# Development of ILC shower clustering algorithm using Deep Neural Network

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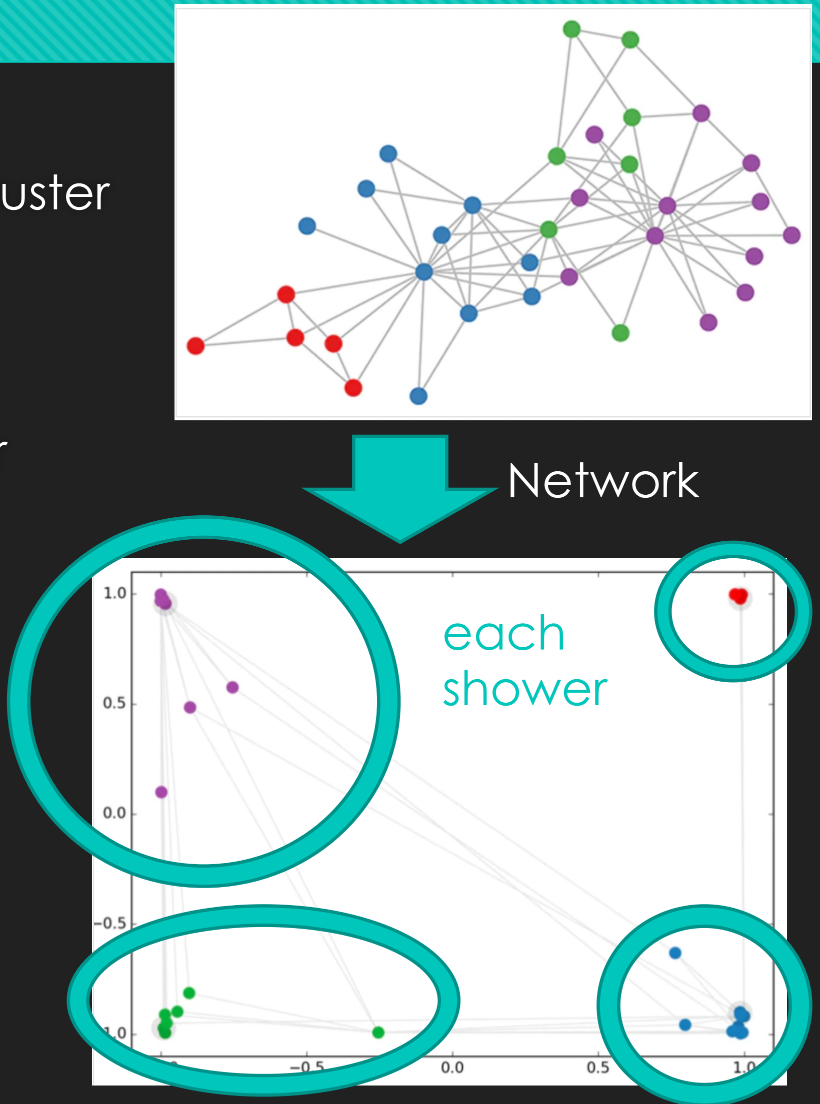
# Shower Clustering by Graph Neural Network

- Shower Clustering :
  Identification that each hits in the calorimeter belongs to which cluster
  → Important role in the Particle Flow Algorithm
- Graph Neural Network :
  Input data is interpreted as graph
  → It helps to represent the relation between the hits in one shower
- Hits that belong to one shower are represented closer together on the graph
- One kind of network : GravNet

