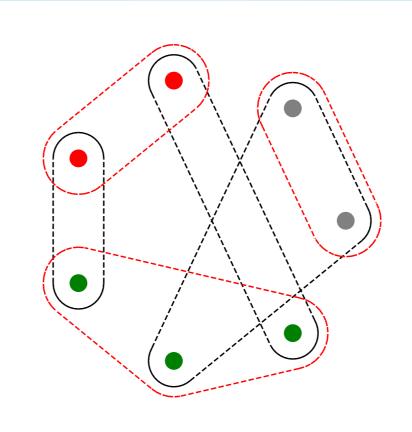
## Graph networks for vertex reconstruction



Jonathan Shlomi, Sanmay Ganguly, Eilam Gross In collaboration with Kyle Cranmer/NYU

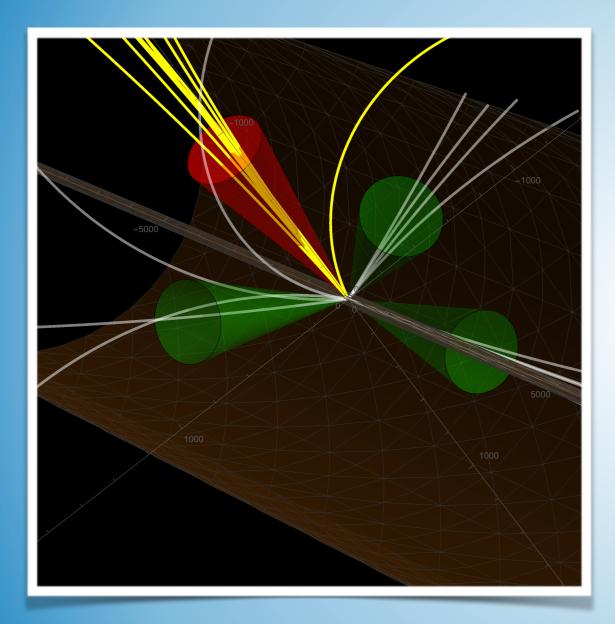
Learning to Discover : Advanced Pattern Recognition Institut Pascal, Orsay

