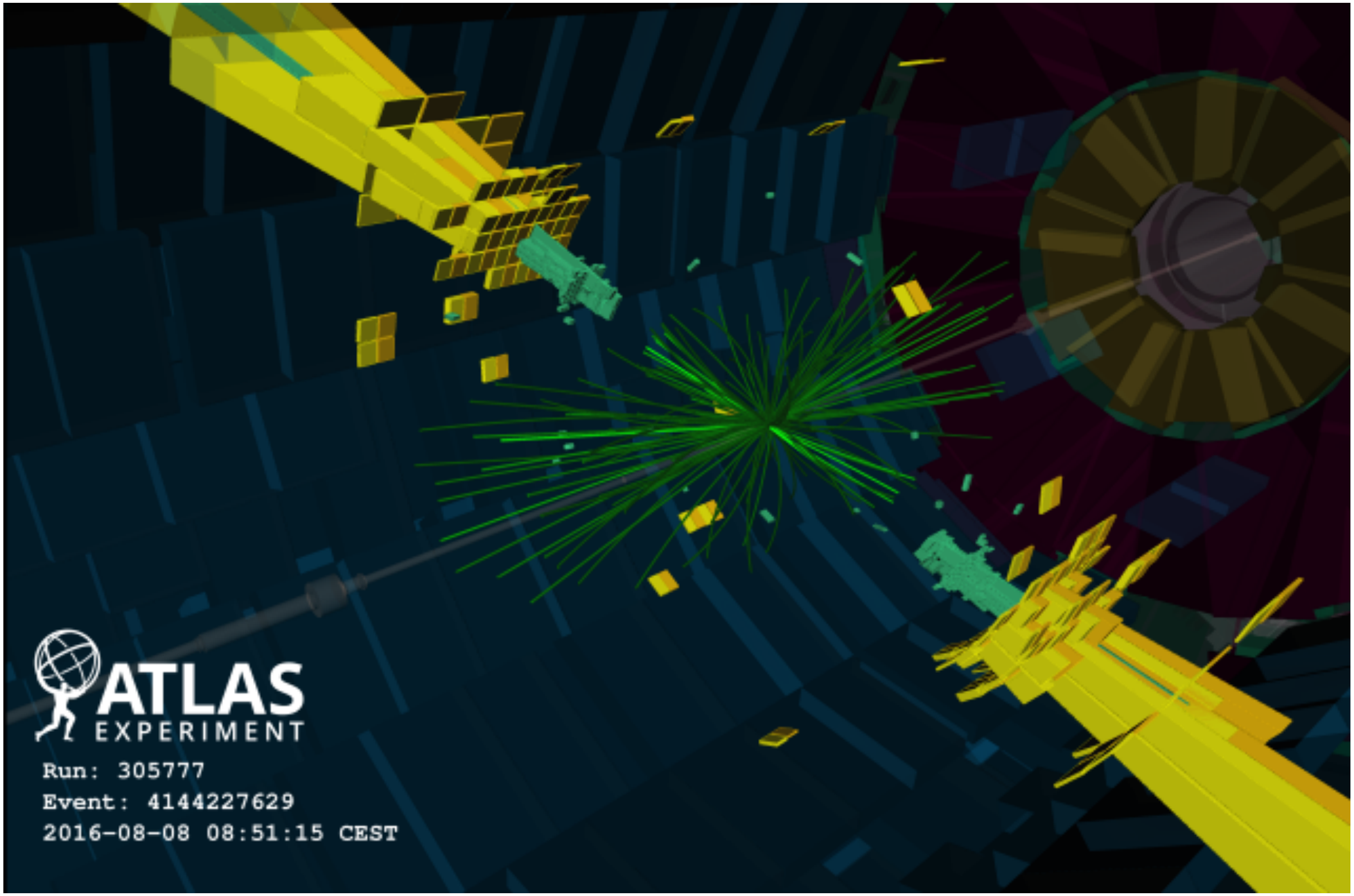
Hammers & Nails 2019

04/08/2019

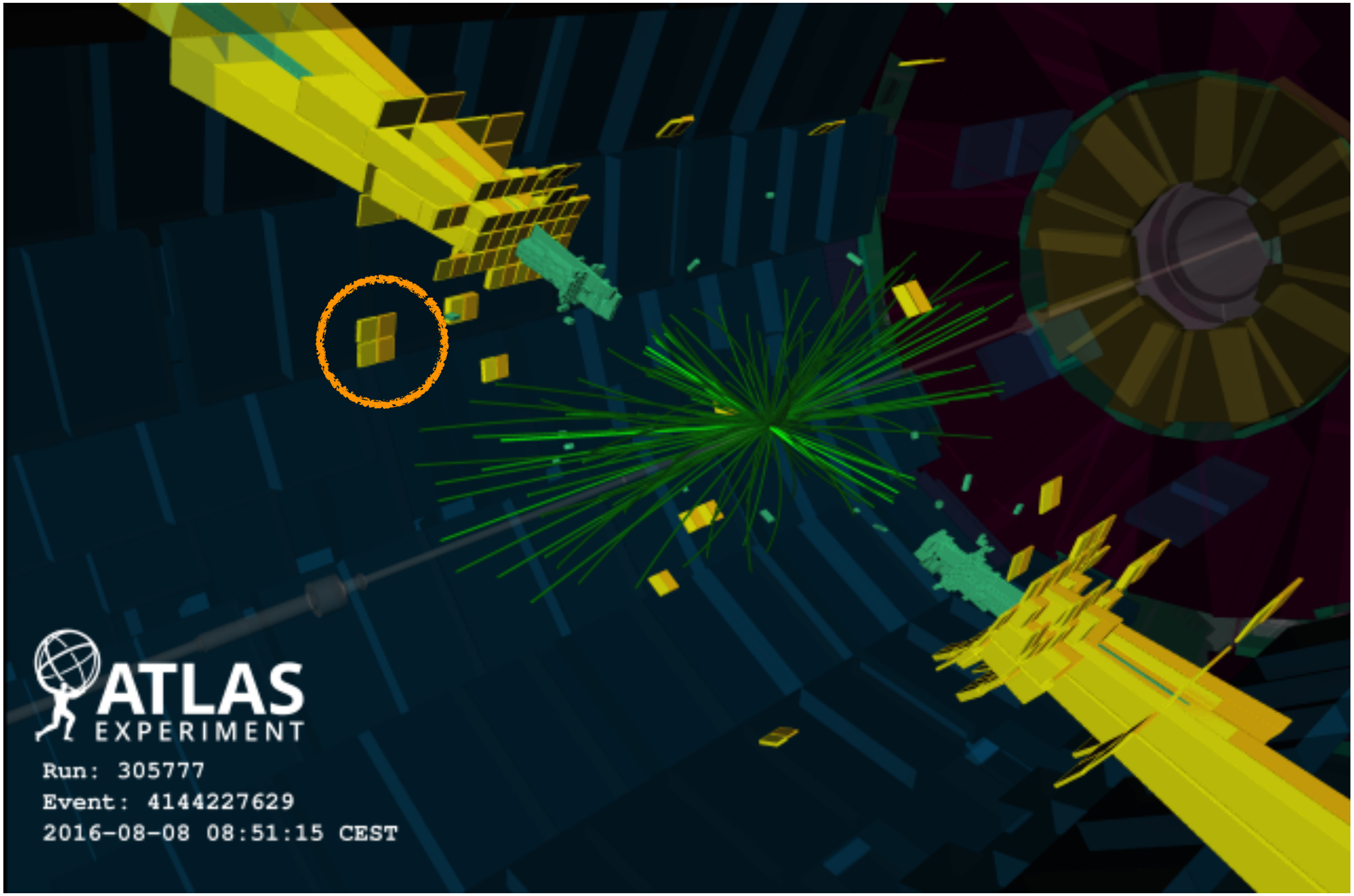
In collaboration with Marumi Kado



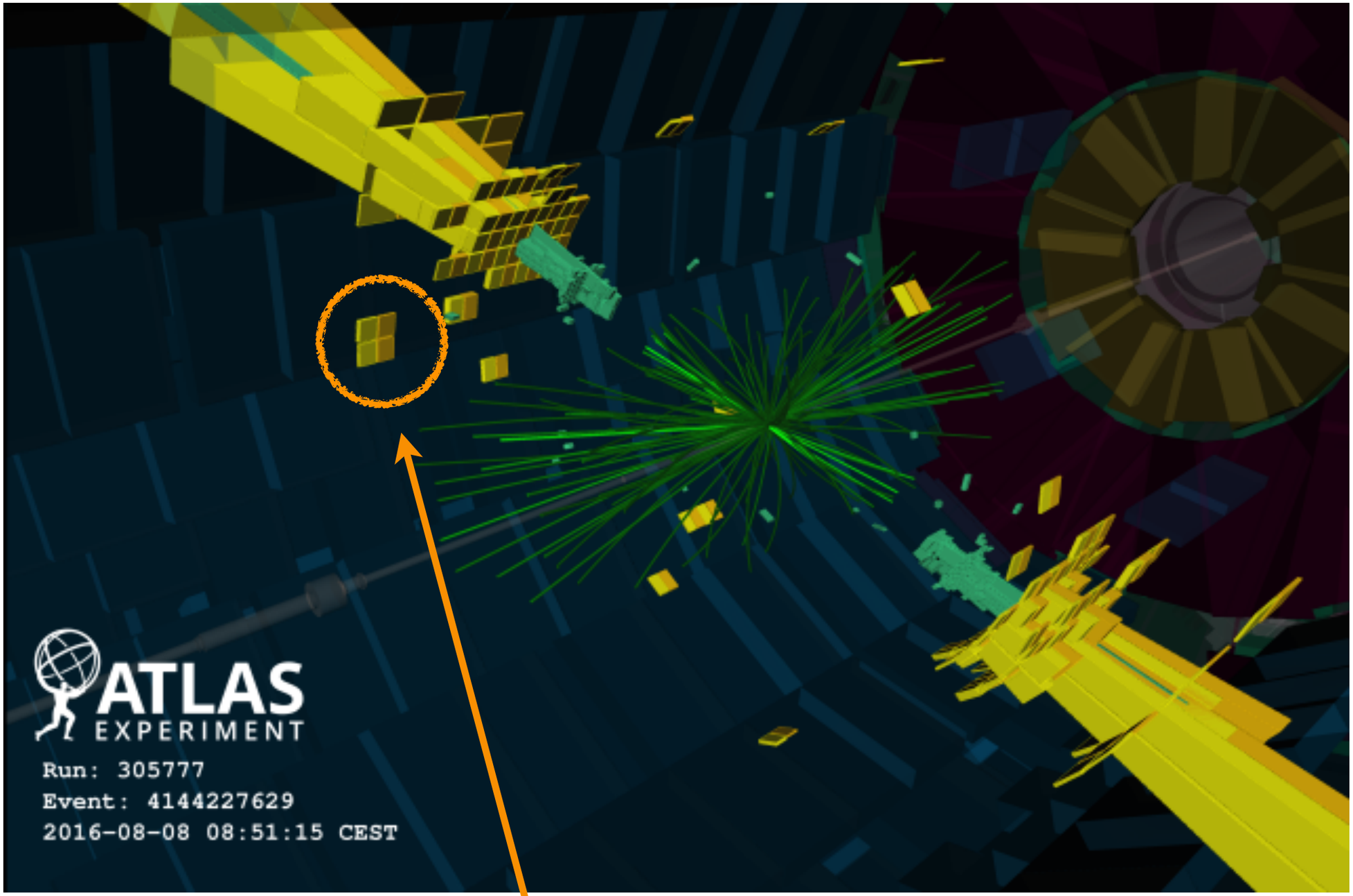
The basic task of energy reconstruction



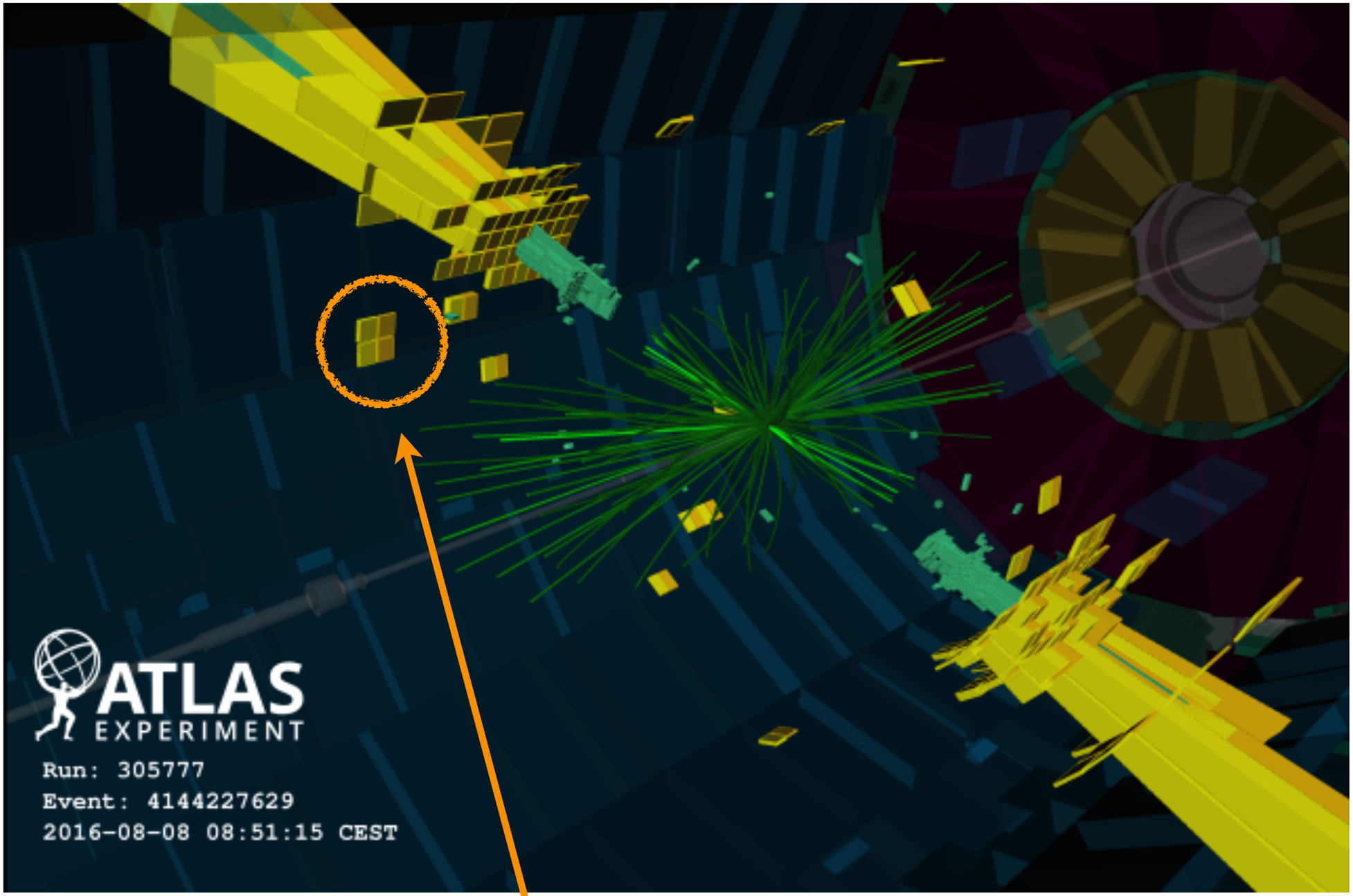
The basic task of energy reconstruction



