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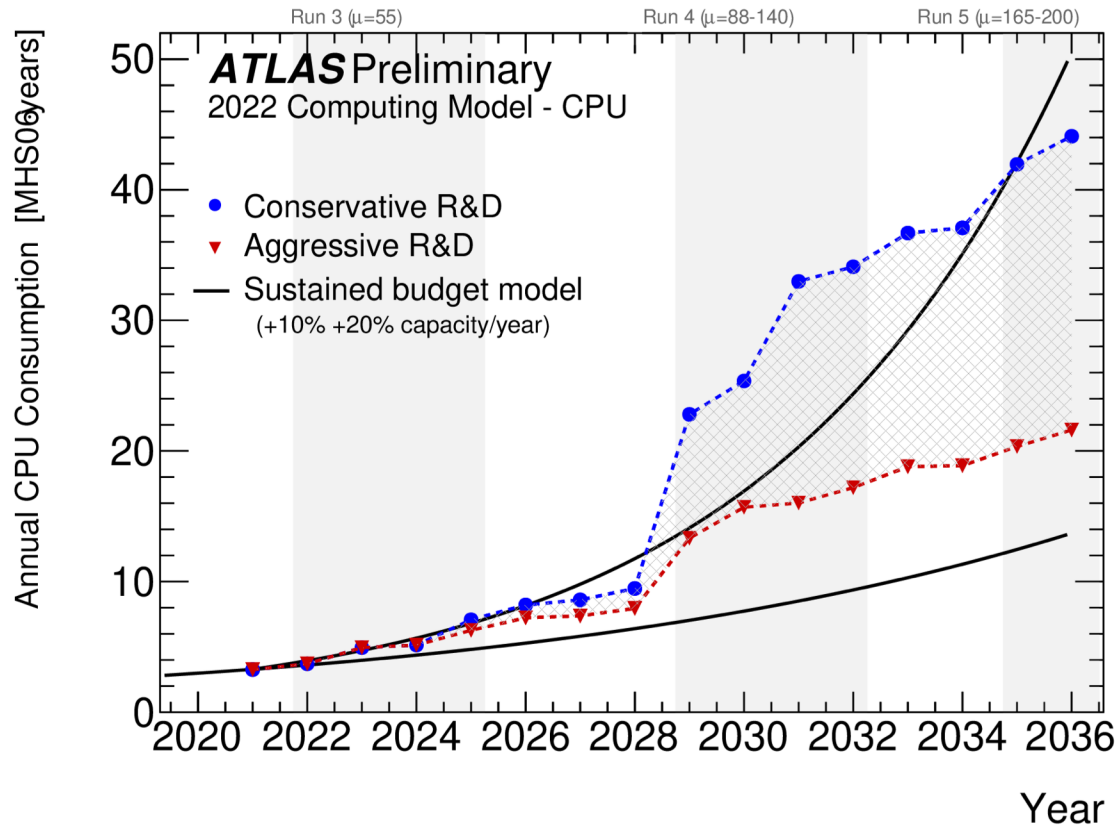
Application of Quantum Annealing with Graph Neural Network Preselection in Particle Tracking at LHC

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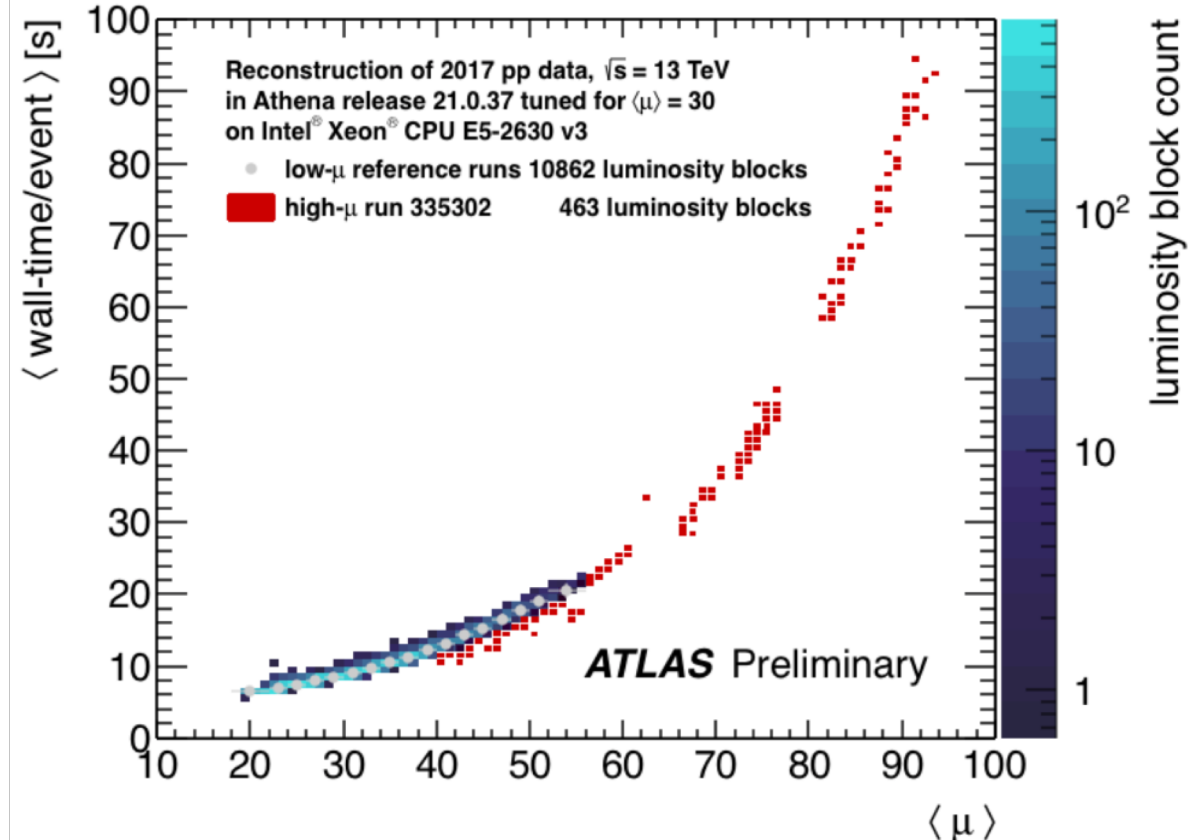
Connecting The Dots 2023

2023/10/12

- HL-LHC is coming
- With larger pile-up ($\langle \mu \rangle \sim 200$) and high readout rate, CPU consumption will dramatically increase.
 - Especially track reconstruction -> New techniques are needed

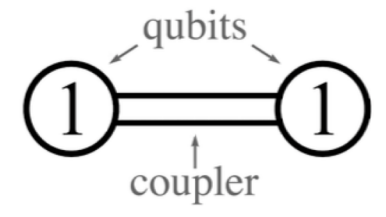
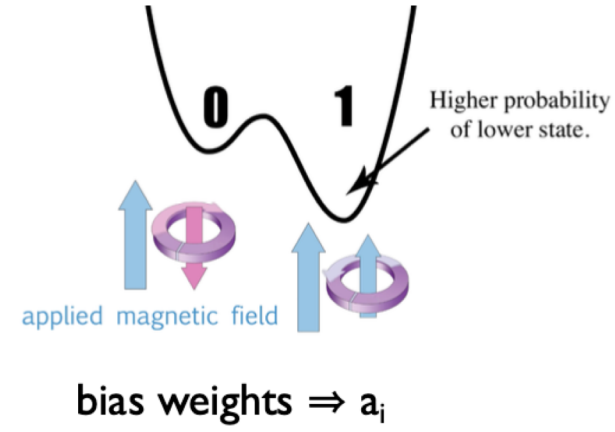
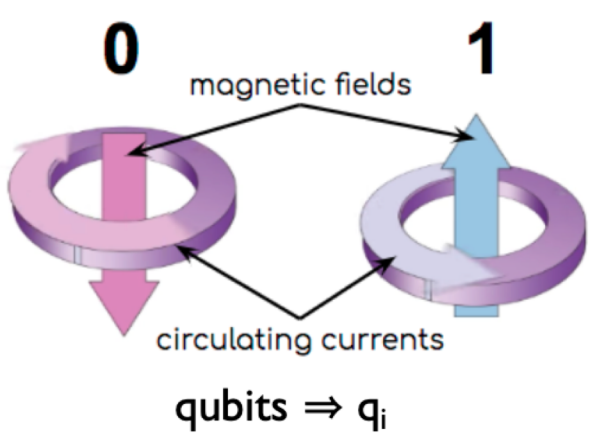


[CERN-LHCC-2022-005](#)



[ATLAS Computing Public Result](#)

- Quantum Annealing:
An optimisation process for finding the global minimum of a given function by using quantum fluctuations.
- Quantum Annealer: The machine which is designed to perform the quantum annealing process.
e.g. D-Wave computers



