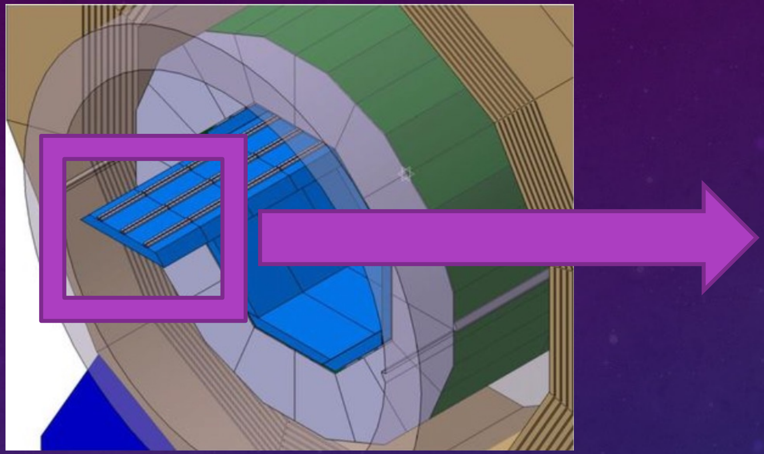
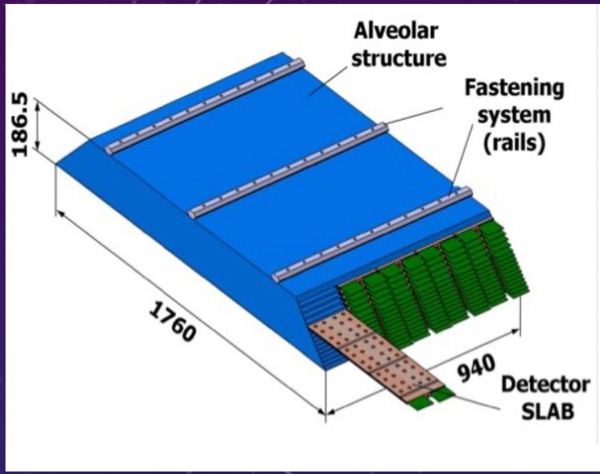
Calorimeter Clustering with Gravnet

KYUSHU UNIV.[A], OSAKA UNIV. RCNP [B], OSAKA UNIV. IDS[C], KYUSHU INSTITUTE OF TECHNOLOGY [D]
SHUSAKU TSUMURA [A], TAIKAN SUEHARA [A], KIYOTOMO KAWAGOE [A],
HAJIME NAGAHARA [B,C], YUTA NAKASHIMA [B,C], NORIKO TAKEMURA[C,D]

ILD / SIW ECAL





- Electromagnetic calorimeter (ECAL): Detects position, momentum, and energy of gamma rays with high granularity
  → Higher accuracy of particle identification: PFA
- ECAL equips a lot of channels (~10^8) to identify each particle.
- Sandwich structure with 30 alternating layers of Si detection layer and W absorption layer.
- W-absorbing layer: Electromagnetic shower is induced when electrons and gamma rays are incident.
  → ~ 24 X_0 in total
- Feature: Moliere radius is small enough to separate each particle

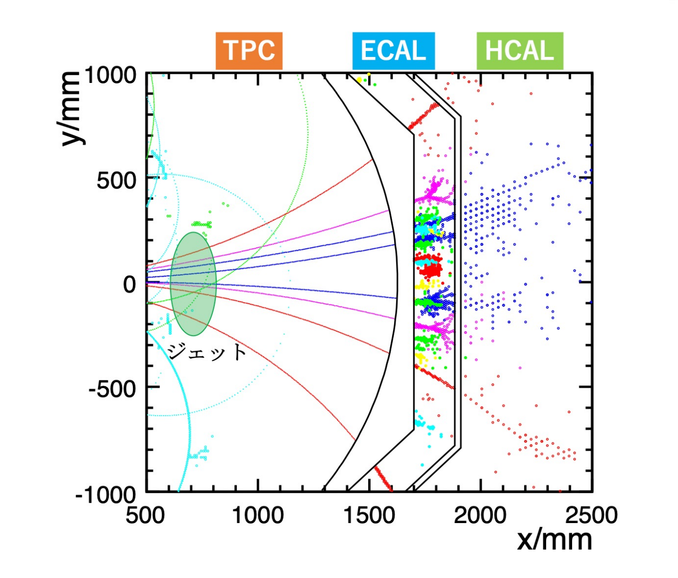
PARTICLE FLOW ALGORITHM (PFA)