The basic task of energy reconstruction

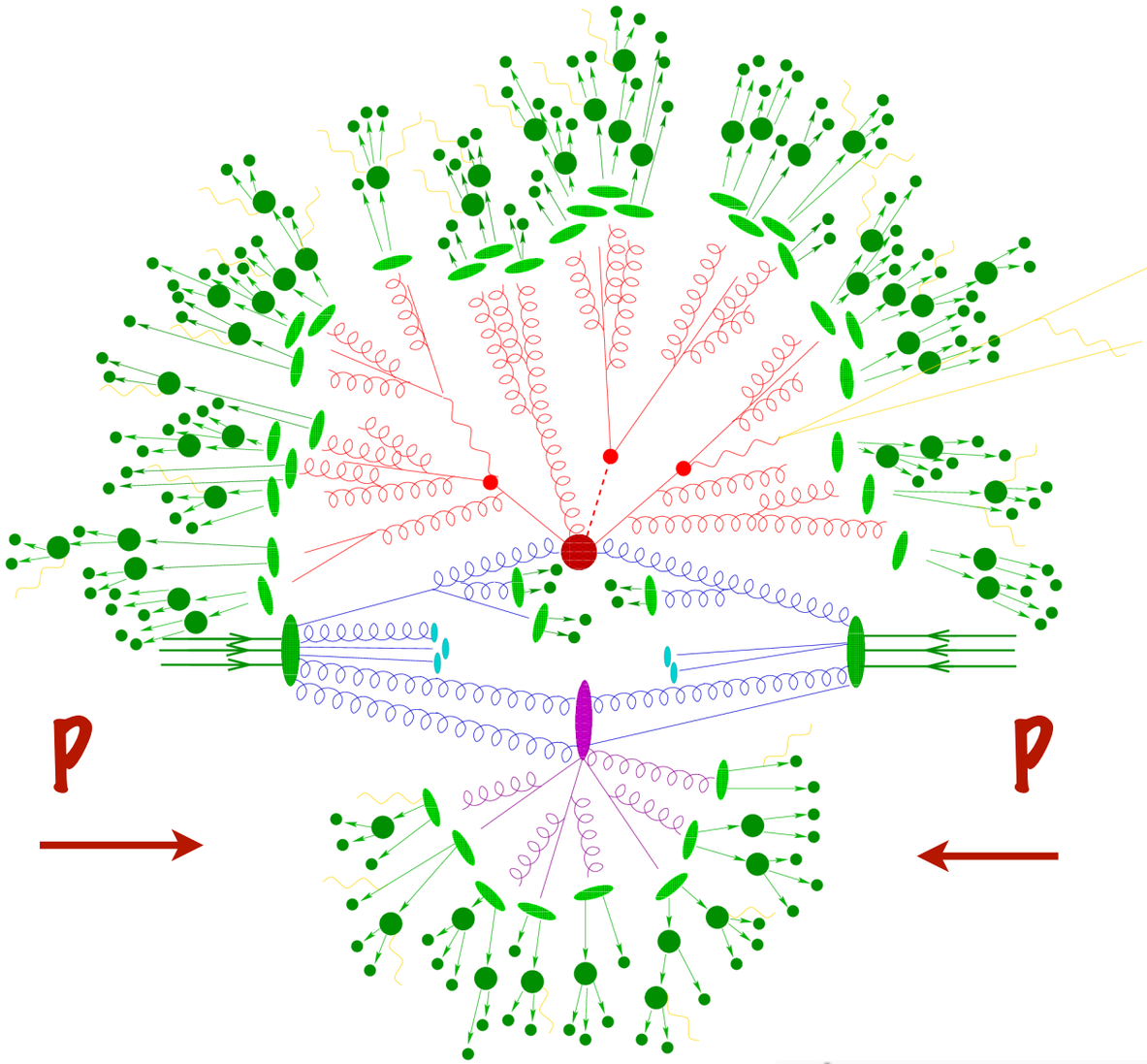


The basic task of energy reconstruction



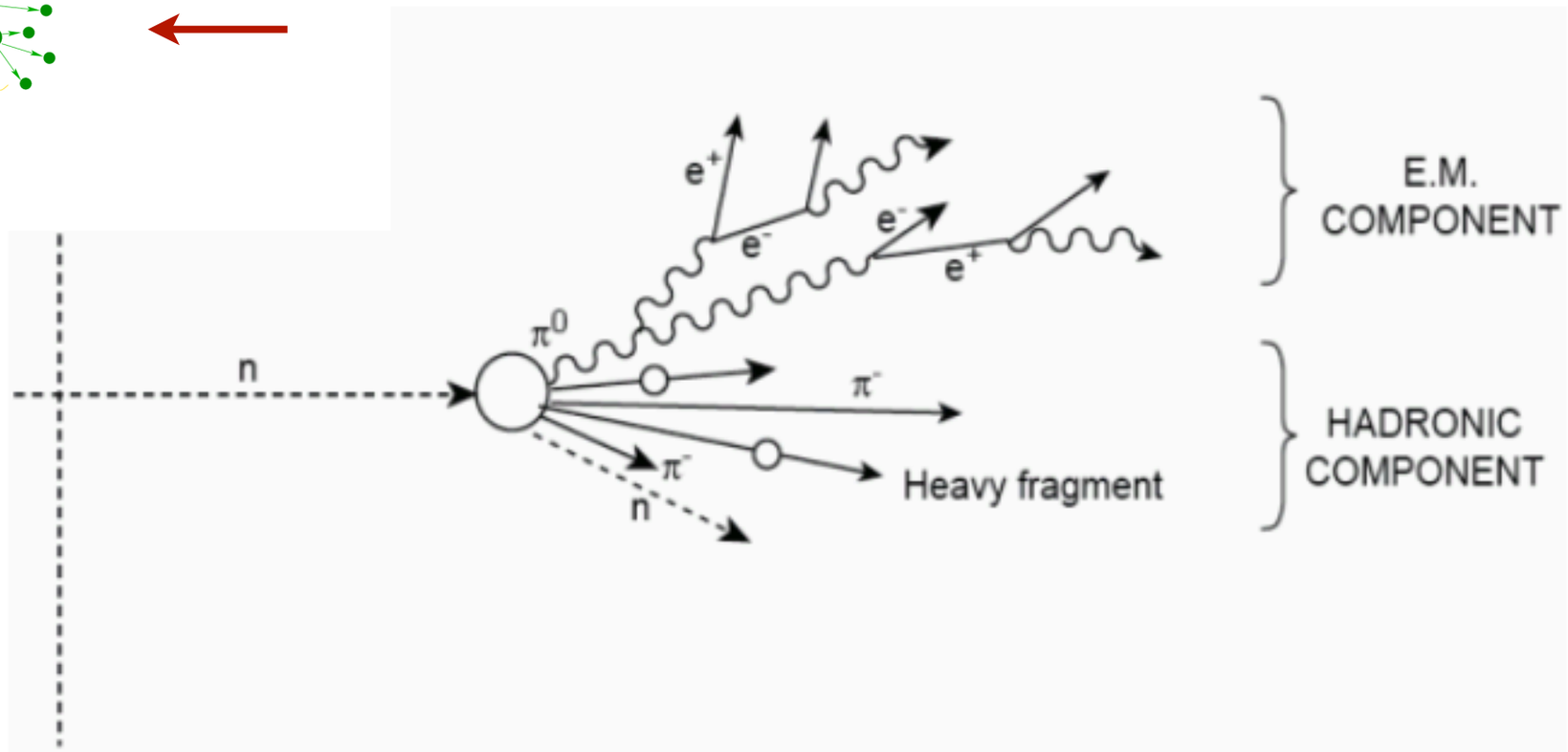
How do these energy deposits form and recorded ?

The basic task of energy reconstruction

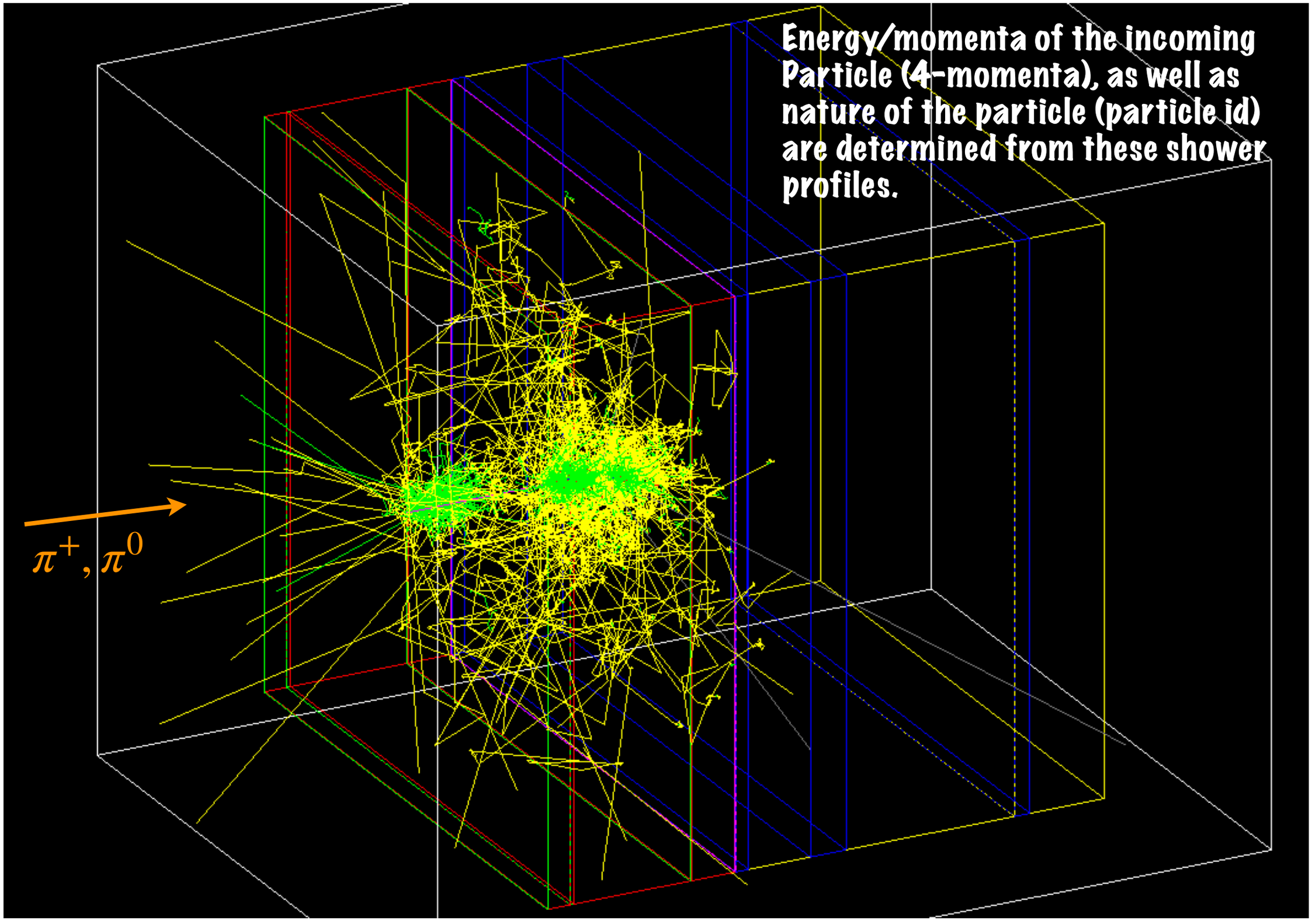


stable hadrons + leptons + photons + ...

