

# Graph Neural Network-based Algorithm for Track Finding in the CBM Experiment

Ivan Kisel<sup>1,2,3,4</sup>, Oddharak Tyagi<sup>1</sup>

<sup>1</sup>Goethe-University Frankfurt, Frankfurt am Main, Germany

<sup>2</sup>Frankfurt Institute for Advanced Studies, Frankfurt am Main, Germany

<sup>3</sup>Helmholtz Research Academy Hesse, Frankfurt am Main, Germany

<sup>4</sup>Helmholtz Center for Heavy Ion Research, Darmstadt, Germany



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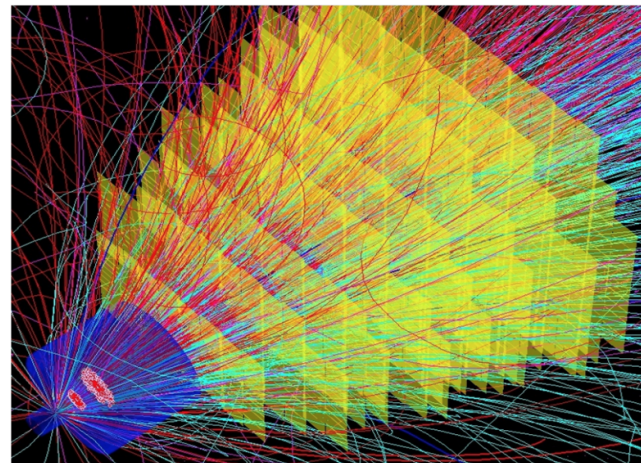
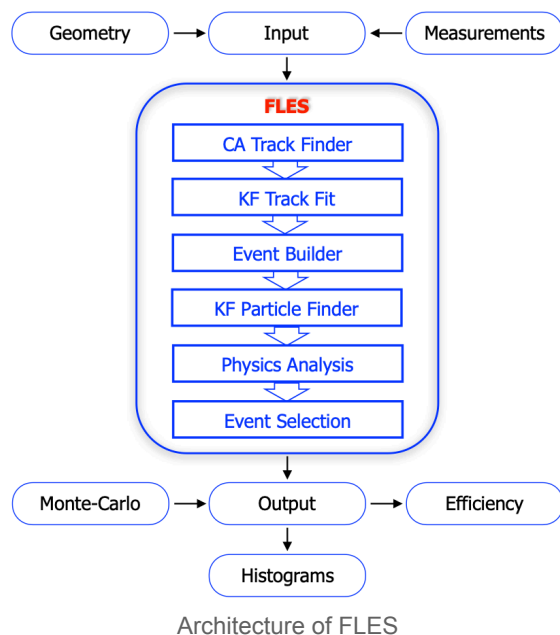
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# Compressed Baryonic Matter (CBM) Experiment

- **Goal:** Explore QCD phase diagram in the region of high baryon densities using high-energy nucleus-nucleus collisions
- Unprecedented **10MHz** event rate will allow study of rare events



