High level reconstruction with DNN for Higgs factories

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collaborating with
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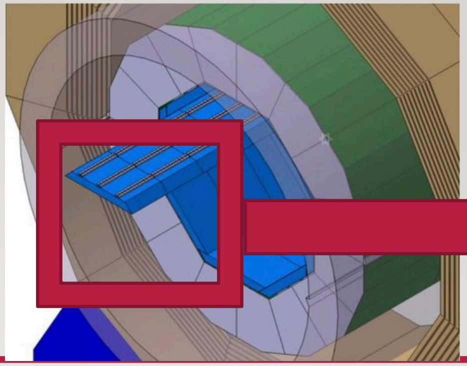
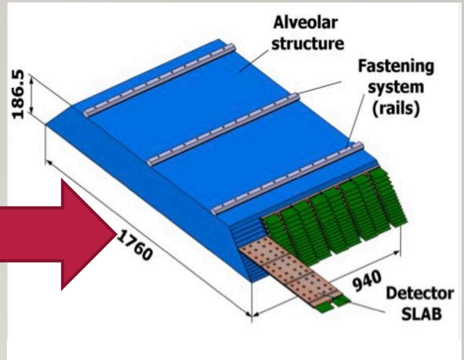
L. Gray, T. Klijnsma (Fermilab)

Contents

- Calorimeter clustering with GravNet/Object condensation
  - Slides from S. Tsumura
- b/c tagging with Graph Attention Network
  - Slides from T. Onoe

3 ILD / SiW ECAL

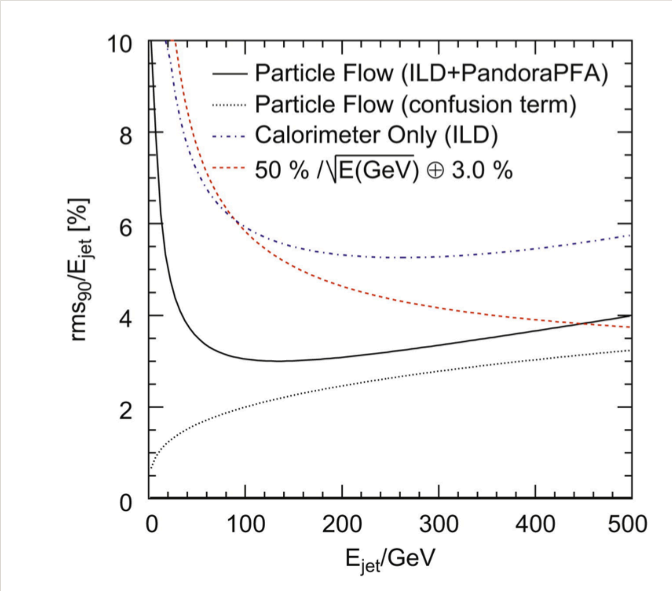


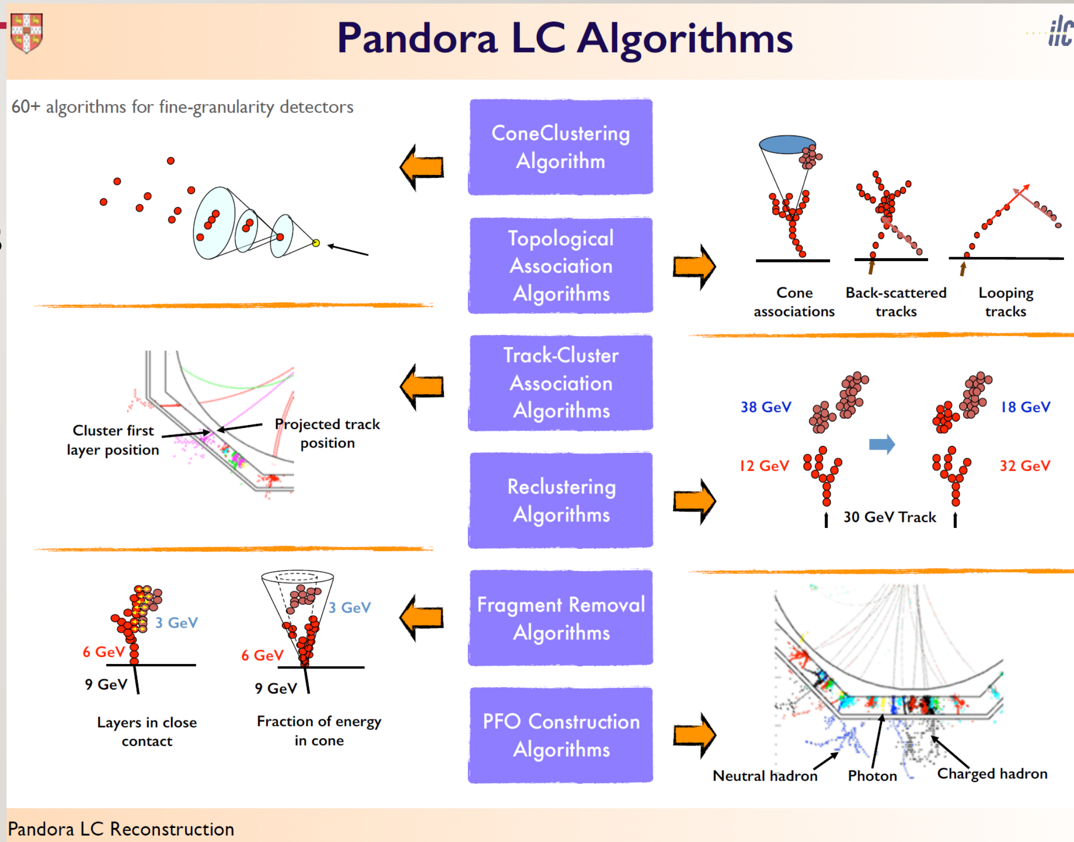


- Electromagnetic calorimeter (ECAL): Detects positions , and energy of gamma rays
  → Higher accuracy of particle identification: PFA
- SiW ECAL equips a lot of channels (~10^8) to identify each particle.
- Sandwich structure with 30 alternating layers of Si detection layer and W absorption layer.
- 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

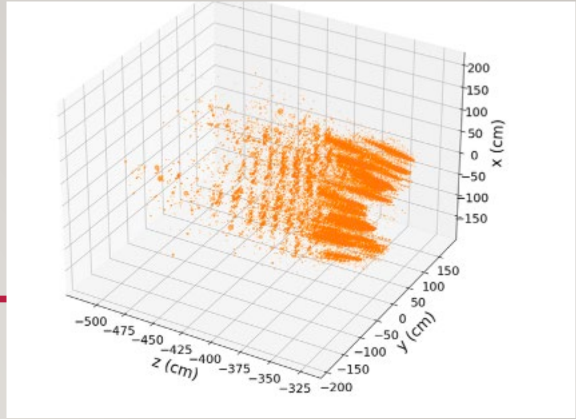
4 Application of Deep Learning to PFA

- Current PFA algorithm : PandoraPFA
  →The pattern recognition based on the human-tuned parameters
- Our targets:
  - Improve performance by reducing confusion term
  - Adding timing information
  - Checking detector effects on
    - Granularity (inc. MAPS?)
    - Timing resolution





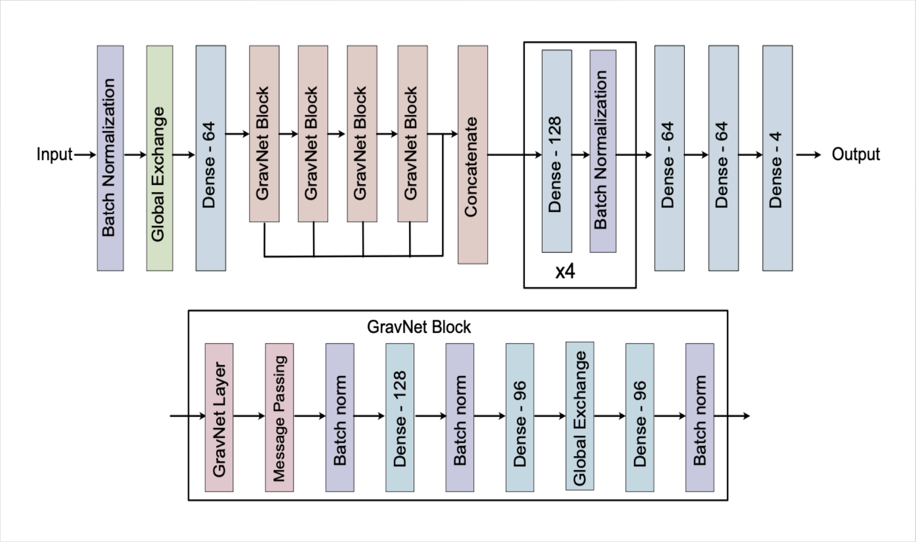
Simple sim with HGCal-like geometry

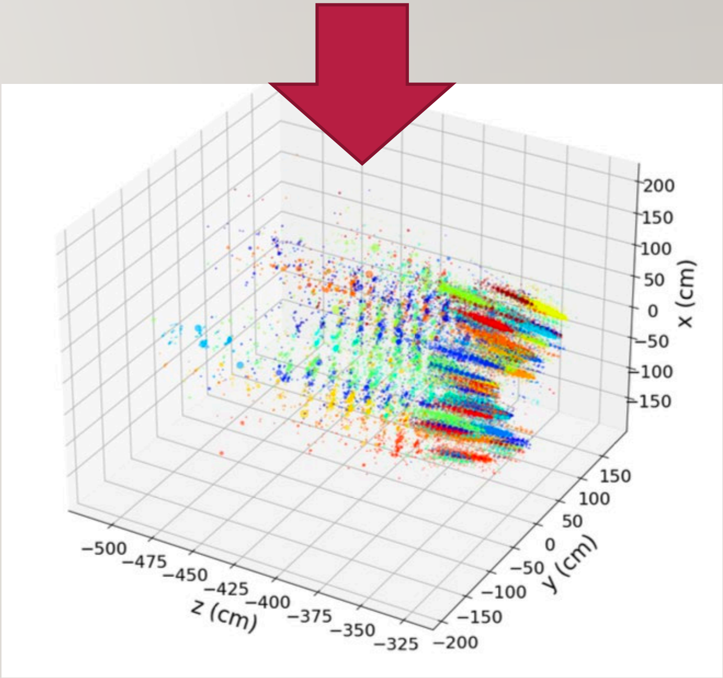


5 Calorimeter Clustering

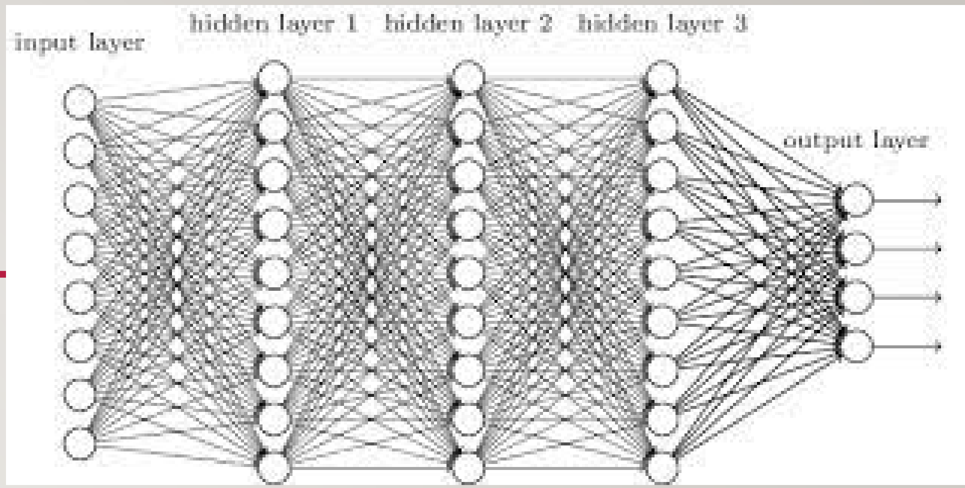
- Input: features of hit in the calorimeter e.g., position, energy, etc.
  → discriminate each cluster
- Deep Learning Architecture
  - Based on Graph Neural Network developed for CMS HGCal

(collaboration with L. Gray et al. (Fermilab))



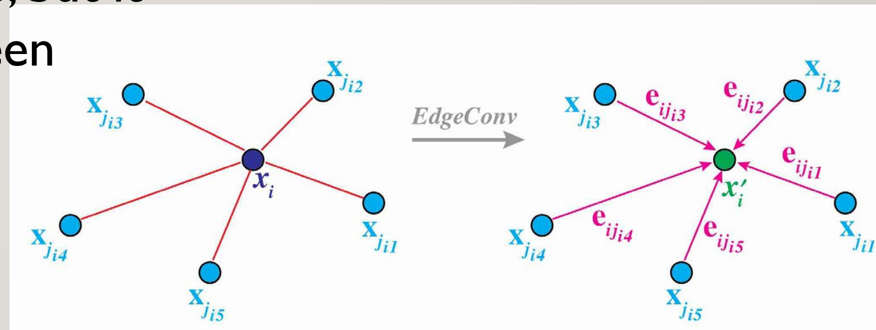


6 Deep Learning



Fully Connected Layer
- One of the most basic structures in deep learning
- Consists of an input layer, a hidden layer, and an output layer
- A more expressive network can be built by increasing the number of layers

Graph Neural Network
- A 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.