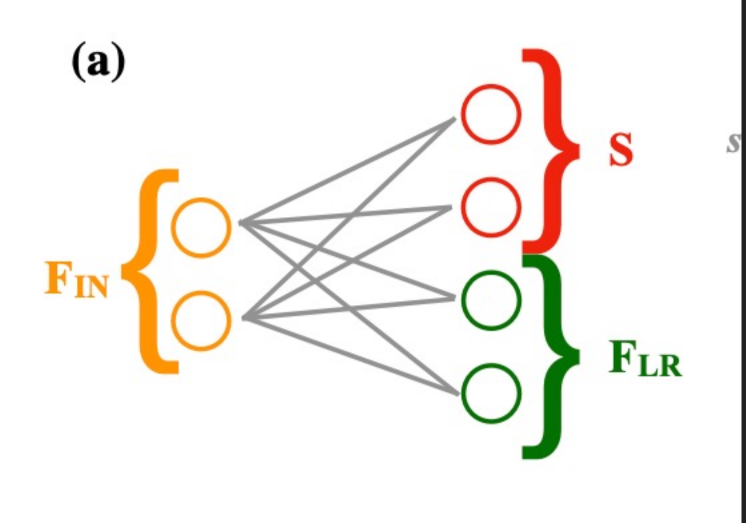


# GravNet - Network

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

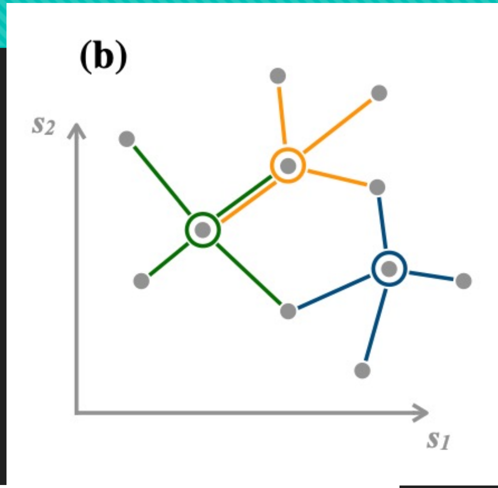
  $B$ : Number of examples including in a batch
  V : Number of hits for each detector
  $\mathrm{F}_{\mathrm{IN}}$ : Number of the features for each hit

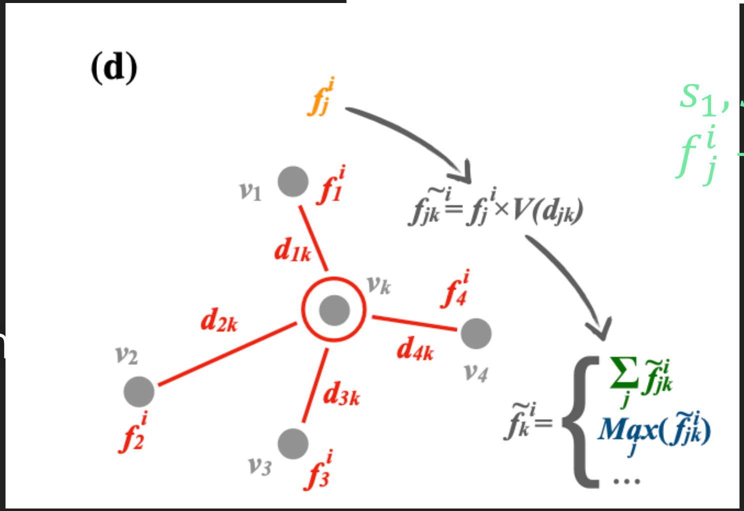
- S : Set of coordinates in some learned representation space
- $F_{LR}$ : learned representation of the vertex features



# 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

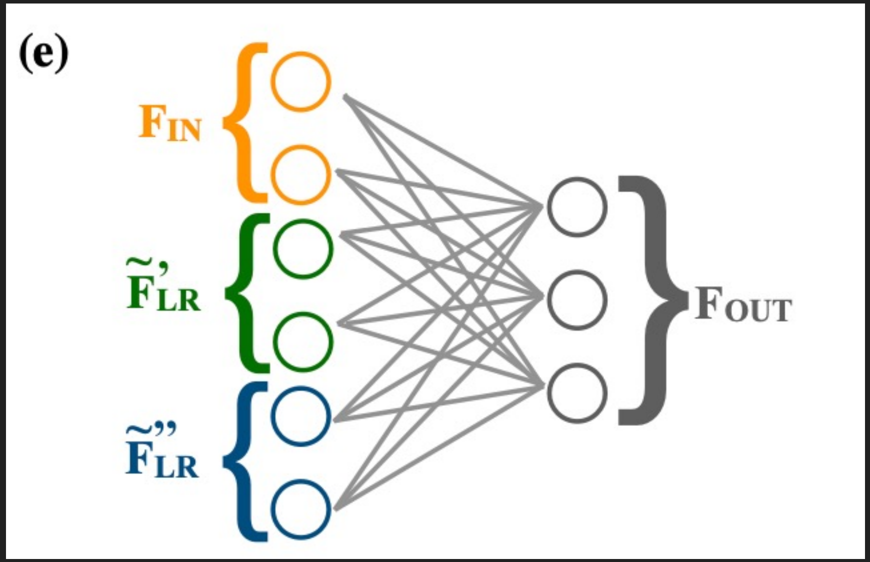



$s_1, s_2 \to S$
$f_j^i \to F_{LR}$

# GravNet

- For each choice of gathering function, a new set of features $\widetilde{f_k}^{i} \in \widetilde{F_{LR}}$ is generated.
- 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.