degree to which a qubit tends to a particular state

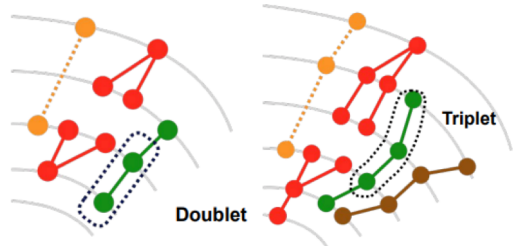
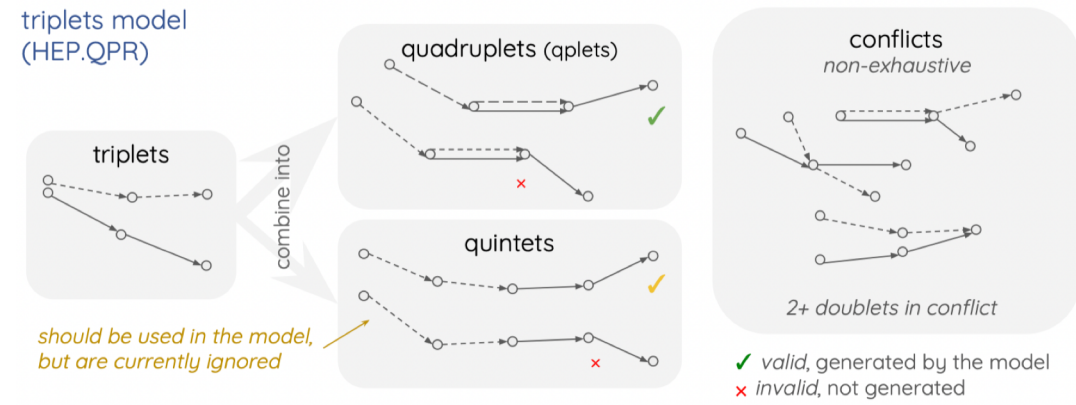
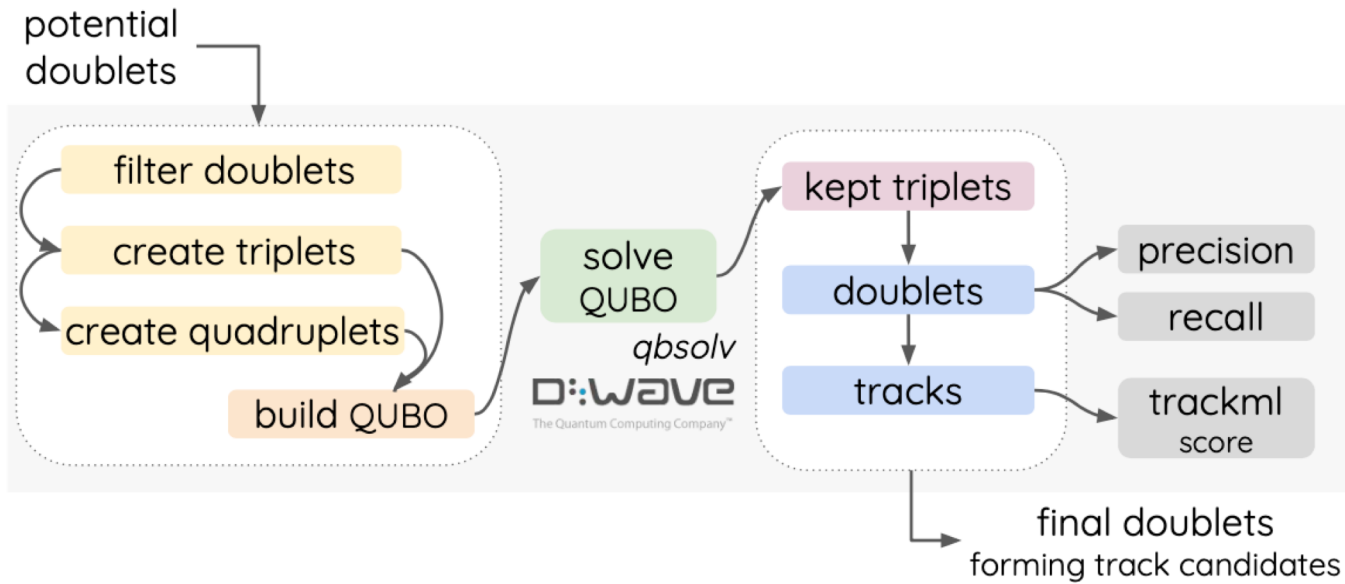
degree to which two qubits tend to the same state

$$O(a; b; q) = \sum_{i=1}^N a_i q_i + \sum_i^N \sum_j^N b_{ij} q_i q_j \quad q_i \in \{0, 1\}$$

QUBO
Quadratic Unconstrained Binary Optimisation

- Quantum Annealer can only deal with the problem which can be transform to a "QUBO" or "Ising" function.

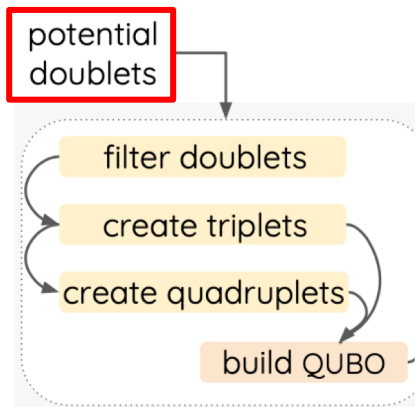
- We found the Quantum Annealing could improve the speed of pattern recognition and provide another way to perform the particle tracking. Result published on: [arXiv: 1902.08324](https://arxiv.org/abs/1902.08324)



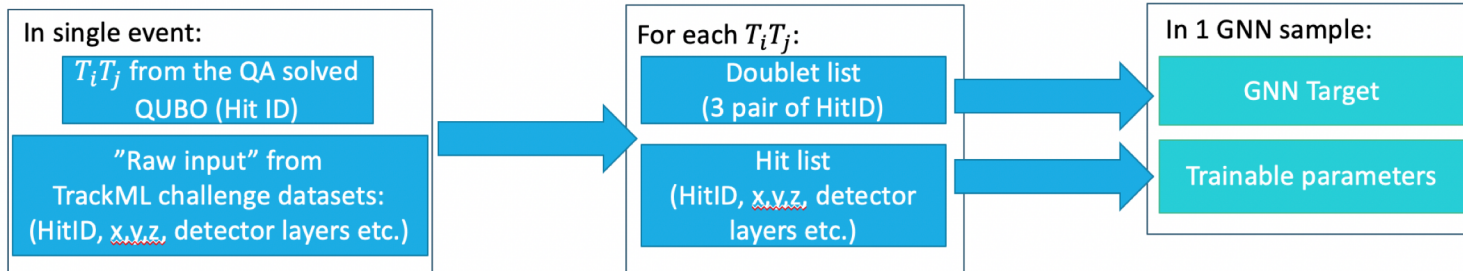
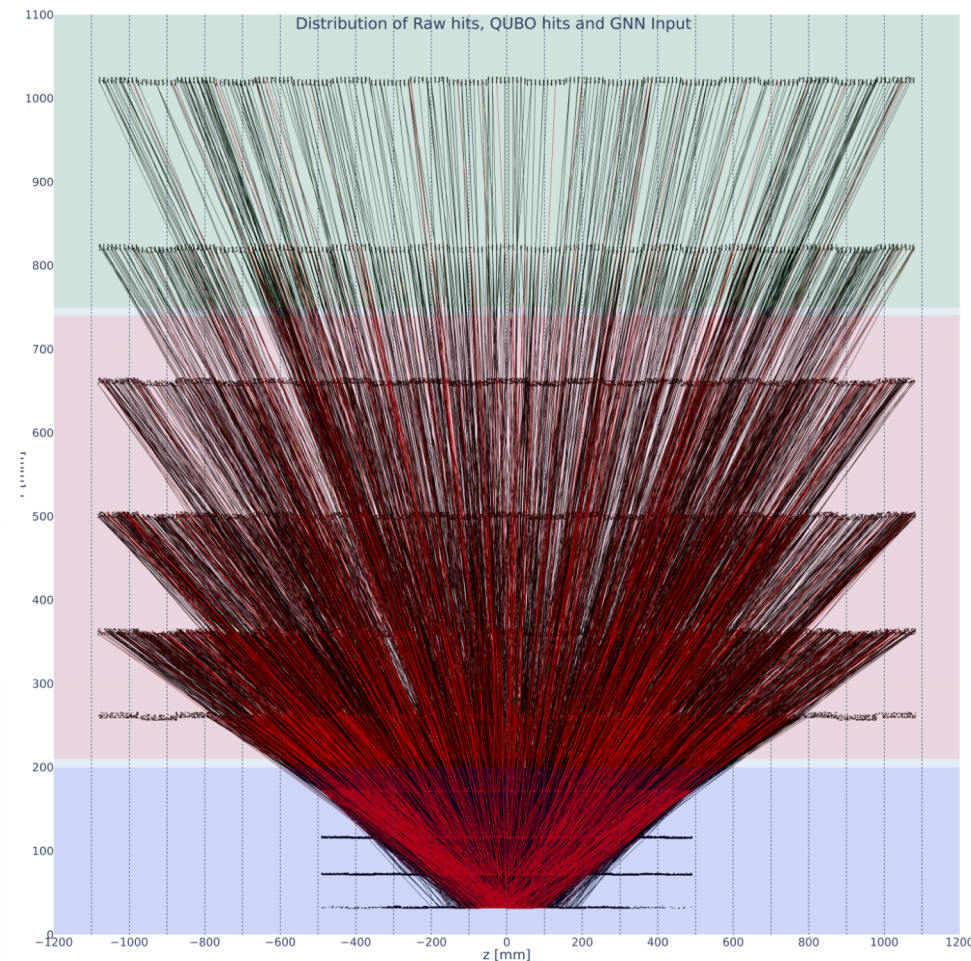
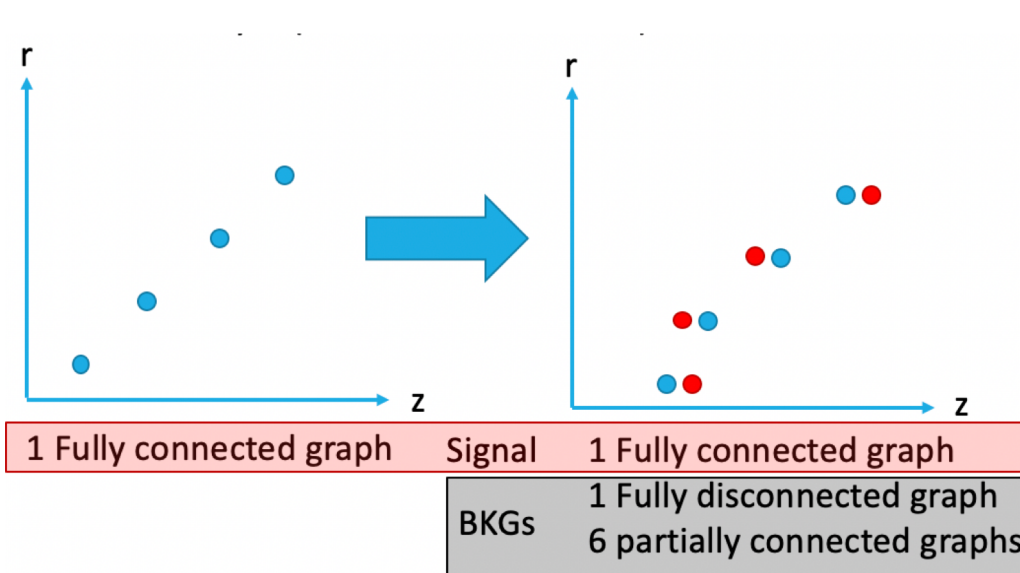
$$O(a, b, T) = \sum_i^N a_i T_i + \sum_i^N \sum_{j < i}^N b_{ij} T_i T_j$$

- T_i : potential triplet
- a_i : Bias weight which has been set to 0.
- b_i : The coupling strength, depending on the relation between T_i & T_j