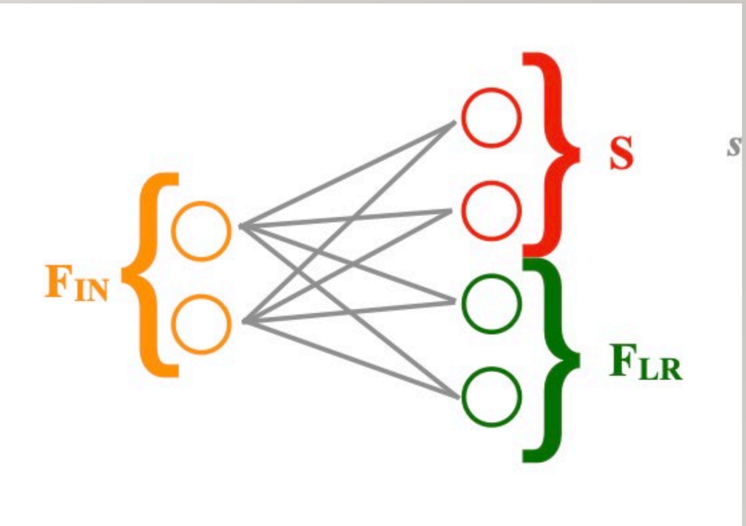


7 GravNet

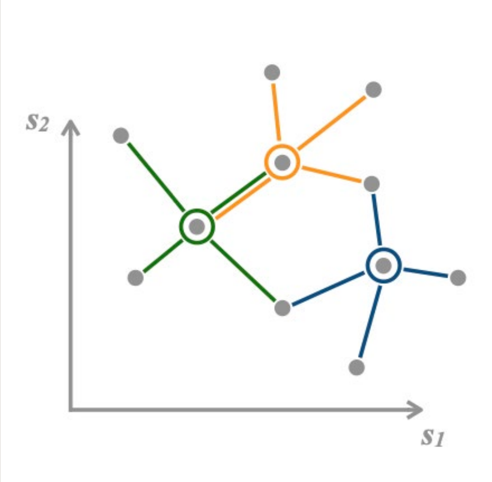
- Input Data : $V \times F_{IN}$

V : Number of hits for each detector

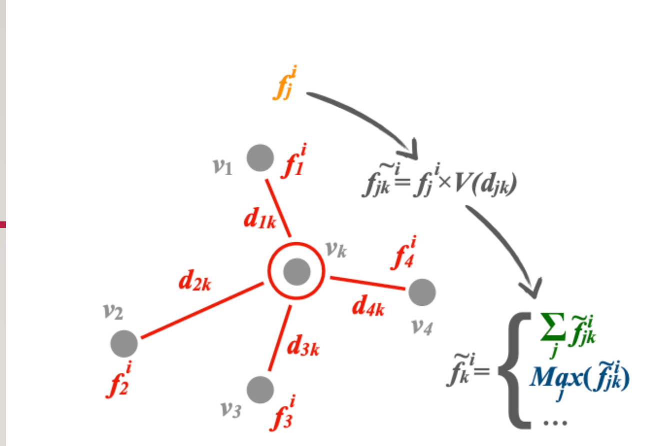
$\mathrm{F_{IN}}$: Number of the features for each hit

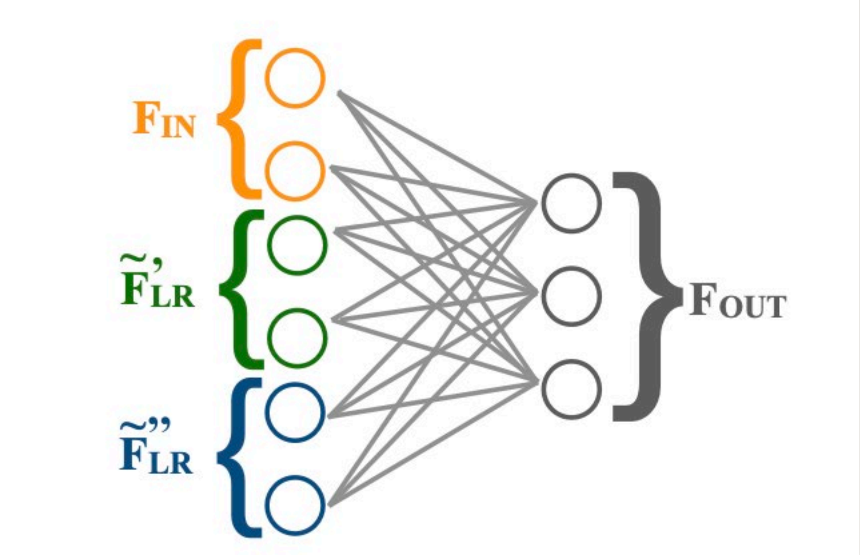


- S : Set of coordinates in some learned representation space
- F_{LR} : learned representation of the vertex features
- Input data of initial dimension $V \times F_{IN}$ is converted into a graph.
- The coordinates of the graph is updated by the learning of the network.



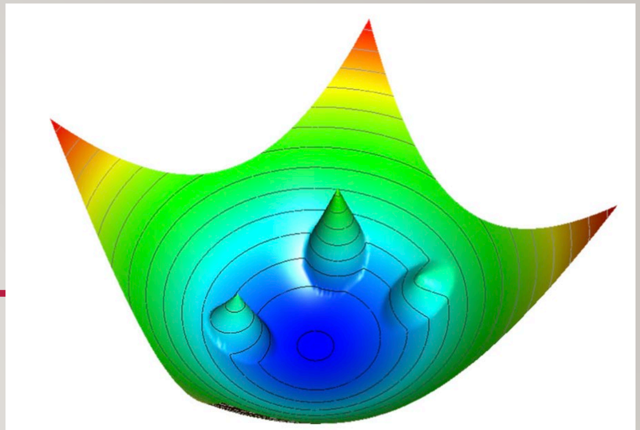
8 GravNet





- 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.

9 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

$$L = L_V + L_\beta$$

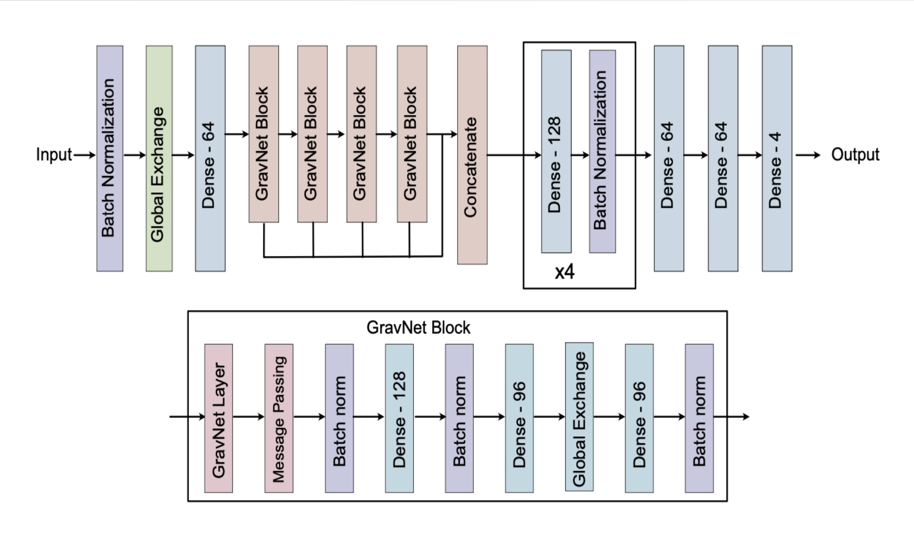
- L_V :The closer the hit is to a particle with high β and belonging to the same particle, the smaller it is, and the more it belongs to a different particle, the larger it is.
  → Equivalent to the attractive and repulsive forces acting on an electric charge
- L_β : Converge β to 1 for only one of each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

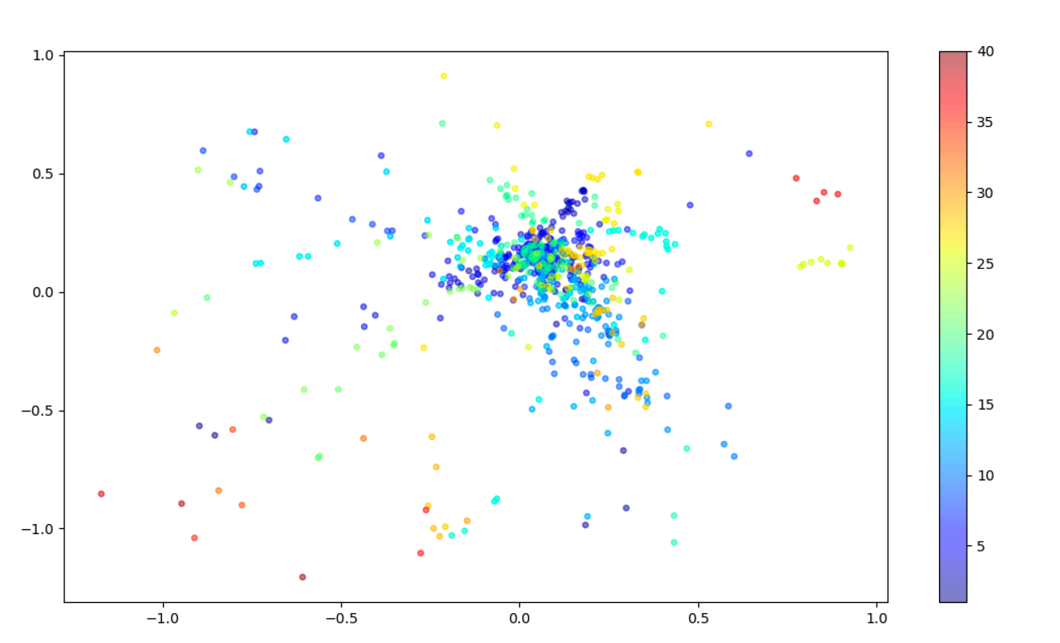
Output of network
- Beta (condensation)
- 2 x coordinate

per hit
Used for clustering

10 Clustering

- Get "condensation point" with hits with beta > threshold
- Cluster other hits to nearest condensation point in the virtual coordinate (of network output)

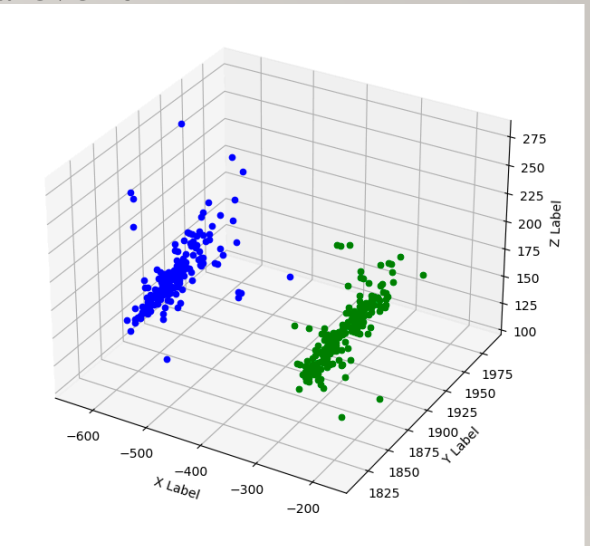




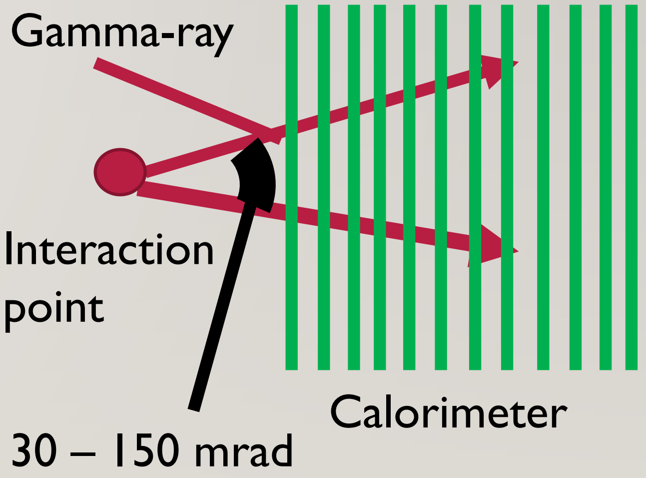
Generation of Input Data

- Two gamma events are generated by ILD detector simulation
- 10000 Events are generated for each of the five data sets from 30 to 150 mrad
- θ: 85/180 π , ϕ: random, momentum: 5.0 GeV

Two gamma event

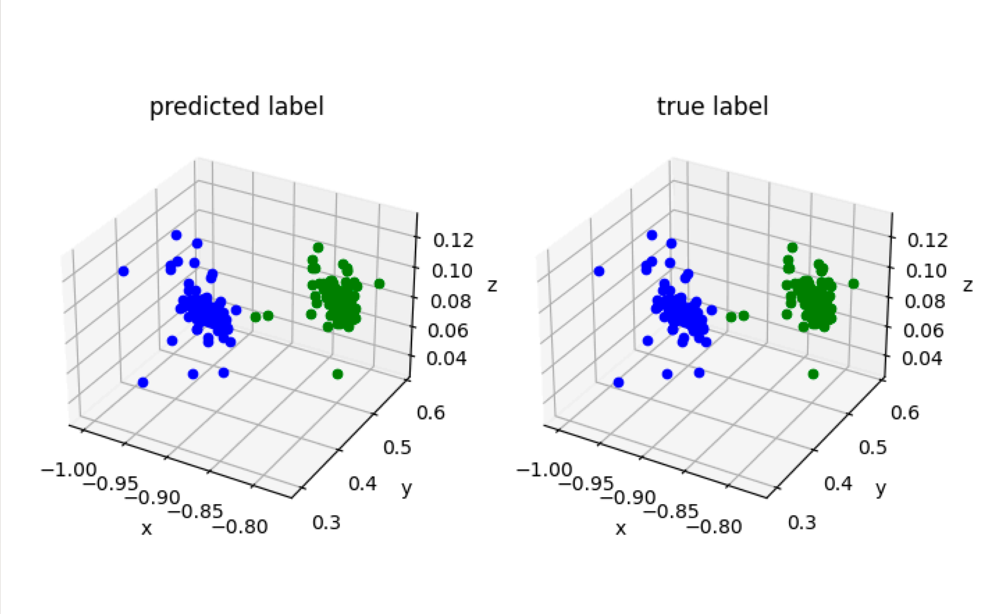


Generation of MC particles → Simulation based on detector geometry by ddsim → Reconstruction of hits in the detector by Marlin

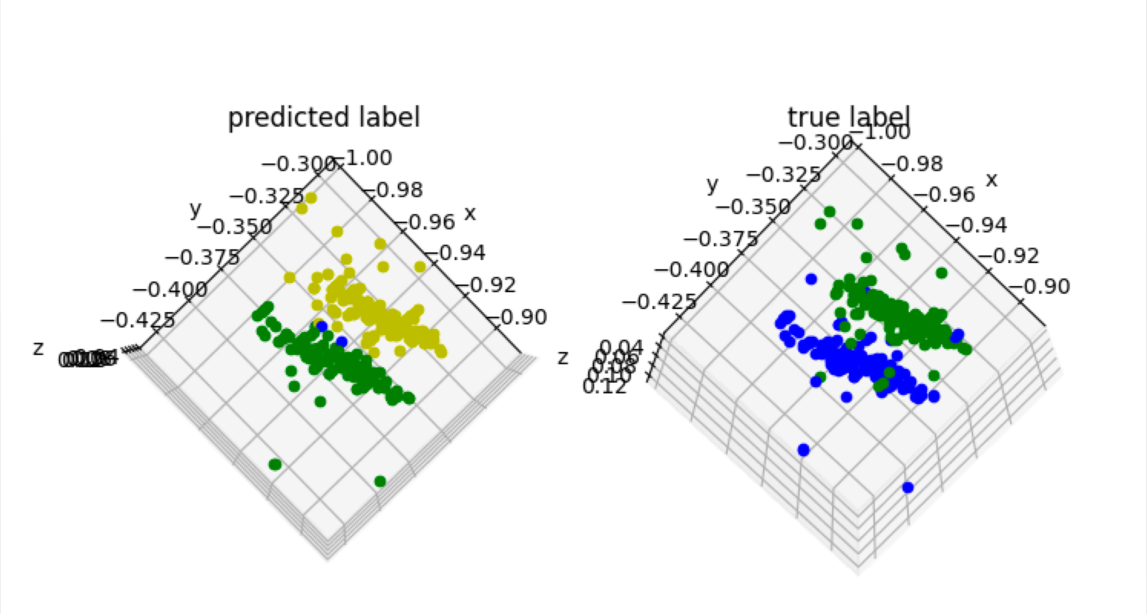


Event Display

Large angle (150 mrad): perfect reconstruction



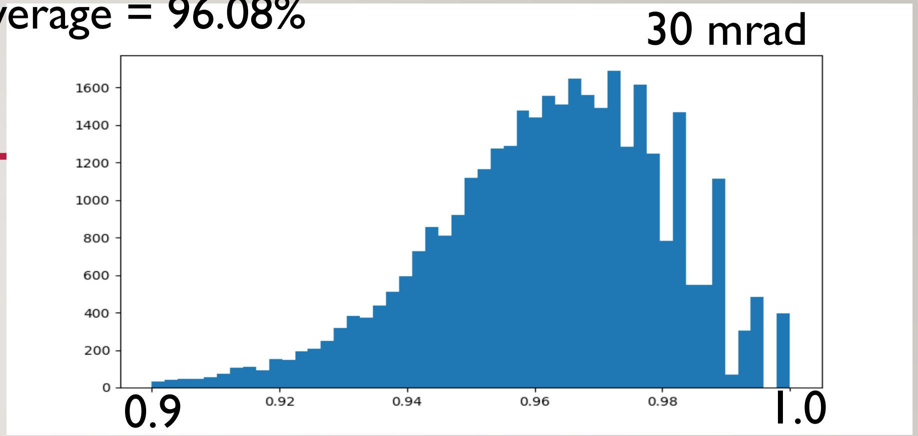
Small angle (30 mrad): a few hits misclustered