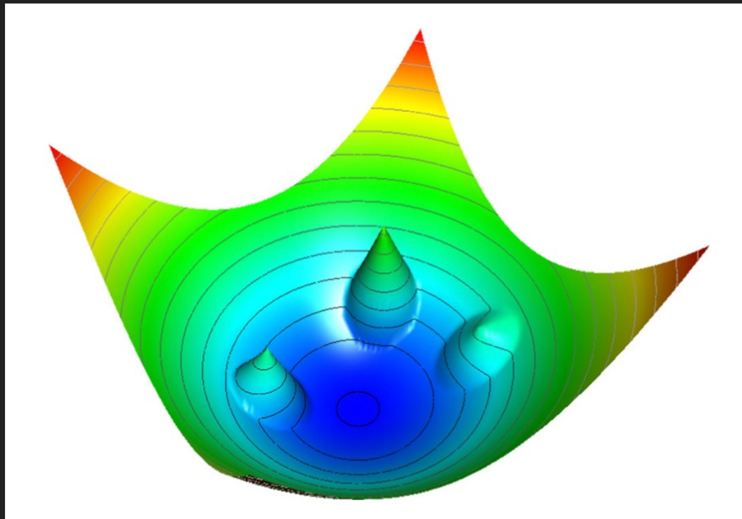
# Loss function – Object Condensation

- The object condensation approach :
  Aiming to accumulate all object properties in condensation points
- Loss function : $L = L_p + s_C(L_\beta + L_V)$
  $s_C$ : scall parameter

