

An LHC application of Quantum Machine Learning and INFN summary

DAVIDE ZULIANI
UNIVERSITY AND INFN OF PADOVA

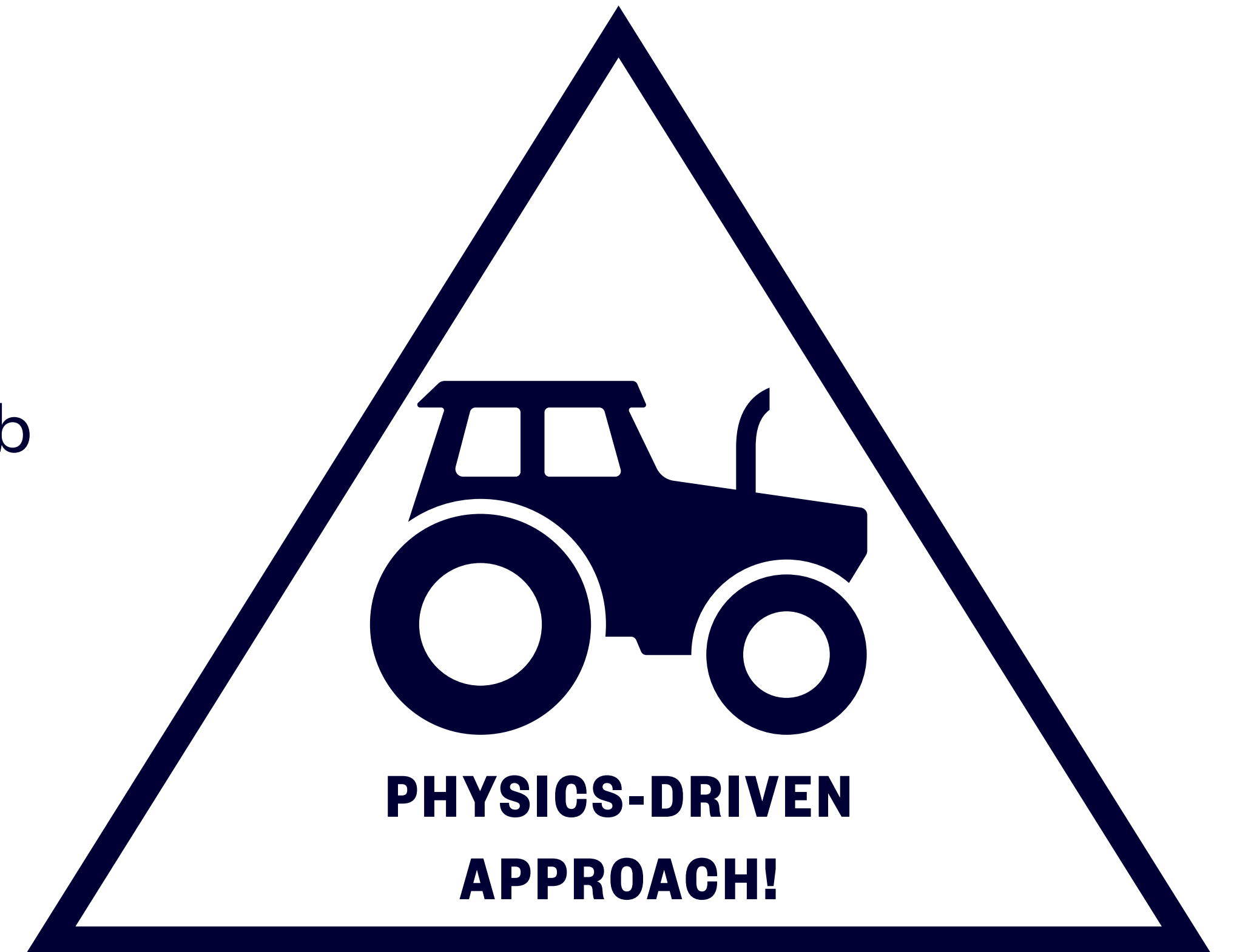
NOVEMBER 2, 2022

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 - Physics case: b -jet charge identification at LHCb
 - Algorithm description and results
 - Future studies and ideas
- **Overview of INFN activities**

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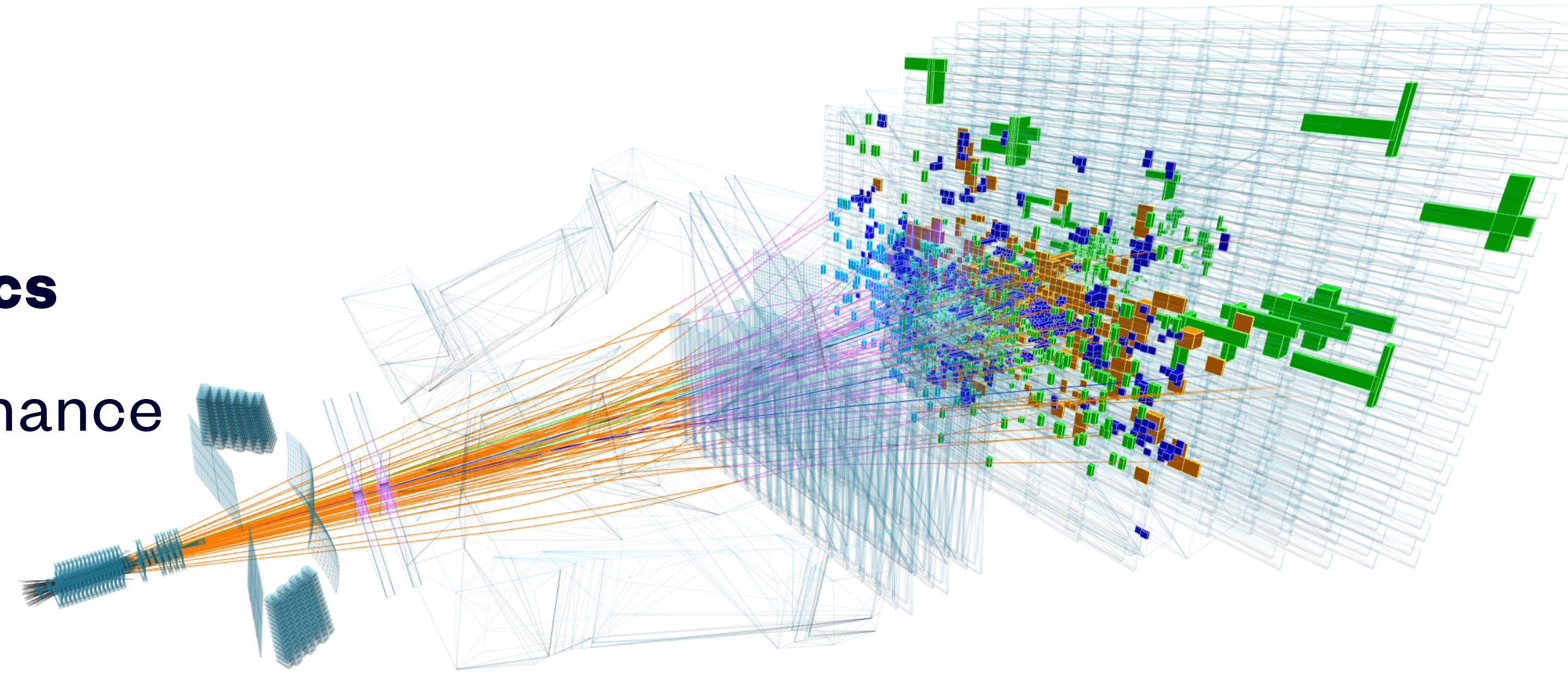
- **Application of QML at LHC**
 - Physics case: b -jet charge identification at LHCb
 - Algorithm description and results
 - Future studies and ideas
- **Overview of INFN activities**



Application of QML at LHC

b -jet charge identification at LHCb

- LHC physics program heavily relies on **jets physics**
- Better jets reconstruction & identification performance
→ better results, but **very challenging!**



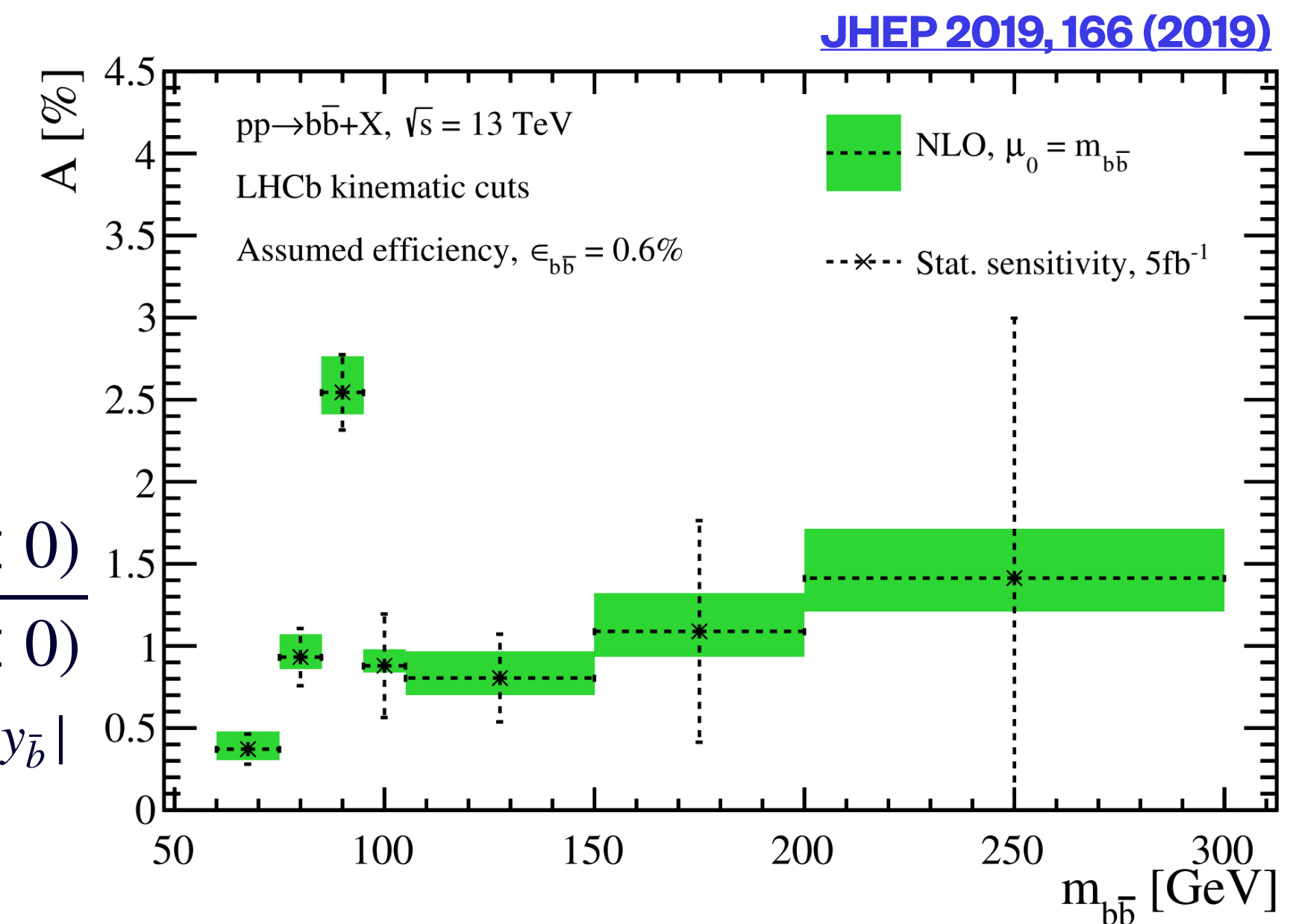
- Example: $b\bar{b}$ asymmetry at LHCb

- **Tension from LEP** measurements makes it interesting to study $b\bar{b}$ charge asymmetry at LHC
- **Statistical uncertainty** is directly related to the **identification algorithm performance**

- Finer binning for $m_{b\bar{b}}$ around Z pole
- Measure contribution from higher orders

$$A_{b\bar{b}}^C = \frac{N(\Delta y > 0) - N(\Delta y < 0)}{N(\Delta y > 0) + N(\Delta y < 0)}$$

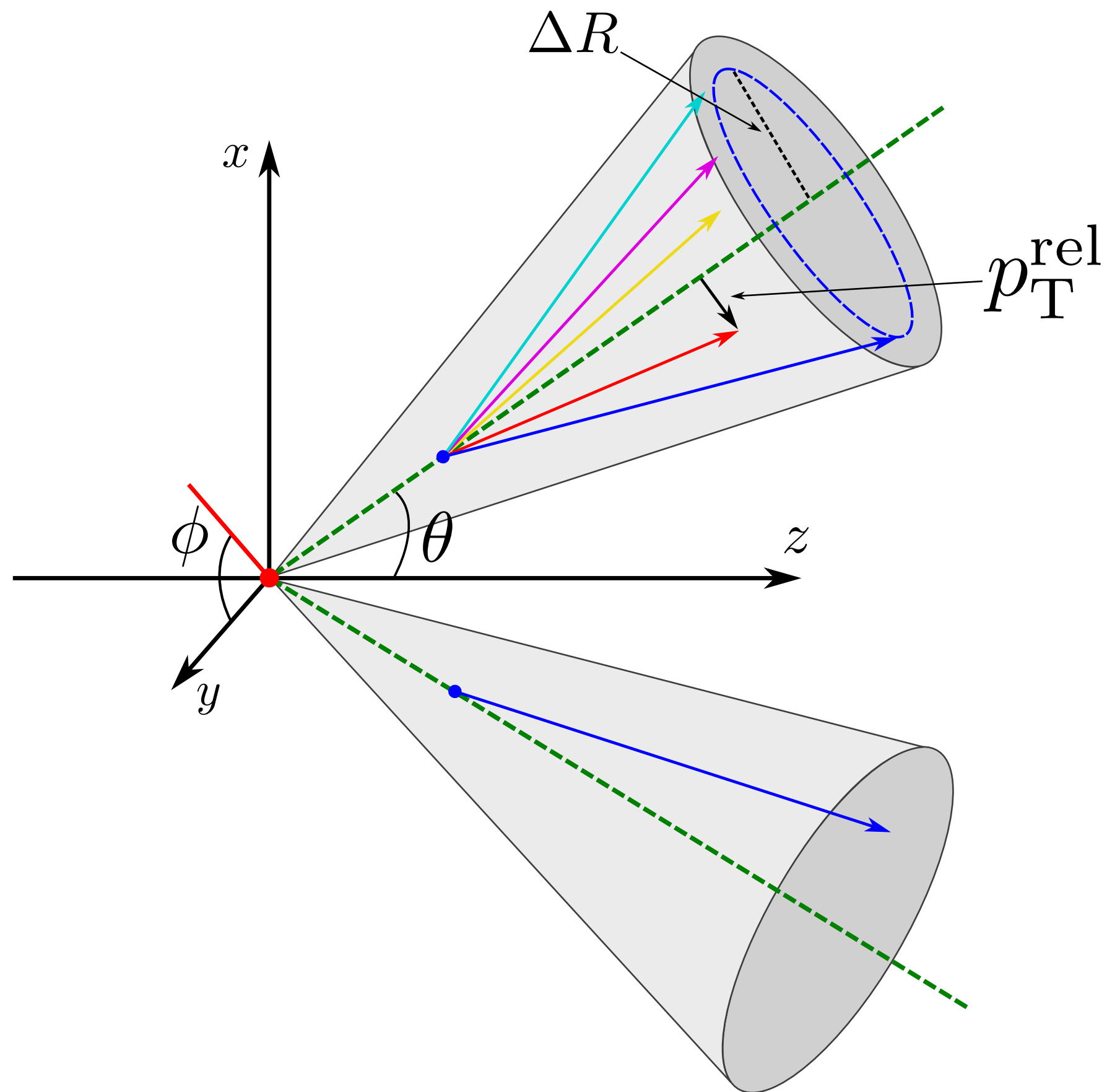
with $\Delta y = |y_b| - |y_{\bar{b}}|$



Application of QML at LHC

b -jet charge identification at LHCb

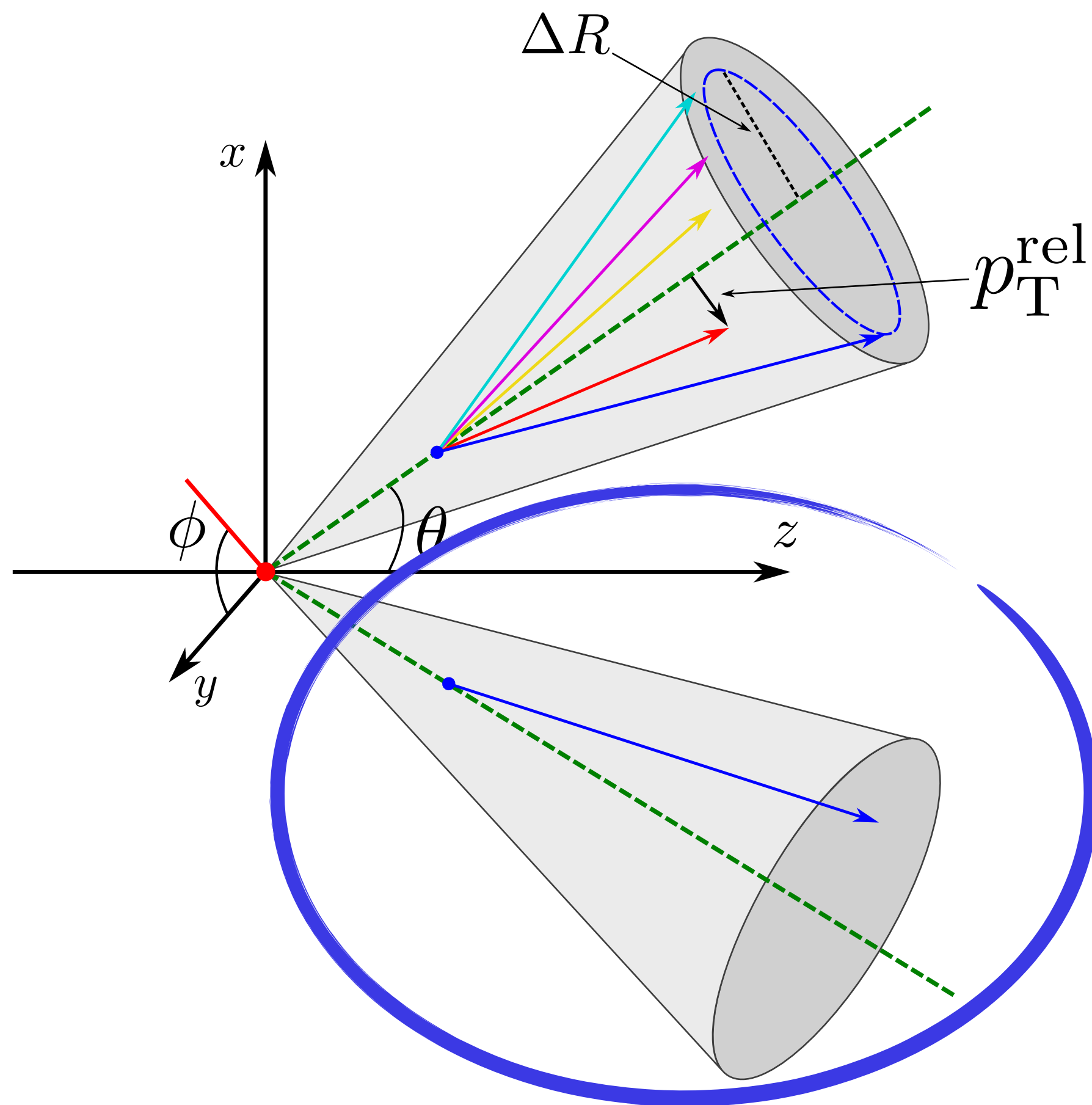
- How can we identify jet charge?