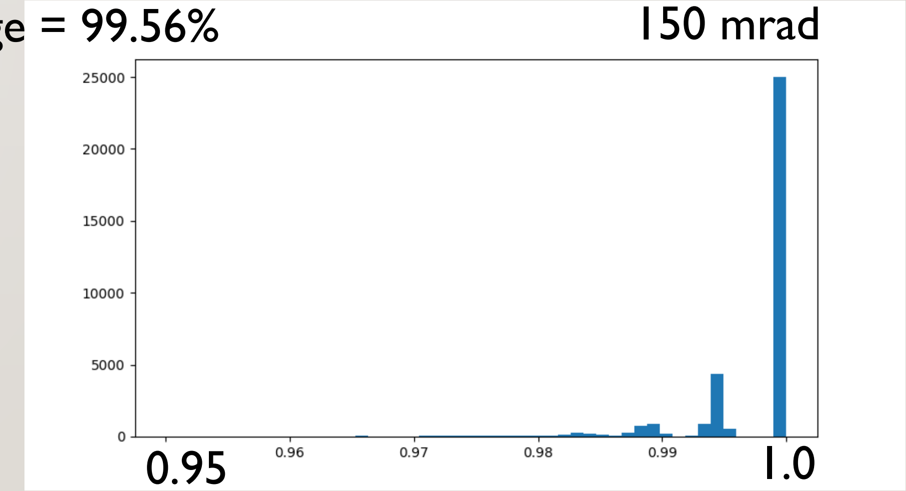
Evaluation of Network

- Accuracy : $\dfrac{\text{Number of hits which is predicted correctly}}{\text{Number of hits with true label of each cluster}}$
- The simulation data includes events where photons are converted into other particles.
- As input data, events with only two clusters are selected

Average = 96.08%



Average = 99.56%



Angle[mrad]	**30**	**60**	**90**	**120**	**150**
Accuracy[%]	96.08	98.64	99.30	99.68	99.56

Plans for PFA in ~this year

- Prepare more complicated data (taus, jets, …)
  - Restructuring data format (npz → awkward arrays)
  - Confirm (or tune) MC truth cluster definition
    - How to treat split clusters
- Track-cluster matching
  - Virtual hit representing a track
    - Position at the entry of calorimeter (with “track” flag)
    - To be forced condensation point – treated by loss function
    - How to integrate momentum (and direction)
      - Additional input to the hit characteristics or add at later stage
- Comparison with PandoraPFA – hoping to be better
  - If better, adapting it to analysis framework (to be used for physics analyses)
- Comparison with timing info included or not included
  - And with different timing resolution

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Jet Flavor Tagging

- Important to identify quarks (b/c/g/uds) of the origin of the jets.
  e.g., Separation of $h \rightarrow b\bar{b}\ /c\bar{c}/q\bar{q}/\ldots$

- Ratio of background can be eliminated determines the limits of analysis cut
- Bottom (b) and charm (c) flavor hadrons have weak interaction
  → b/c hadrons have finite decay lengths
  → Can be identified by finding vertices

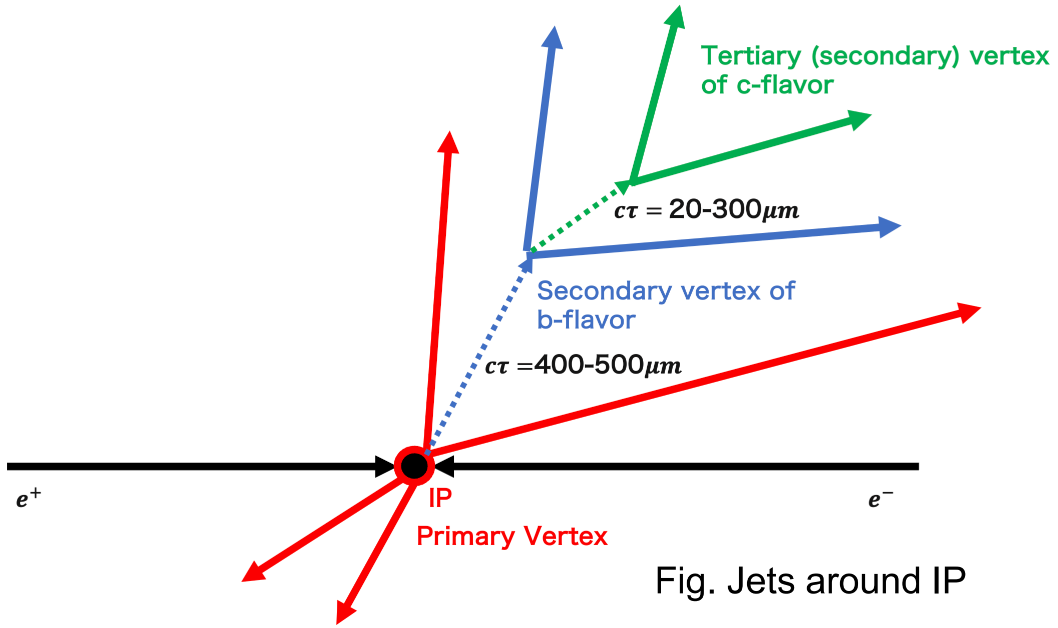


Fig. Jets around IP

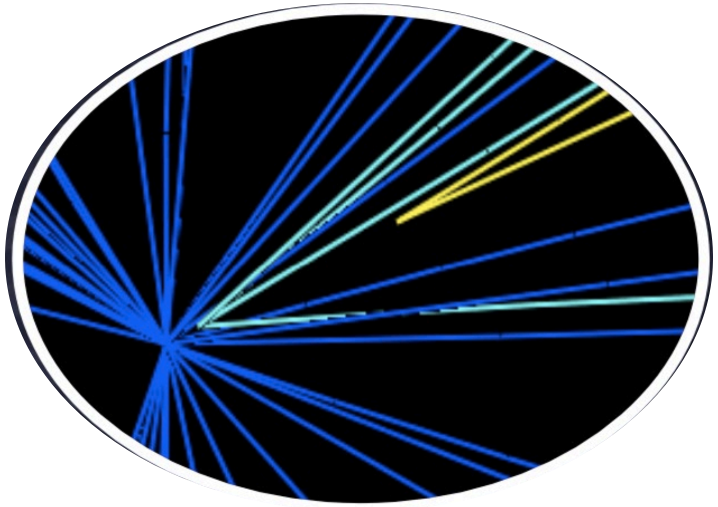


Fig. Monte Carlo simulation of the jet near the IP

Graph Data Approach

Concept

Data is represented as a graph

→ Graph structure data can contain interrelationship by connections

(Fully-connected neural network has no specific relation between nodes)

→ Reduced loss of information when compared to physical phenomena

→ High accuracy of identification is expected

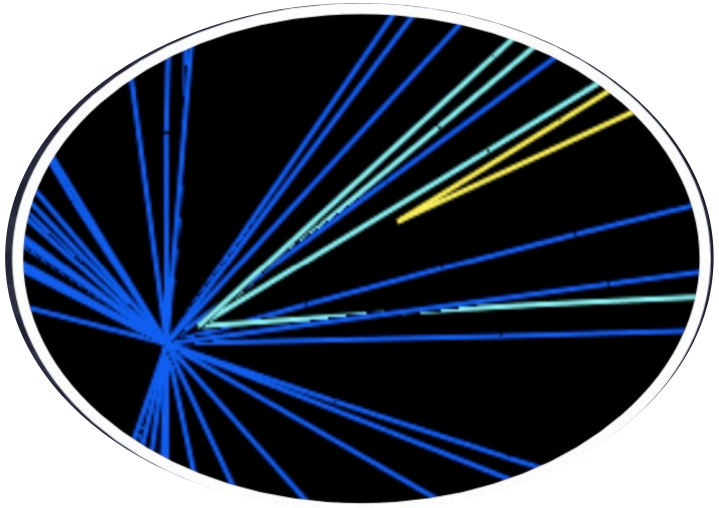


Fig. Event display of Monte-Carlo simulation

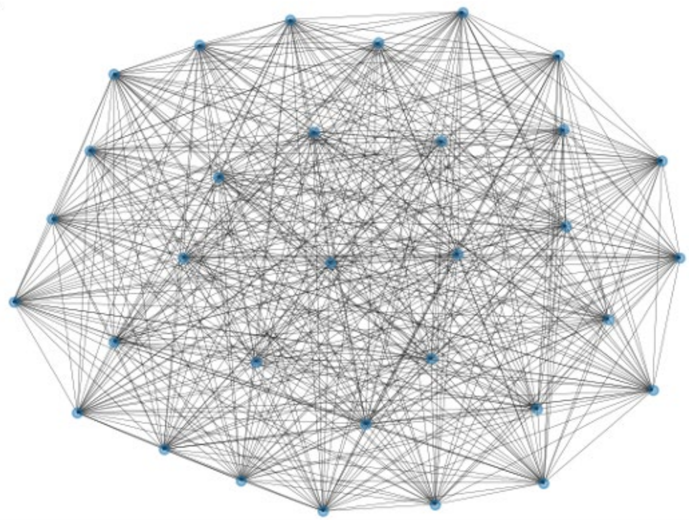


Fig. example of a jet as a graph

Training Data information

Data

- 240,000 jets of 250 GeV ILD full simulation data
  $[\, e^+e^- \rightarrow \nu\bar{\nu}h \rightarrow \nu\bar{\nu}b\bar{b}/c\bar{c}/q\bar{q} \;\; (q = u, d, s)]$

- Build one graph per one jet
- Define the tracks as nodes in the graph
- Edges connect between track pairs

Track Input	
$\mathbf{d_0}$	**Longitudinal distance from track to IP**
$\boldsymbol{\phi}$	**Azimuthal angle of track**
$\boldsymbol{\omega}$	**the curvature of the track**
$\mathbf{z_0}$	**Transverse distance from track to IP**
$\tan\lambda$	**dz/ds in sz plane**
$\sigma(\mathbf{d_0})$	**Uncertainty of** $\mathbf{d_0}$
$\sigma(\mathbf{z_0})$	**Uncertainty of** $\mathbf{z_0}$

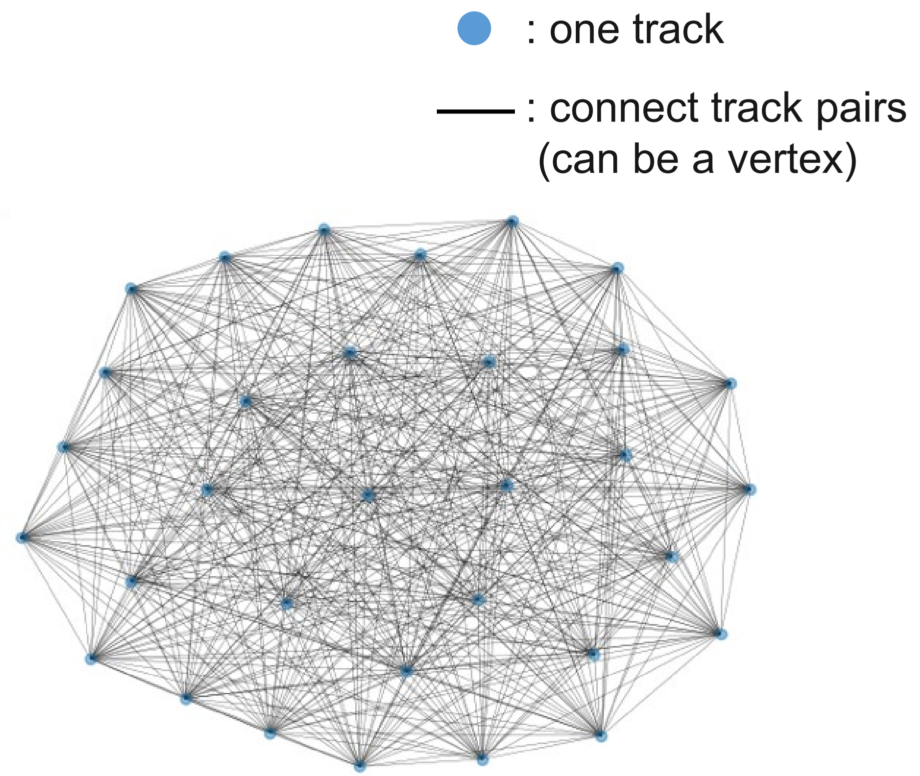


Fig. example of a jet as a graph

Graph Training and GAT

- How to train with graph data (Graph Neural Network; GNN)
  ... Aggregate features from neighboring nodes and update

- We suggest Graph Attention Network (GAT) , a GNN with attention mechanism
- Attention mechanism ... Learn the importance score for each weight
  Take as a coefficient for update parameter.

→ Aimed by attention expressing whether tracks has the same vertex.