24 October 2019

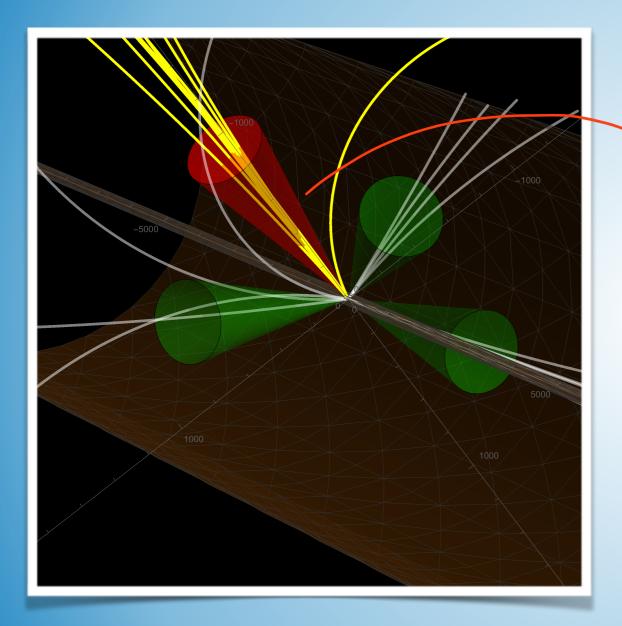


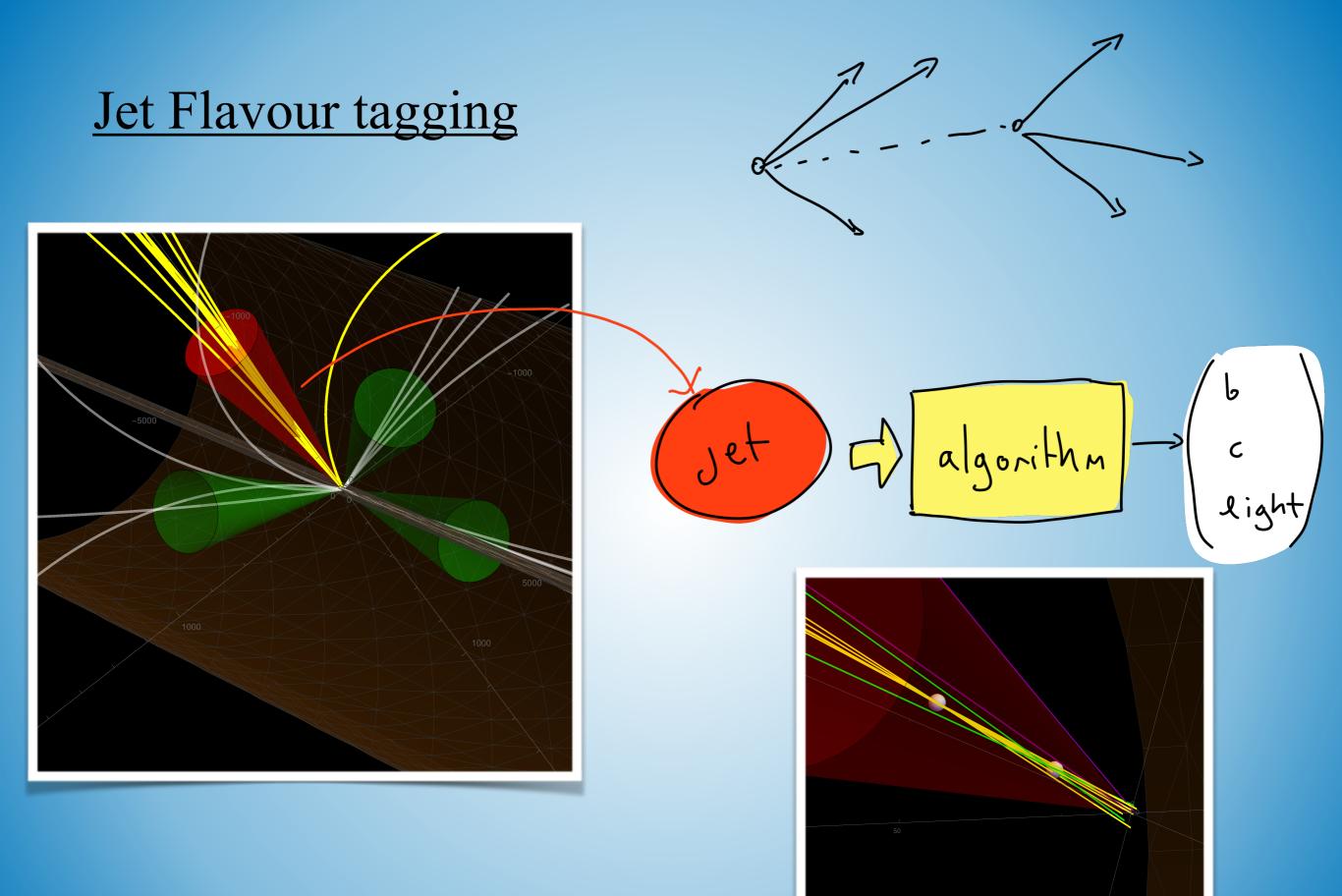


## Jet Flavour tagging



## Jet Flavour tagging

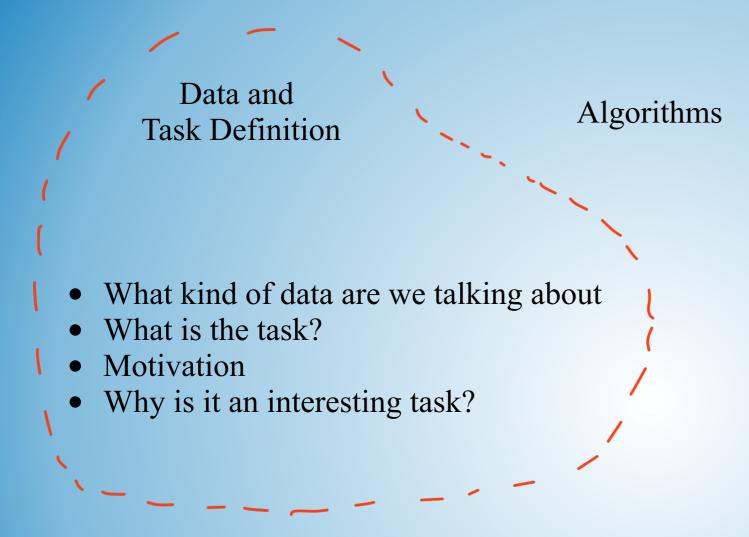




#### Data and Task Definition

#### Algorithms

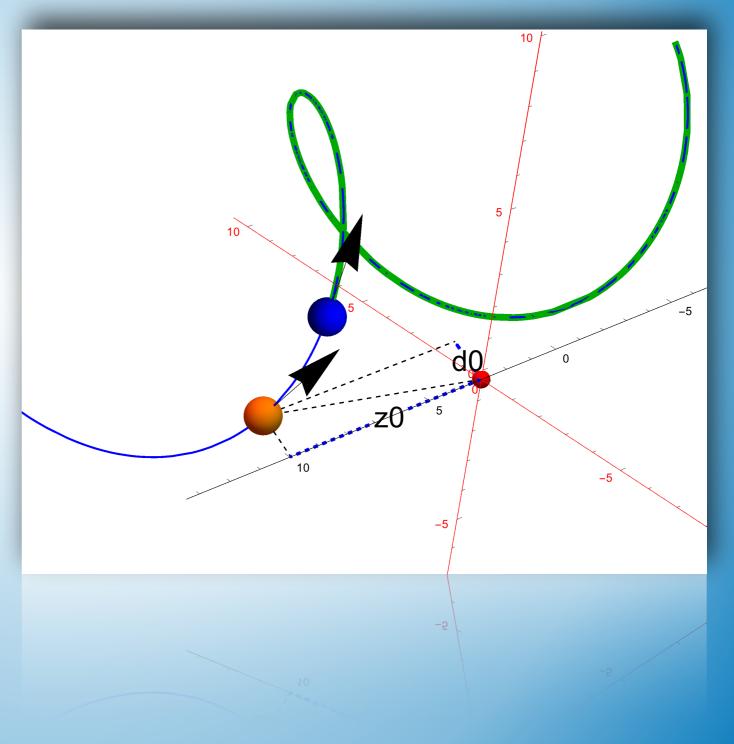
Performance Evaluation + Event Display



Performance Evaluation + Event Display

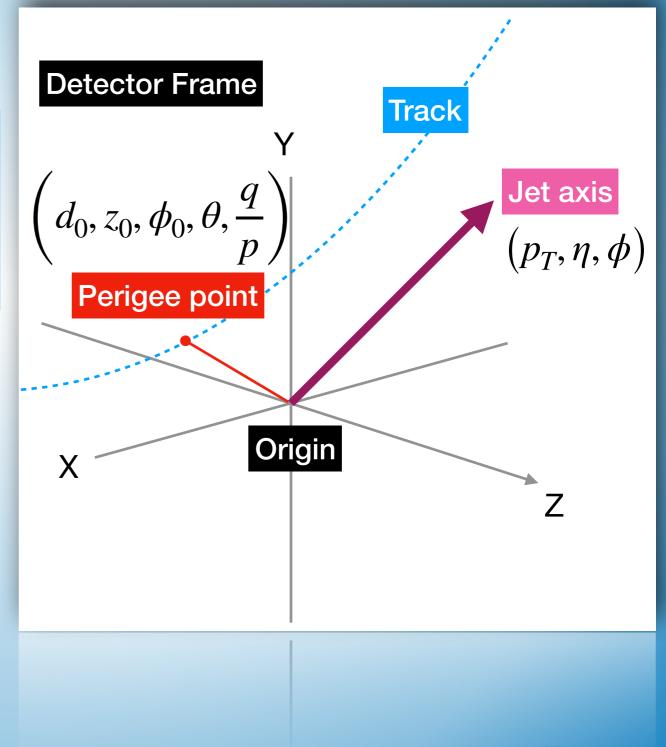
#### The Dataset

• A set of tracks (perigee parameters + cov matrix)

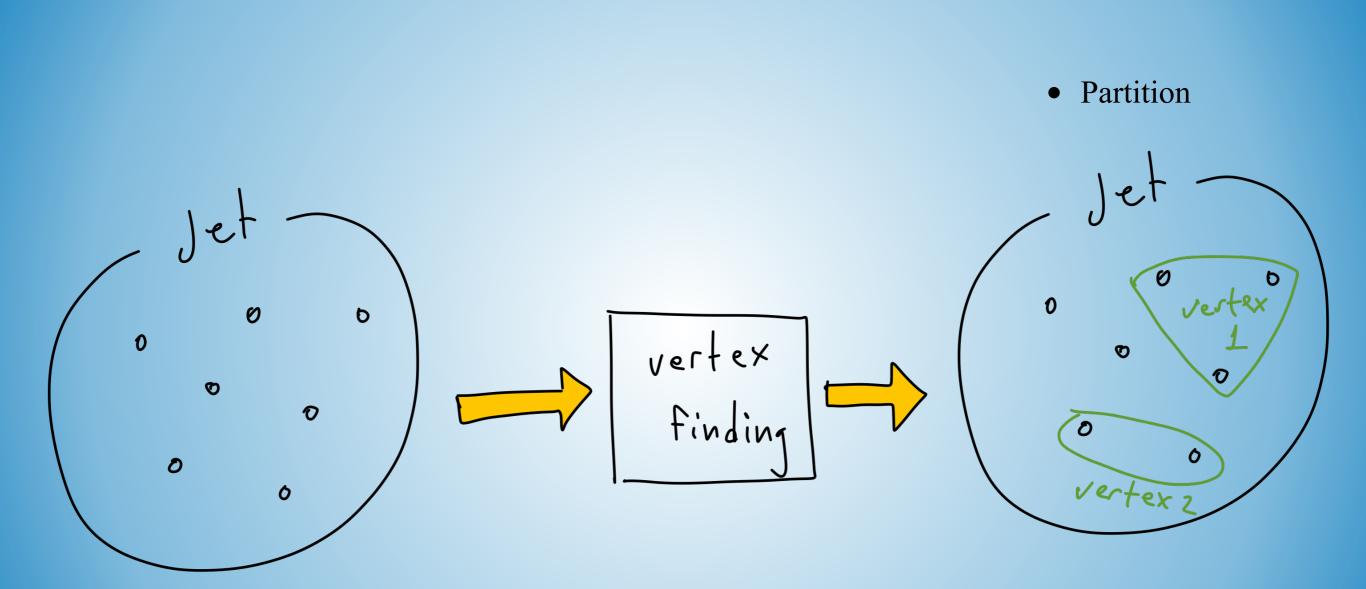


#### The Dataset

- A set of tracks (perigee parameters + cov matrix)
- Jet direction
- Jet momentum