Application of QML at LHC

b -jet charge identification at LHCb

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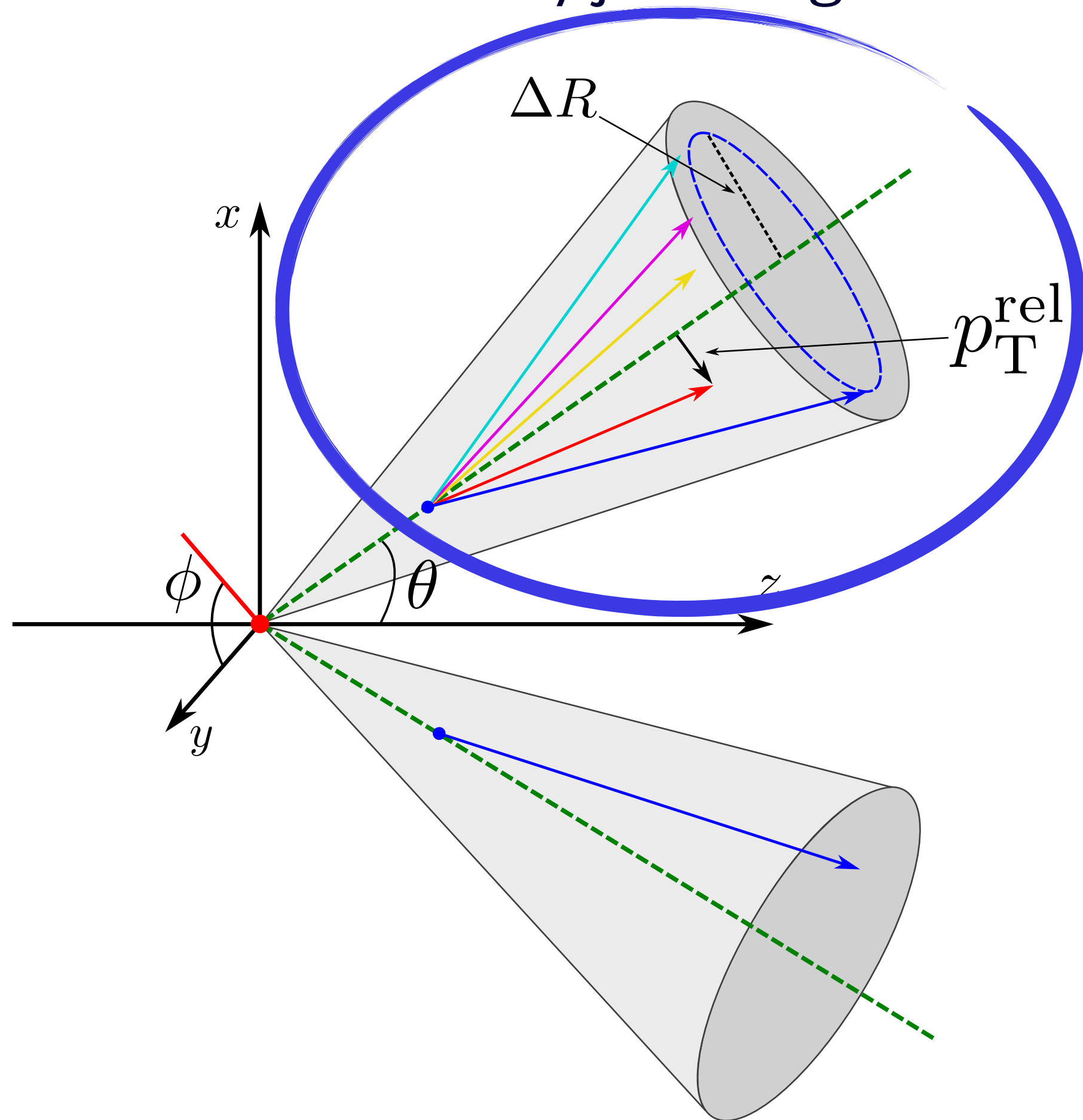
Exclusive approach

- 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 and discriminate between b and \bar{b} -jets

Application of QML at LHC

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Inclusive approach

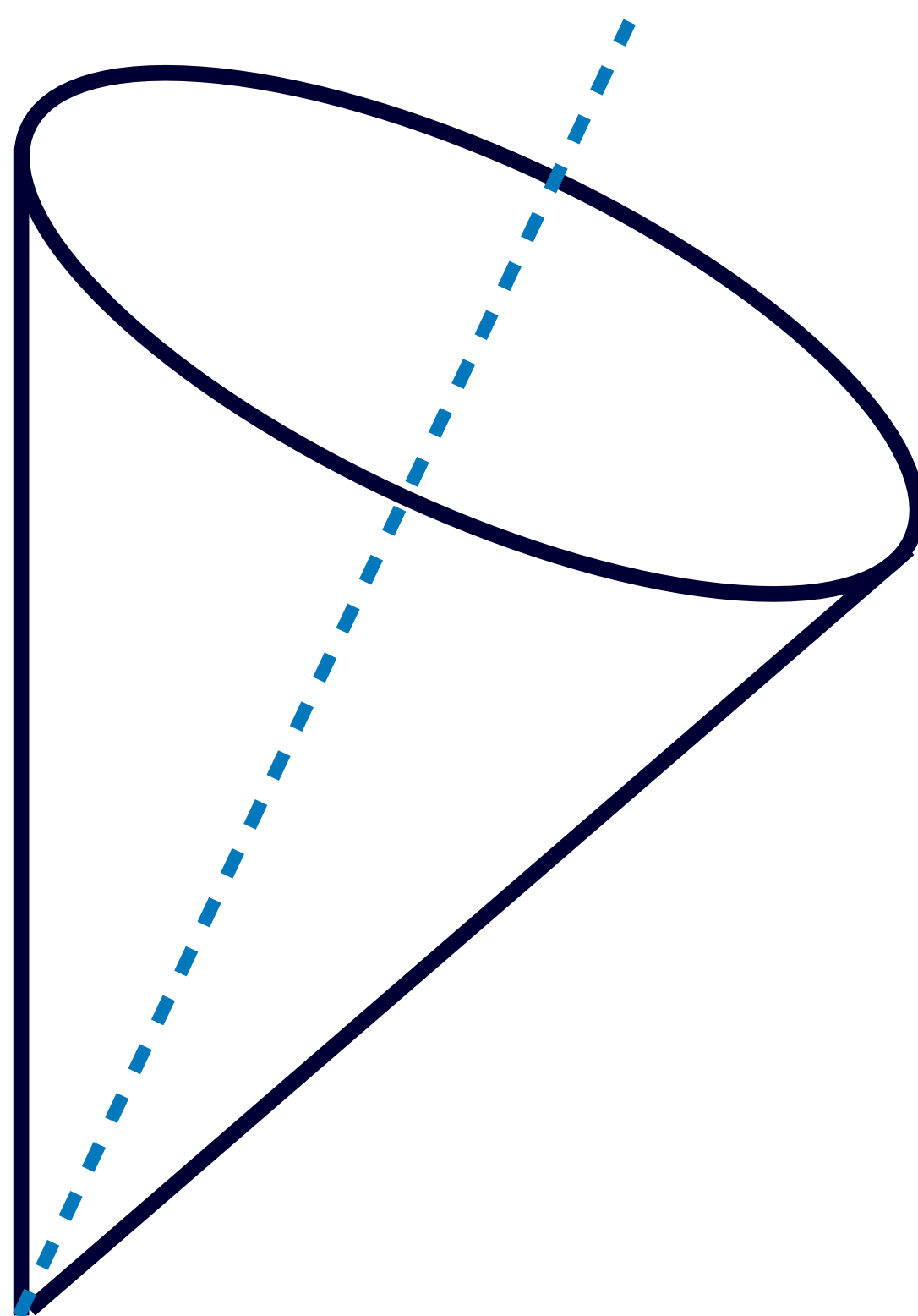
- It uses **all the information** coming from the **jet substructure**
- e.g. get the kinematic properties of all the particles inside the jet
- Given the amount of information, **Machine Learning** tools are well suited!

Exclusive approach

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Application of QML at LHC

b -jet charge identification at LHCb



- 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, testing and evaluation

THEY RESEMBLE DATA!

Application of QML at LHC

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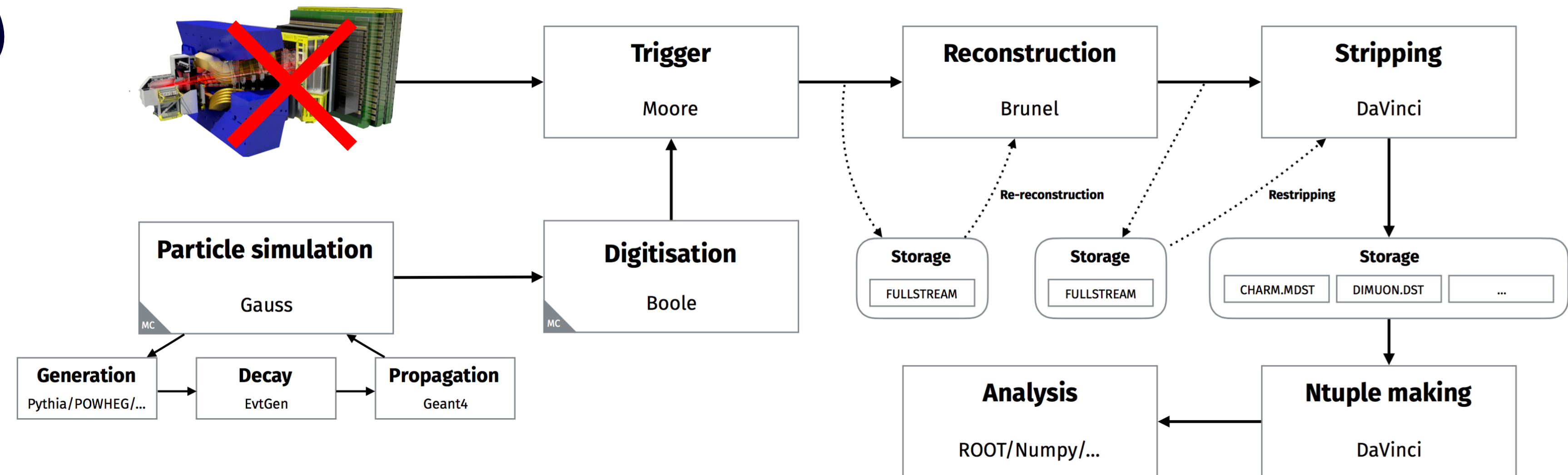
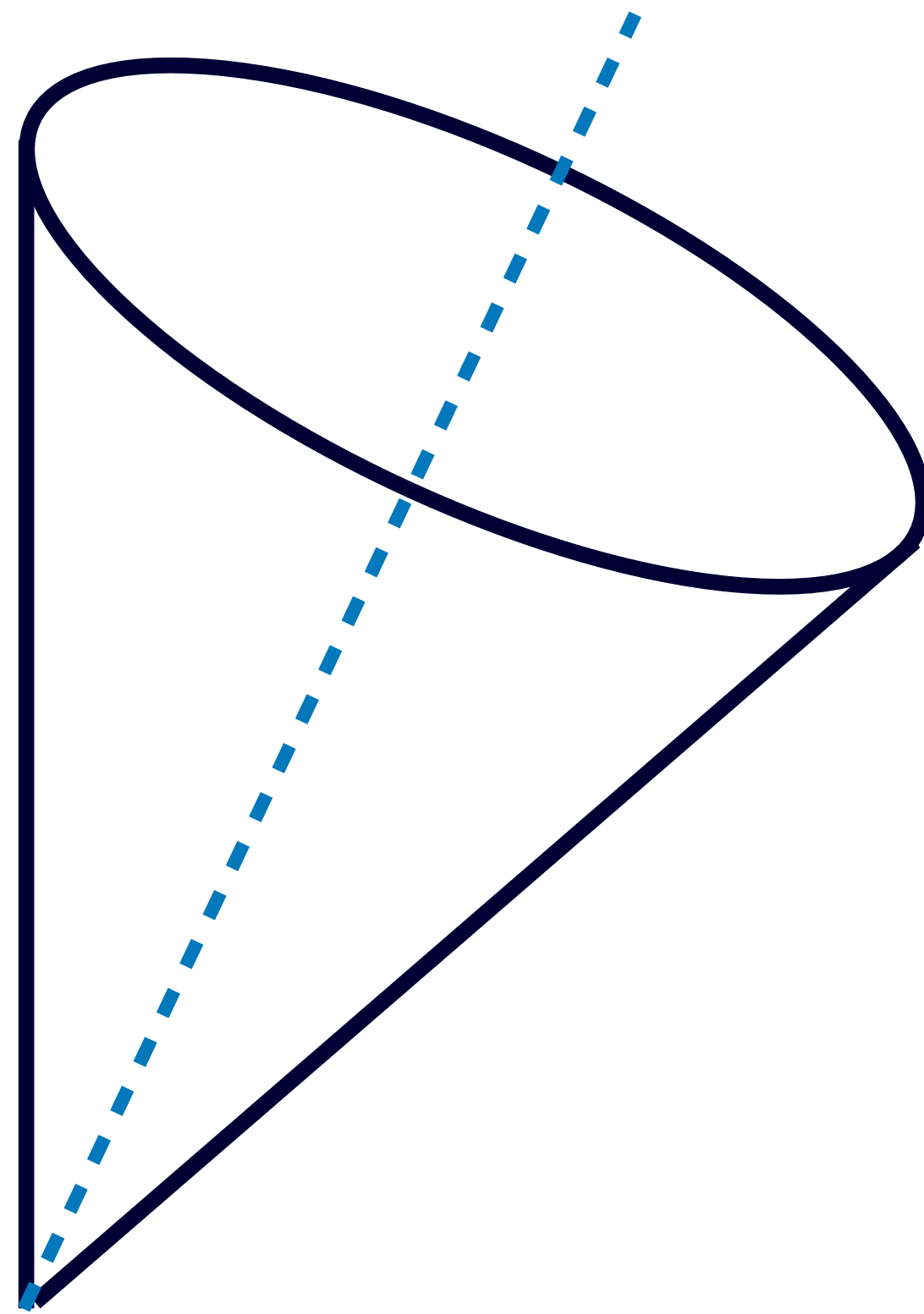
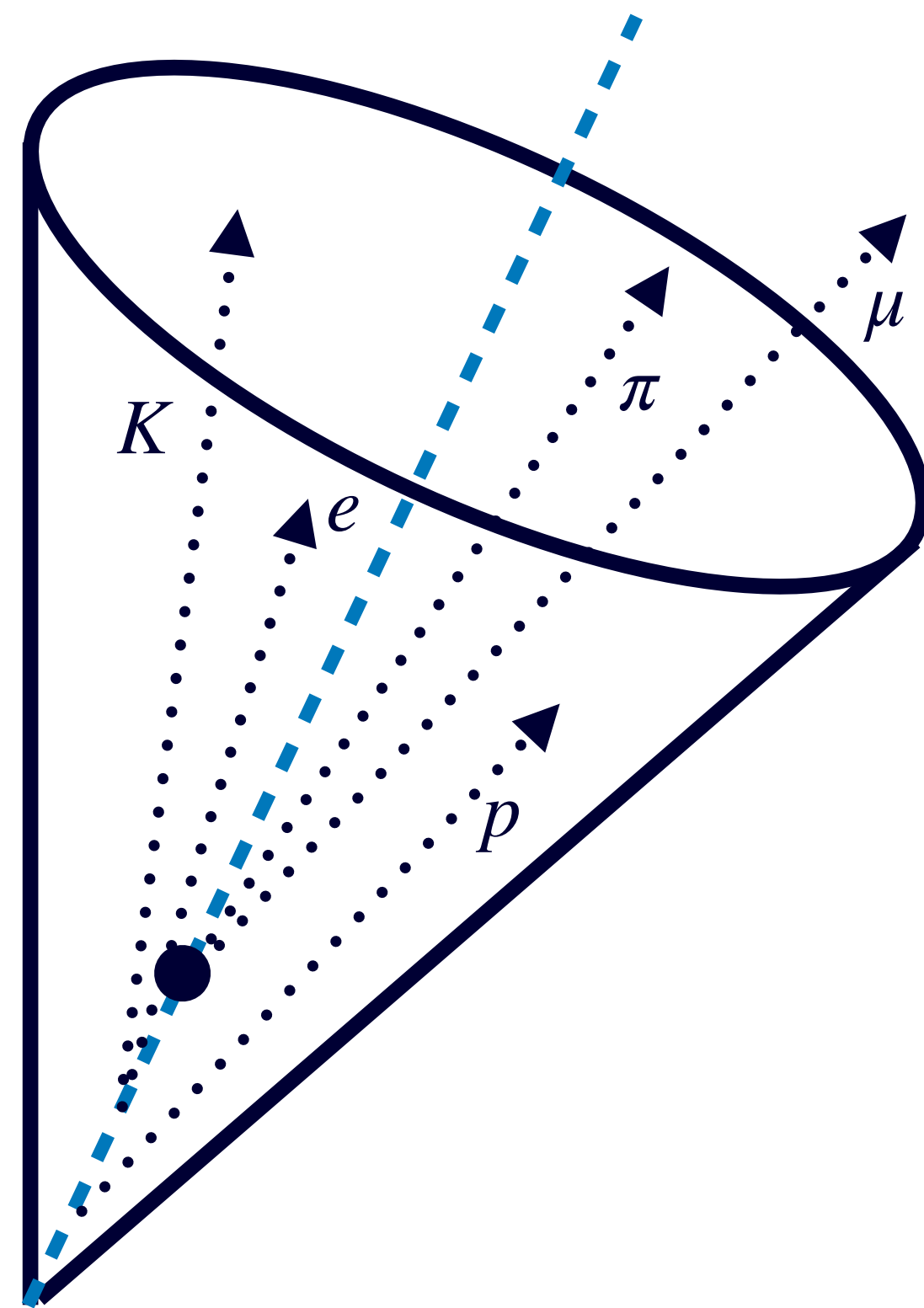


Image taken from <https://lhcb.github.io/starterkit-lessons/first-analysis-steps/dataflow.html>

Application of QML at LHC

b -jet charge identification at LHCb



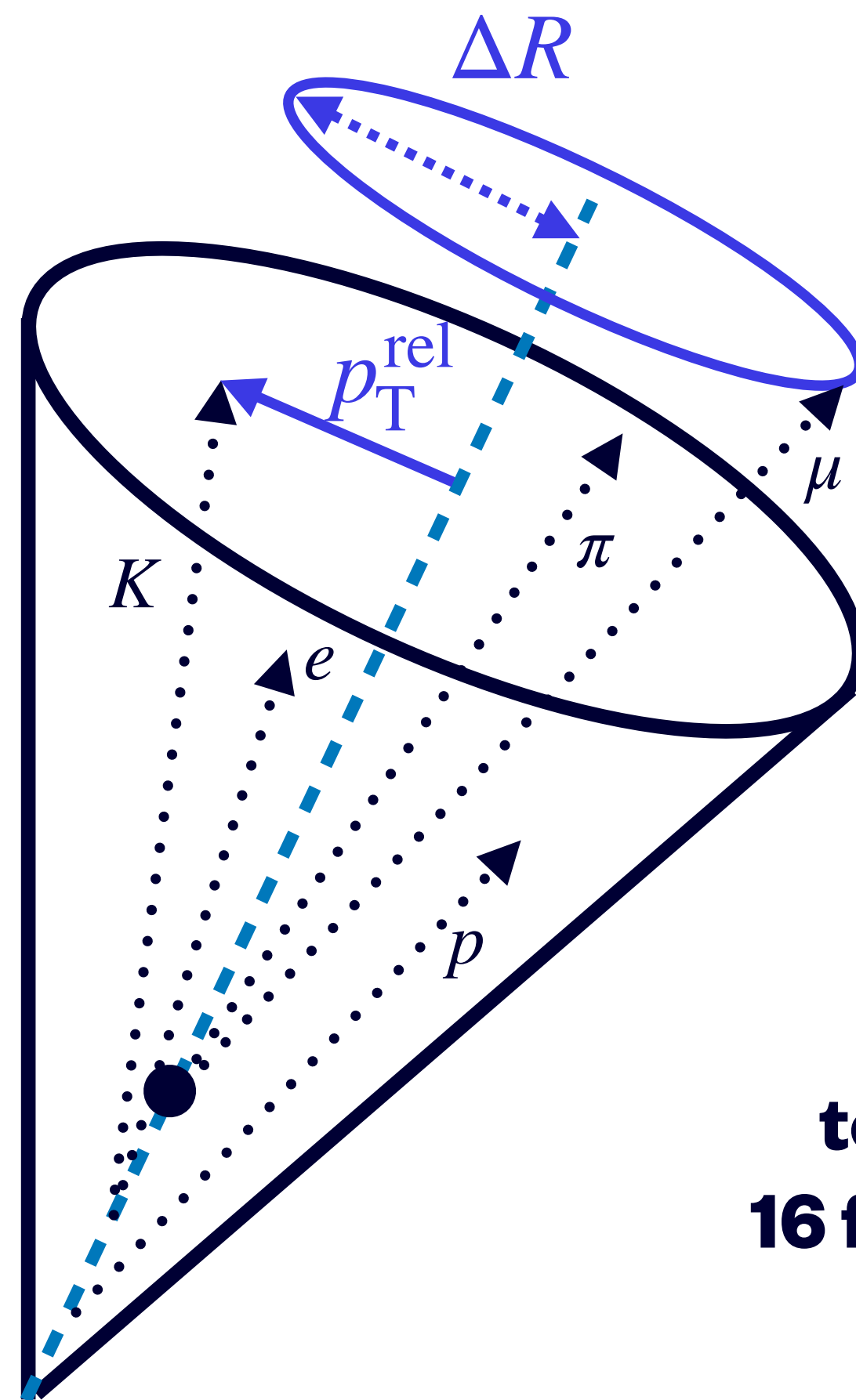
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muon electron pion kaon proton

