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# Quantum Machine Learning for b-jet charge identification

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On behalf of the **LHCb Collaboration**

 ICHEP 2022  
BOLOGNA

ICHEP 2022  
XLI

International Conference  
on High Energy Physics  
Bologna (Italy)

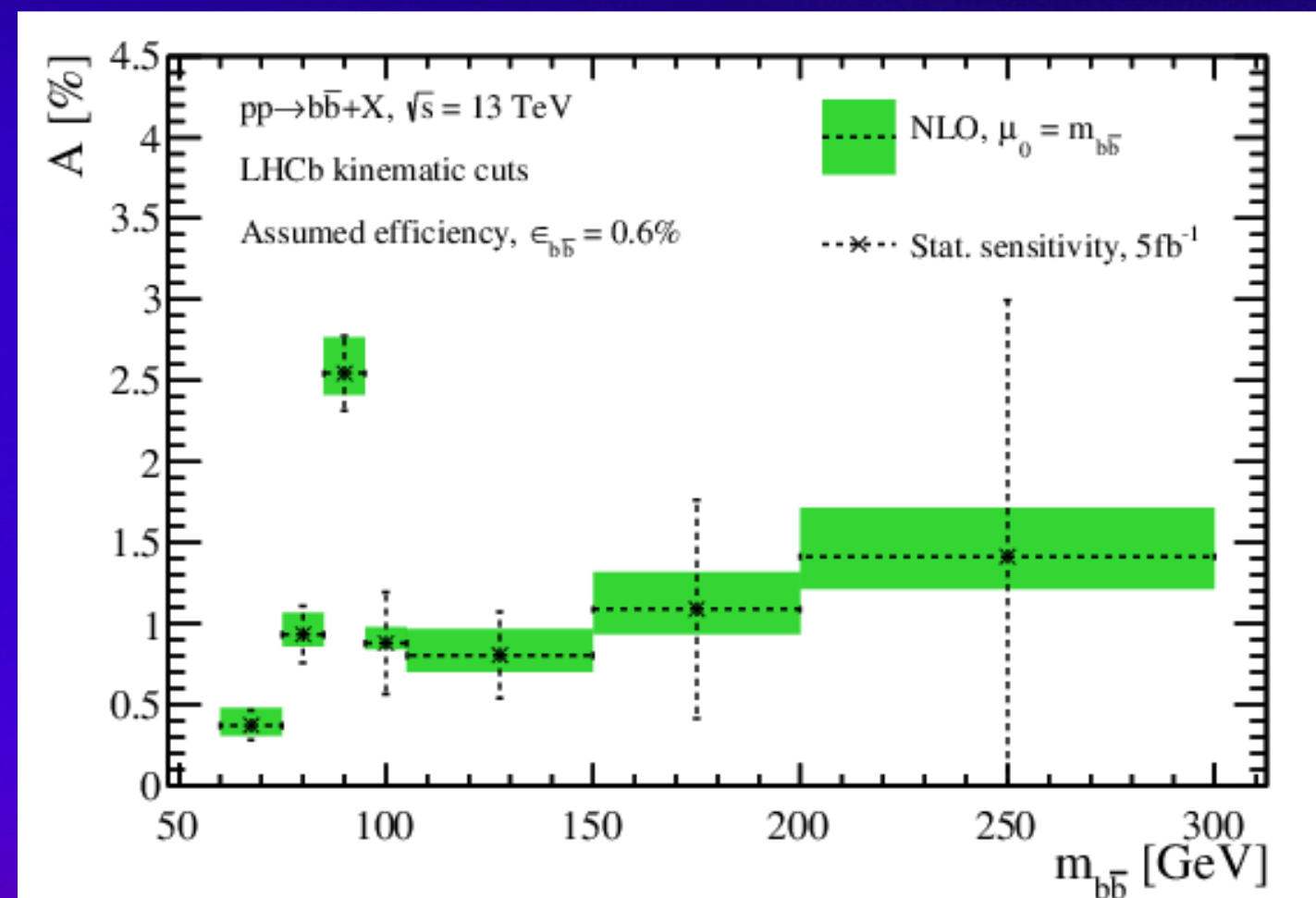
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# Jet identification

## Aka “the problem”

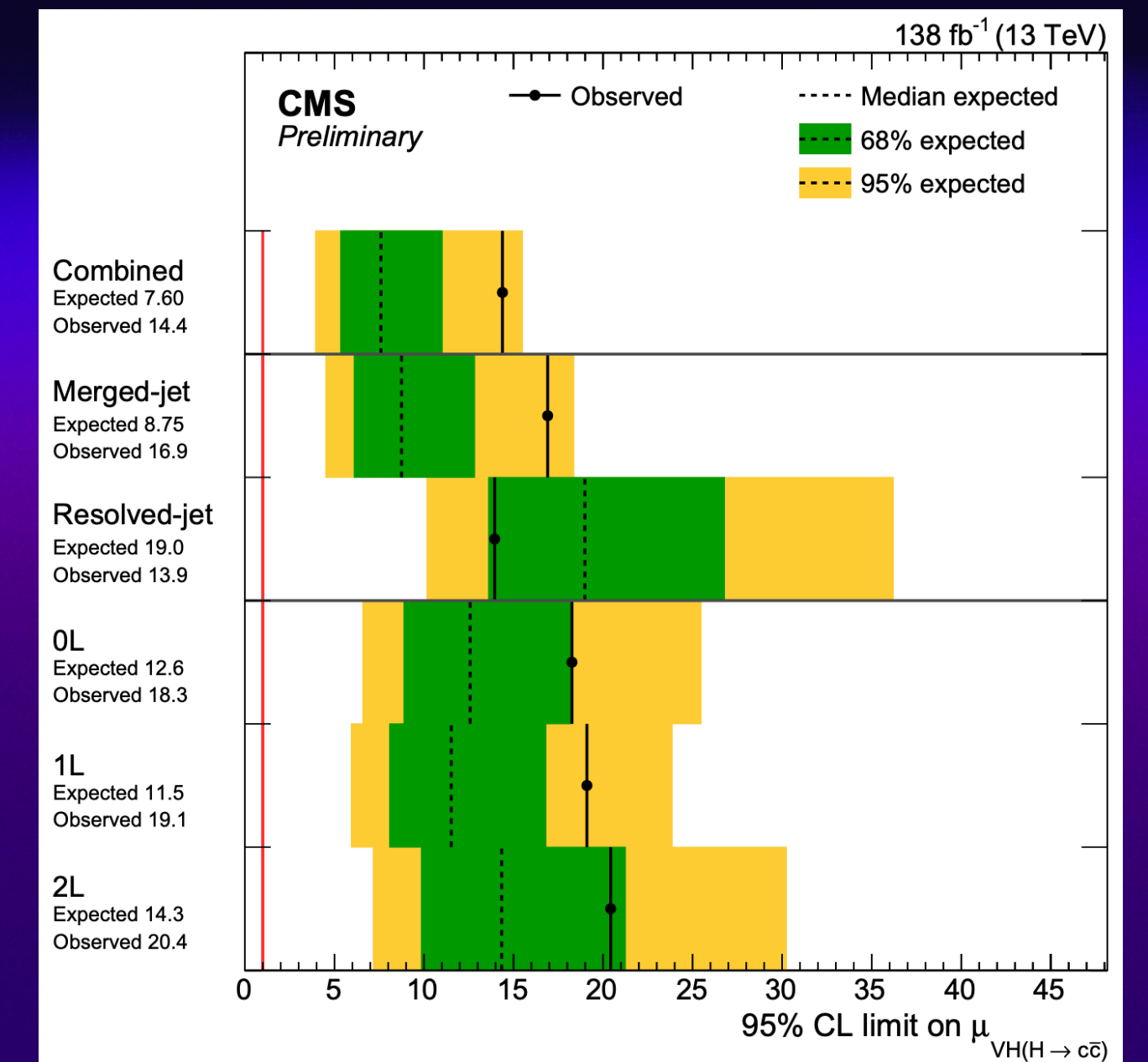
- At hadron colliders it is mandatory to reconstruct and identify jets
- Several interesting physics studies, for example:
  - Angular asymmetries of b-quark pair production
  - Higgs identification

$$A_{b\bar{b}}^C = \frac{N(\Delta y > 0) - N(\Delta y < 0)}{N(\Delta y > 0) + N(\Delta y < 0)} \quad \text{with } \Delta y = |y_b| - |y_{\bar{b}}|$$



Jet charge identification

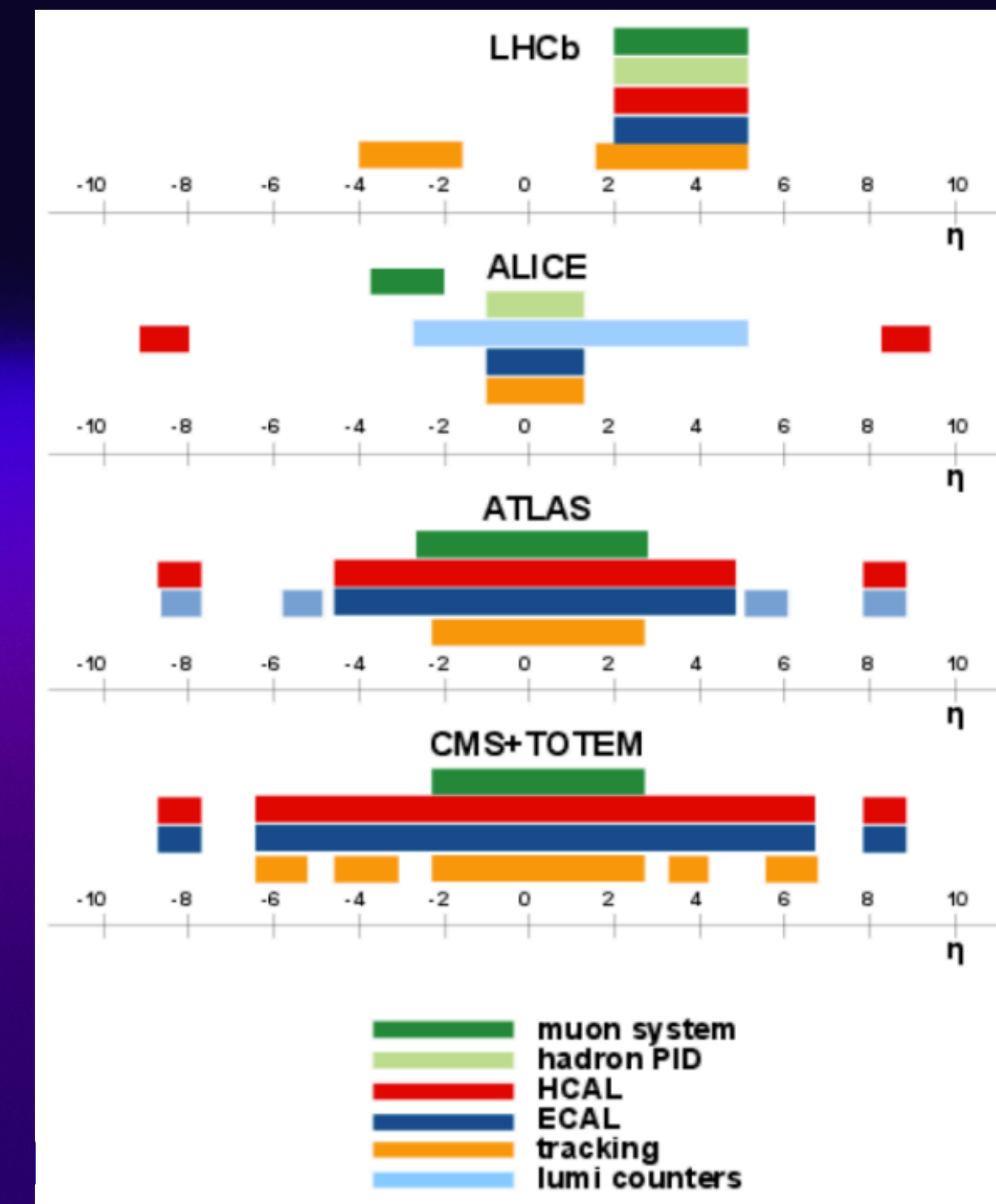
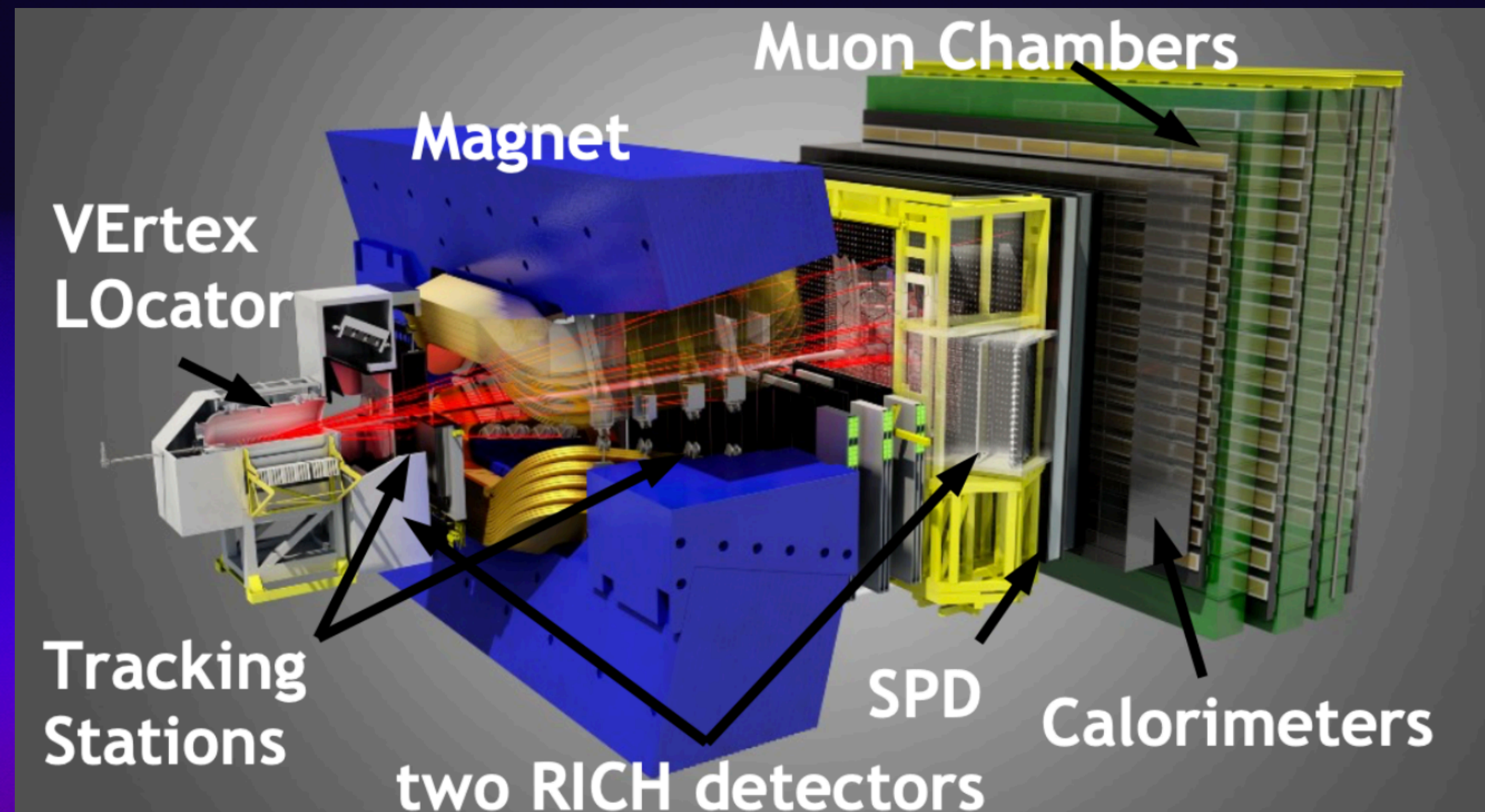
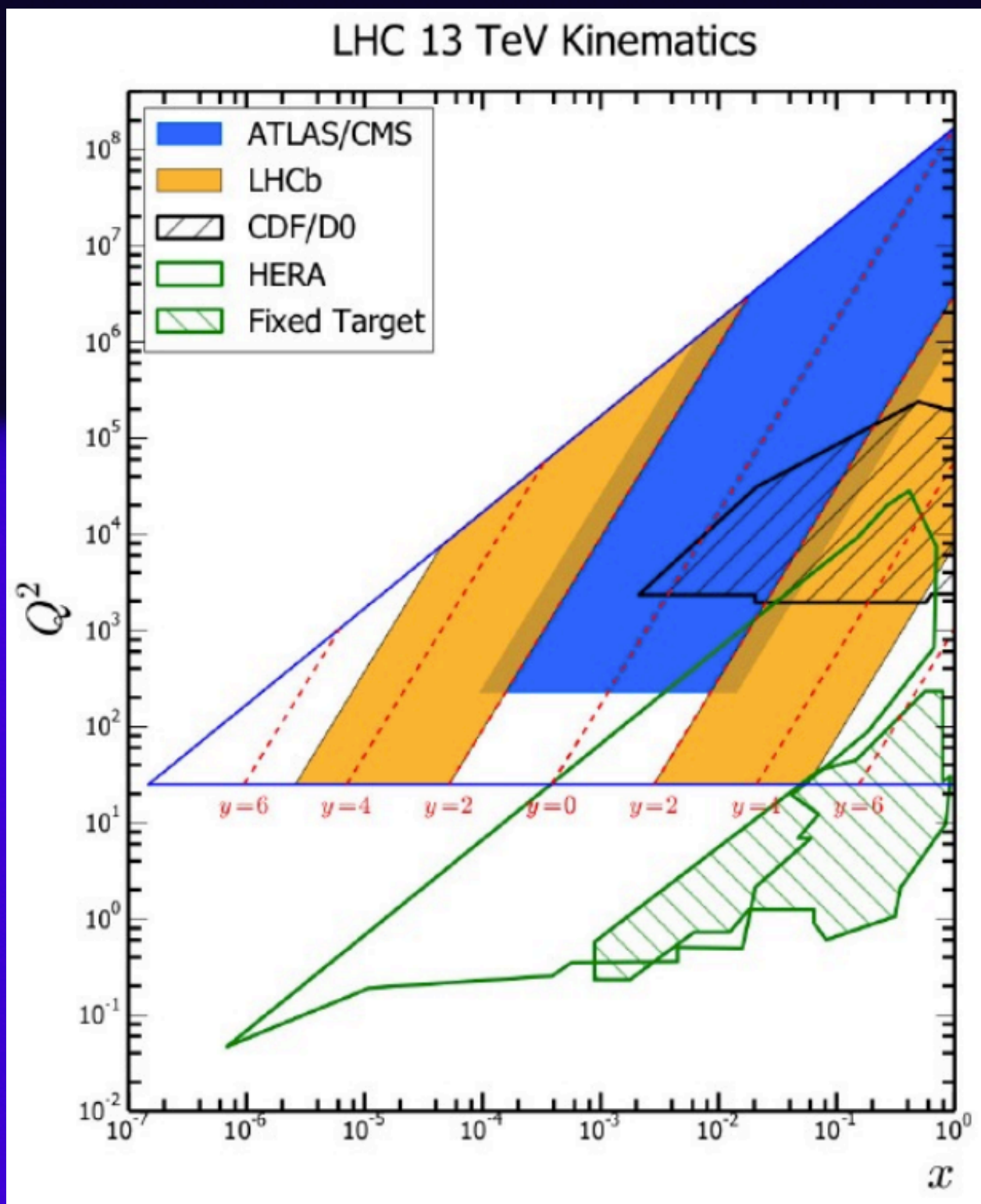
Jet flavour identification