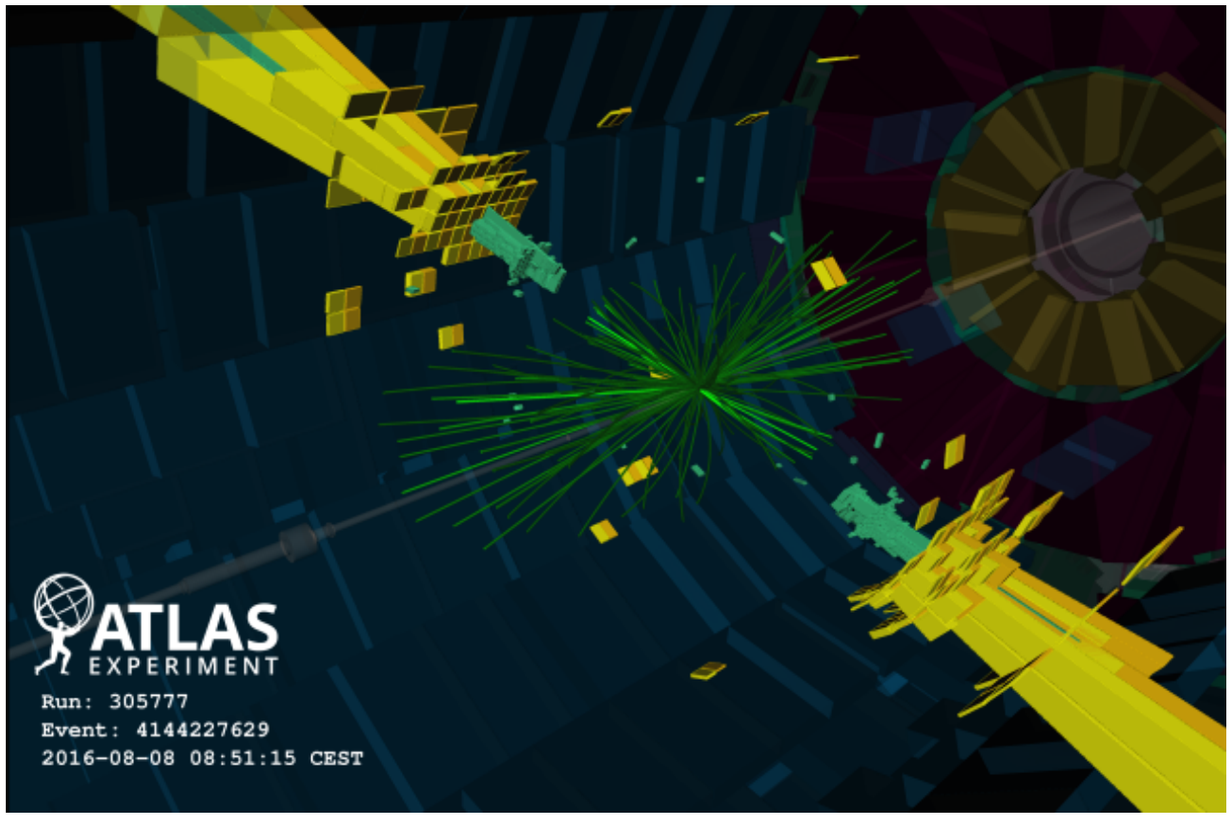
reaches the detector & deposits energy

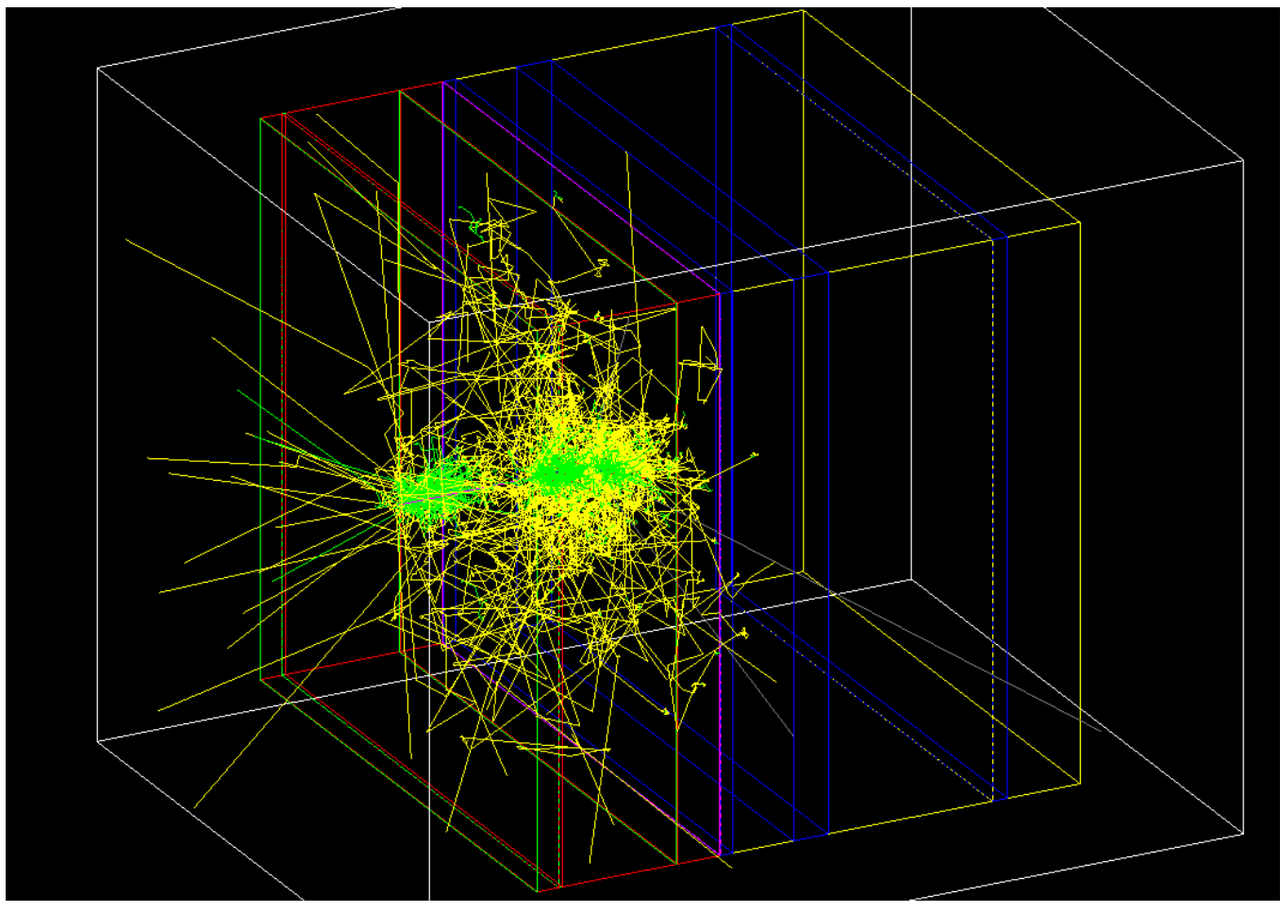


How these showers actually look like?