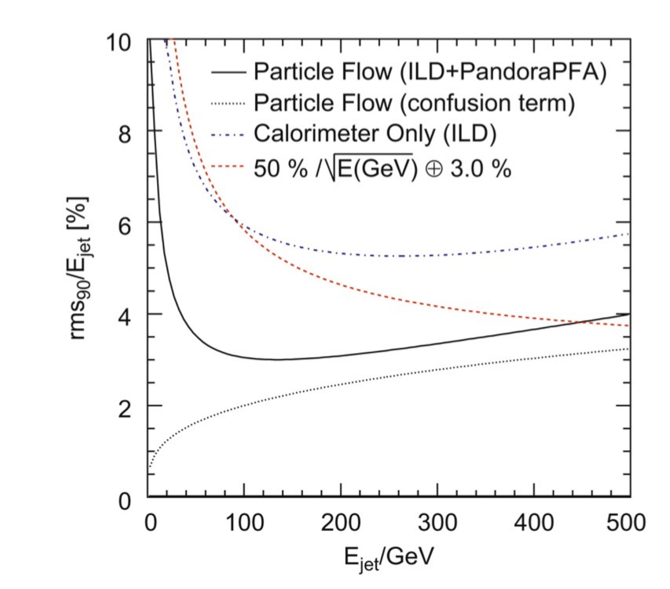
- A method to obtain higher jet energy resolution by reconstructing the particle trajectory for each type of particle in the jet.
- Charged particles: Tracker
- Photons : ECAL
- Neutral hadrons : HCAL
- Resolution of a calorimeter for a single particle :

Perfect PFA: $\sim 20\%/\sqrt{E(GeV)}$

PandoraPFA : $\sim 30\%/\sqrt{E(GeV)}$

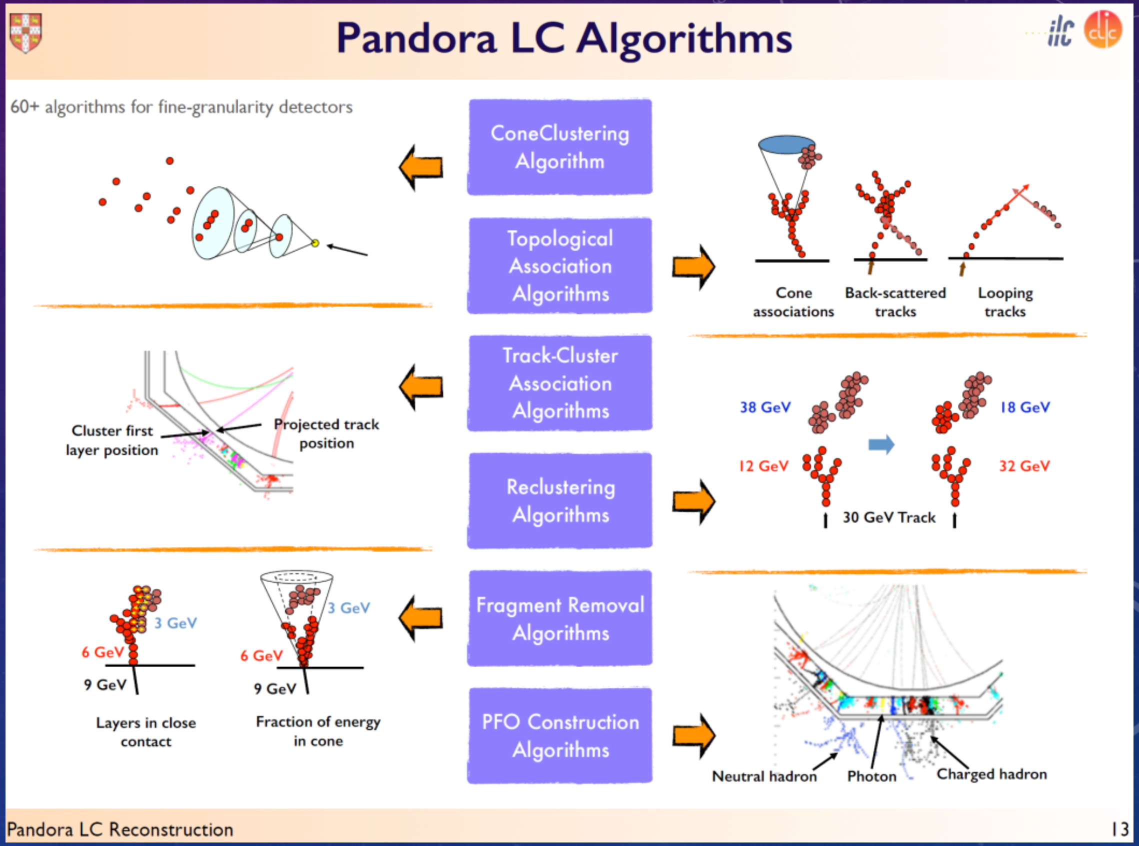
w/o PFA : $50\ - 60\%/\sqrt{E(GeV)}$





APPLICATION OF DEEP LEARNING TO PFA

- Current PFA algorithm : PandoraPFA
  →The pattern recognition based on the manual cutting
- The main problem: Confusion effect
  → The particles impinge too close to each other
- We may achieve better accuracy by considering the hidden and complicated relationships among the hit information
- Aim to further improve performance by using deep learning technique.