# Jet charge identification at LHCb

## Where and How

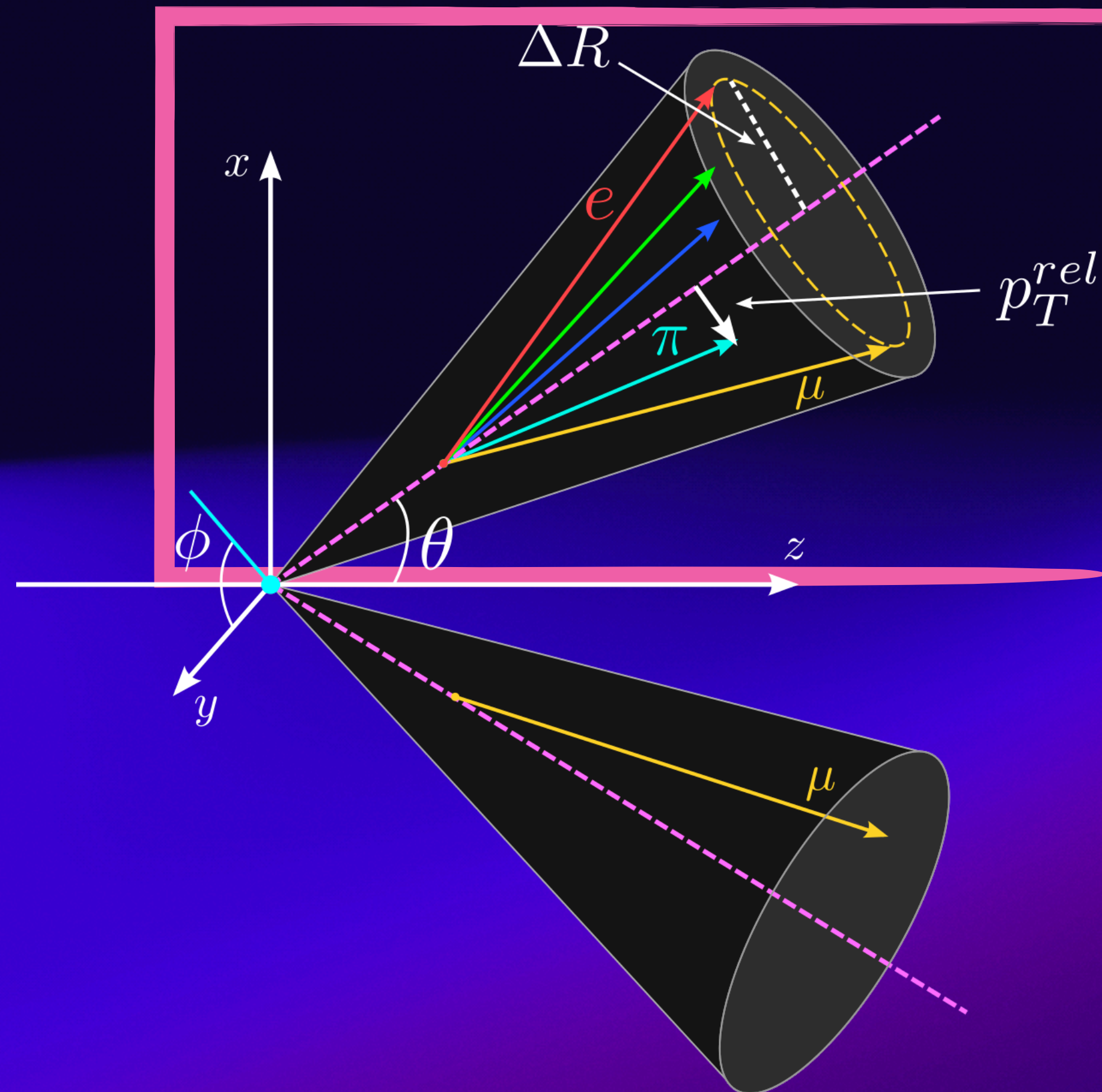
- LHCb is a **forward spectrometer** originally designed to study  $b$ - and  $c$ -hadron physics
- **Unique phase space region** ( $2 < \eta < 5$ ) complementary to ATLAS & CMS



# Jet charge identification at LHCb

## Where and How

- In principle there are two different approaches to identify the charge of a jet



### Inclusive approach

- It uses all the information coming from the jet substructure
- e.g. get the kinematic properties of all the particles inside the jet
- Given the amount of information → Machine Learning!

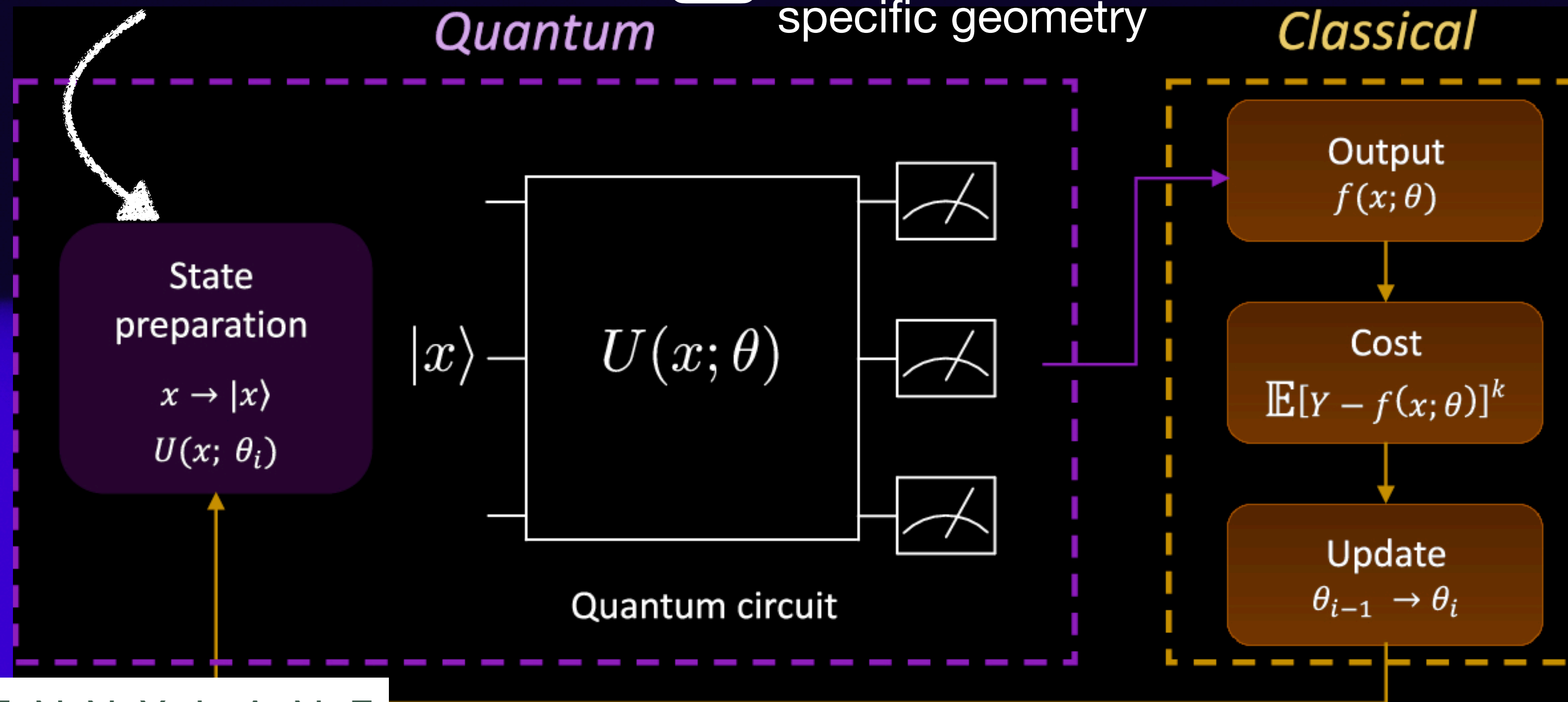
### Exclusive approach

- Use a specific physics process to infer the quark flavour
- So far used at LHCb → “muon tagging”
- A muon coming from the semi-leptonic decay of a b quark ( $\mathcal{B} = 10\%$ ) is used to tag the jet

