Quantum Machine Learning at LHCb

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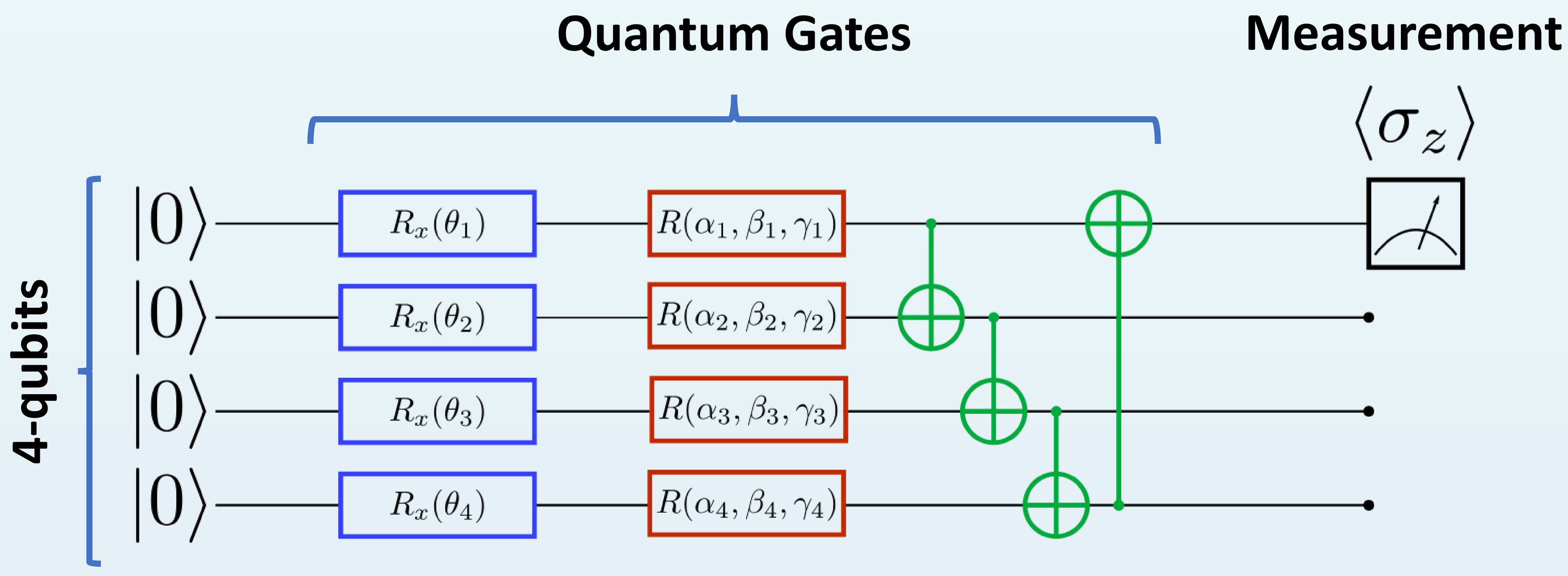
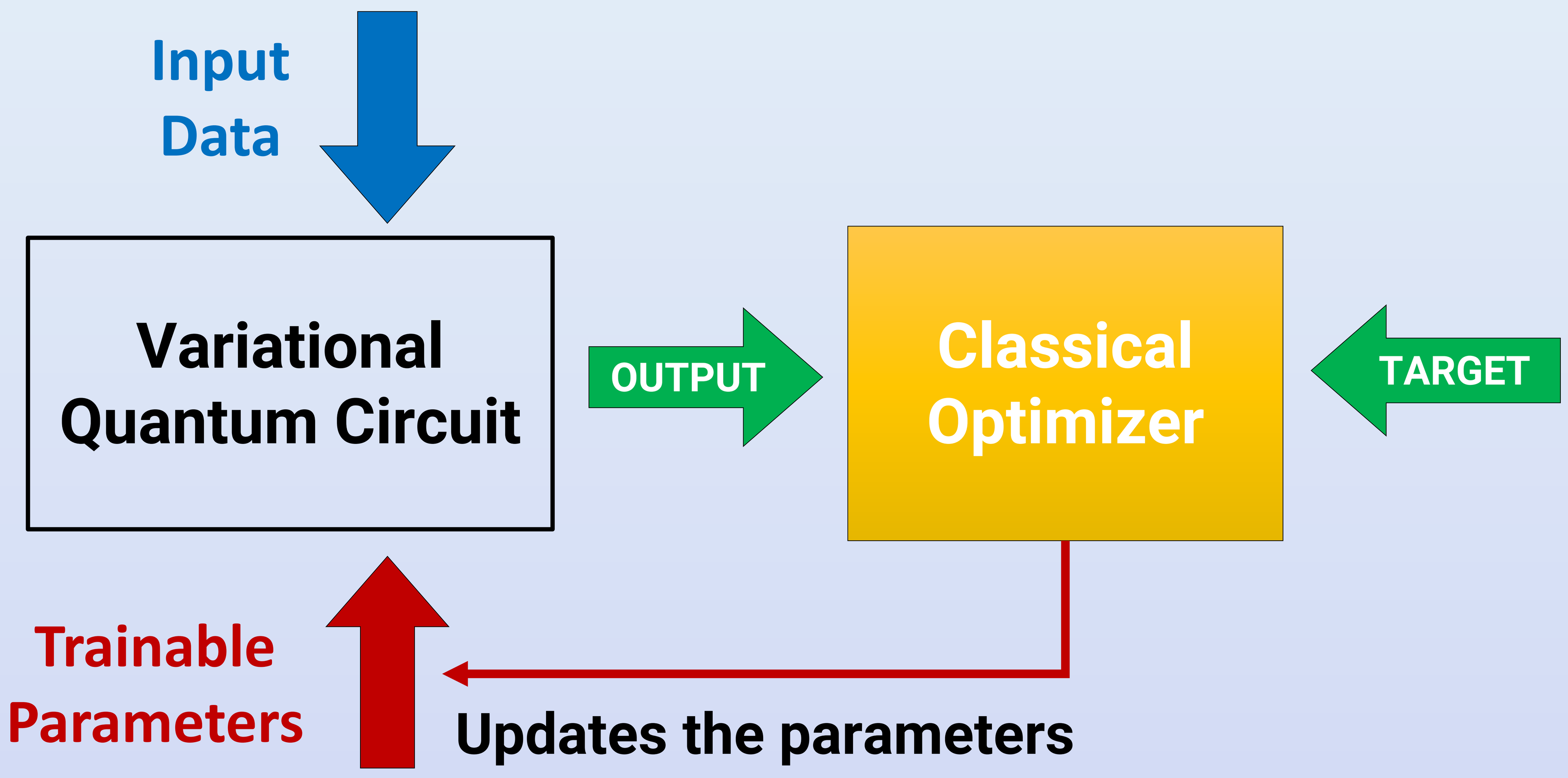
QUANTUM COMPUTING

