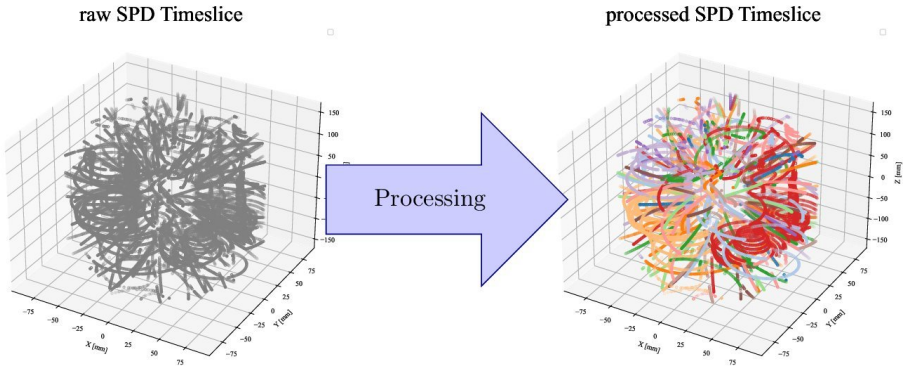
Graph Attention Neural Network for Clustering Particle Tracks by Events in the SPD experiment.

[1,2]Omelianchuk S., [2,3]Ososkov G., [2]Talochka Y., [2]Voytishin N.

[1]Branch of MSU in Dubna,
[2]JINR MLIT,
[3]Dubna state University

The main task is to classify tracks by events.



Each color corresponds to its own event. For instance, sea-blue tracks are from event:5.

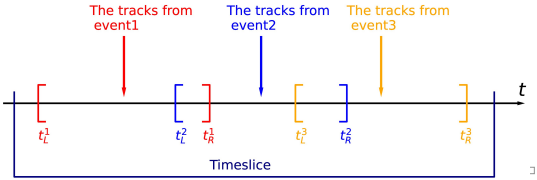
Timeslice simulation

We take events from Official SPD ROOT MC simulation that were reconstructed using Neural Network by A. Didorenko.

Our algorithm for sampling reconstructed tracks in time slices.

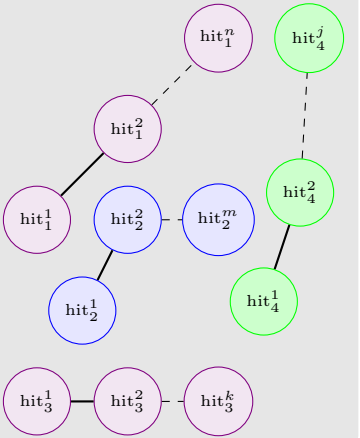
$$\mathrm{P}(k) = \frac{\overline{N}_{ev}{}^{k}}{k!} e^{-\overline{N}_{ev}} \qquad t^{i}_{L/R} = \frac{i \mp 0.49(r+1)}{N_{ev} - 1}$$

where $\overline{N}_{ev}$ is the average number of events in a timeslice, r is the overlap parameter for tuning the time resolution of the detector and $t^{i}_{L/R}$ are the left and right bounds of the drift time for the i-th event. Parameters highlighted in blue are customizable.