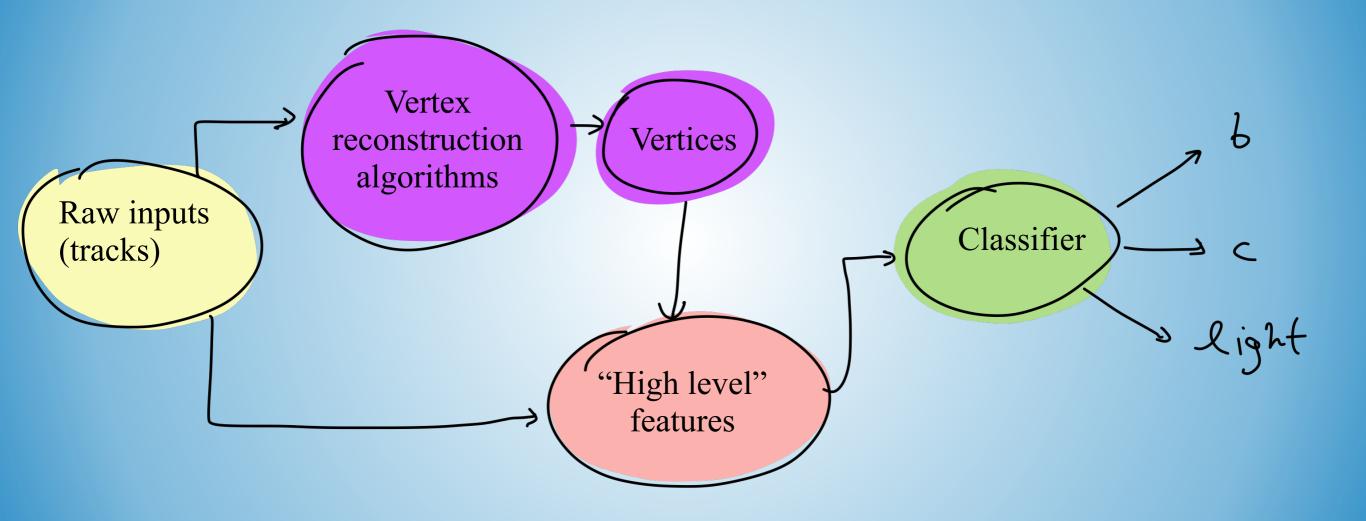


### The Task



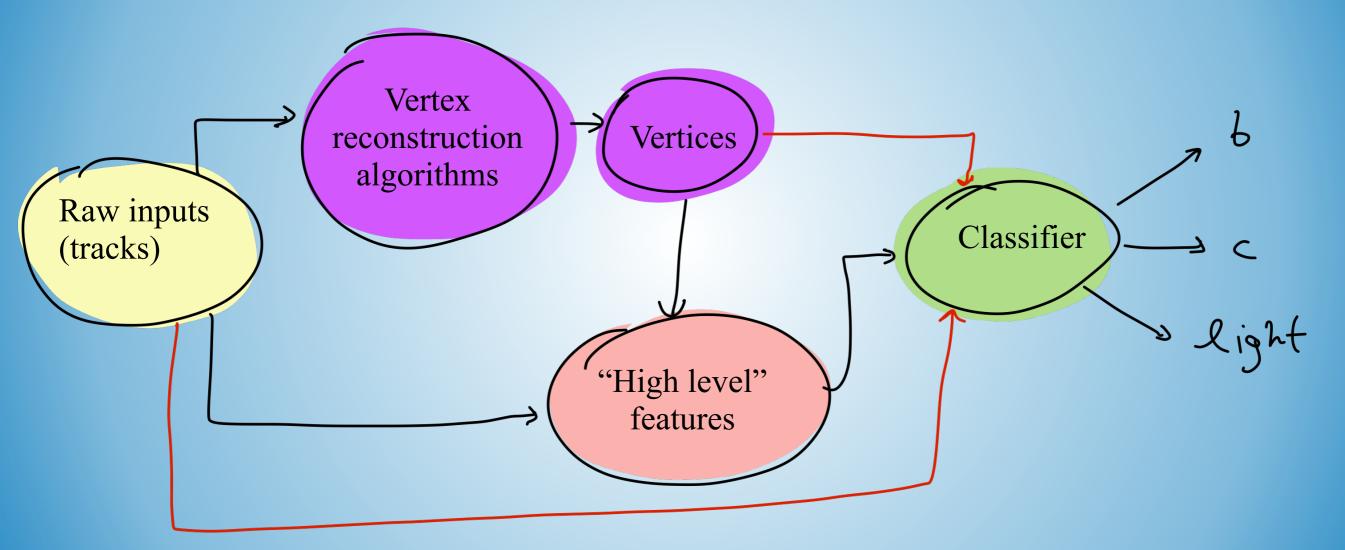
#### The Task

#### What we know so far about ML for flavour tagging



#### The Task

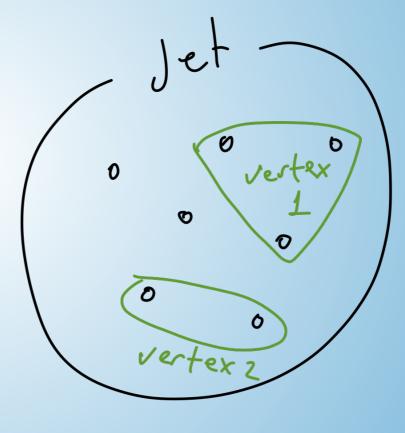
Adding the "low" and "medium" level features to the neural network classifier is helping the classification performance



#### Motivation - zooming in on the vertex finding

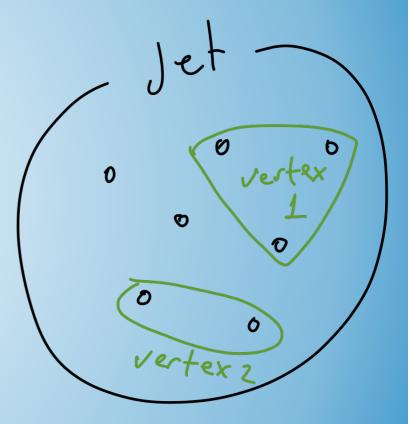
• End-to-End solution Existing algorithms require multiple stages and manual fine-tuning

• Context Sensitive Vertex finding can we take into consideration factors other than "geometry"



### Why is it an interesting task?

- Easy. small sets, easy to explore, easy to compare solutions
- Not straight-forward Classification It is clustering, but fully supervised clustering (more exotic)
- Room for improvement



#### Motivation - better charm tagging

Out of the three classes (b, c, light) - charm is the hardest to correctly identify If we have a better picture of the underlying decay, we can identify them more effectively

~ 80% efficiency

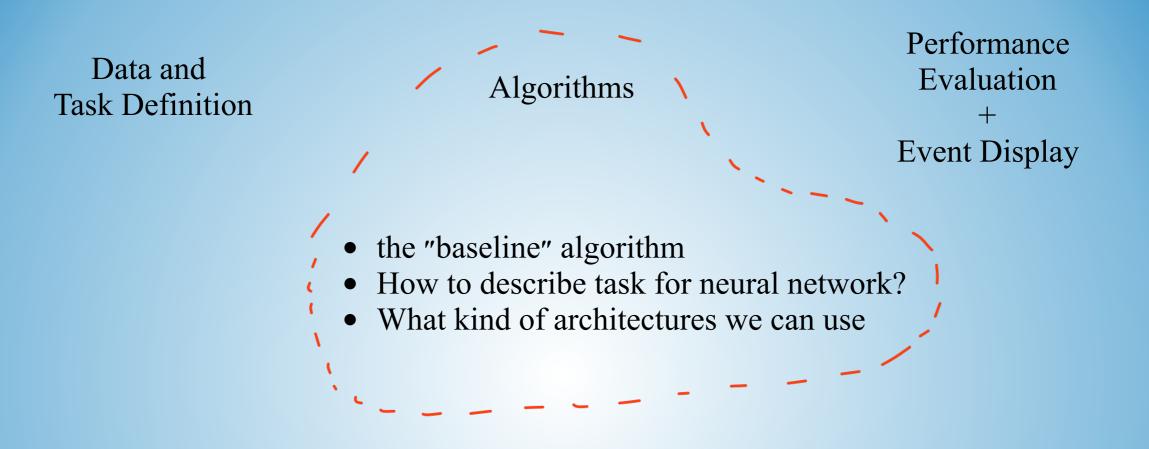
jets

~ 40% efficiency

#### The Dataset

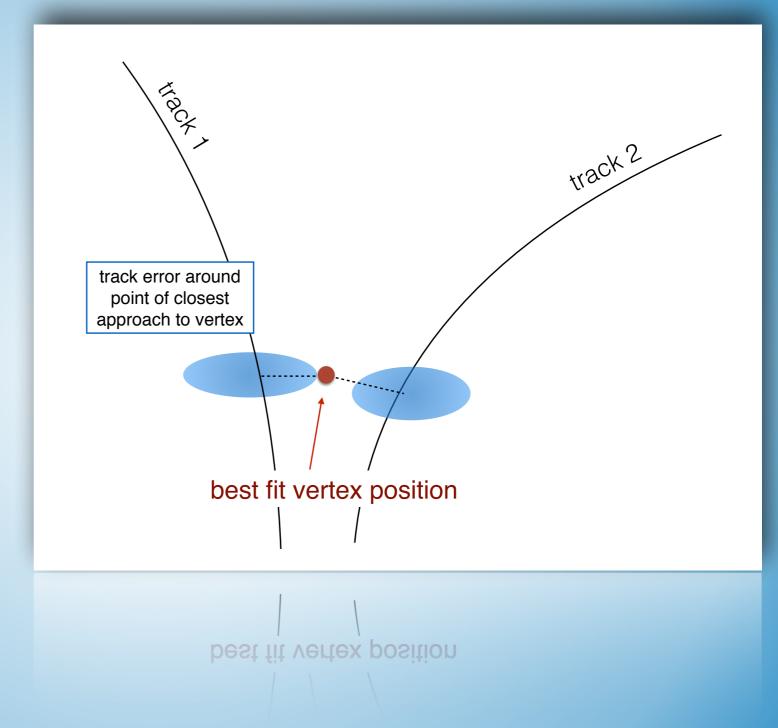
This dataset is generated with a "fast simulation", meaning the truth particles are "smeared" Ideally we would need a "full simulation" but for the purposes of trying different algorithms this is sufficient.