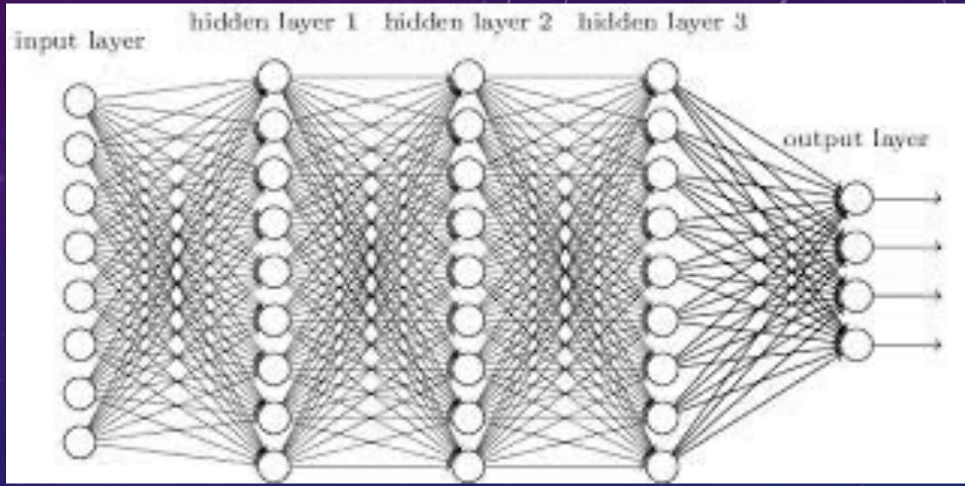
DEEP LEARNING

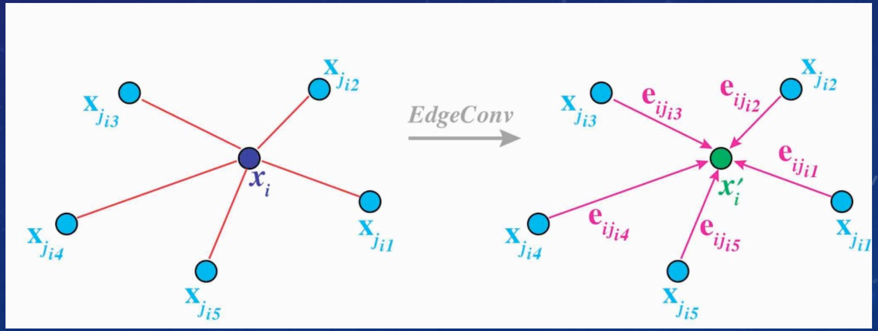
Fully Connected Layer

- One of the most basic structures in deep learning
- Consists of an input layer, a hidden layer, and an output layer
- More expressive network can be built by increasing the number of layers → Performance can be improved by inserting Batch Normalization, etc. in between

Graph Neural Network

- Network is constructed as a graph consisting of nodes (points) and edges (lines)
- Not only can it learn the features of materials with a graph-like structure, but it can also be used in many ways, such as expressing the relationship between features as a graph.