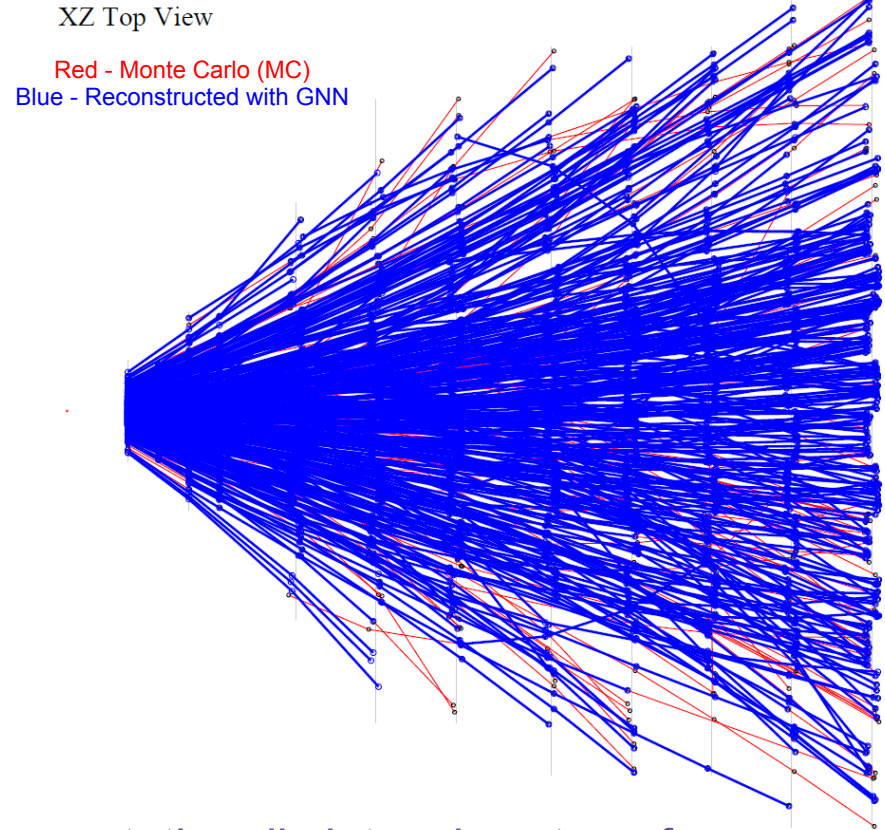
Tracks from central 25 A.GeV AuAu event with GEANT simulation of tracking stations

- **First-Level Event Selector (FLES)** is responsible for real-time reconstruction and filtering of events from continuous data stream. Fully software-based trigger.
- Requires **fast** and **high-precision** track finding algorithm

# Track Finding

- Algorithm to group hits produced by one particle together
- Hits registered on two detectors
  - **Micro Vertex Detector (MVD)** - 4 MAPS stations
  - **Silicon Tracking System (STS)** - 8 double-sided Silicon strip stations
- Both detectors lie in magnet allowing **1%** momentum resolution
- On average a 10A.GeV AuAu collision produces
  - *1000s* of charged particles
  - **~400** reconstructible tracks ( $\geq 4$  hits)

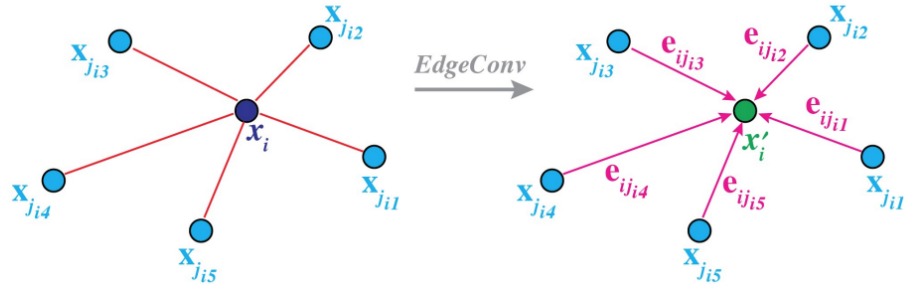
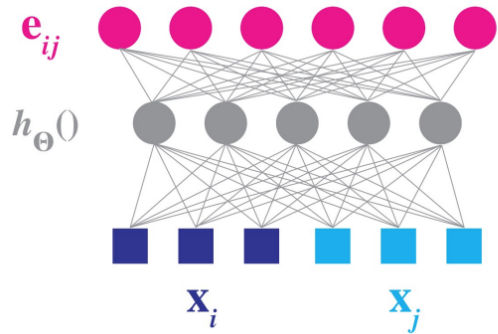
Event display for 10A.GeV Central AuAu



Track Finding is the most computationally intensive step of reconstruction

# Graph Neural Network (GNN)-based tracking algorithm

We apply a custom **Graph Edge Convolution** message passing (similar to Kipf and Welling 2017)



Computing edge feature (left) and message passing via EdgeConv  
Wang et al. 1801.07829

Our algorithm has the following features:

- Direct use of physics with **KF**
- Uses ensemble of **small, focused networks** rather than one big, black box
- Aimed at improving reconstruction of short-lived particles → **Independent of Primary Vertex (PV)**

Broad steps of algorithm

1. **Sparse Graph Creation** with Metric Learning
2. **Doublet Filtering** via GNN
3. **Triplet** creation, fitting and filtering with KF
4. **Candidate Construction**, fitting and filtering with MLP Classifier
5. **Candidate Competition** with conditional strip exchange

# Sparse Graph Creation - Metric Learning

- Train MLP with **hinge loss** to learn coordinate transformation ( $\mathbb{R}^3$  to  $\mathbb{R}^6$ ) where:
  - Hits from the same track clustered together
  - Different track clusters pushed apart

 Cluster hits from same track

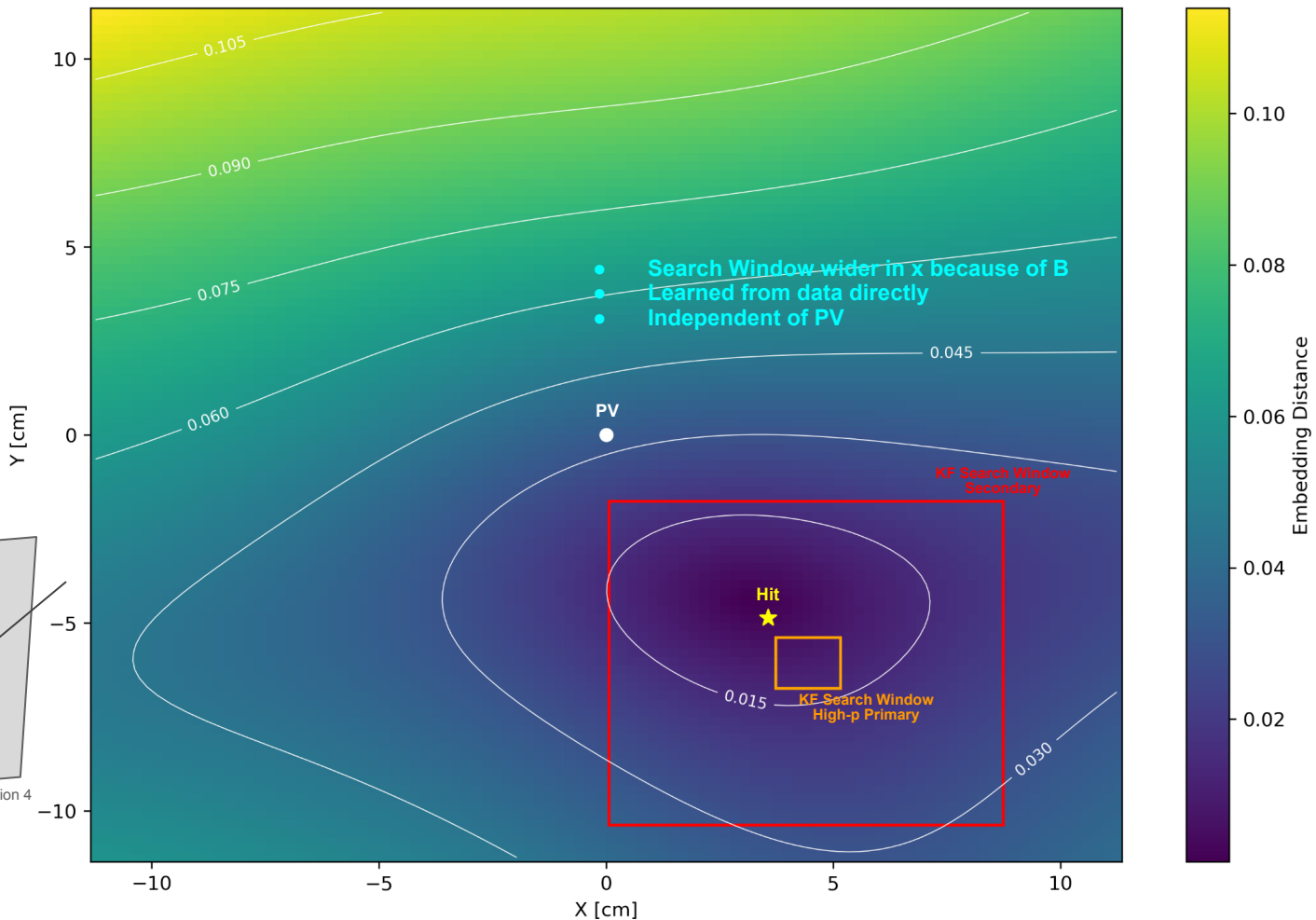
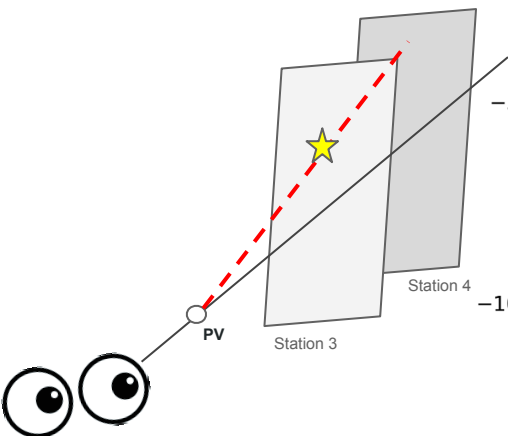
$$\mathcal{L} = \frac{1}{n_{true}} \sum_{true} d_{true}^2 + \frac{1}{n_{fake}} \sum_{fake} \max(\lambda - d_{fake}^2, 0)$$

