Quantum Computing Applications at LHCb

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Physics at LHCb

- LHCb is a **general purpose forward detector that** studies phase-space regions complementary to other experiments
- LHCb can rely on:
  - Excellent tracking performance
  - Excellent Particle Identification (PID)
  - Good calorimeter reconstruction
- The LHCb Data Processing and Analysis (DPA) project explores **new innovative analysis techniques**
- **Quantum Computing** (QC) may help in **improving** analysis performance for several tasks:
  - Jets reconstruction and classification
  - Track reconstruction
  - …
- The latest studies on QC and Quantum Machine Learning (QML) at LHCb are shown

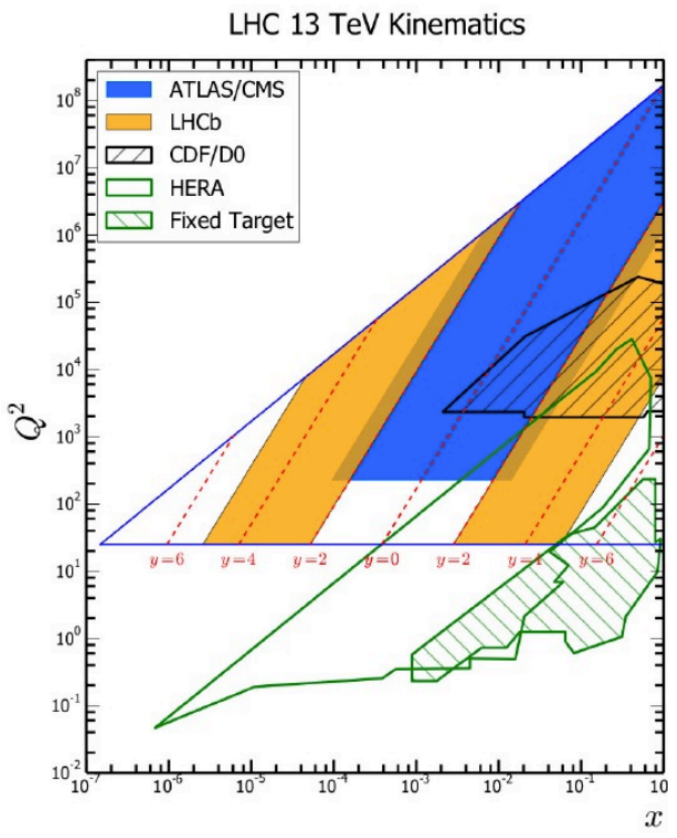

Figure 1: $x - Q^2$ plot showing the phase-space region studied by LHCb (in yellow) with respect to other experiments

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- A. Alves Jr. et al. The LHCb Detector at the LHC, JINST 3 (**2008**) S08005
- LHCb DPA project, https://lhcb-dpa.web.cern.ch/lhcb-dpa/index.html

b-jet identification with QML

- At LHCb it is possible to **distinguish** jets produced by b and $\bar{b}$ quarks
- This is fundamental to measure **angular $b\bar{b}$ asymmetries**
- An **inclusive** approach using features coming from the **jet substructure** has been used
- A QML algorithm has been applied to the **full LHCb simulation** of $b\bar{b}$ di-jets events at 13 TeV
- Two circuit structures have been studied:

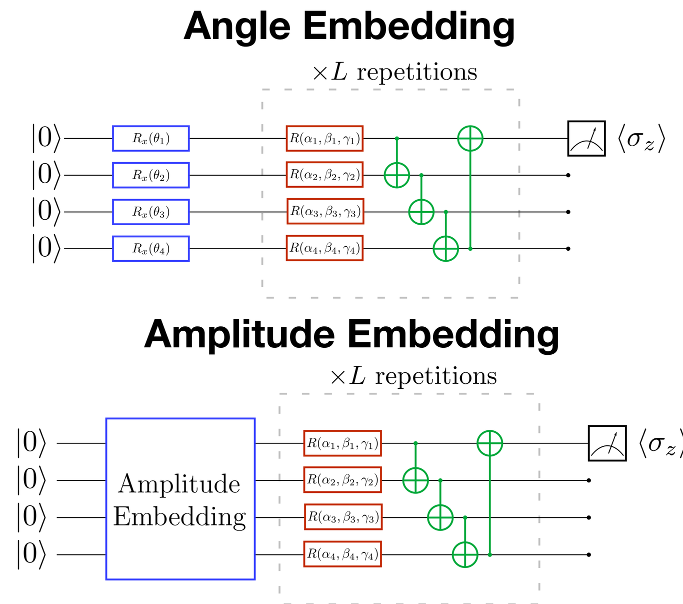


Figure 2: scheme of Angle and Amplitude Embedding circuits on four qubits register