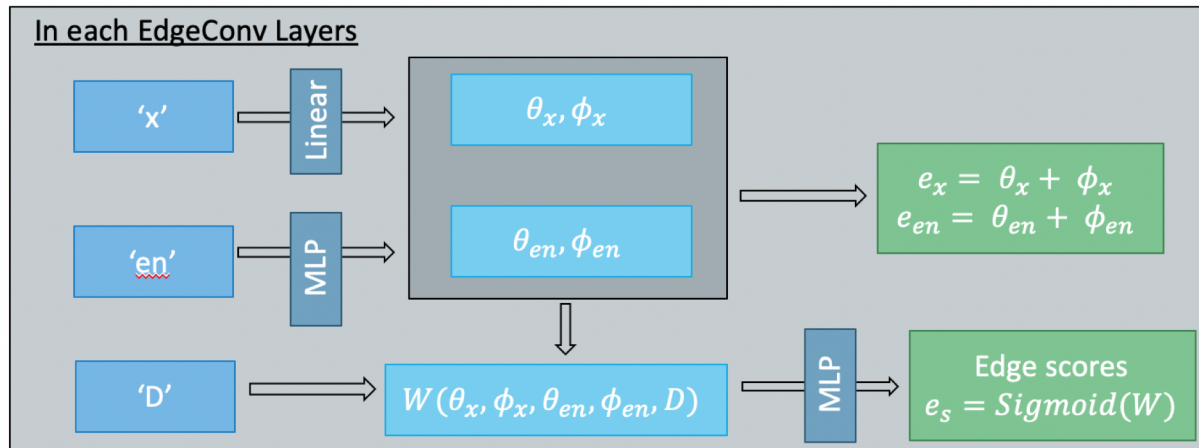
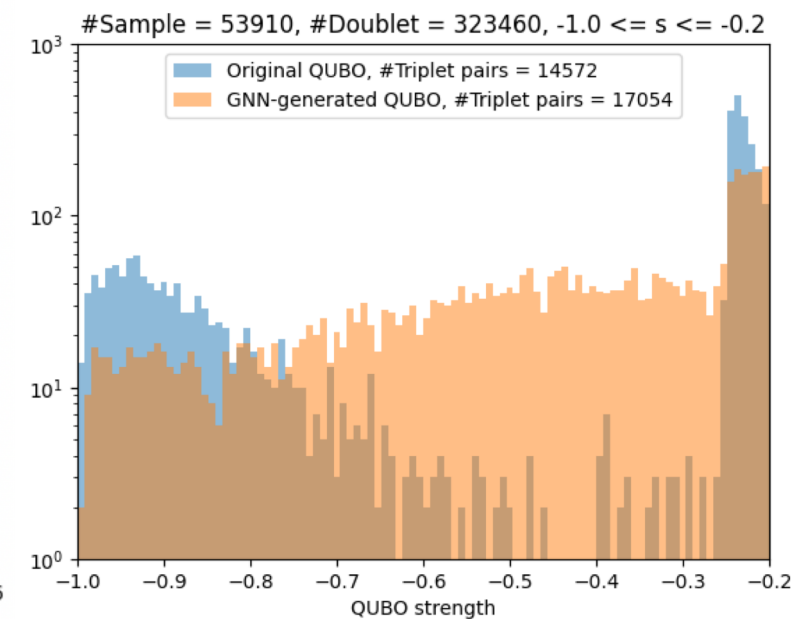
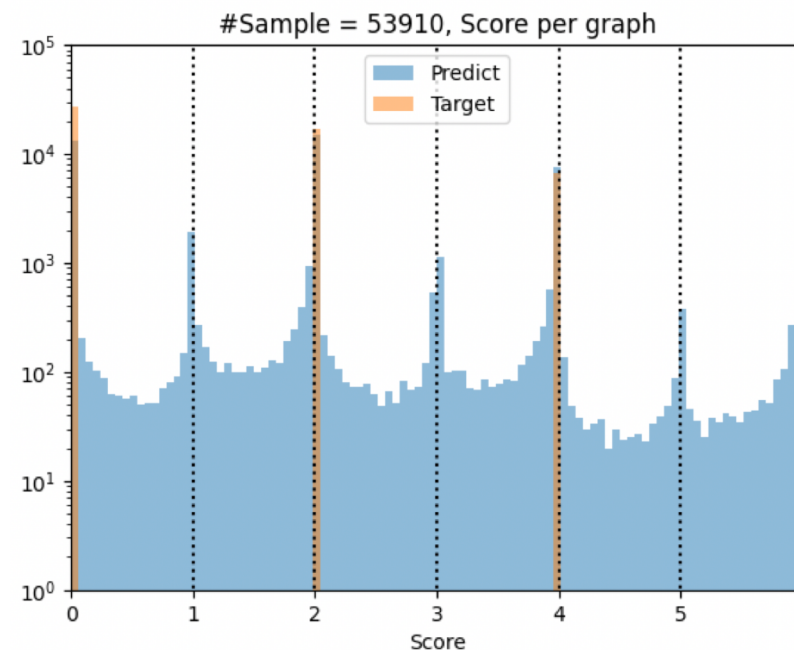
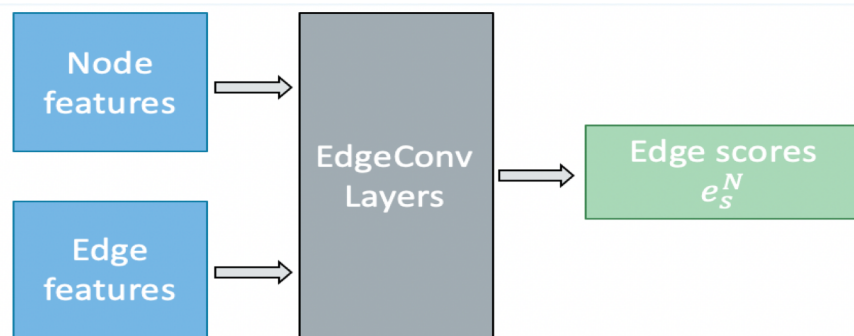
We wonder can we improve the tracking performance by implement the GNN technique in the doublet building section



- A test has been carried out by considering a graph which contain 1 track with 4 hits.



Node features 'x'	Node features 'en'	Edge features 'D'
x	r	Δr
y	Detector layer ID	Δz
z	Detector volume ID	Curturve $\text{atan2}(\Delta r, \Delta z)$
	Detector module ID	



Conclusion of Phase I

- Graph: 4 hits only, nearby hits = BKGs
- Edge classification
- Result: The network didn't recognise that $e_{ij} = e_{ji}$ in this bi-directed graph
- QUBO strength doesn't look like the target at all.
- [Talk @ CHEP2023](#)

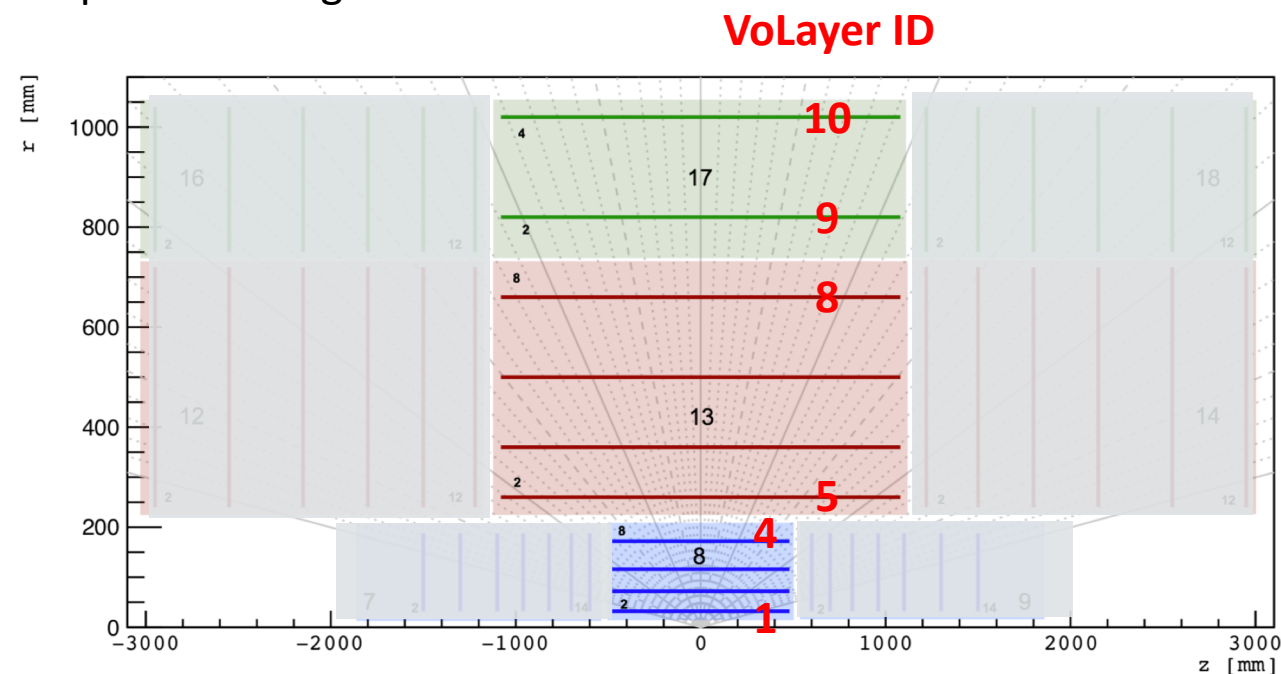
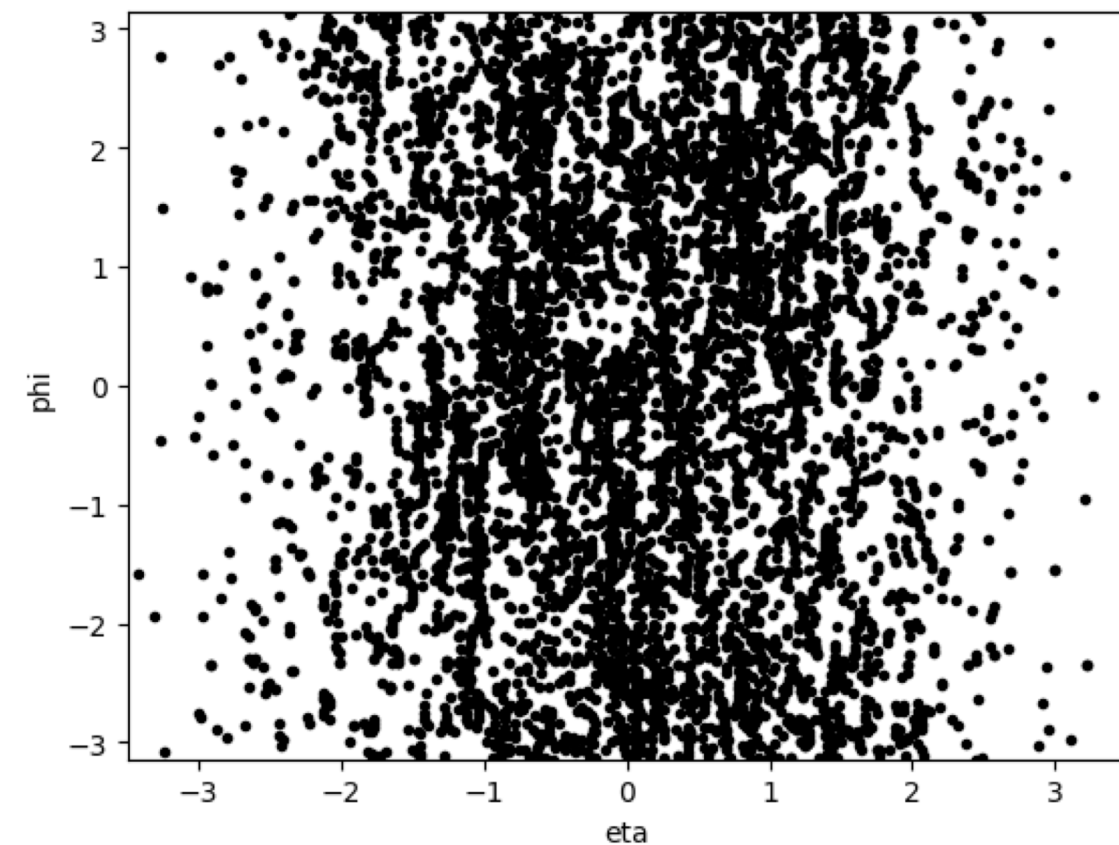
Main goal in phase II:

- Classify doublet that can be form the QUBO from the “nature” geometry.
- Make a usable QUBO based on GNN results.

A **bi-directed graph** is formed with the following node features:

Node features 'x'	Node features 'h'
r	eta
phi	VoLayer ID
z	

- Hit ID also pass through the network but not being use in the pattern recognition.

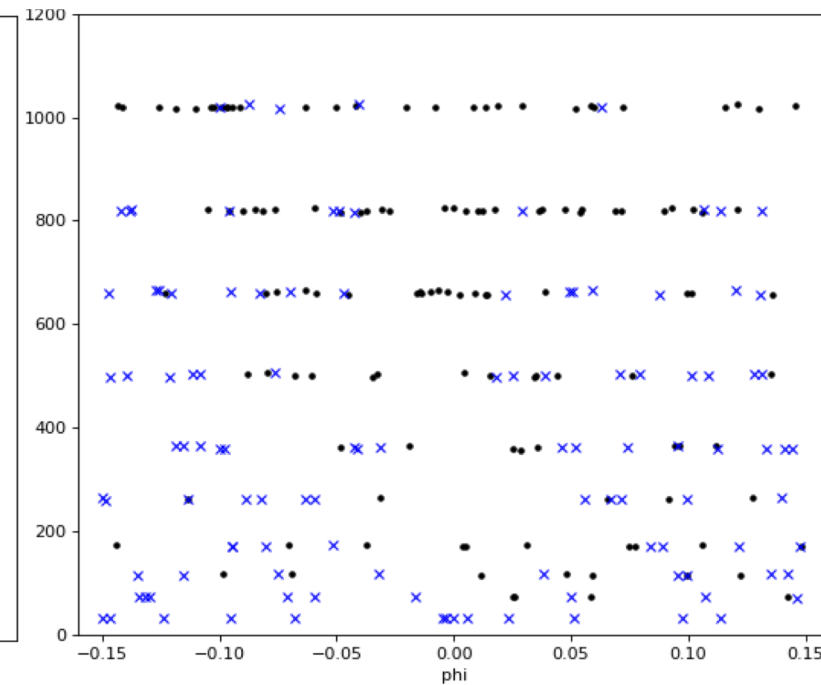
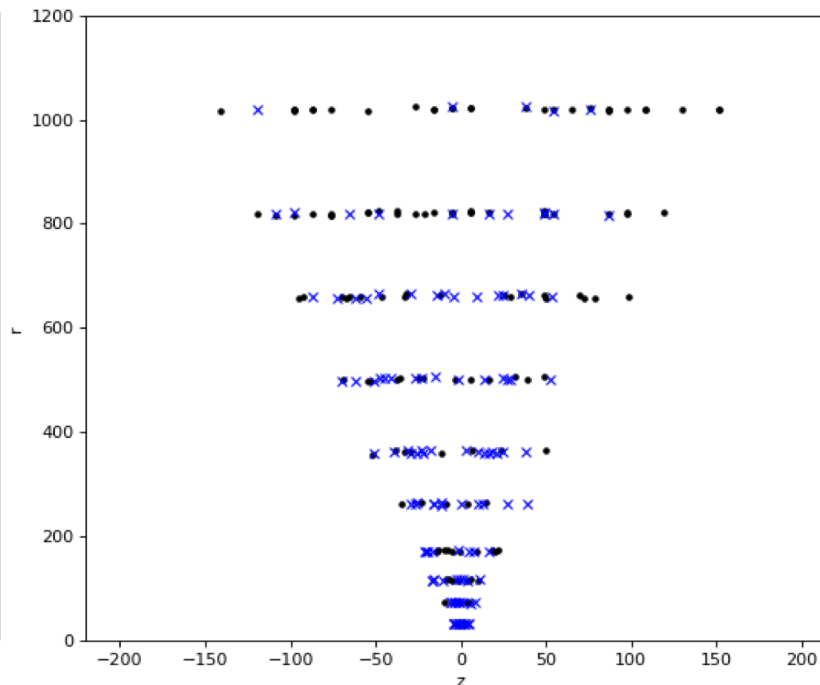
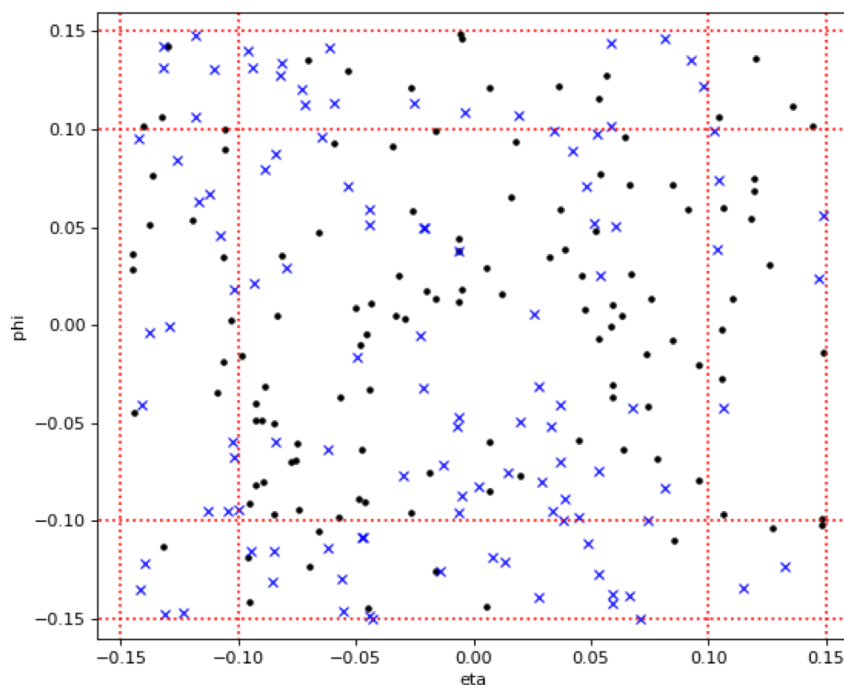


A small sample is used to train the network. We focus on $|\eta| \leq 1$ region.

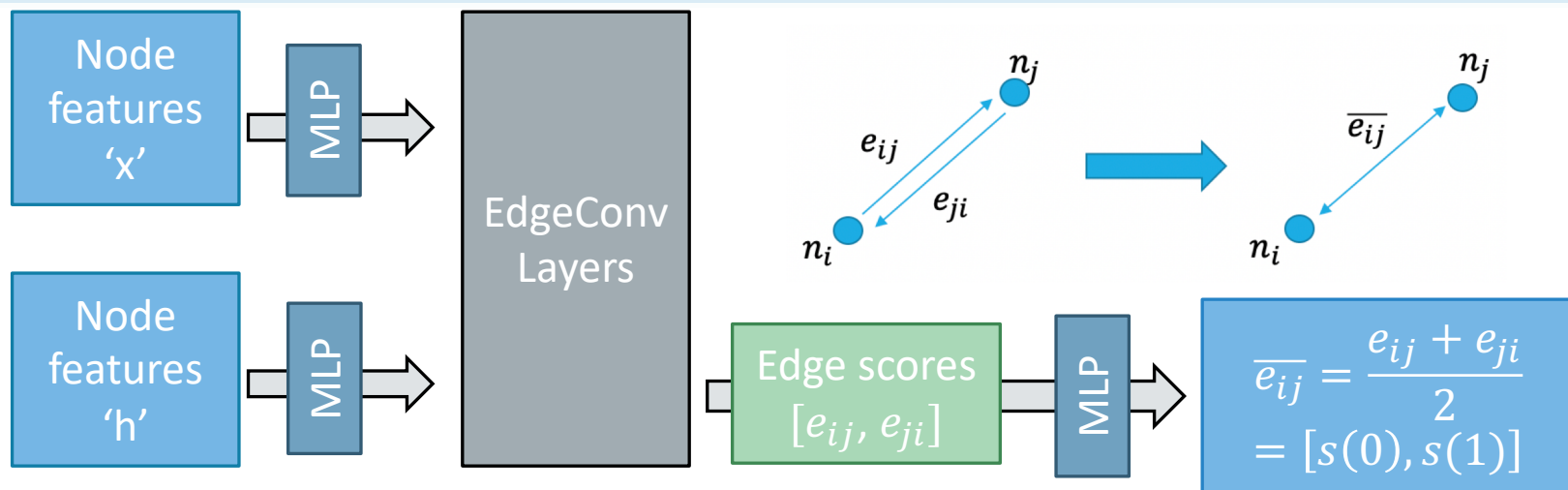
- To further simplify the graph (mainly number of edges) we only consider $|\phi|, |\eta| < 0.15$ in the training
- Also edges can only being formed under these conditions:
 - $|dz| < 50$
 - $|d\phi| < 0.2$

Event 1001	#Nodes	#Edges	Edges/node
$ \eta < 1.0$	51	398	7.8
$ \eta < 1.5$	141	1866	13.2
$ \eta < 2.0$	267	4806	18

× Signal (hits from QUBO doublets)
● BKGs (hits which is not being used in QUBO doublets)



Network architecture



- Our training **target**, is to **match the doublet** which being use in the QUBO in the same $|\eta|, |\phi|$ region.
- By comparing the Hit ID from the nodes which formed the edges, one can calculate the confusion matrix for each graph.