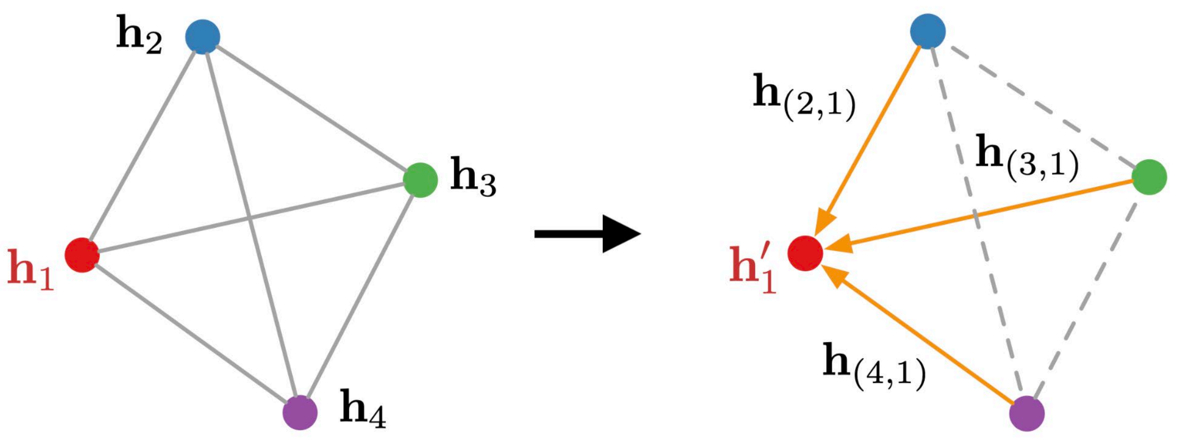


Fig. Graph Training

arXiv [1710.10903]

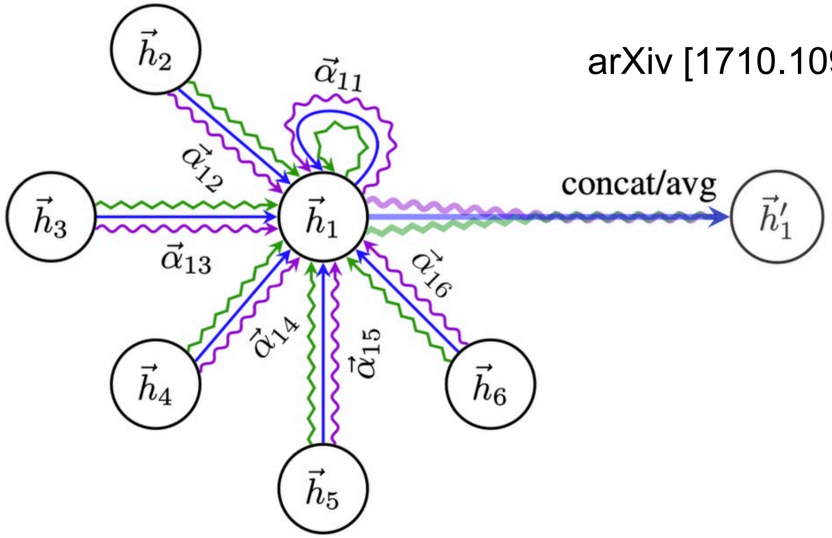


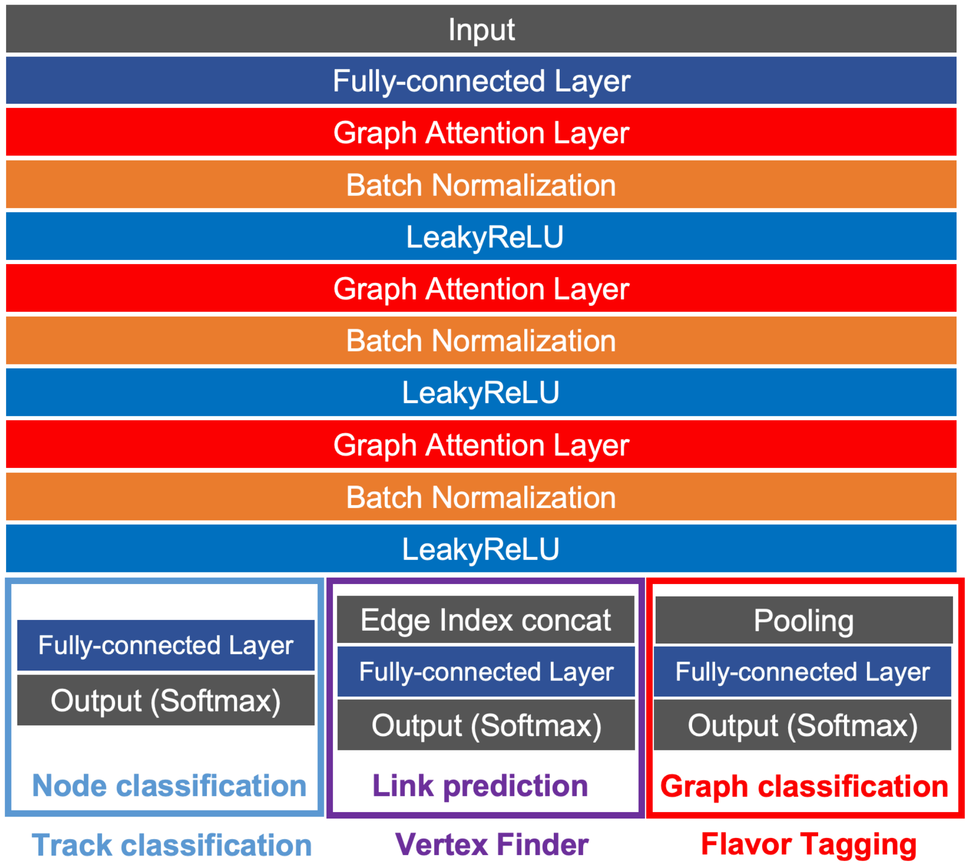
Fig. Graph Attention Network

Training and Network architecture

- Node classification means the origin of tracks as vertices
- Link prediction means whether to form a vertex
- Graph classification means jet flavor tagging
- Loss function

$$L_{total} = L_{Flavor} + \alpha L_{Vertex} + \beta L_{Edge}$$
$$(\alpha \cong 3, \beta \cong 1)$$

Network architecture



Node classification

Label	Description
PV	From primary vertex
SVBB	From secondary vertex of b
SVCC	From secondary vertex of c
TVCC	From tertiary vertex of b
Others	From another particle

Link prediction

Label	Description
Connected	tracks are connected
Not-connected	tracks are not connected

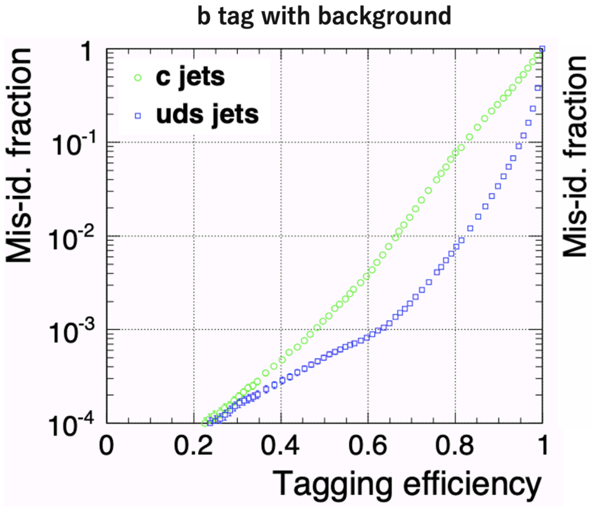
Graph Classification

Label	Description
$b\bar{b}$	the final state of $b\bar{b}$
$c\bar{c}$	the final state of $c\bar{c}$
$q\bar{q}$	the final state of $q\bar{q}$ $(q = u, d, s)$

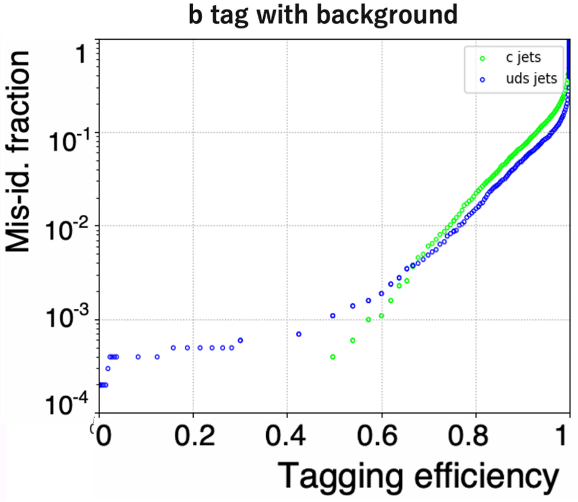
Evaluation of GNN

B tag effciency with background

LCFIPlus

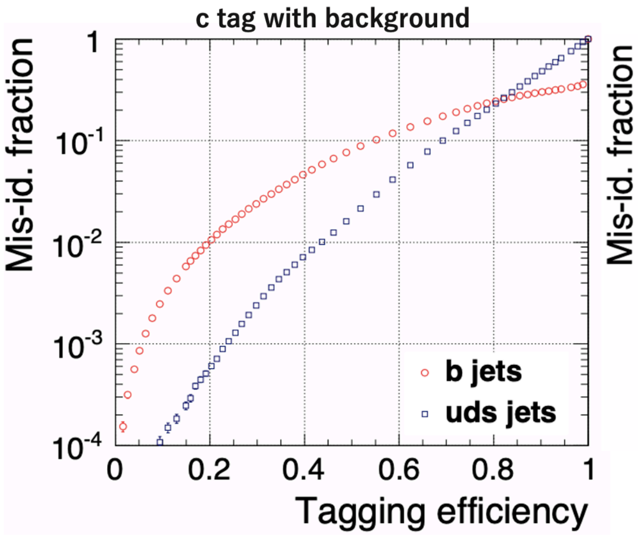


Graph Approach

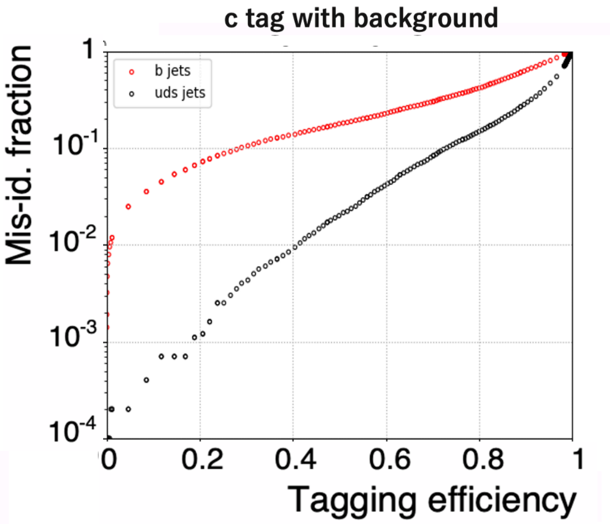


C tag efficiency with background

LCFIPlus



Graph Approach



Tagging efficiency = 0.8	background	Mis-id fraction	
		LCFIPlus	GNN
b jet	c jet	0.073	0.021
	uds jet	0.007	0.015
c jet	b jet	0.22	0.40
	uds jet	0.24	0.14

- For b jet, the ratio of c jet background is reduced.
- For c jet, the ratio of uds jet background is reduced.

- Integrated of Flavor Tagging with Vertex Finder
  → Implementation with low-level of input than LCFIPlus

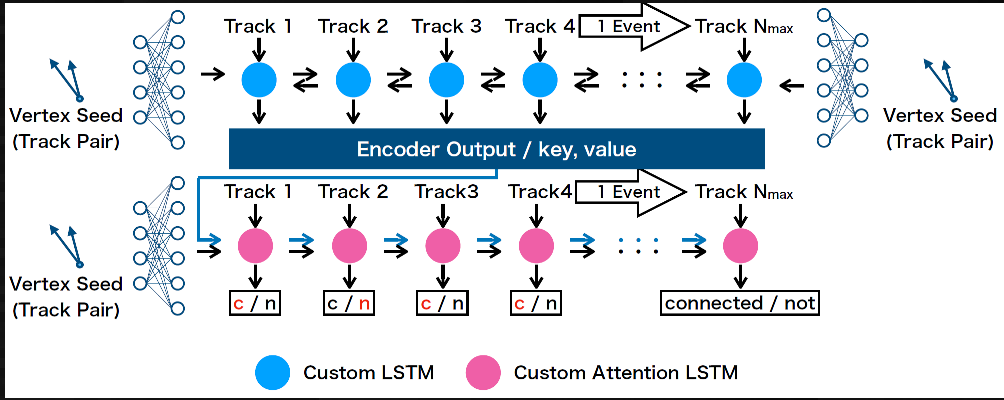
Status and plans in flavor tagging

- Tuning of the GAT-based flavor tagging
  - Investigate reasons for degraded performance on node/edge classification
  - Connecting output (or nearly-output) of node/edge to flavor tagging
- Another methods to be considered
  - Importing LHC method (ParticleNet, LorentzNet etc.)
  - Transformer-like method (graph transformer, set transformer etc.)
- Compare among algorithms as well as LCFIPlus
  - Import it to the analysis framework if better than LCFIPlus
- Considering timing information to be included
  - Dependence of timing resolution also to be seen

Backup slides

Appendix: quark flavor tagging with DNN

- Modified LSTM with attention NIMA 1047 (2023) 167836



Performance of vertex finding in this network

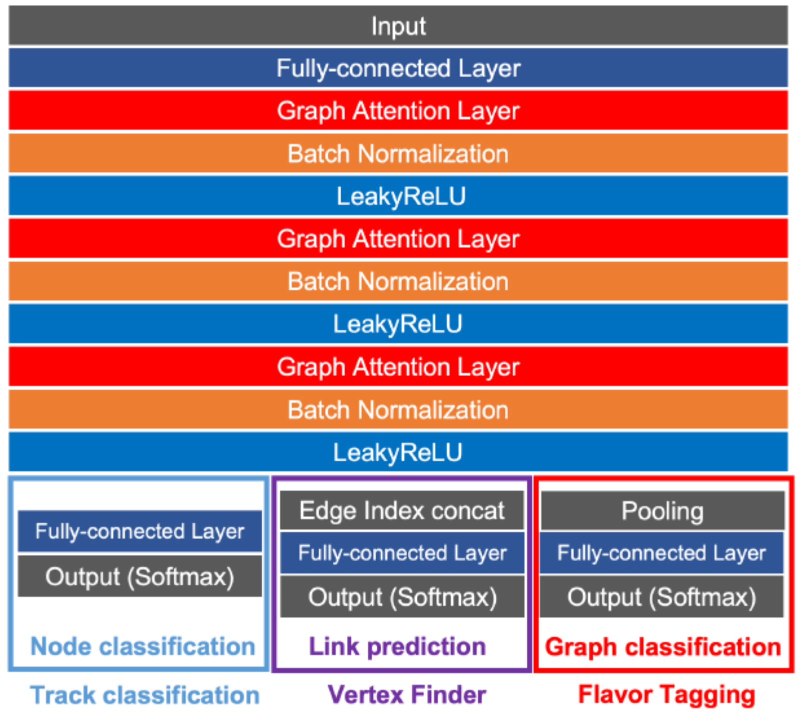
Criteria / True label	Primary	Bottom	Charm	Others
All tracks	307 657	187 283	180 143	42 888
In secondary vertex	2.2%	63.3%	68.4%	9.5%
– of same decay chain		62.3%	67.2%	
– of same parent		38.1%	36.2%	6.4%

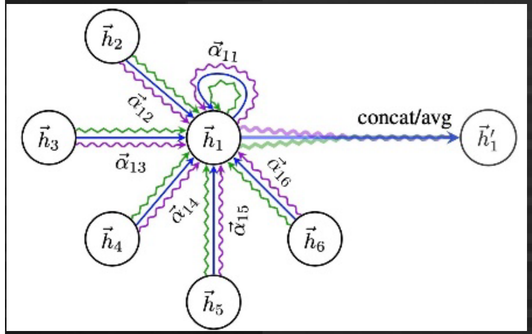
Performance for vertex finding in LCFIPlus

Criteria / True label	Primary	Bottom	Charm	Others
All tracks	307 657	187 283	180 143	42 888
In secondary vertex	0.2%	57.9%	60.3%	0.5%
– of same decay chain		57.5%	59.9%	
– of same parent		34.0%	37.2%	0.3%

Flavor tagging with GNN (ongoing effort)

- Simultaneous classifications of nodes, edges and graphs





Graph Attention Network (GAT)

