WIFAI 2024

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INFN
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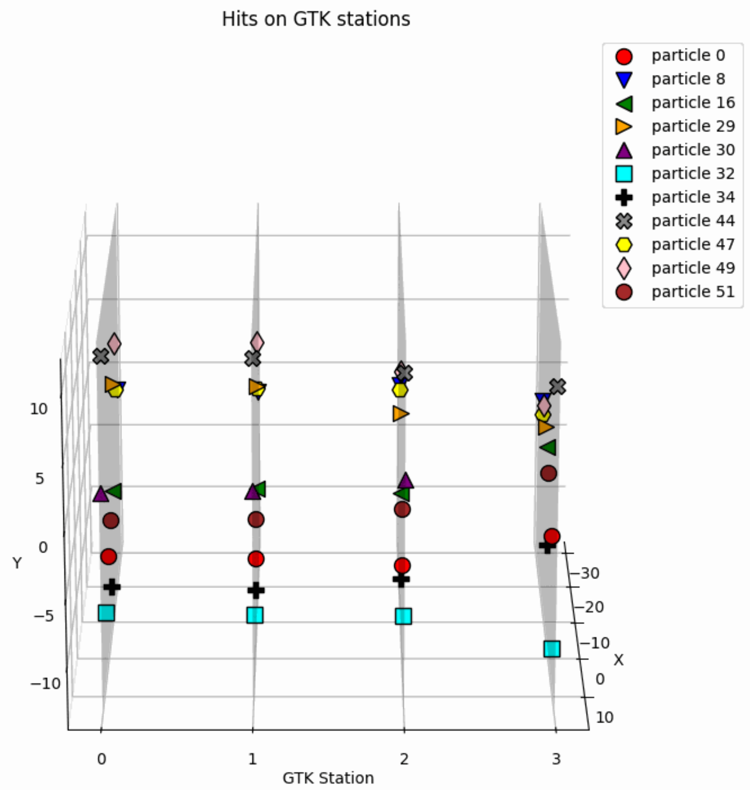
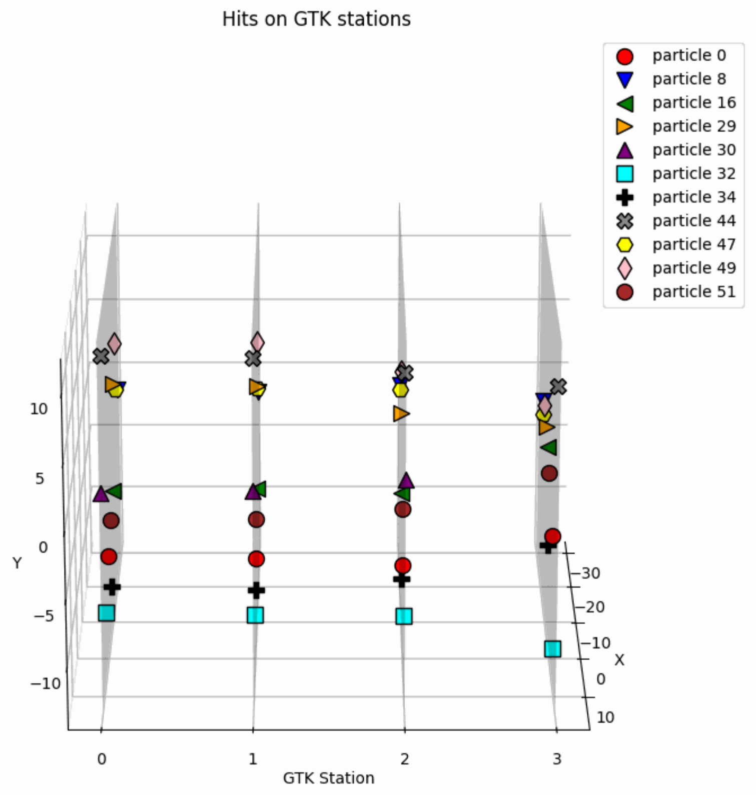
PINlab
PERCEPTION AND INTELLIGENCE

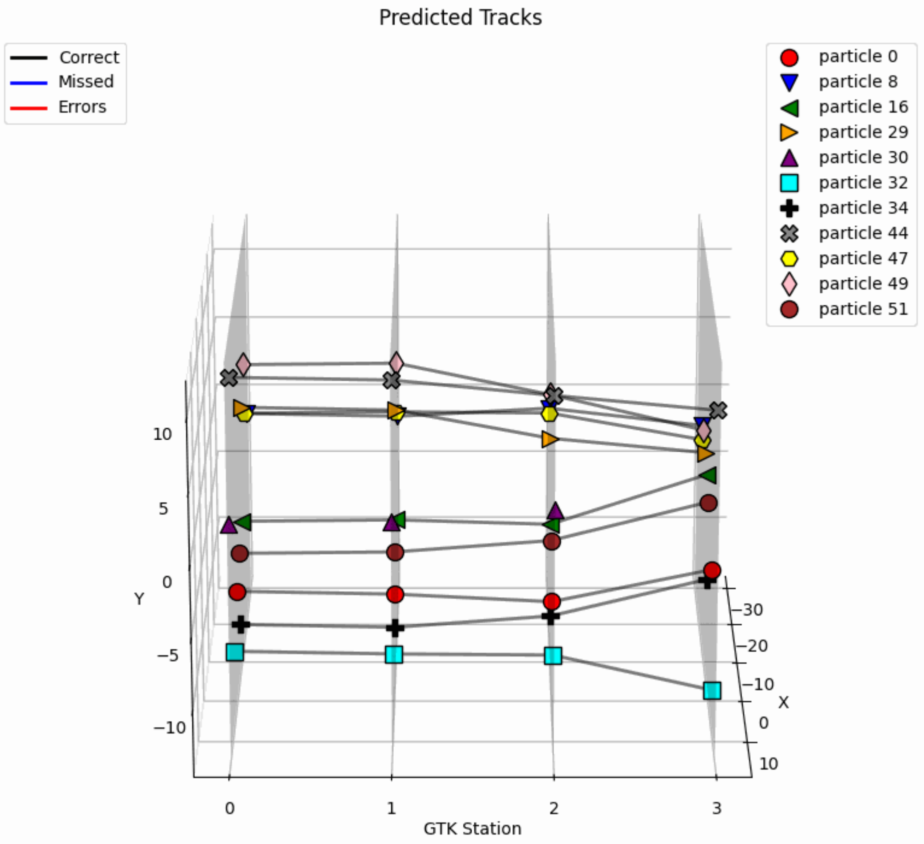
SAPIENZA
UNIVERSITÀ DI ROMA

Particle Tracking



Particle Tracking





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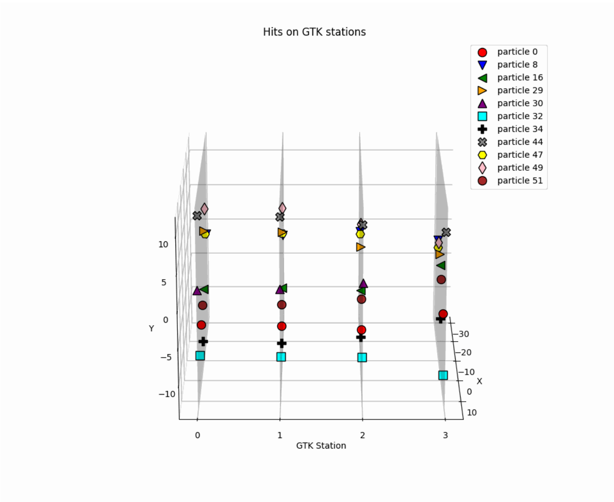

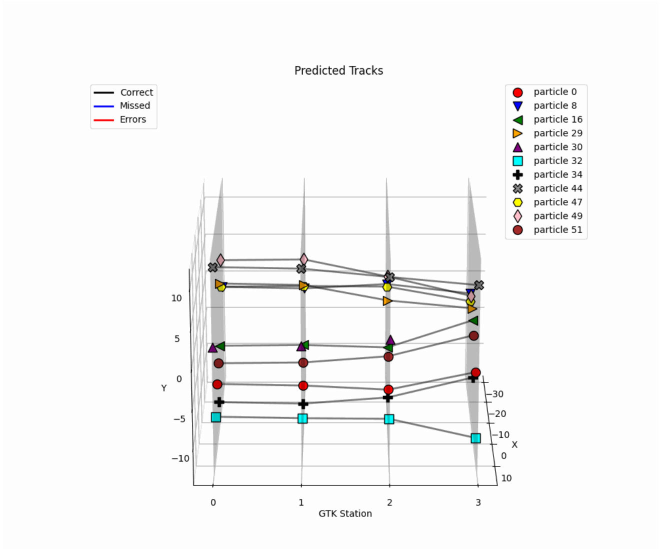

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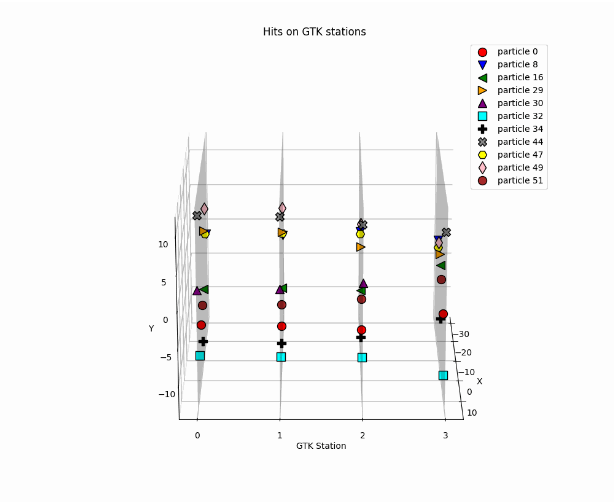
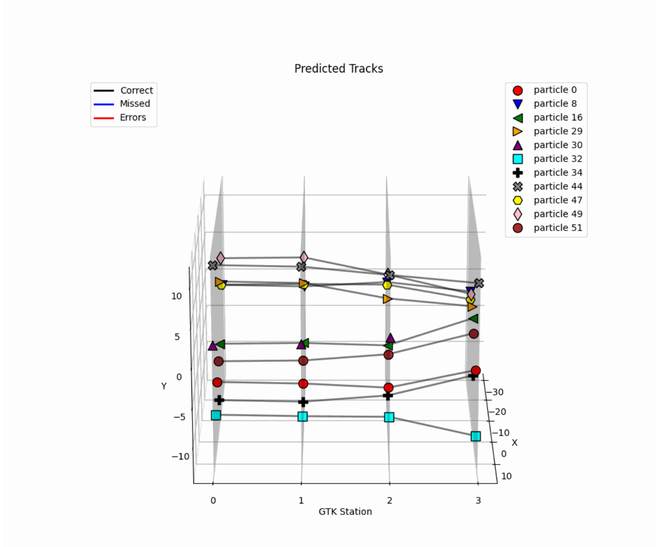
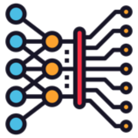


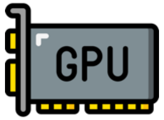


Motivations

Despite the variety of approaches and theoretical models tested in physical experiments, what they all have in common is the very **large volume of complex data** they produce