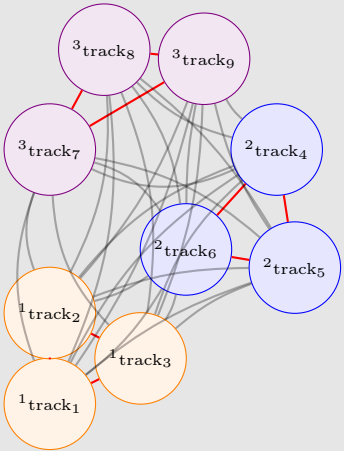


Track-GANN Model

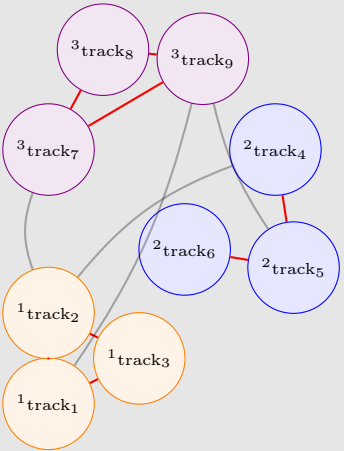
Graph of Hits



Graph of Tracks

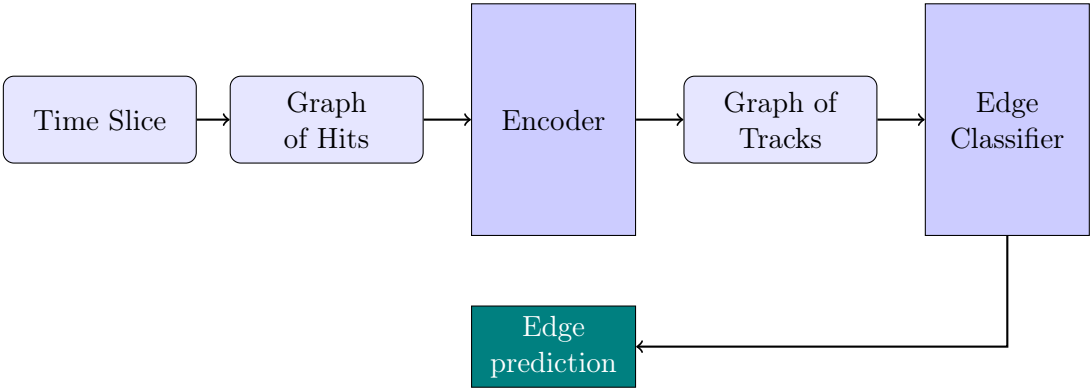


Final Graph

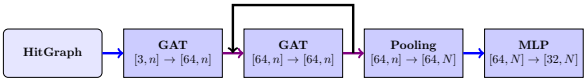


Track-GANN Model

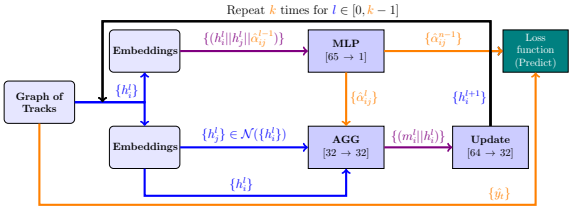
The general architecture of the model contains two main blocks: Encoder and Classifier.



Track-GANN Model



(a)



(b)

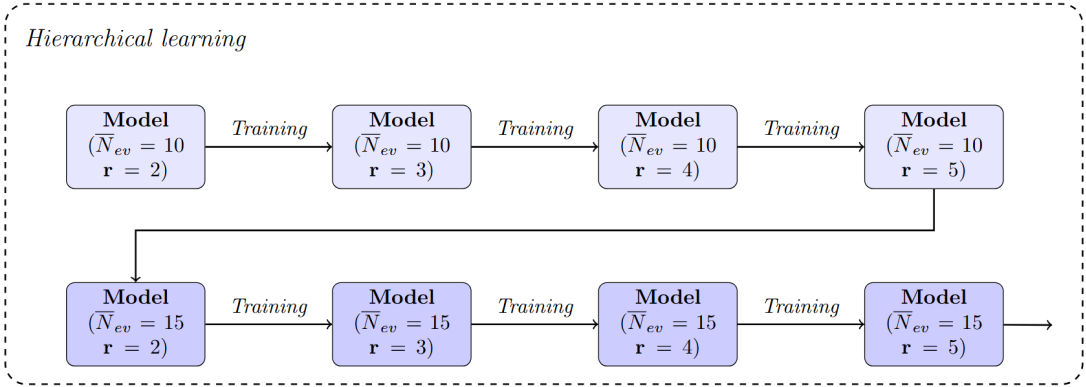
The Track-GANN architecture consist of 2 main blocks.

Inference of Track-GANN:

Time slice → Encoder (a) → Graph of Tracks → Edge Classifier (b) → Prediction

Heirarchical training

The main idea is to train model on simple examples with parameters $r, \overline{N}_{ev}$.



One epoch: 800 time slices. Parameters for target sample: $\overline{N}_{ev} = 10, r = 5$. Training processing time $\simeq (15 - 20)$ time slices/sec.