Tagging efficiency = 0.8	background	Mis-id fraction	
		LCFIPlus	GNN
b jet	*c* jet	0.073	0.021
	uds jet	0.007	0.015
c jet	*b* jet	0.22	0.40
	uds jet	0.24	0.14

Partially better than LCFIPlus

25 GRAVNET - NETWORK -

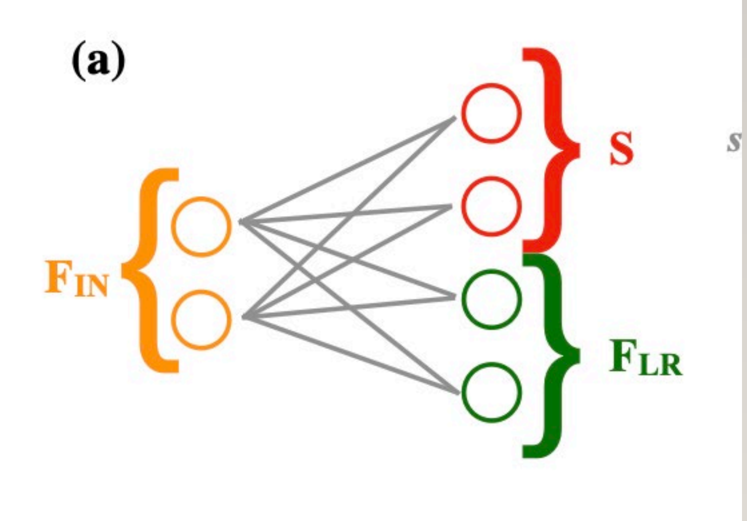
- Input Data : $B \times V \times F_{IN}$

  B ： Number of examples including in a batch

  V ： Number of hits for each detector

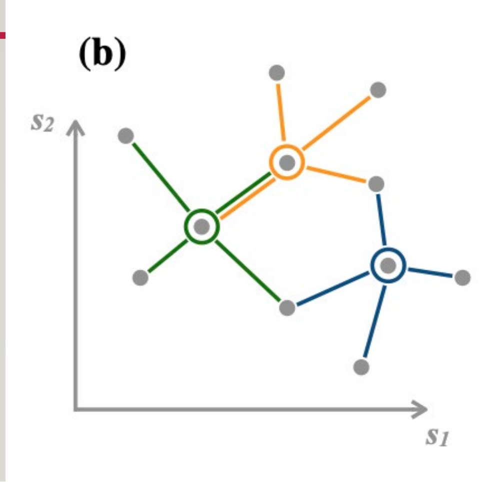
  $\mathrm{F_{IN}}$ ： Number of the features for each hit

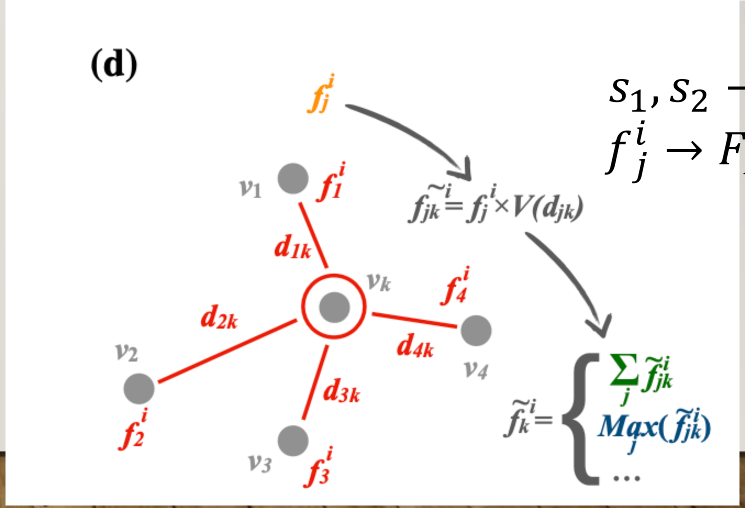
- S : Set of coordinates in some learned representation space
- F_{LR} : learned representation of the vertex features



26 GRAVNET

- Input example of initial dimension $V \times F_{IN}$ is converted into a graph.
- the f_j^i features of the v_j vertices connected to a given vertex or aggregator v_k are converted into the $\widetilde{f_{jk}}^i$ quantities, through a potential
  (function of euclidean distance d_{jk}).
- The potential function $V(d_{jk})$ is introduced to enhance the contribution of close-by vertices.
  Example: $V(d_{jk}) = \exp(-d_{jk}^2)$
- The $\widetilde{f_{jk}}^i$ functions computed from all the edges associated to a vertex of aggregator v_k are combined, generating a new feature $\widetilde{f_k}^i$ of v_k.
  Example : the average of the $\widetilde{f_{jk}}^i$ across the j edges / their maximum

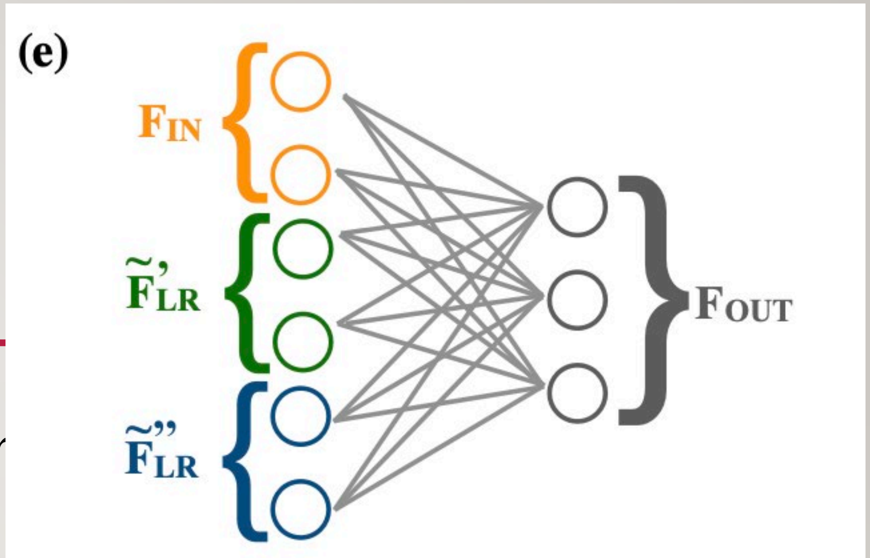




$s_1, s_2 \rightarrow S$

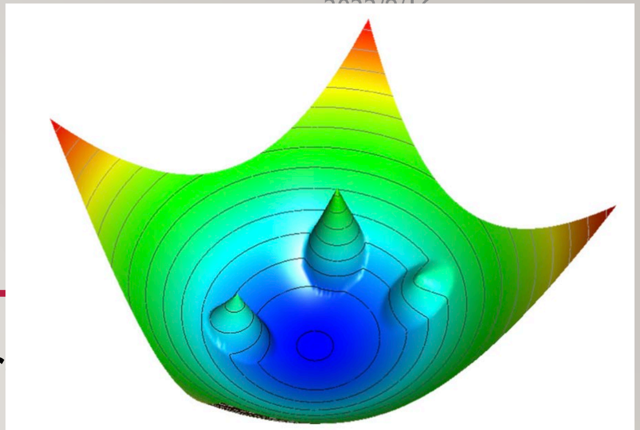
$f_j^i \rightarrow F_{LR}$

GRAVNET



- For each choice of gathering function, a new set of featur
- The $\widetilde{F_{LR}}$ vector is concatenated to the initial vector.
- Activation function : tanh
- The F_{OUT} output carries collective information from each vertex and its surrounding.

28 Object Condensation



- Get the output from GravNet as β and output whether the hit seems to be a r
  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

29 LOSS FUNCTION - NETWORK LEARNING -

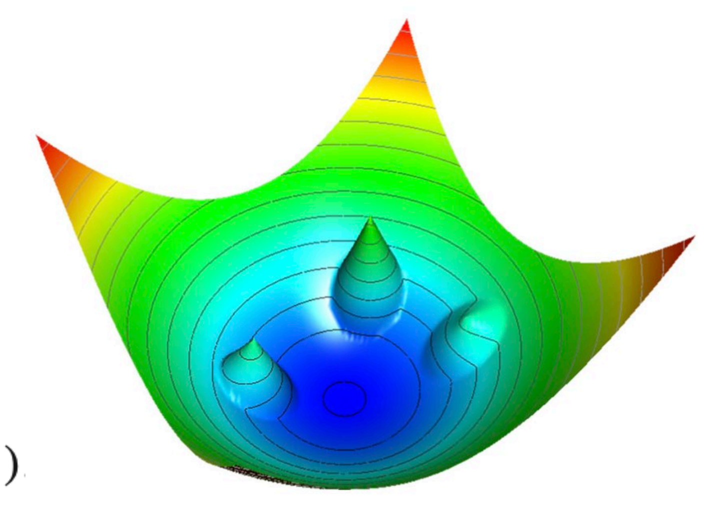
- The value of β_i $(0 < \beta_i < 1)$ is used to define a charge q_i per vertex i

$$q_i = \operatorname{arctanh}^2 \beta_i + q_{\min} \quad (\beta_i \to 1 : q_i \to +\infty)$$

- The charge q_i of each vertex belonging to an object k defines a potential $V_{ik}(x) \propto q_i$
- The force affecting vertex j can be described by

$$M_{ik} = \begin{cases} 1\ (vertex\ i\ belonging\ to\ object\ k) \\ 0\ (otherwise) \end{cases}$$

$$q_j \cdot \nabla V_k(x_j) = q_j \nabla \sum_{i=1}^{N} M_{ik} V_{ik}(x_j, q_i)$$



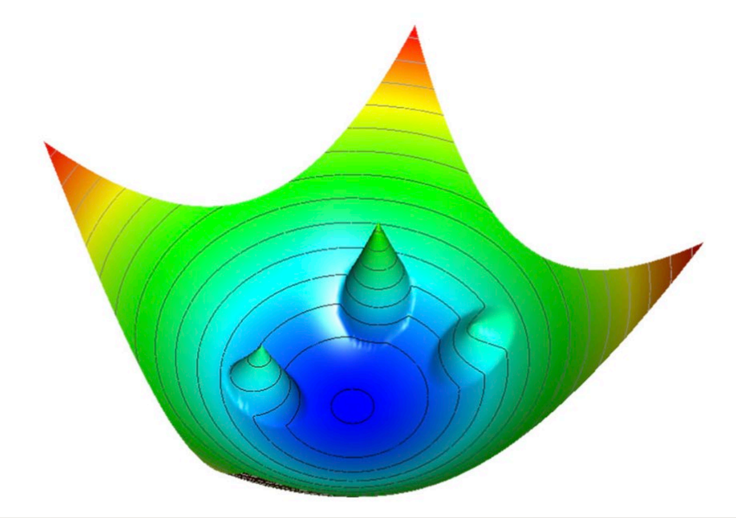
30 LOSS FUNCTION

- The potential of object k can be approximated :

$$V_k(x) \approx V_{\alpha k}(x, q_{\alpha k}), \quad \text{with } q_{\alpha k} = \max_i q_i M_{ik}.$$

- An attractive and repulsive potential are defined as :

$$\check{V}_k(x) = \|x - x_\alpha\|^2 q_{\alpha k}, \text{ and}$$
$$\hat{V}_k(x) = \max(0, 1 - \|x - x_\alpha\|) q_{\alpha k}.$$



- The total potential loss L_V :

$$L_V = \frac{1}{N} \sum_{j=1}^{N} q_j \sum_{k=1}^{K} \left(M_{jk} \check{V}_k(x_j) + (1 - M_{jk}) \hat{V}_k(x_j) \right).$$

31 LOSS FUNCTION

- The L_V has the minimum value for $q_i = q_{\min} + \epsilon \; \forall i$
- To enforce one condensation point per object, and none for background or noise vertices, the following additional loss term L_β is introduced :

$$L_\beta = \frac{1}{K}\sum_k (1 - \beta_{\alpha k}) + s_B \frac{1}{N_B}\sum_i^N n_i \beta_i,$$

s_B : hyperparameter describing the background suppression strength
K : Maximum value of objects
N_B : Number of background
n_i : Noise tag (if noise, it equals 1.)

- The loss terms are also weighted by $\operatorname{arctanh}^2 \beta_i$:

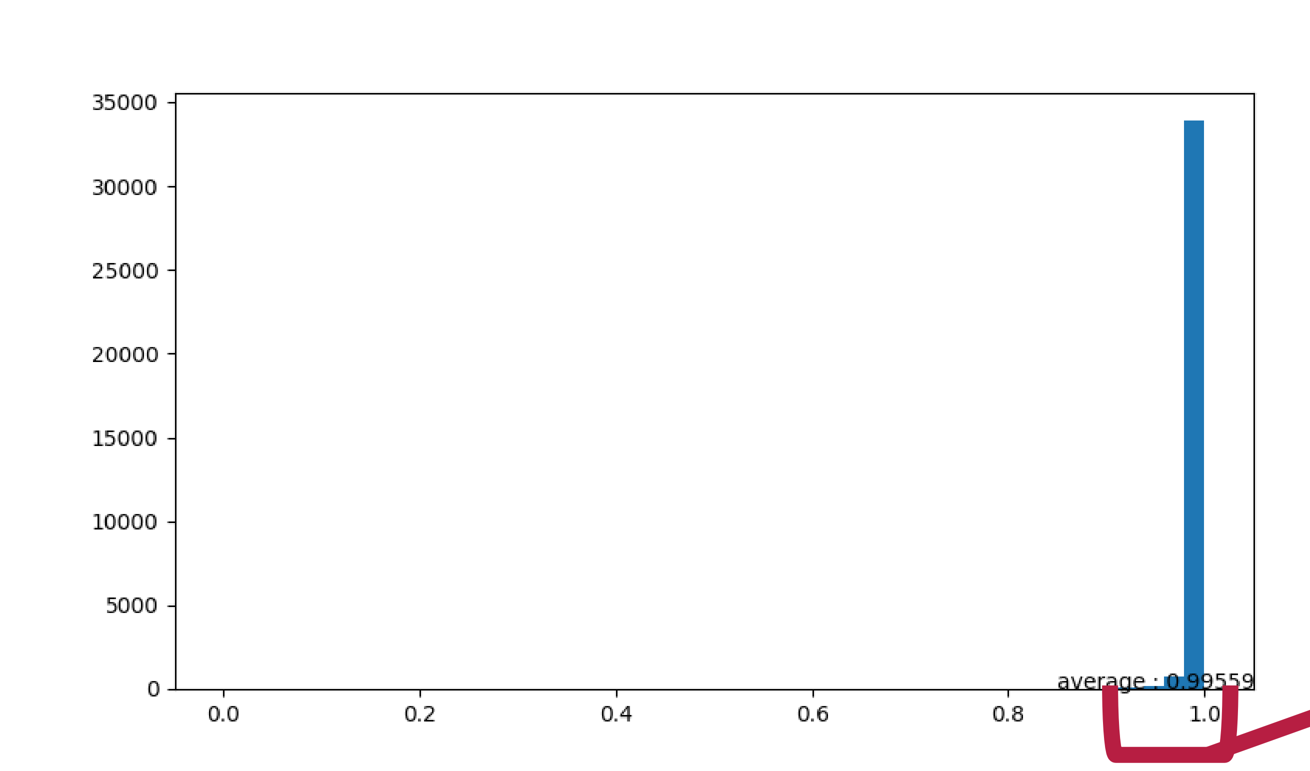
$$L_p = \frac{1}{\sum_{i=1}^N \xi_i} \cdot \sum_{i=1}^N L_i(t_i, p_i)\, \xi_i, \text{ with}$$

$$\xi_i = (1 - n_i) \operatorname{arctanh}^2 \beta_i .$$

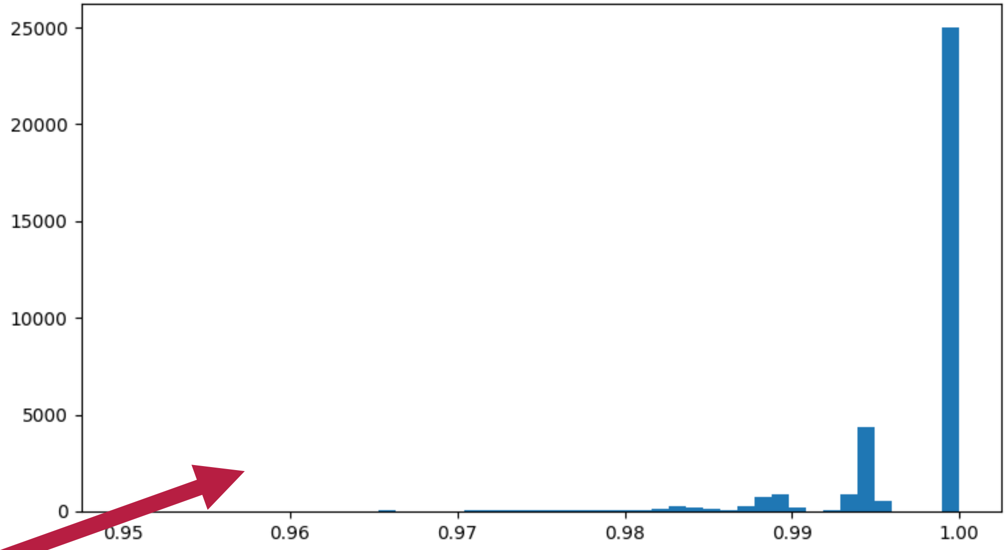
p_i: Featutes
$L_i(t_i, p_i)$: Loss term (Difference between true labels and outputs of network)