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Application of QML at LHC

b -jet charge identification at LHCb



total of
16 features

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- Run 2 condition ($\sqrt{s} = 13$ TeV)
- ~700.000 jets, divided into training, testing and evaluation
- For each jet, 5 types of particles are considered:

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- And for each type of particle, three features are considered:
 - Transverse momentum relative to jet axis p_T^{rel}
 - Distance relative to jet axis ΔR in the (η, ϕ) plane
 - Charge of the particle q

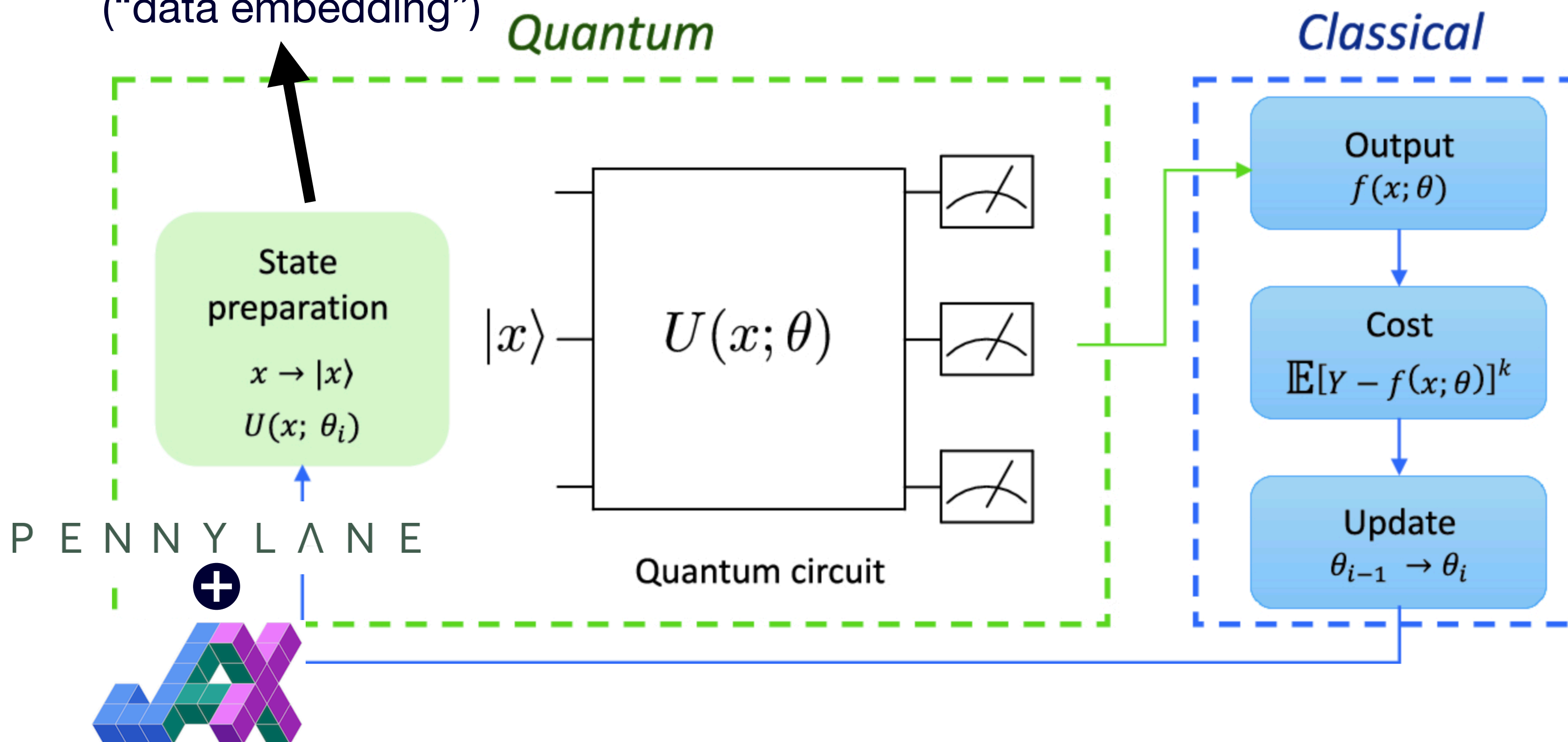
- + a global variable, the total jet charge $Q = \frac{\Sigma(p_T^{\text{rel}})q}{\Sigma(p_T^{\text{rel}})}$

THEY RESEMBLE DATA!

Application of QML at LHC

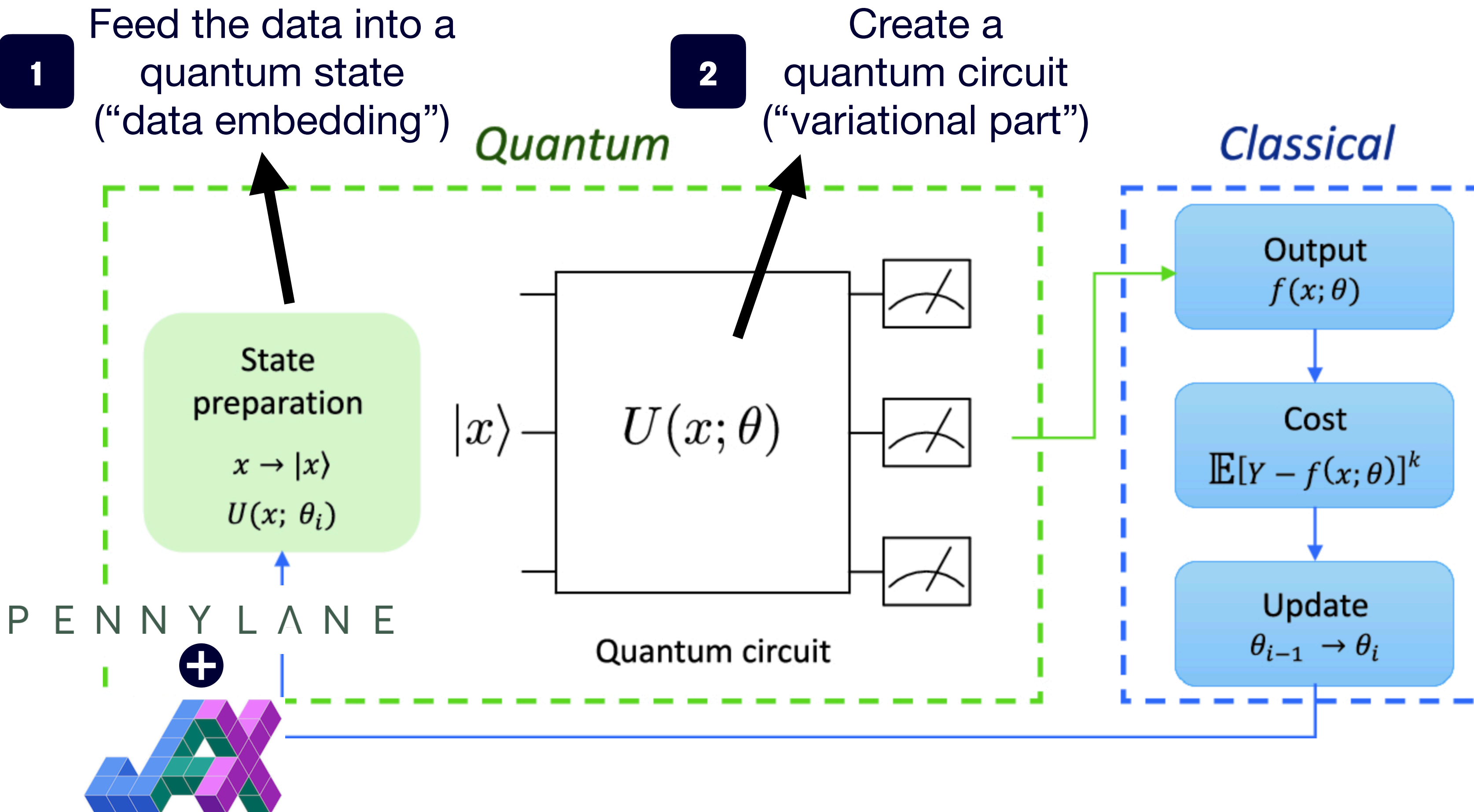
Algorithm description, Variational Quantum Classifier (VQC)

1 Feed the data into a quantum state (“data embedding”)



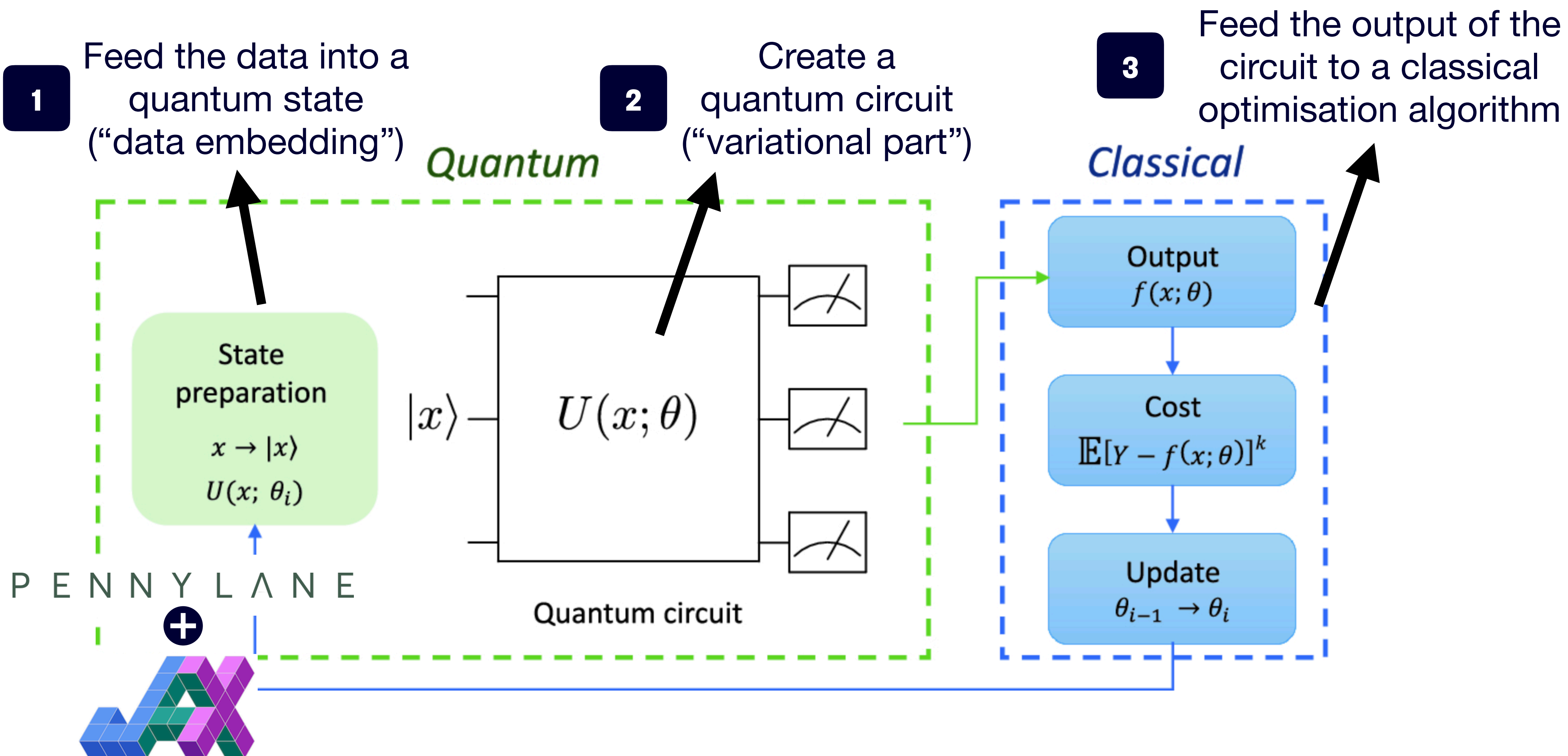
Application of QML at LHC

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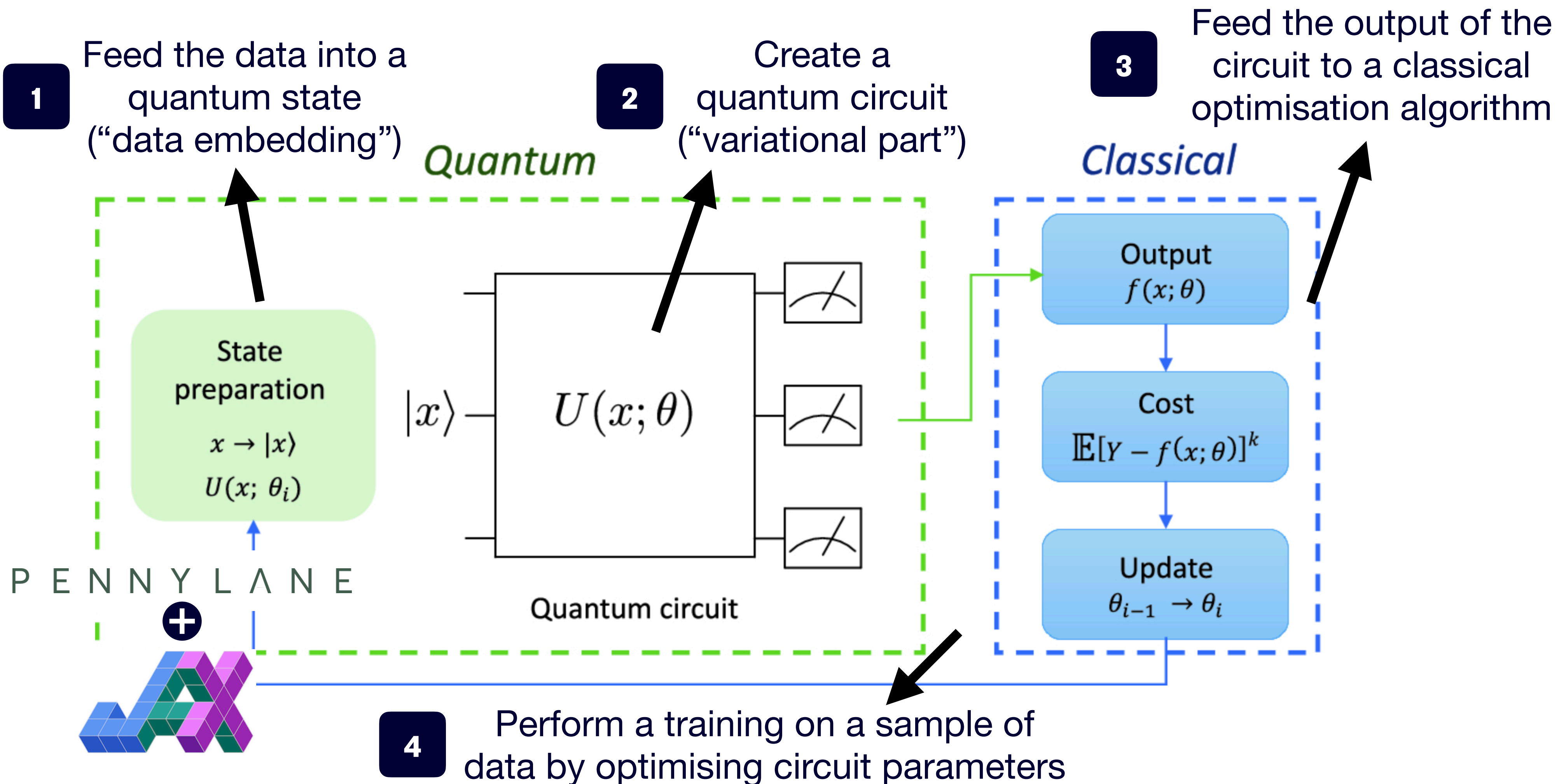
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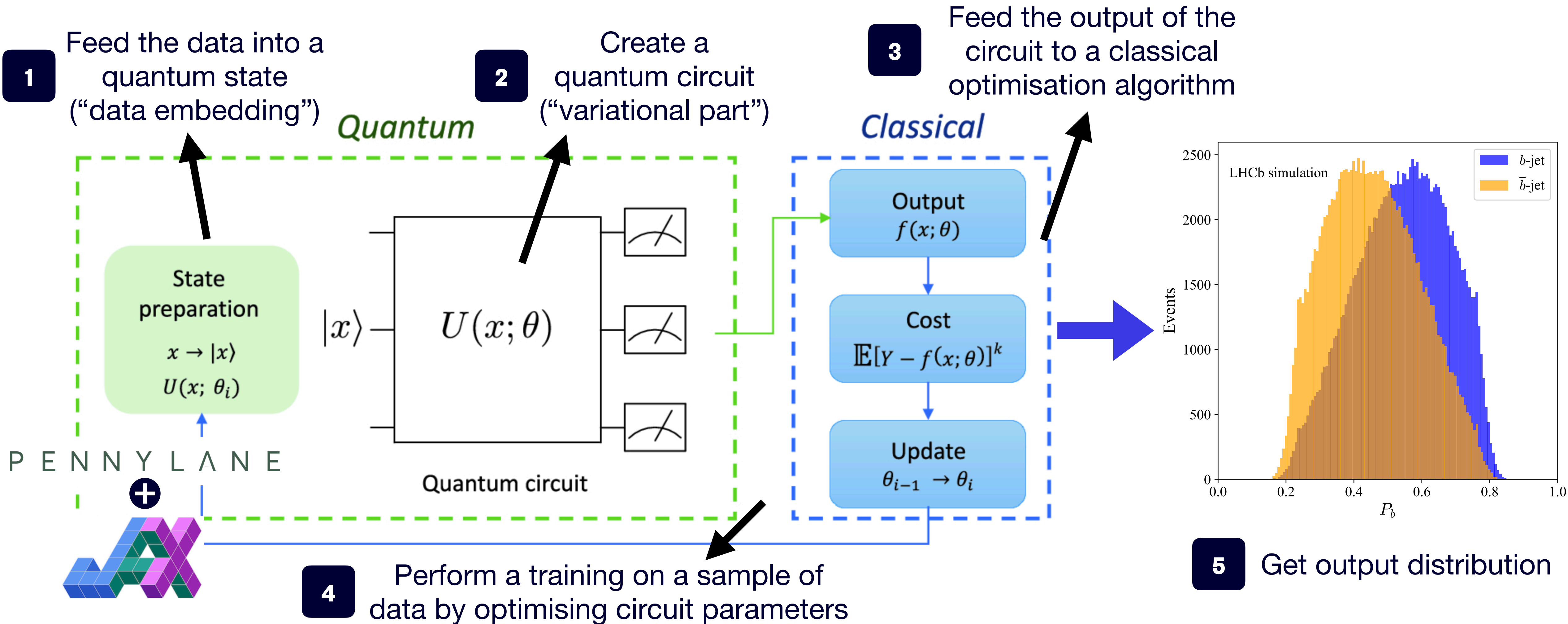
Application of QML at LHC

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Application of QML at LHC

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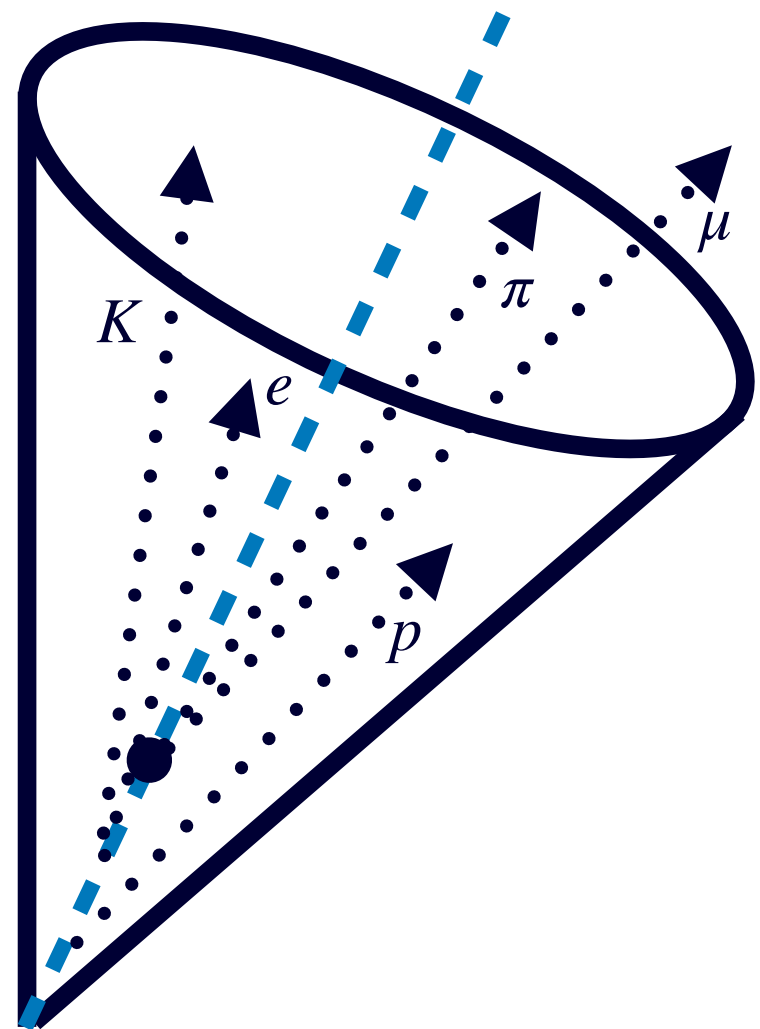