# Going to quantum

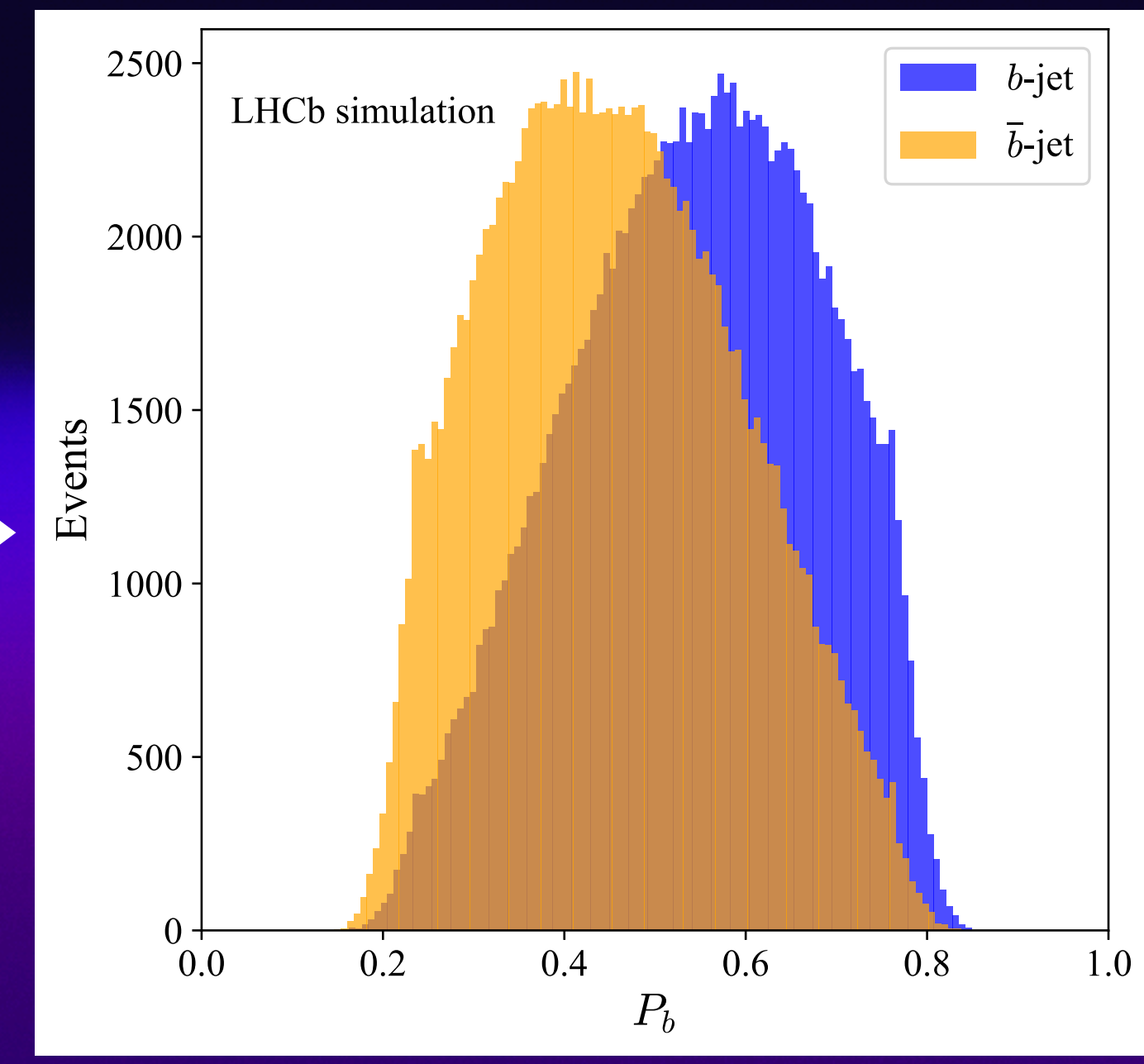
## QML with Variational Quantum Classifier

- 1** Feed the data into a quantum state (“data embedding”)
- 2** Create a quantum circuit with a specific geometry
- 3** Feed the output of the circuit to a classical optimization algorithm



P E N N Y L A N E

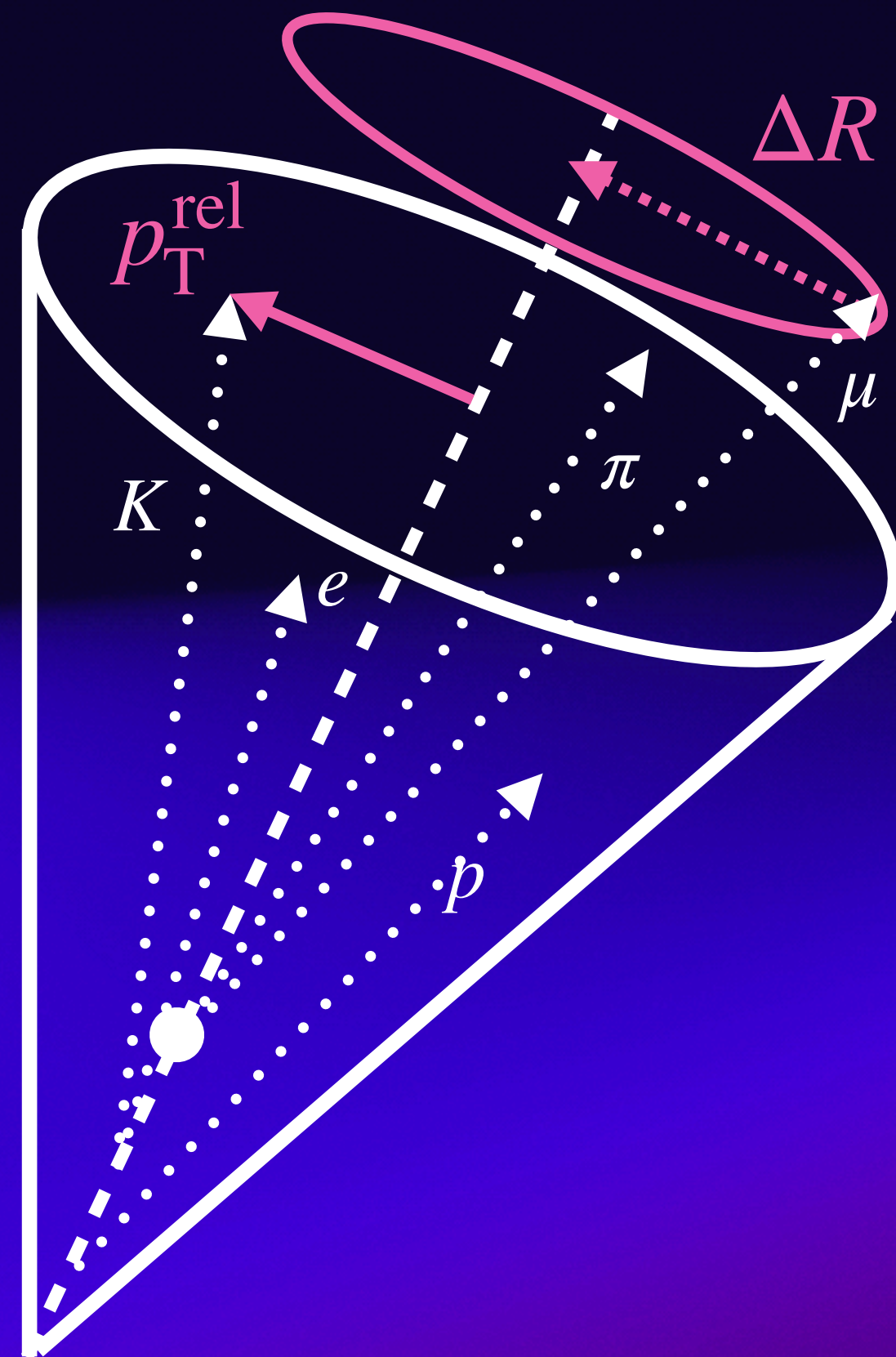
- 4** Perform a training on a sample of data by optimizing circuit parameters



- 5** Get output distribution

# Going to quantum

## The dataset



- Sample of  $b\bar{b}$  di-jets events have been simulated with the official LHCb simulation framework
- Run 2 condition ( $\sqrt{s} = 13$  TeV)
- ~700.000 jets, divided into training (60%) and testing (40%)
- For each jet, 5 types of particles are considered:

**muon   electron   pion   kaon   proton**

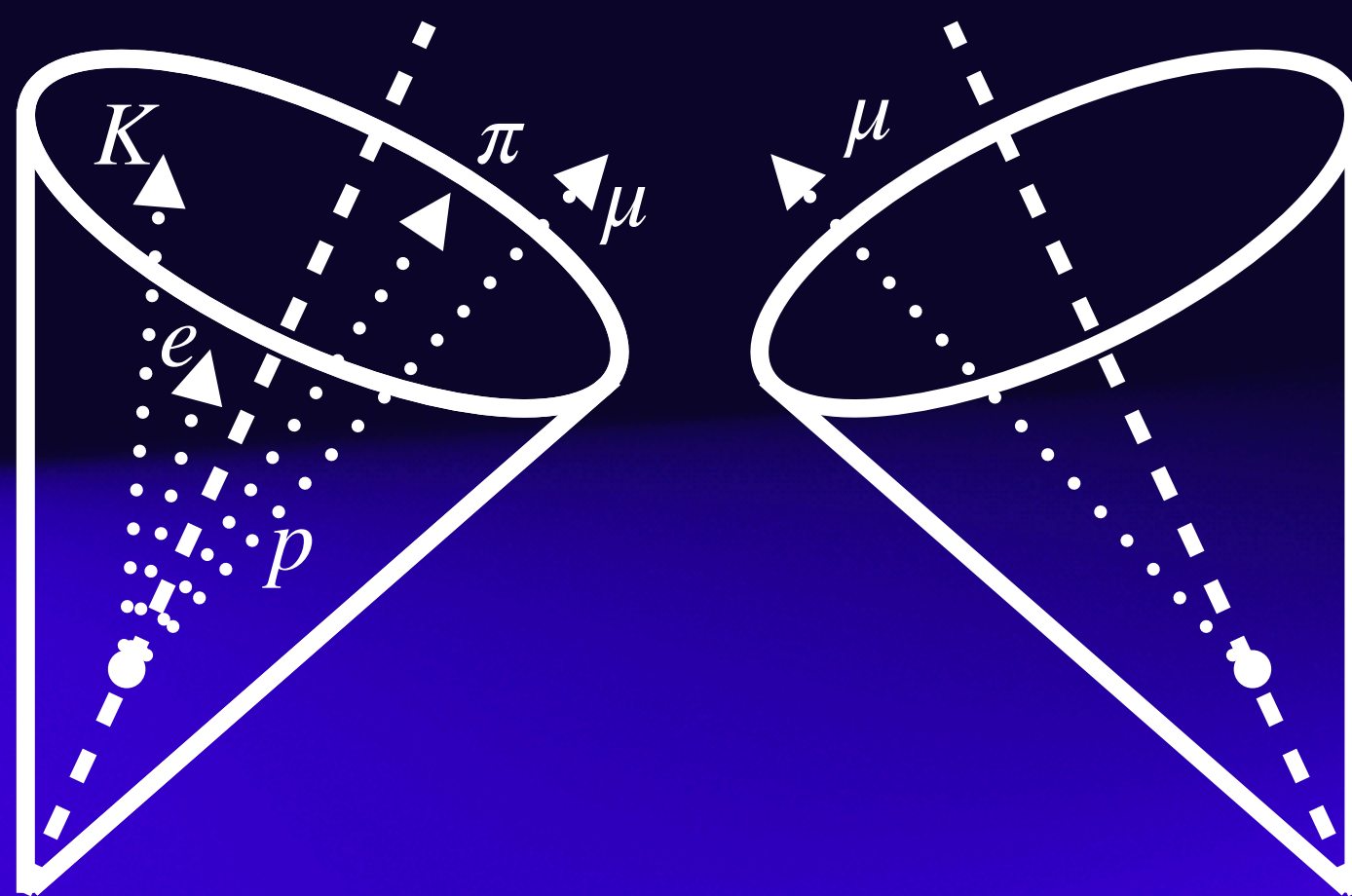
- And for each type of particle, three features are considered:
  - Transverse momentum relative to jet axis  $p_T^{\text{rel}}$
  - Distance relative to jet axis  $\Delta R$
  - Charge of the particle  $q$
- + a global variable, the total jet charge  $Q = \frac{\Sigma(p_T^{\text{rel}})q}{\Sigma(p_T^{\text{rel}})}$

# b-jet charge identification with QML

## Try to get a complete study

- To perform a complete study of this algorithm and its application, we have considered several aspects