EVALUATION

- Accuracy = $\frac{Number\ of\ hits\ with\ predicted\ label\ correctly}{Number\ of\ \ hits\ with\ true\ label}$
- Opening angle = 0.5 rad (the largest one)
- Event selection : events which include 2 clusters



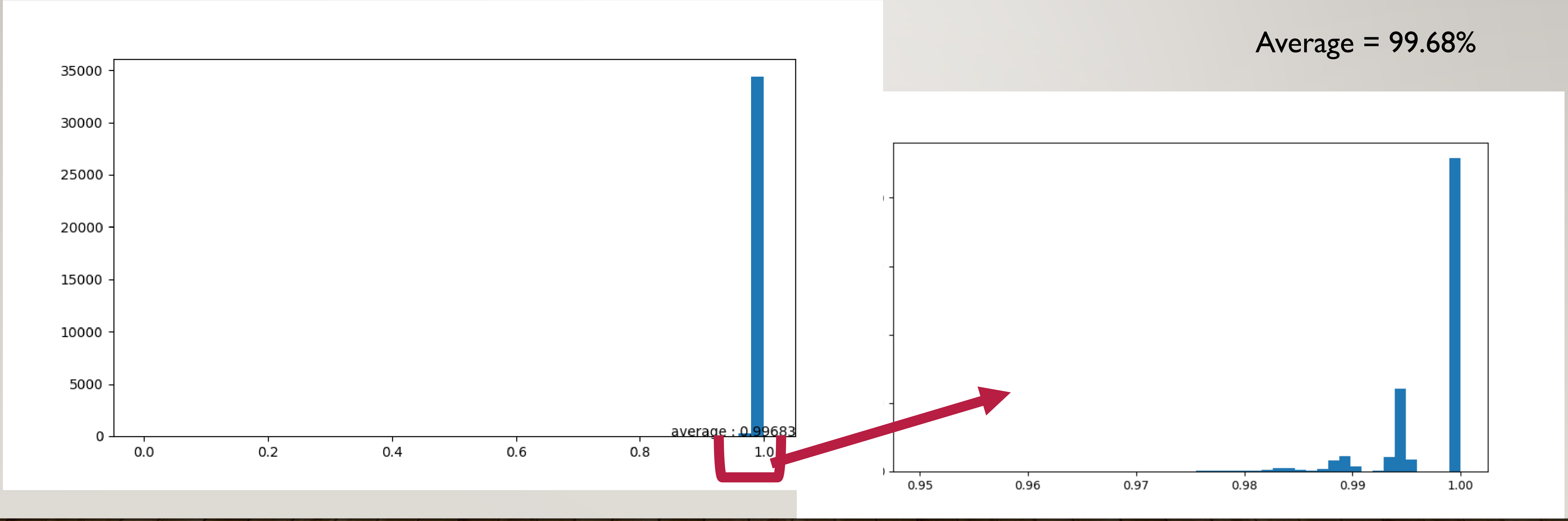
Average = 99.56%



EVALUATION

Opening angle = 0.4 rad

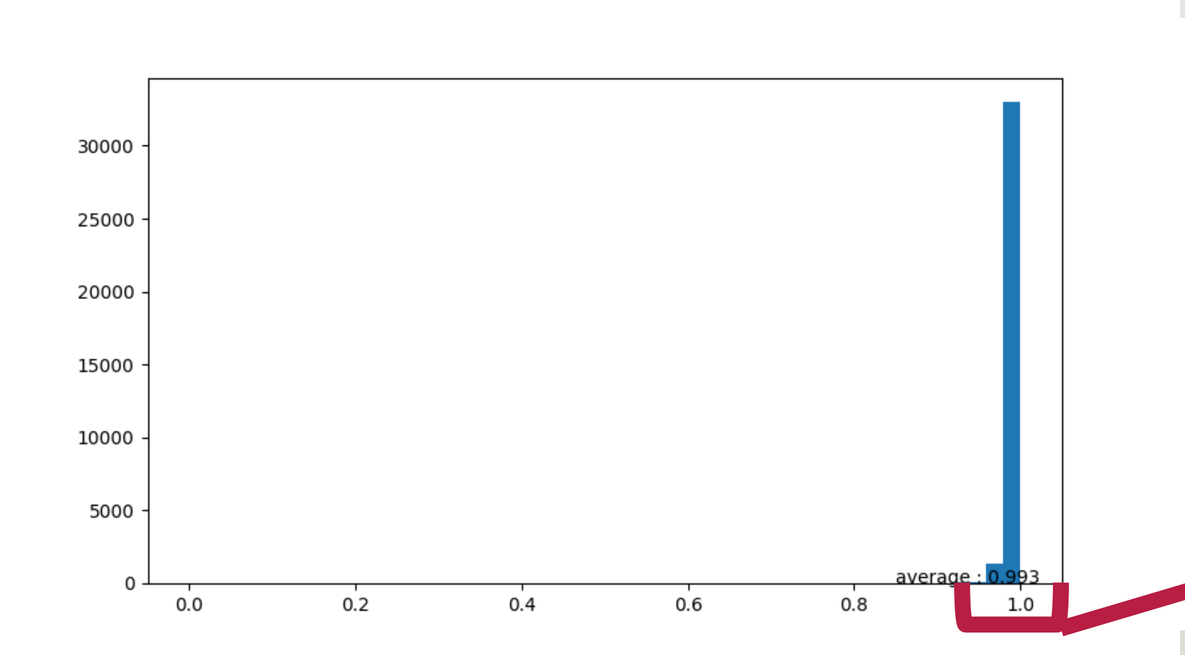
Average = 99.68%

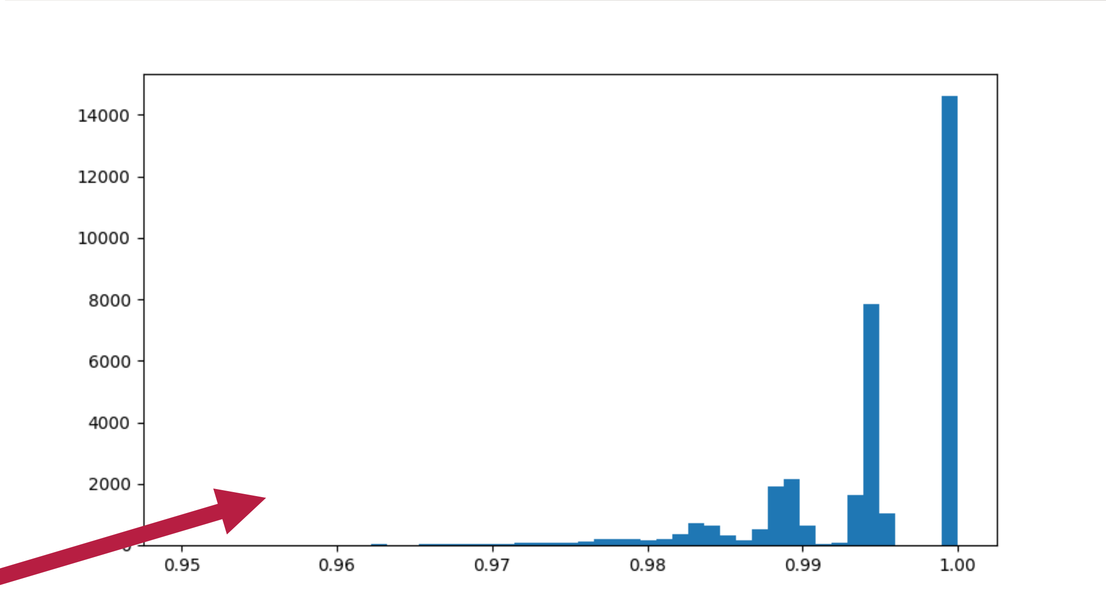


EVALUATION

Opening angle = 0.3 rad