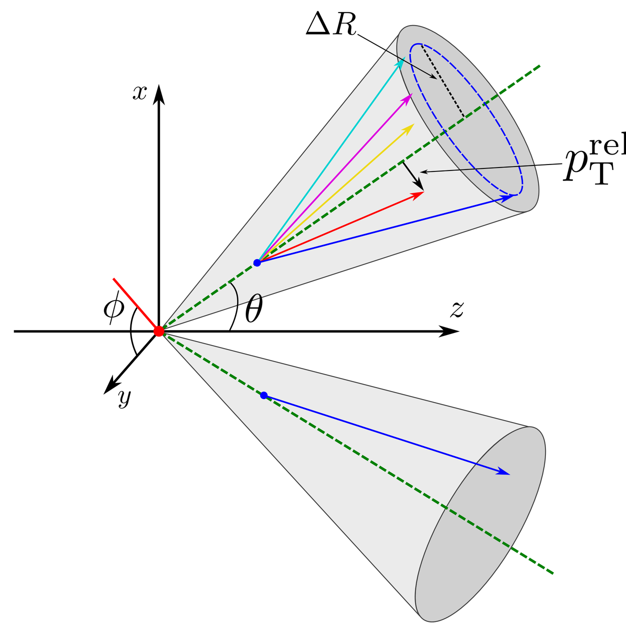


Figure 3: sketch of inclusive (upper jet) and exclusive (lower jet) approaches to b-jet charge identification

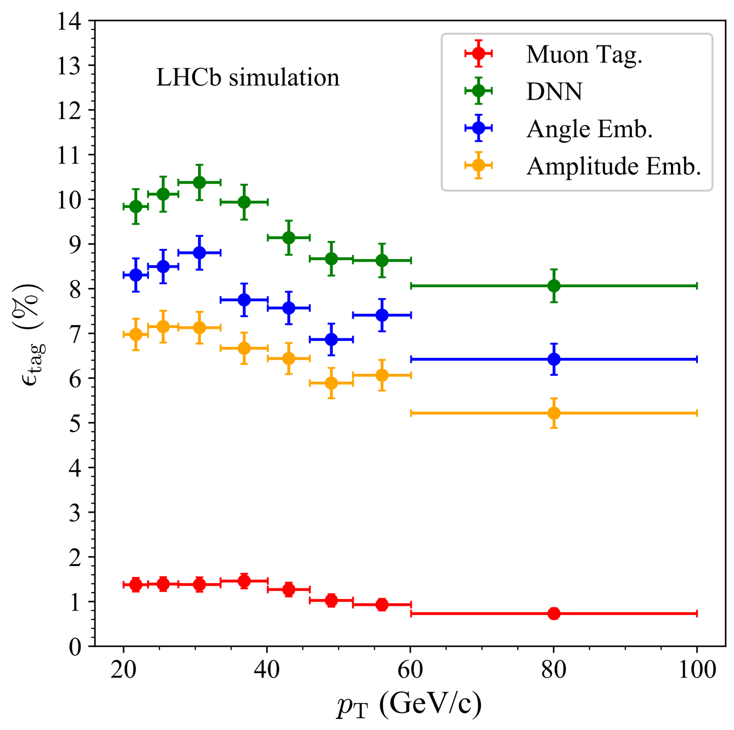


Figure 4: tagging power ϵ_{tag} as a function of jet p_T for QML and classical methods

- Circuits have been simulated with **Pennylane** library
- The figure of merit is the **tagging power** ϵ_{tag}:

$$\epsilon_{tag} = \epsilon_{eff}(2a-1)^2 \qquad \epsilon_{eff} = \text{efficiency} \qquad a = \text{mistag}$$

- Results have been compared with a standard **Deep Neural Network** (DNN) and with the LHCb **muon tagging** algorithm
- For **low number of qubits**, the DNN and the QML perform **similarly**
- For high number of qubits (16), the Angle Embedding structure approaches the DNN performance → still **room for improvement**!