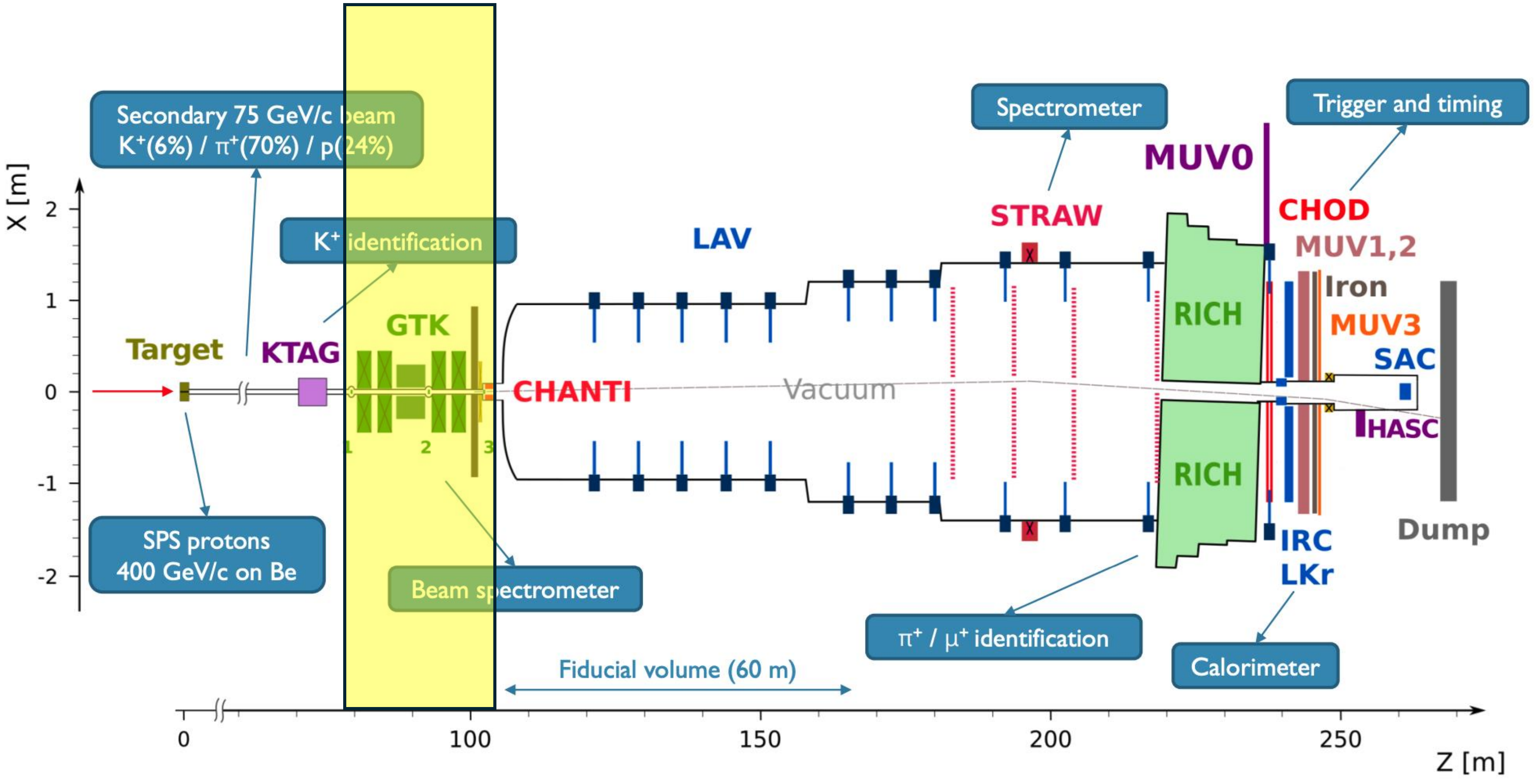


This data challenge calls for powerful computing methods like **Machine Learning** and **Deep Learning**

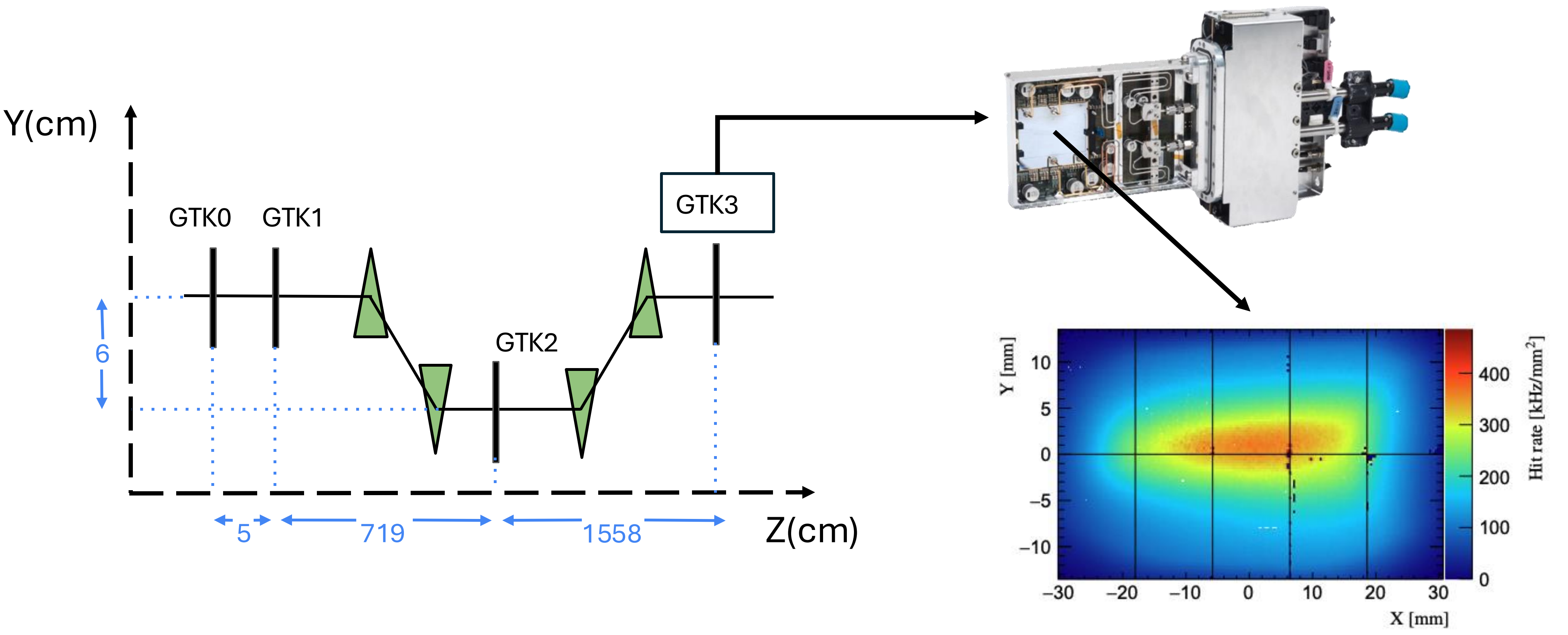


GPU parallelization and memory capacity allow to drastically reduce computational time

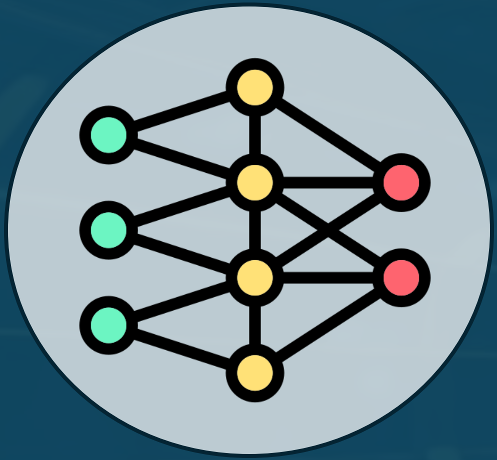
Introduction: NA62 experiment



Introduction: Giga Tracker Stations

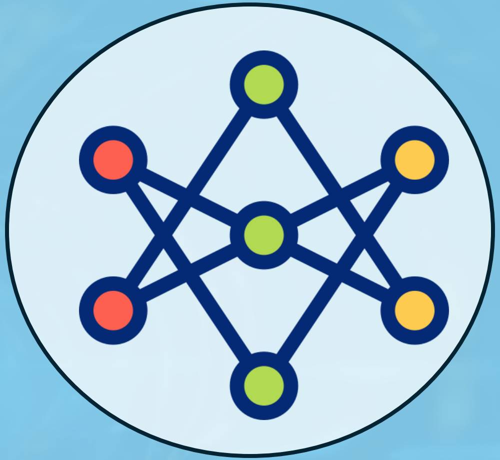


Proposal



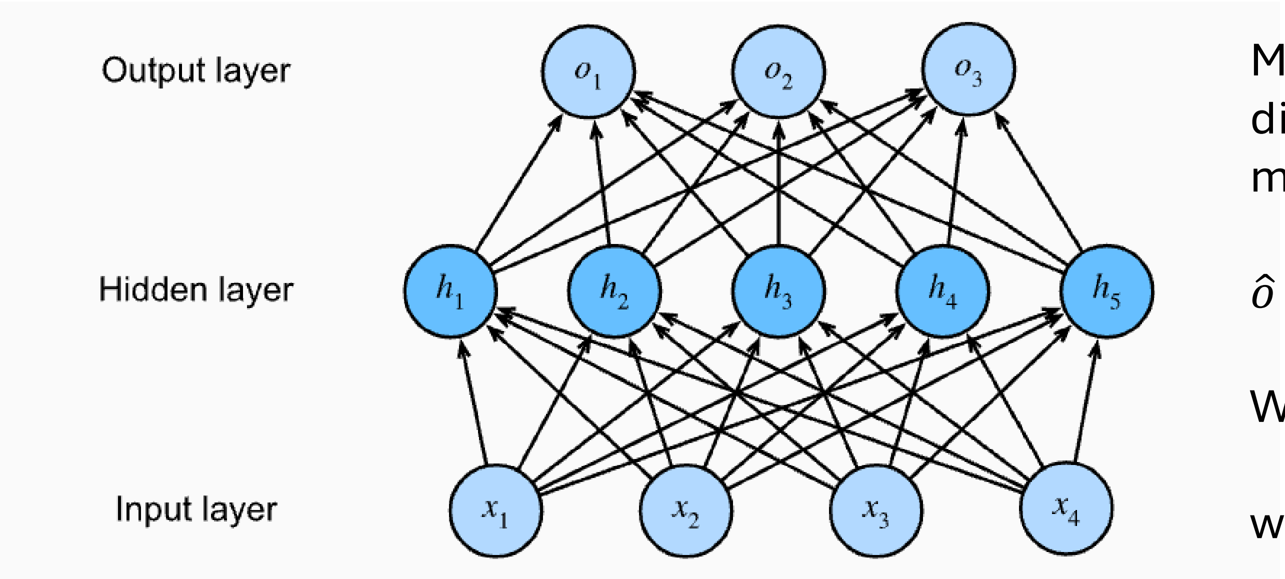
Multi-Layer Perceptron

Transformer



Graph Neural Network

Multi-Layer Perceptron



MLP is an architecture made up of composable and differentiable layers that optimizes its weights (W, b) by means of **Back-Propagation** to minimize a loss function L.

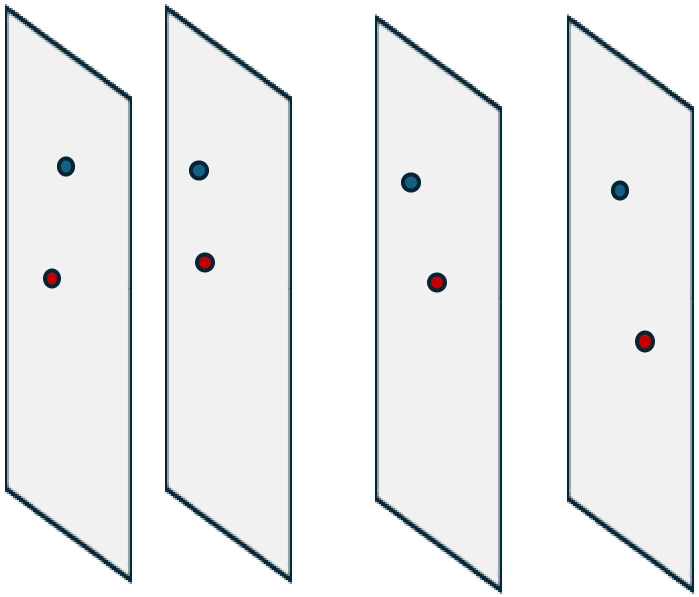
$\hat{o}$ = f(x) $= \sigma_2(W_2 \sigma_1(W_1 x + b_1) + b_2)$

W*, b* = argmin L(o, $\hat{o}$)