Application of QML at LHC

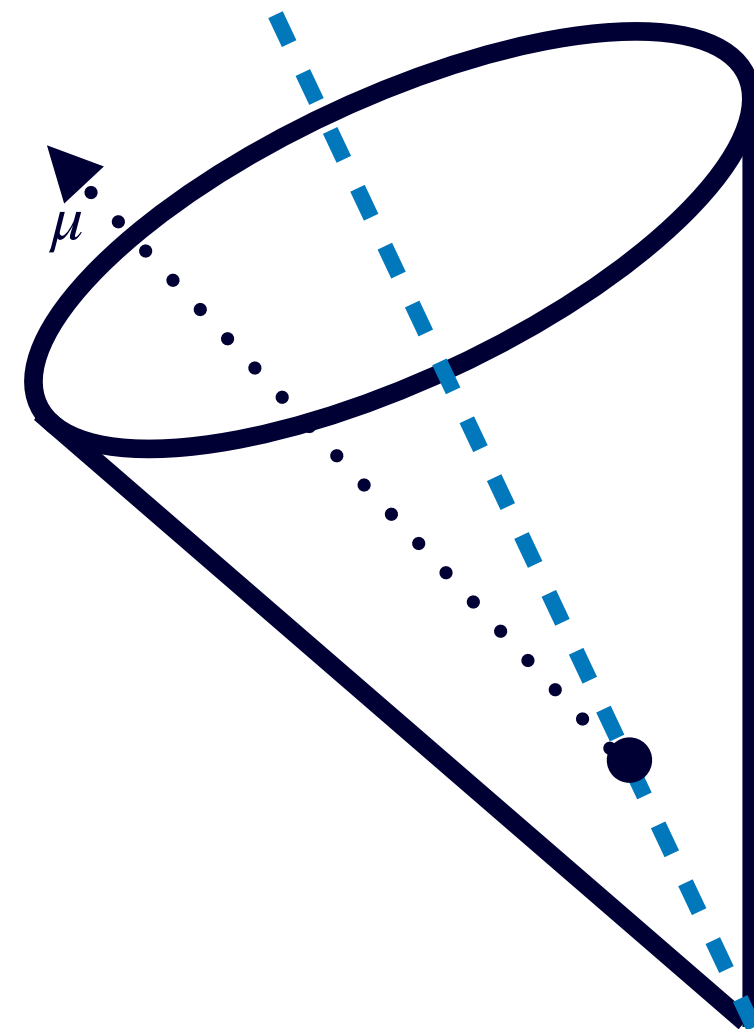
Algorithm description

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

Different sets of features



“complete” set of features
16 variables



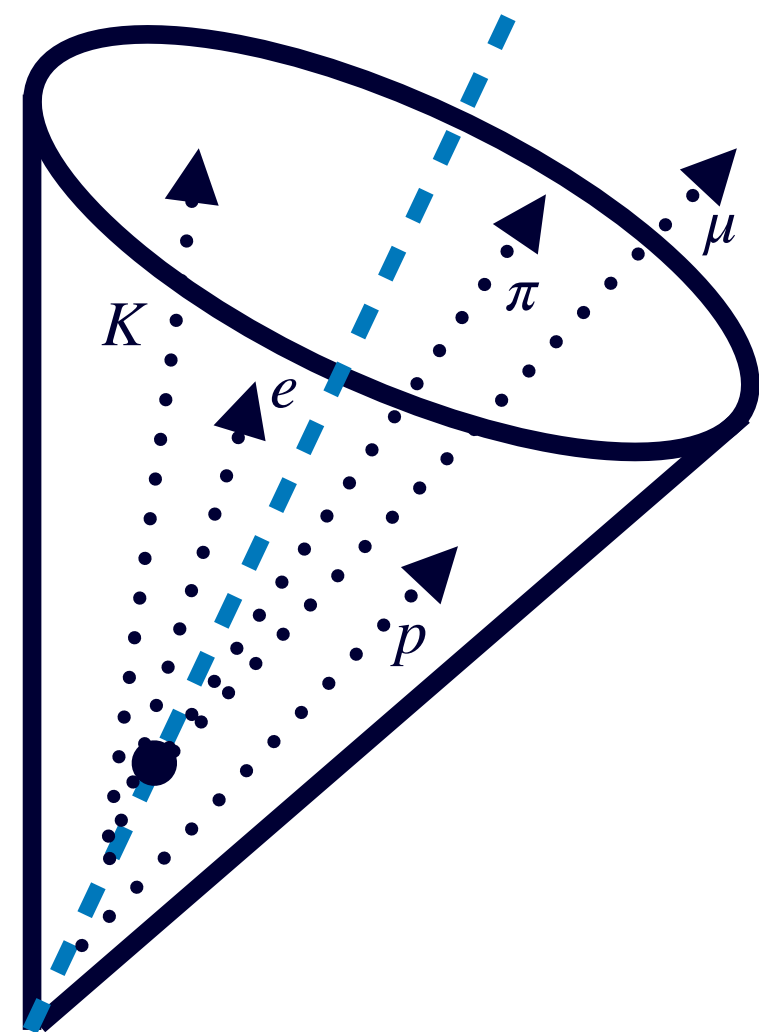
“muon” set of features
 $\mu + Q = 4$ variables

Application of QML at LHC

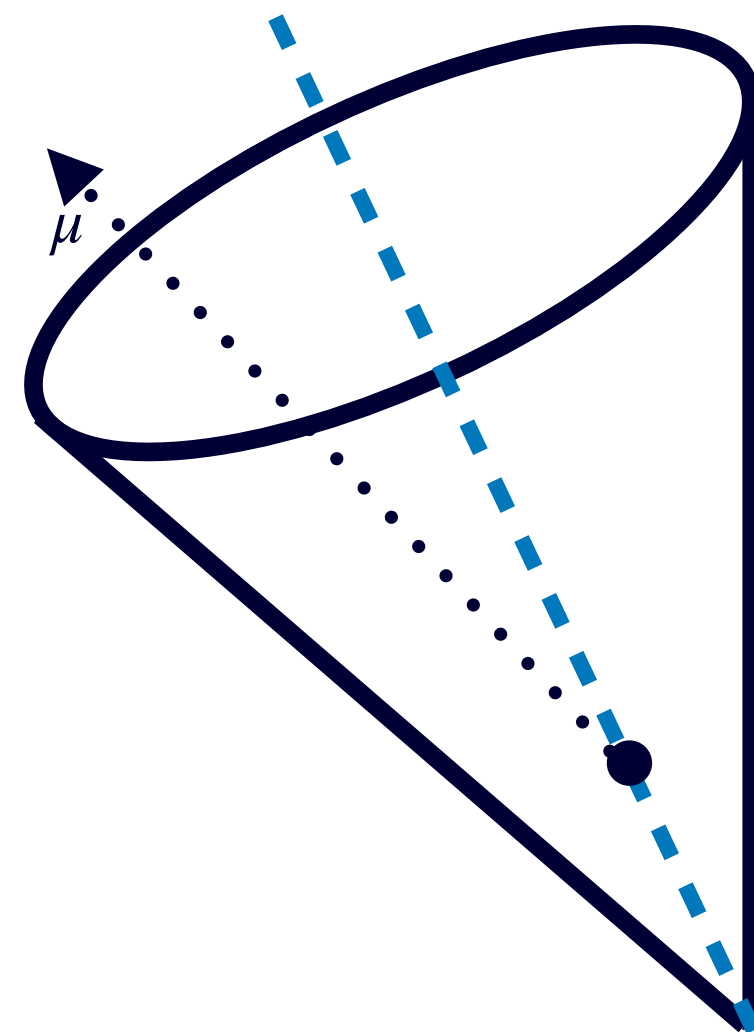
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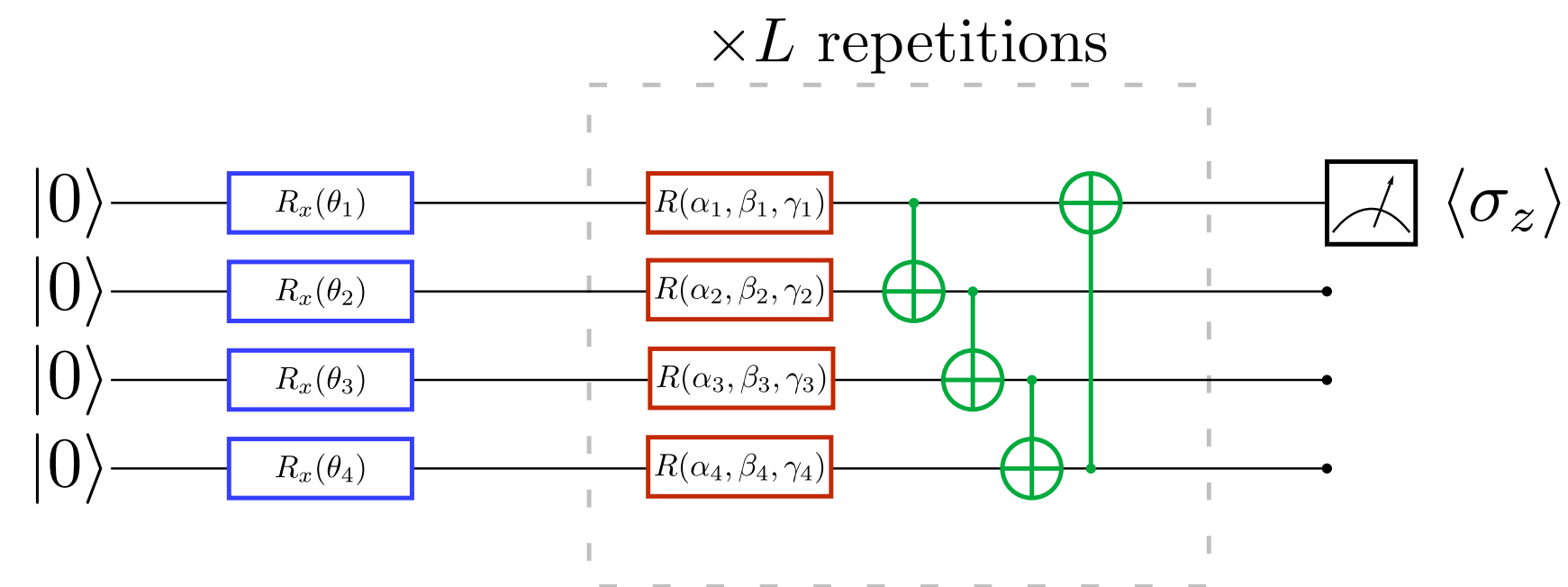
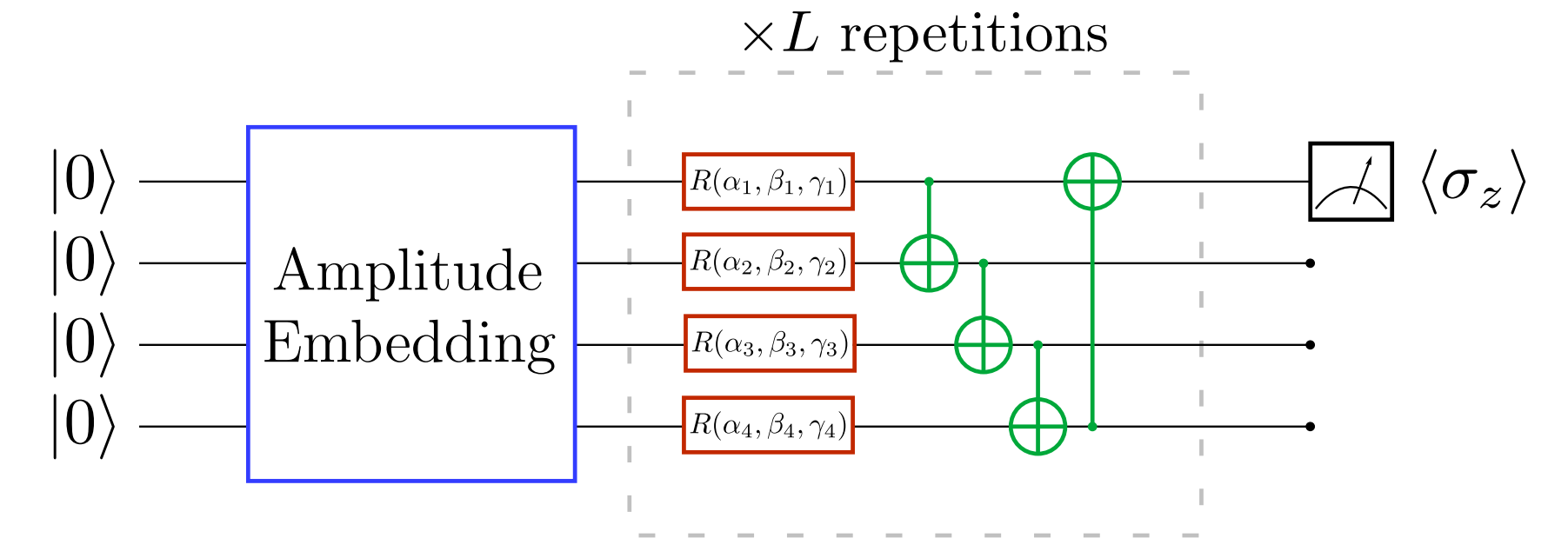


“muon” set of features
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Different embedding circuits

Amplitude Embedding

$$|x\rangle = \sum_{i=1}^{2^n} x_i |n_i\rangle$$



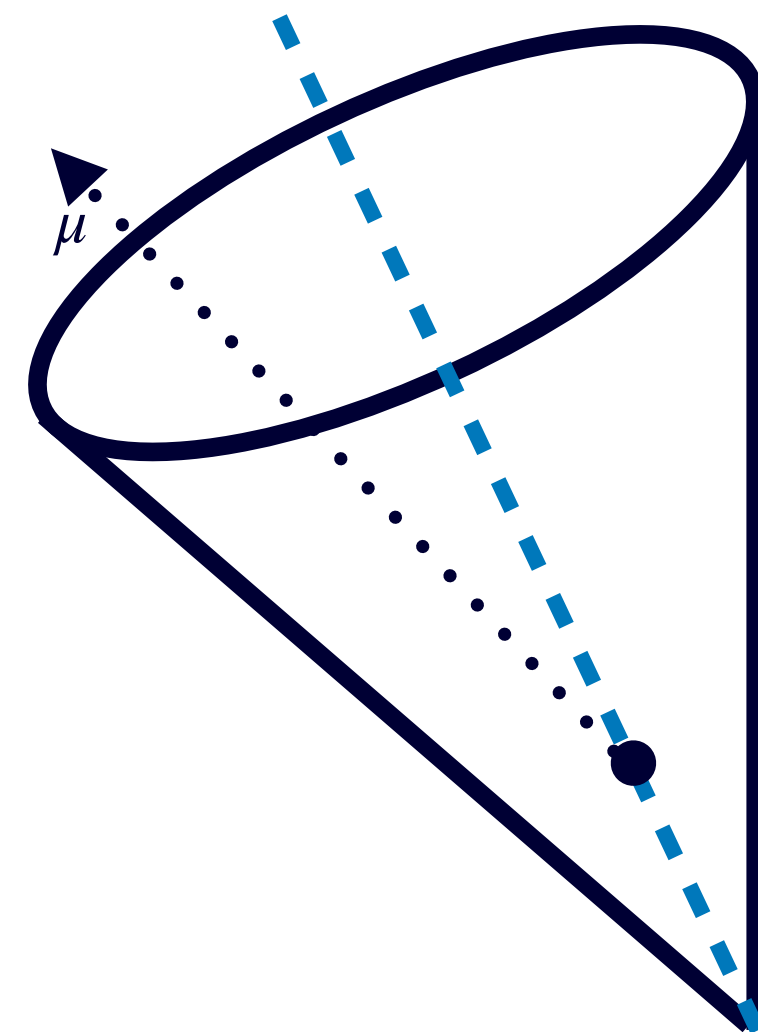
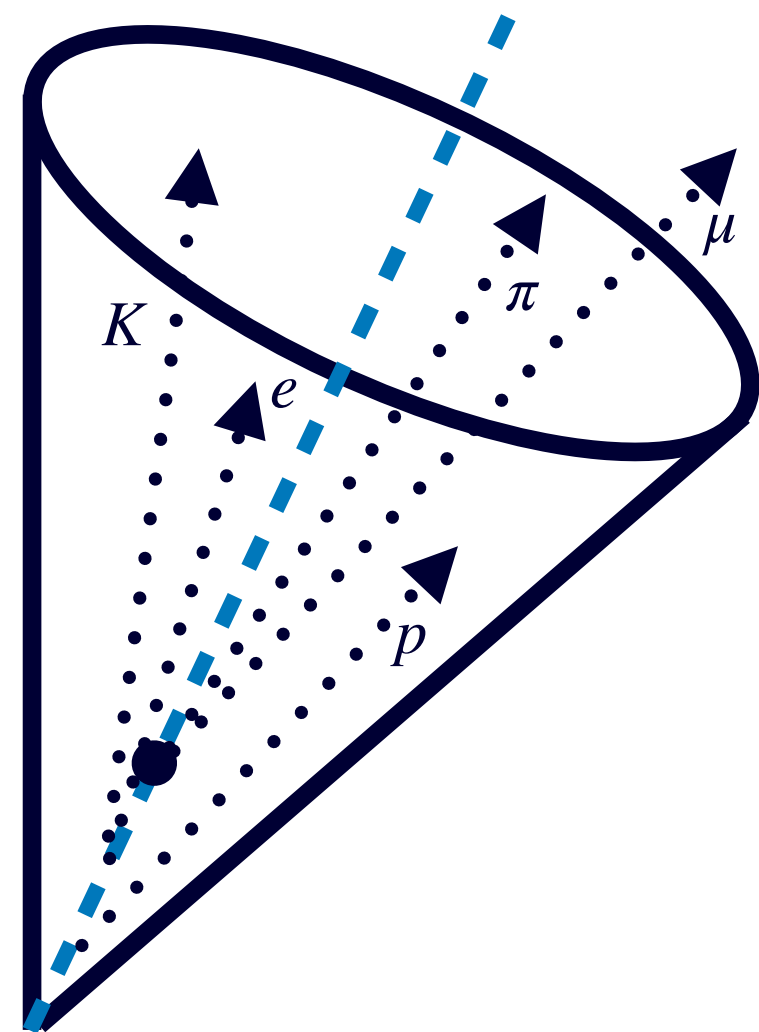
Angle
Embedding