+ ideal track



### the "baseline" algorithm

Adaptive vertex finding/fitting



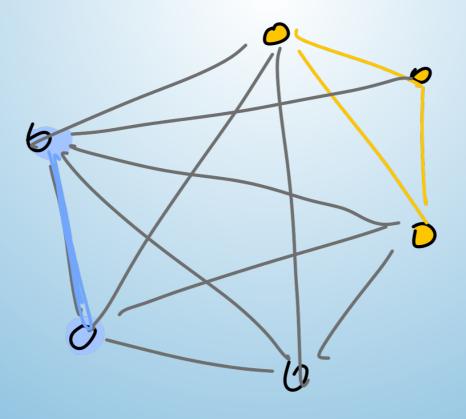
#### https://rave.hepforge.org/

W. Waltenberger. "RAVE: A detector-independent toolkit to reconstruct vertices". In:IEEETrans. Nucl. Sci.58 (2011), pp. 434–444

#### How to describe the task for a neural network?

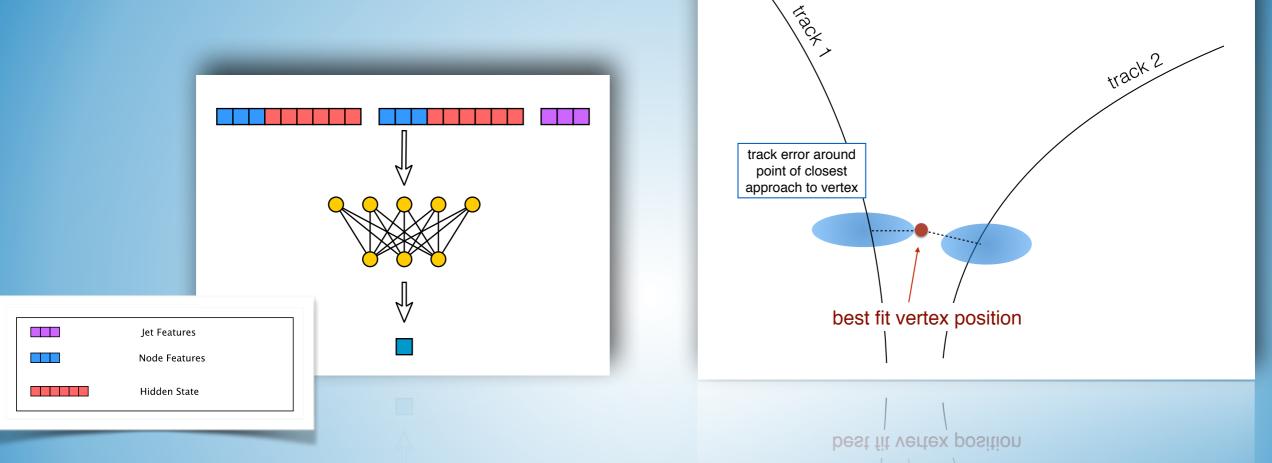
Take the set of tracks, and describe the tracks as nodes in a graph, Fully connect the graph with edges between every node

Now the task can be thought of as "edge classification"



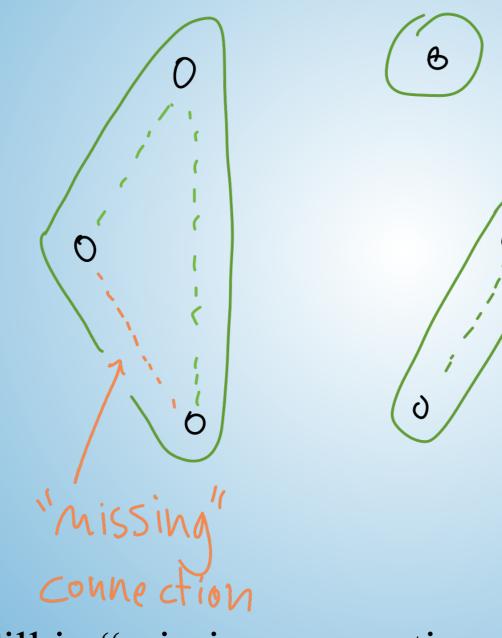
### the "baseline" neural network solution

### Track pair classifier:



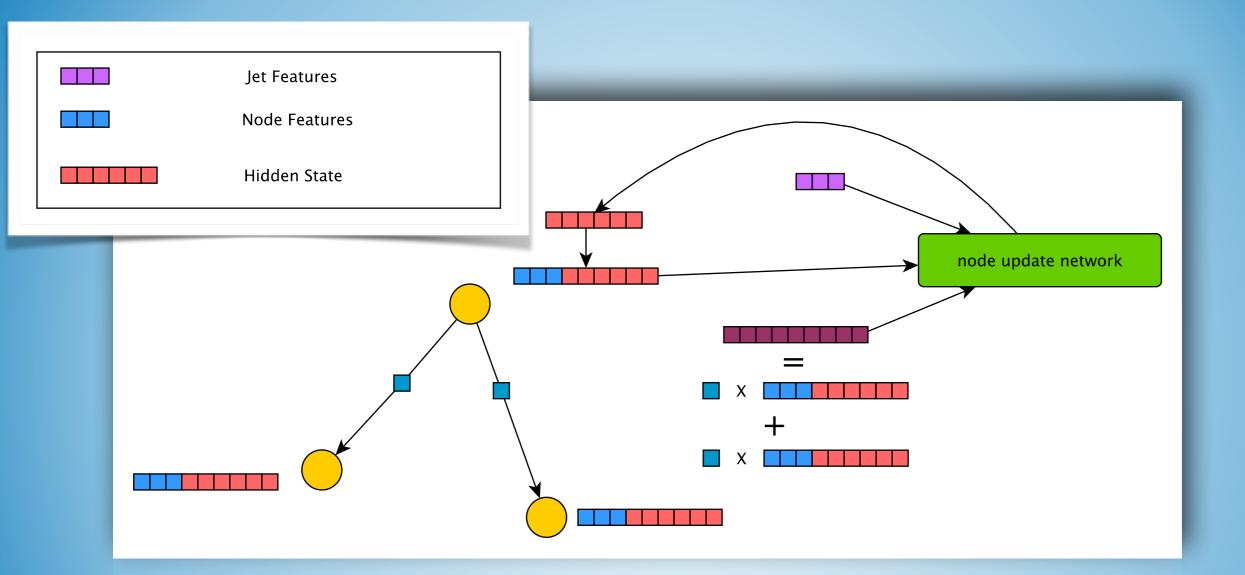
#### **Binary classifier:**

input: a pair of tracks (+jet 4 vector) output: is this pair in the same vertex Once the pairs are classified, join together clusters for tracks that have connecting edges



Fill in "missing connections"