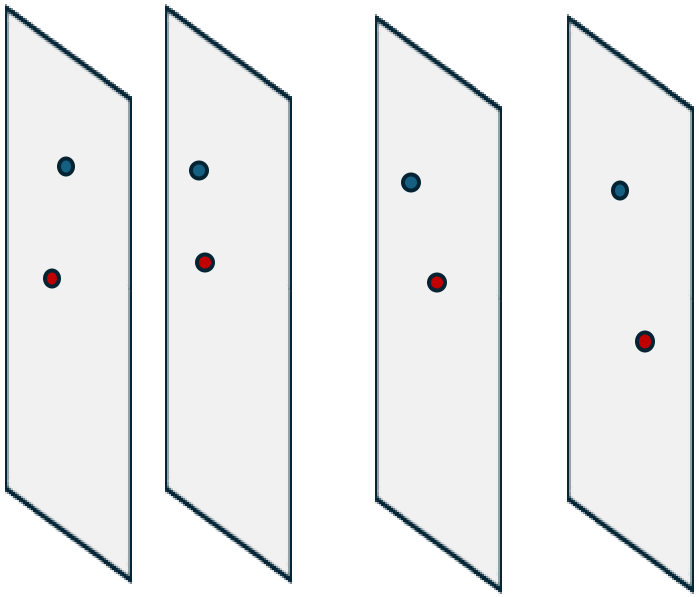
where σ *is an activation function*

* Image from Dive into Deep Learning, chapter 5

Multi-Layer Perceptron



Multi-Layer Perceptron



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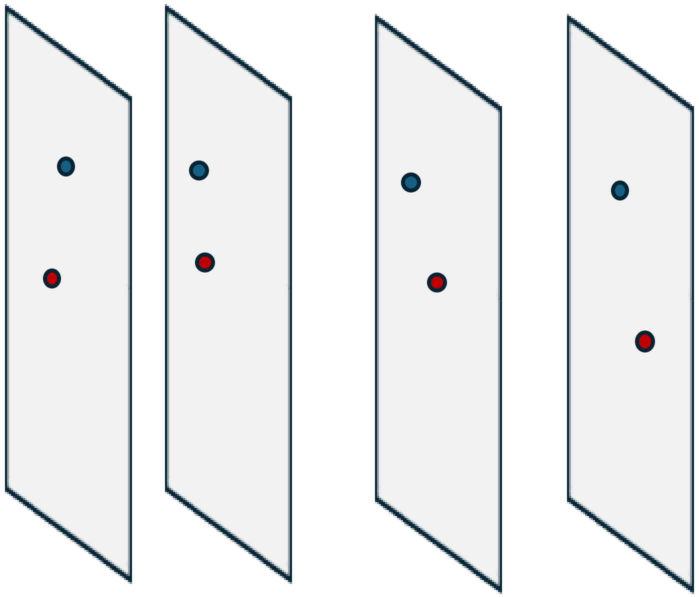
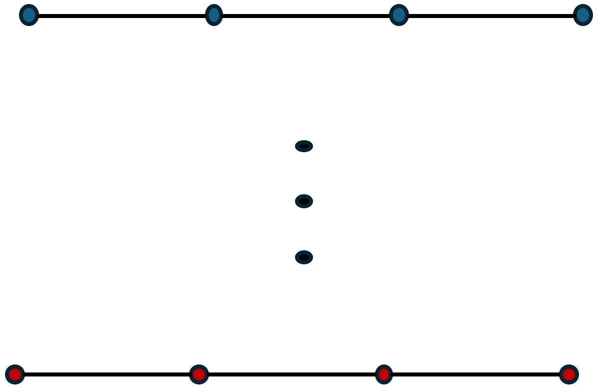
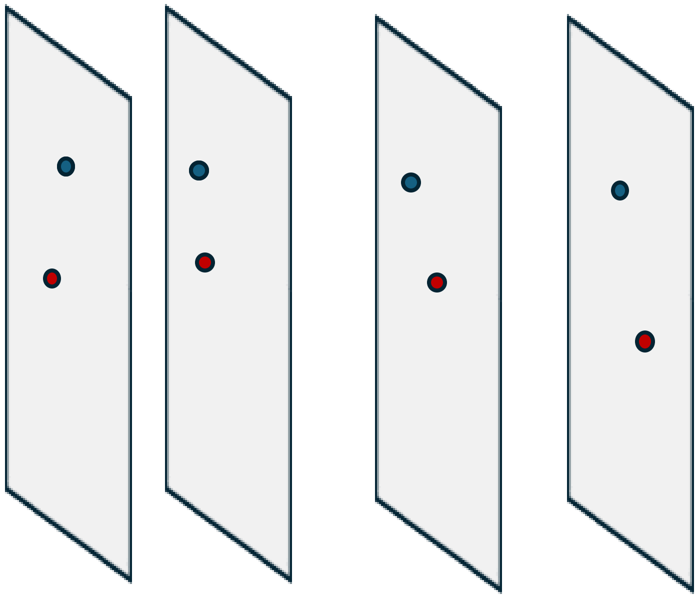


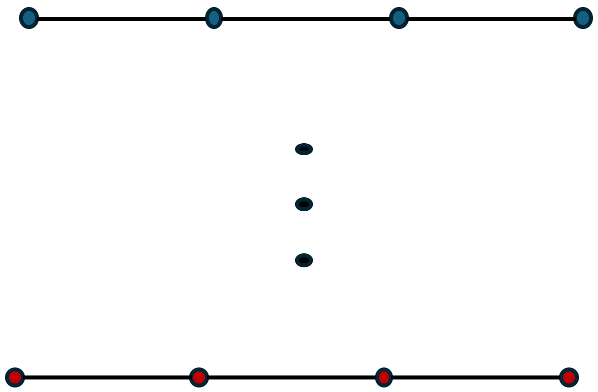
Admissible track combinations



Multi-Layer Perceptron

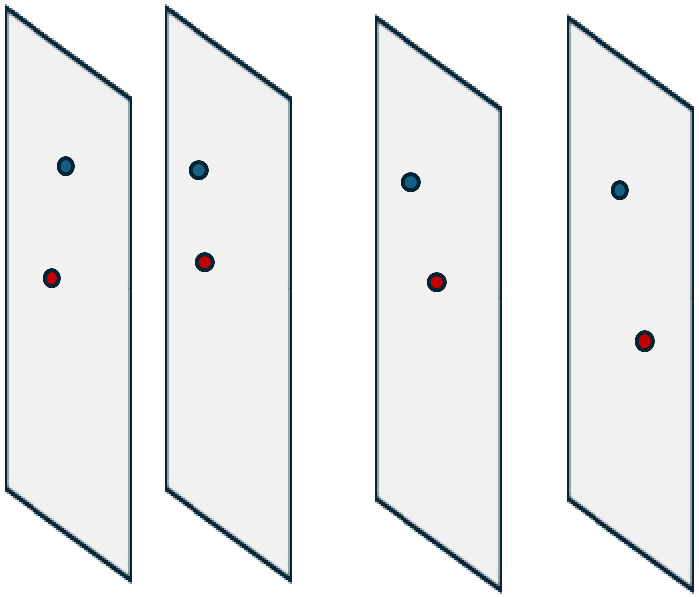


Admissible track combinations

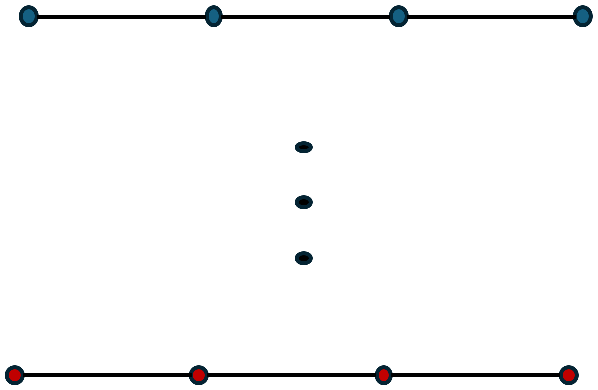


Not admissible track combination

Multi-Layer Perceptron

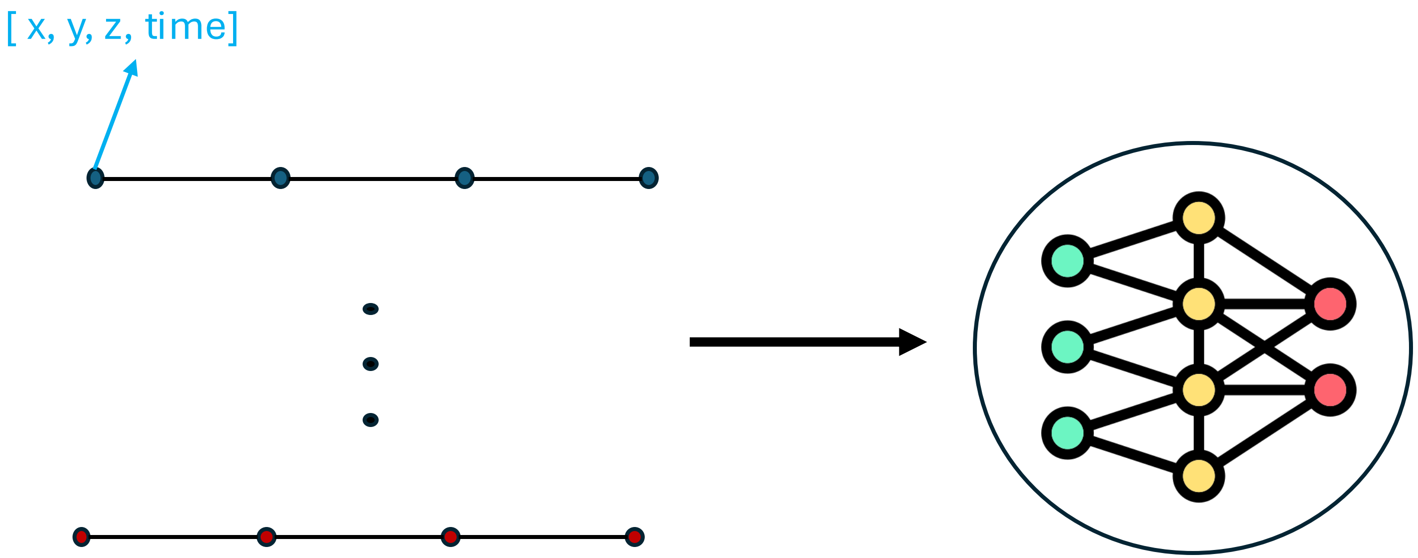


Admissible track combinations

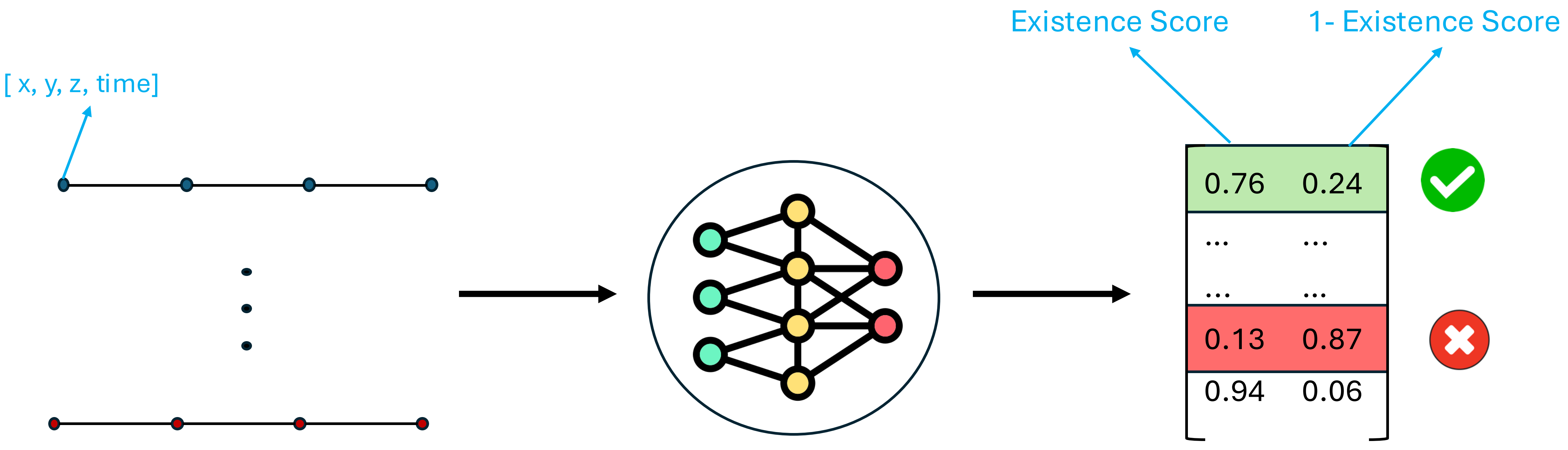


Not admissible track combination

Multi-Layer Perceptron



Multi-Layer Perceptron



Multi-Layer Perceptron: results

Efficiency $= \dfrac{\#\, correctly\ predicted\ tracks}{\#\, total\ true\ tracks}$

Purity $= \dfrac{\#\, correctly\ predicted\ tracks}{\#\, total\ predicted\ tracks}$

FAKE

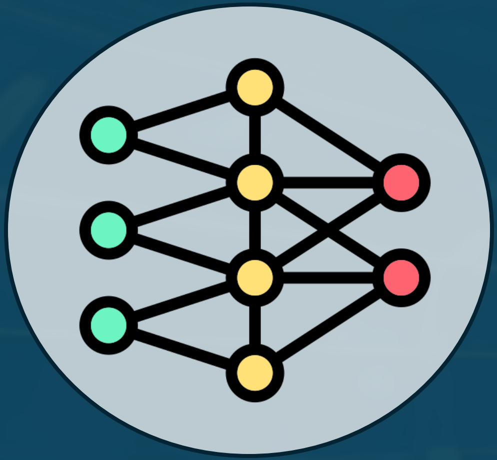
Fake Tracks $= \dfrac{\#\, wrongly\ predicted\ tracks}{\#\, total\ true\ tracks}$