Application of QML at LHC

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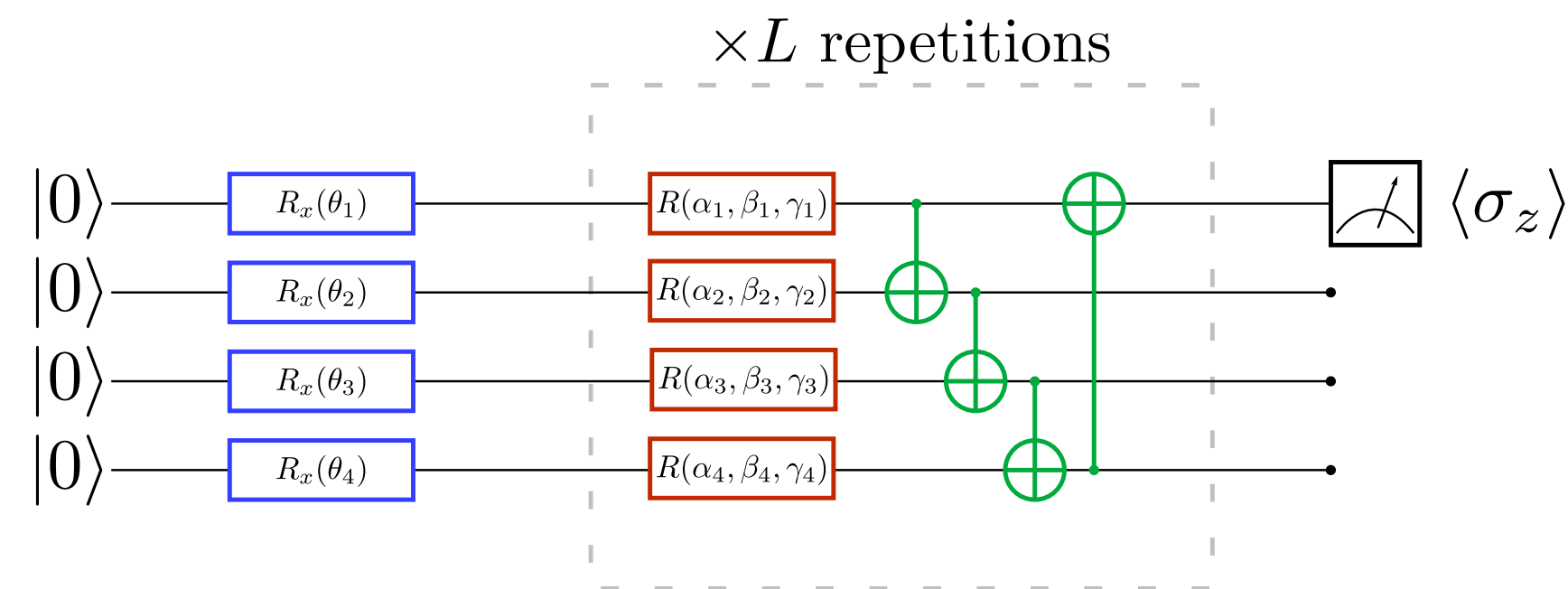
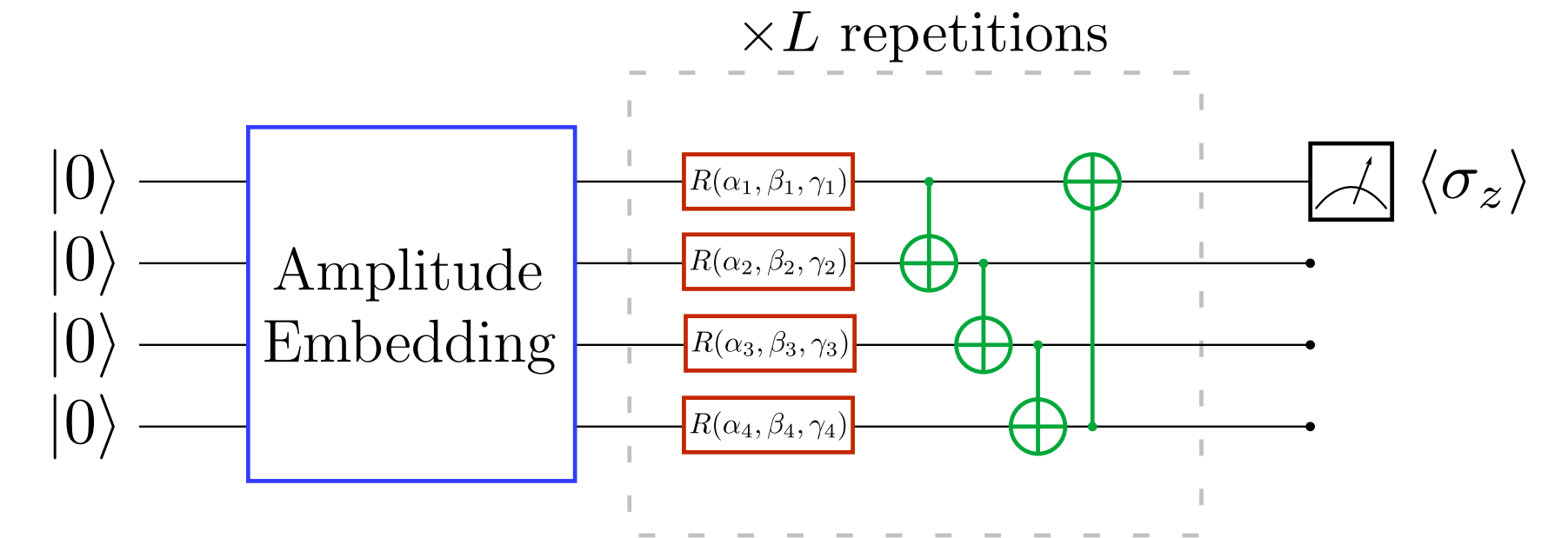
“complete” set of features
16 variables

“muon” set of features
 $\mu + Q = 4$ variables

Different embedding circuits

Amplitude Embedding

$$|x\rangle = \sum_{i=1}^{2^n} x_i |n_i\rangle$$



Angle
Embedding

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

Application of QML at LHC

Algorithm description

- A typical figure of merit for this kind of problems is the **tagging power**

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

$$\epsilon_{\text{eff}} = \text{efficiency} = \frac{\# \text{ tagged jets}}{\# \text{ jets}}$$

$$\omega = \text{mistag} = \frac{\# \text{ wrongly tagged jets}}{\# \text{ tagged jets}}$$

- It can be interpreted as the **effective fraction of correctly identified jets**, important for **asymmetry measurements**:

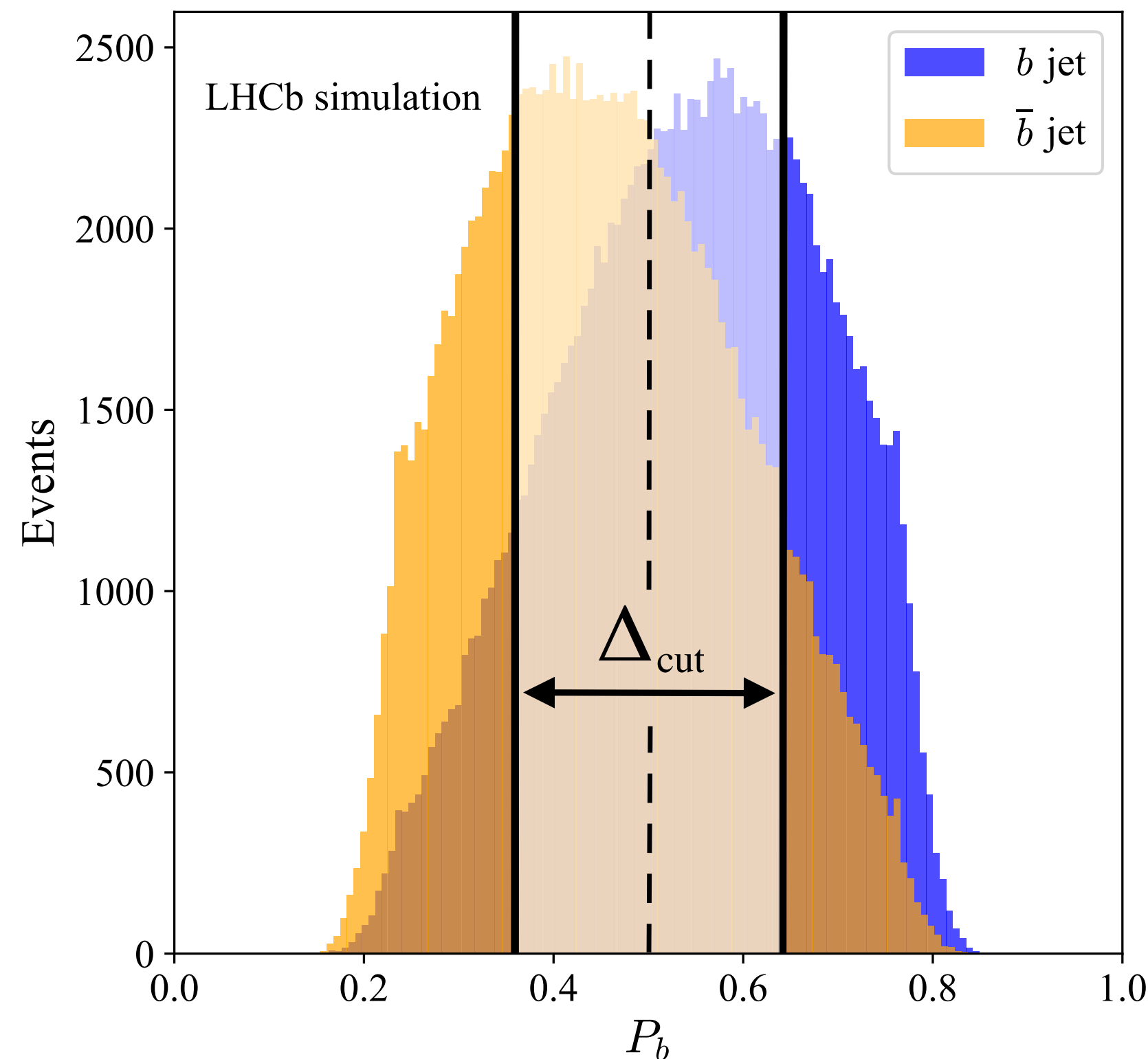
$$\sigma \propto \frac{1}{1 - 2\omega}$$

where σ = statistical uncertainty

Application of QML at LHC

Algorithm description

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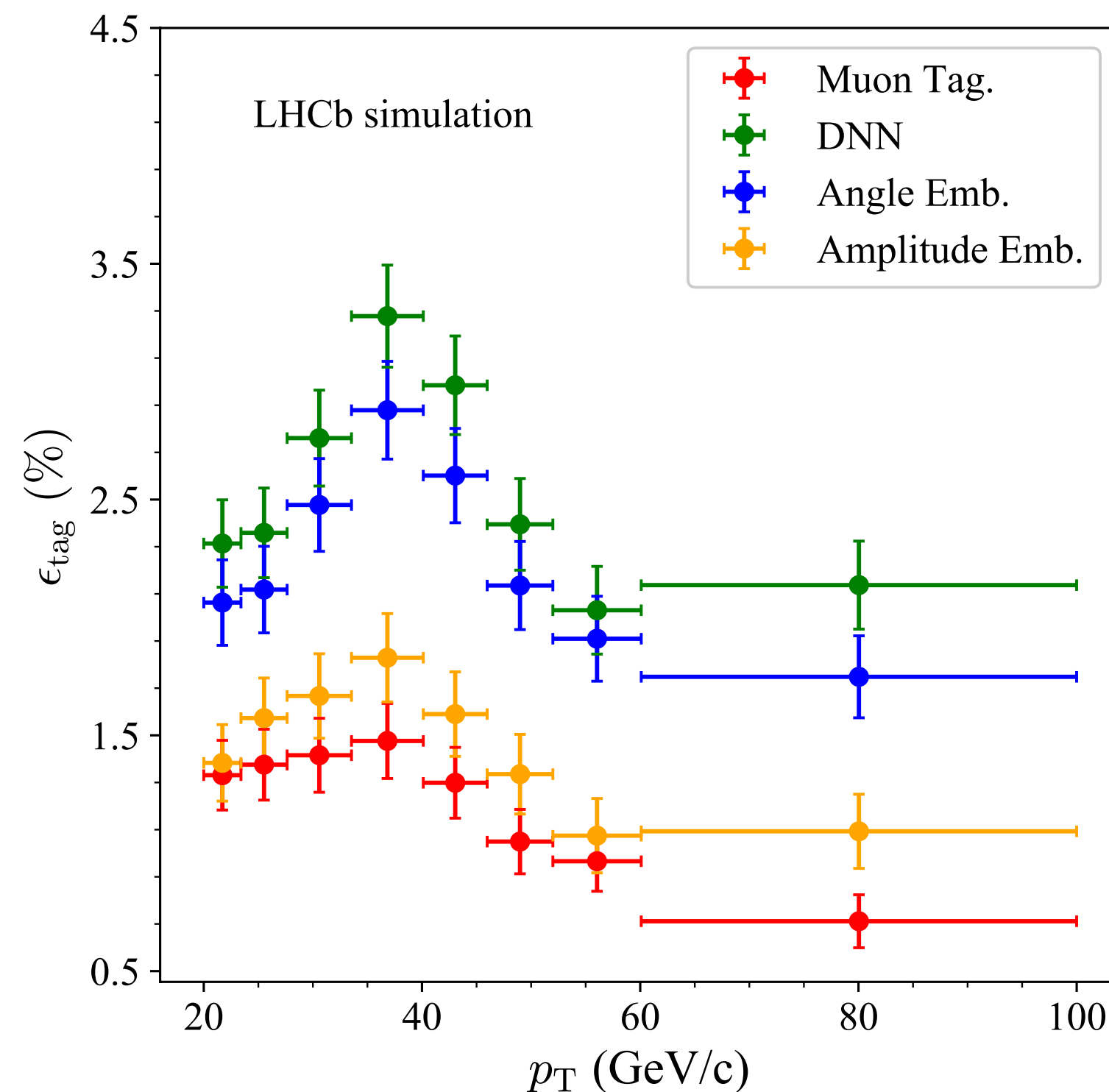
- Optimised cut** Δ_{cut} over output distribution: reduce efficiency but also reduce mistag, therefore **increasing tagging power**

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

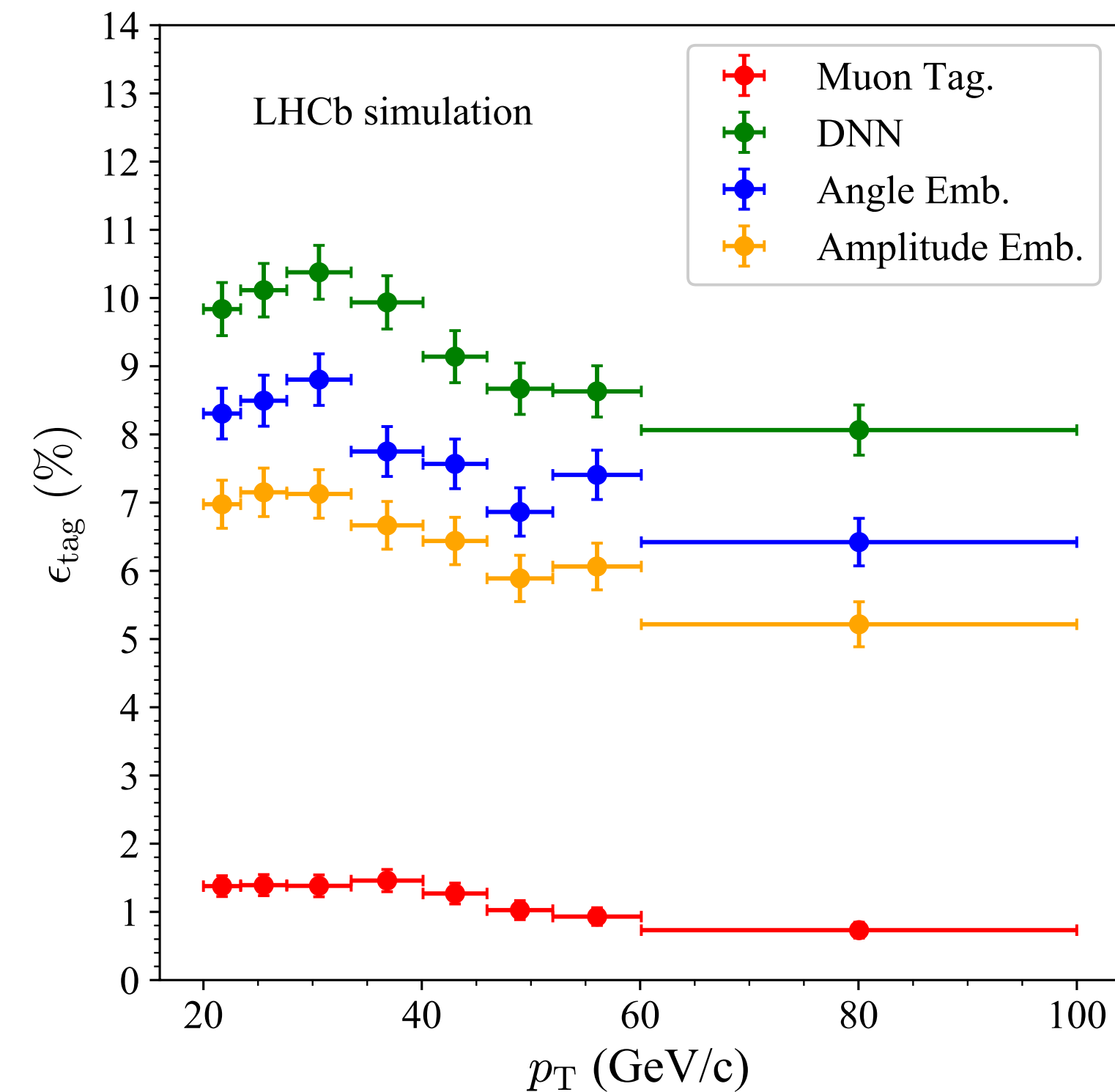
Application of QML at LHC

Results for tagging power

“muon” set of features



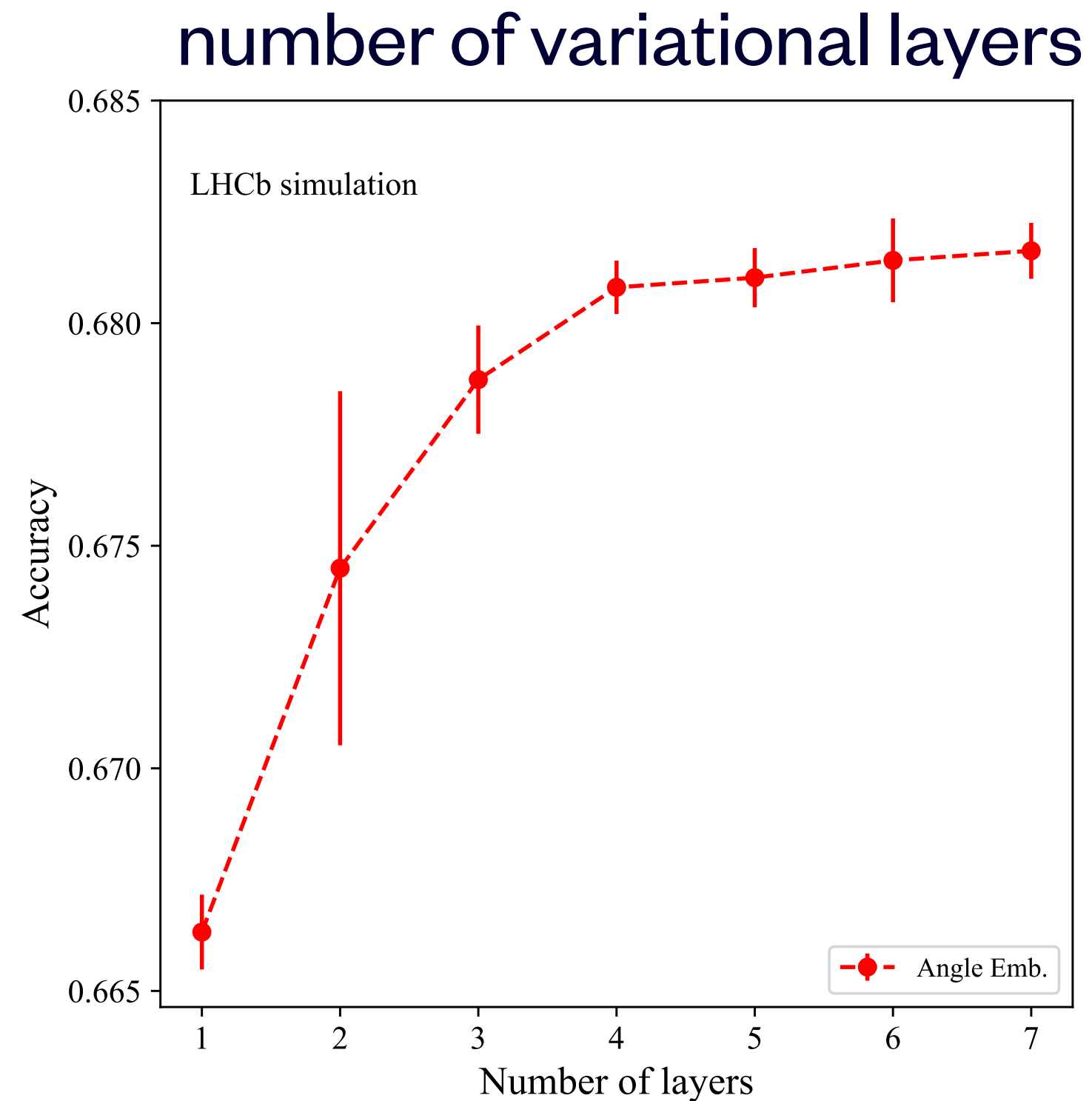
“complete” set of features



- For muon dataset (up to 4 qubits), Angle Embedding circuit is **comparable to DNN**, Amplitude Embedding not performing as good
- For complete dataset (up to 16 qubits), **QML performs slightly worse than DNN**