- **Basic idea:** performing computations using quantum mechanical systems
- **The Qubit** is the elementary unit of information of a quantum computer
- It is **2-level quantum system** that can be manipulated by **quantum gates**
- **Quantum circuit:** multiple qubits manipulated by a collection of quantum gates





MACHINE LEARNING WITH QUANTUM CIRCUITS

Variational Quantum Classifier algorithm

1. Data are fed into a quantum circuit with **trainable gate parameters**
2. Measurements of the final quantum state are mapped to **classification predictions**
3. A **classical optimizer** compares predictions with targets and updates the parameters of the circuit

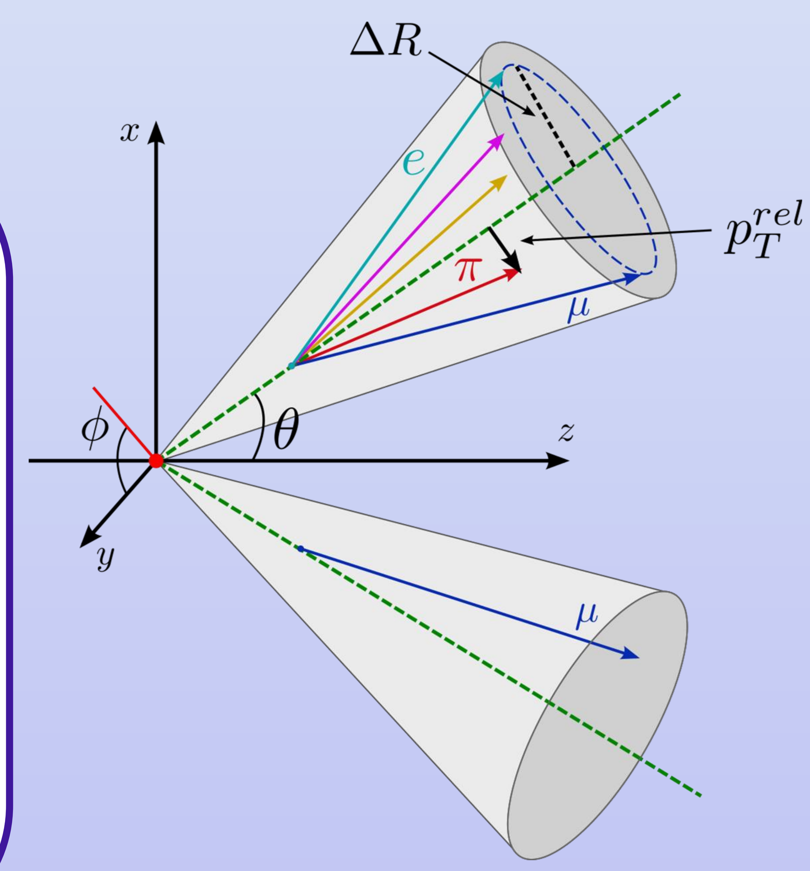
DATASET Open Data[2]

$pp \to b\bar{b}$ inclusive di-jets sample of **LHCb simulations** at $\sqrt{s} = 13$ TeV. 5 types of particles are considered, selecting the ones with the **highest p_T^{rel}** in the jet:

$\mu \quad K \quad \pi \quad e \quad p$

For each particle	Global variable
$Q \quad p_T^{rel} \quad \Delta R$	$Q_{tot} = \frac{\sum_i p_T^i q^i}{\sum_i p_T^i}$

16 variables from the jet structure



b vs $\bar{b}$ TAGGING WITH QUANTUM MACHINE LEARNING

- In b-jets, the information on the charge of the b-quark is **diluted** in the particles produced in the hadronization and fragmentation processes
- **Inclusive** Quantum Machine Learning (QML) algorithm for the **charge tagging of b-jets**
- **Entanglement** could allow quantum models to **exploit correlations** among jet's particles