In each EdgeConv Layers

$$x_i^{l+1} = \text{mean}[\theta_{x,m}(x_j^l - x_j^l) + \phi_{x,m}(x_i^l)]_j$$

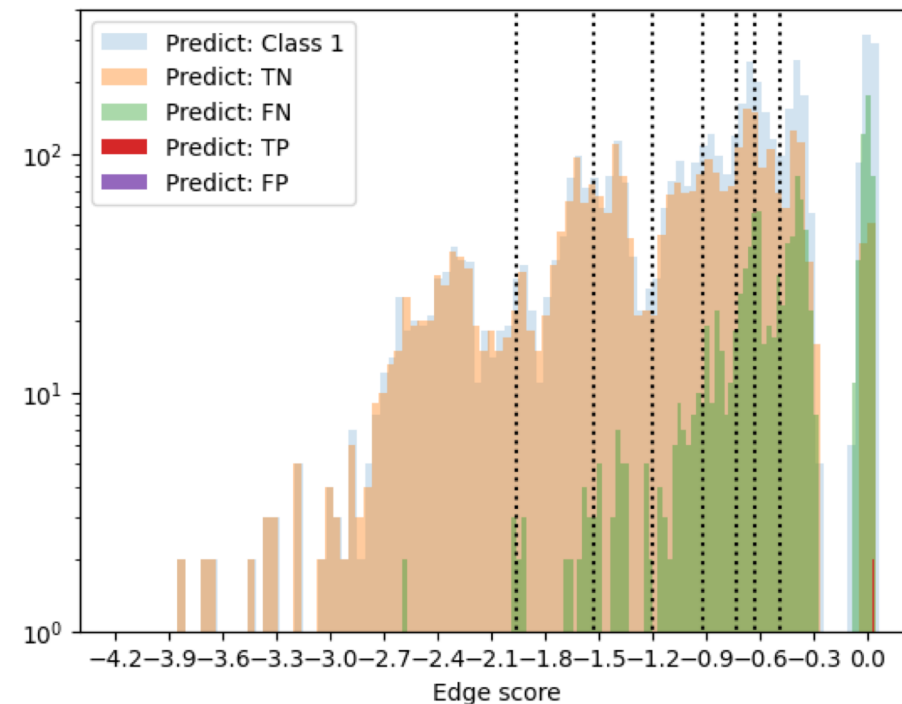
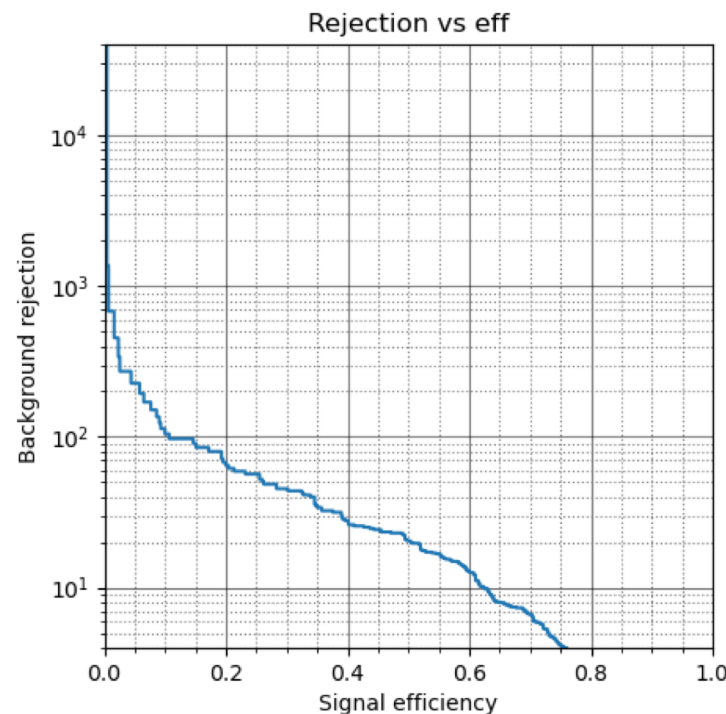
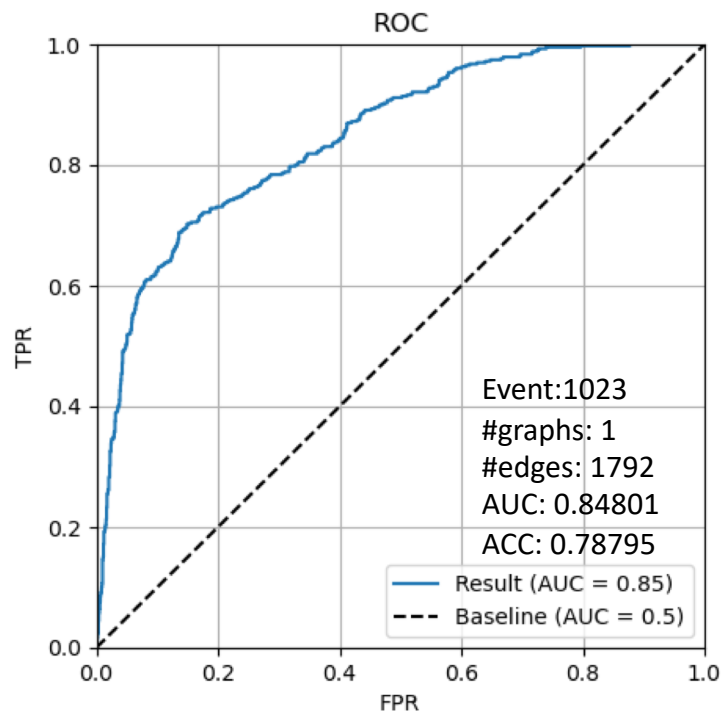
$$h_i^{l+1} = \text{mean}[\theta_{x,m}(h_j^l - h_j^l) + \phi_{x,m}(h_i^l)]_j$$

$$e_{ij}^1 = W(\theta_x, \phi_x, \theta_{en}, \phi_{en})$$

$$e_{ij}^{l+1} = e_{ij}^l + W(\theta_x, \phi_x, \theta_{en}, \phi_{en})$$

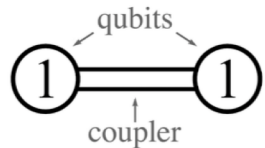
- Since we are constructing a bi-directed graph, a doublet is represented by 2 edges, and we have 2 classes for each edges.
- By taking average score between e_{ij} and e_{ji} , we ensure that both edges going into opposite directions reserve the symmetry.
- The score, \bar{e}_{ij} contain 2 values: $s(0)$ and $s(1)$, which is the score for the edges belongs to class 0 (BKG-like), and belongs to class 1 (Signal-like), respectively.

After training the model, we use one of the events to generate the QUBO, as QUBO is an event-based object.



TP = 68	FP = 17
FN = 363	TN = 1344

Threshold	100%	90%	80%	70%	60%	50%	40%	30%
score	-4.3	-1.96	-1.53	-1.2	-0.923	-0.73	-0.631	-0.49
#Doublets	4648	4188	3719	3256	2789	2326	1860	1396



$$O(a; b; q) = \sum_{i=1}^N a_i q_i + \sum_i^N \sum_j^N b_{ij} q_i q_j \quad q \in \{0, 1\}$$

bias weight a_i	influences one qubit q_i	-1 1	q_i tends to collapse into 0. q_i tends to collapse into 1.
coupling strength b_{ij}	influences two qubits q_i and q_j	-2 2	both q_i and q_j tend to collapse into 1. at least one of q_i and q_j tends to collapse into 0.

In the code, 3 steps to create a QUBO:

1: Set Qbits with their weight (doublets with a common weight)
e.g. ('23472_31455_38557', '23472_31455_38557'): 0

2: exclusion couplers

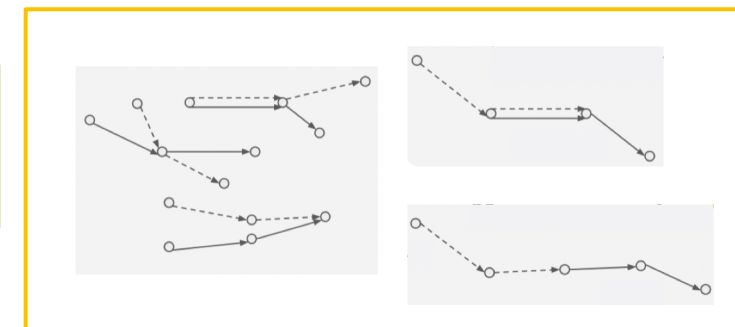
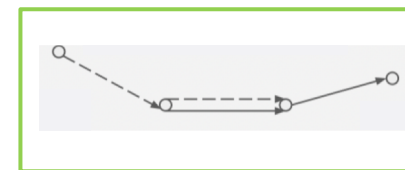
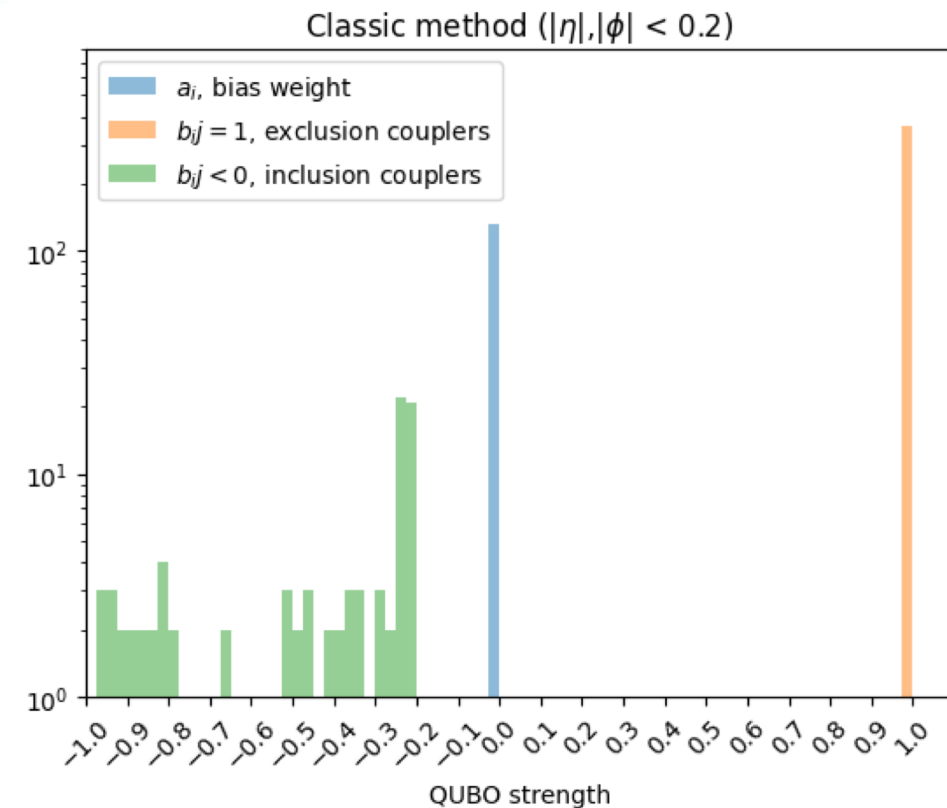
Add more entries to QUBO, e.g.:

('83840_90726_96873', '76774_83829_96873'): 1

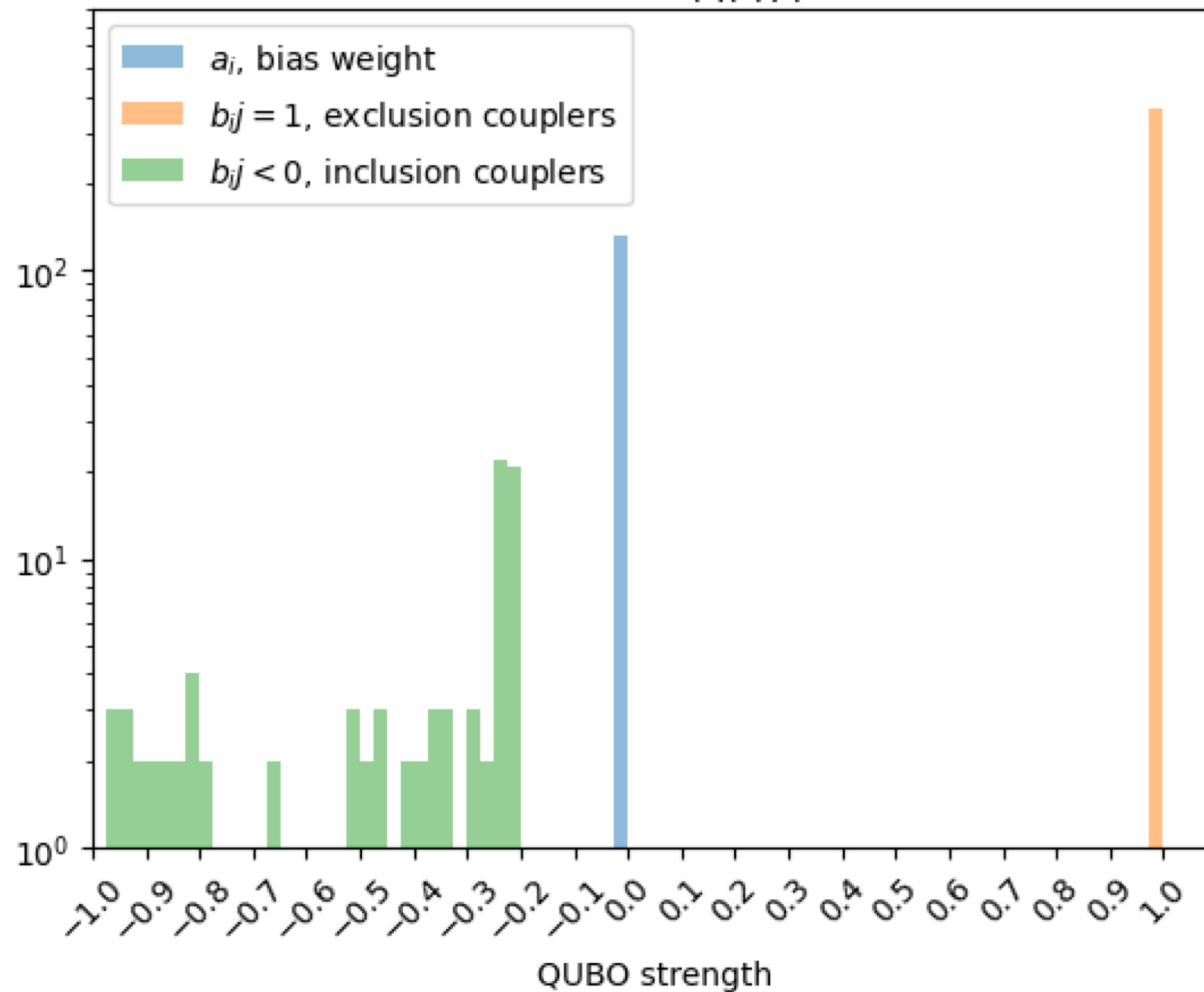
3: inclusion couplers

Add more entries to QUBO, e.g.:

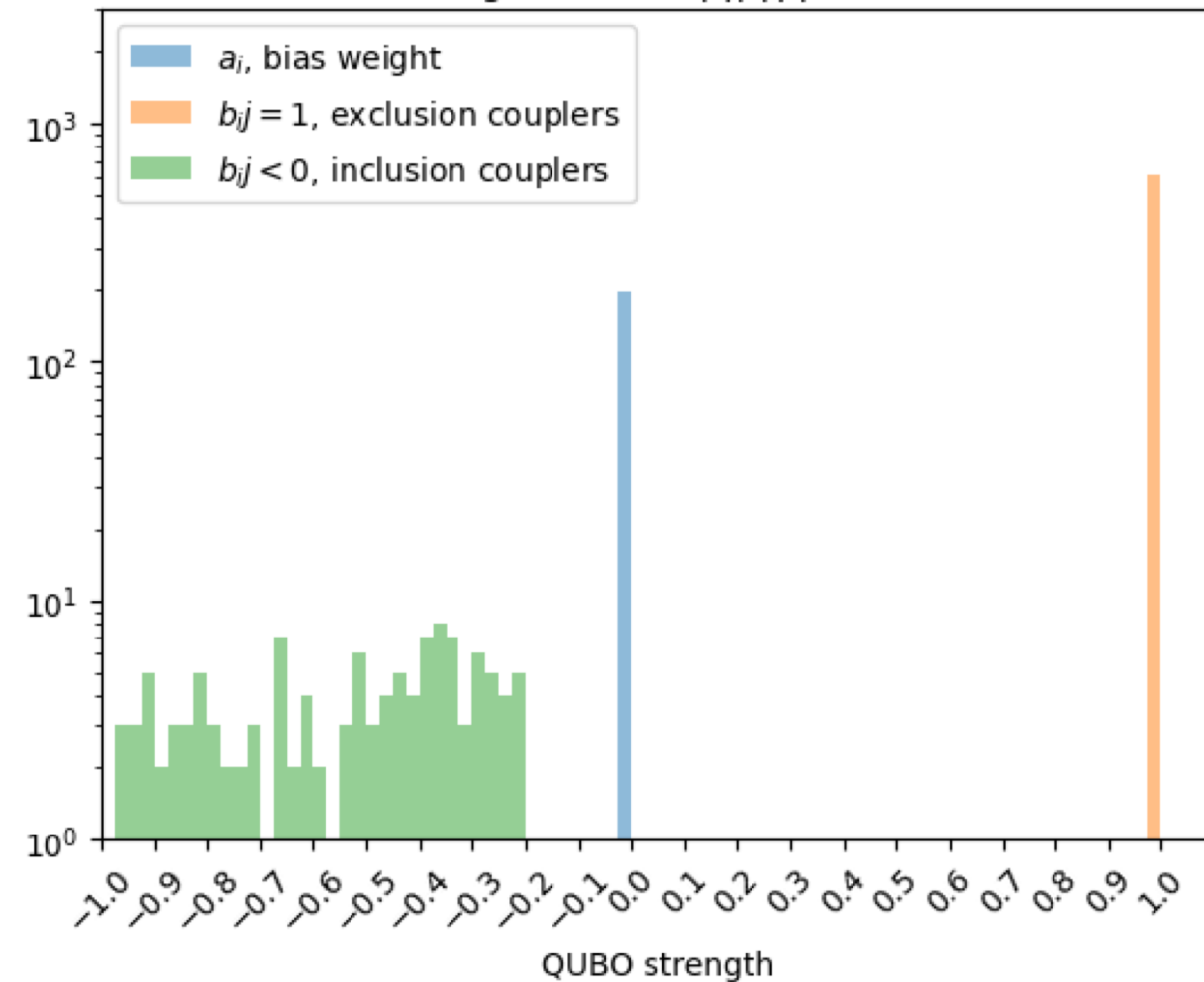
('18380_27166_34273', '27166_34273_40293'): -0.6423072319215068



Classic method ($|\eta|, |\phi| < 0.2$)