Application of QML at LHC

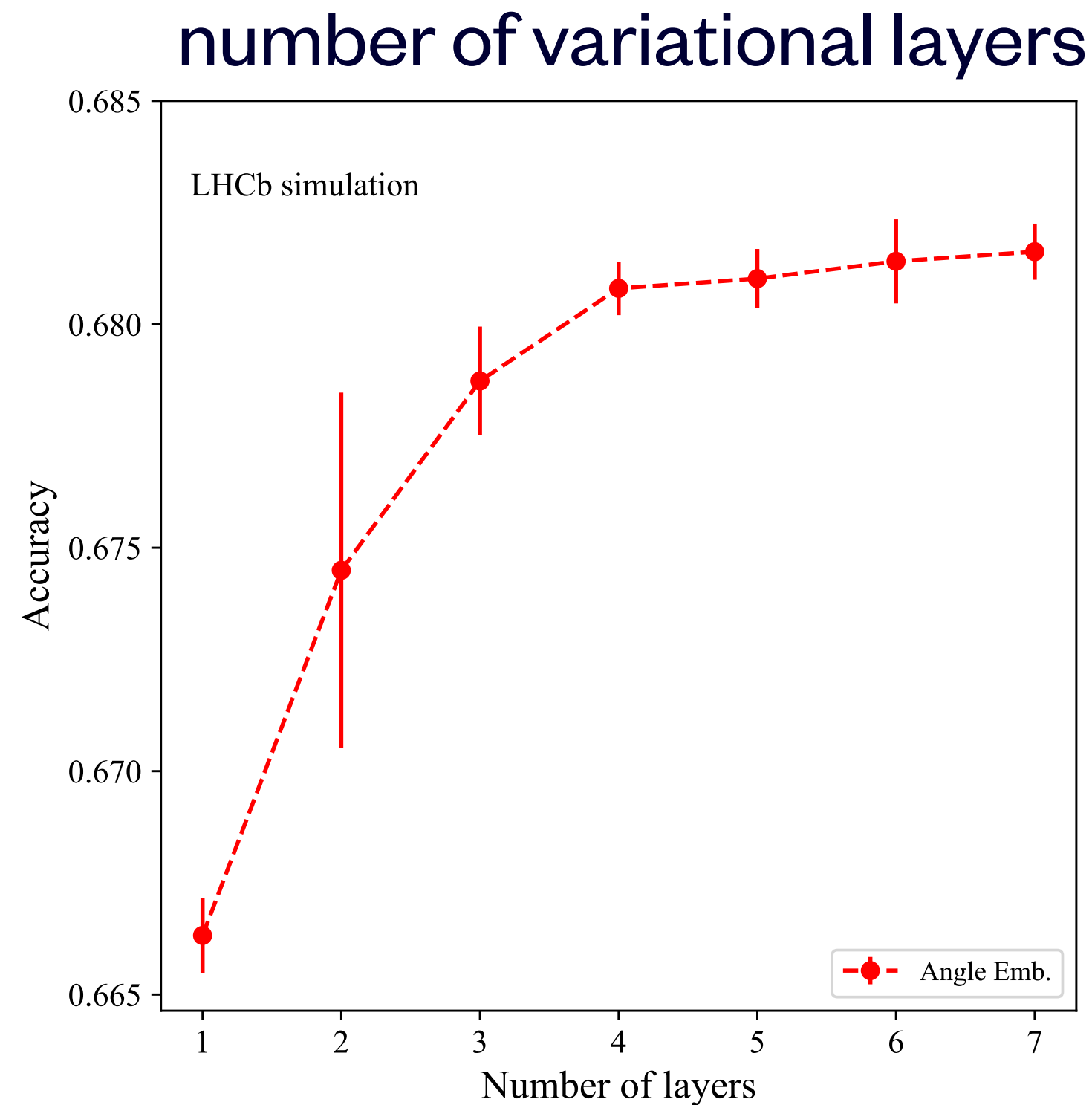
Other results for 4 qubits circuit (muon set of features)



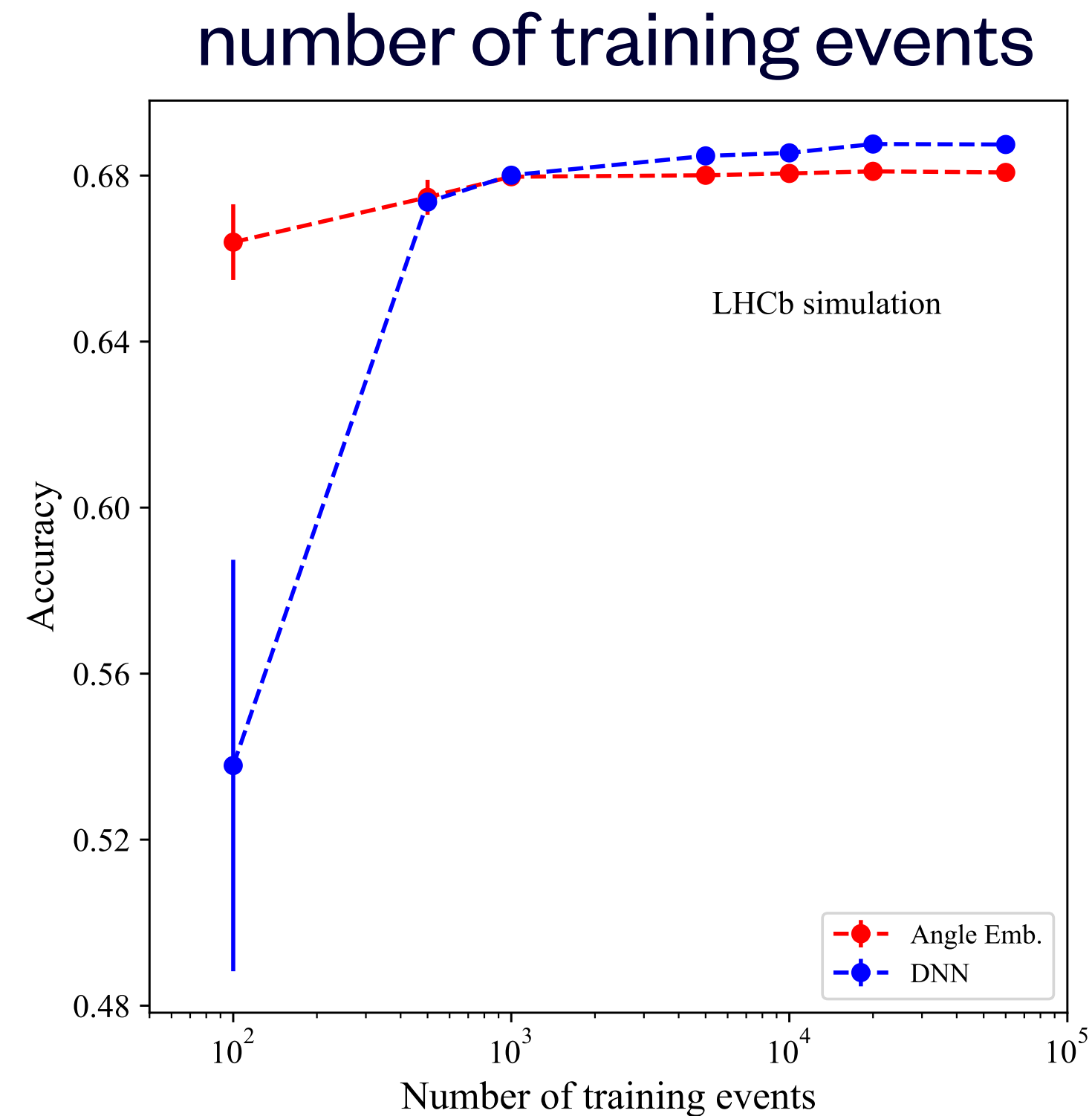
- Accuracy saturates after 5/6 variational layers
- A **trade-off** between performance and complexity

Application of QML at LHC

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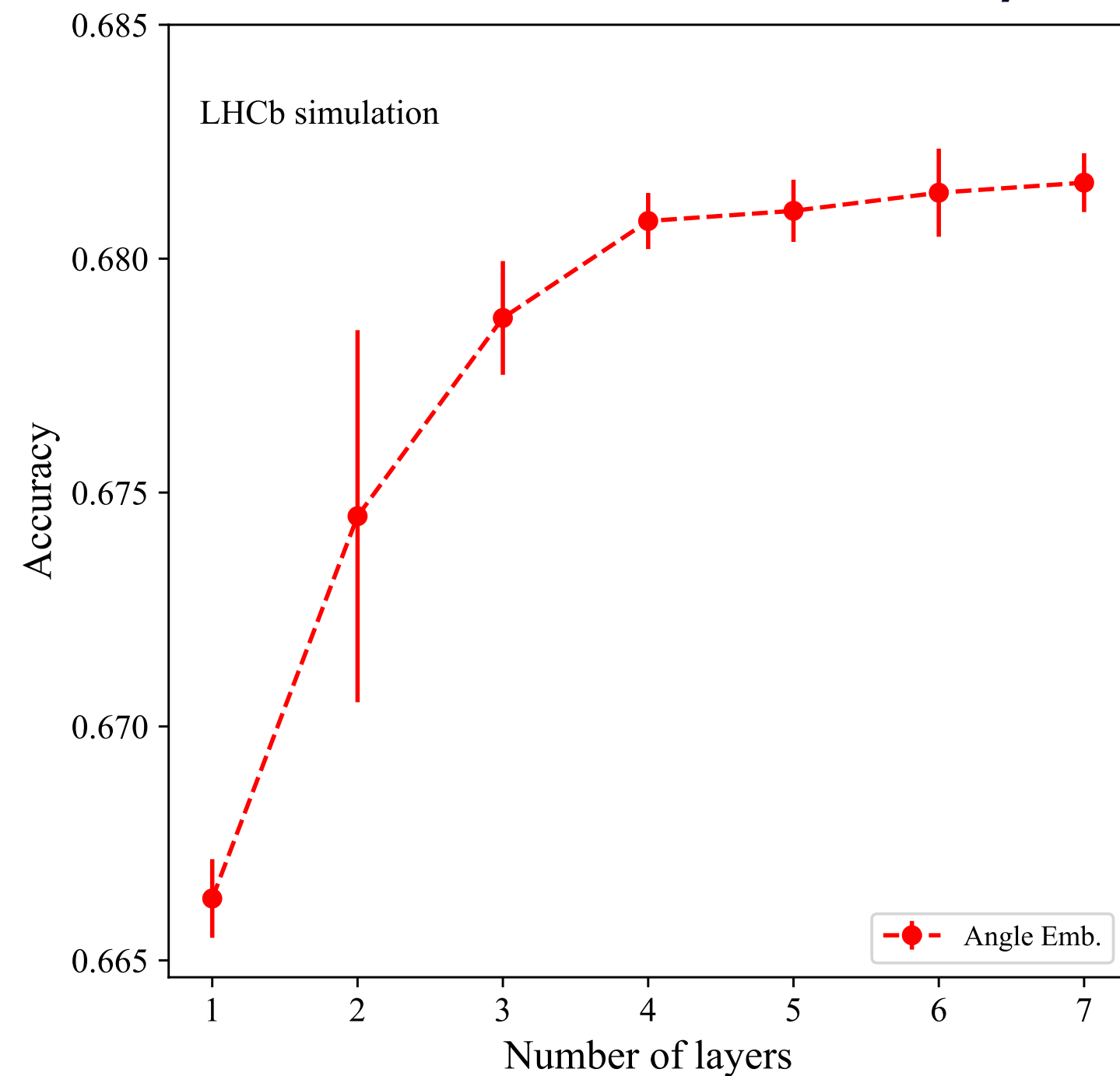


- For a low number of training events, the Angle Embedding **performs better** than the DNN

Application of QML at LHC

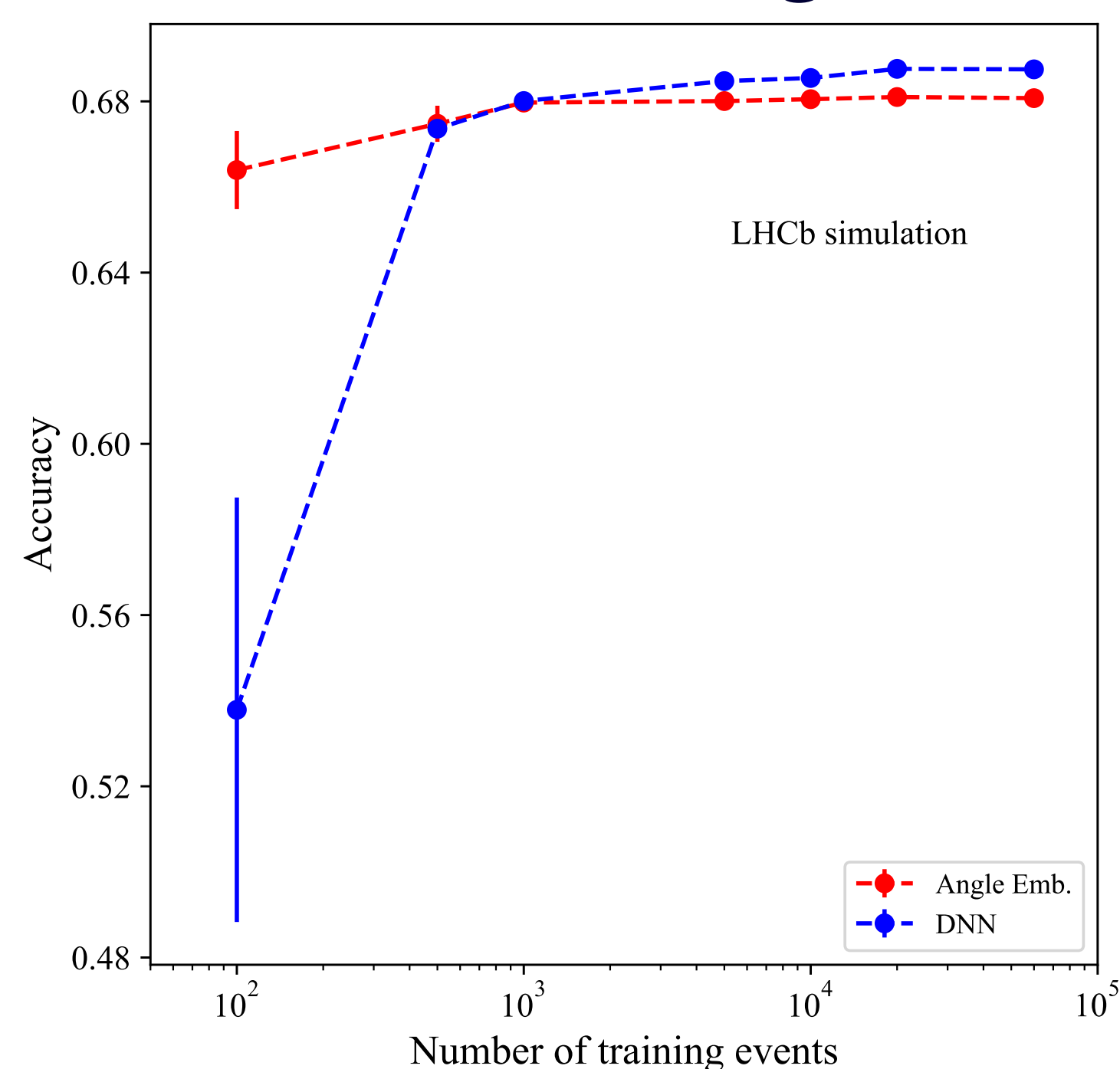
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number of variational layers



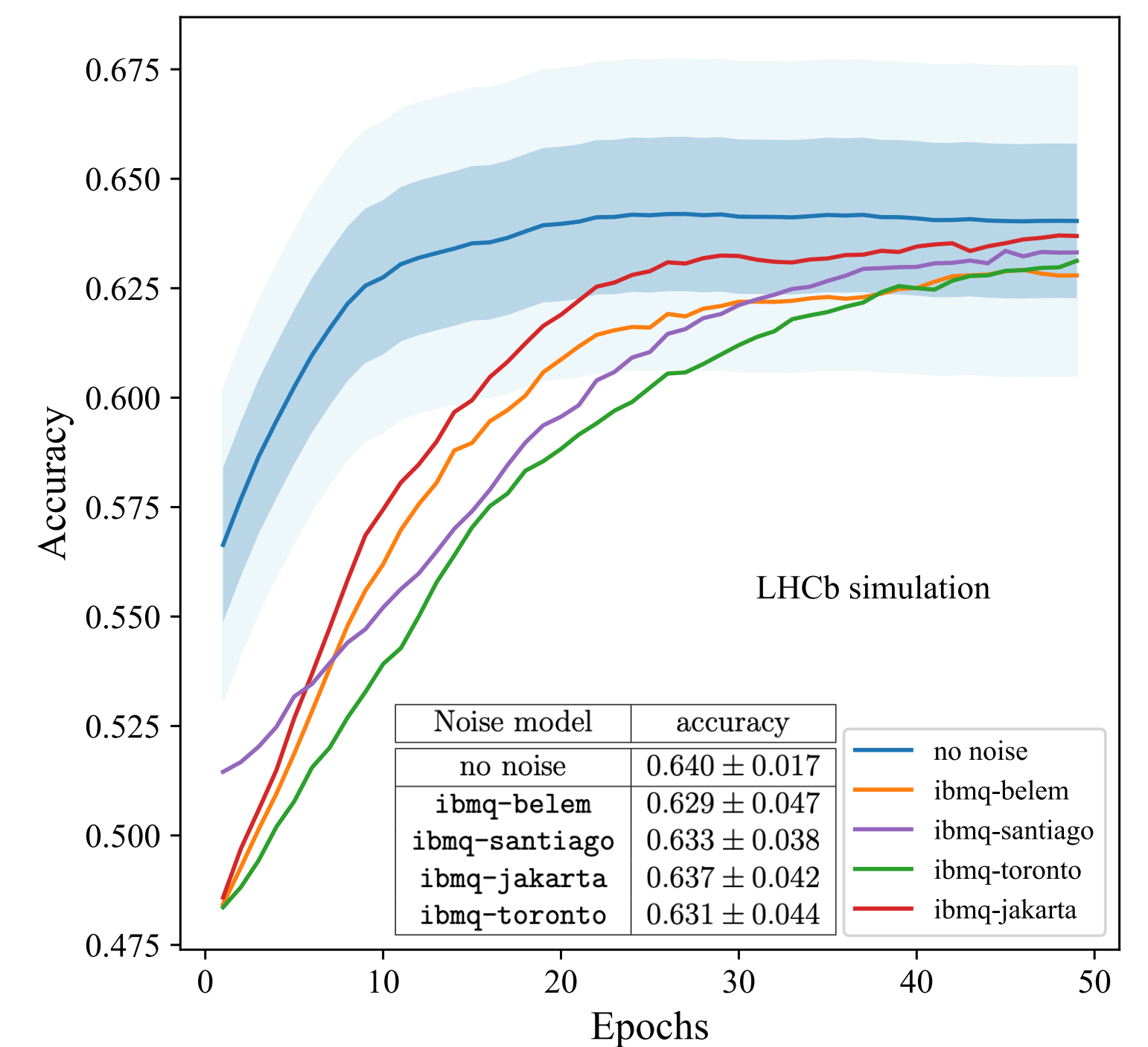
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PENNYLANE ⊕ Qiskit
noise contribution



- Simulate noise contribution from several IBM backends
- **Simpler structures are robust to noise**

Future studies and ideas

What to expect in the next months

tests on hardware **preliminary**

MODEL4f 3Layers	Accuracy	AUC ROC	Secs. x jet	
Simulator	0.78	0.82	0.01	
Manila Opt 2 Shots 1024	0.74	0.79	0.12	MANILA
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- Several tests on different IBM machines
- Transpiling and error mitigation studies
- **Preliminary performance similar to simulations**

MORE IN THE FUTURE...