Update of loss term

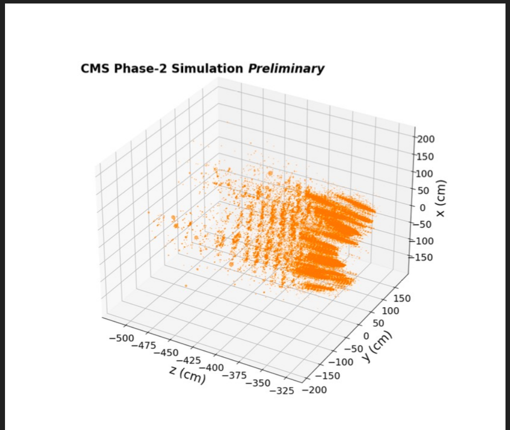
Identification of noise

Assignment of vertices for each shower

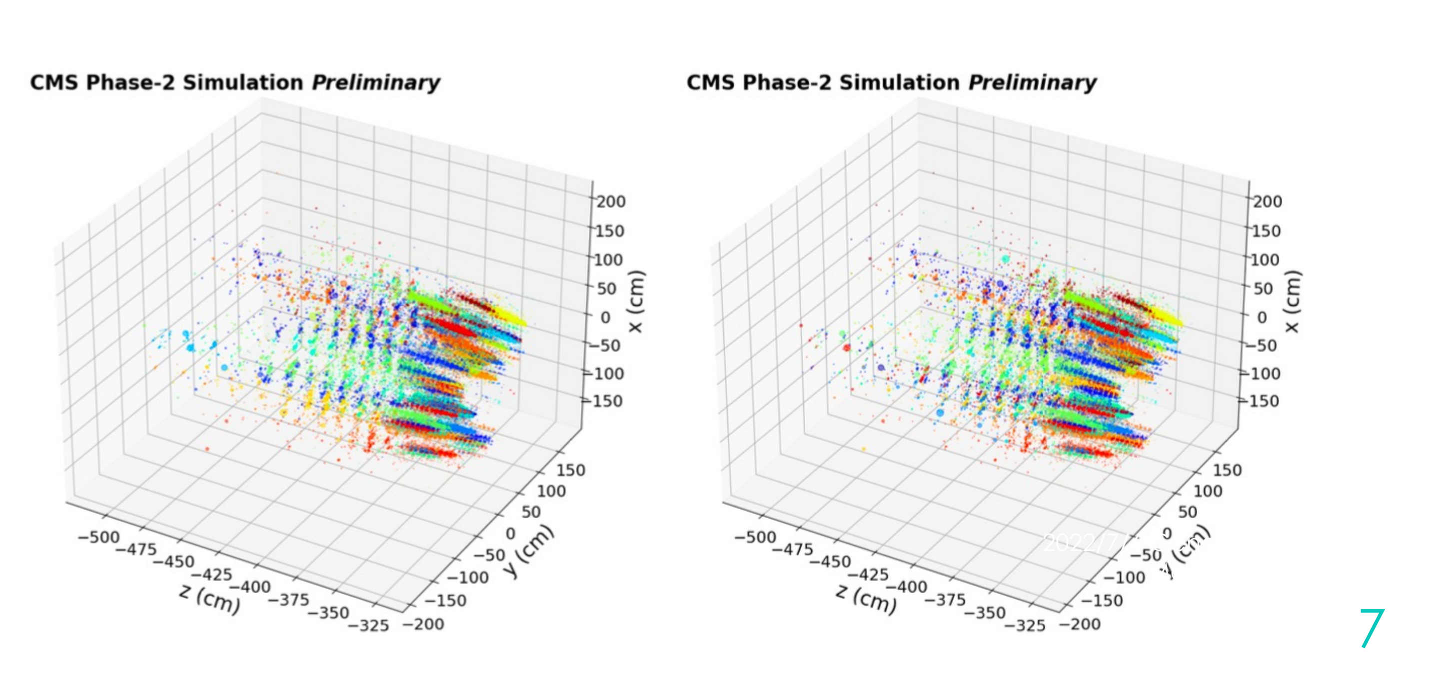


# CMS Results

- Shower particle type (selected randomly) :
  electrons / muons / photons / charged and neutral pions /
  charged, neutral, charged, short- and long- lived kaons




True Cluster Predicted Cluster



# Apply GNN for ILC

- Current clustering algorithm of ILC : PandoraPFA
  → Improve by the Graph Neural Network (GNN)
- Task : Preparation of input data (Numpy)