- Performance has been evaluated depending on several aspects:
  - **Number of training events**: for low number of training events QML seems to perform better than classical algorithms
  - **Number of variational layers**: after some repetitions of variational layers, performance saturates
  - **Noise**: simulated noise contribution from IBM backends, structures with few qubits are robust to noise

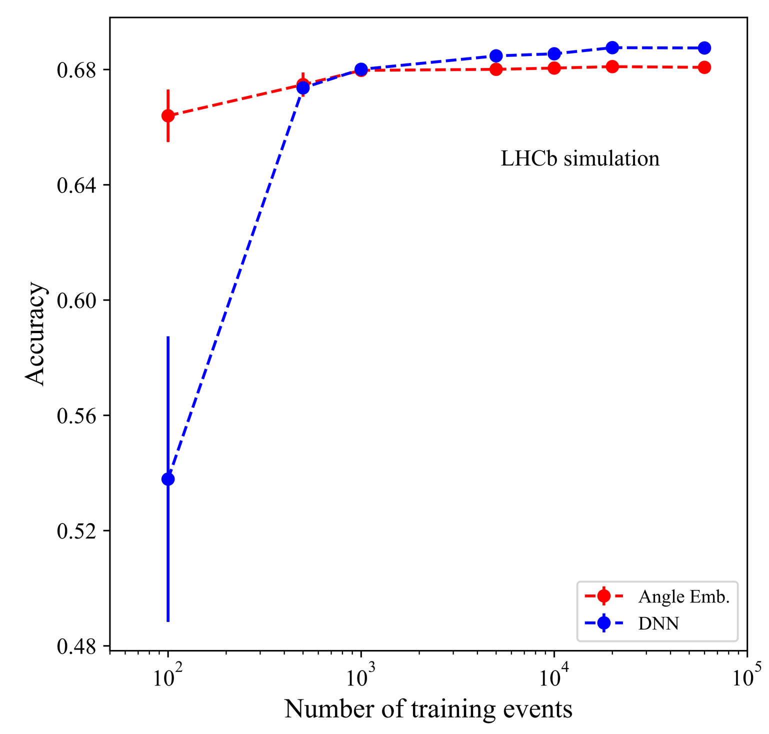


Figure 5: testing accuracy as a function of the number of training events for the DNN (blue) and the Angle Embedding circuit (red)

References
- Gianelle A. *et al.*, Quantum Machine Learning for *b*-jet charge identification. *J. High Energy Phys.* 2022, 14 (**2022**)
- LHCb Collaboration (2020). Simulated jet samples for quark flavour identification studies. CERN Open Data Portal

b- vs c-jet on IBM Hardware

- b vs c-jet classification is fundamental for several physics channels, such as **Higgs decay** to $b\bar{b}/c\bar{c}$
- Starting point: LHCb performance on Secondary Vertex (SV) tagging with BDTs
- SV is required in jets, **SV features** are used as input feature to QML and BDT
- Simulations are performed with Pennylane+JAX

