Physics/Software

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Evaluation

- $\text{Accuracy} = \dfrac{\text{hits in each cluster predicted correctly}}{\text{True hits in each cluster}}$
- Output of network :
  β vector (elements = hits) : condensation point
  cluster space coordinates matrix (elements = hits×arbitary): Presentation space coordinates

→ Matching Method

→ We can get the list [True cluster label],[Hit ID]

Ex)

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matches : [[[8], [130]], [[3], [84, 120, 89, 55, 823, 88]], [[28], [1759, 1709, 68]], [[7], [65, 66, 72,\
 126]], [[9], [414, 896]], [[2], [1591]], [[5], [137, 128, 122, 144, 57, 895]], [[30], [362, 1760, 1782,\
 1758]], [[1], [1685, 1773]], [[12], [369]], [[29], [901, 1785]], [[33], [953]], [[4], [3143]], [[15], [\
87]], [[48], [1712]], [[8, 10, 6], [130]], [[48, 19], [1712]]]
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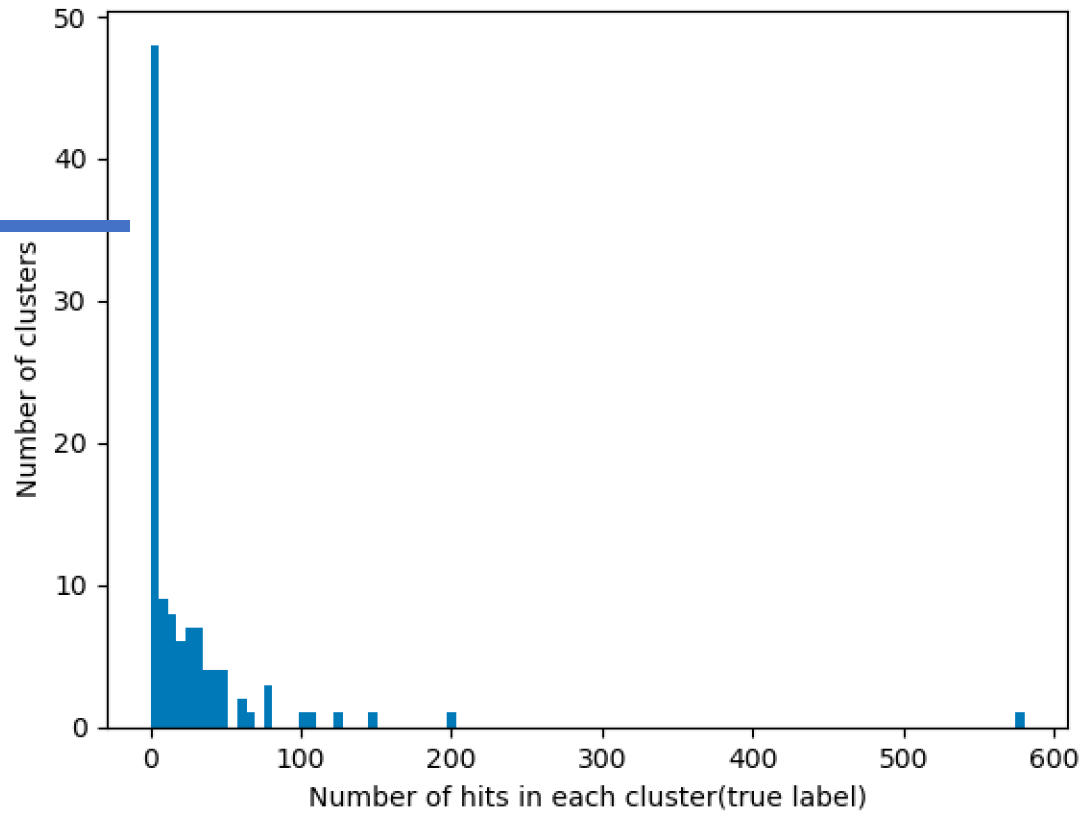
→Problem : Fewer than I expected / Multi-tagged of cluster are attached to several hits.

Bias of input data

- Many showers include hits fewer than 10

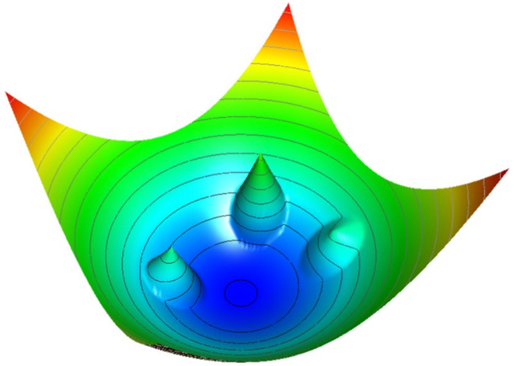
may cause
inefficient
learning



Plan : Reduce data fewer than 10
Double particle gun simulation

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

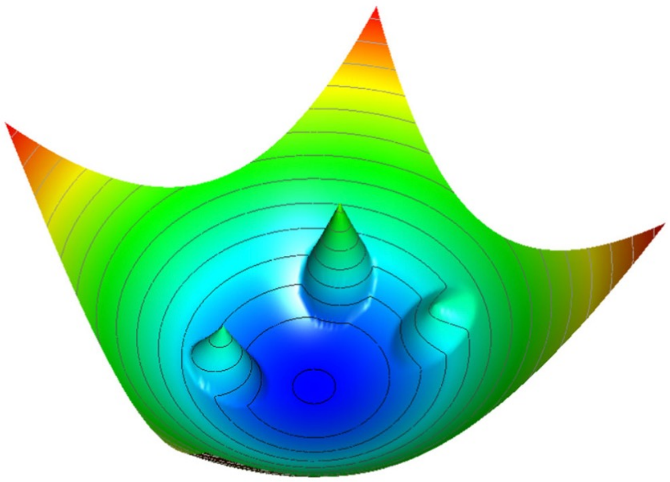
$$q_i = \mathrm{arctanh}^2 \beta_i + q_{\min} \quad (\beta_i \rightarrow 1 : q_i \rightarrow +\infty)$$

- 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 :

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

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

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 $\mathrm{arctanh}^2\,\beta_i$:

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

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

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