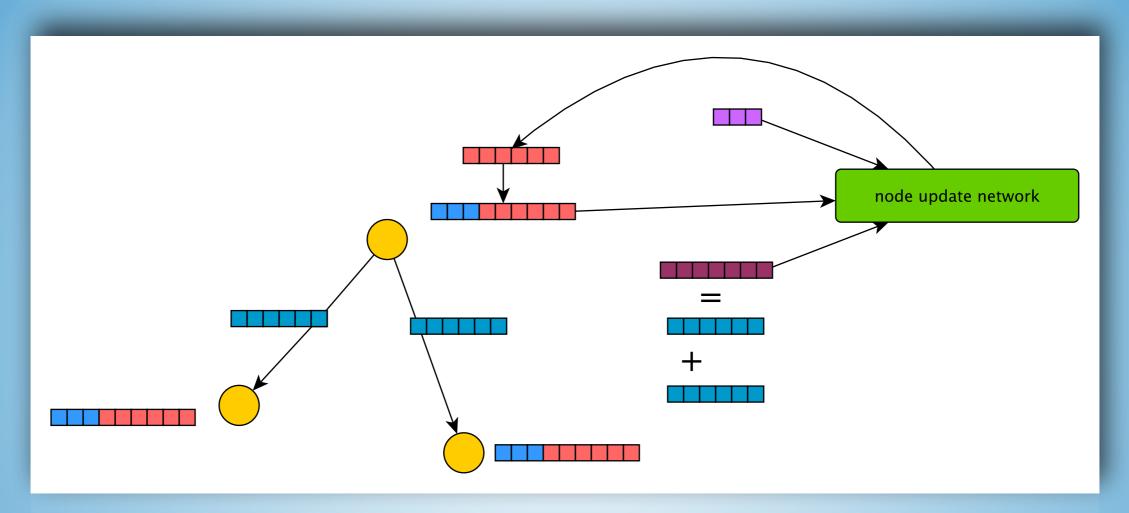
### Message passing "graph neural network"



Each "node" (track) looks at a weighted sum of the rest of the nodes in the jet, and updates its latent representation.

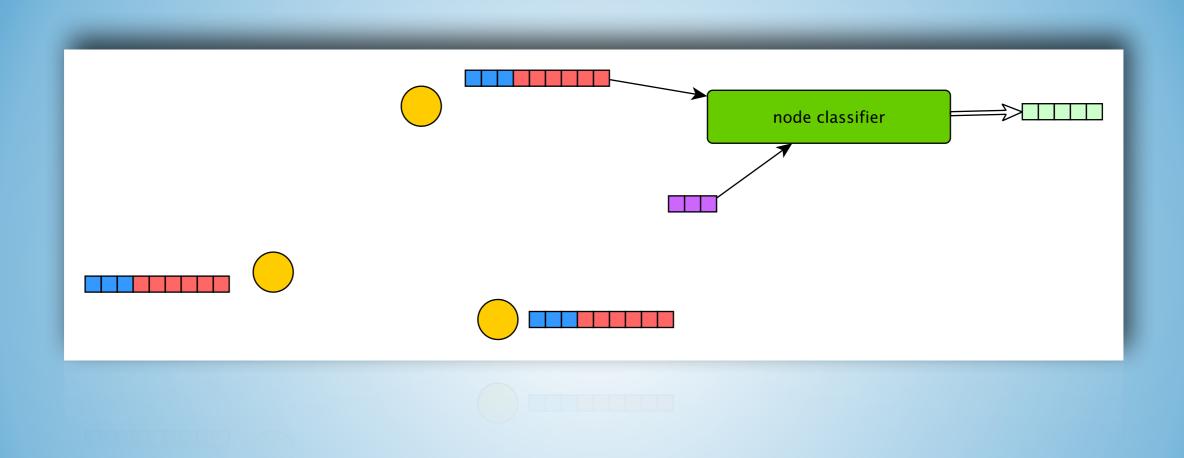
Then - apply same binary classifier as baseline solution

# Message passing "graph neural network" + edge latent representation



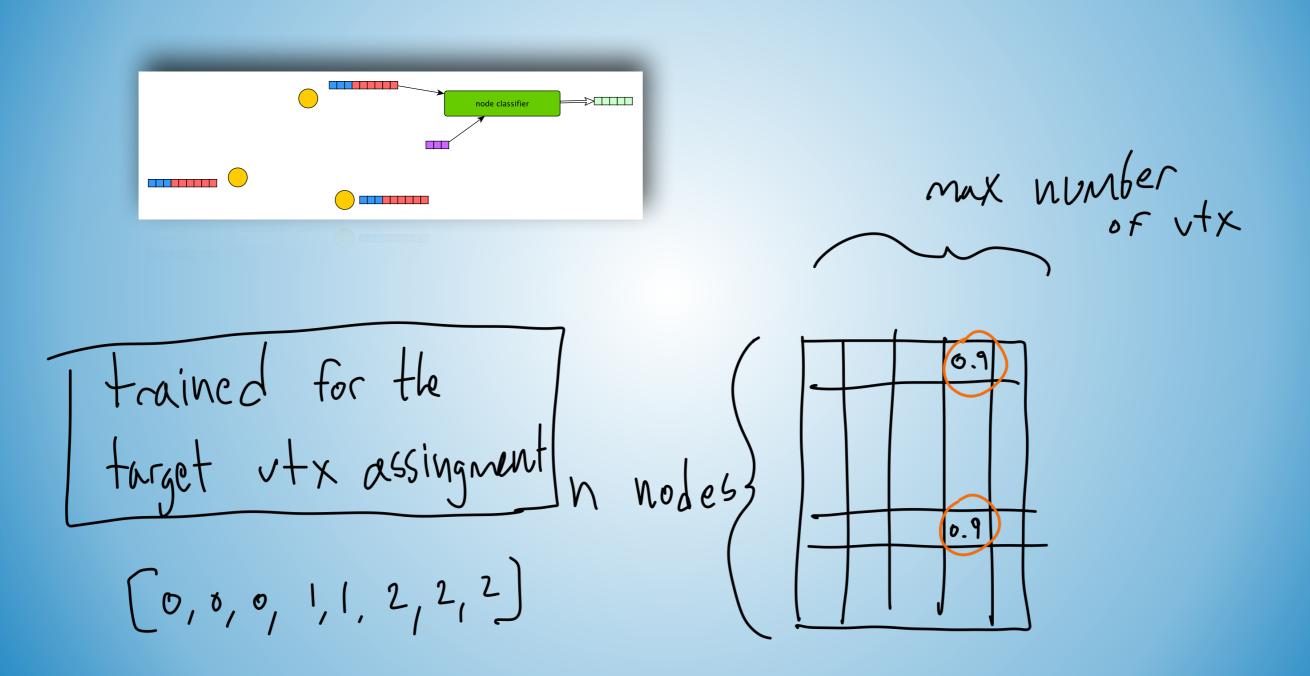
The weighted sum of node representations is replaced by a sum of edge latent representations

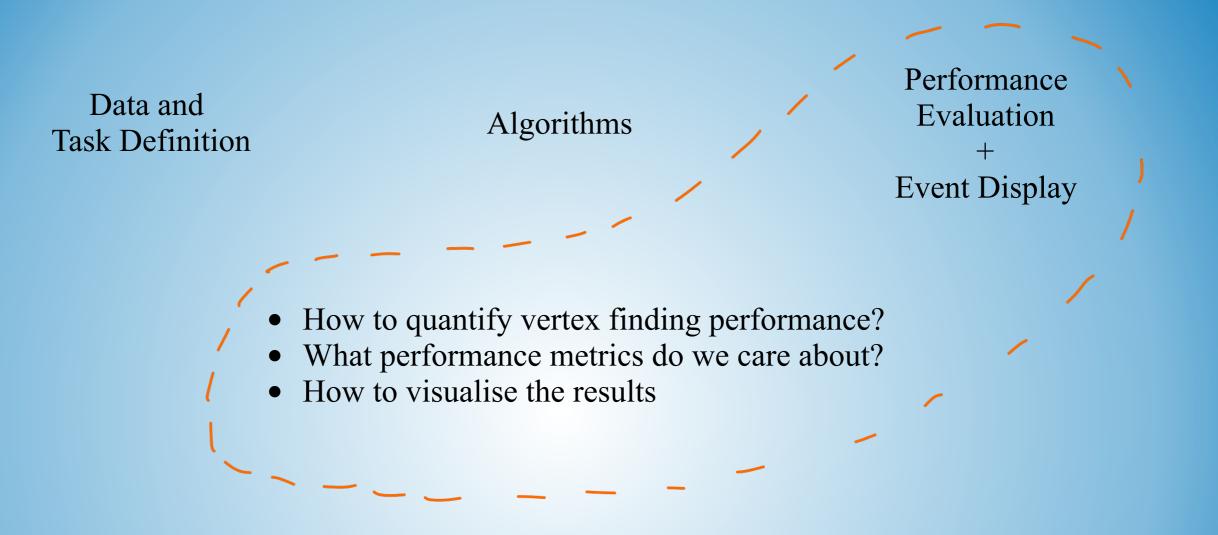
# Message passing "graph neural network" + node classification