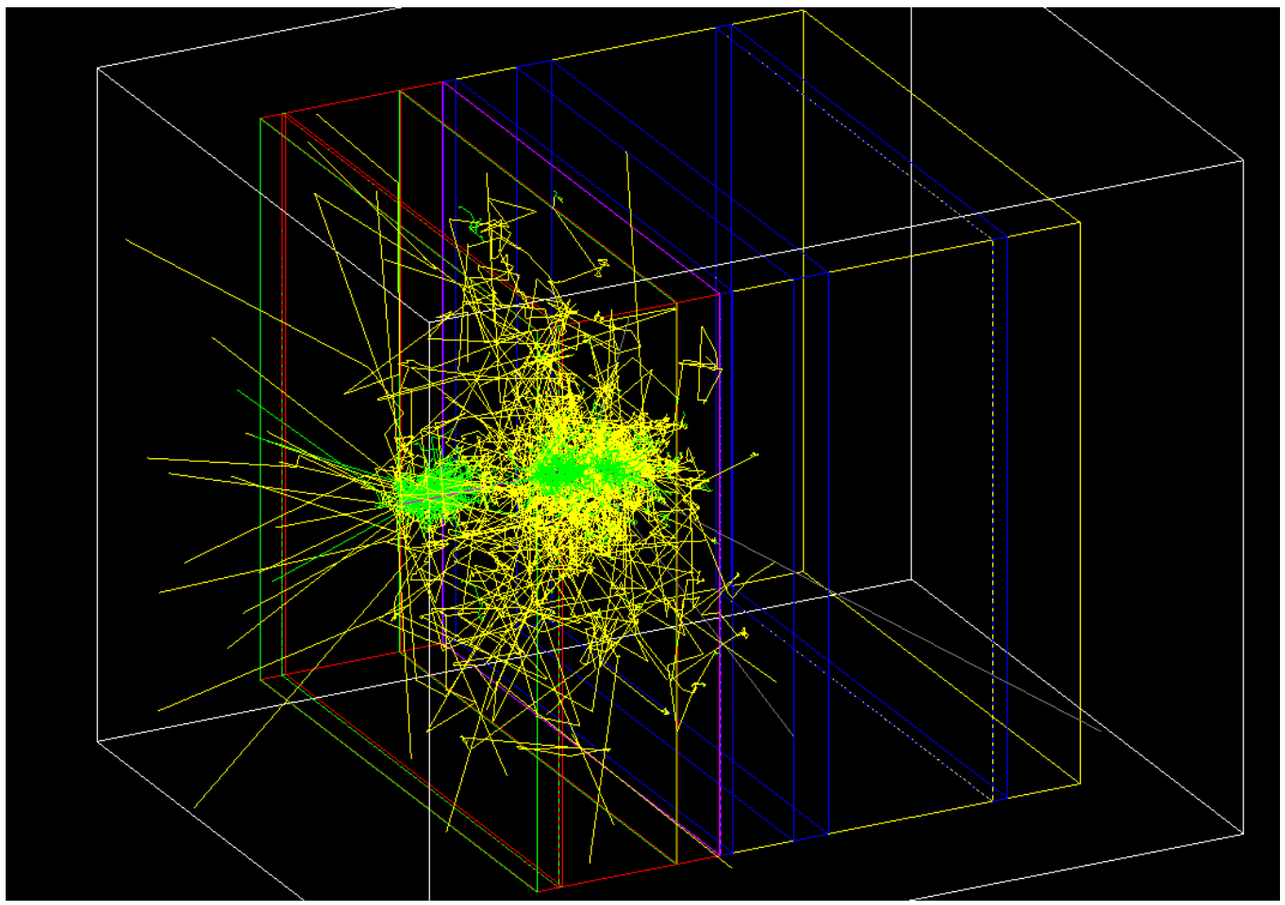


The basic task of energy reconstruction

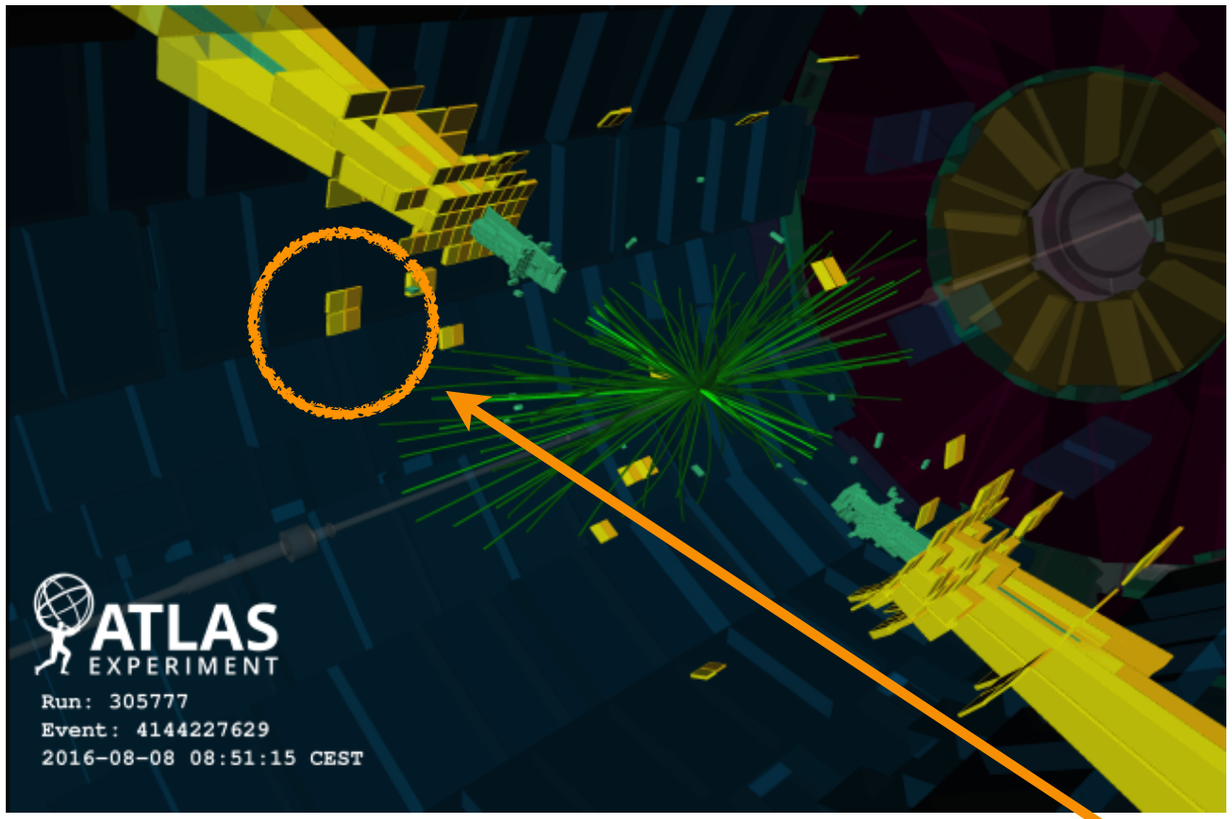


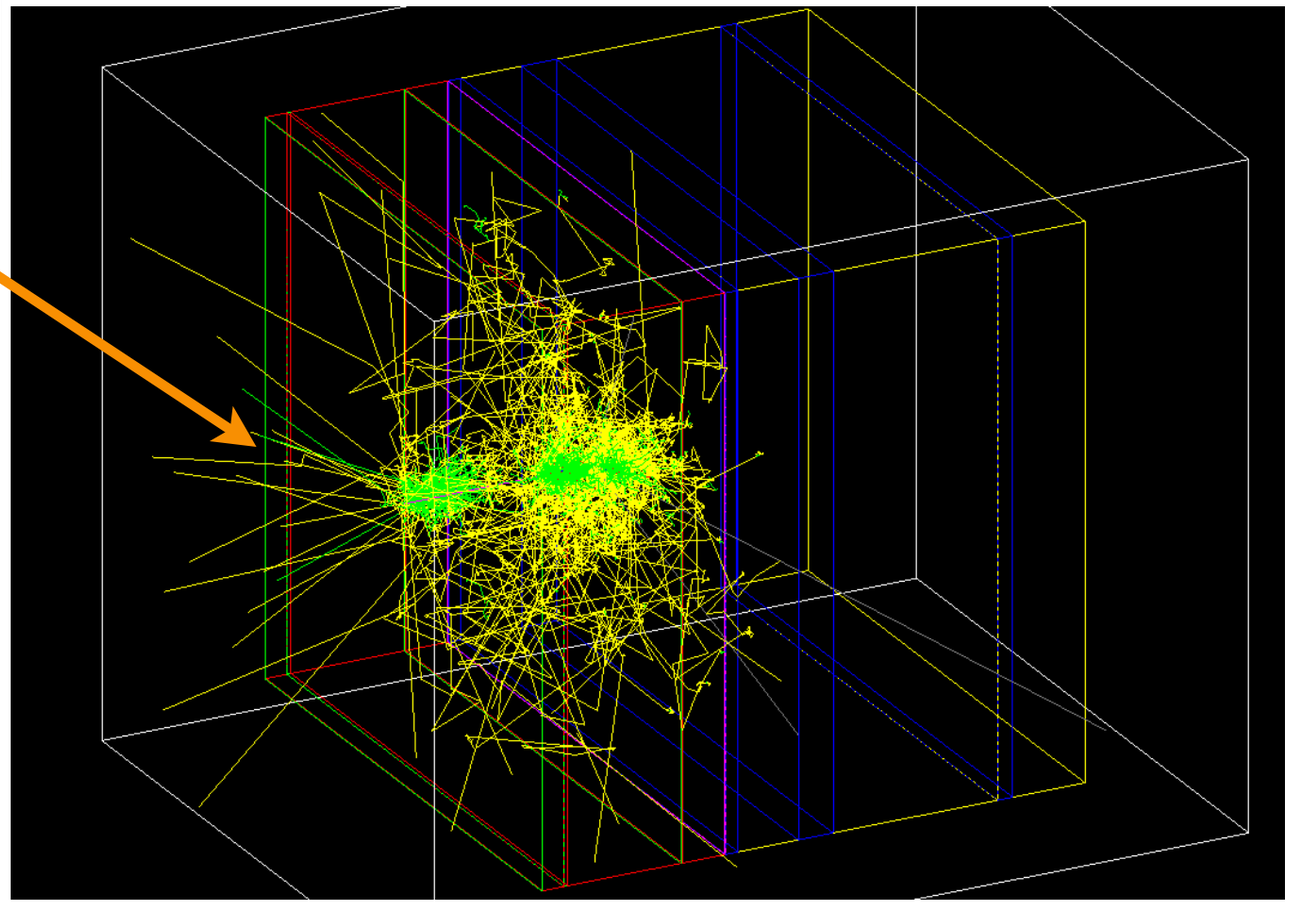


The basic task of energy reconstruction

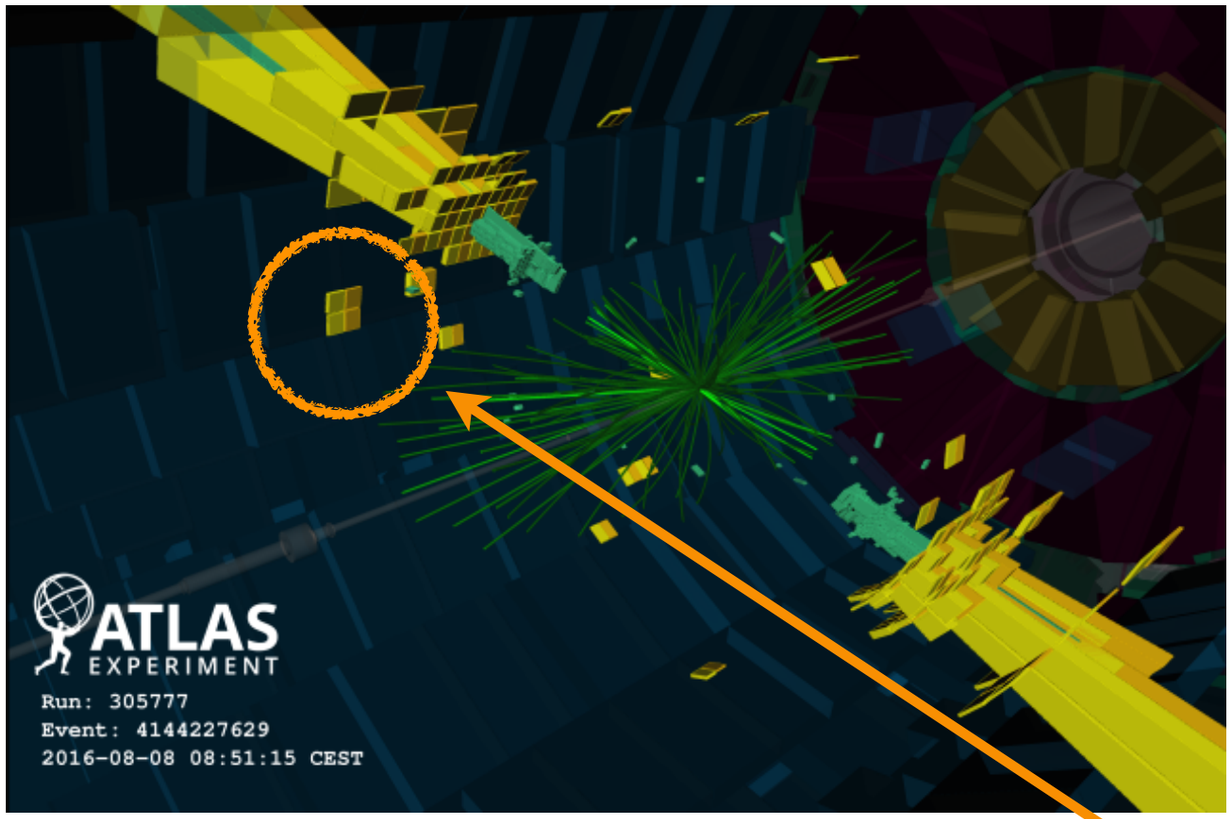


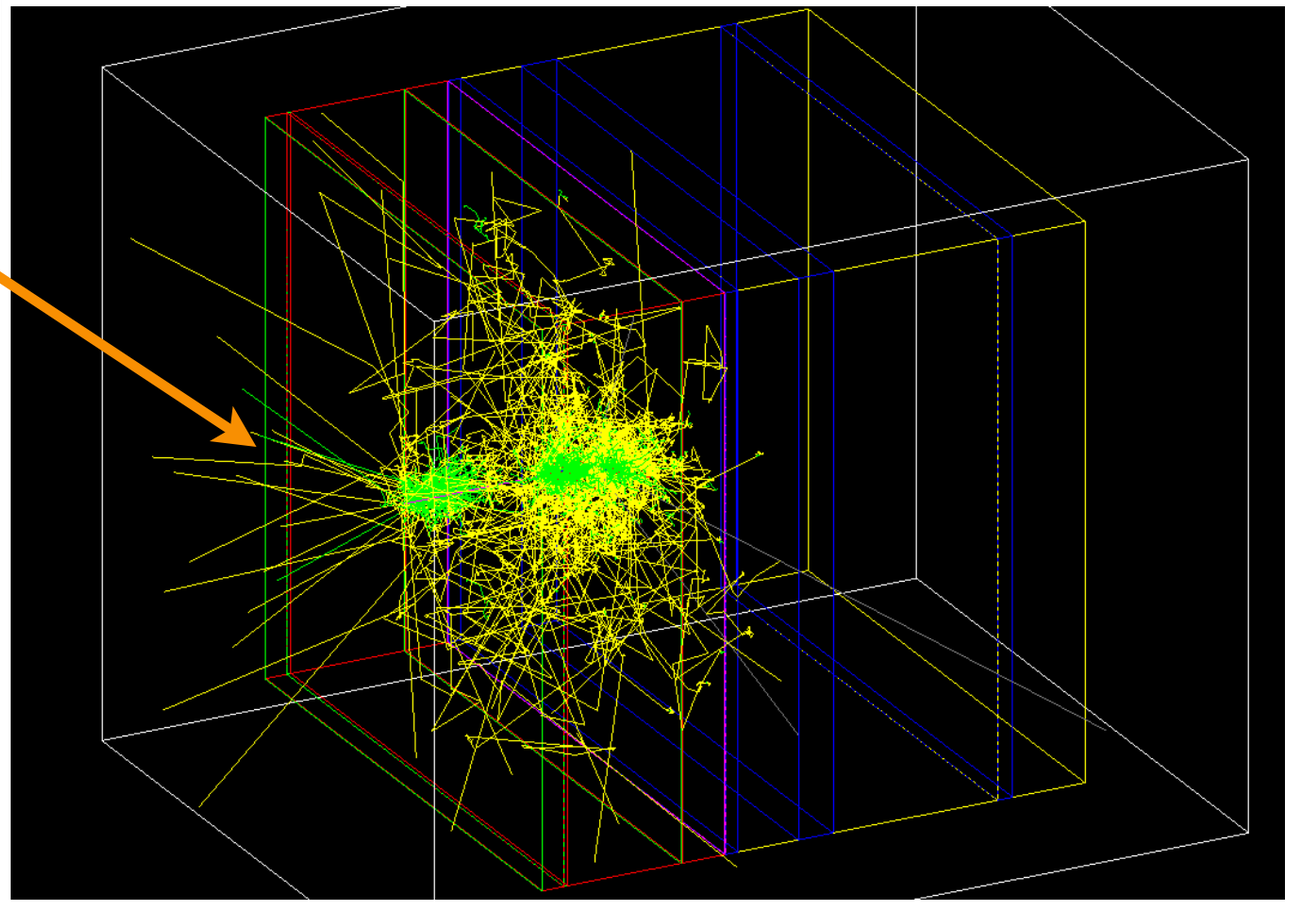
The basic task of energy reconstruction





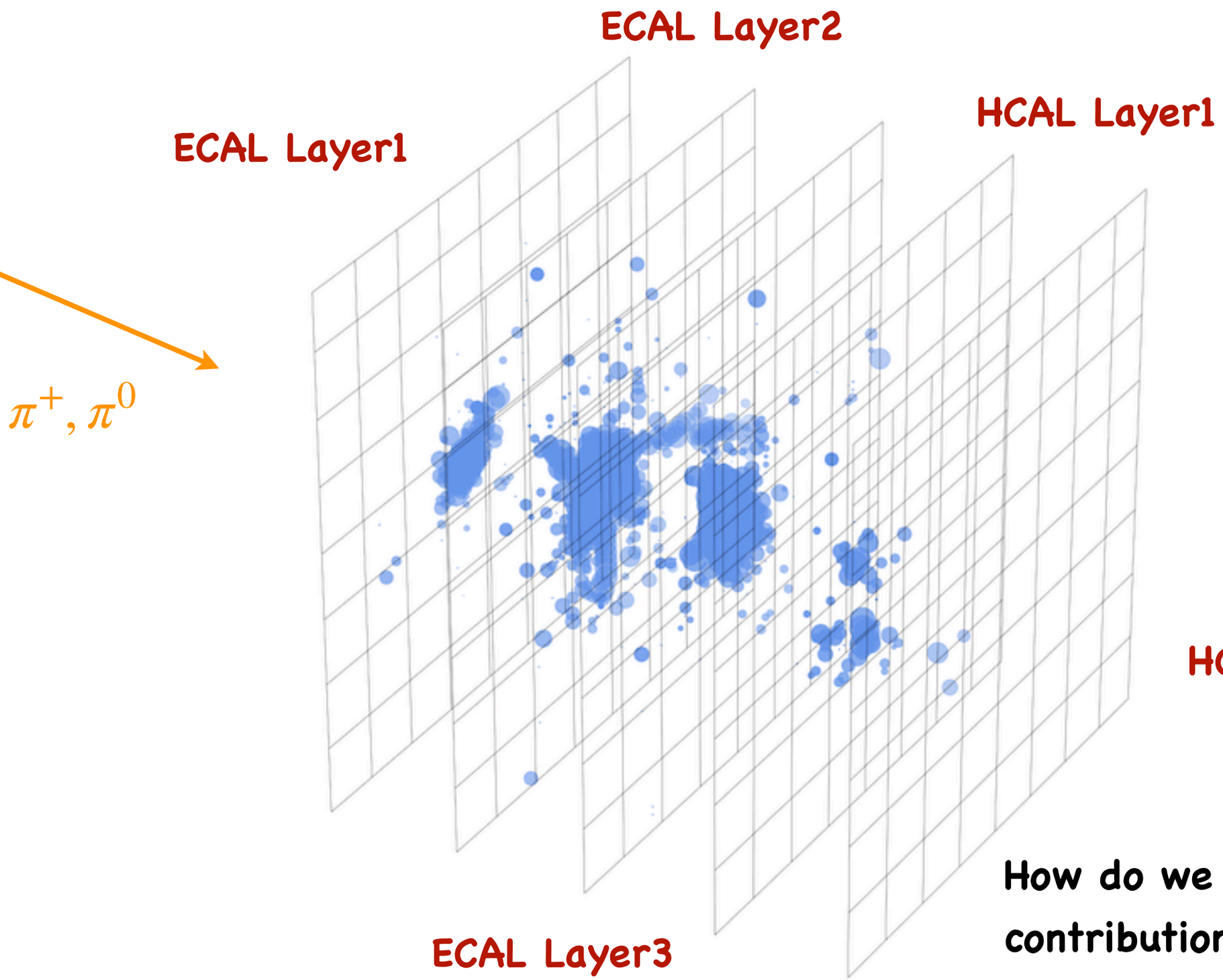
The basic task of energy reconstruction





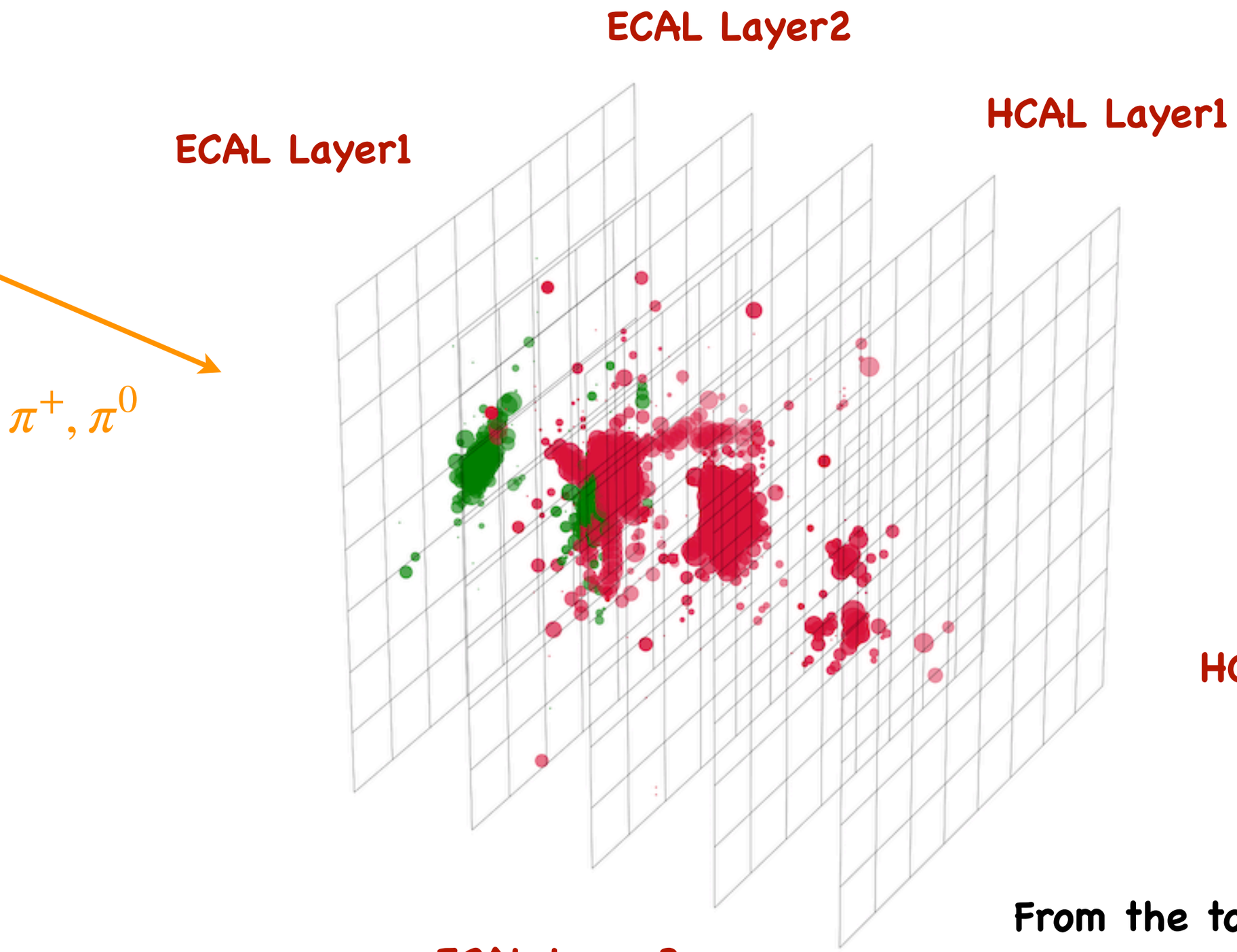
The cells are accumulation of energy, deposited by the shower steps.