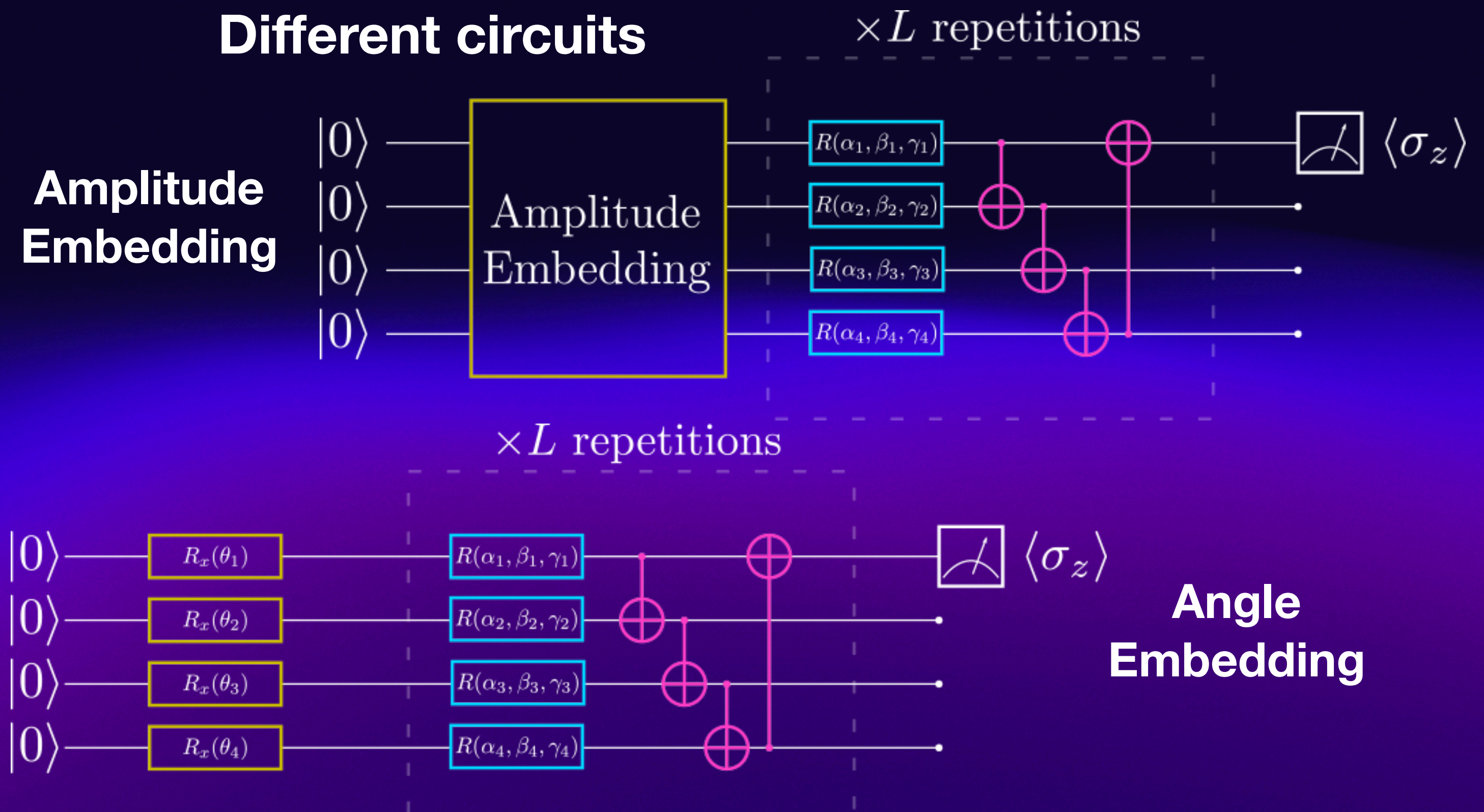
### Different datasets



“Complete” dataset  
16 variables

“Muon” dataset  
 $\mu + Q =$   
4 variables

### Different circuits



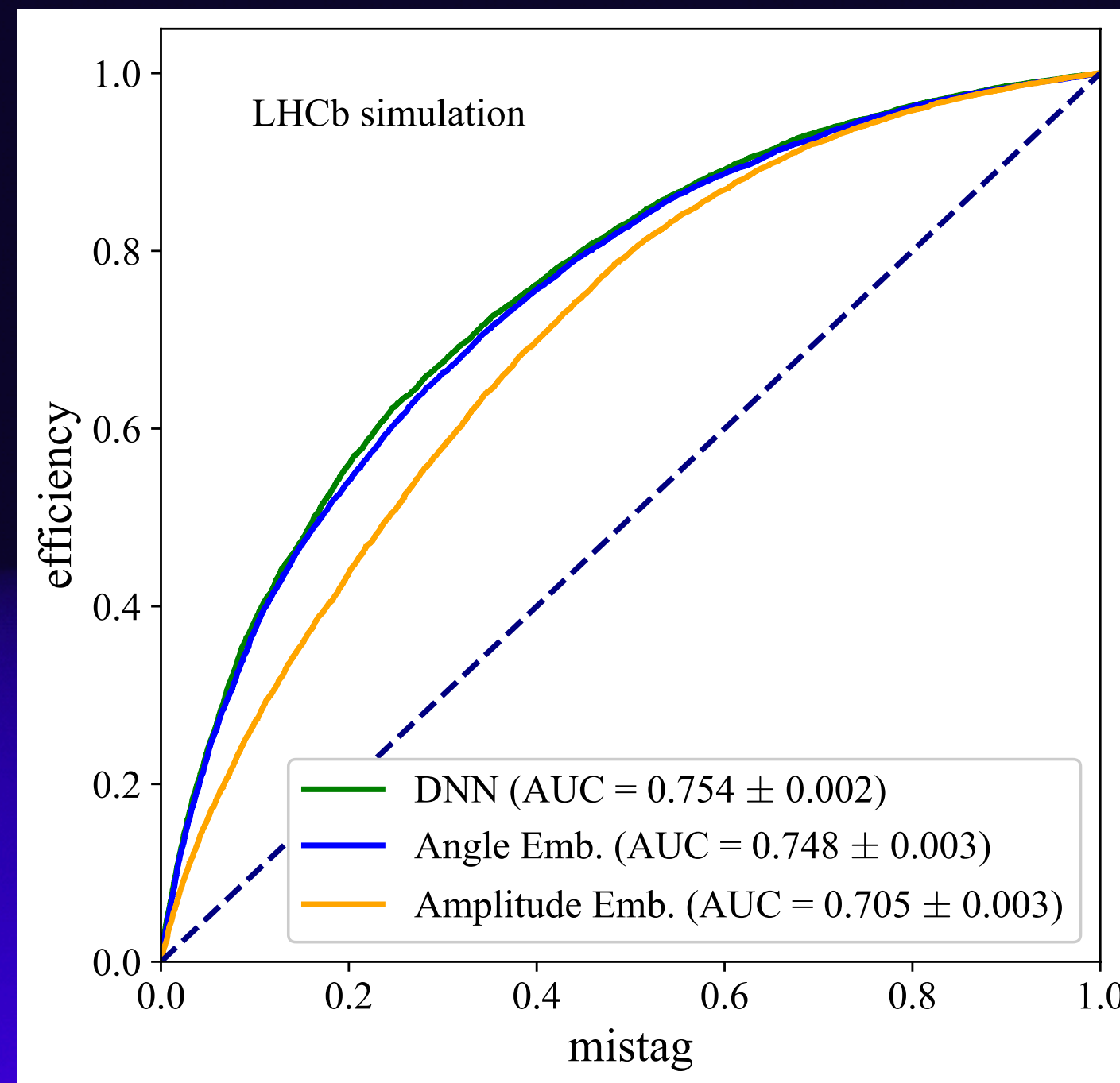
- Results are compared with a standard Deep Neural Network (DNN) using same input variables

# b-jet charge identification with QML

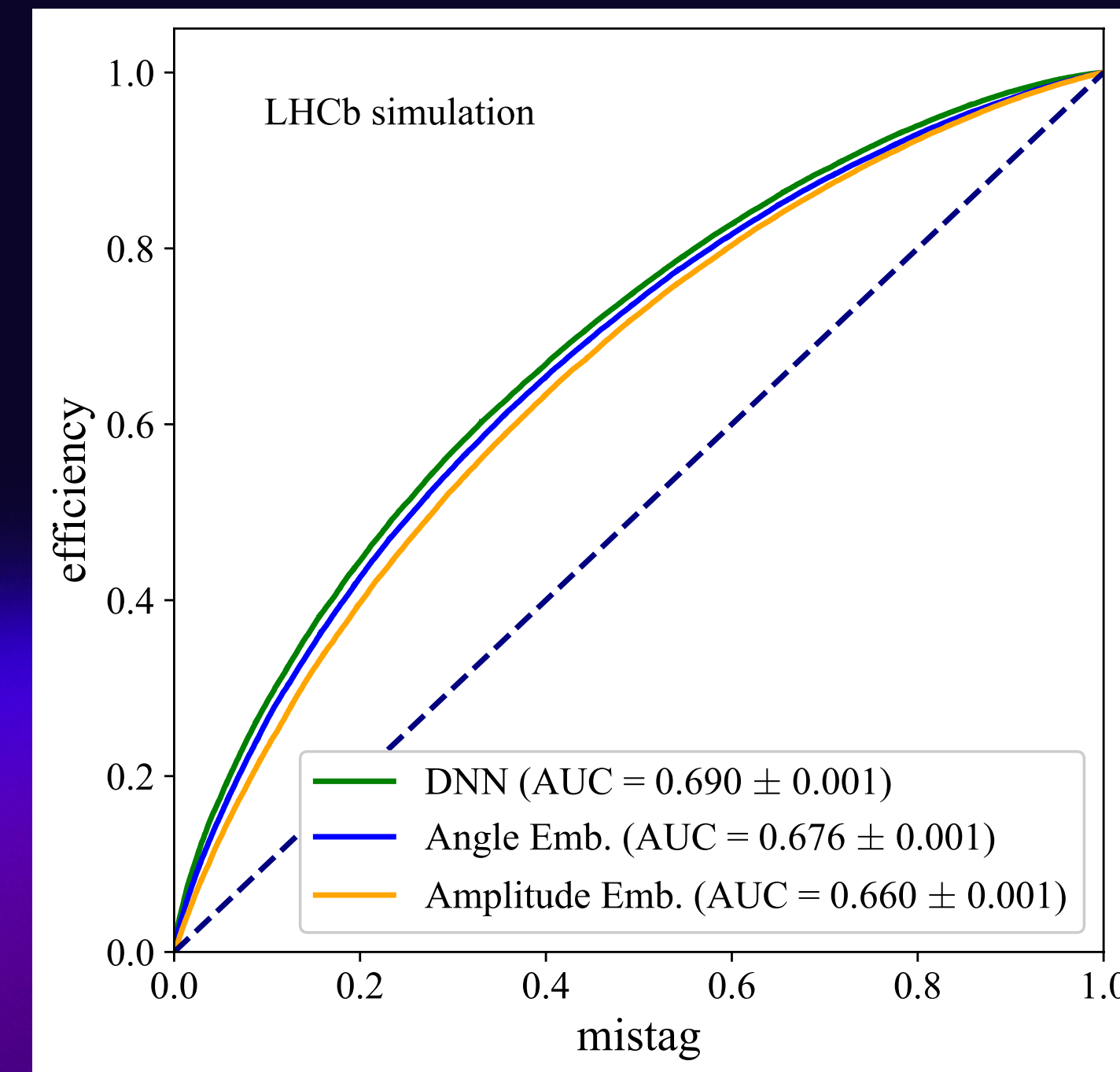
## Algorithm performance

- A typical figure of merit for performance is the Receiving Operating Characteristic (ROC) curve

**Muon  
dataset**



**Complete  
dataset**



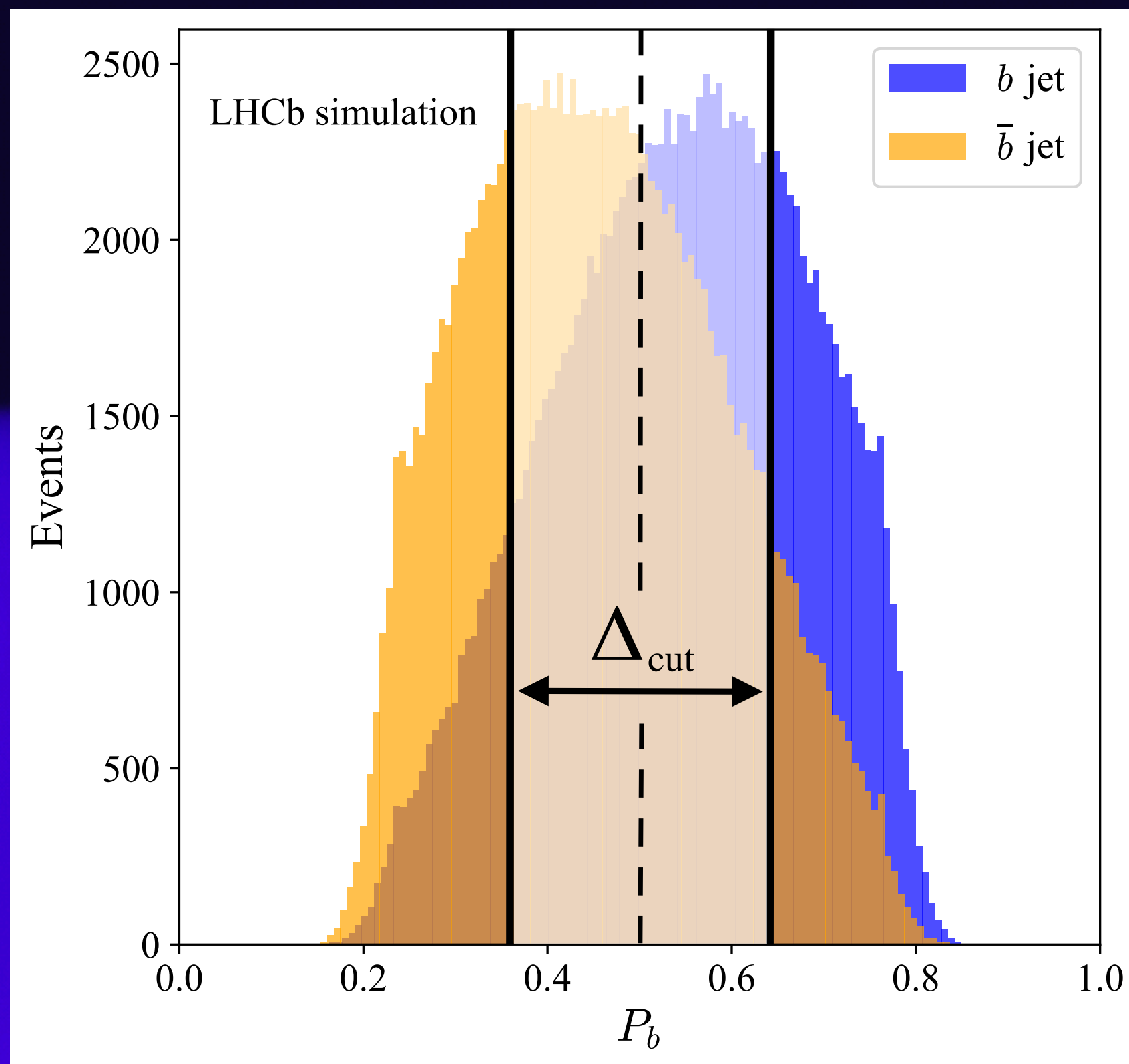
- The Angle Embedding circuit performs better than the Amplitude Embedding circuit, for both the Muon and the Complete dataset
- For the Muon dataset the Angle Embedding circuit performs as good as the DNN