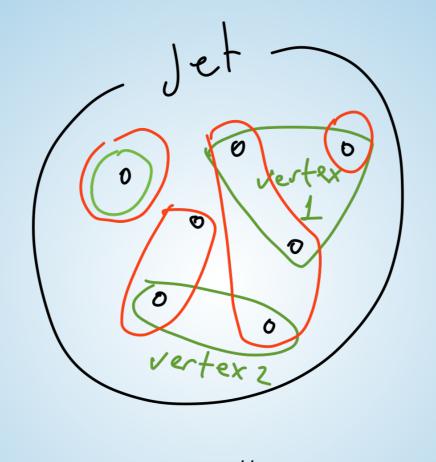
Instead of predicting a binary classification for the pairs of tracks, Output a multi-class output for the individual nodes

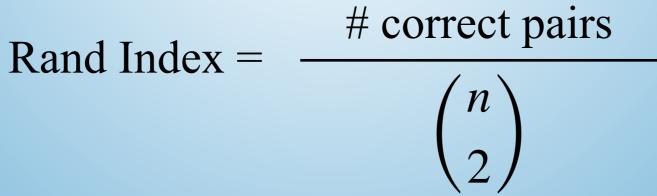
# Message passing "graph neural network" + node classification





How to quantify vertex finding performance?

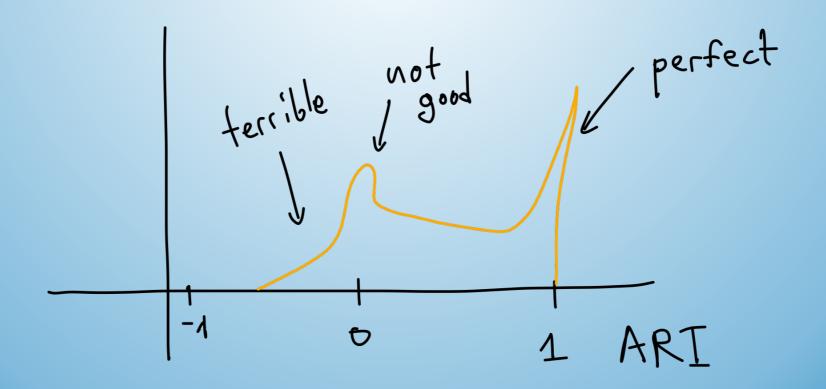


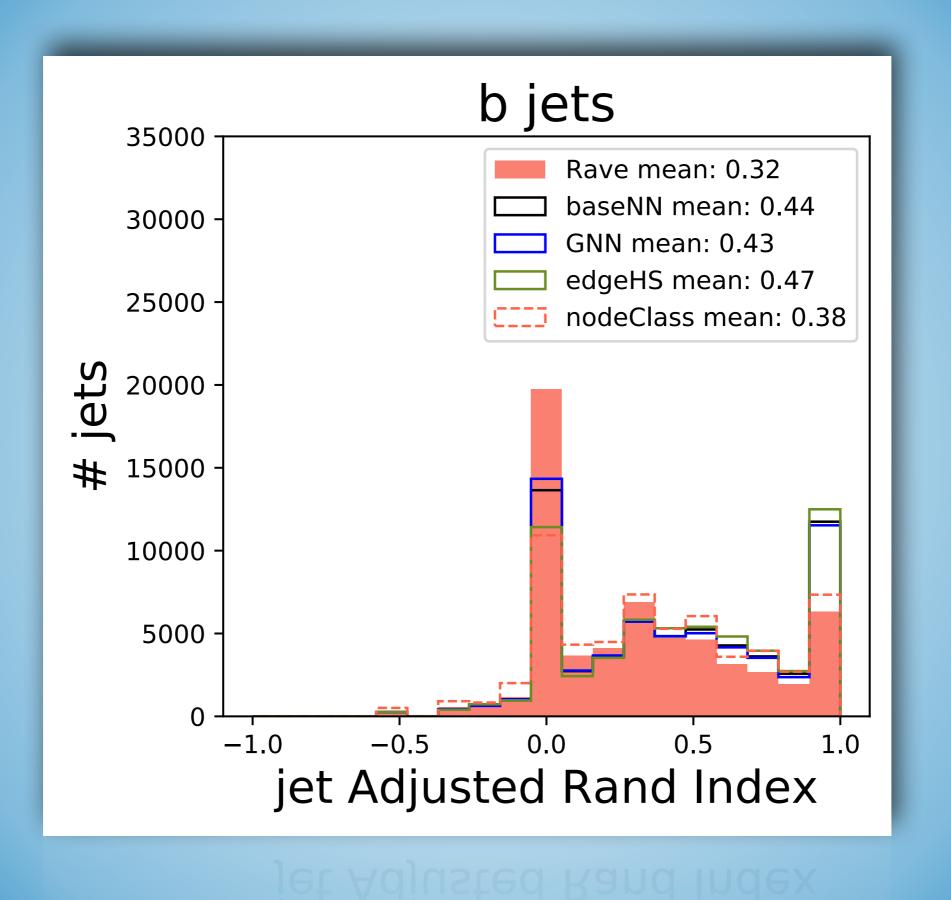


How to quantify vertex finding performance?

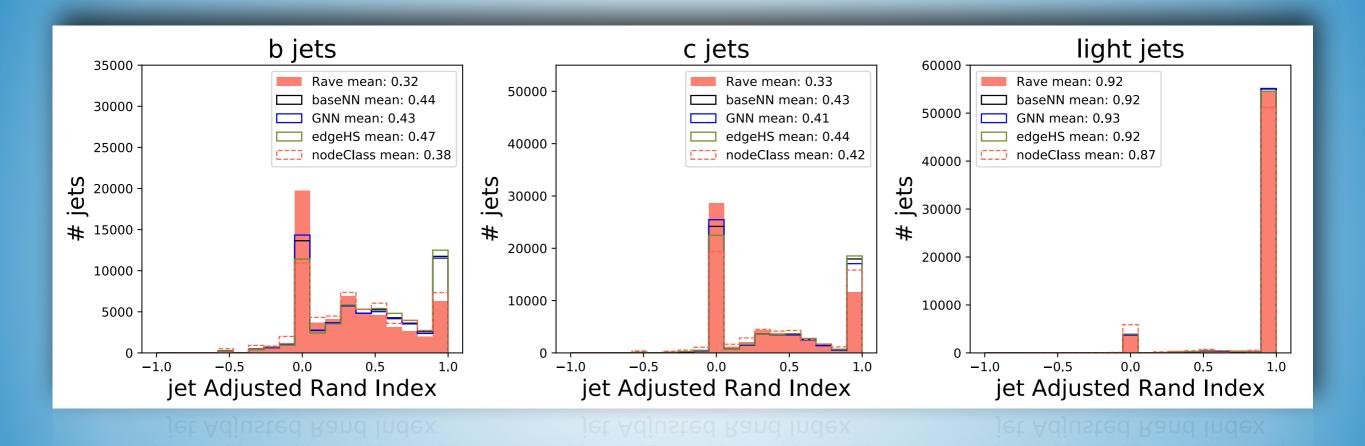
Adjusted Rand Index = 
$$\frac{\text{RI} - \text{E[RI]}}{1 - \text{E[RI]}}$$

Adjusted Rand Index = 
$$\begin{cases} 1 \text{ perfect} \\ 0 \text{ as good as random guessing} \\ < 0 \text{ worse then guessing} \end{cases}$$