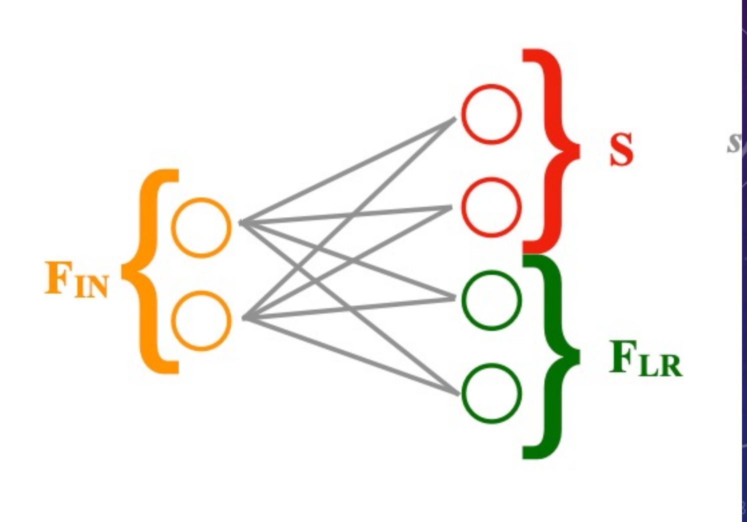
GRAVNET

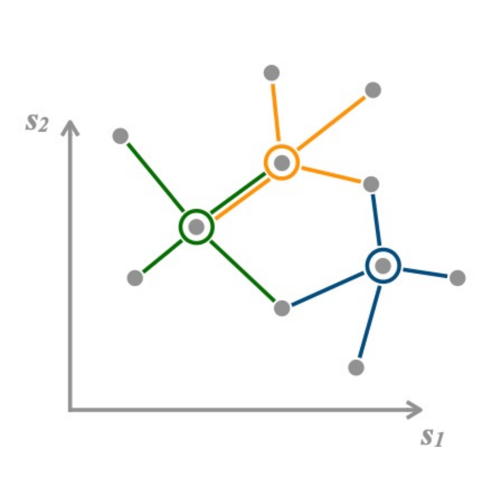
- Input Data : $V \times F_{IN}$

V : Number of hits for each detector

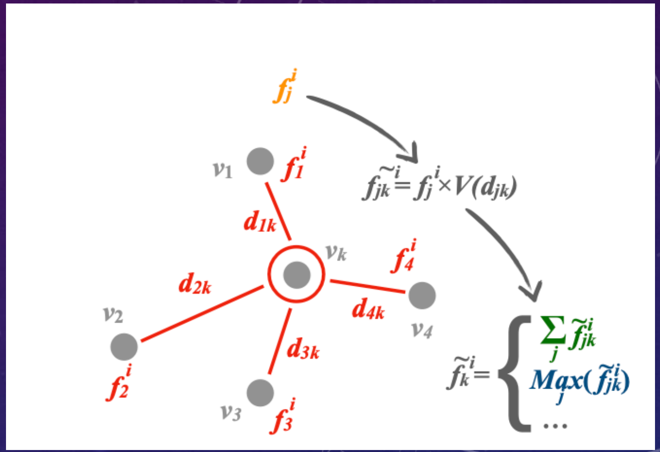
$\mathrm{F_{IN}}$: Number of the features for each hit

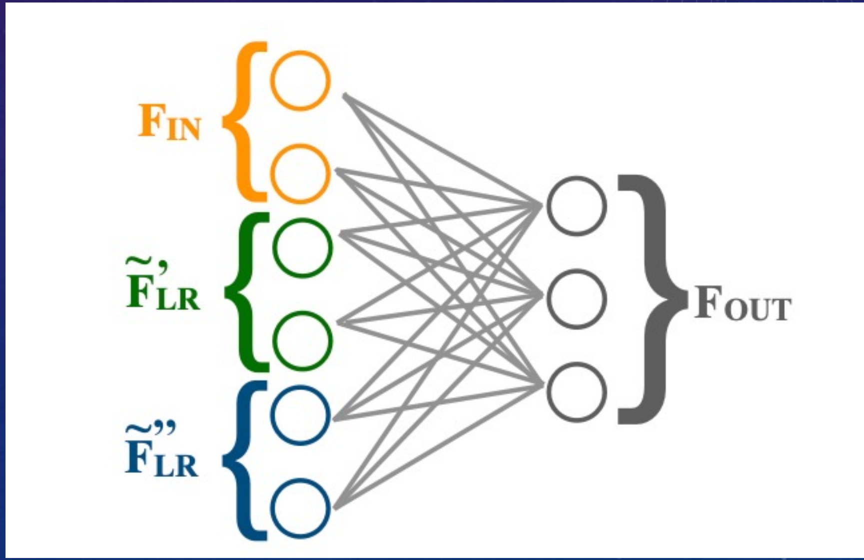
- S : Set of coordinates in some learned representation space
- F_{LR} : learned representation of the vertex features
- Input data of initial dimension $V \times F_{IN}$ is converted into a graph.
- The coordinates of the graph is updated by the learning of the network.