# b-jet charge identification with QML

## The physics perspective

- Once performance of the algorithm is assessed, we focus on the physical interesting quantities
- A typical figure of merit for this kind of problems is the **tagging power**



$$\epsilon_{\text{tag}} = \epsilon_{\text{eff}} (1 - 2\omega)^2$$

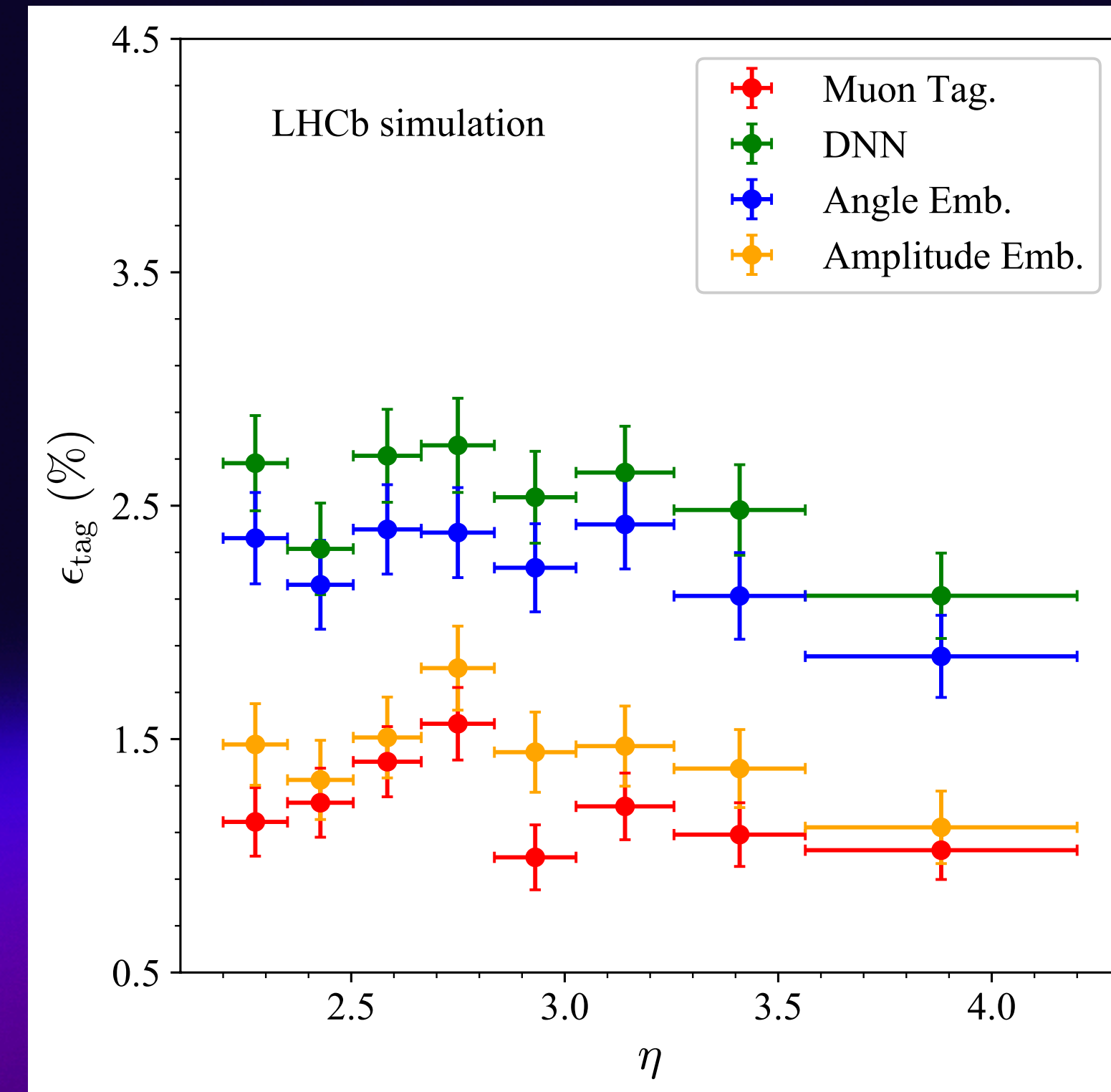
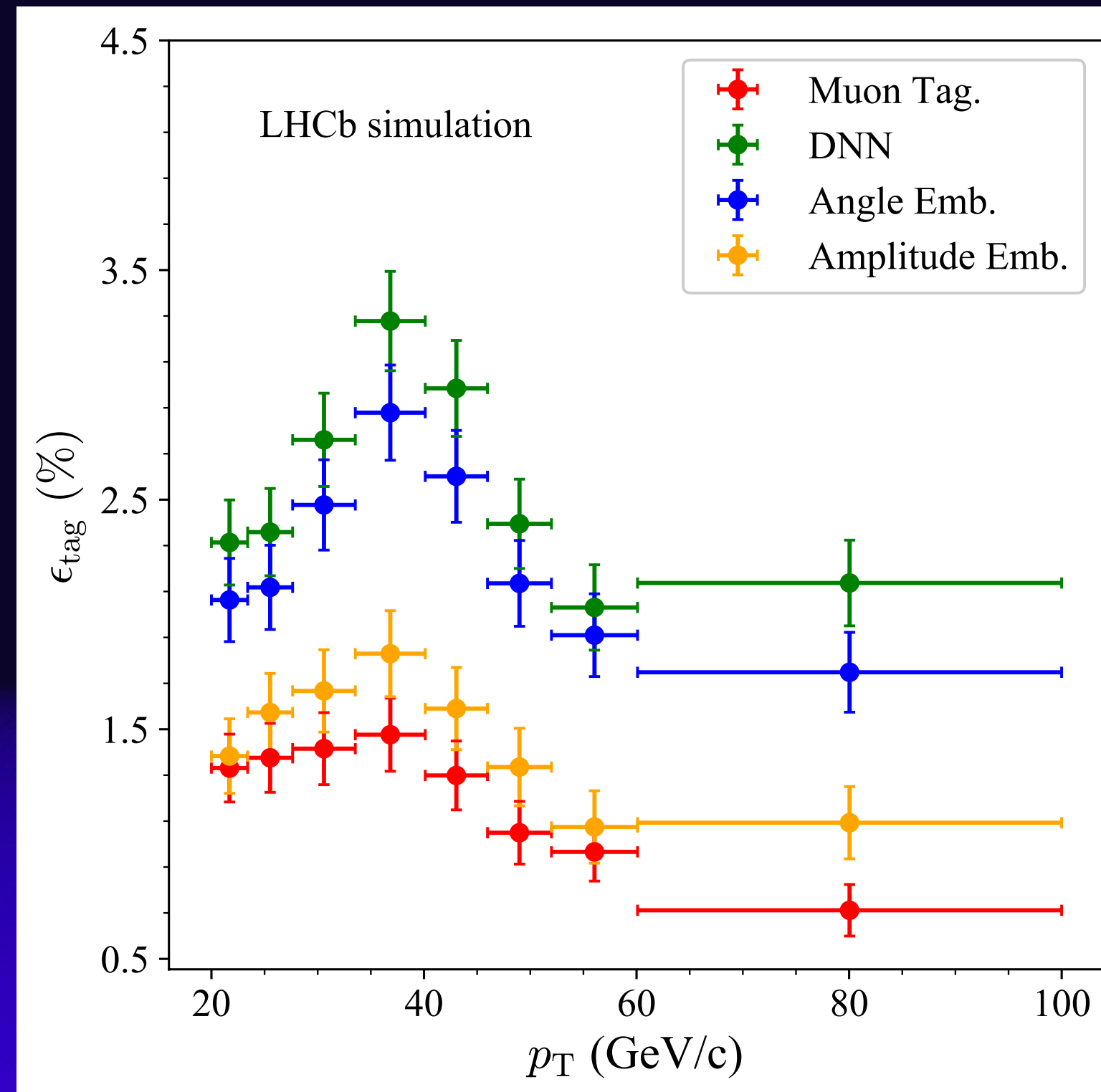
$$\epsilon_{\text{eff}} = \text{efficiency} = \frac{\# \text{ tagged jets}}{\# \text{ jets}} \quad \omega = \text{mistag} = \frac{\# \text{ wrongly tagged jets}}{\# \text{ tagged jets}}$$

- It can be interpreted as the effective fraction of correctly identified jets (e.g. relevant for asymmetry measurements)
- Optimized cut  $\Delta_{\text{cut}}$  over output distribution: reduce efficiency but also reduce mistag, therefore increase tagging power

Dataset	Classifier		
	DNN	Angle Embedding	Amplitude Embedding
Muon	0.30	0.25	0.16
Complete	0.21	0.19	0.12

# b-jet charge identification with QML

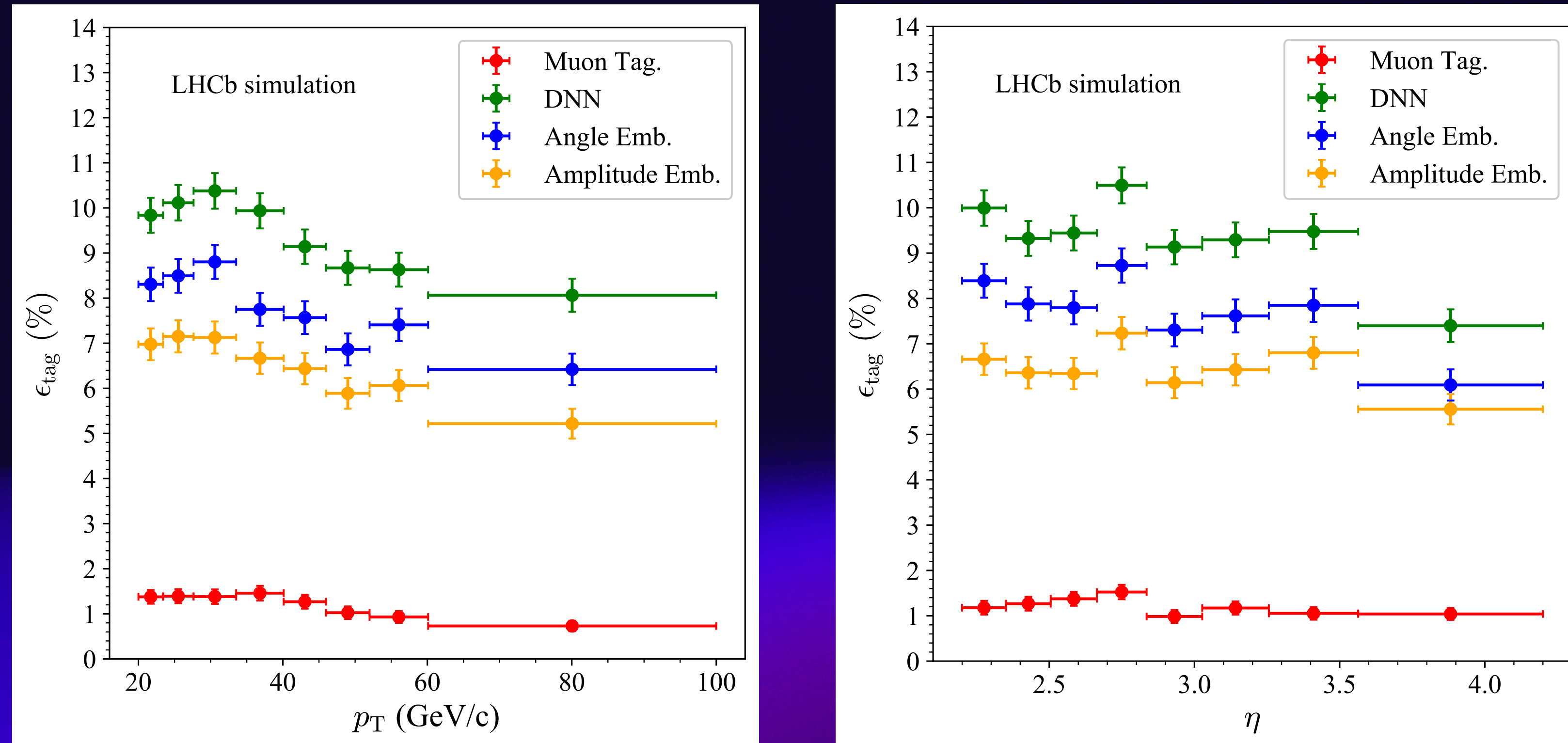
## Results for tagging power — muon dataset



- Tagging power is shown as function of jet  $p_T$  and pseudorapidity  $\eta$
- Angle Embedding circuit is comparable to DNN, Amplitude Embedding not performing as good

# b-jet charge identification with QML

## Results for tagging power — complete dataset



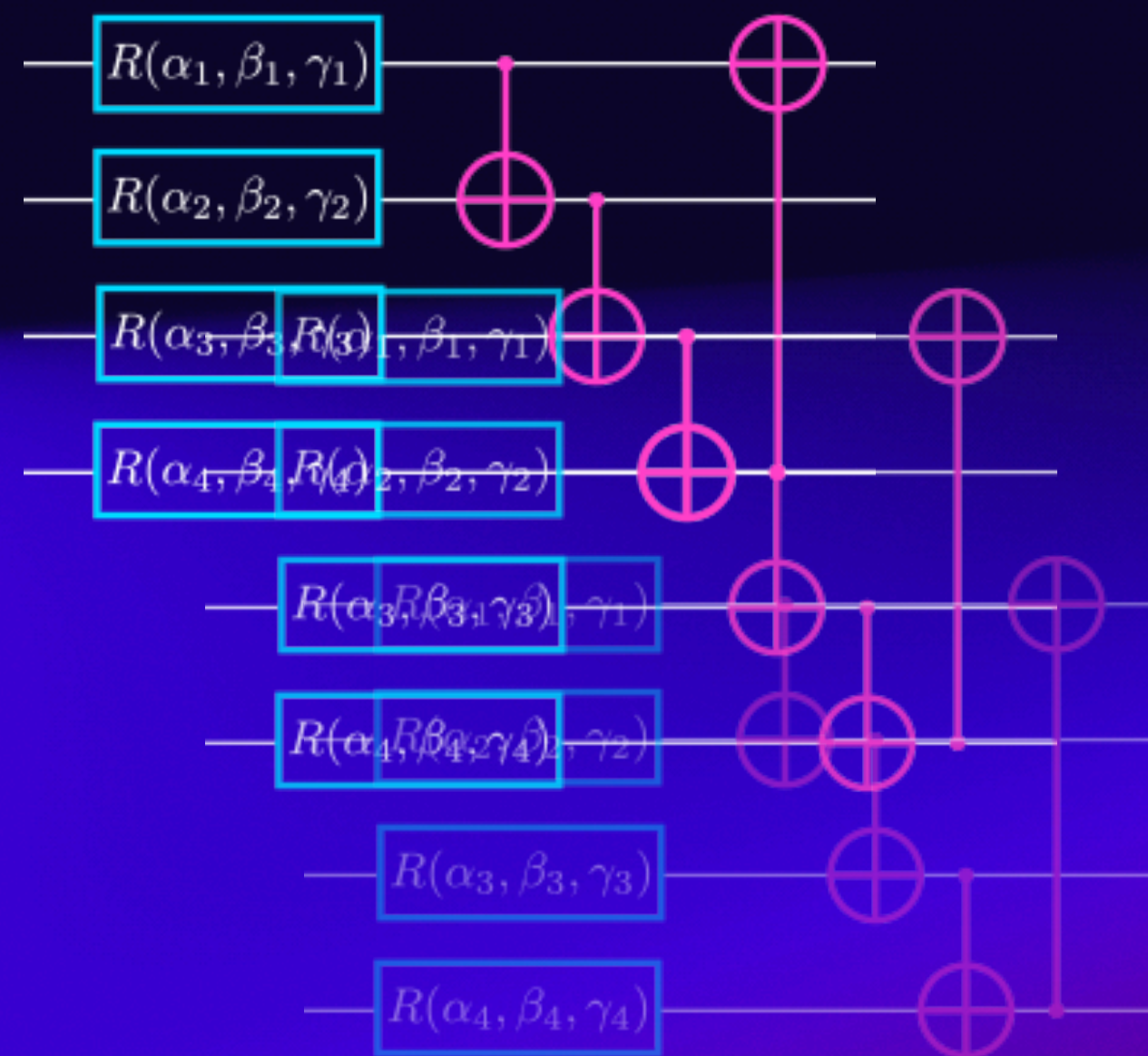
- Tagging power is shown as function of jet  $p_T$  and pseudorapidity  $\eta$
- Both quantum circuits have lower performance  $\rightarrow$  room for improvement!