Margin

 Hits from different tracks pushed apart

## Front-on View

Hits with lower embedding distance (blue) are ranked higher when creating doublets.  
Compared with KF search window.

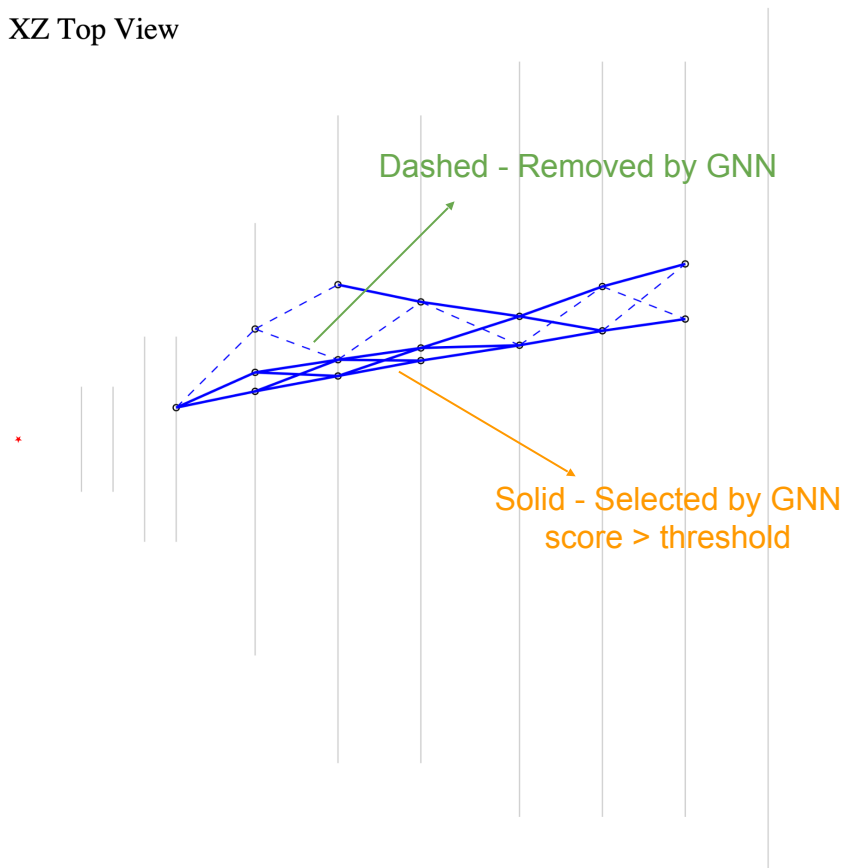


# GNN - Filter Doublets

- Doublets created from **k-Nearest Neighbours** on learned distance are edges of graph
- GNN with custom **edge convolution** message passing
- All doublets with **score < threshold** are filtered out
- Trained on sparse graph created with metric learning (not random graph)