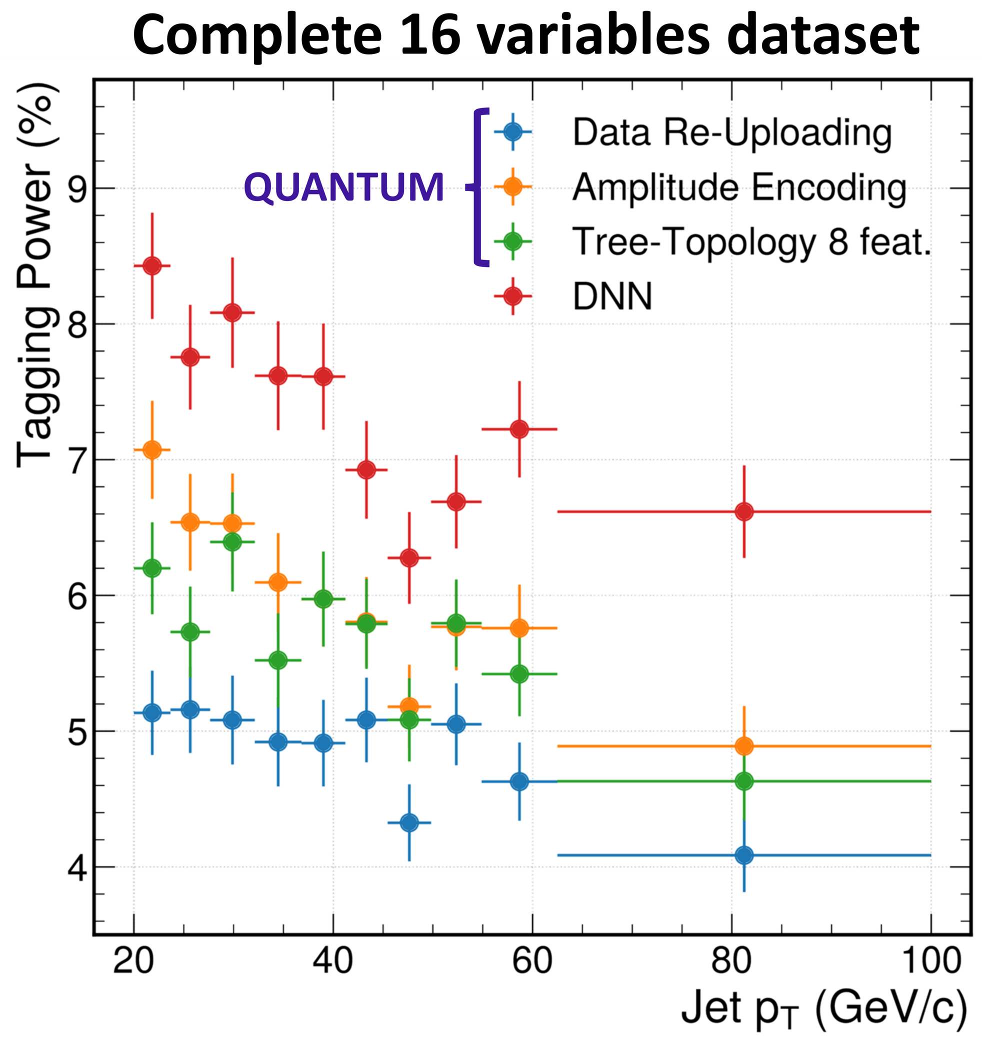
RESULTS

- Several quantum models have been tested on **noiseless simulators**
- Quantum models are compared to a **Deep Neural Network** (DNN) and tagging with the muon charge (μ-tag) in terms of the ***b*-jet charge tagging power**