The basic problem



How do we estimate energy contribution from each individual source ?

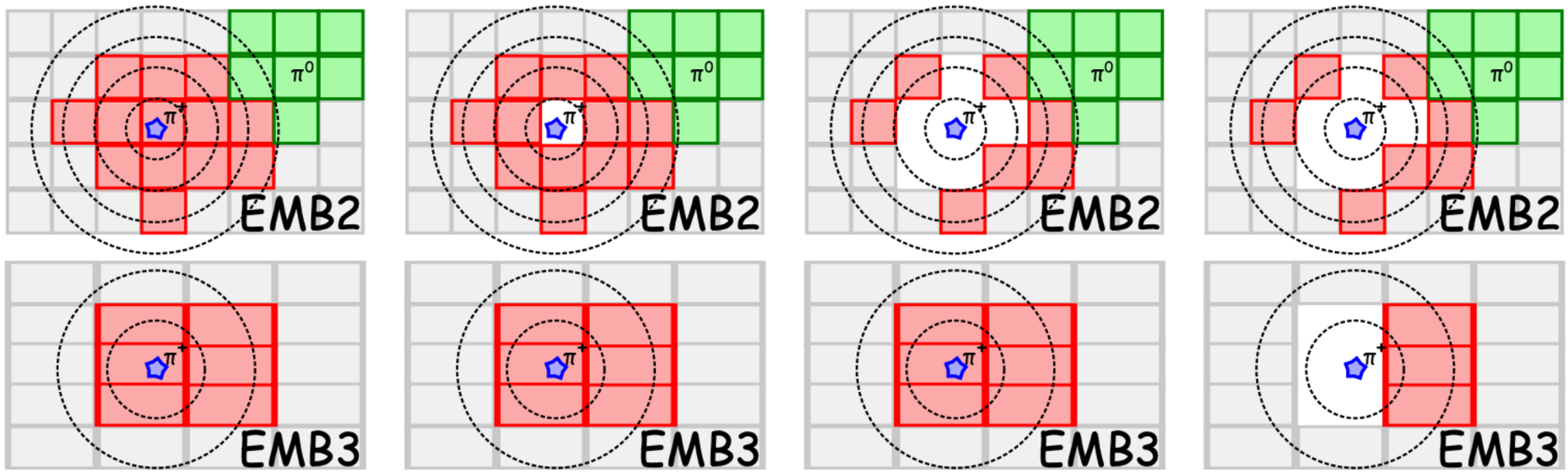
The basic problem



From the total energy deposit, what's the best way to predict?

Energy budget in a given cell

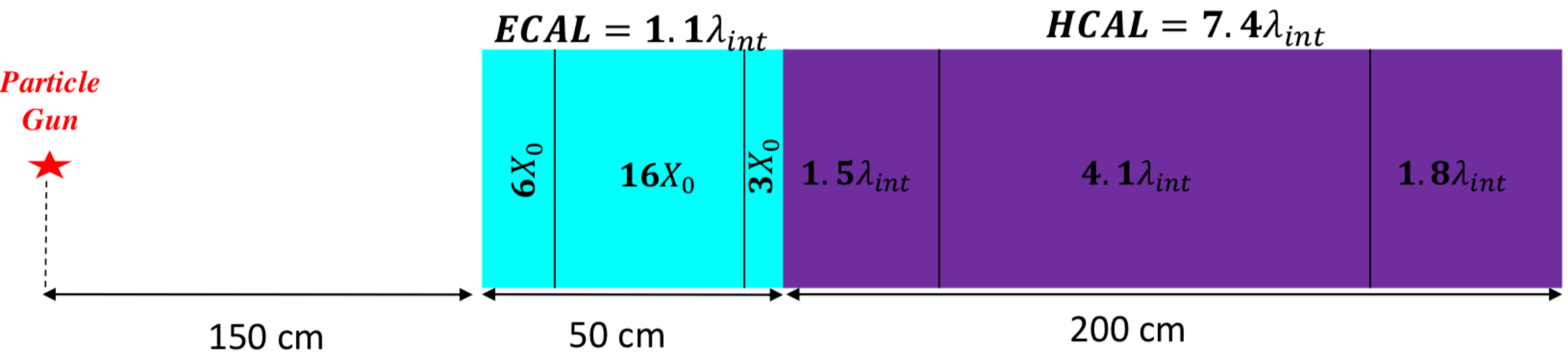
1703.10485



☑ If there is significant overlap of charged/neutral energy per cell, this technique is bound to give erroneous results.

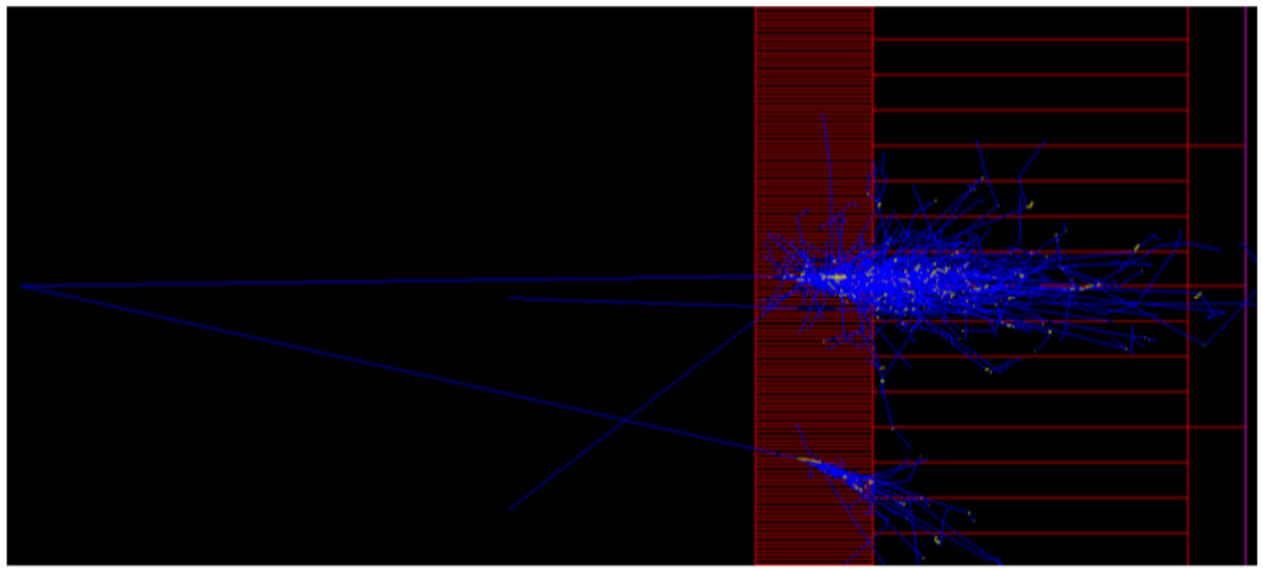
☑ Can pixel wise energy regression do better ?