- NA62 MC reproducing the datataking condition in 2022
- 200156 events {-10 ns, +10 ns} wrt KTAG reference time
- The models were implemented on an RTX 3060Ti Trio with 8 GB equipped with a Ryzen 7 3700X CPU
- 60% Train, 20% Validation, 20% Test
- Training on Train Set
- Hyper-parameters using Validation Set
- Results on Test Set

Efficiency	Purity	Fake Tracks
70.06 %	92.3 %	39.45 %

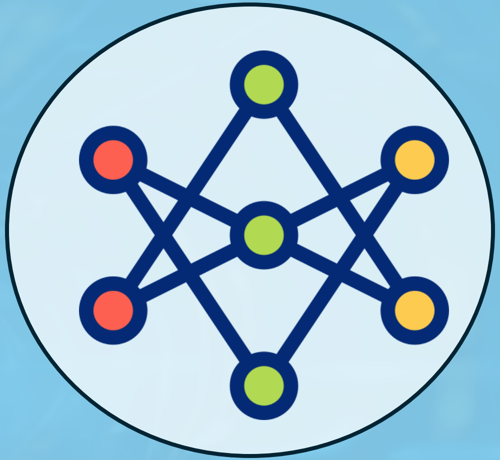
Multi-Layer Perceptron: conclusion

- Local awareness
- Poor Performances
- Big GPU memory needed to store all admissible combinations
- Slow computations
- **Class Imbalance**



Multi-Layer Perceptron

Transformer



Graph Neural Network

Transformer

Attention Is All You Need

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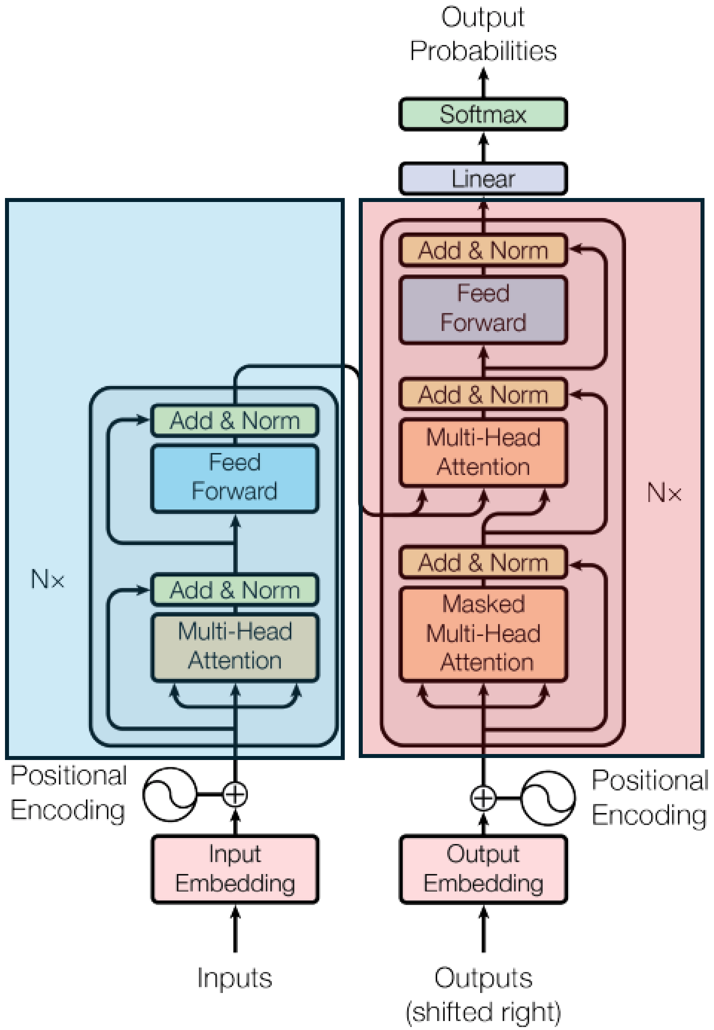
Presented in 2017 and now widely adopted due this their incredible performances and parallelization.

They represented a revolution in Natural Language Processing, Computer Vision and Multimodal Learning

Transformer



Encoder: processes the input sequence by applying self-attention to capture relationships between all tokens in the sequence. It then passes the resulting representations through feed-forward layers to create a context-aware representation of the input data

Decoder: uses this representation to generate the output sequence, often performing tasks like translation or text generation

Note: we used only the Encoder

Transformer

Local awareness

If we have n hits per station, we will create:

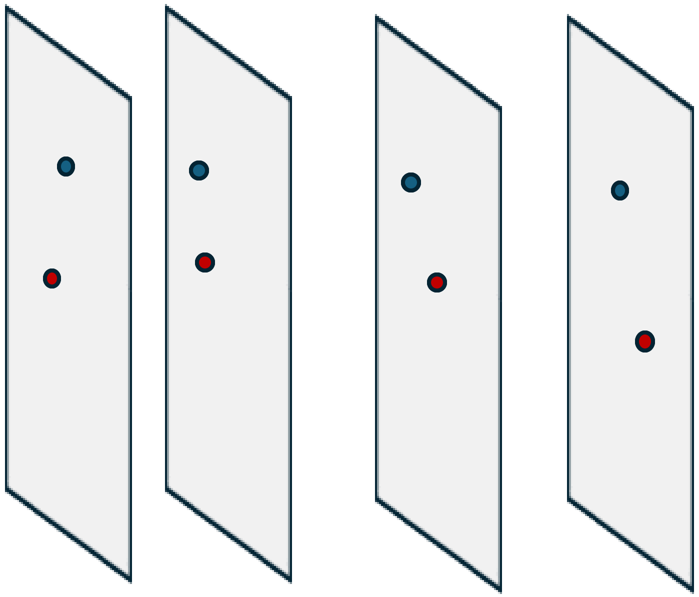
- n^4 (GTK0-GTK1-GTK2-GTK3)
- n^3 (GTK0-GTK2-GTK3)
- n^3 (GTK1-GTK2-GTK3)

Total: n^4+2n^3

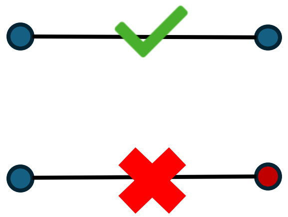
Global awareness with Transfomer

What if move the problem from tracks to edges?

Transformer

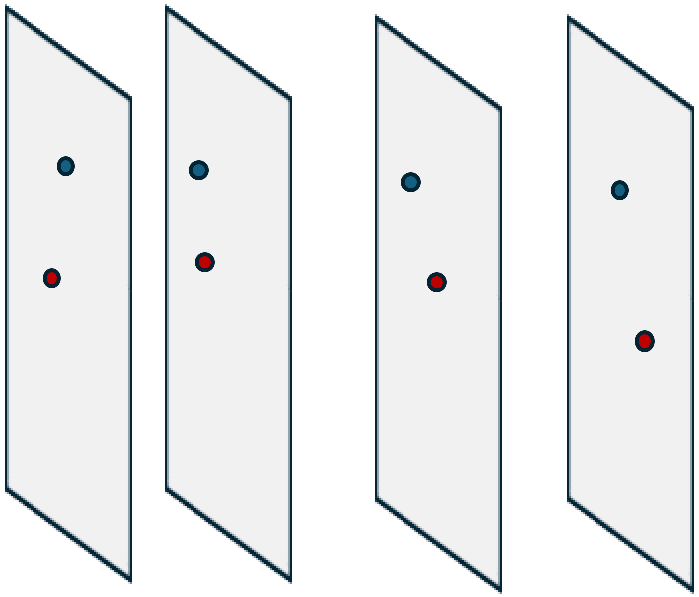


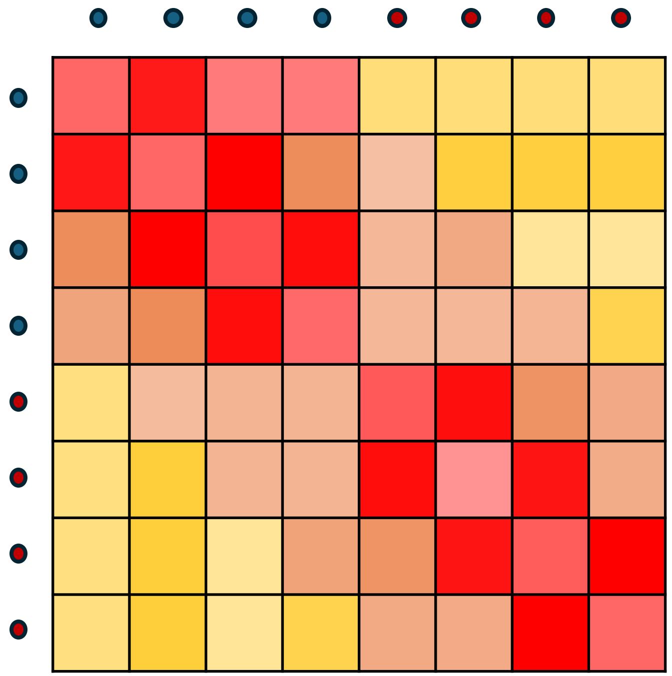
Binary Classification



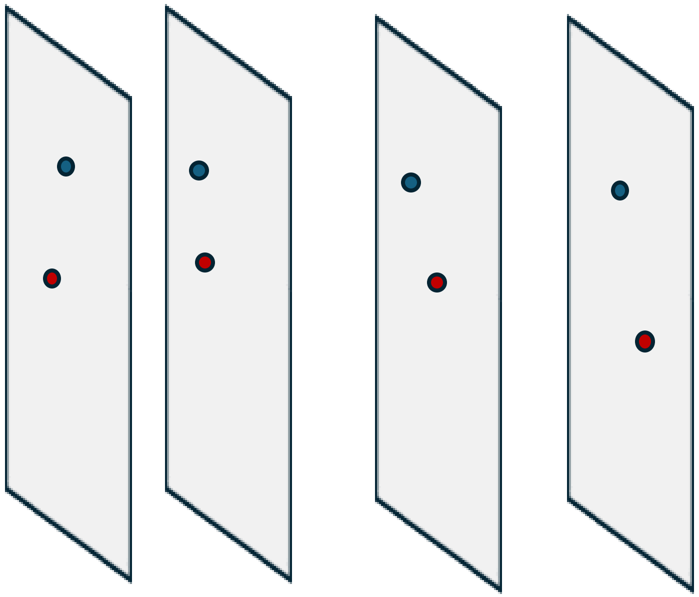
The number of candidates we need to evaluate is $(4n)^2 = 16n^2 << n^4 + 2n^3$