Future studies and ideas

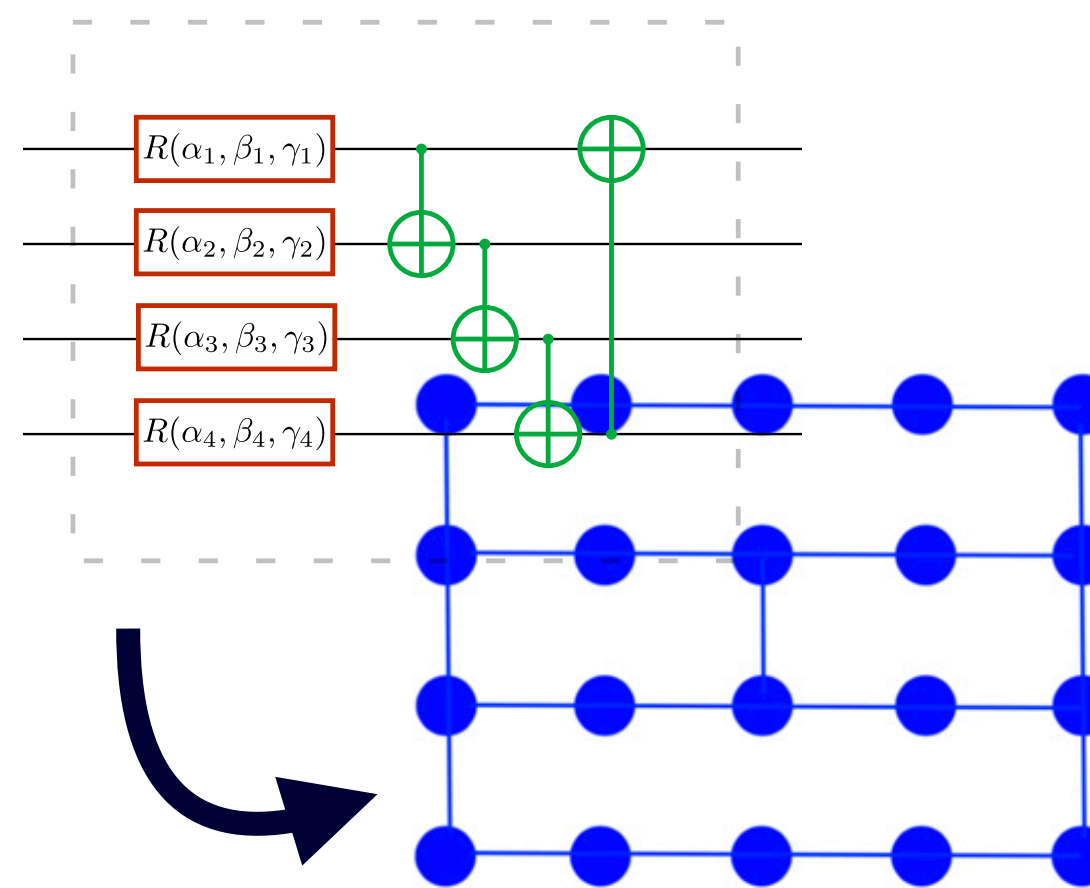
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intelligent circuit design



- Can't scale up to many layers
- Is there a clever way to build our circuit?
- **Quantum TTN** show interesting features in this sense

MORE IN THE FUTURE...

Future studies and ideas

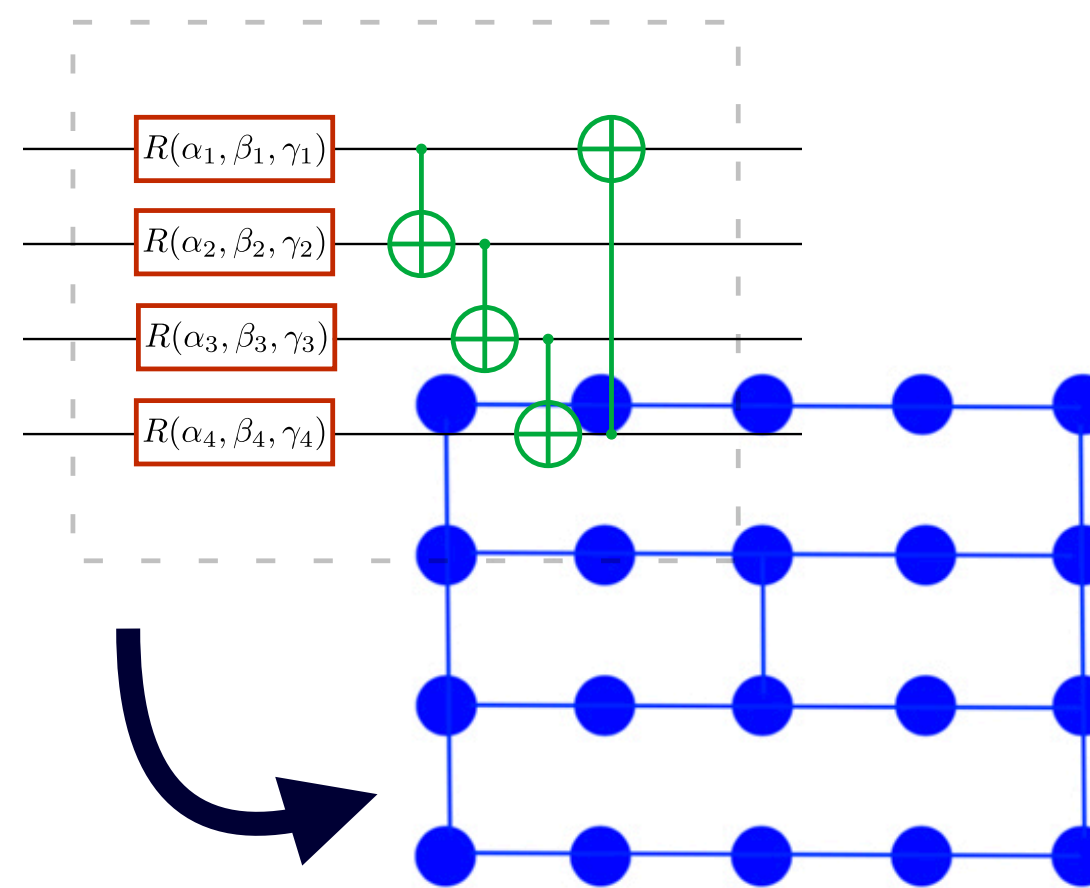
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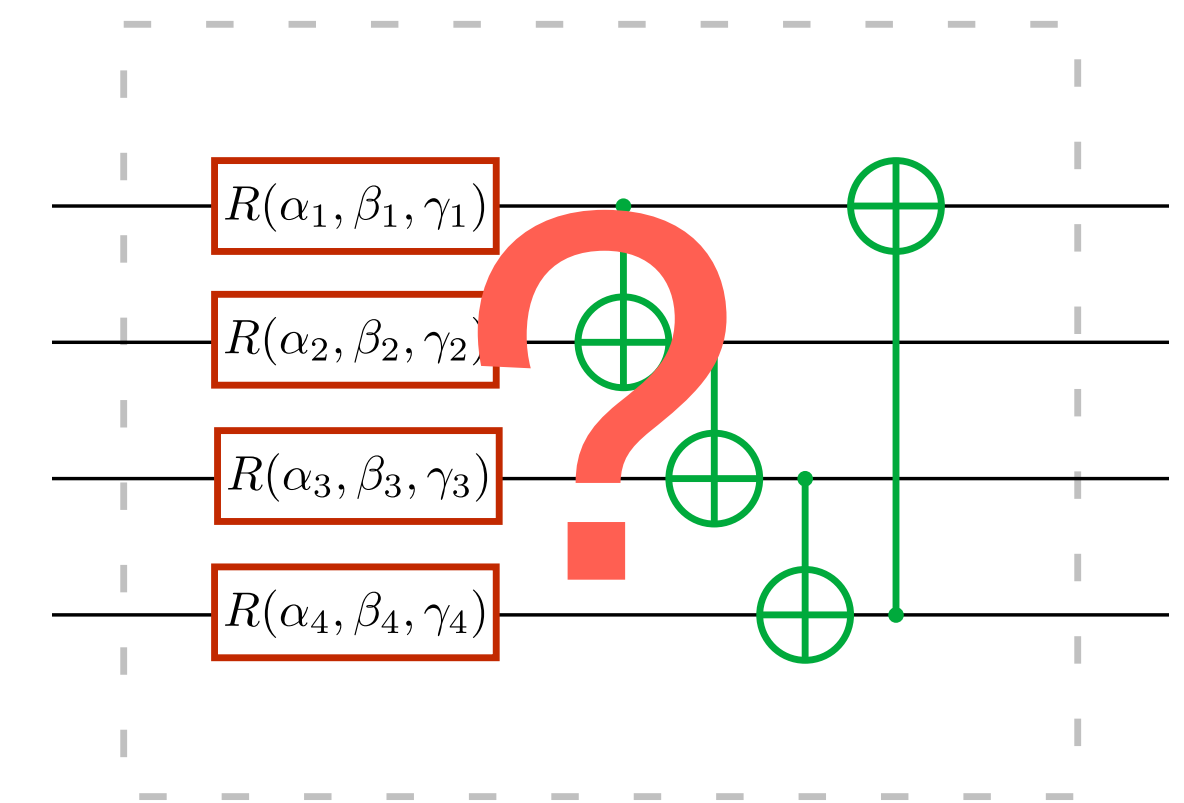
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correlations between qubits



- What (and where) is the quantum advantage?
- Can we measure **correlations** between qubits?
- How to use this information?

MORE IN THE FUTURE...

Overview of INFN activities

- INFN is deeply involved in **many QC activities for HEP**

CERN welcomes INFN and IIT as new members of its IBM Quantum Network hub

15 JULY, 2022

RATHER NEW!



- Ongoing projects in different areas of interest and expertise

SIMULATION AND THEORY

**SEE TALK BY
A. ROGGERO**

**QUANTUM COMPUTING
ALGORITHMS**

**QUANTUM SENSING AND
COMMUNICATION**

**SEE TALK BY
C. BRAGGIO**

- Early involvement already in 2018 (**QT @ INFN**)
- INFN is also part of the **QuantERA programme**



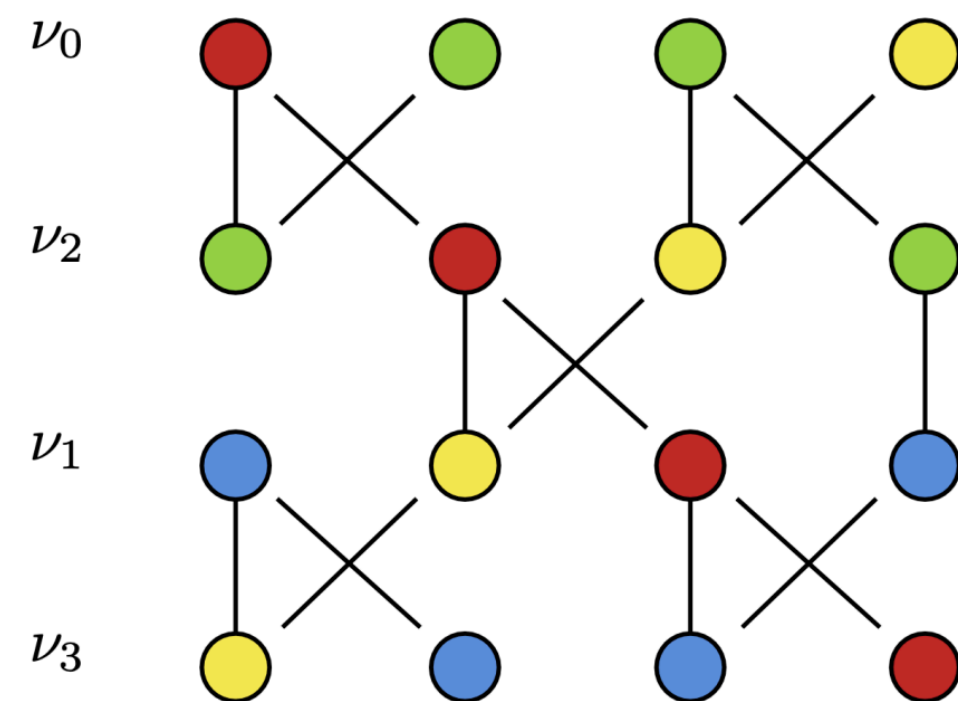
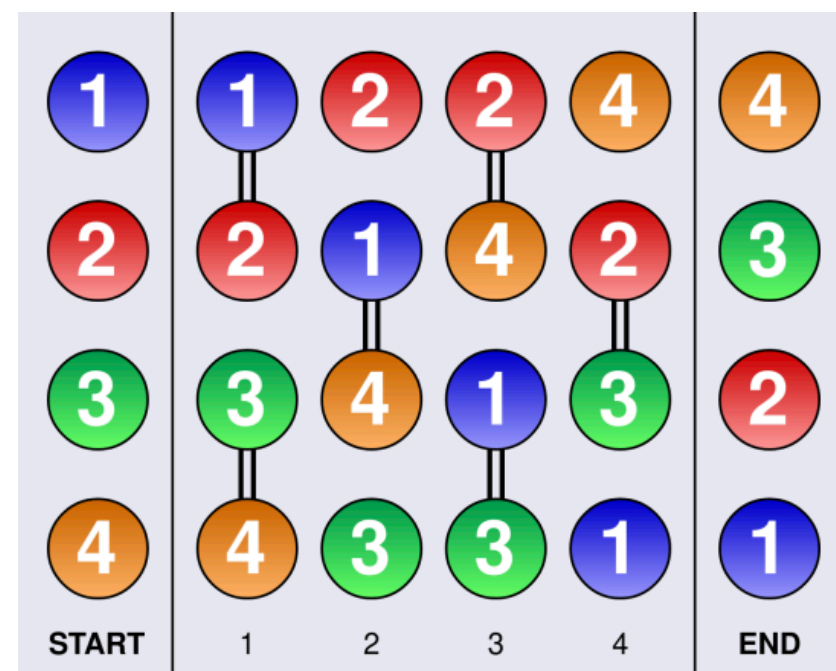
Overview of INFN activities

Simulation and theory

- Describe N interacting neutrinos with Hamiltonian by means of quantum simulations

$$H = \sum_i \frac{\Delta m^2}{4E_i} \vec{B} \cdot \vec{\sigma}_i + \lambda \sum_i \sigma_i^z + \frac{\mu}{2N} \sum_{i<j} (1 - \cos(\phi_{ij})) \vec{\sigma}_i \cdot \vec{\sigma}_j$$

- Simulate one- and two-body interactions with SWAP network

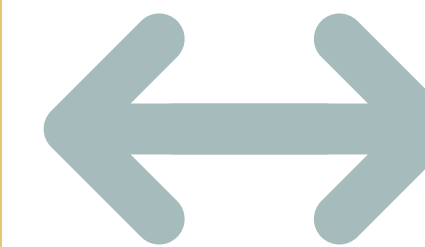


- Recent progress using trapped ions with all-to-all connectivity show very low infidelities

by V. Amitrano et al., arXiv:2207.03189 (2022)

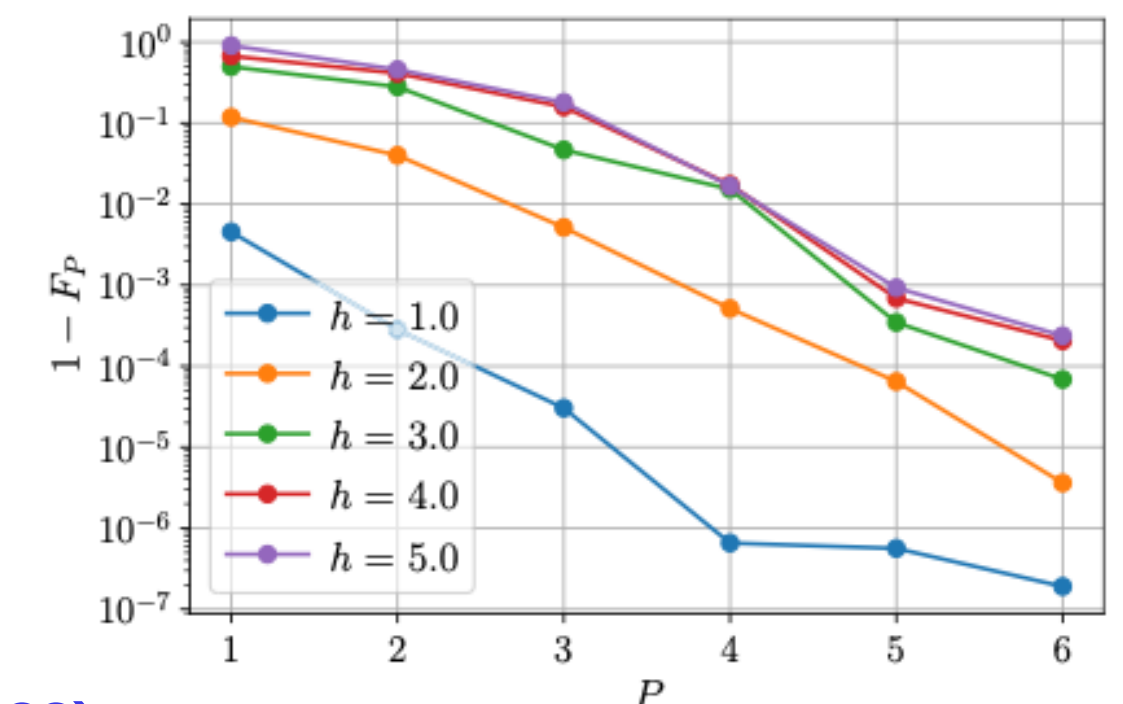
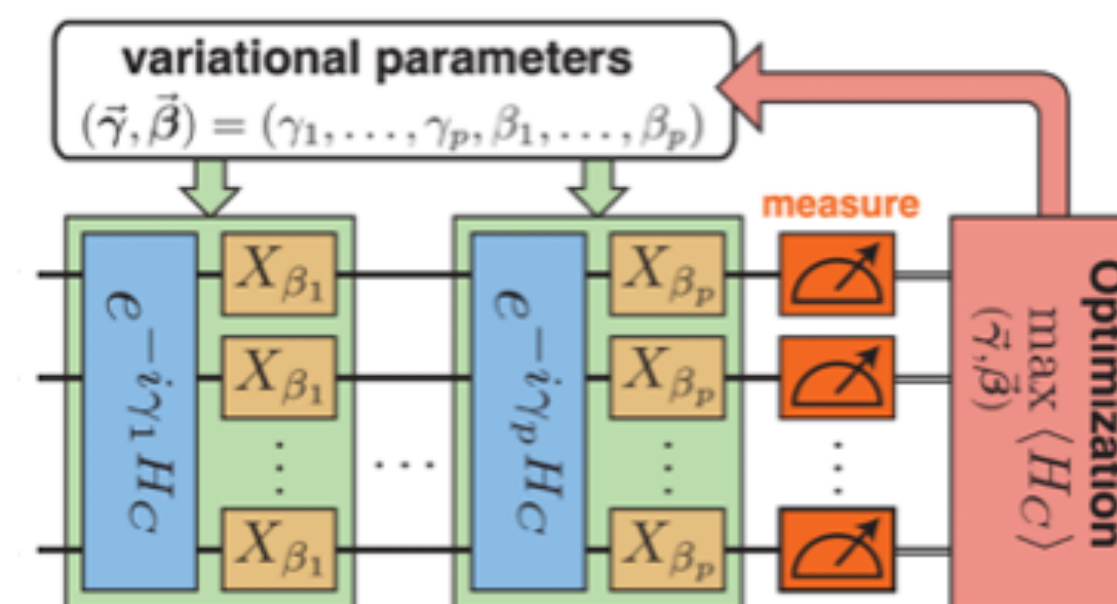
- Quantum simulation of lattice gauge models on a real quantum computer
- Overcome old idea of classical approximation and numerical methods

High Energy
Quantum Field Theory



Quantum Many Body
Model on a Lattice

- Recent results on a near-term quantum simulator

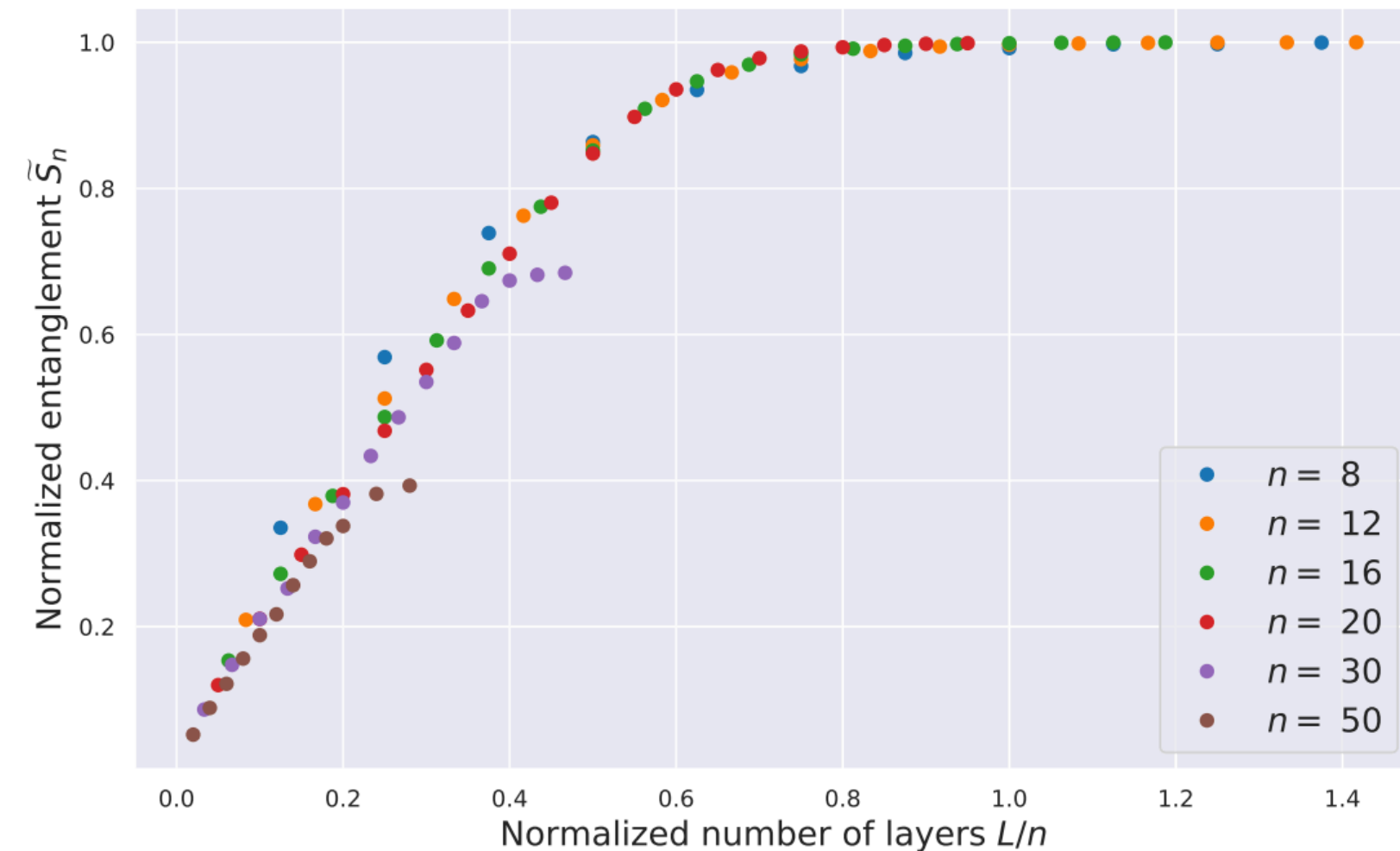


by L. Lumia et al., PRX Quantum 3, 020320 (2022)