GNN filtering reduces triplet combinatorics significantly

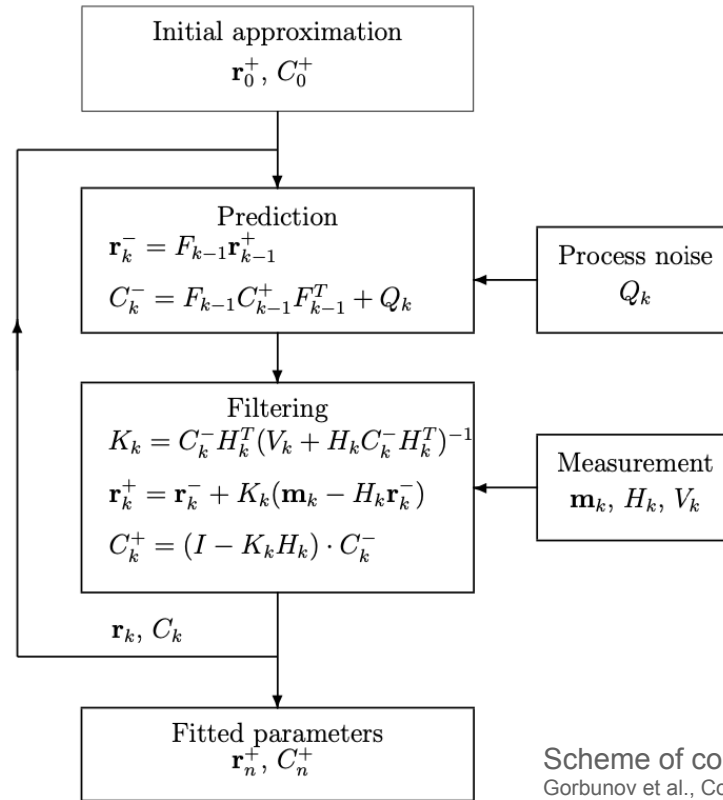
XZ Top View



Event display showing GNN filtering on small event

# Kalman Filter (KF)

- Computes **unbiased mean** and **minimum covariance** parameters for the state of a linear system
- Minimizes **risk**
- **Recursive**: The state estimate becomes independent of initial estimate as observations are added