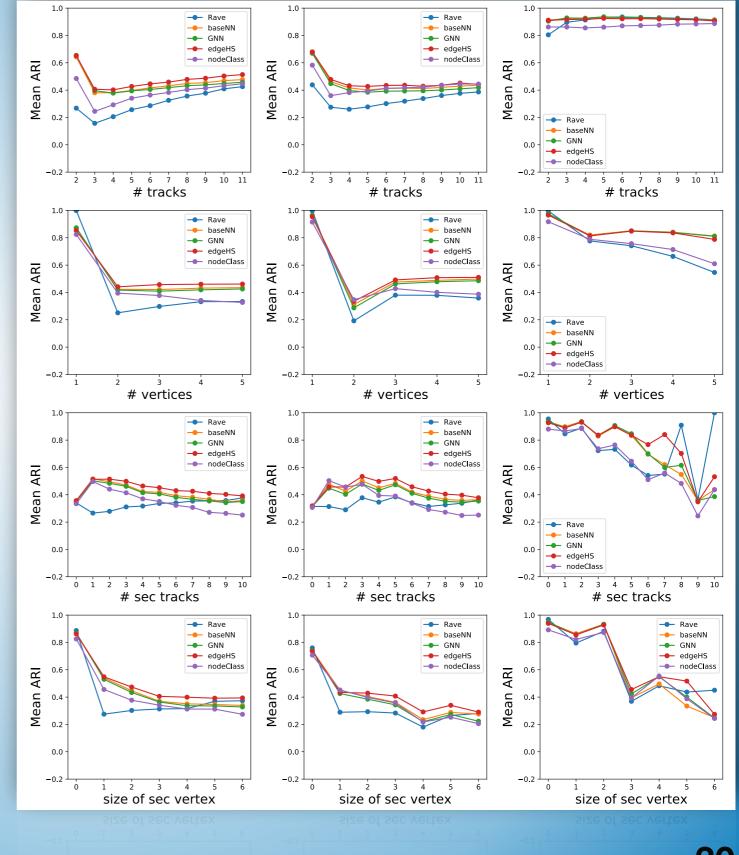
# Slight (very slight) improvement for the neural networks over the geometric algorithm



Another small advantage to the network with edge latent representation

## The same picture remains when we look at the mean ARI as a function of:

#tracks,
#vertices,
# of displaced tracks,
size of the secondary vertex,

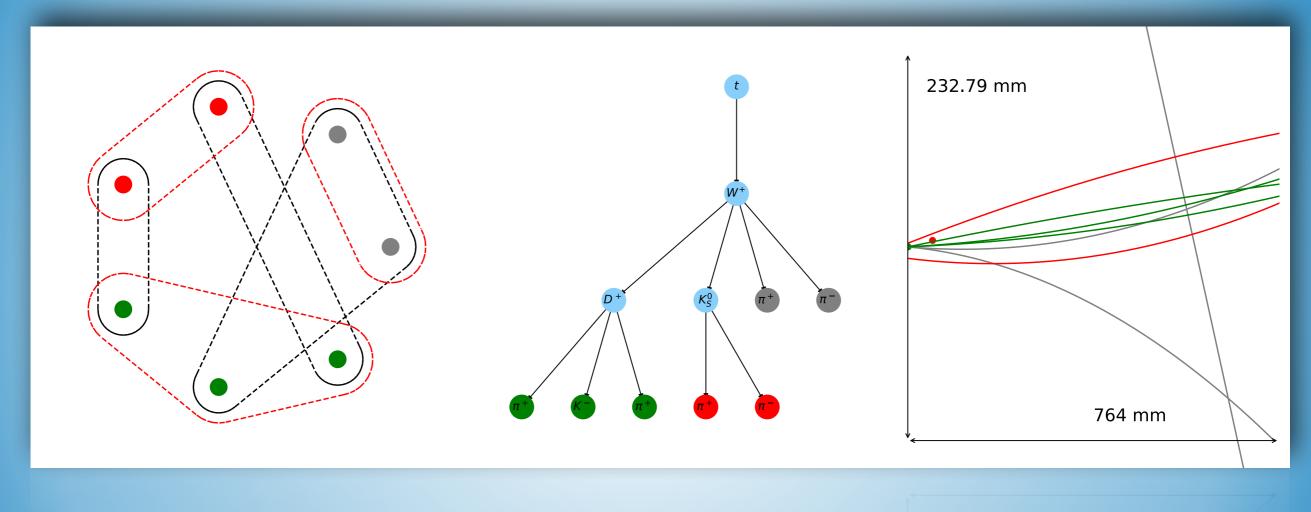


A really great way to understand the dataset is to visualise individual examples -

What we need:

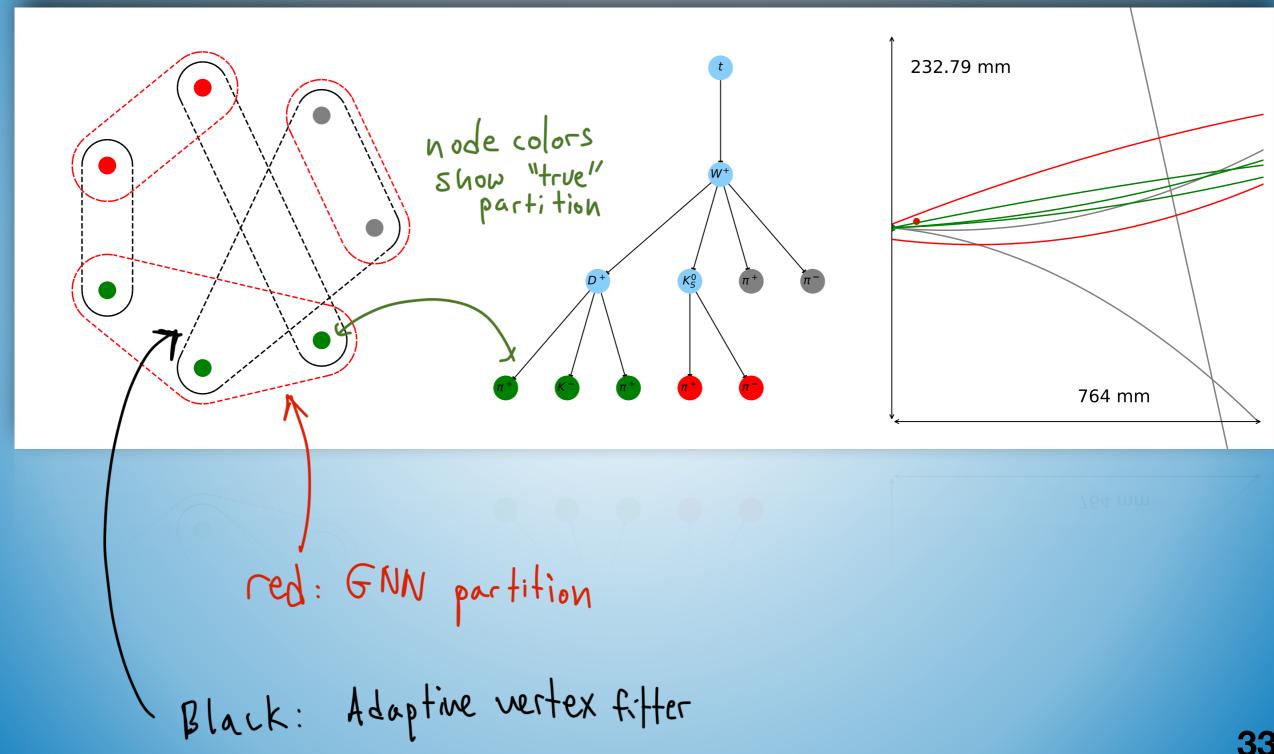
- to see the secondary vertices and tracks clearly
- To understand what tracks the algorithm clustered together
- To know what the "truth" was