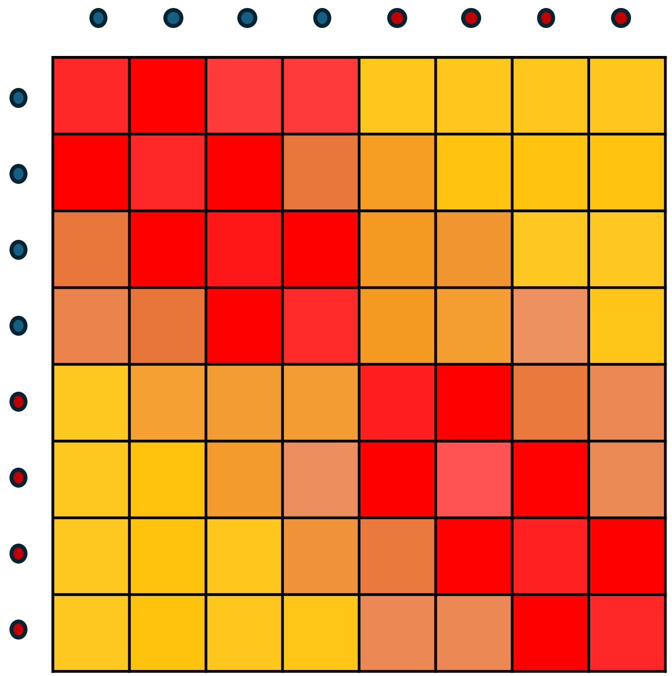
Transformer



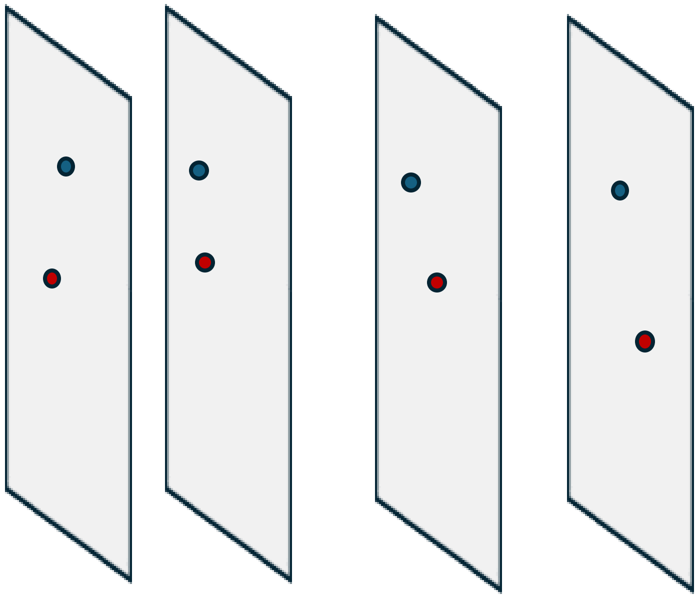


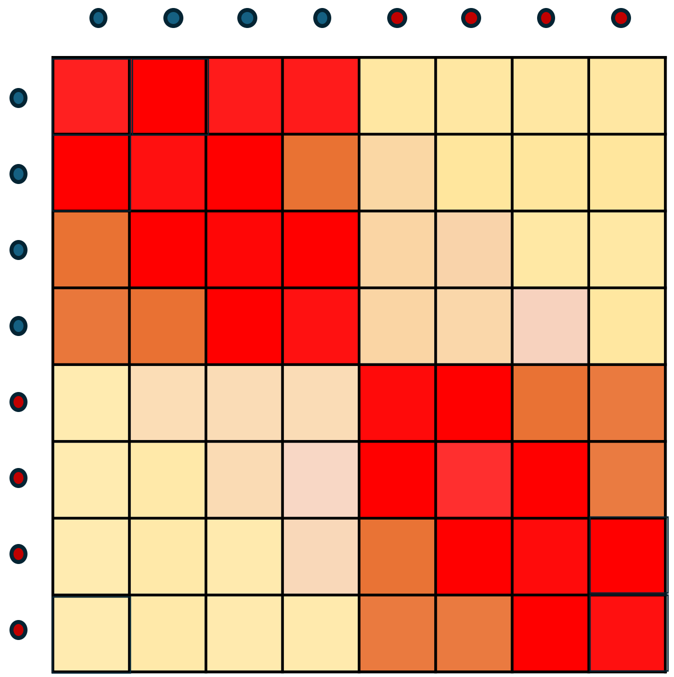
Transformer



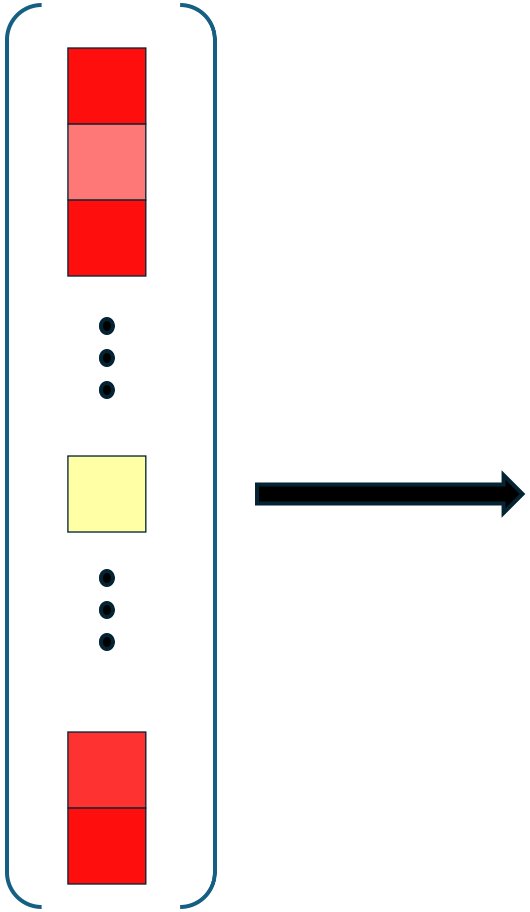


Transformer



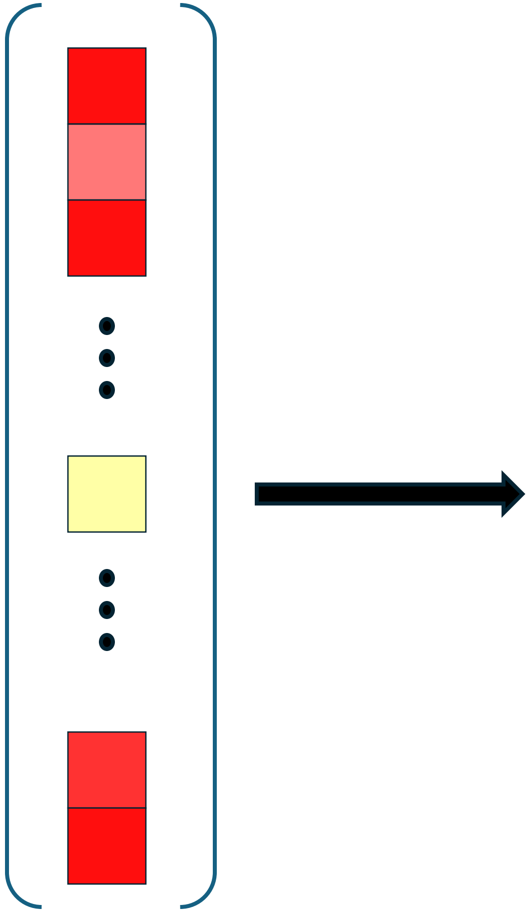


Transformer



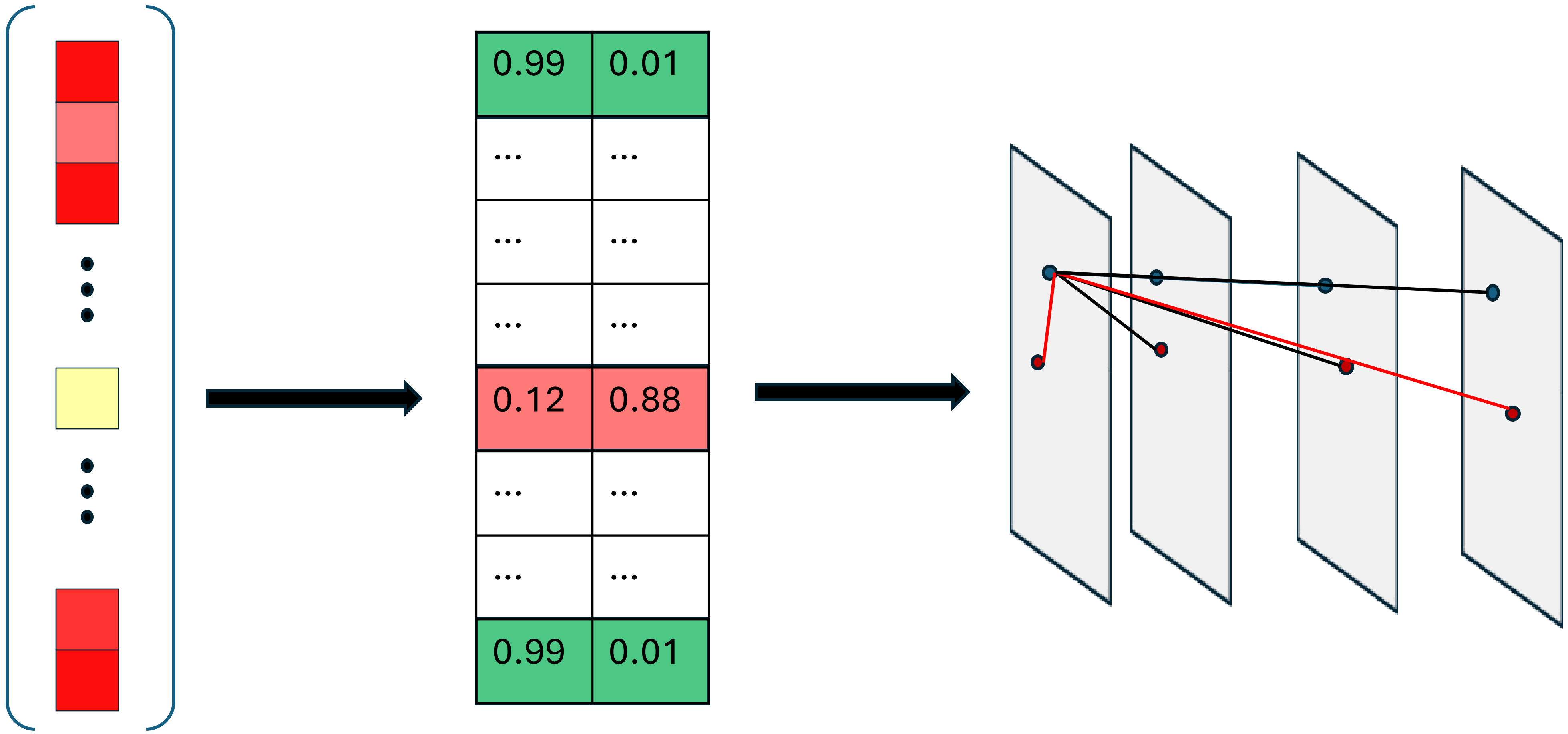
0.99	0.01
…	…
…	…
…	…
0.12	0.88
…	…
…	…
0.99	0.01

Transformer



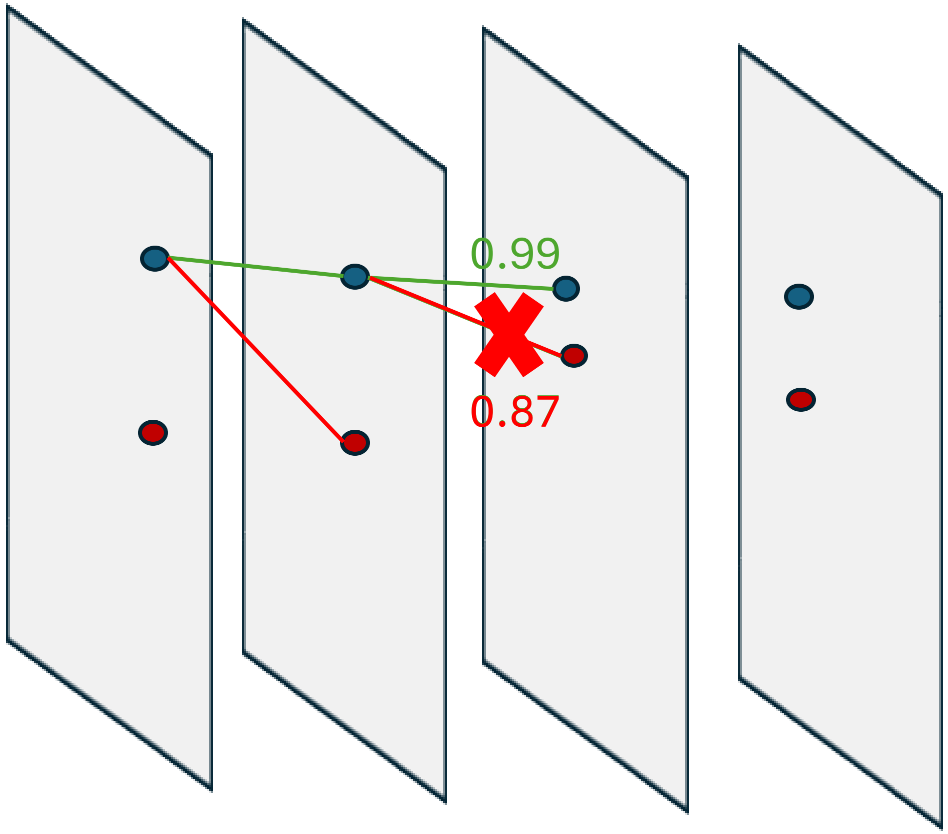
0.99	0.01
...	...
...	...
...	...
0.12	0.88
...	...
...	...
0.99	0.01

Transformer



Transformer

Max Edge selection



Transformer

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Purity $= \dfrac{\#\ correctly\ predicted\ tracks}{\#\ total\ predicted\ tracks}$