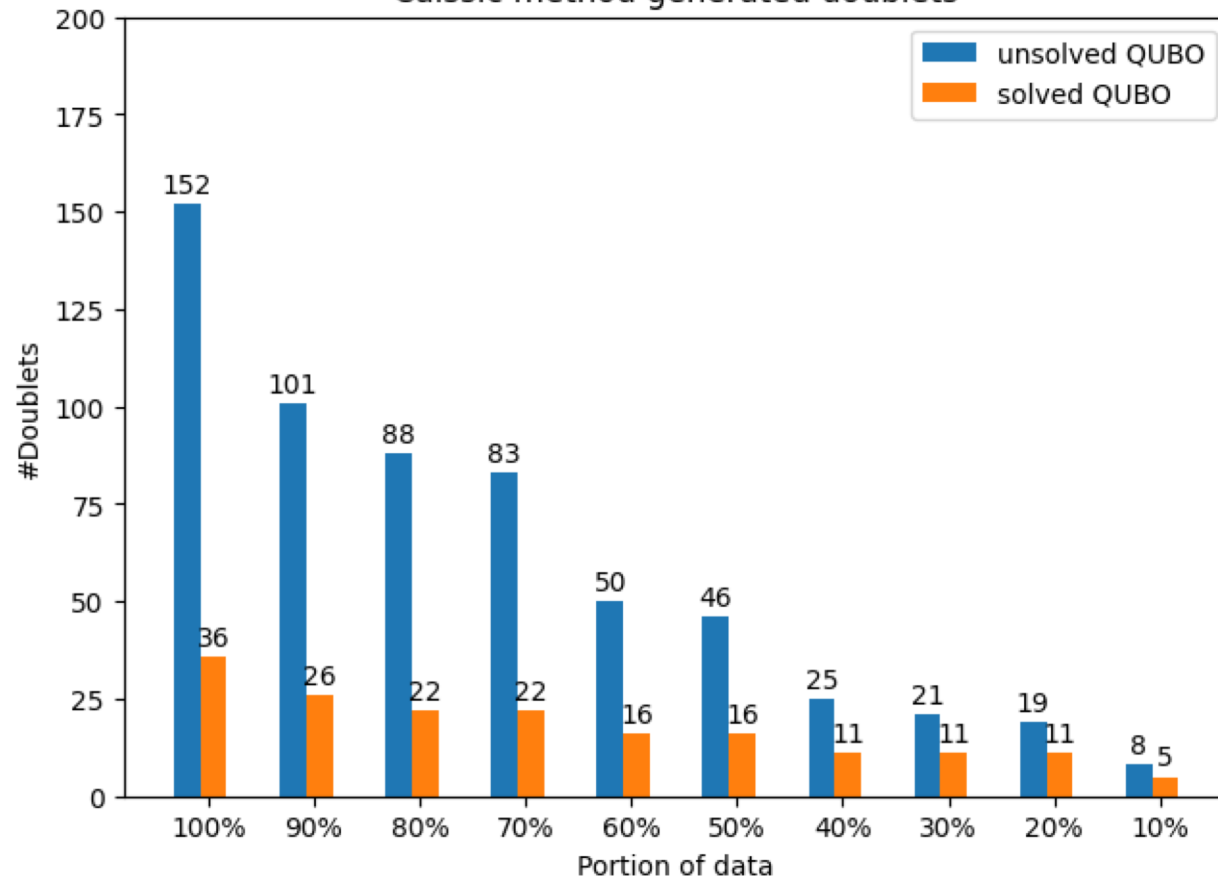


GNN generated ($|\eta|, |\phi| < 0.2$)

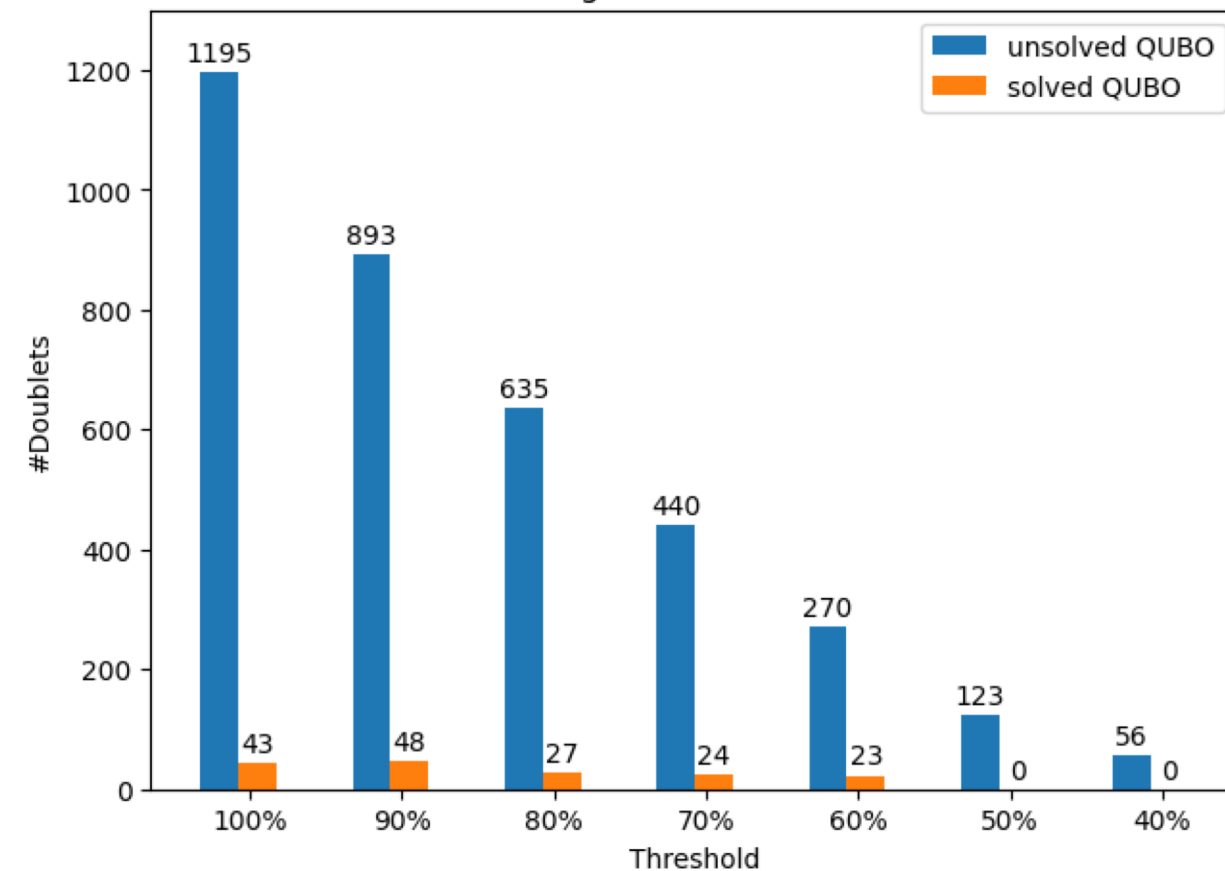


- Simulated Annealing Sampler has been used to solve the QUBO
- Simulated Annealing Sampler: An annealing process performed with CPU rather than QPU

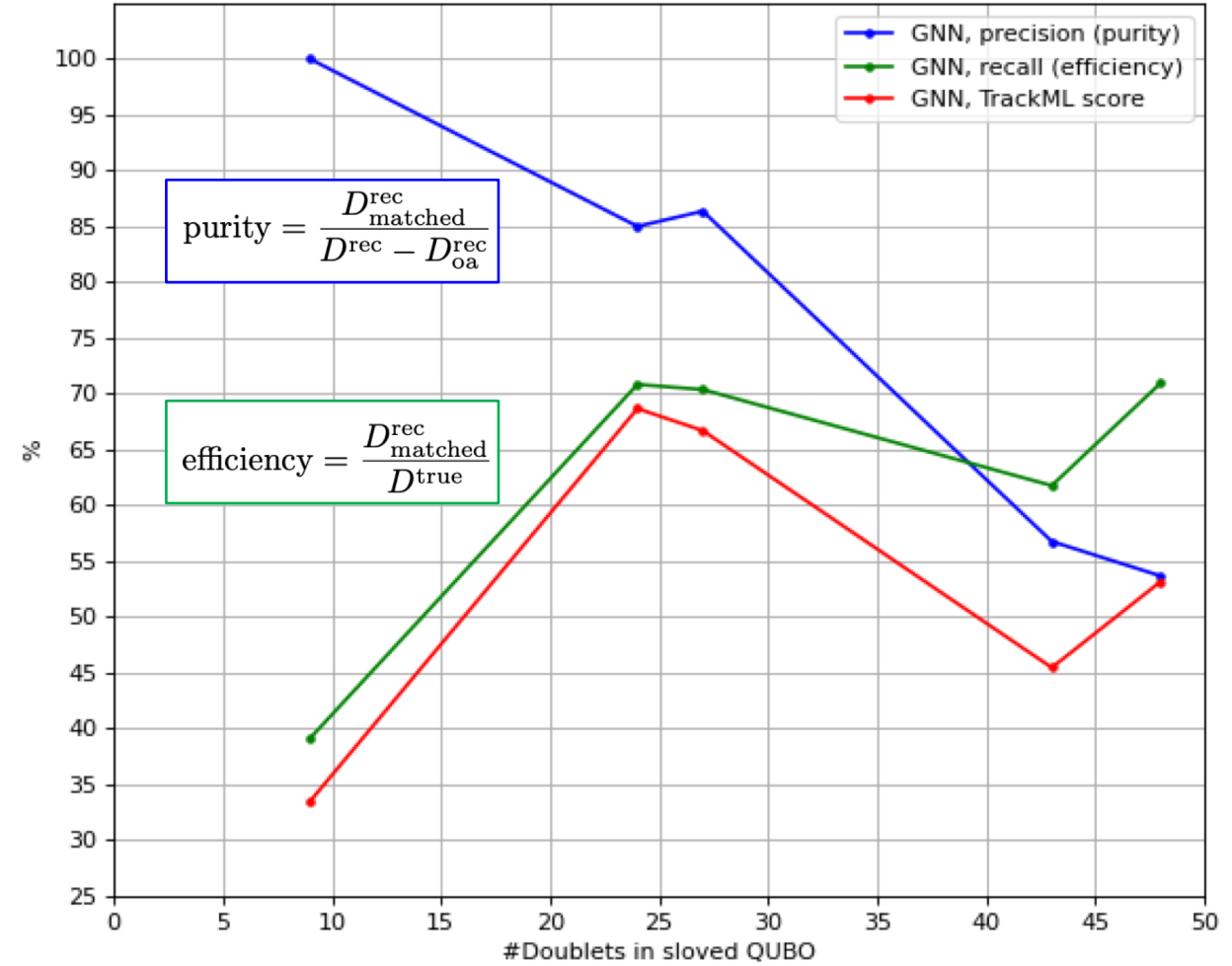
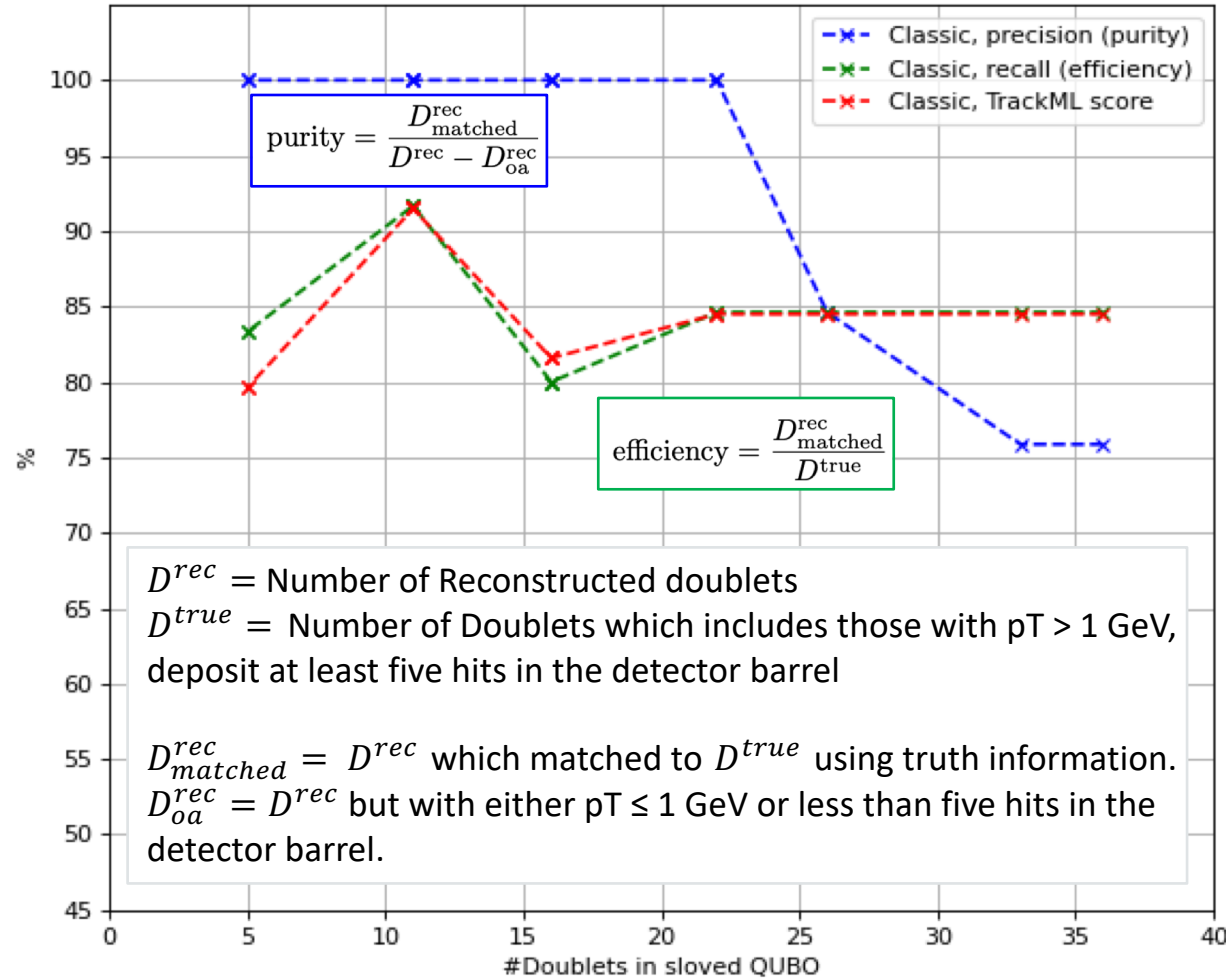
Classic method generated doublets