GRAVNET

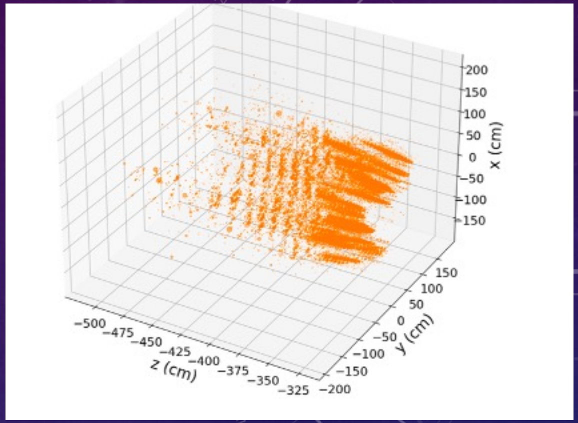


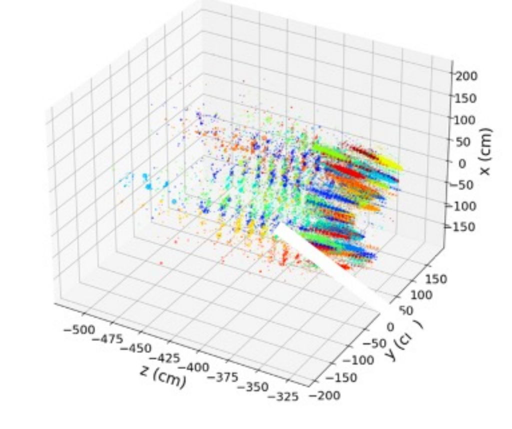


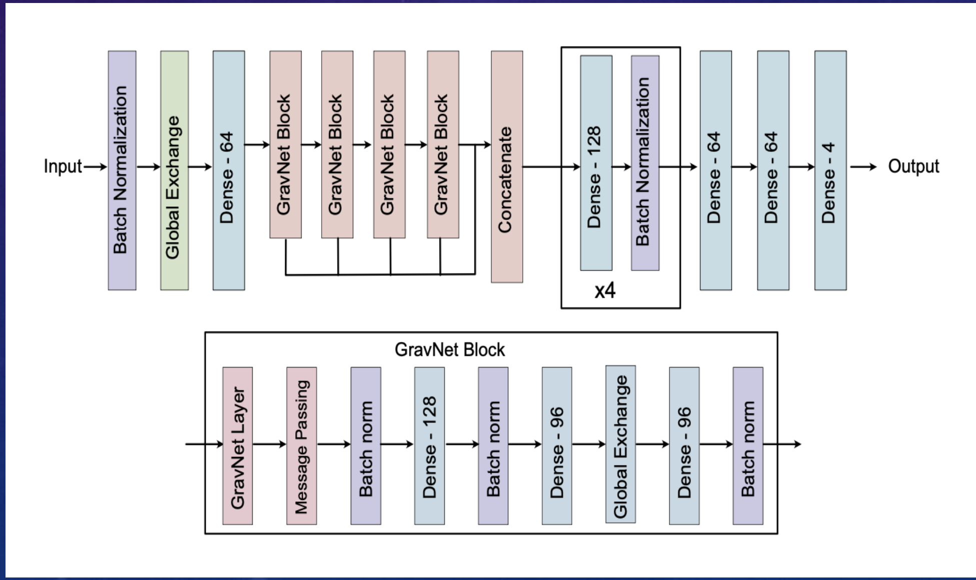
- The contribution of each point is bigger depending on the distance between the points
- The output is calculated for each point based on the contribution
- At last, the outputs ($\widetilde{F_{LR}}$) are concatenated with the initial inputs and previous outputs and pass the FC layer.
- The F_{OUT} output carries collective information from each vertex and its surrounding.

SHOWER CLUSTERING

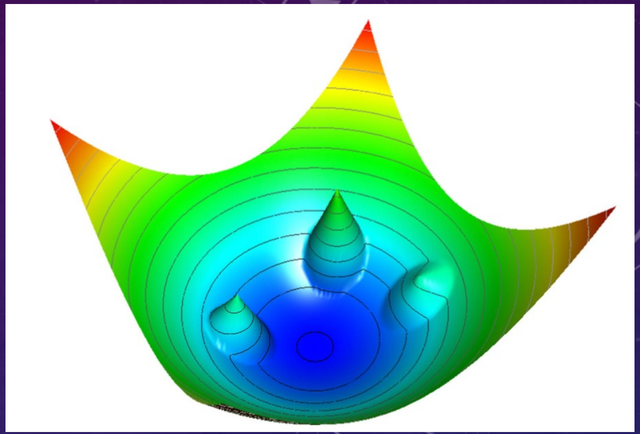
- Input: feature values of hits in the calorimeter e.g., position, energy, time, etc.
- Output: β/coordinates in the representation coordinate for each hit (explained in later slides)
- Deep Learning Architecture
  - Developed for a CMS detector that has a lot of separated channels for PFA







Object Condensation



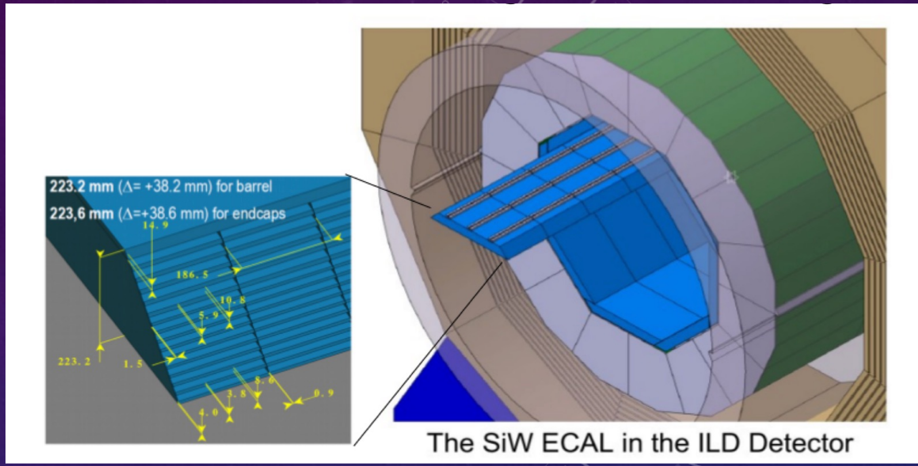
- A loss function technique to recognition for multi-object
- Get the output from GravNet as β and output whether the hit seems to be a representative point of the particle ($0 < \beta < 1$)
- Employs two terms as Loss terms to improve cluster and background identification