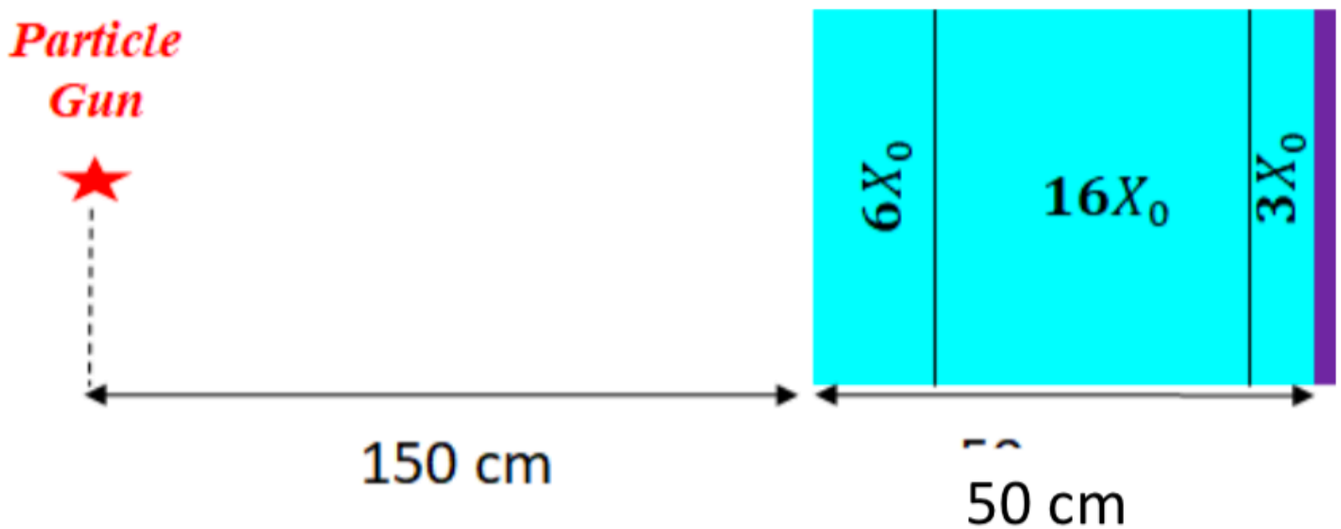
Basic setup to create the dataset

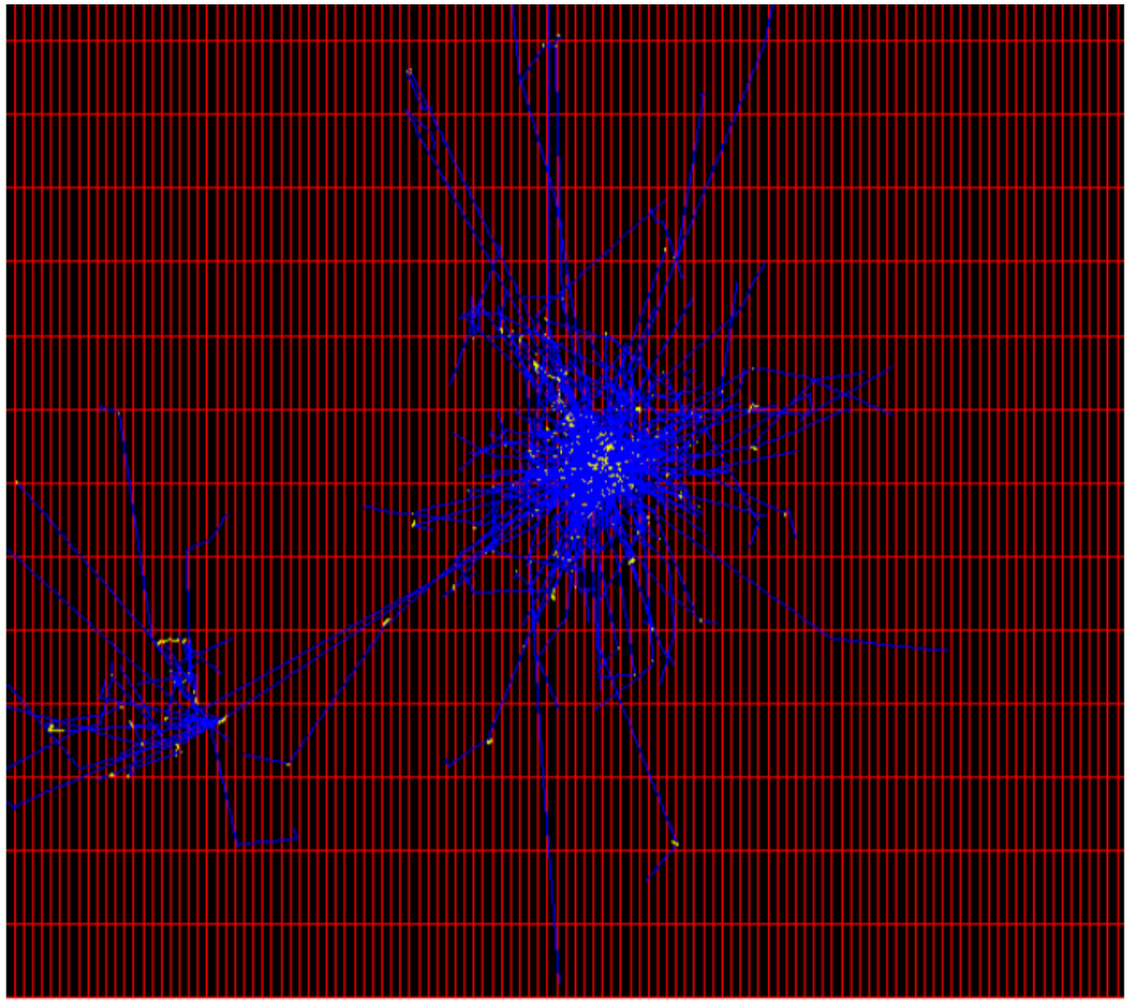


ECAL: Pb (passive) + LAr (active)
HCAL: Fe (passive) + Scint. (active)

Basic setup to create the dataset

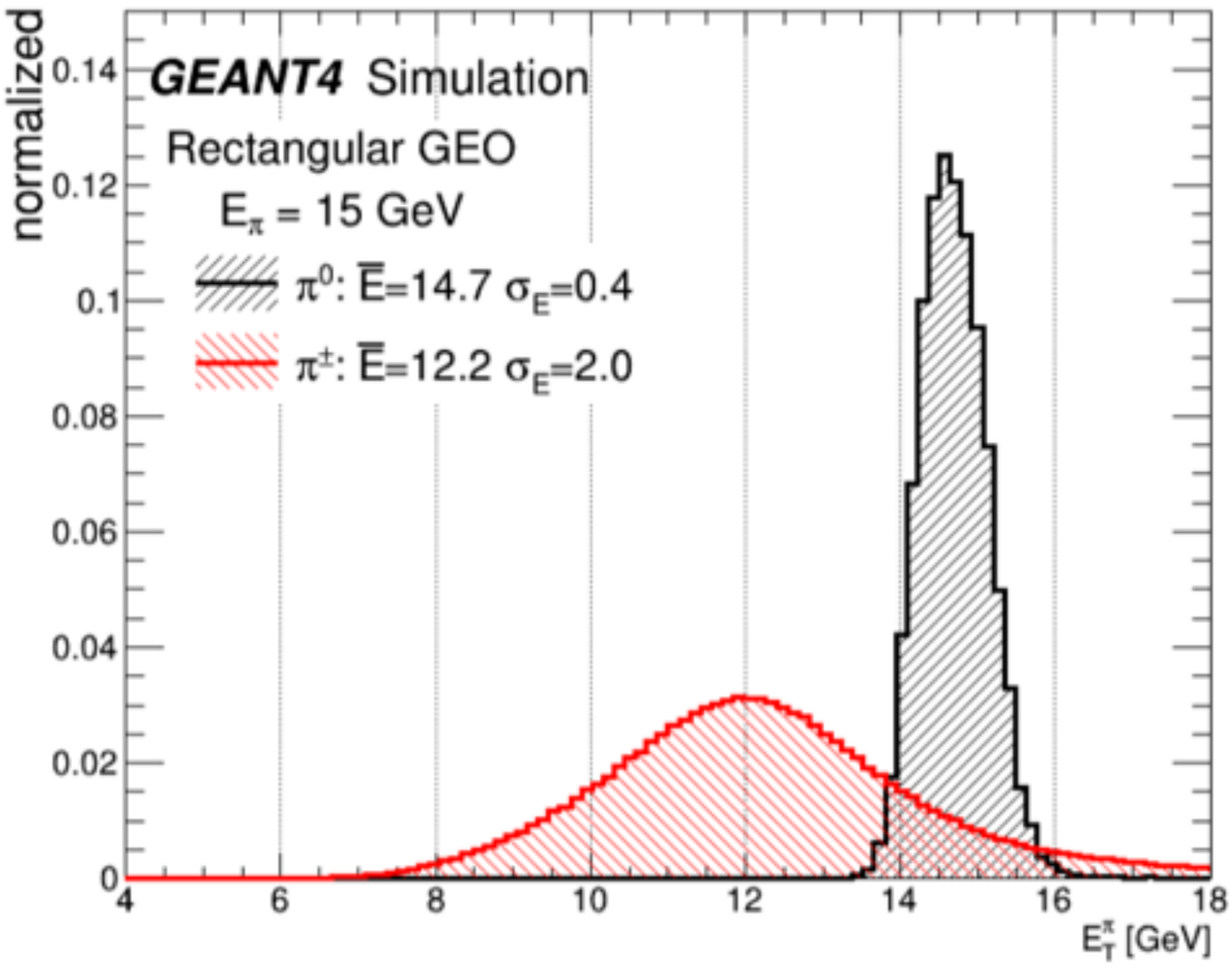






Pi0 decay to 2γ, which visible for low momentum pion decays

Basic setup to create the dataset



Our GEANT4 simulation takes into account the ATLAS calorimeter granularity, the proper composition of absorber/scintillator material as well as accordion geometry of calorimeter to produce a realistic energy response.

We can also trace back the shower to determine the particle origin.

Machine learning setup

Input :