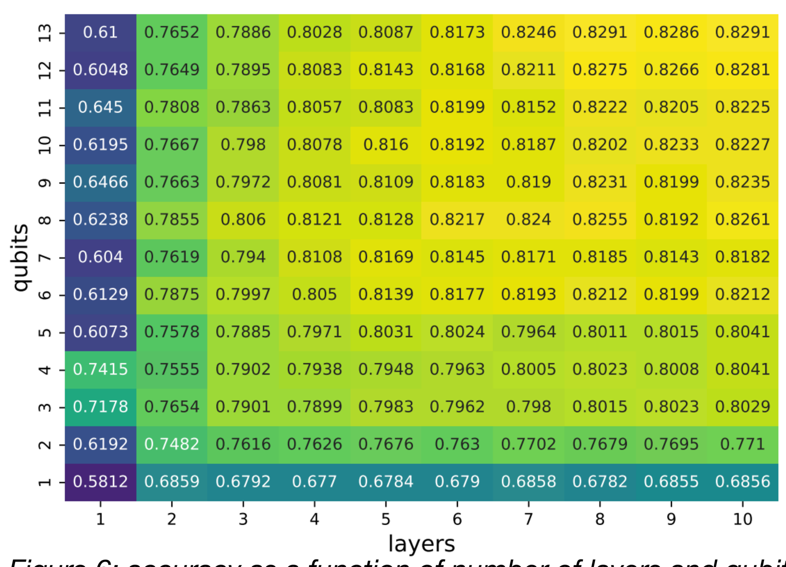


Figure 6: accuracy as a function of number of layers and qubits

- Dependence on **scaling** and **data embedding** has been assessed
- Performance with respect to number of layers and qubits has been studied
- QML algorithms perform **as good as BDT**
- Evaluation has been performed on **IBM quantum computers** `ibmq_toronto` and `ibm_nairobi`

- Hardware results for low number of qubits and **low number of gates** show **comparable results** to simulations
- **Transpiling study** shows importance of **careful circuit design**
- In the pipeline:
  - **Error mitigation** and scaling to more qubits
  - **Correlations** between qubits using entanglement entropy to get physics insights

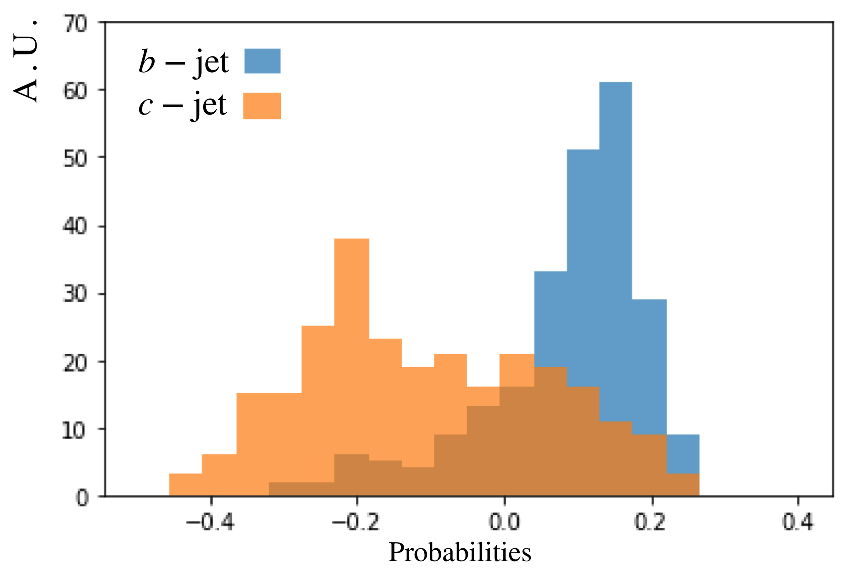


Figure 7: evaluation results for b (blue) and c-jet (orange) classification for `ibmq_toronto` quantum computer on 1000 events

References
- LHCb Collaboration, Identification of beauty and charm quark jets at LHC, JINST 10 (2015) 06
- Ballarin M. *et al.*, Entanglement entropy production in Quantum Neural Networks, arXiv:2206.02474

Ising-like approach to track reconstruction

Track reconstruction

- The **LHCb tracking system** is responsible for reconstructing the trajectories of **charged particles** produced in the pp collisions
- Particles leave signals (**hits**) flying through the detector. Original trajectories (**tracks**) are reconstructed from the set of 3D hits