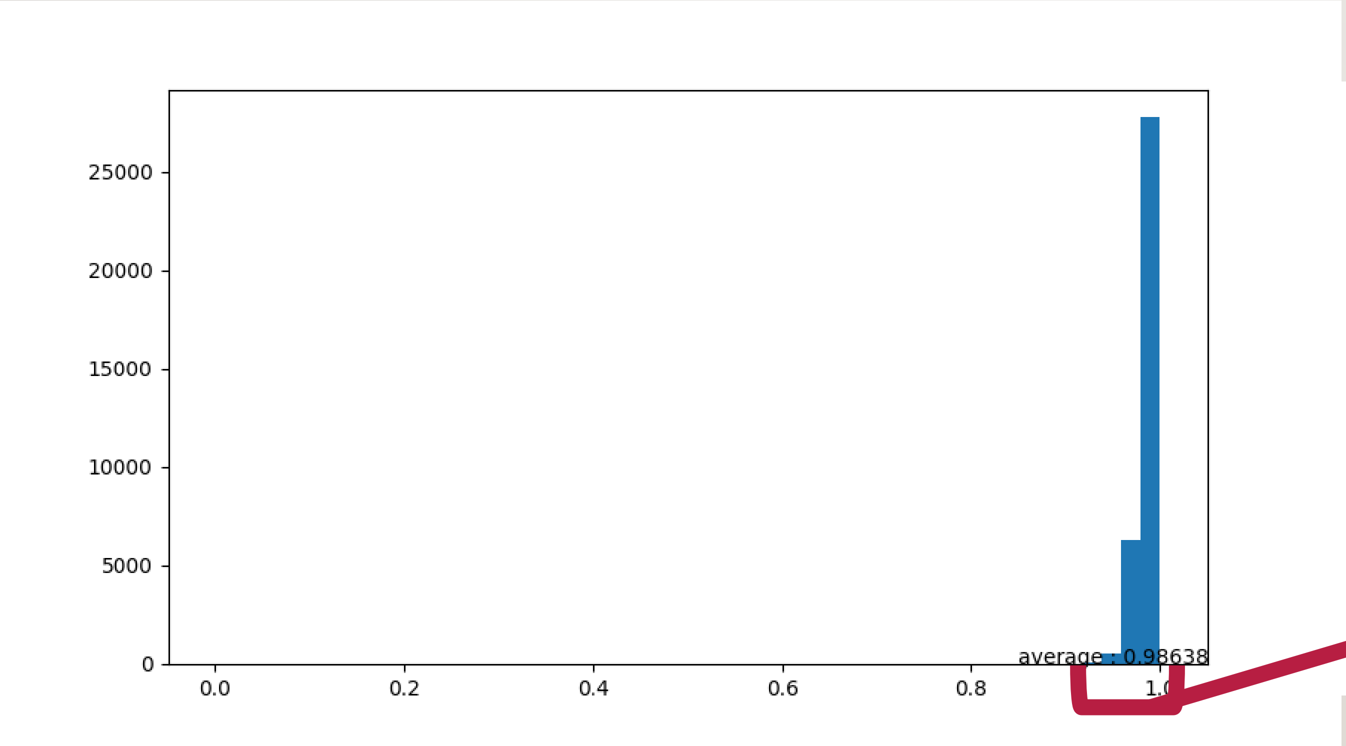
Average = 99.30%



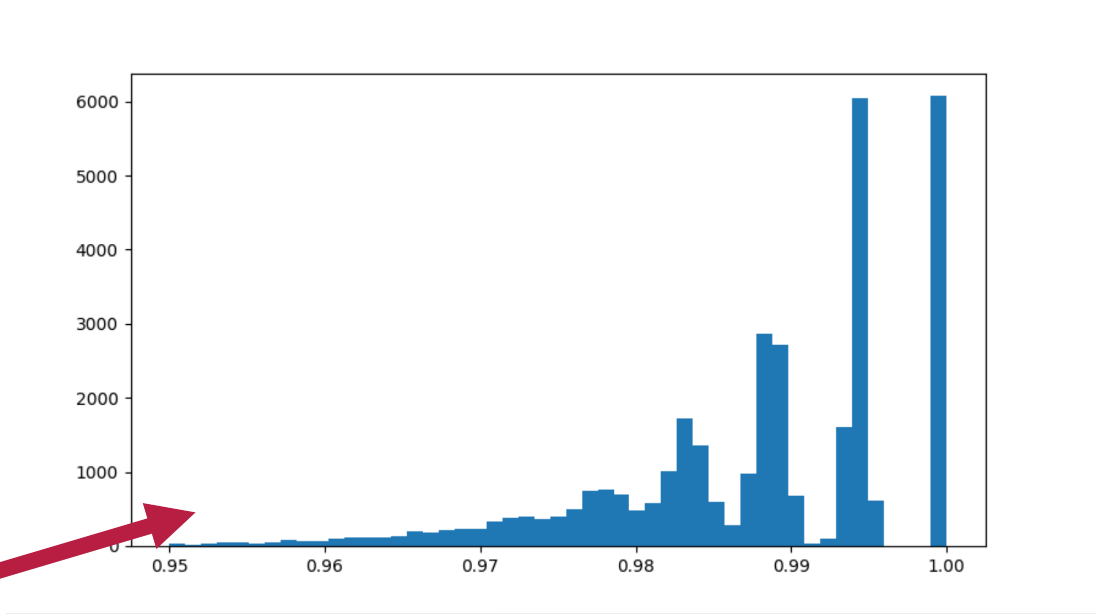


EVALUATION

Opening angle = 0.2 rad



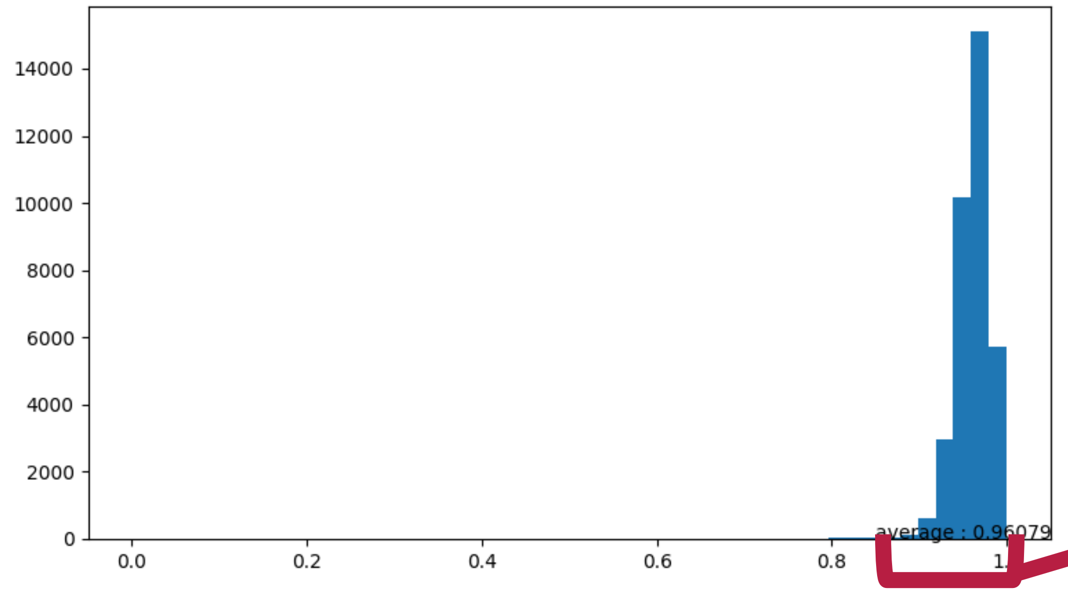
Average = 98.64%

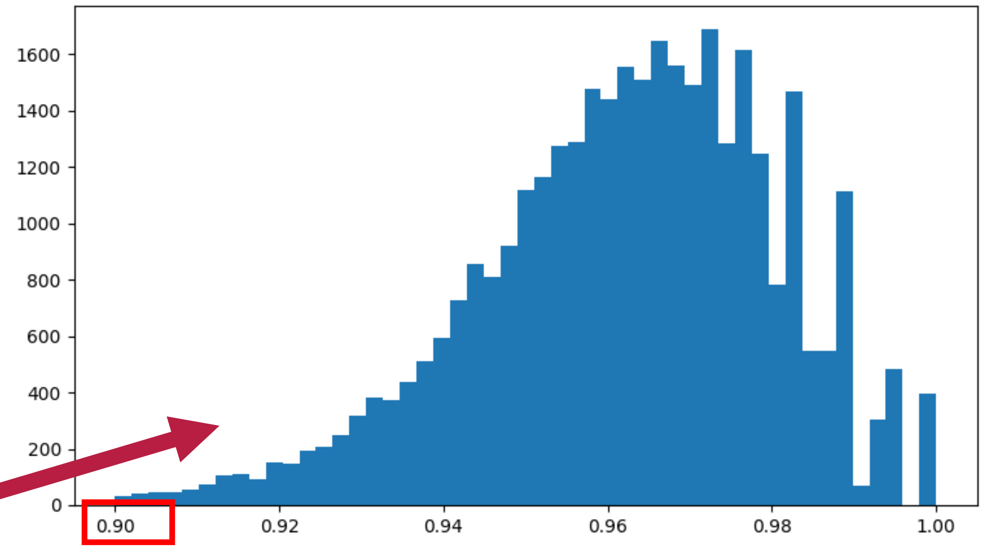


EVALUATION

Opening angle = 0.1 rad (the smallest one)

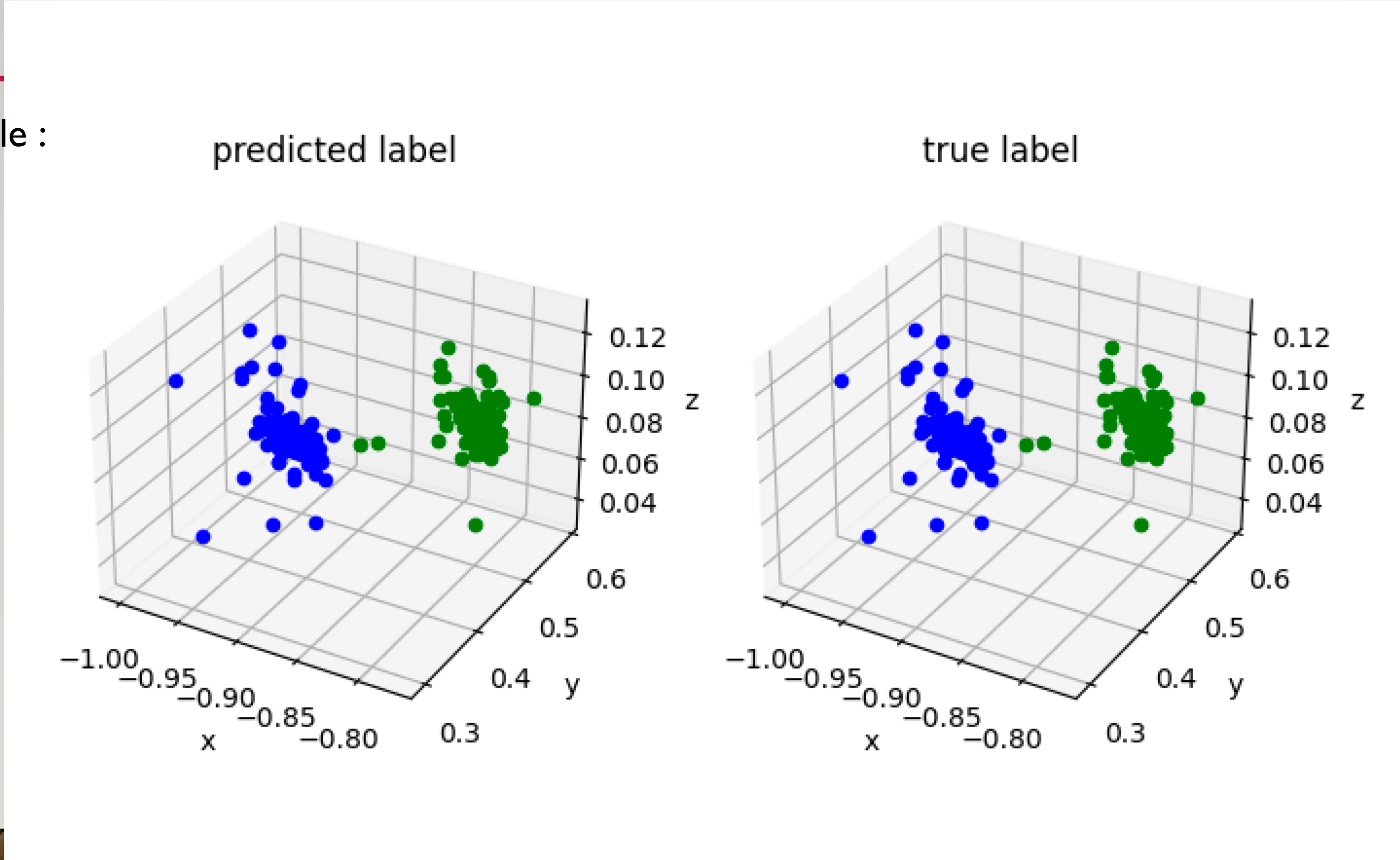
Average = 96.08%





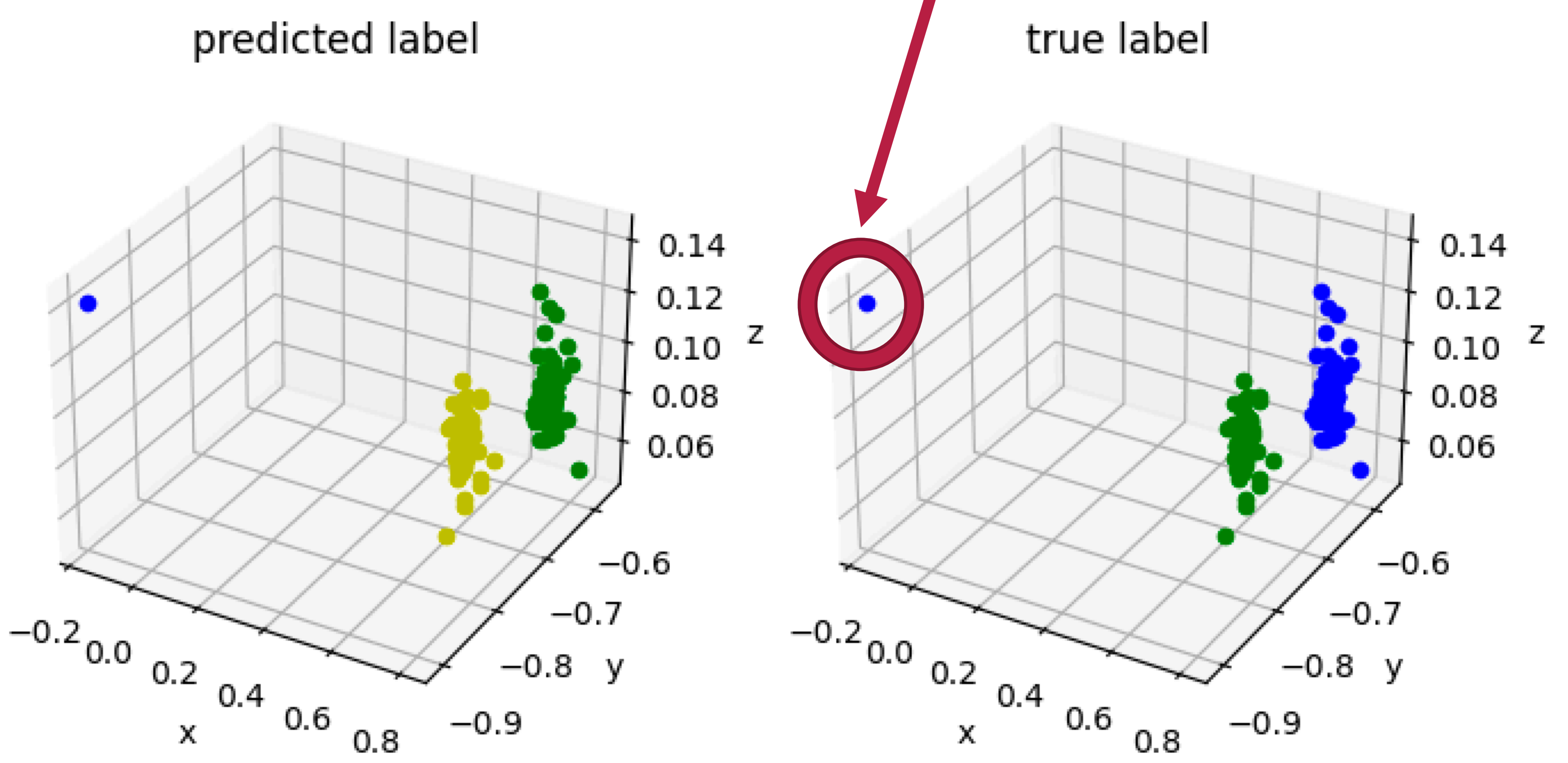
COMPARISON BETWEEN PREDICTION AND TRUE LABEL

Good example :