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

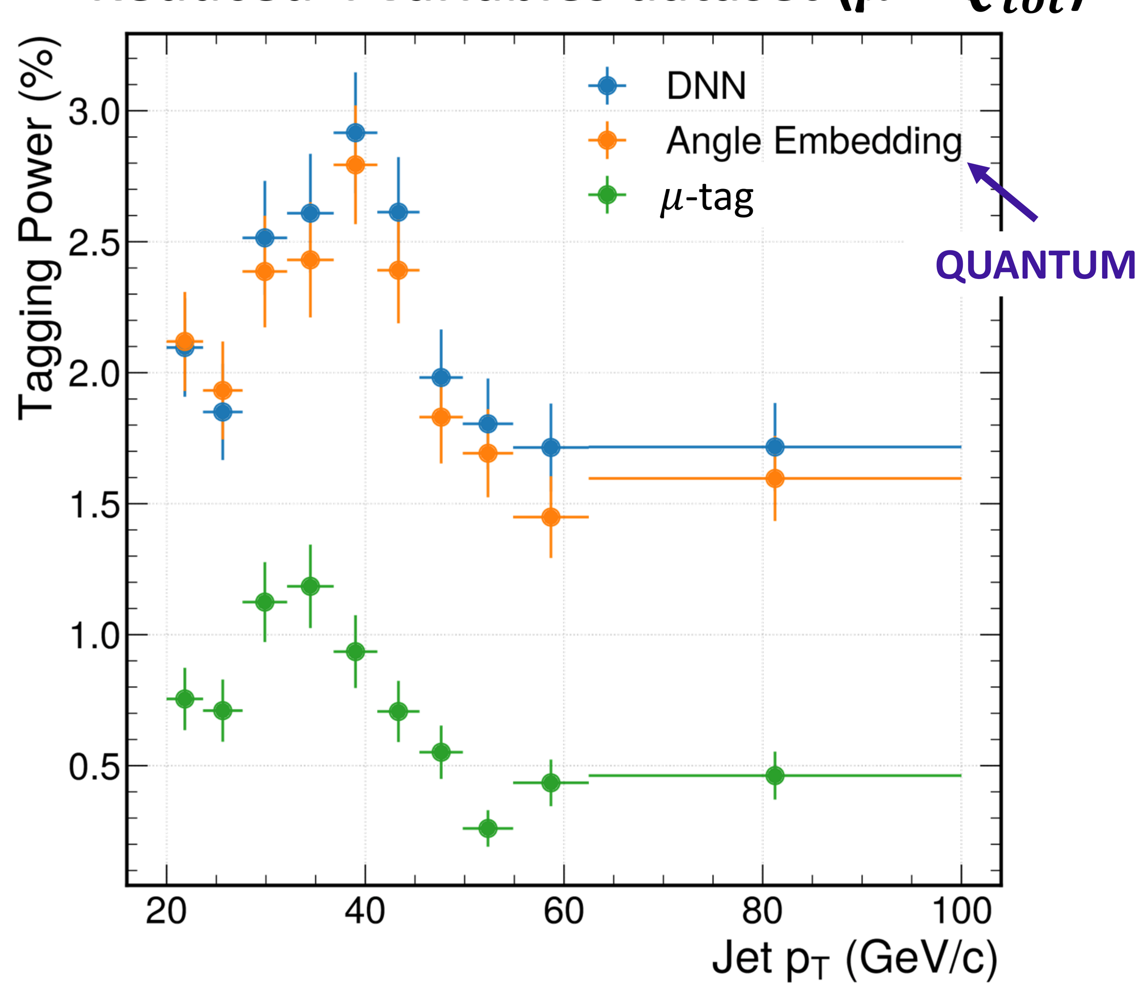
Efficiency (ϵ_{eff}) — Mistag (ω)

Complete 16 variables dataset



DNN performs better on the complete dataset. QML models were trained on 1/50th of jets due to computational constraints

Reduced 4 variables dataset ($\mu + Q_{tot}$)



DNN and QML show the same performance on a reduced dataset. Both outperform μ-tag. The same number of jets was used for training

POSSIBLE APPLICATION

Forward-Central $b\bar{b}$ production asymmetry

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

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

The **statistical uncertainty** on the asymmetry is directly related to the ***b*-jet charge tagging power**

$$\sigma[A_{b\bar{b}}^{FC}] \propto \frac{1}{\sqrt{\epsilon_{tag}}}$$

REFERENCES

1. *A. Gianelle, D. Lucchesi, D. Nicotra, L. Sestini, D. Zuliani (2021).* First implementation of Quantum Machine Learning algorithms for b-jet tagging at LHCb. https://indico.cern.ch/event/1053287/
2. *LHCb collaboration (2020).* Simulated jet samples for quark flavour identification studies. CERN Open Data Portal. http://doi.org/10.7483/OPENDATA.LHCB.N75T.TJPE