Overview of INFN activities

Simulation and theory

- Entanglement entropy production in QNN
- QNN characterisation by means of Tensor Networks tools

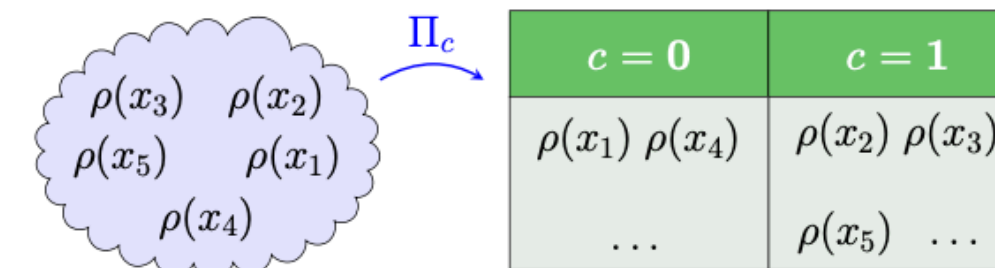


- The most promising regime for quantum advantage is a **trade-off** between high **entanglement** and **expressibility**

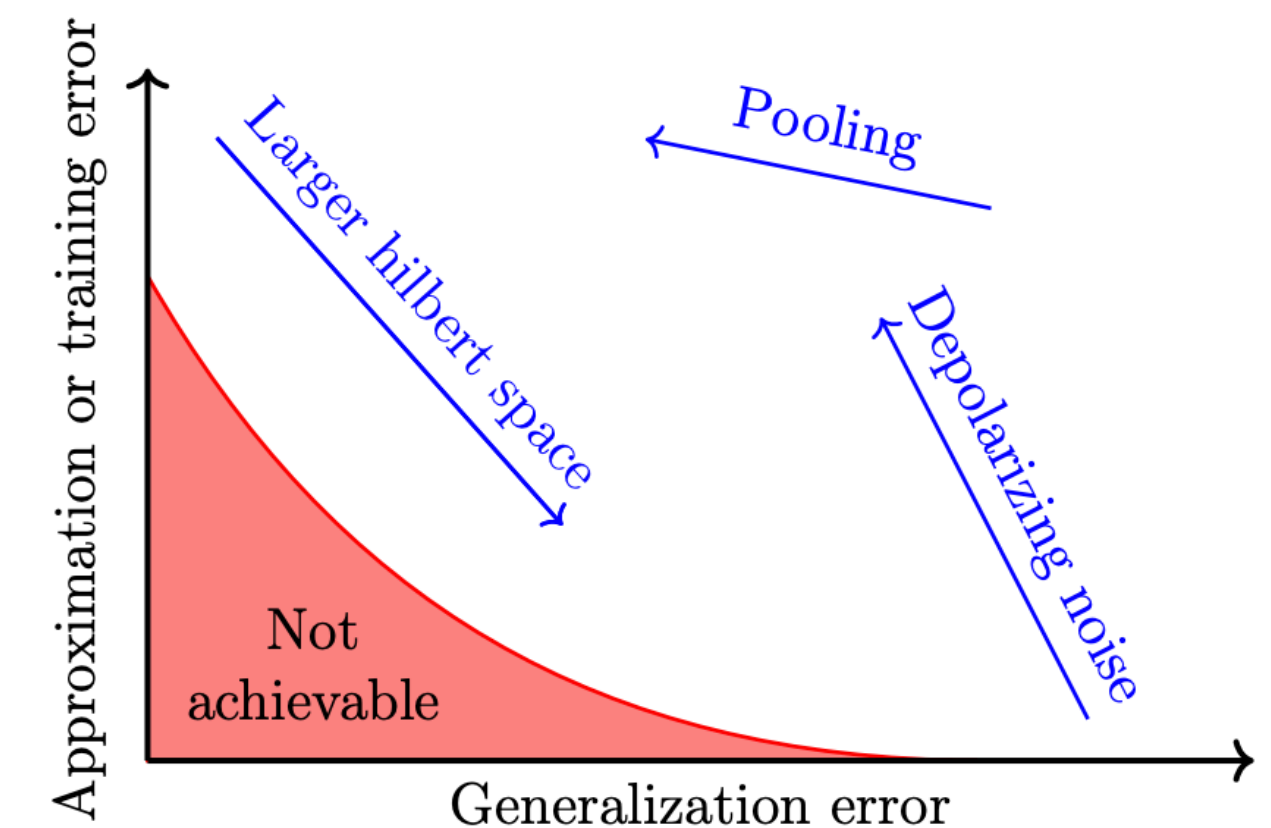
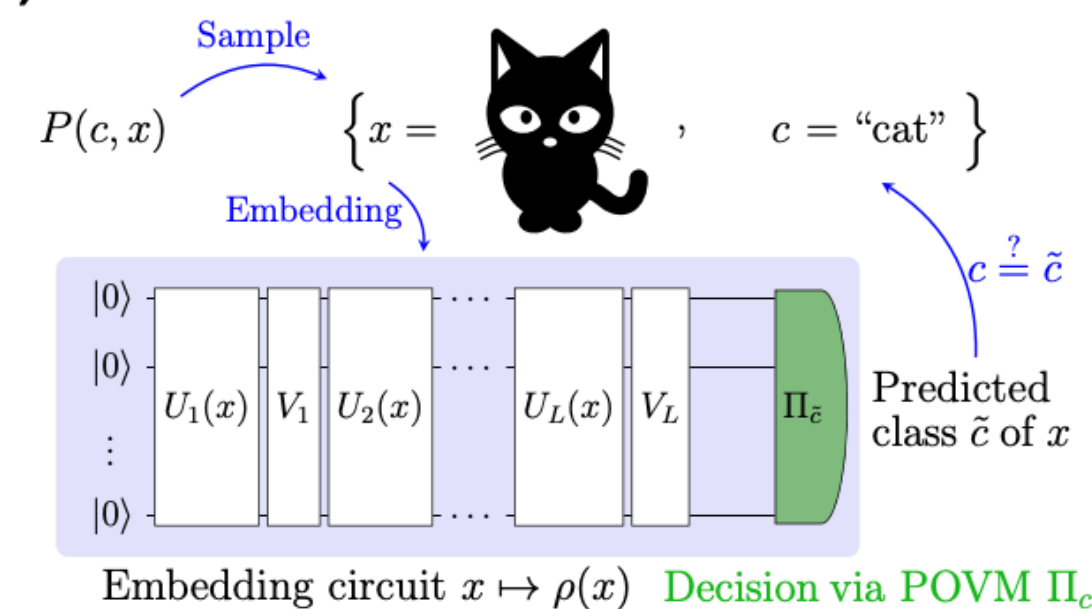
by M.Ballarín et al., arXiv:2206.02474

- Study generalisation in QML
- Quantify the generalisation and approximation capability of QML classification problems

(a) Quantum state classification



(b) Classification of classical data



- Analysis can be applied to models of moderate complexity

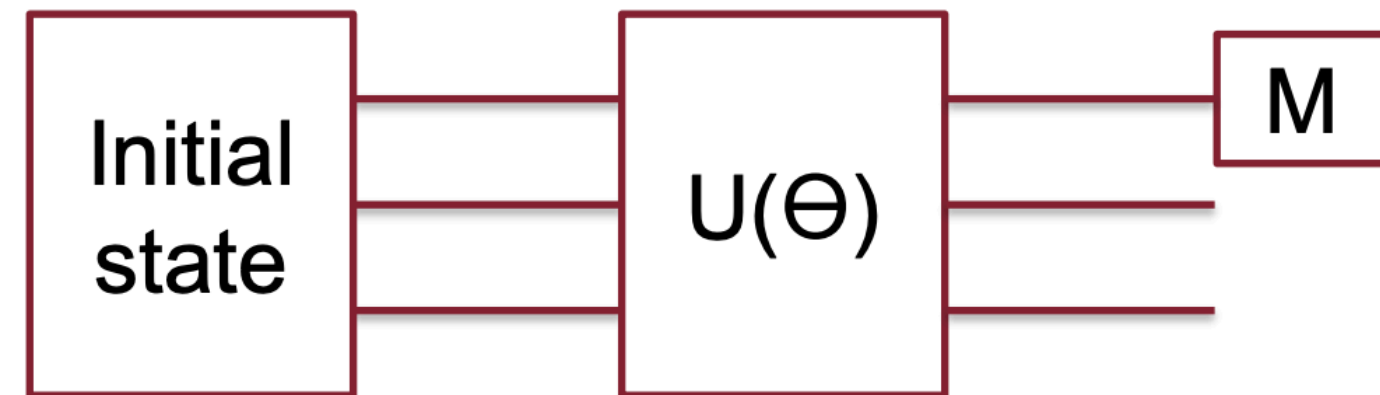
by L.Banchi et al., PRX Quantum 2.040321 (2021)

Overview of INFN activities

Classification in HEP and Gravitational Waves

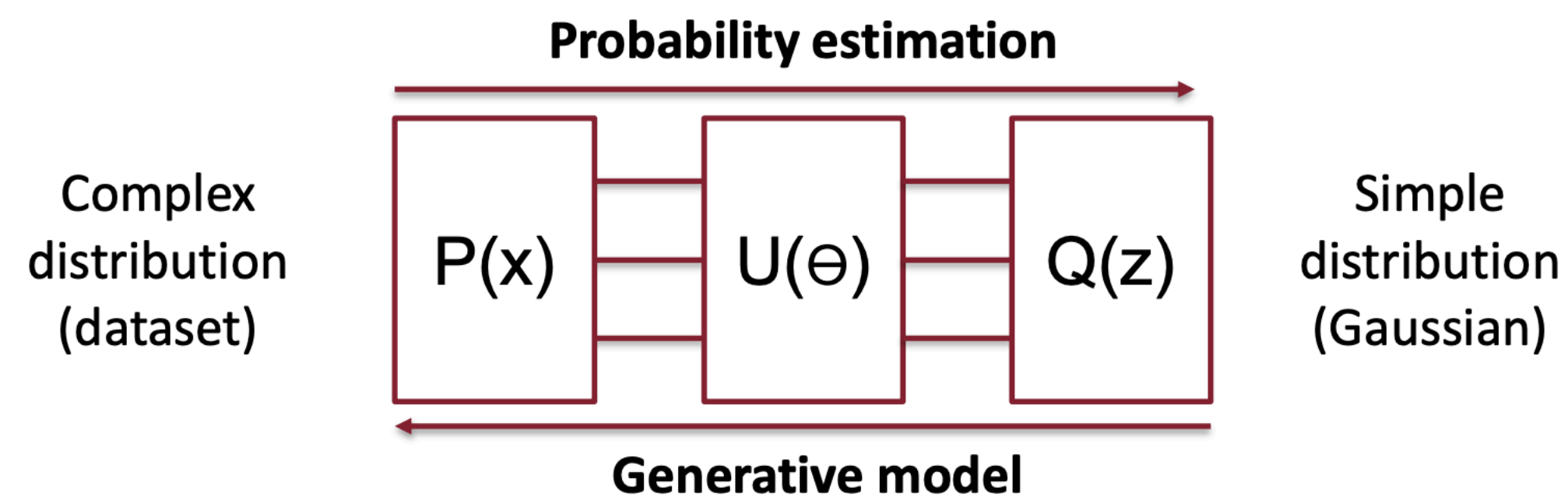
- **Anomaly detection task**

- Identification of long-lived particles in ATLAS



- **Generative models**

- Simulation of particles-matter interaction



- GW signals are deeply embedded in **detector noise**
- Matched filtering between data and signal templates

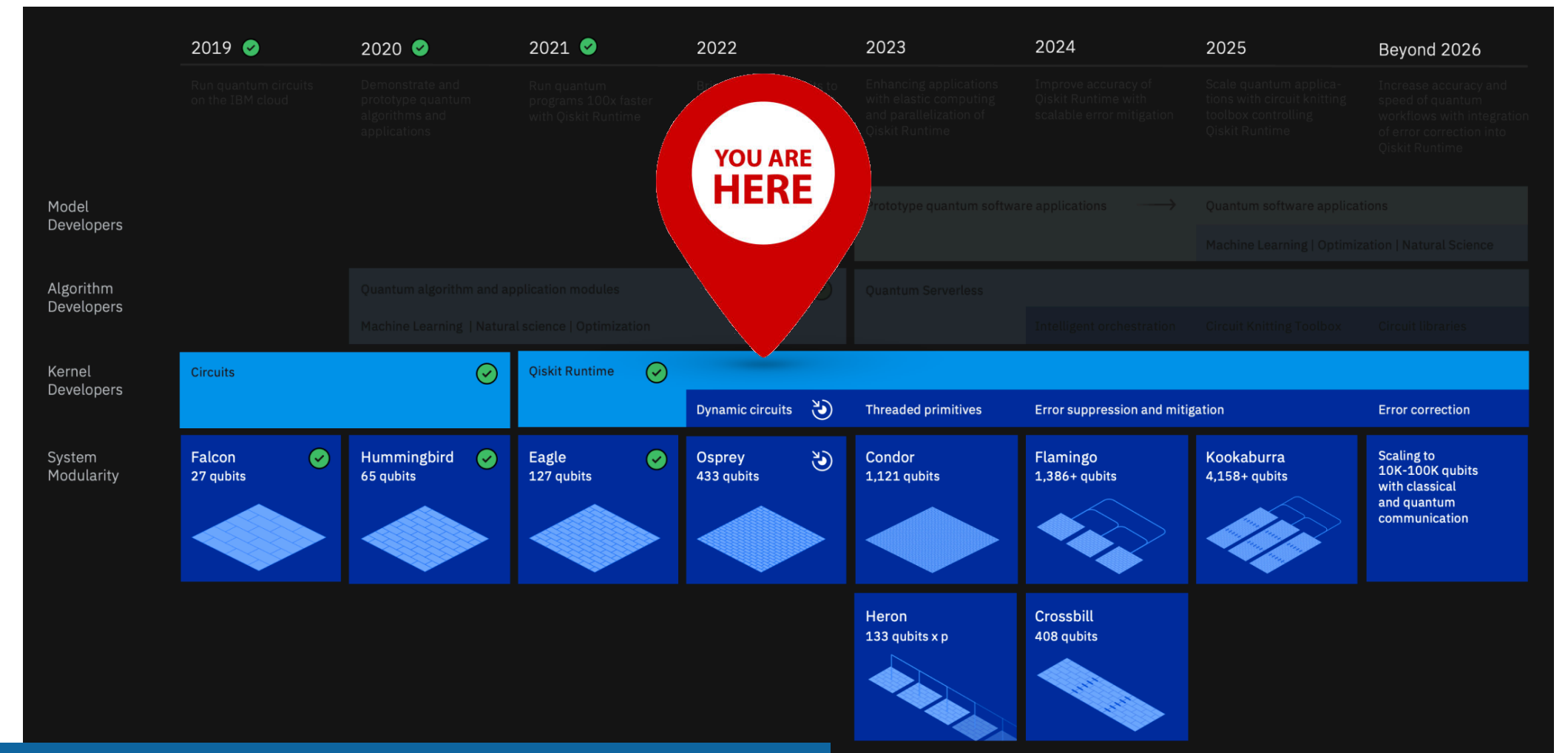
- **Computationally not feasible**

$$N_{\text{tot}} \approx 5.6\pi \times 10^{-9} K_f K_{\text{sky}} \left(\frac{T_{\text{FFT}}}{\delta t} \right)^{3+j_{\text{max}}} \prod_{j \leq j_{\text{max}}} \left(\frac{T_{\text{obs}}}{\tau_{\text{min}}} \right)^j \approx 10^{21}$$

- Several proposals to use quantum algorithms
 - Quantum Hough Transform
 - Polynomial speed-up w.r.t. classical
 - QML
 - Already classical ML seems promising

Conclusions

- An application of QML to a **real LHC physics** case has been presented
- While QML doesn't show any advantage, it behaves **almost as good as classic ML**
- Nice PoC for future studies and application
- Possible **new ideas** on
 - Leveraging **quantum** aspects of QML
 - Applicability to **near-term devices**
- **Many INFN activities** of QC for HEP in **different areas of interest**
- Significant boost expected from the **national center for HPC and QC**, currently being built

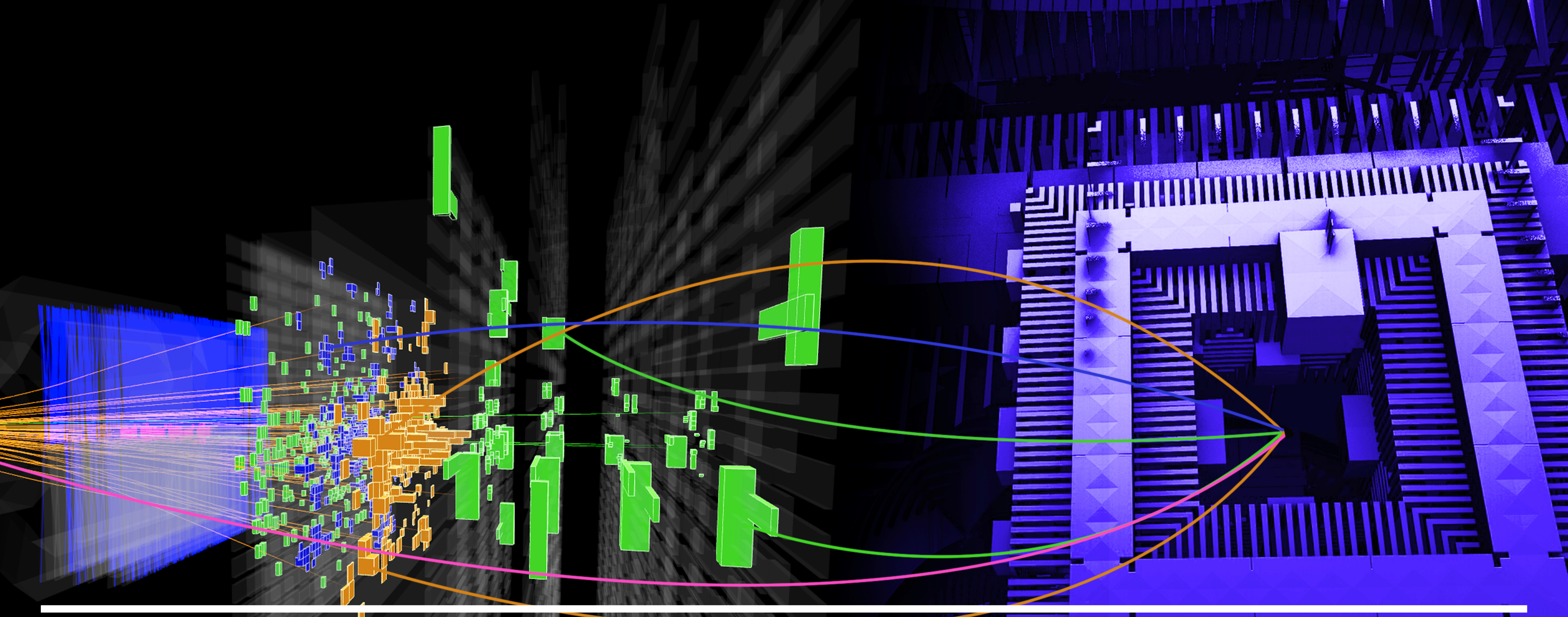


Quantum Computing @ INFN

14–15 Nov 2022
Bologna
Europe/Rome timezone

ICSC
Centro Nazionale HPC,
Big Data e Quantum Computing





Thank you for your attention!