Fake Tracks $= \dfrac{\#\ wrongly\ predicted\ tracks}{\#\ total\ true\ tracks}$

Multi-Layer Perceptron

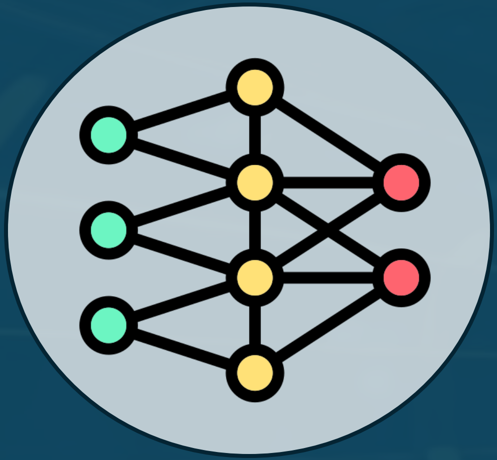
Efficiency	Purity	Fake Tracks
70.06 %	92.3 %	39.45 %

Transformer

Efficiency	Purity	Fake Tracks
95.95 %	98.62 %	1.22 %

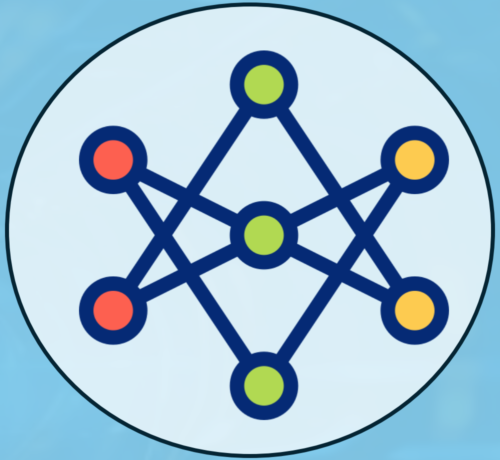
Transformer

- Solved class imbalance
- Global awareness
- Efficient computations
- Many computations to consider all the connections



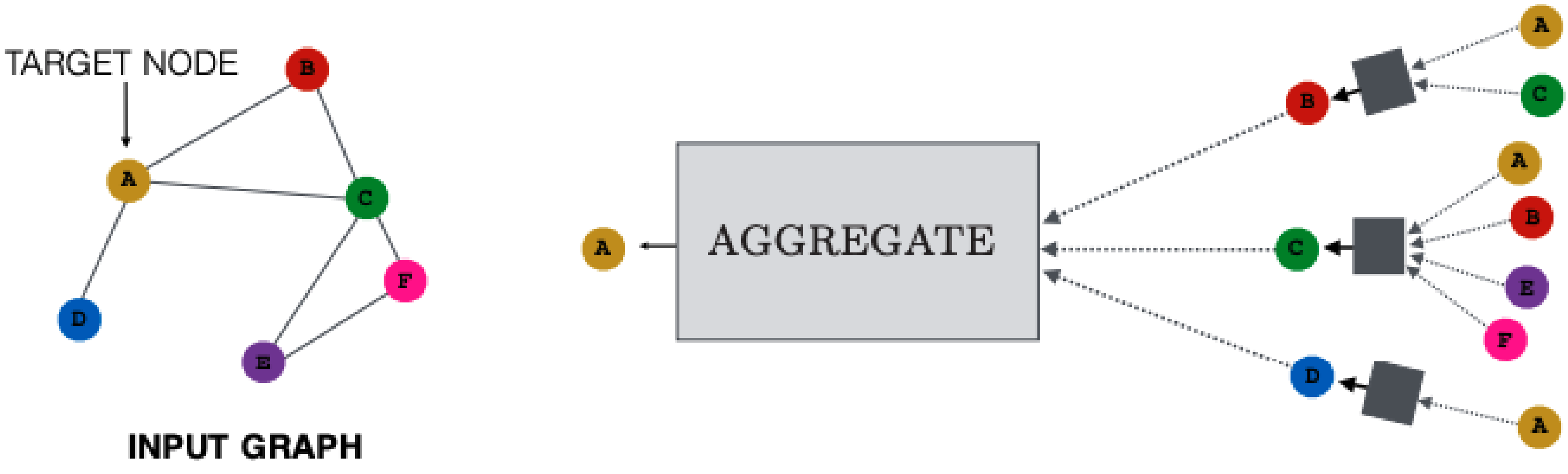
Multi-Layer Perceptron

Transformer



Graph Neural Network

Graph Neural Network



Graph Neural Networks are a type of neural network designed to work with graph-structured data.

They **propagate** and **aggregate** information across nodes and edges in a graph, allowing them to learn representations that capture the relationships and structure within the data

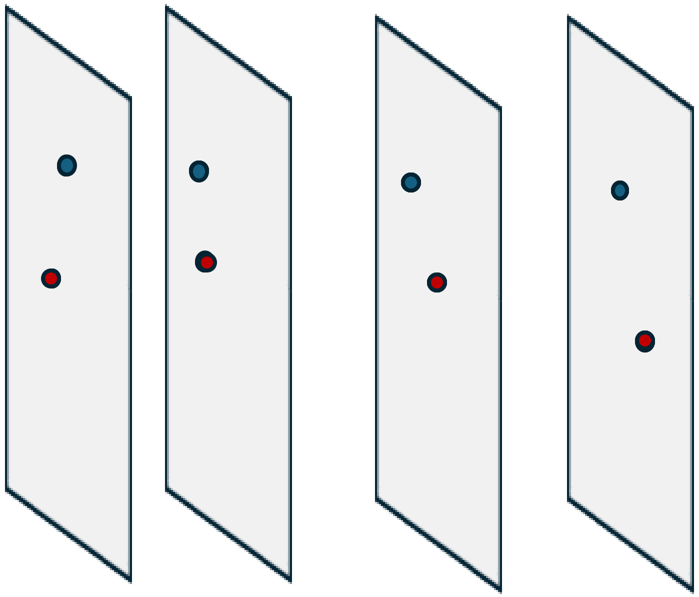
* Image from "Representation Learning on Graphs: Methods and Applications"

Graph Neural Network

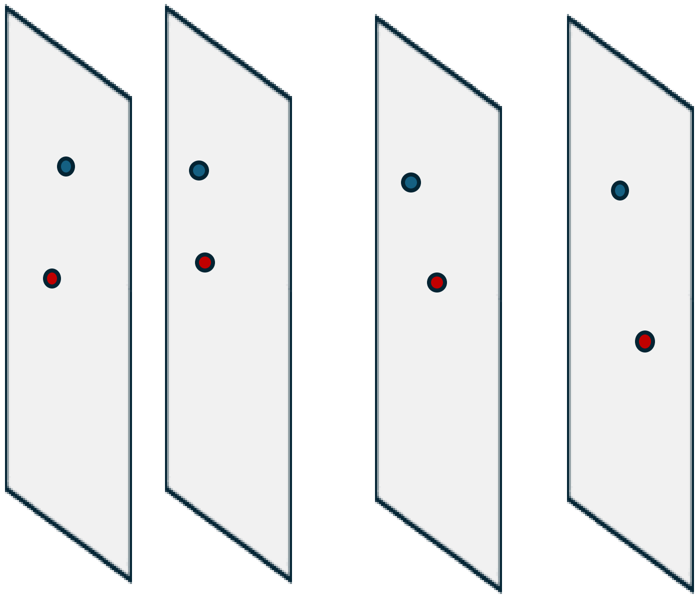
Many computations to consider all the connections

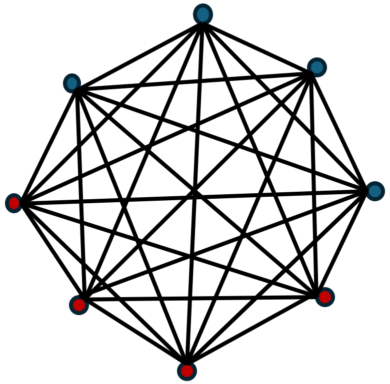
Graphs allow to decide the topology (e.g. the connections between nodes)

Graph Neural Network

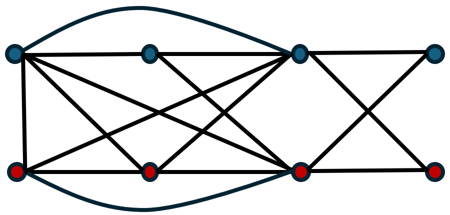


Graph Neural Network





Complete Graph

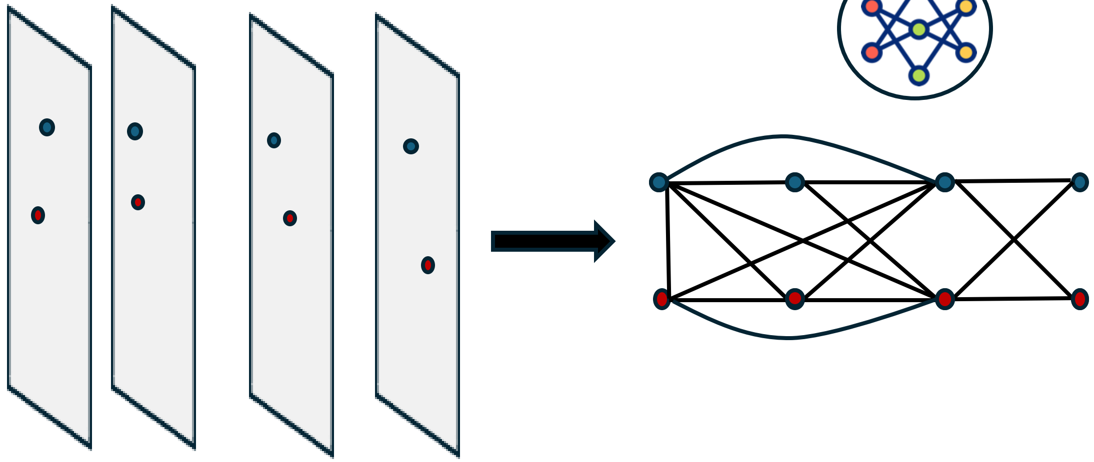


Sparse Graph

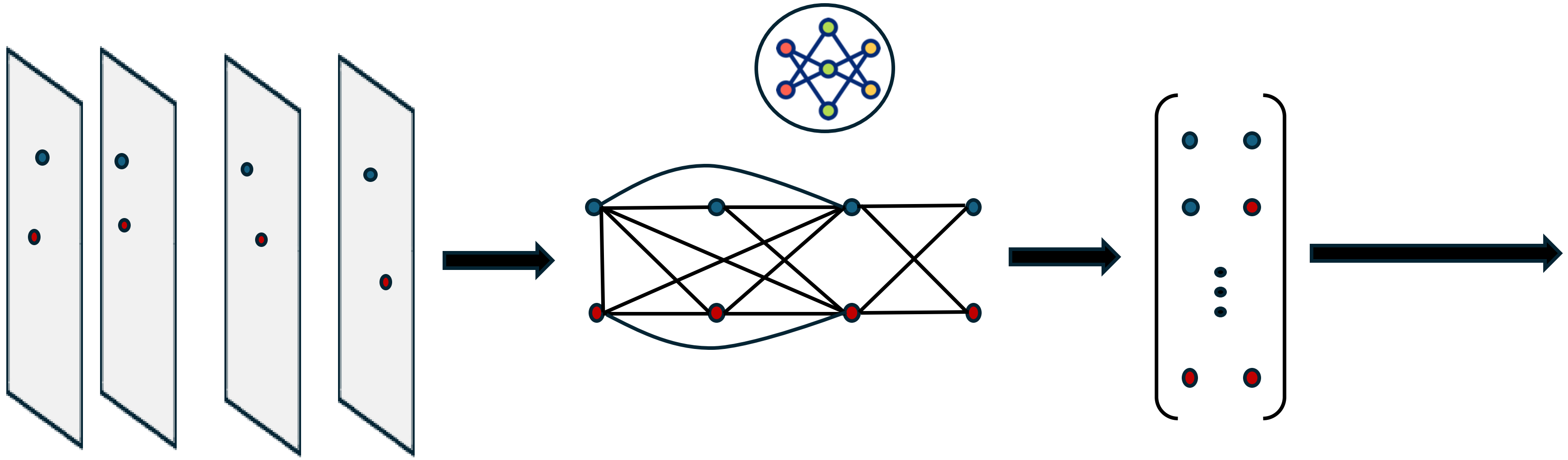
If we consider possible edges between hits:
- $2n^2$ (GTK0-GTK1 and GTK0-GTK2)
- n^2 (GTK1-GTK2)
- n^2 (GTK2-GTK3)