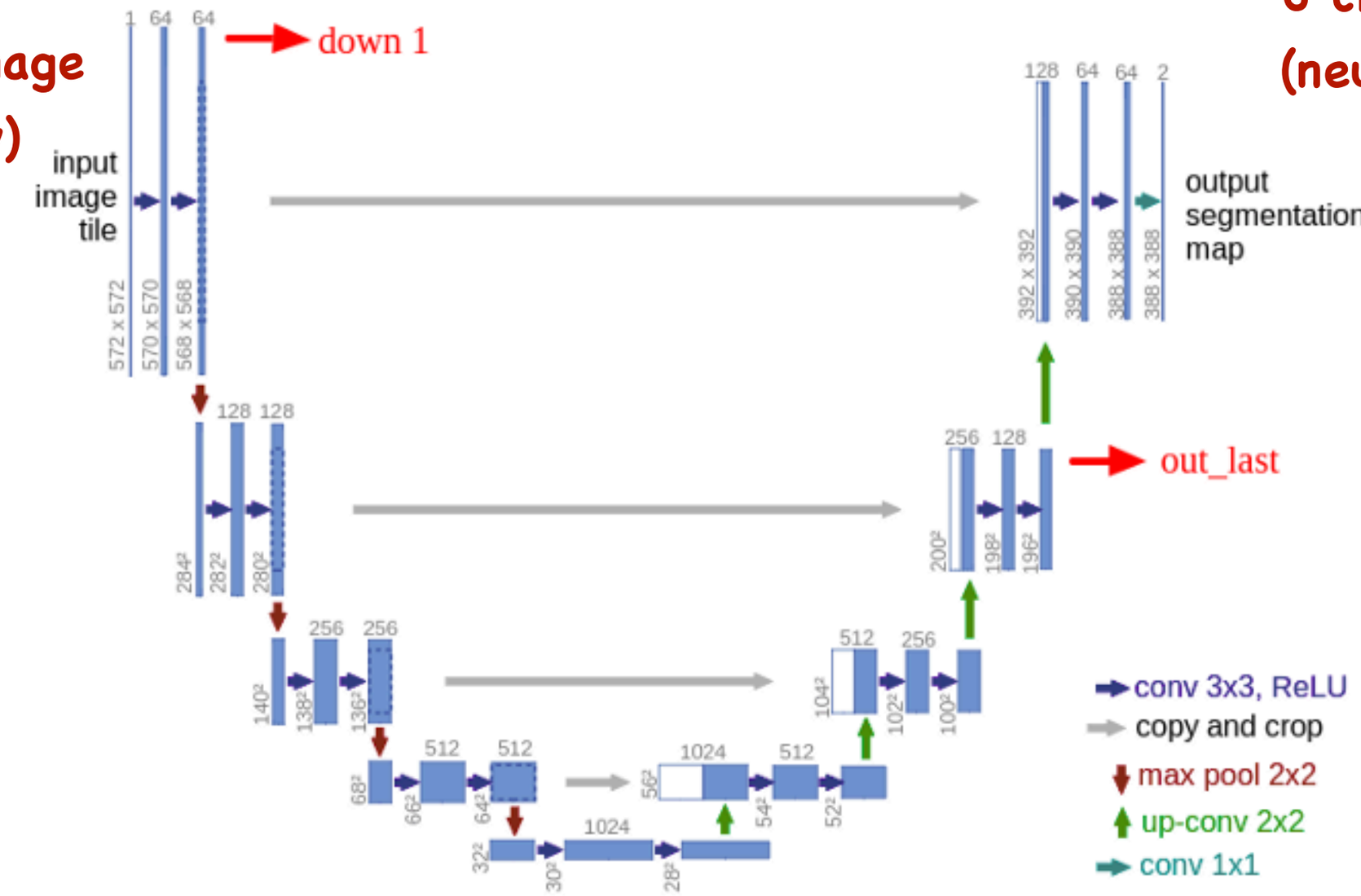
6 channel image

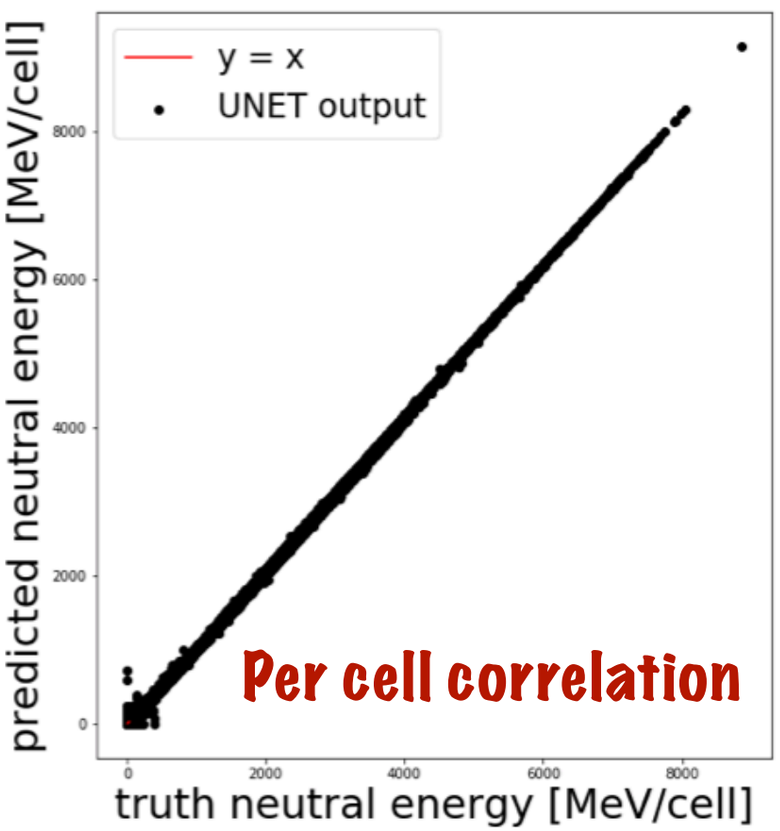
(total energy)

Input :

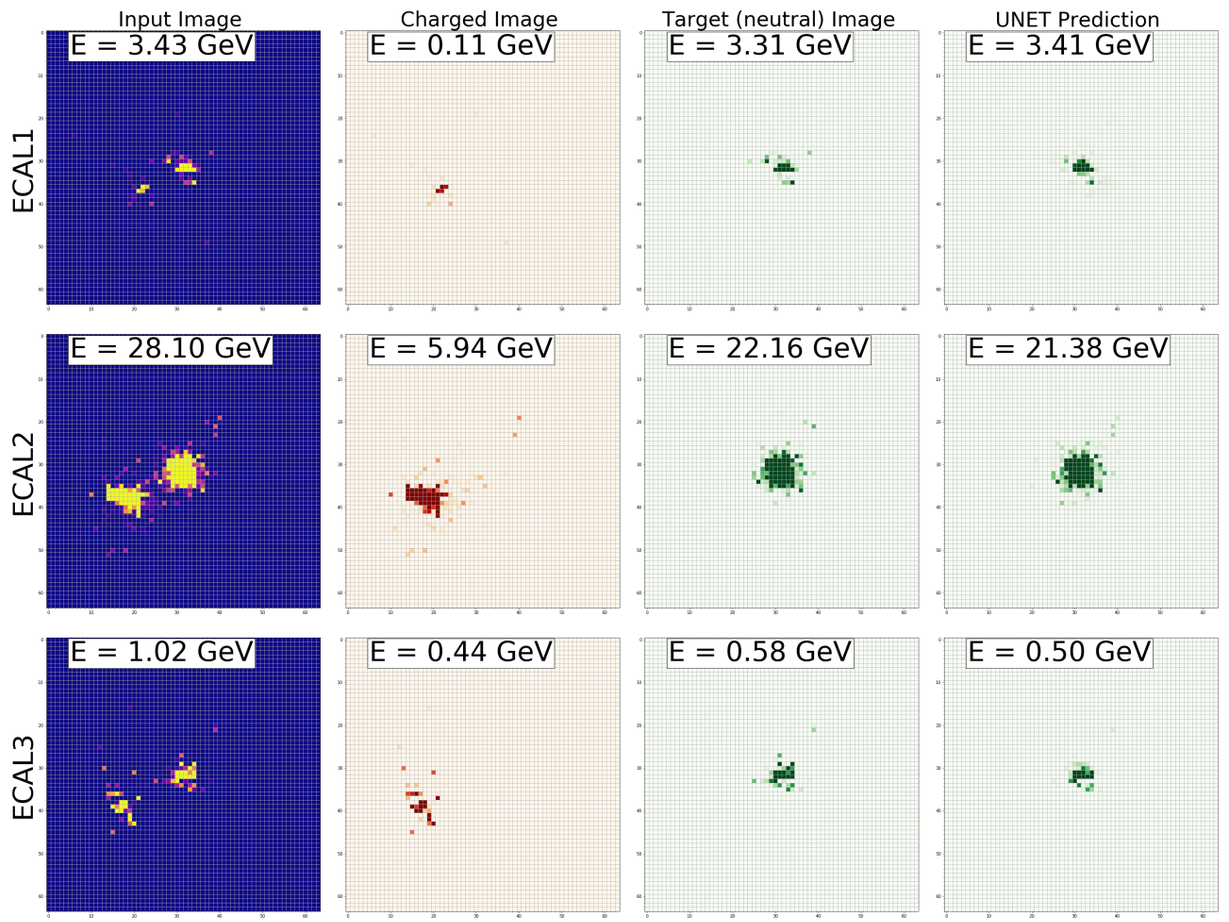
6 channel image

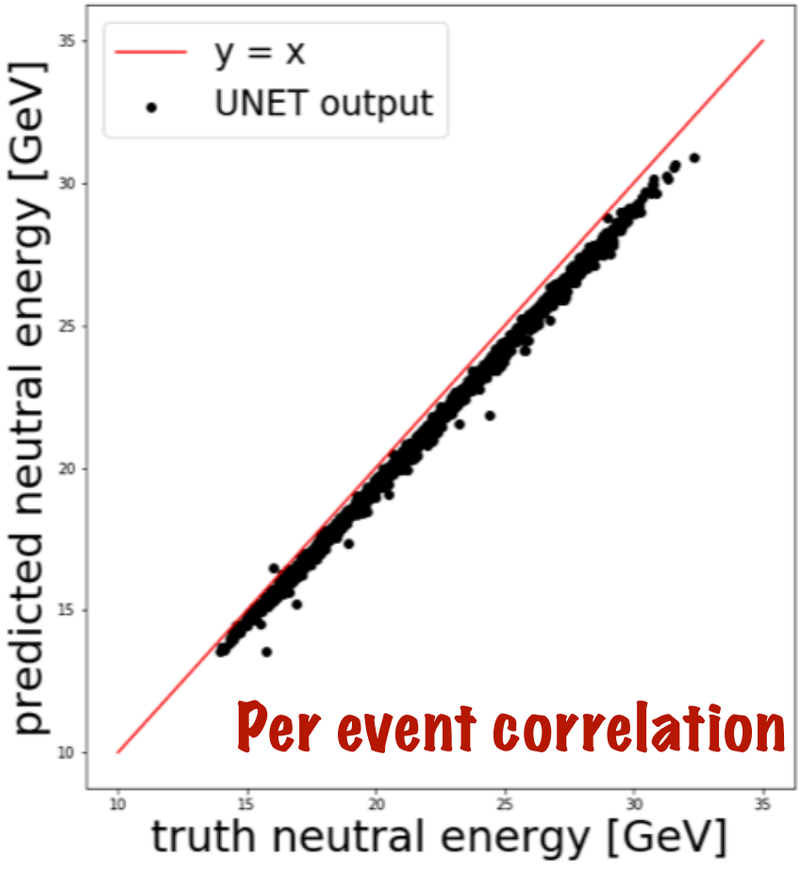
(neutral energy)