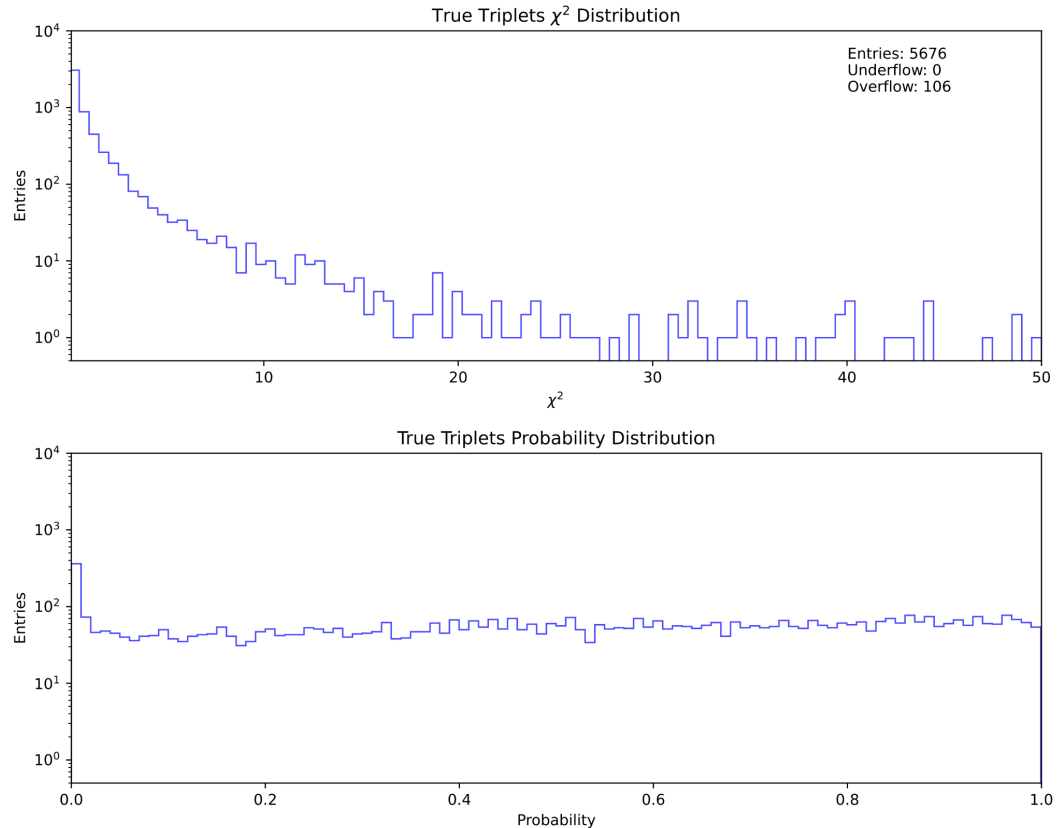


Scheme of conventional Kalman Filter.  
Gorbunov et al., Comp. Phys. Comm. 178 (2008) 374

KF is an optimal linear estimator

# Fit Triplets - KF

- Doublets sharing middle hit form **triplets**
- Triplets fit with KF to get track parameters
- A **fit quality measure  $\chi^2$**  is defined using fit parameters and measurements
- Bottom shows probability that observed  $\chi^2$  exceeds the value  $\chi^2$  by chance, even for a correct model =  $1 - \text{cdf}(x)$  where  $x$  is  $\chi^2$ -distributed
- Work only with triplets from this point onwards