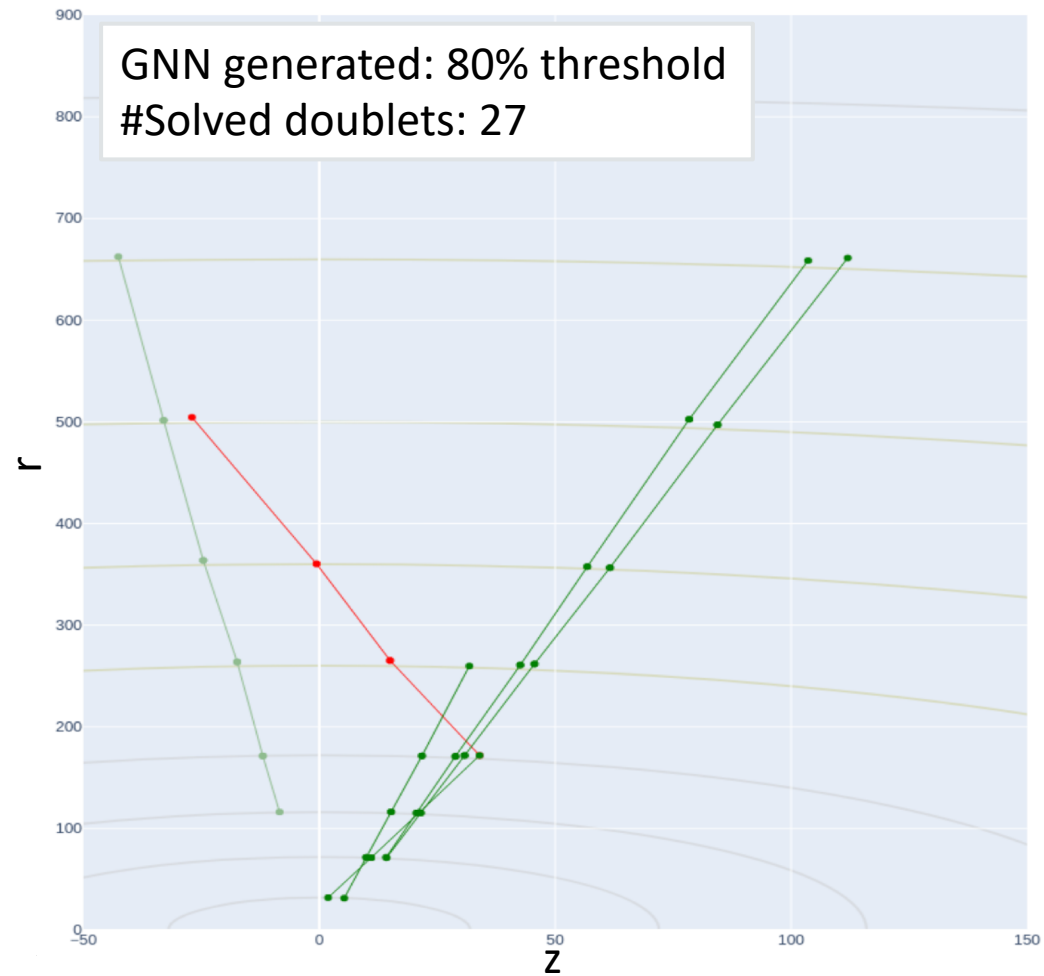
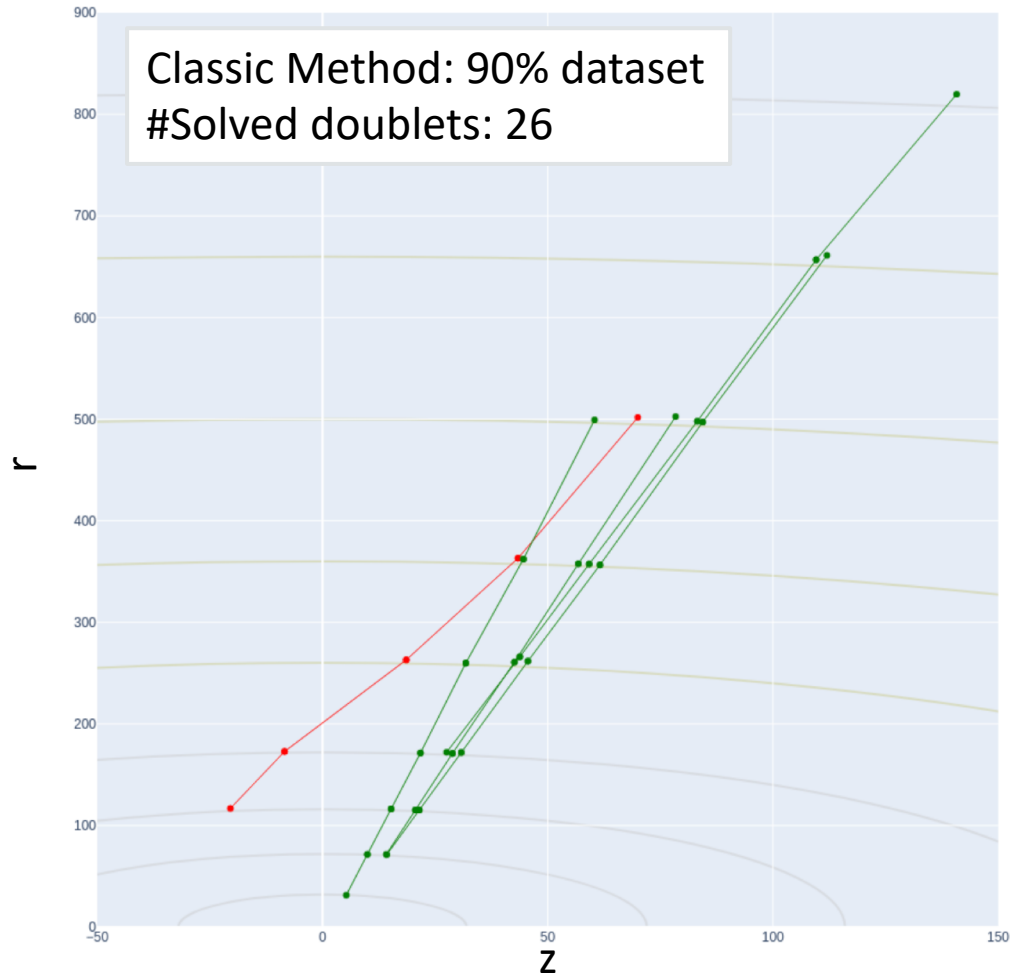


GNN generated doublets



The track reconstruction performance of an event can be judged by TrackML score, efficiency (recall) and purity(precision).





- Fake doublets
- Reconstructed doublets (without the momentum acceptance)
- Reconstructed doublets (within the momentum acceptance)

Conclusion

- A GNN has been implemented into the Quantum annealing-based tracking algorithm.
- In phase I, the network didn't recognise the opposite edges between 2 nodes should form a single doublet.
- In Phase II, the following improvement has been made:
 - A more general graph has been used.
 - The network architecture has been improved, and the average edge score between opposite edges are considered.
 - Instead of calculating the probability, the target matching is preformed.
 - The GNN generated doublets are being used to construct QUBO, and the strength looks different to the original QUBO.
 - The QUBO generated based on the GNN model, have much more doublets.
 - However, the tracking performance of the solved QUBO is worse.

Outlook

- Phase II model looks ok, but still have more room to improve.
- In Phase III, we are aiming to:
 - Improve the ROC
 - Redefine the task: matching doublets -> purely edge classification
 - Try to use k-nn graph / graph clustering instead of bi-directed graph.
 - Steady with a larger dataset.
 - Construct triplet / triplet pair objects from GNN.