- Balanced Focal Loss:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}\omega_i(1-p_t)^{\gamma}\ln(p_t) \qquad \omega_i = y_i\omega_p + (1-y_i)\omega_n$$

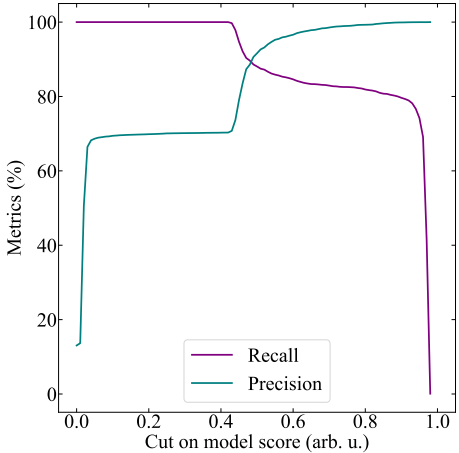
where y_i is the truth label of edge, $p_t = p_i$ if the edge is false, $p_t = (1 - p_i)$ if the edge is true, p_i is the model prediction, N is the number of edges, $\omega_p, \omega_n, \gamma$ are adjustable parameters.

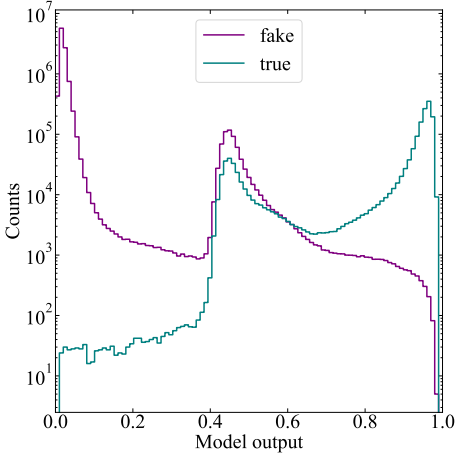
- Metrics:

$$\text{Precision} = \frac{TP}{TP+FP} \quad \text{Recall} = \frac{TP}{TP+FN}$$

The i-th edge is true if the model's prediction $p_i > 0.5$

Results





Edge score distributions for true and false edges (right); recall and precision of edge classification as functions of the threshold (cut value) applied to the edge score (left) for Track-GANN5.

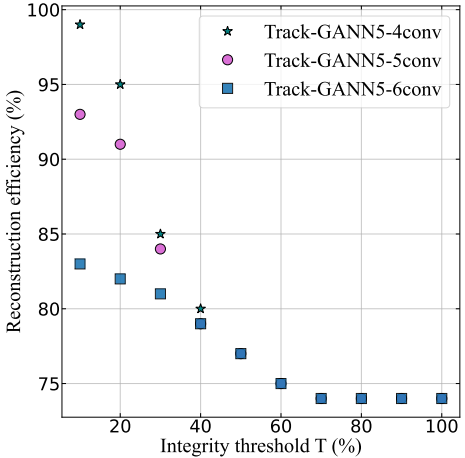
Efficiency

For final clustering after Track-GANN5 processing, we use the Louvain method to remove the remaining false edges in the Graph of Tracks.

We compute the reconstruction efficiency within an individual timeslice using the following formula:

$$Eff = \frac{\sum_{i,j} m_{ij}}{N_{ev}}; \quad m_{ij} = \begin{cases} 1 \text{ if } \frac{\hat{y_i} \cap y_j}{N_{ev}} \geq T \\ \quad \text{and } \frac{\hat{y_i} \cap y_j}{\widehat{N_{ev}}} \geq T; \\ 0 \text{ otherwise;} \end{cases}$$

where y_i is the track cluster, N_{ev} is the number of events in an timeslice, and T is the integrity threshold.



Conclusions

Successes:

- The model achieves 73% reconstruction efficiency at a 99% integrity threshold. This indicates that 73% of events are fully reconstructed, with the remainder are partially processed.
- Hierarchical learning allows the model to be adjusted for new data.
- Processing speed on Nvidia V100 Tesla GPU: $\sim$ 10 timeslices/sec.

Limitations:

- Sufficient event time resolution is required.

Thank you for your attention!