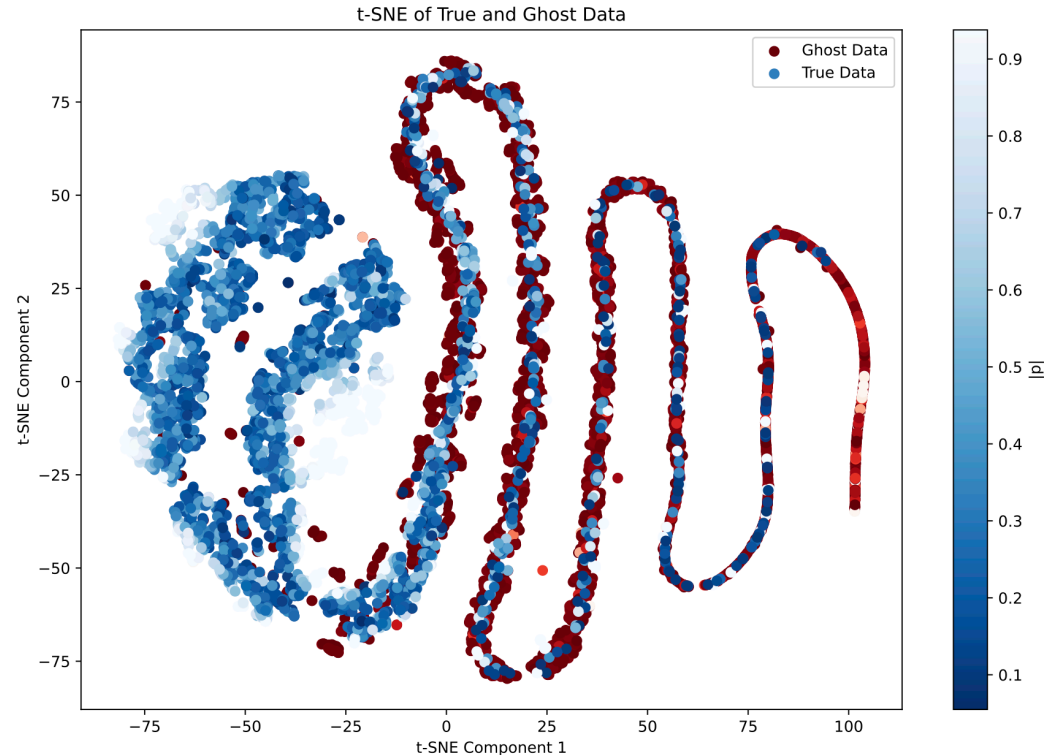


Flat probability distribution shows KF fit is correct

# Track candidates and t-SNE analysis

t-SNE is a non-linear dimensionality reduction technique for visualizing complex data

- Overlapping triplets are combined to form **track candidates**
- Clones and ghosts dominate the set of track candidates created
- Fit track candidates with KF
- We train **MLP classifier** to filter out ghost candidates
  - 13 input features from KF fit
  - 3 hidden layers of width 32
- Candidates with score below threshold are removed from candidate pool



t-SNE shows perfect classification into true and ghost candidates is impossible

# Track Competition

- We need to find true tracks from overlapping tree of filtered track candidates
  - Remove **Clones** - Multiple reconstructions of one true track
  - Remove **Ghost** - Tracks without corresponding true track

## Algorithm

1. Track candidates **sorted** by length(longer) and  $\chi^2$  (smaller)
2. Iterate down sorted list and
  - a. Add track to reconstructed list if all hits are on active strips
  - b. If any hits are inactive
    1. Search among found tracks for one that uses strip
    2. If found track is longer and has higher  $\chi^2$  – **Exchange strip ownership**. Now both tracks are found
  - c. Mark all strips of hits in track as inactive
3. Result is list of reconstructed tracks

This novel '**altruistic**' competition scheme allows more shorter tracks to be reconstructed

**New track competition method outperforms CA!**

# Results - Efficiency

Track Category	CA Efficiency (%)	GNN Efficiency (%)	Change (%)	N MC Tracks
All tracks	95.7	96.9	▲ 1.2	412
Primary high-p	99.1	99.2	▲ 0.1	232
Primary low-p	97.3	98.2	▲ 0.9	97
Secondary high-p	95.5	96.7	▲ 1.2	29
Secondary low-p	78.6	84.3	▲ 5.7	53
Clone level	5.1	5.1	▬ 0.0	-
Ghost level	2.2	2.9	▼ 0.7	-
MC tracks/ ev found	394/412	399/412	▲ 5	-

MC track is found if  $\geq 70\%$  hits of a reconstructed track match

Results for 10 A.GeV Central Au+Au collisions → Most challenging reconstruction conditions

We show improvement over the CA Track Finder!

## Results - Short-lived Particles

Particle	CA	GNN	Change (%)	Total MC
$K_S^0$	3553	3713	▲ 4.5	4289
$\Lambda^0$	7222	7522	▲ 4.0	8903

10 A.GeV Central AuAu  
Avg over 1k events

- Count short-lived particles with both decay products reconstructed
- GNN finds  $\sim 4\%$  more short-lived particles compared to CA Track Finder
- Similar improvement expected for other decays

# Summary

- Full Artificial Neural Network based algorithm implemented in CBMROOT using **ANN4FLES** package - No external dependencies!
- Improved overall track finding efficiency by **1.5%**
- Improved low-momentum secondary track efficiency by **6%**
- Improved S/B and reconstruction counts for short-lived particles

## KEY REFERENCES:

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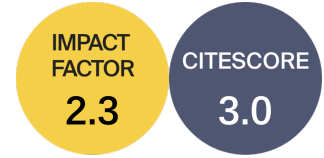


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