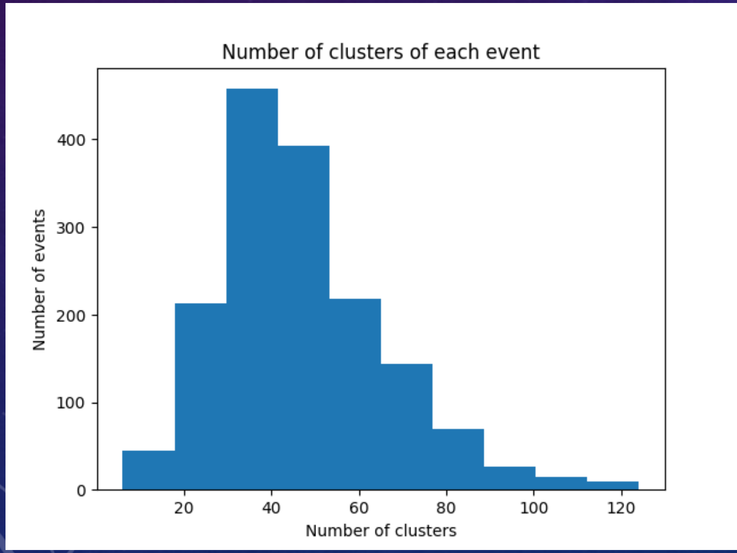
$$L = L_V + L_\beta$$

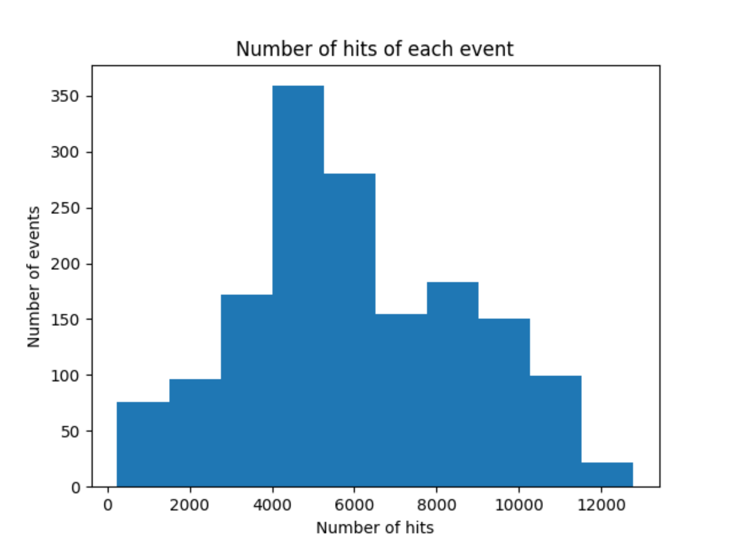
- L_V : The closer the hit is to a particle with high β and belonging to the same particle, the smaller it is, and the more it belongs to a different particle, the larger it is.
  → Equivalent to the attractive and repulsive forces acting on an electric charge
- L_β : Converge β to 1 for only one of each particle corresponding to a true cluster
  The remaining β works its way closer to 0

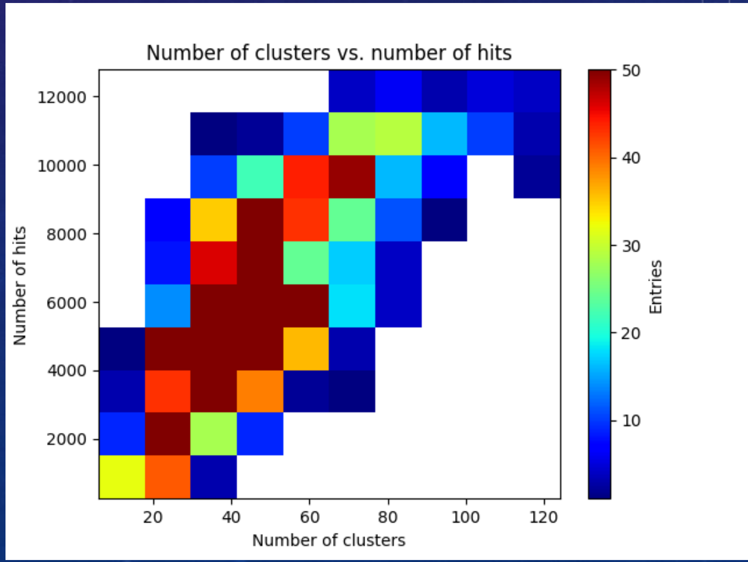
SIMULATION DATA

- ILD 500 GeV Simulation Data
- $e^+e^- \rightarrow Z^* \rightarrow 2q$ events
- Clustering showers obtain hit information (Energy , x, y, z) measured in Ecal / Hcal section
- There are about 1000-10000 hits / 10 – 80 clusters in each event