# b-jet charge identification with QML

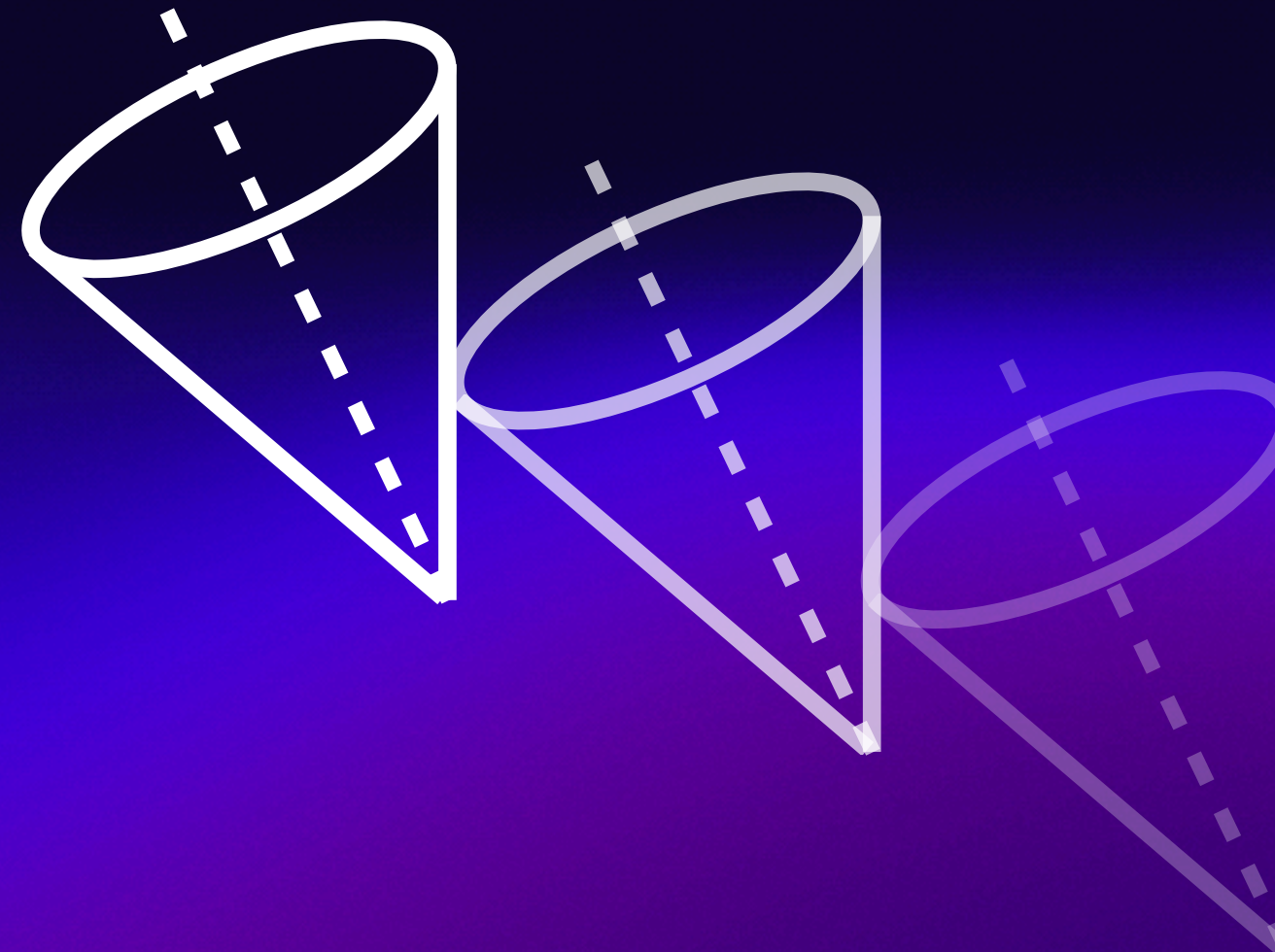
## Try to get a complete study (2)

- To perform a complete study of this algorithm and its application, we have considered several aspects

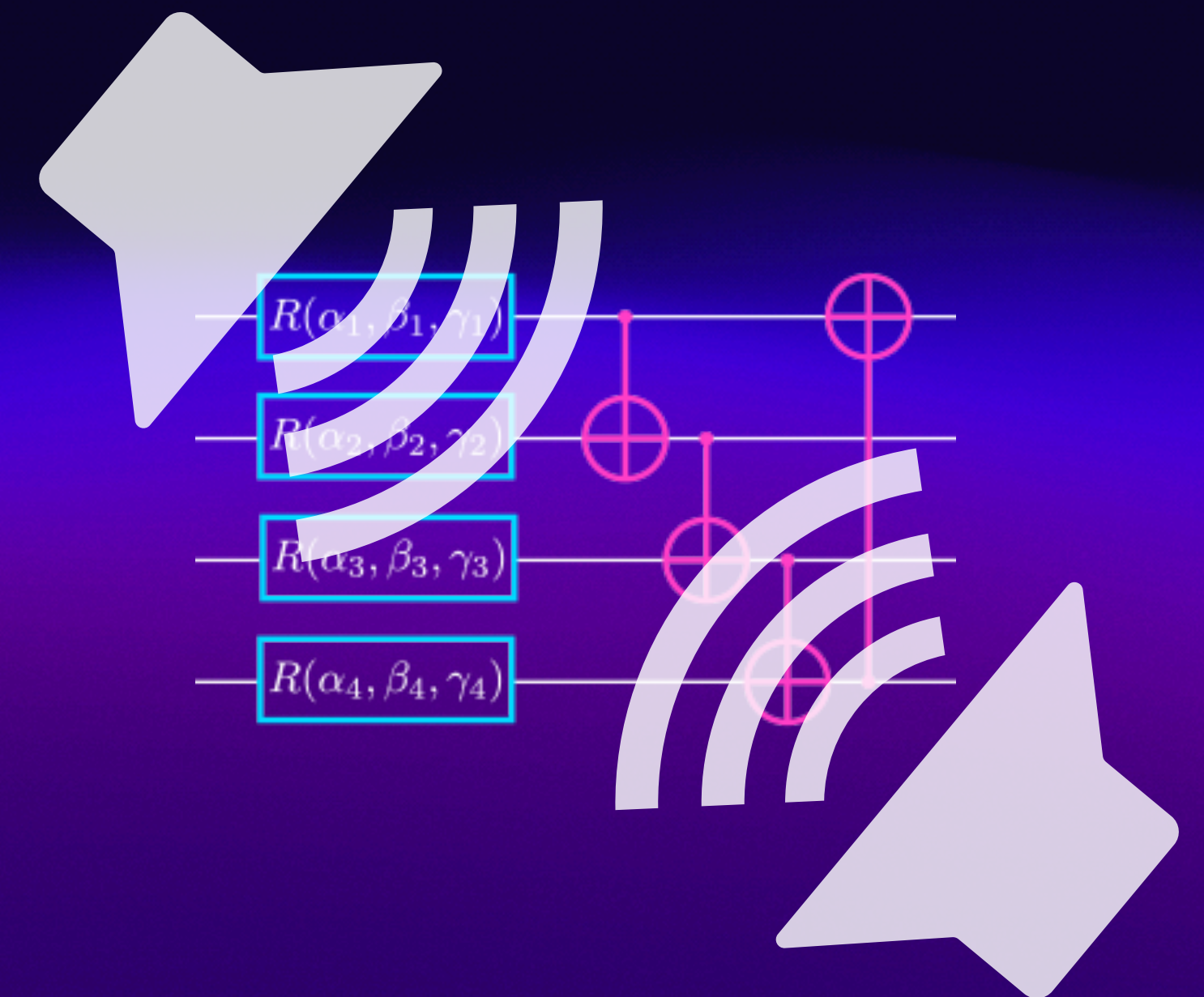
Number of  
variational layers



Number of  
training events

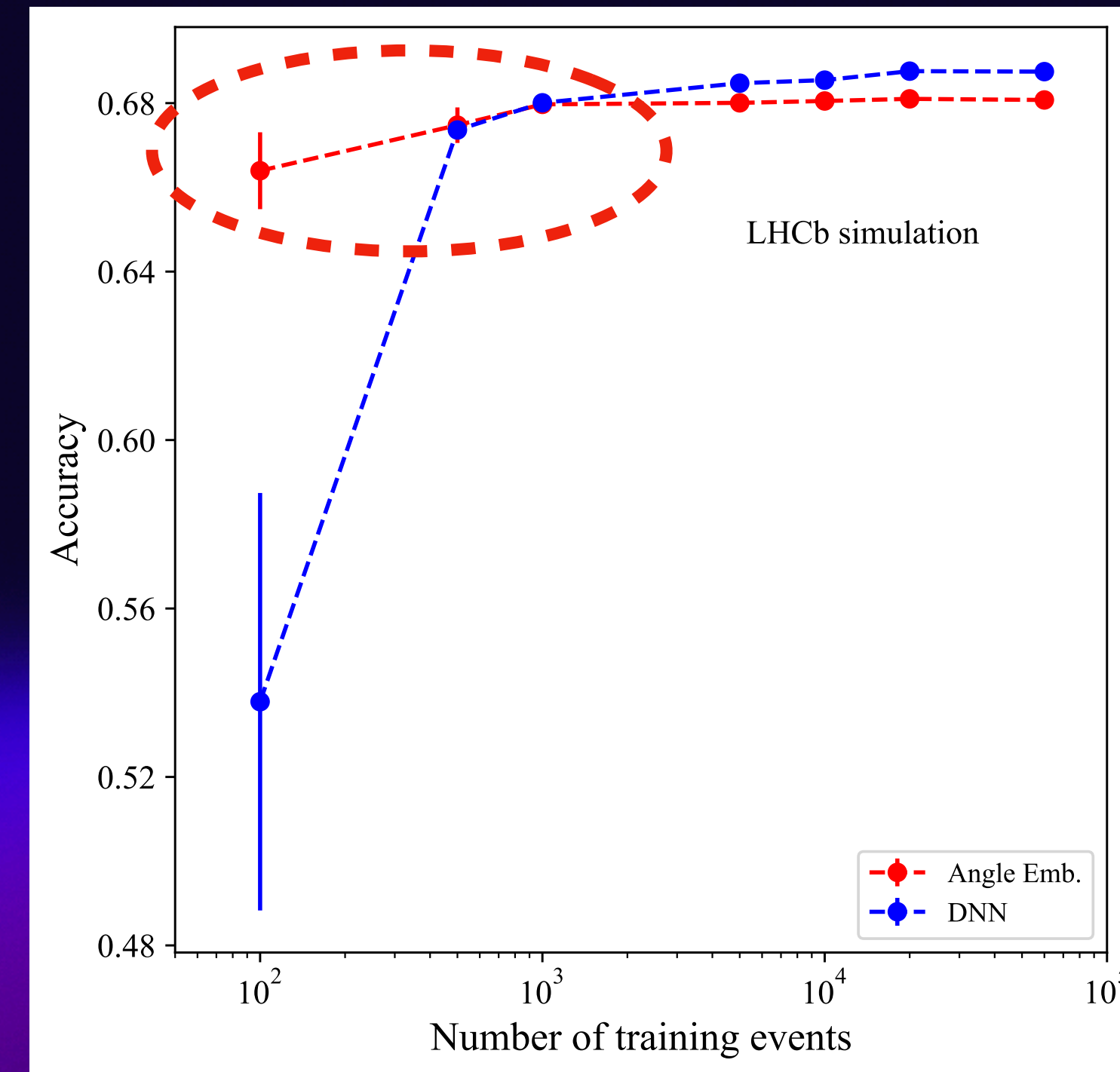
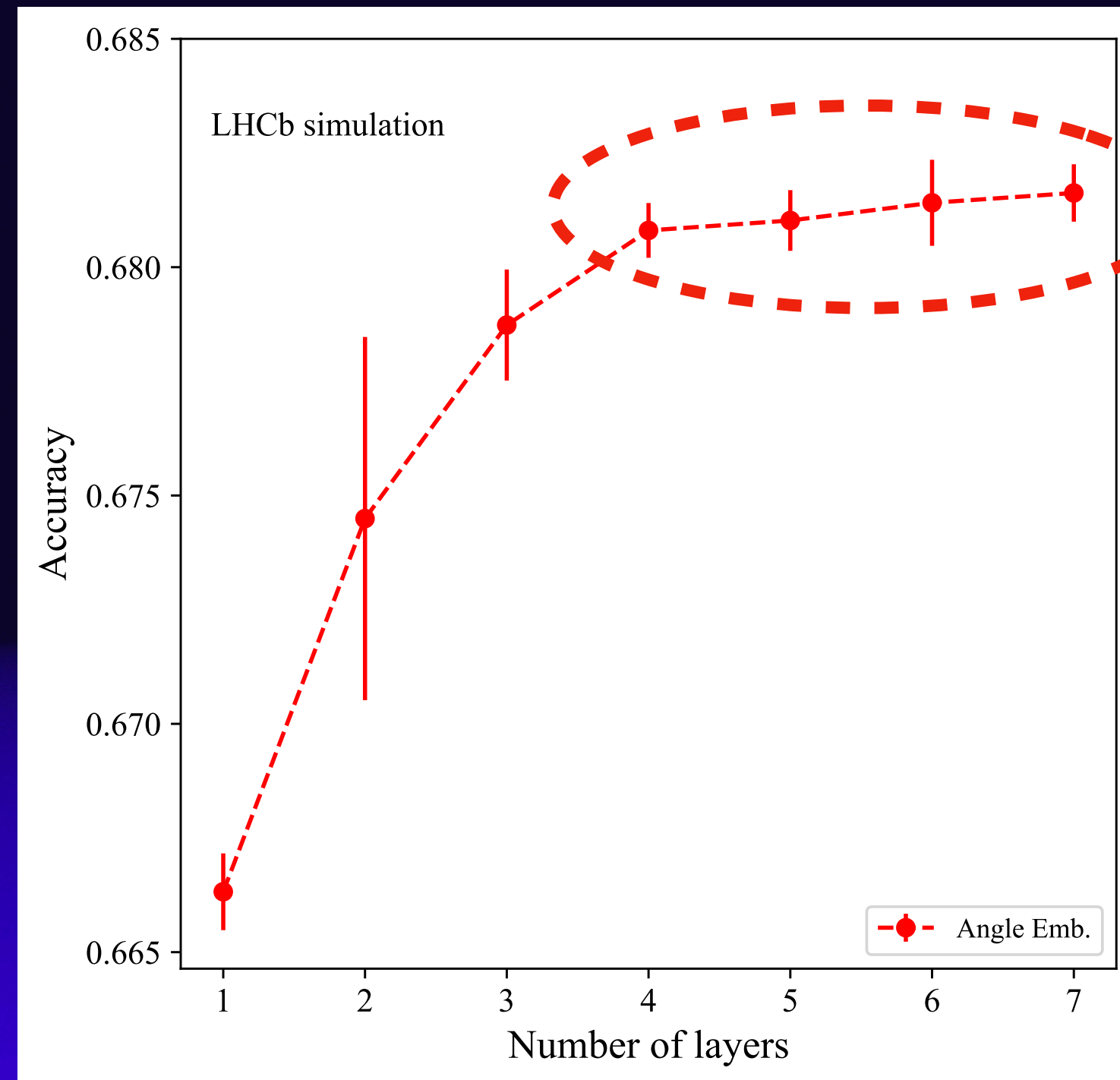