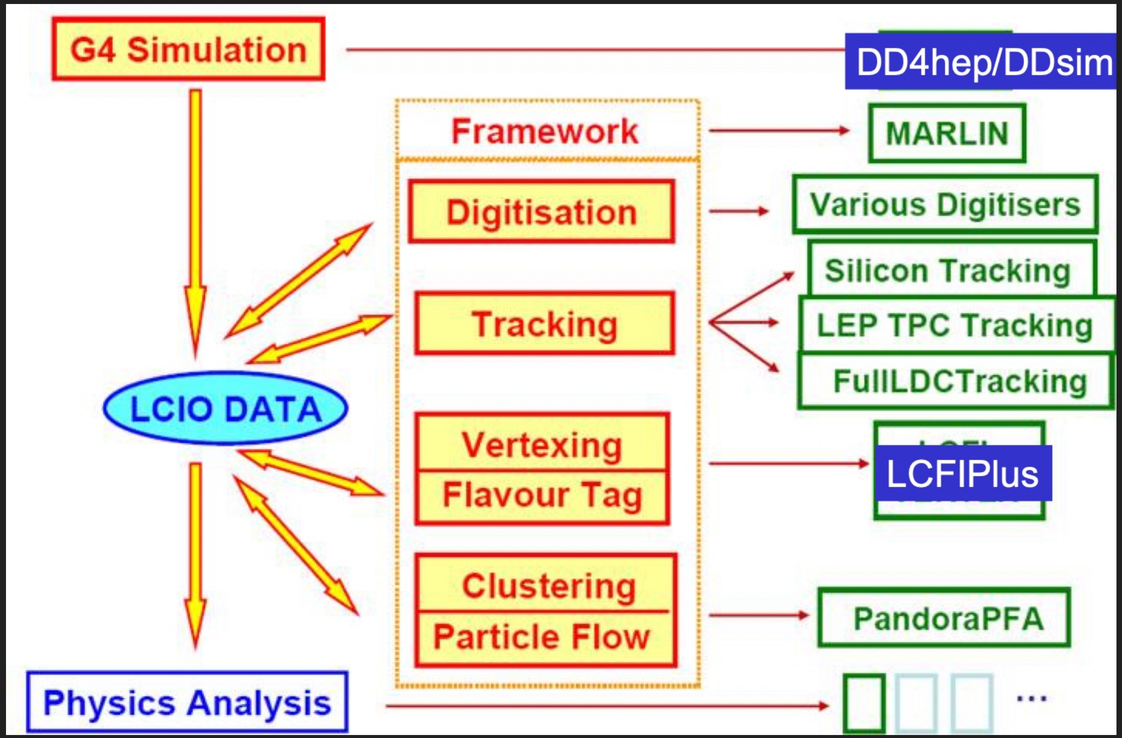
LCIO file

↓ Extract

Collection data

↓ Write

Numpy file



# Summary

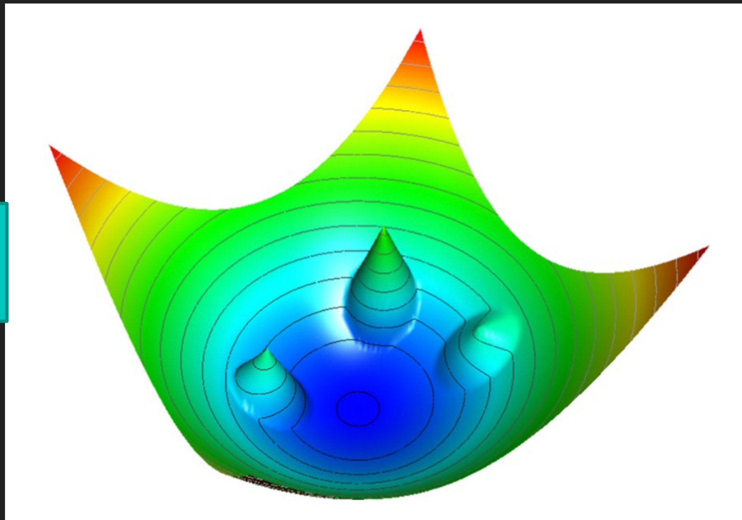
- Graph Neural Network using GravNet and Object condensation is useful for the shower clustering algorithm
- GravNet represent the features of hit points as distance-weighted graph and aggregate the hits of one shower
- Object condensation method improve the identification of each shower
- I need to implement the input data of the ILC simulation as Numpy file and confirm if the GravNet improve the accuracy.

# Backup

# Loss function - Network Learning -

- The object condensation approach :
  Aiming to accumulate all object properties in condensation points

| Assignment of vertices for each sower | Identification of noise | Update of loss term |
| --- | --- | --- |



- The value of $\beta_i$ $(0 < \beta_i < 1)$ 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

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

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

# Loss function

- The potential of object k can be approximated :

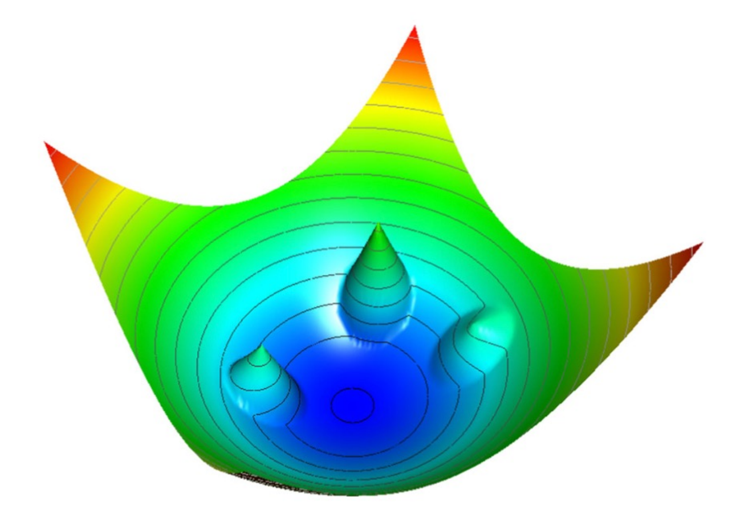
$$V_k(x) \approx V_{\alpha k}(x, q_{\alpha k}), \quad \text{with } q_{\alpha k} = \max_i q_i M_{ik}.$$

- An attractive and repulsive potential are defined as :

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

- The total potential loss $L_V$ :

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



# Loss function

$s_B$ : 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 $L_V$ 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 $L_\beta$ is introduced :

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

- 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)

# Loss function

- If high efficiency instead of high purity is required :

$$L'_p = \frac{1}{K}\sum_{k=1}^{K}\frac{1}{\sum_{i=1}^{N} M_{ik}\xi_i}\cdot\sum_{i=1}^{N} M_{ik} L_i(t_i, p_i)\xi_i.$$

- In practice, individual loss terms might need to be weighted differently :

$$L = L_p + s_C(L_\beta + L_V)$$

Update of loss term

Identification of noise

Assignment of vertices for each sower