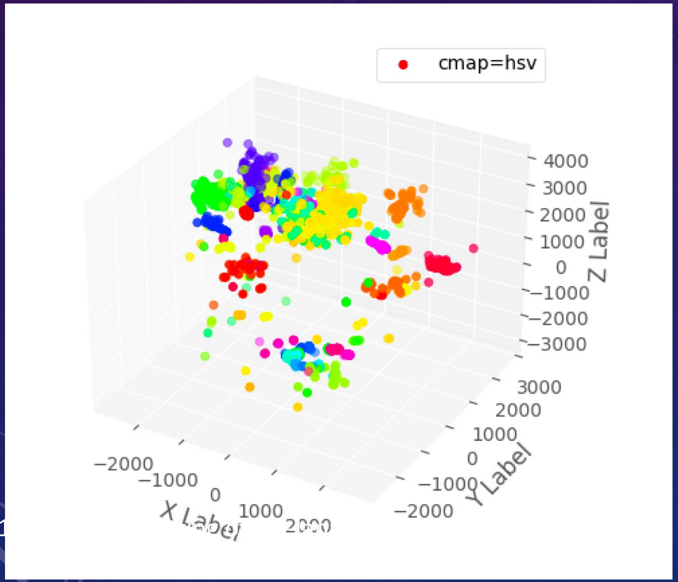




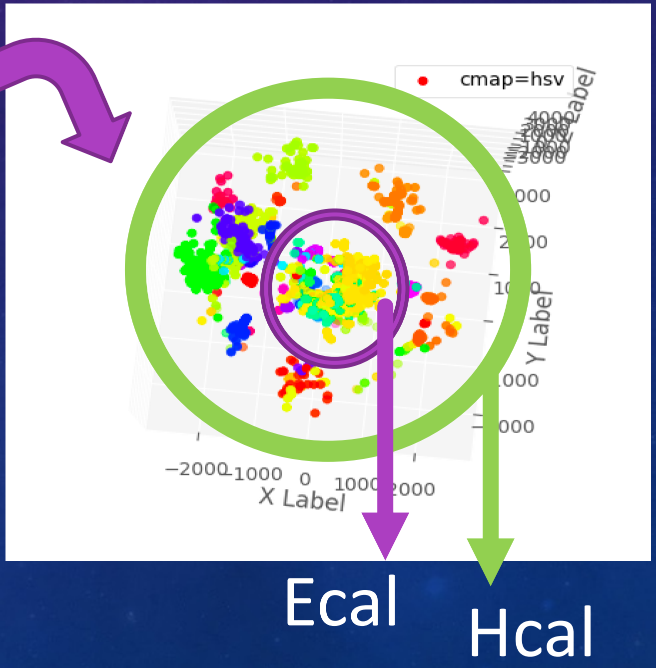
Data profile

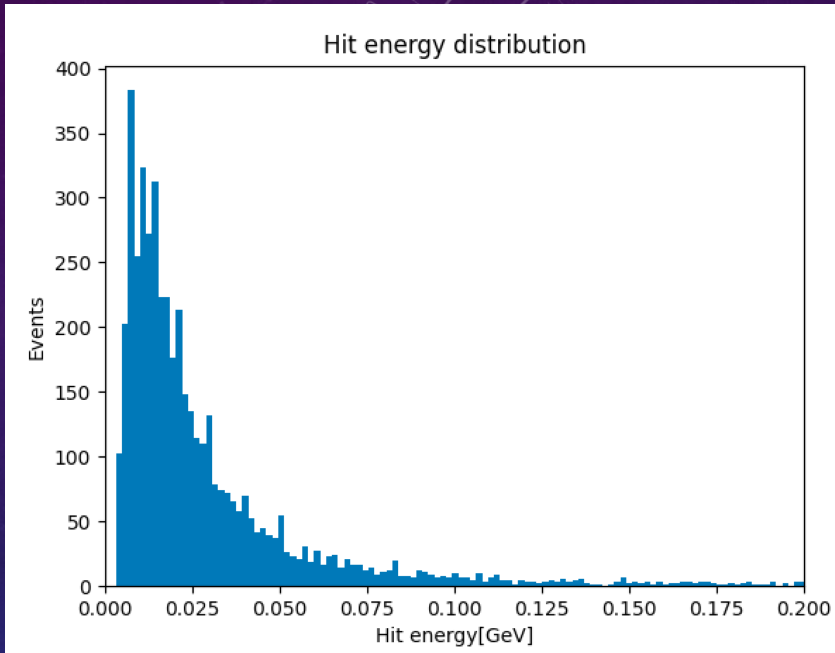
- Data at Ecal and Hcal hits.
- Number of events : 1600

Hit position(one event)