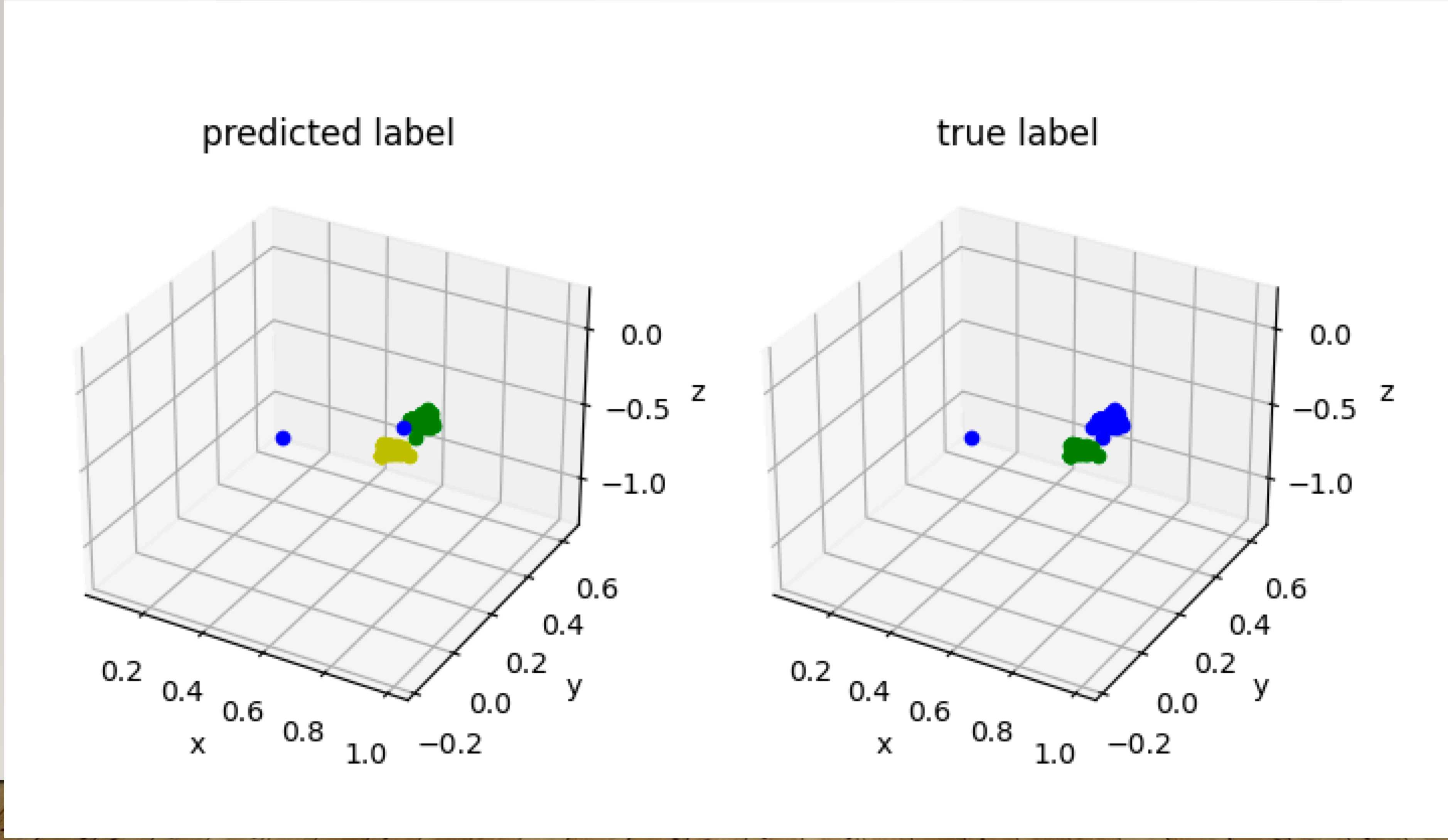


COMPARISON BETWEEN PREDICTION AND TRUE LABEL

The case in which there is a distant hit

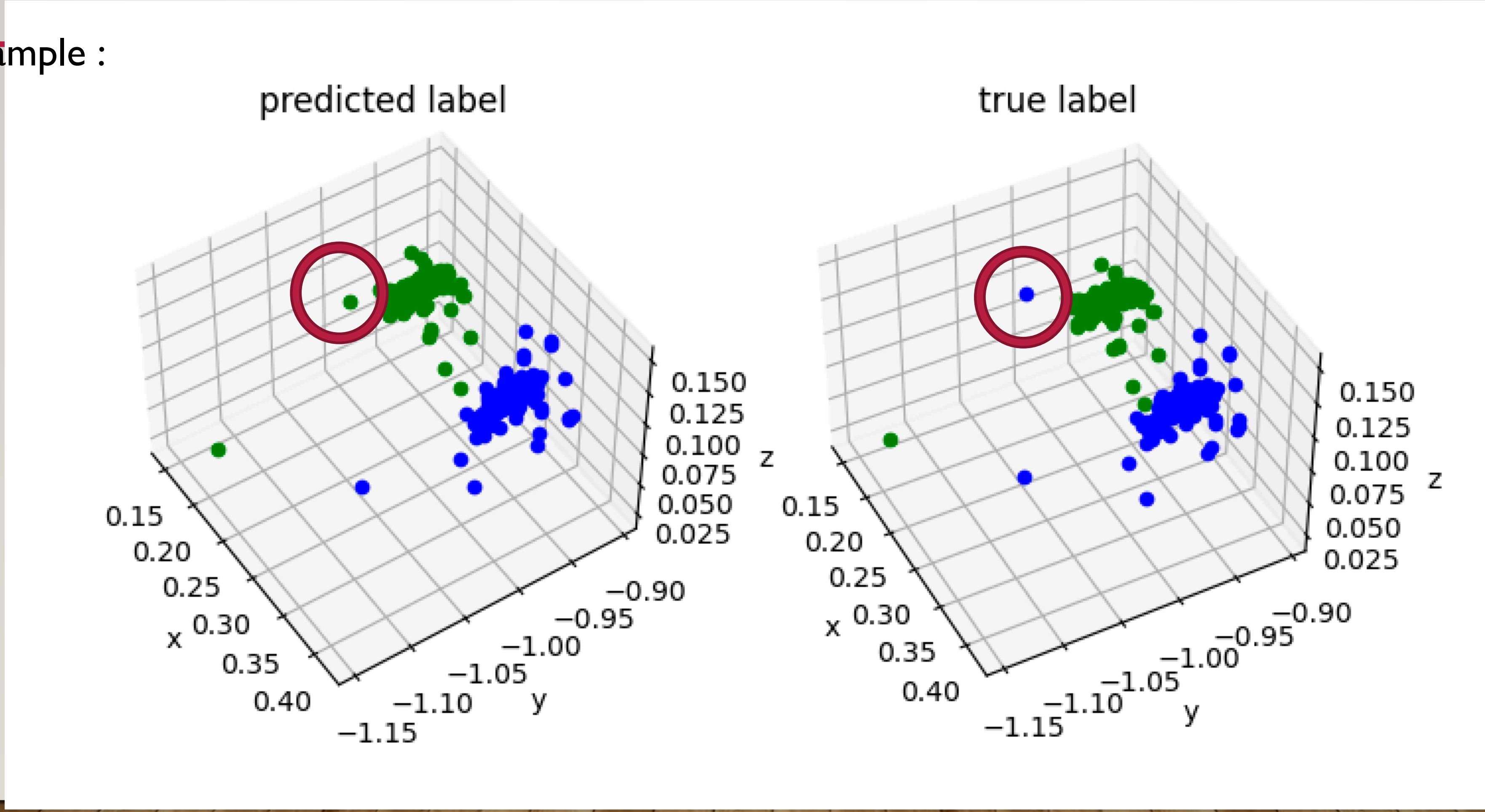


COMPARISON BETWEEN PREDICTION AND TRUE LABEL

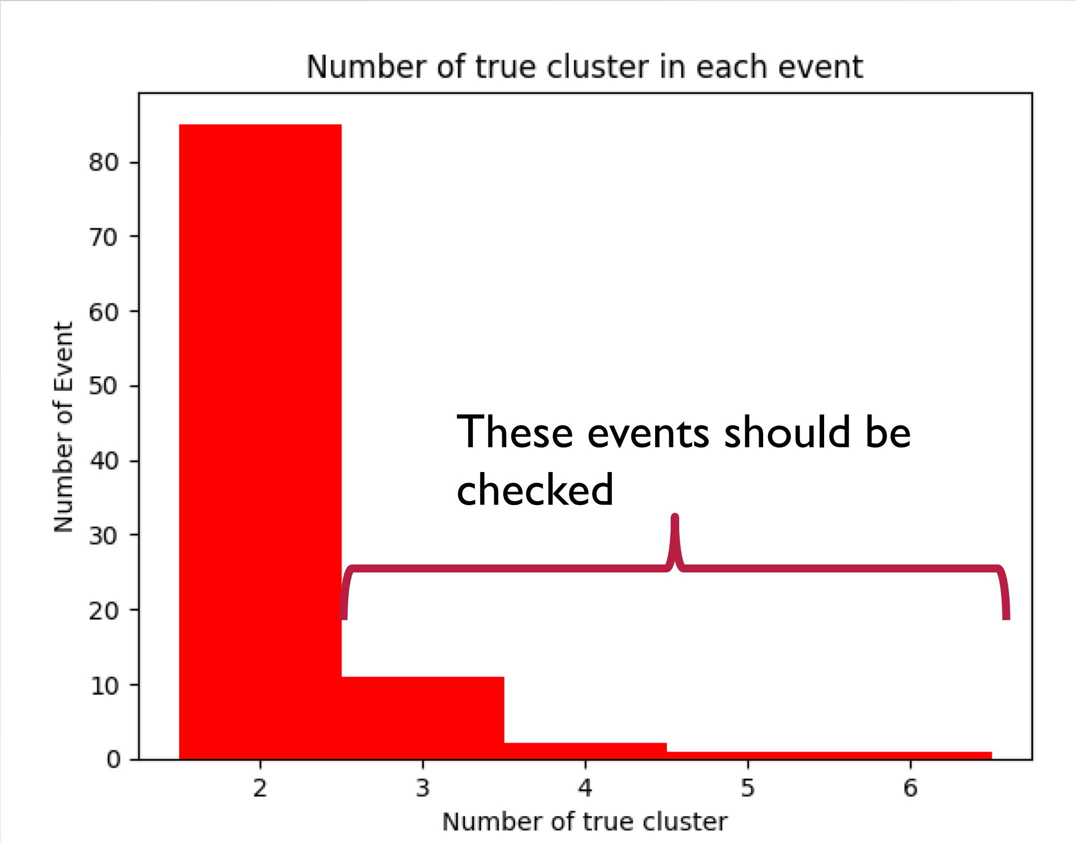


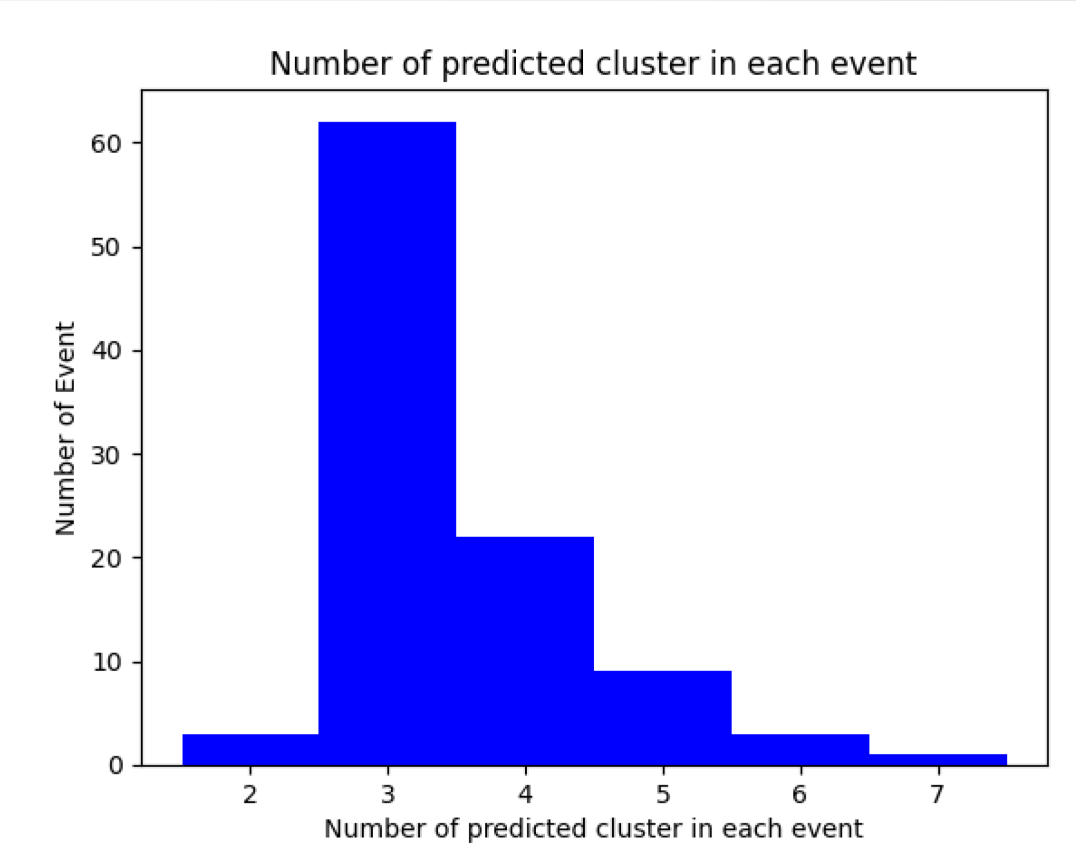
COMPARISON BETWEEN PREDICTION AND TRUE LABEL

Confusion example :



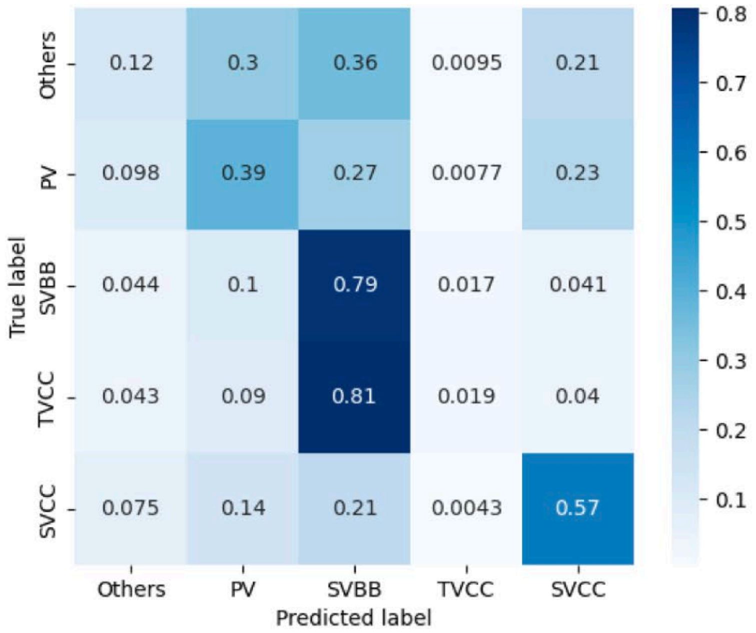
NUMBER OF CLUSTER IN EACH EVENT(JUST 100 EVENTS)



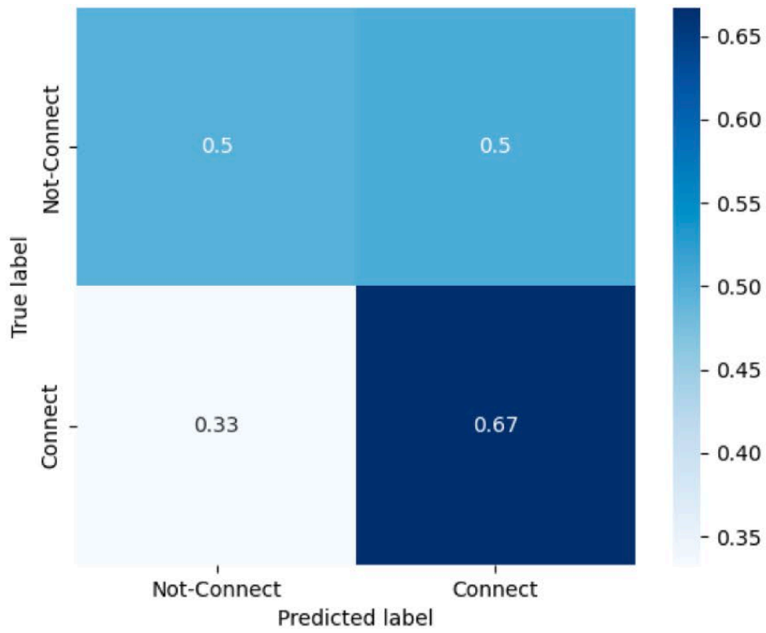


Result of GNN

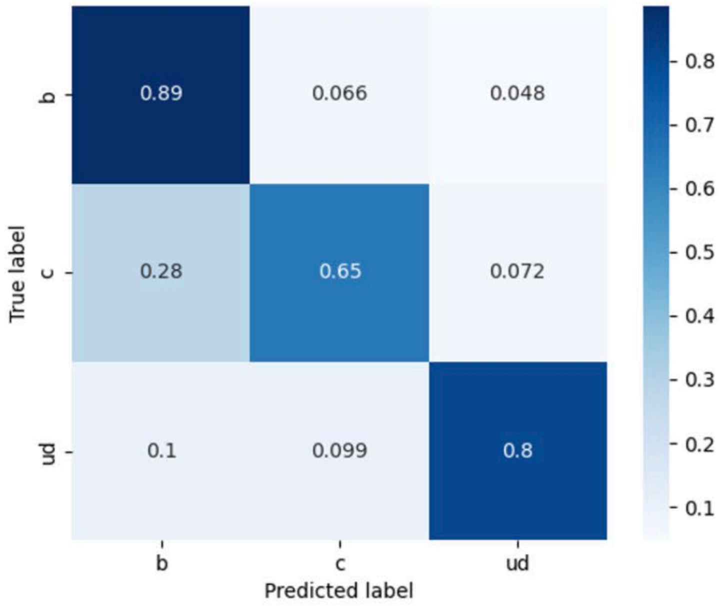
Node classification



Link prediction



Graph classification



- Not much classification of TVCC and SVCC
- Edge connection is not good
- As a graph, we got better accuracy than nodes and edges