This 3-piece event display gives us all the information,

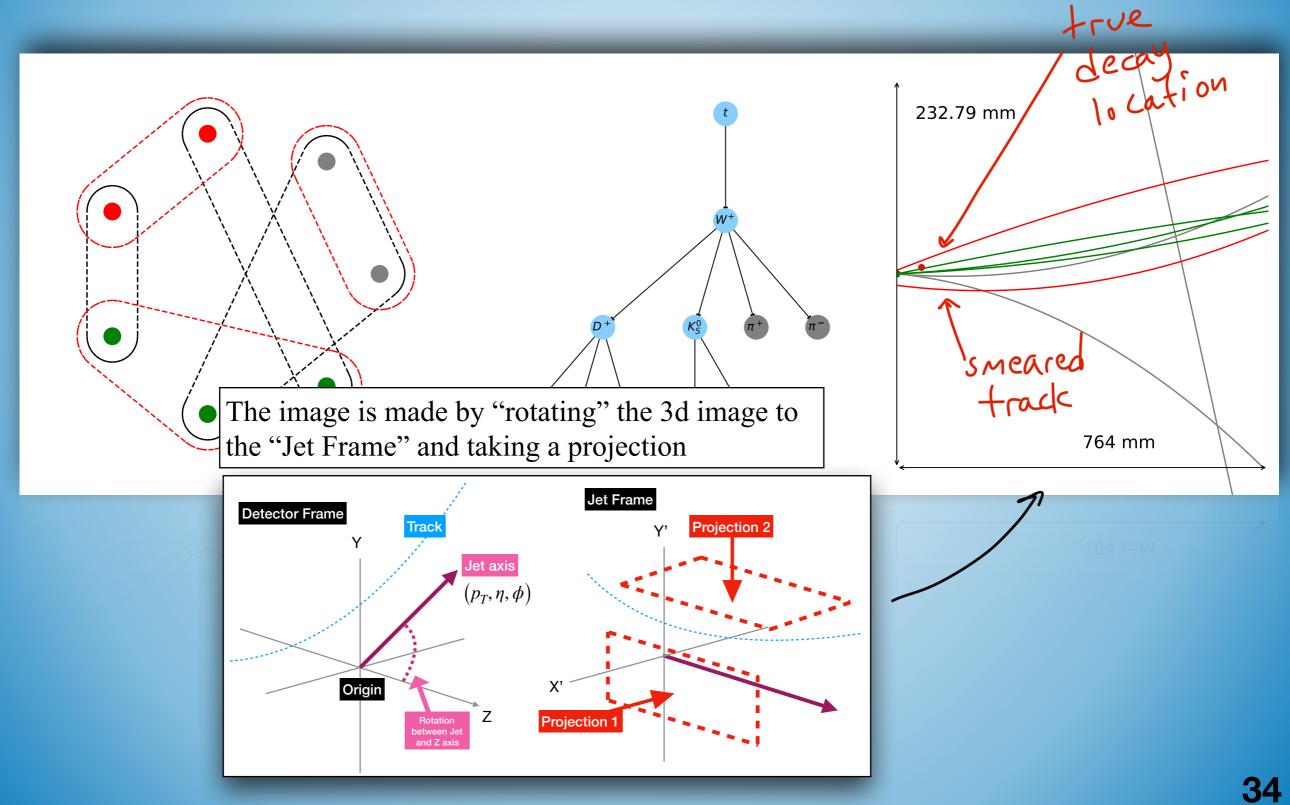


764 mm

This 3-piece event display gives us all the information,



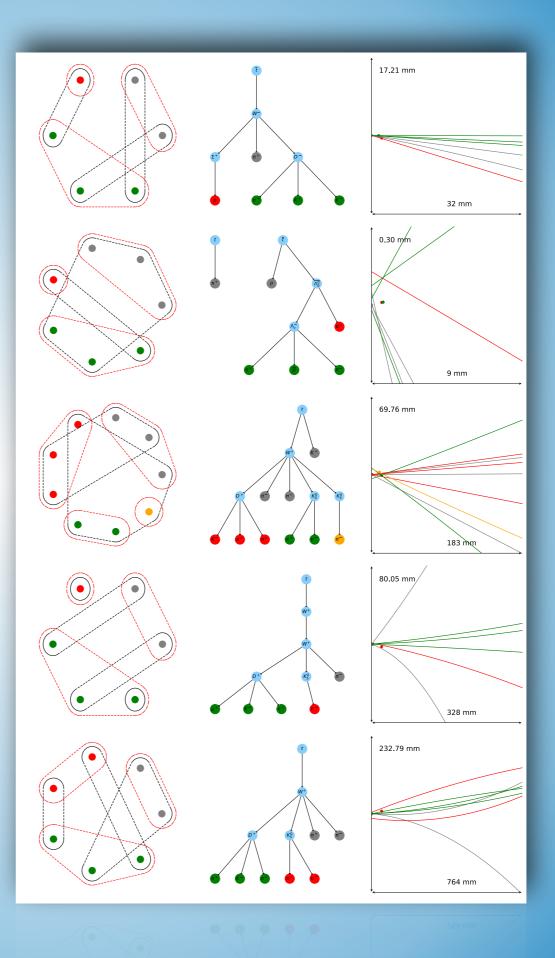
This 3-piece event display gives us all the information,



#### And its easily browsable in a Jupyter notebook

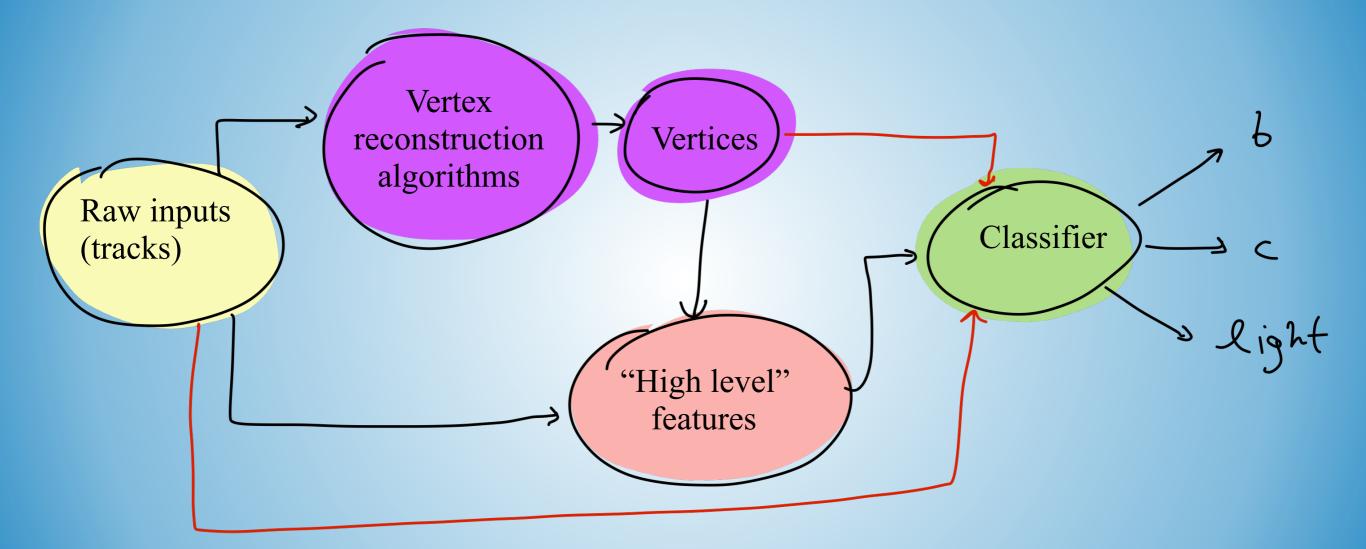
In [62]: np.where( ( algo\_ari['edgeHS']==1 ) & (algo\_ari['Rave']<0.2) & (sec\_vtx\_max\_size\_all\_jets > 2)
 & (n\_vertices > 2))[0]

Here are some examples of the neural network performing much better than the adaptive vertex fitter



#### **Summary**

• Neural networks are a viable option for this task



- Graph neural networks are a natural fit for the task
- The GNN performs better than the baseline algorithm, but there is a lot of room for improvement - looking for an architecture that takes the context into account

#### Next Step

- Use particle flow particles (include neutral particles in the vertex finding)
- Release the dataset to the world to try out different solutions

#### **Open** question

- Scalability to large graphs (event-level vertex finding)
- What are the causes for vertex finding "failure"