Noise



# b-jet charge identification with QML

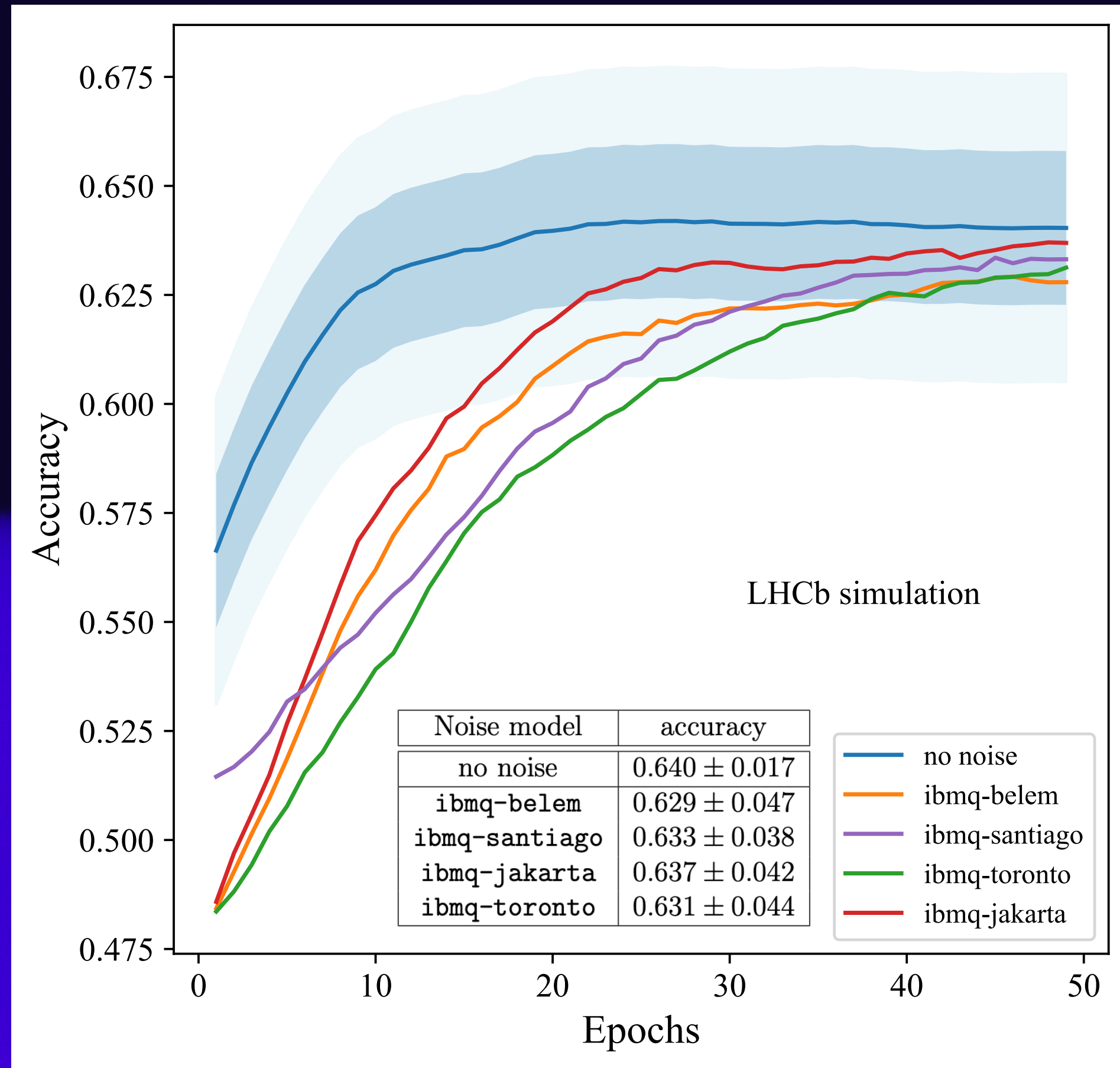
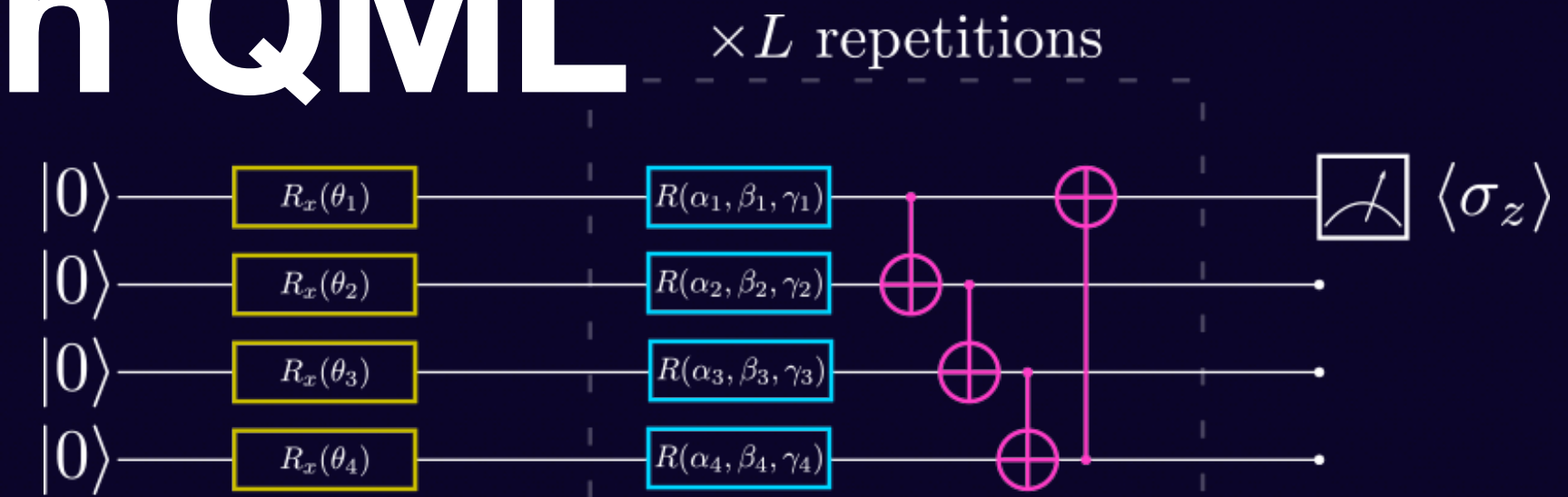
Try to get a complete study — performance



- Accuracy computed using the muon dataset (4 qubits)
- **Accuracy saturates for >5 variational layers**
- For a low number of training events, the Angle Embedding performs better than the DNN

# b-jet charge identification with QML

Try to get a complete study — noise



- Finally, the impact of noise has been studied for the 4 qubit circuit
- Using the *pennylane-qiskit* library, it's possible to simulate noise coming from different IBMq machines



- Results are averaged over five rounds of training, using five independent training subsets of 1000 jets each
- Simpler Angle Embedding circuit, with just 3 variational layers
- Noisy simulations take more epochs to perform training
- Structure quite robust to noise, accuracy within error

# Conclusions

## Or maybe just the beginning

- A first, exploratory but “real-life” study of QML for b-jet charge identification at LHCb has been presented
- The problem has been studied by considering several aspects:
  - For the muon dataset, QML approaches standard DNN
  - Dependence on # layers and # training events has been assessed
  - Simple structures have been proven to be robust to noise
- Continue to explore this exciting (and fairly new) topic:
  - Possibly access hardware (at first for testing, but also for training)
  - New “exercises” (e.g. b- vs c-jet identification)
  - Different architectures (annealing?)