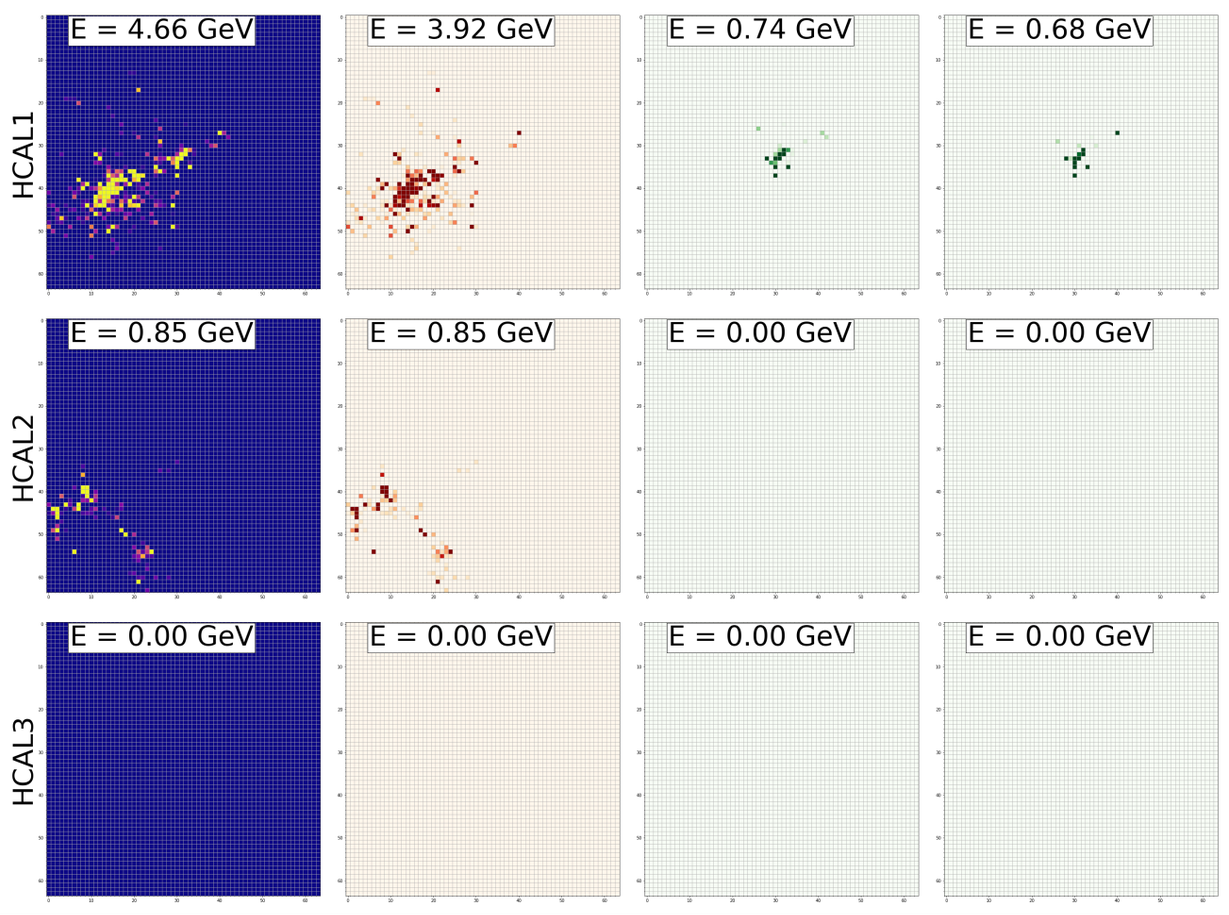




Event Display



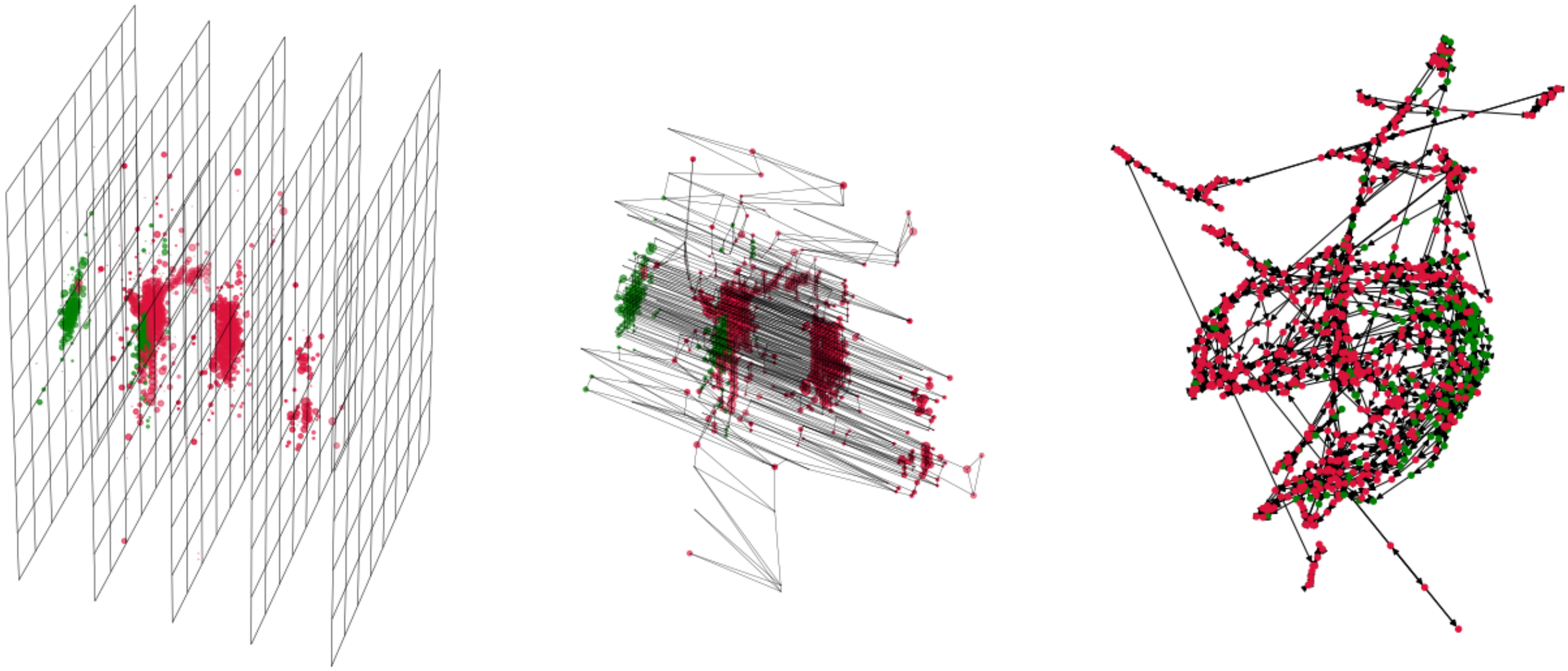




Summary

- ☑ We aim to build a robust energy regressor per calorimeter cell.
- ☑ The target is to have a ML based energy flow method and increase EM/hadronic energy response.
- ☑ With a proper particle identification, its possible to build a full ML based pflow method.
- ☑ Initial image based method has decent performance.
- ☑ Will try out alternative GNN methods.

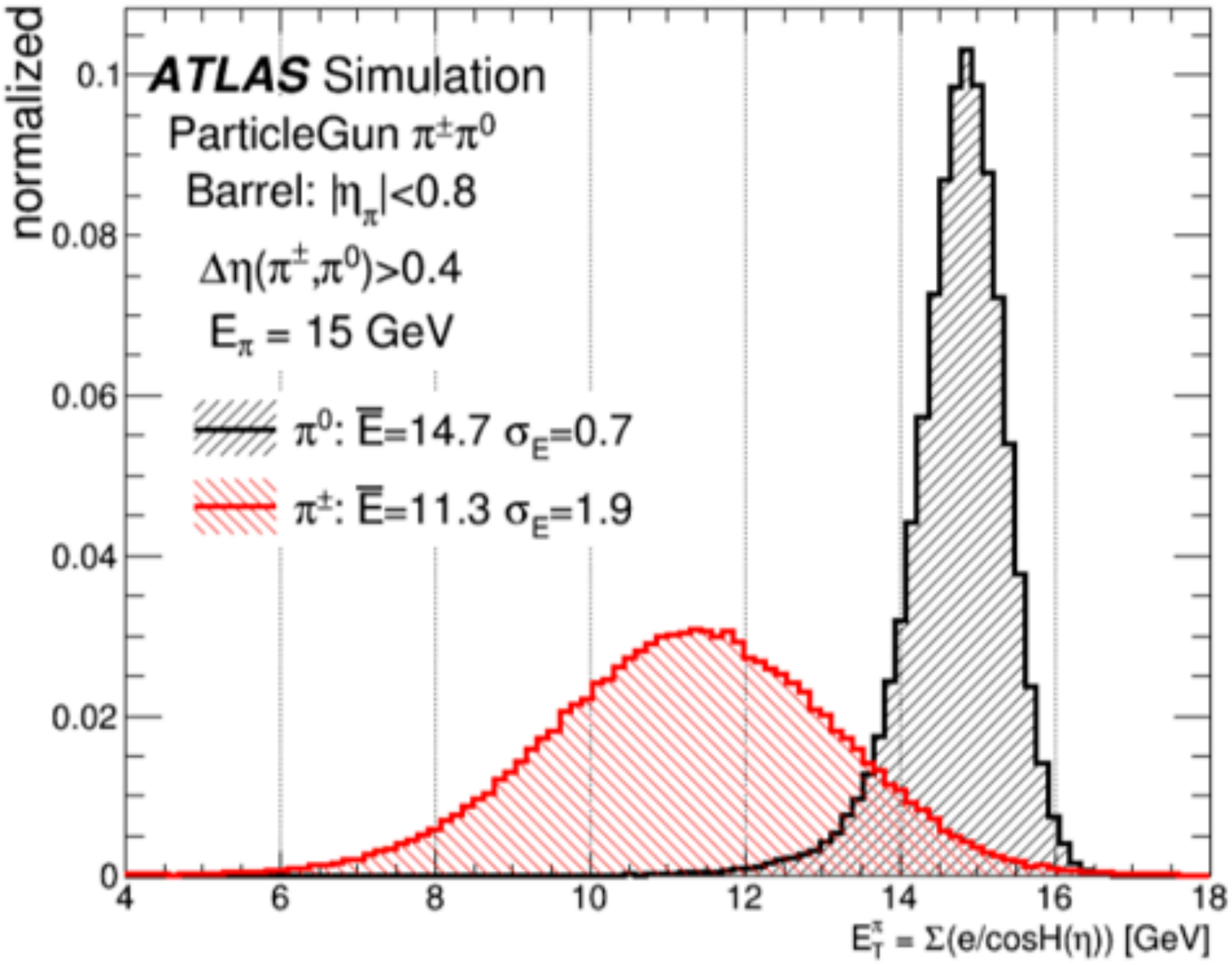
Outlook : GNN, an alternative attempt



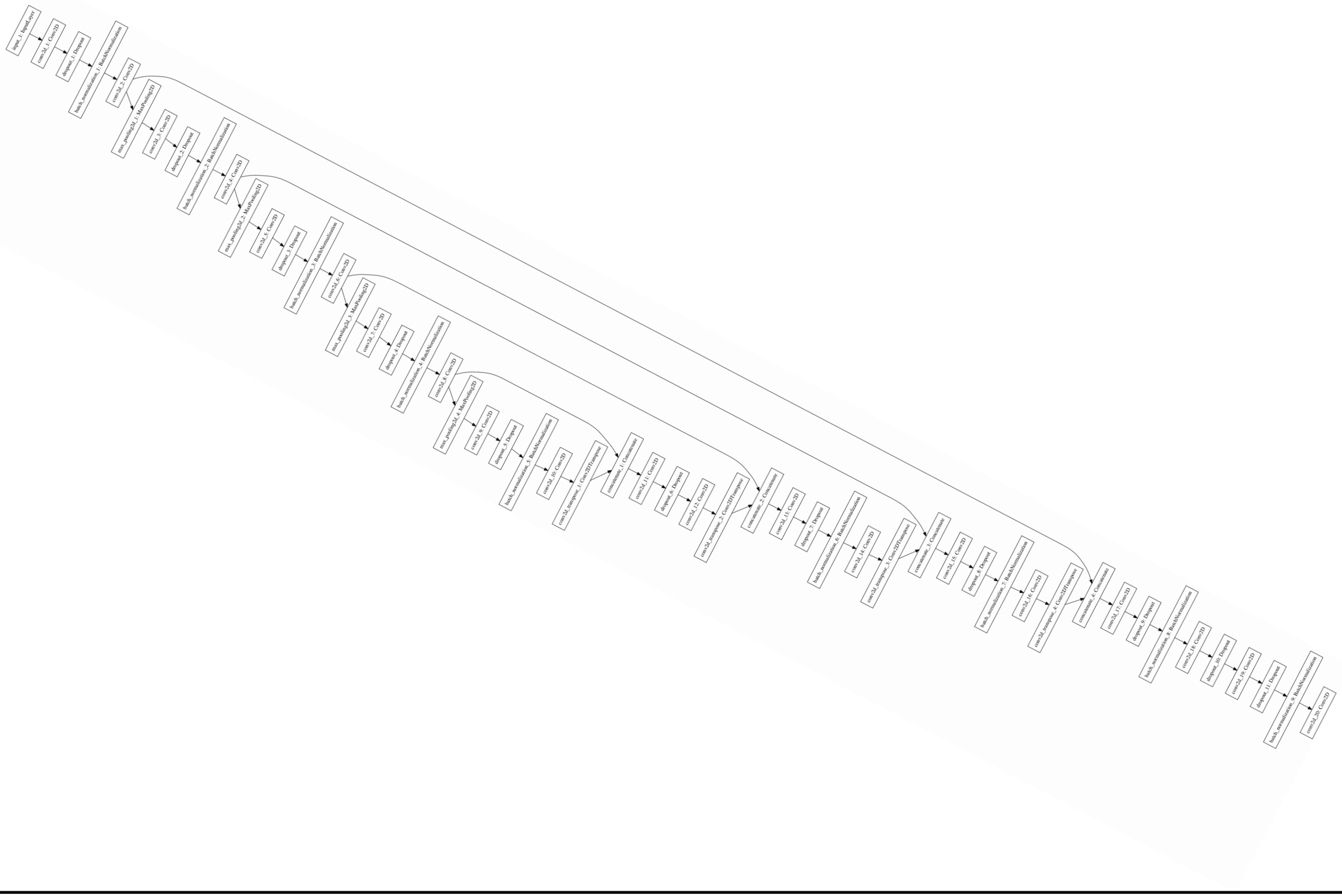
Will try to make a graph from the energy cells and try yo do a node regression.

Backup

ATLAS Simulation



UNET model


input_1: InputLayer
conv2d_1: Conv2D
dropout_1: Dropout
batch_normalization_1: BatchNormalization
conv2d_2: Conv2D
max_pooling2d_1: MaxPooling2D
conv2d_3: Conv2D
dropout_2: Dropout
batch_normalization_2: BatchNormalization
conv2d_4: Conv2D
max_pooling2d_2: MaxPooling2D
conv2d_5: Conv2D
dropout_3: Dropout
batch_normalization_3: BatchNormalization
conv2d_6: Conv2D
max_pooling2d_3: MaxPooling2D
conv2d_7: Conv2D
dropout_4: Dropout
batch_normalization_4: BatchNormalization
conv2d_8: Conv2D
max_pooling2d_4: MaxPooling2D
conv2d_9: Conv2D
dropout_5: Dropout
batch_normalization_5: BatchNormalization
conv2d_10: Conv2D
conv2d_transpose_1: Conv2DTranspose
concatenate_1: Concatenate
conv2d_11: Conv2D
dropout_6: Dropout
conv2d_12: Conv2D
conv2d_transpose_2: Conv2DTranspose
concatenate_2: Concatenate
conv2d_13: Conv2D
dropout_7: Dropout
batch_normalization_6: BatchNormalization
conv2d_14: Conv2D
conv2d_transpose_3: Conv2DTranspose
concatenate_3: Concatenate
conv2d_15: Conv2D
dropout_8: Dropout
batch_normalization_7: BatchNormalization
conv2d_16: Conv2D
conv2d_transpose_4: Conv2DTranspose
concatenate_4: Concatenate
conv2d_17: Conv2D
dropout_9: Dropout
batch_normalization_8: BatchNormalization
conv2d_18: Conv2D
dropout_10: Dropout
conv2d_19: Conv2D
dropout_11: Dropout
batch_normalization_9: BatchNormalization
conv2d_20: Conv2D