Total: $4n^2 < 16n^2$

Graph Neural Network

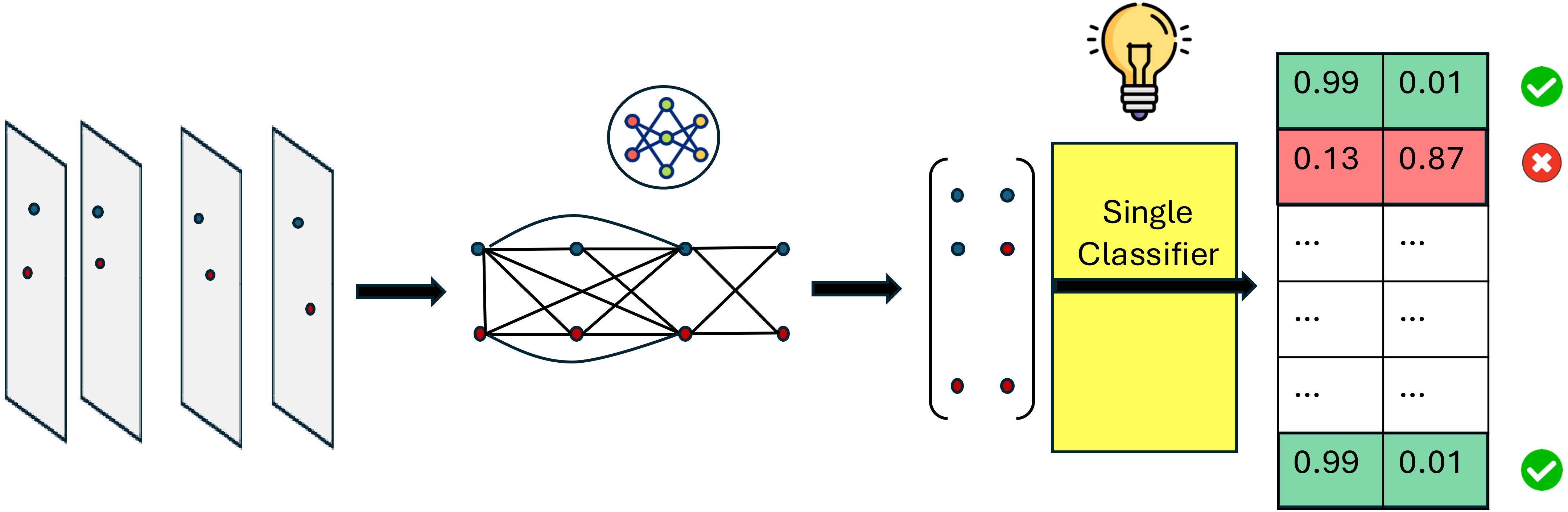


Graph Neural Network

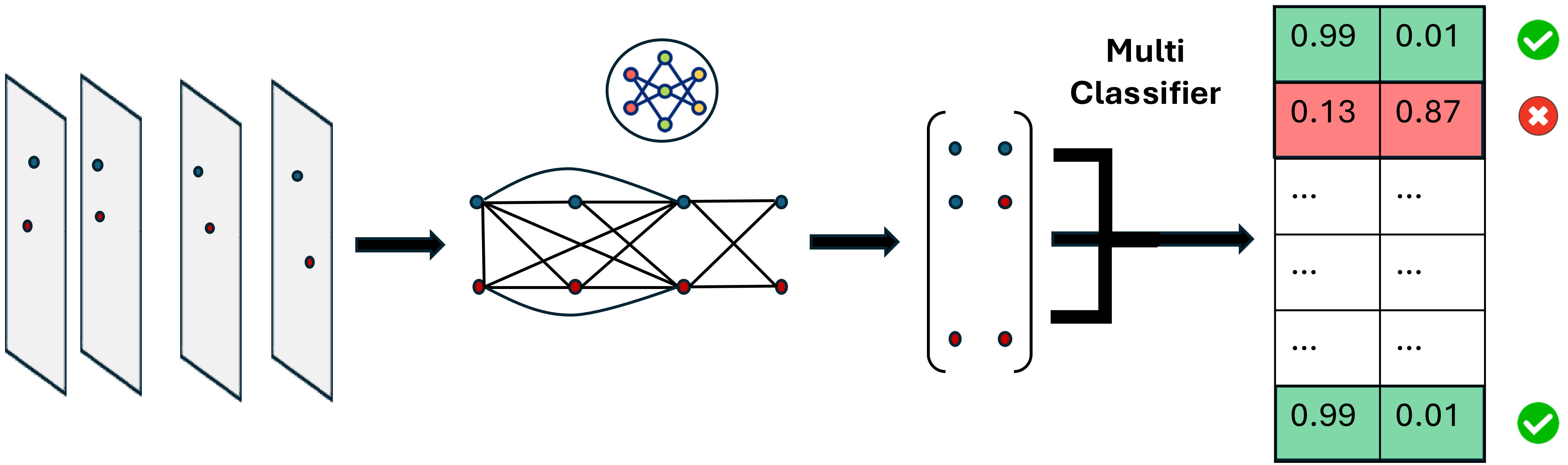


0.99	0.01
0.13	0.87
…	…
…	…
…	…
0.99	0.01

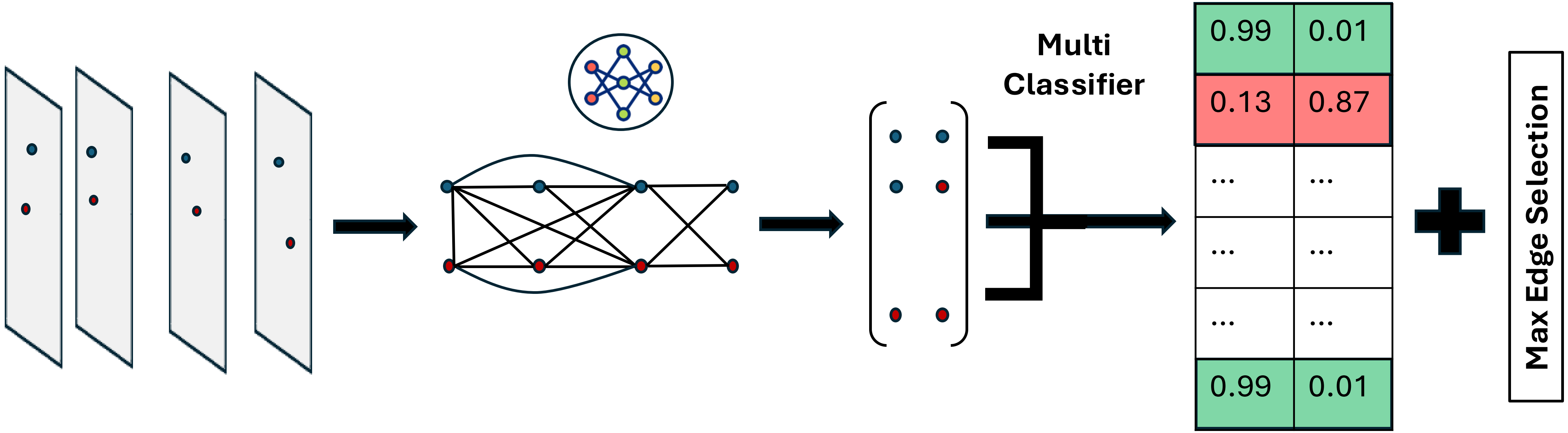
Graph Neural Network



Graph Neural Network



Graph Neural Network



Graph Neural Network

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Fake Tracks $= \dfrac{\#\ wrongly\ predicted\ tracks}{\#\ total\ true\ tracks}$

Multi-Layer Perceptron

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Transformer

Efficiency	Purity	Fake Tracks
95.95 %	98.62 %	1.22 %

Graph Neural Network*

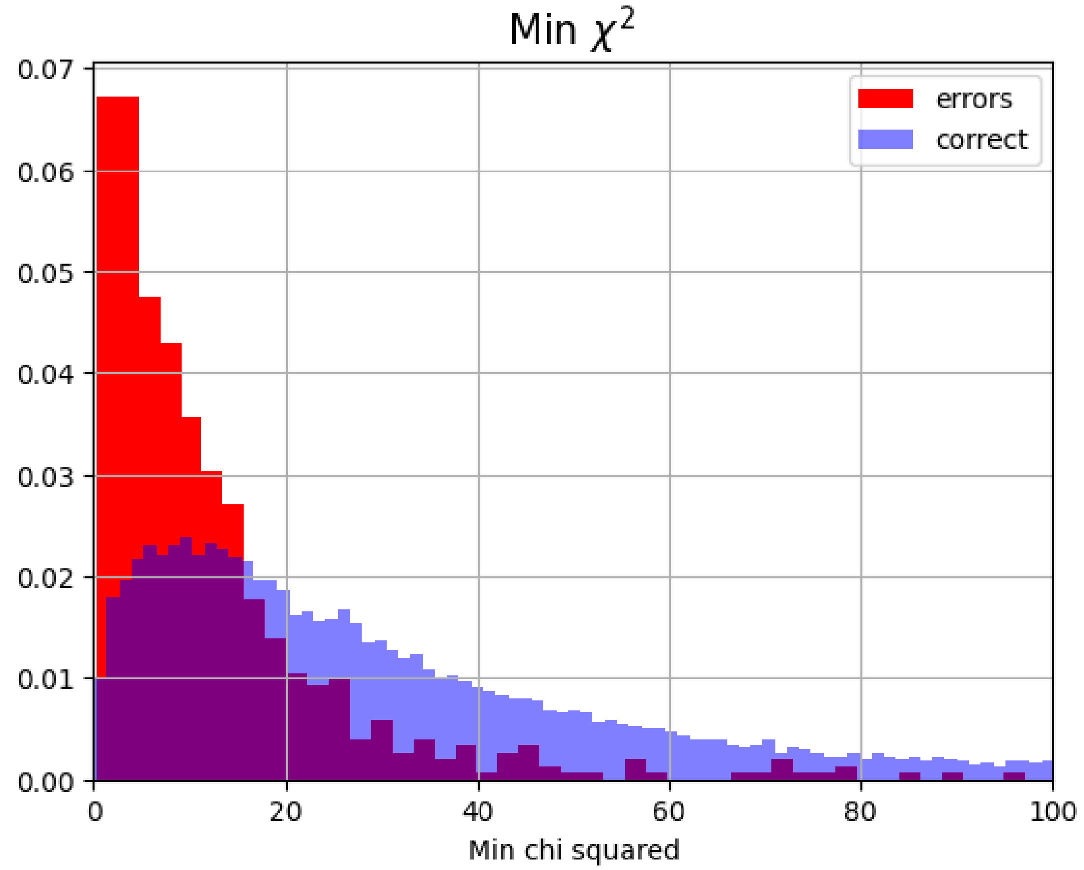
Efficiency	Purity	Fake Tracks
94.78 %	99.78 %	0.21 %

* Direct, Fully-connected graph with Graph Convolutional Network and Multi-Classifier

Graph Neural Network

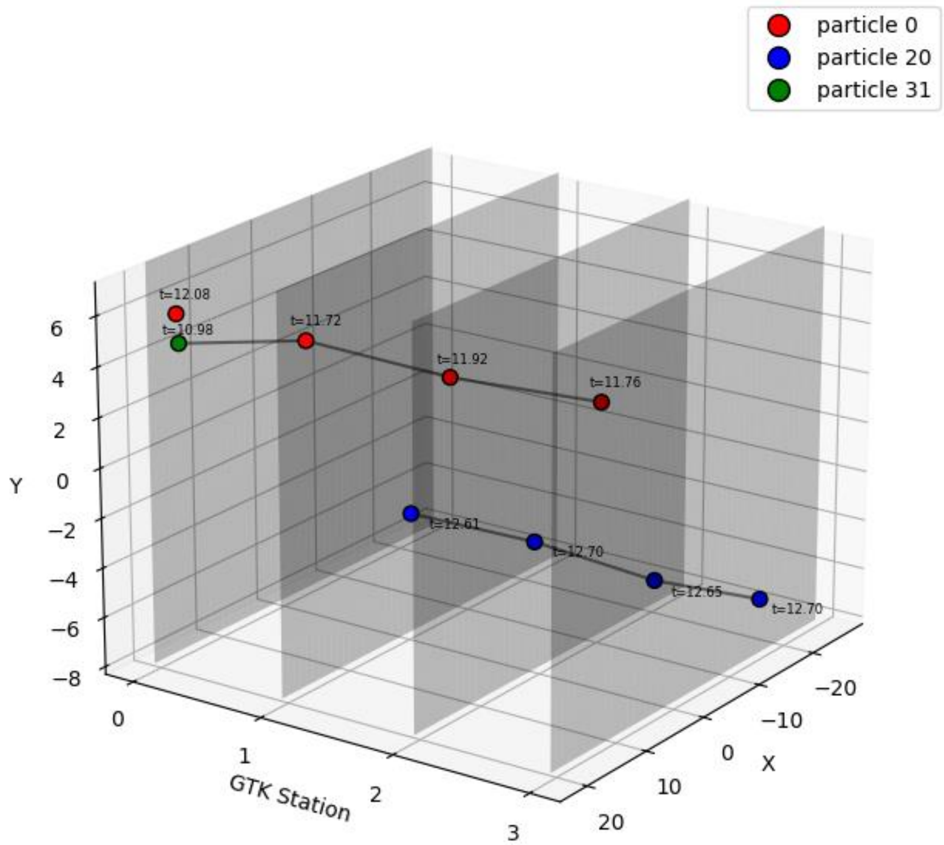
Difficulty Score

$$\chi^2 = \min_{k=0,1,2,3}\left(\min_{1\le i<j\le n} [(x_{i,k} - x_{j,k})^2 + (y_{i,k} - y_{j,k})^2 + (t_{i,k} - t_{j,k})^2] \right)$$