**Paper accepted  
by JHEP!**

**Thank you for your attention**  
**Questions, comments?**



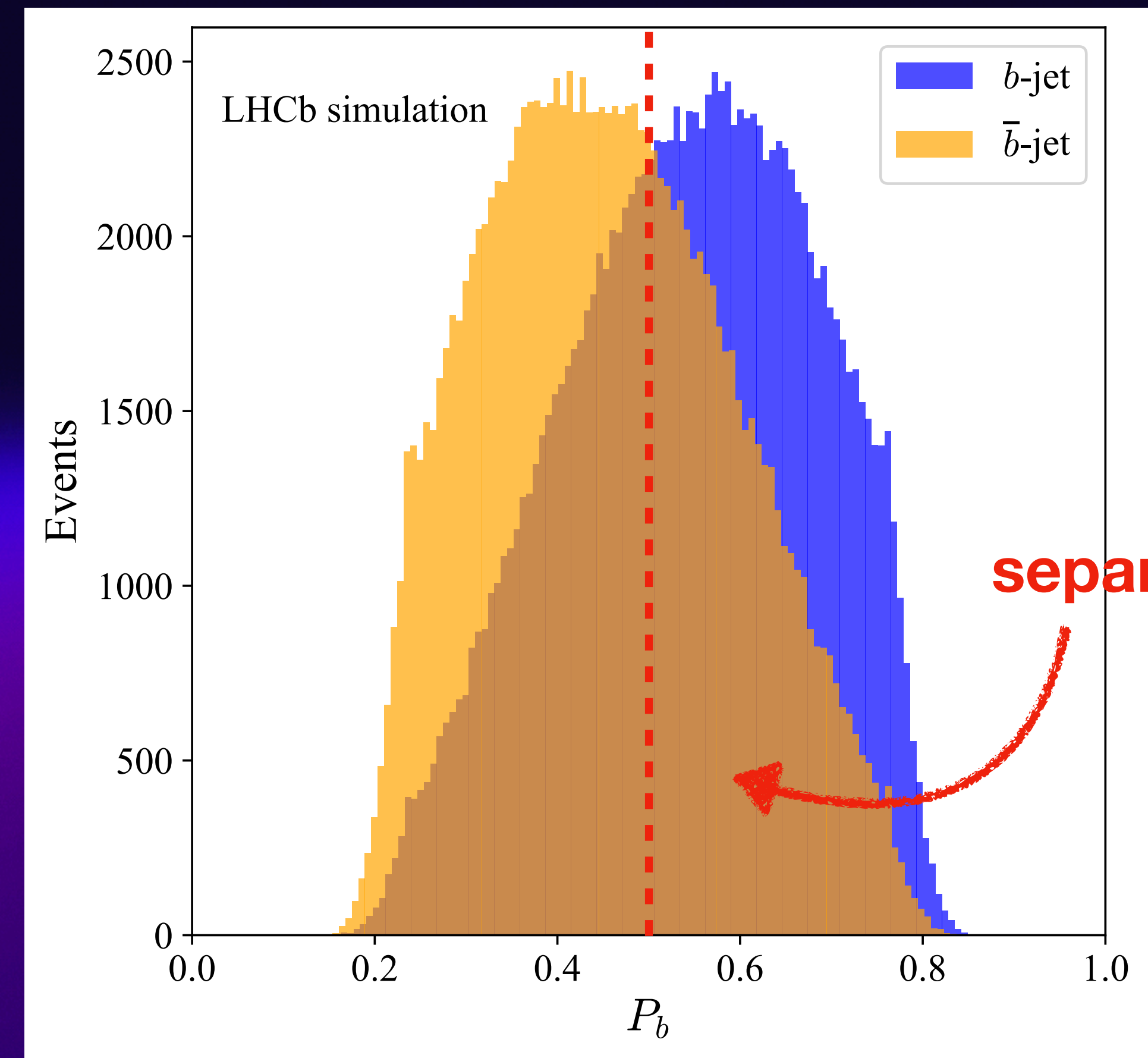
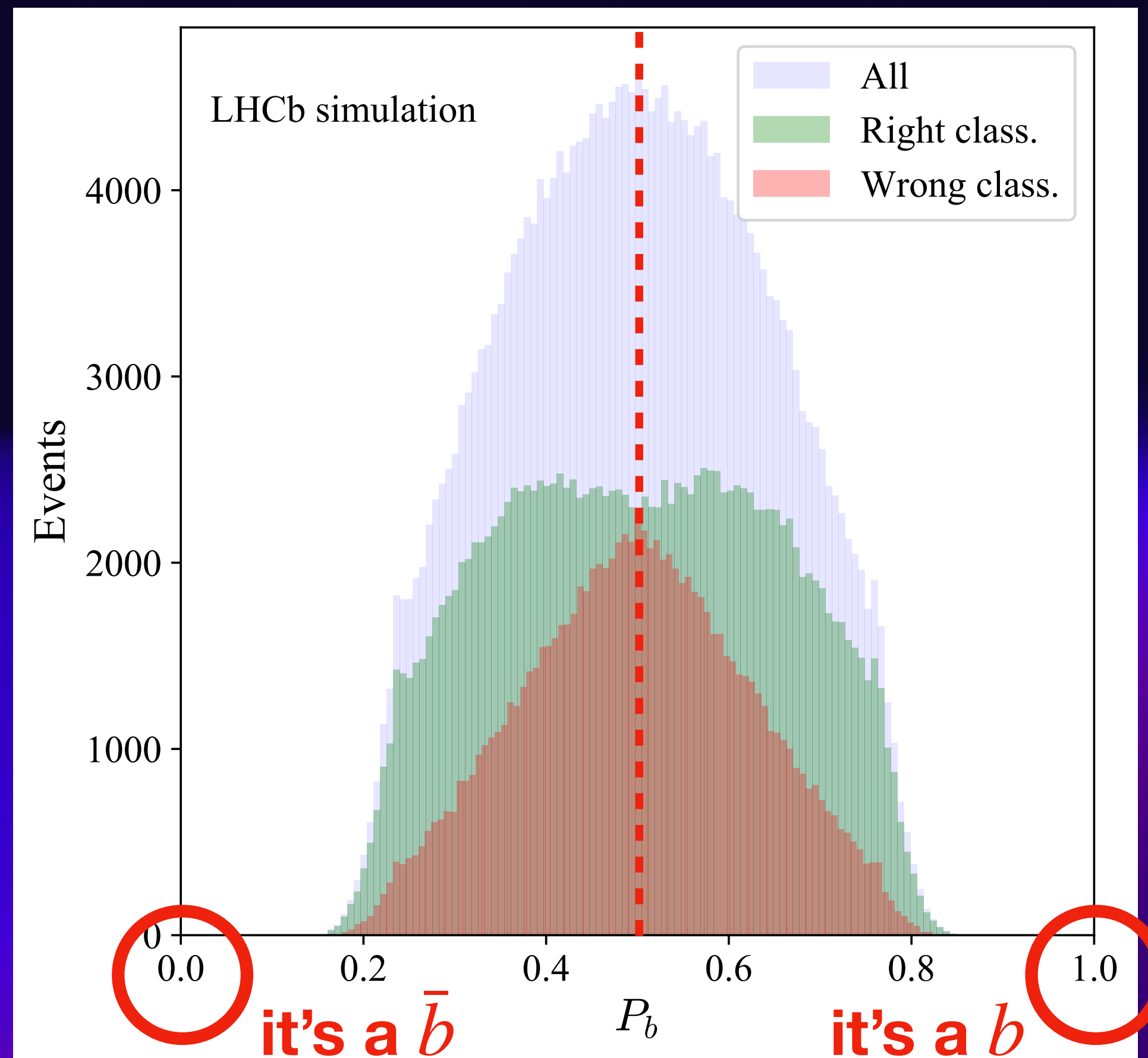
**Backup slides**

# b-jet charge identification with QML

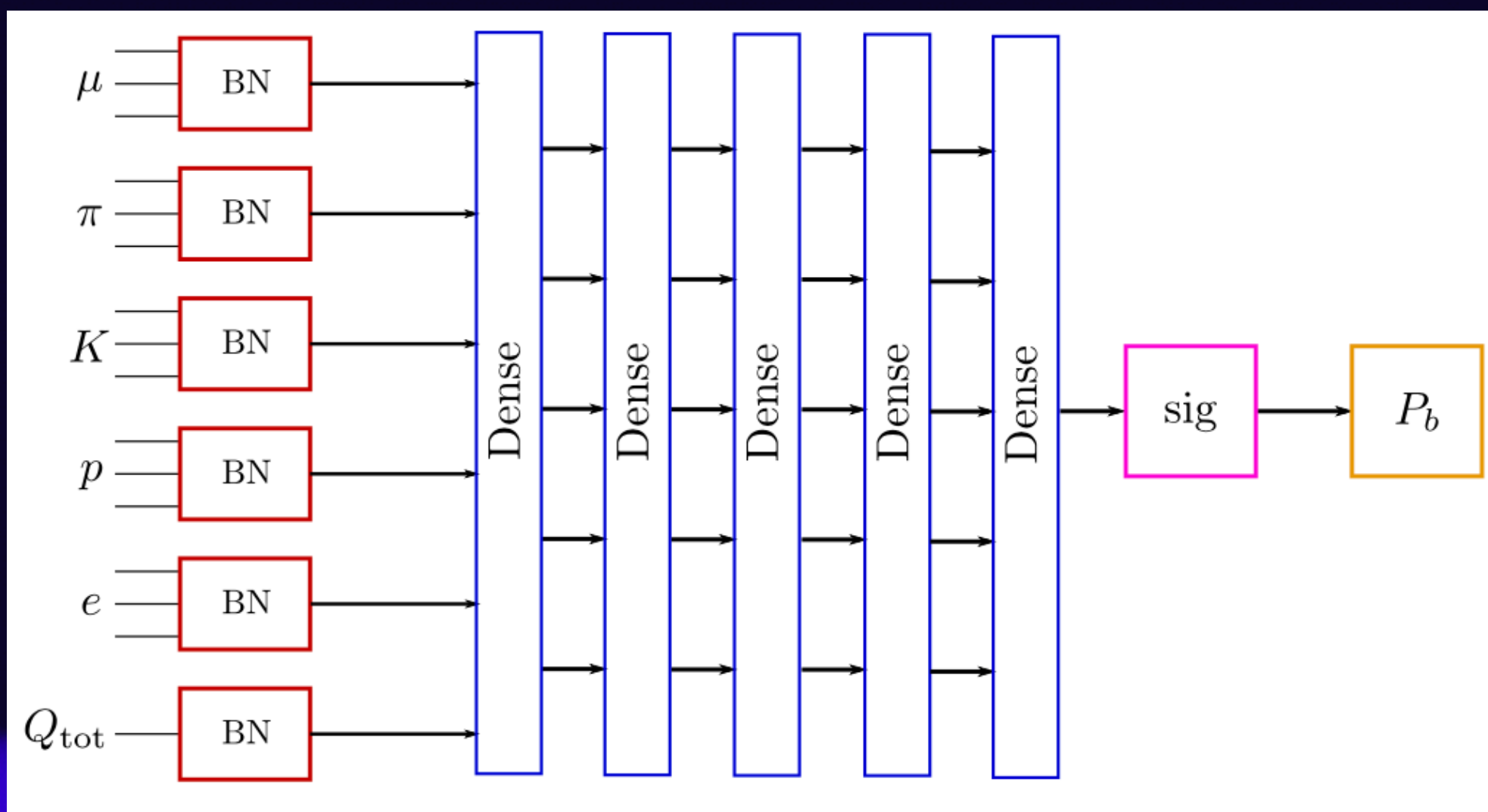
## Algorithm performance

- A look at the output distribution gives an idea of the goodness of the algorithm

Angle Embedding  
complete dataset (16 qubit)

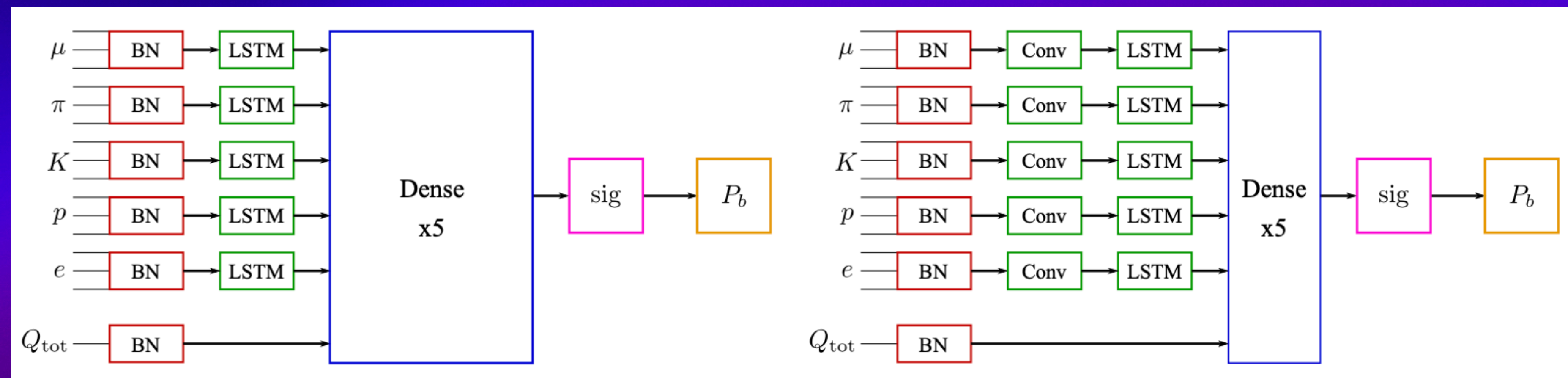


# DNN structures

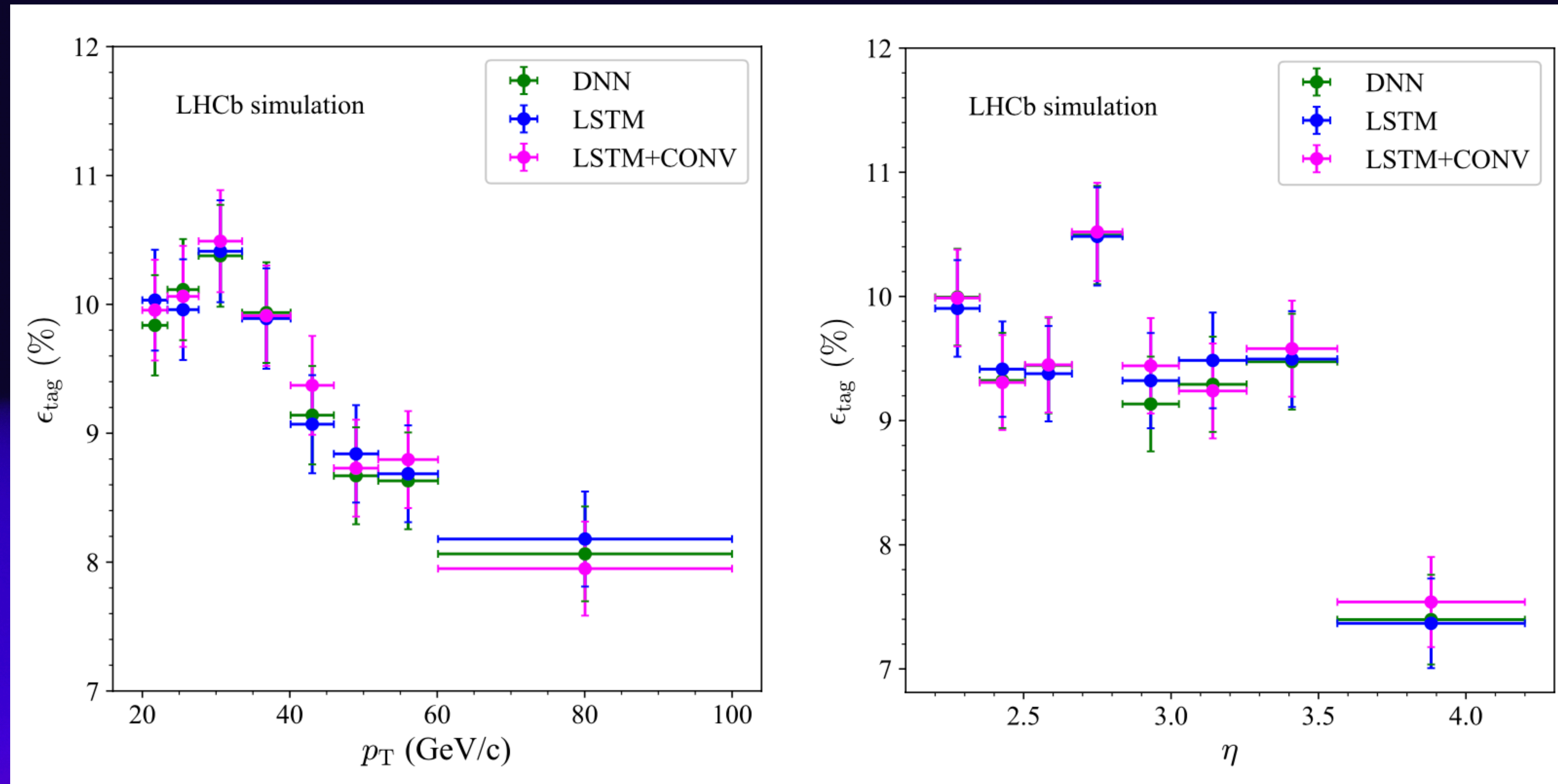


“Standard” DNN

DNN with LSTM and CONV



# DNN performance



# Unoptimised tagging power