From upper side

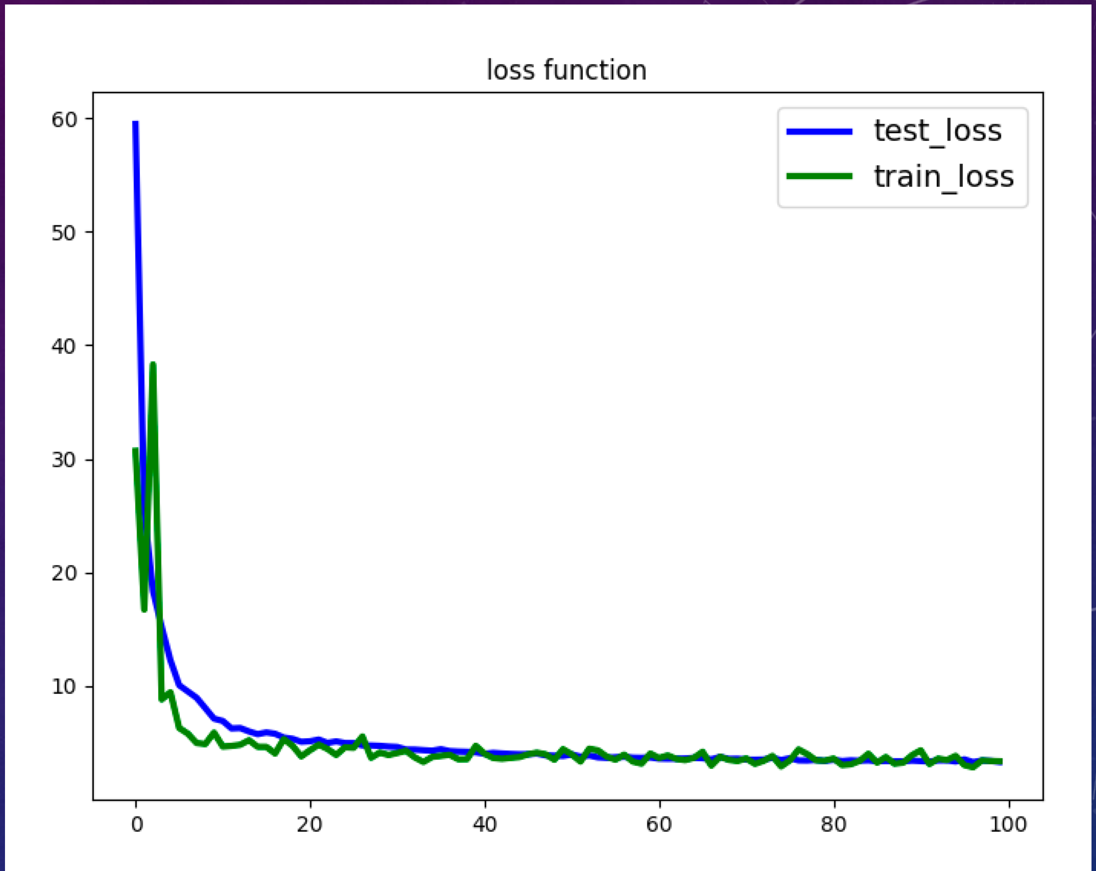




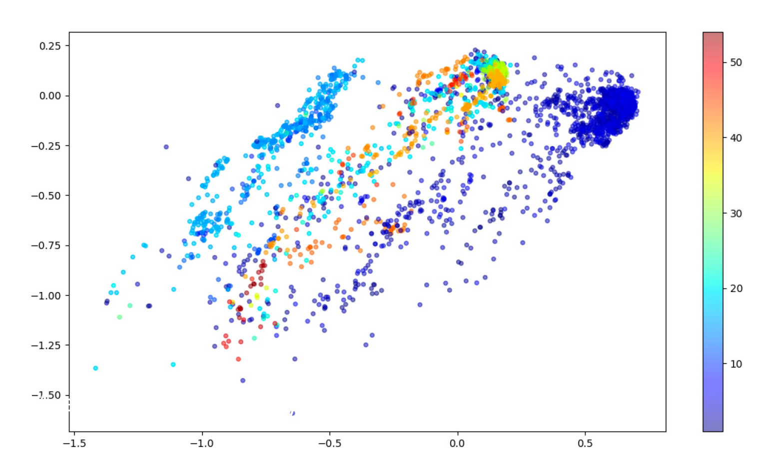
Hit energy distribution
(one event)

Results

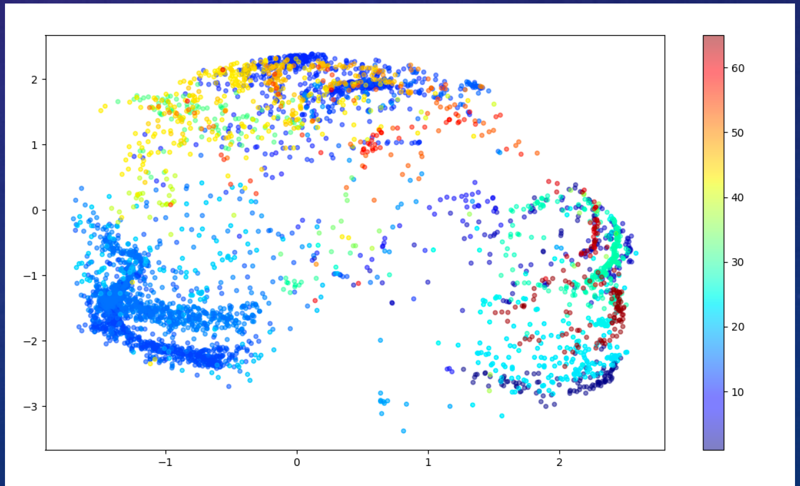
- Loss functions of both training and training data are decreasing
  → Learning works correctly.



Representation Space (2D)



Before training



After 70 epochs

SUMMARY

- Graph Neural Networks are applied to the PFA and shower clustering algorithms in the ILC analysis framework.
- Sixteen hundreds events of Hit data measured with Ecal /Hcal are used as simulation data.
- The training results showed a decrease in the loss function for both the training and evaluation data.

Plan :

- We are planning to prepare simpler input data to evaluate the performance of GravNet more efficiently.
  - Data includes two shower events generated from only the two MC particles
- Evaluation of the network as

$$\text{Accuracy} = \frac{\text{hits in each cluster predicted correctly}}{\text{True hits in each cluster}}$$