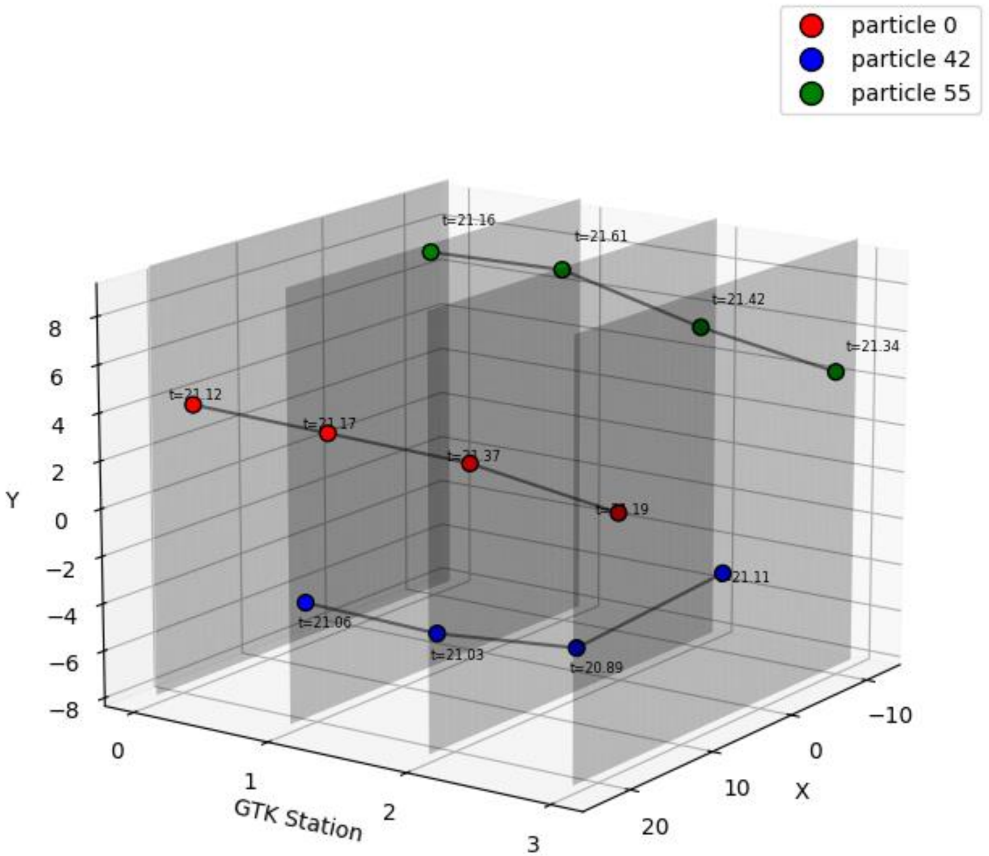


Graph Neural Network

Example of an error



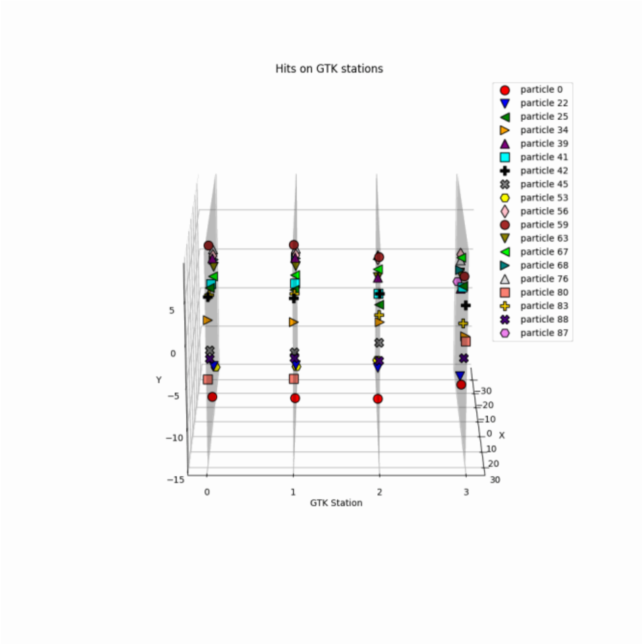
Example of a good prediction

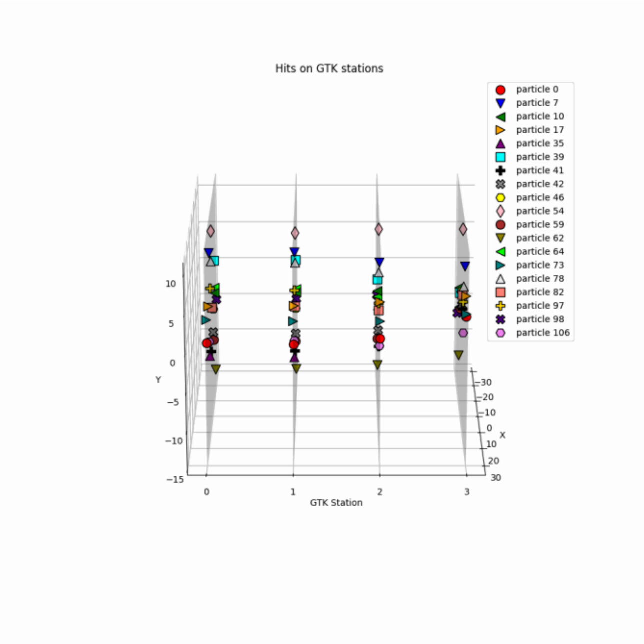


Graph Neural Network

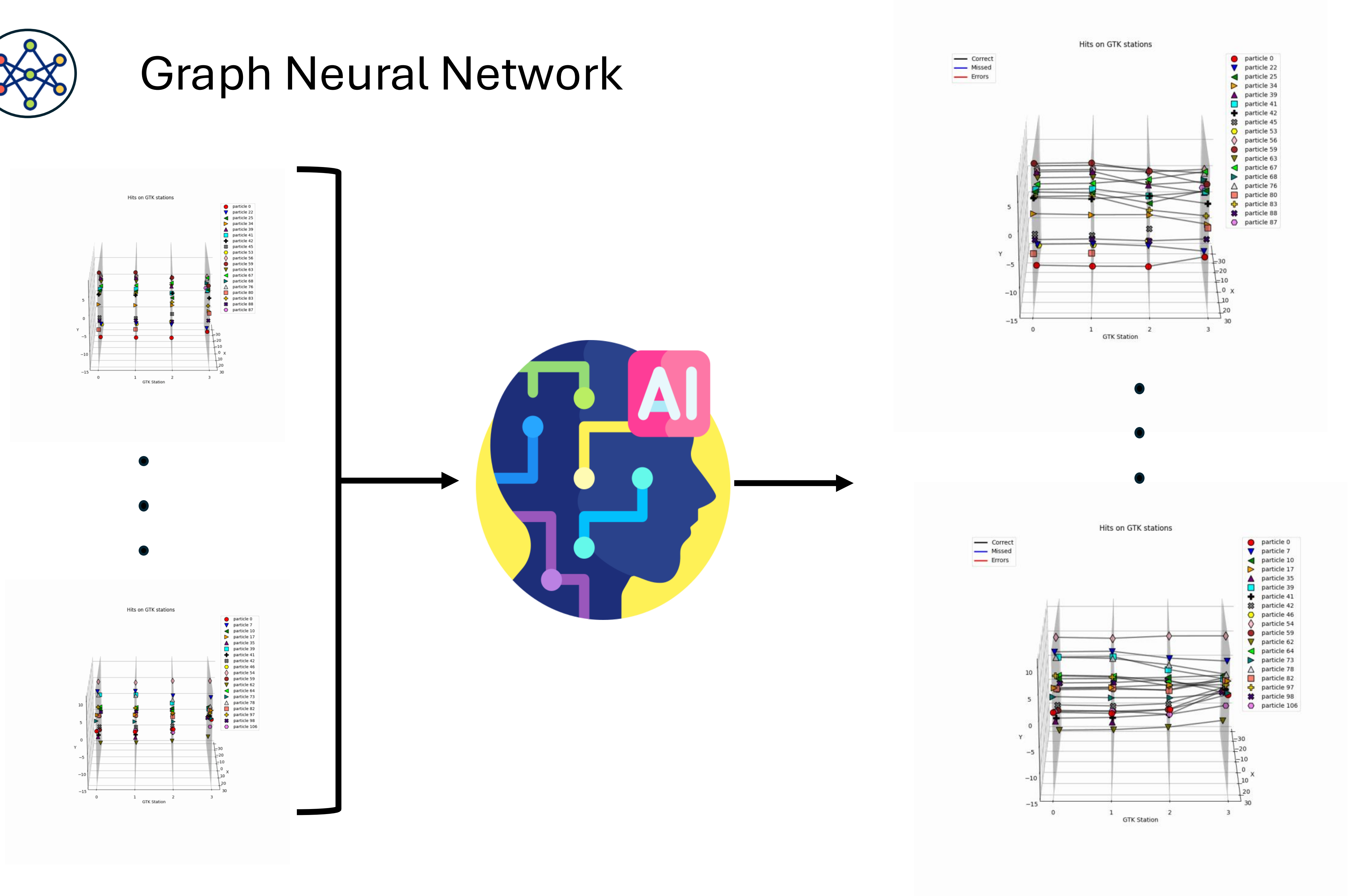
- Solved class imbalance
- Global awareness
- Computationally Efficient
- Flexible Topology

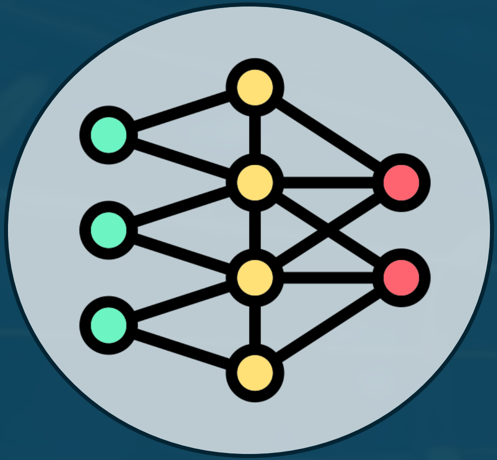
Graph Neural Network





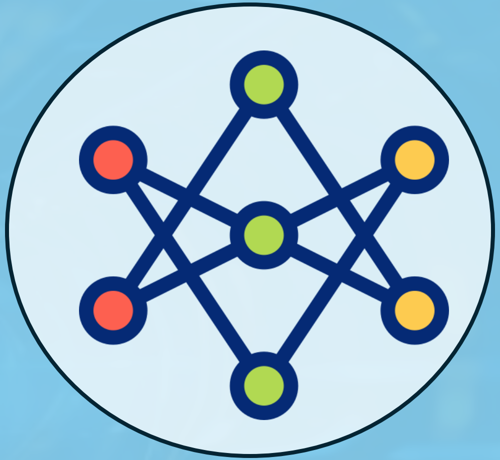
Graph Neural Network





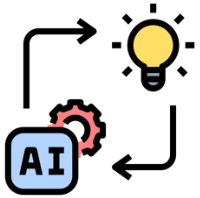
Multi-Layer Perceptron

Transformer

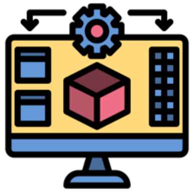


Graph Neural Network

Conclusions



- Machine Learning algorithms can be used to track particles



- 3 different algorithms were proposed (MLP, Transformer, Graph Neural Network)

Acknowledgments

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