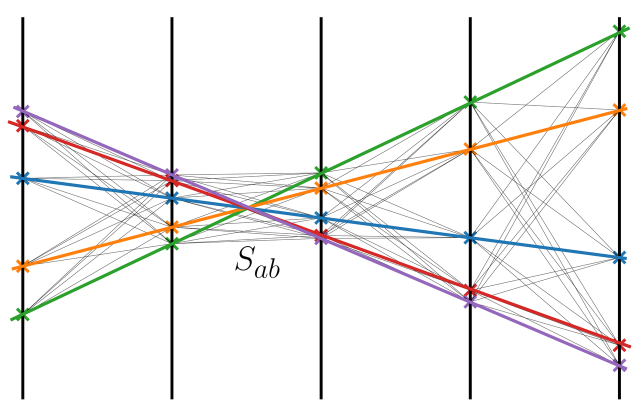
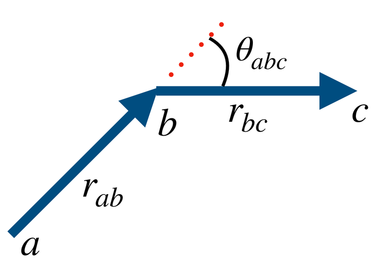


*Figure 8: Toy model of an event in the tracking system: a collection of **hits** left by the **charged particles** in the **detector layers**. The grey lines S_{ab} represent all the **candidate segments** between subsequent detectors. Coloured segments are the real track segments.*

- The **Denby-Peterson (DP) algorithm** solves a track reconstruction problem as a segment classification optimising the Hamiltonian

$$\mathcal{H} = -\frac{1}{2}\left[\sum_{a,b,c}\frac{\cos^{\lambda}\theta_{abc}}{r_{ab}+r_{bc}}S_{ab}S_{bc} - \alpha\left(\sum_{b\neq c}S_{ab}S_{ac} + \sum_{a\neq c}S_{ab}S_{cb}\right) - \beta\left(\sum_{a,b}S_{ab} - N\right)^2\right]$$

- It **favours aligned** and **short** pairs of segments and **penalises** pairs of segments that share the **same head** or the **same tail**
- It keeps the number of **active segments** close to the **number of hits** N



QAOA algorithm

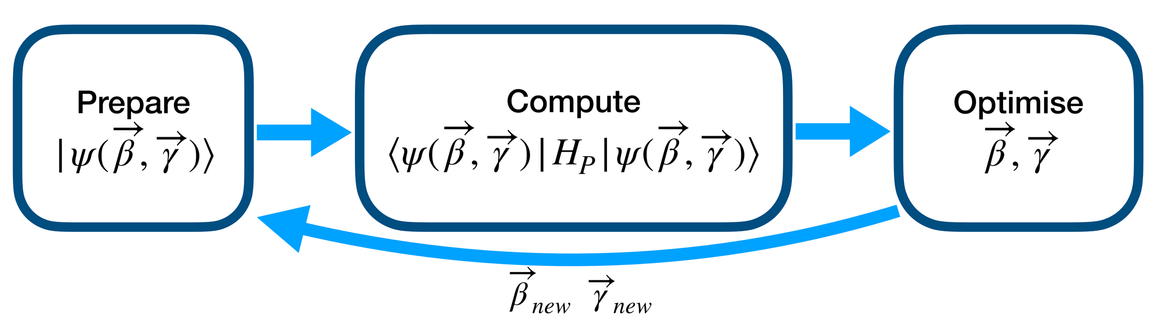
- The **Quantum Approximate Optimisation Algorithm (QAOA)** finds approximate solutions to combinatorial problems.
- $\mathcal{H}$ is used as a **problem Hamiltonian** H_P
- A **mixing Hamiltonian** H_M is defined, which usually takes the form of

$$H_M = X_1 + X_2 + \ldots X_N$$

where each X_i is a Pauli X gate applied to the i-th qubit.
- The following state is constructed

$$|\psi(\vec{\beta},\vec{\gamma})\rangle = e^{-i\beta_n H_M}e^{-i\gamma_n H_P}e^{-i\beta_{n-1}H_M}e^{-i\gamma_{n-1}H_P}\ldots e^{-i\beta_1 H_M}e^{-i\gamma_1 H_P}|\psi_0\rangle$$

where $|\psi_0\rangle = H^{\otimes N}|0\rangle$
- The coefficients $\vec{\beta}$ and $\vec{\gamma}$ are optimised by a classical optimiser to minimise the expectation value $\langle\psi(\vec{\beta},\vec{\gamma})|H_P|\psi(\vec{\beta},\vec{\gamma})\rangle$



Quantum Hopfield neural network

- **Hopfield networks** are a class of **recurrent neural networks** usually employed in the contexts of pattern recognition and associative memories

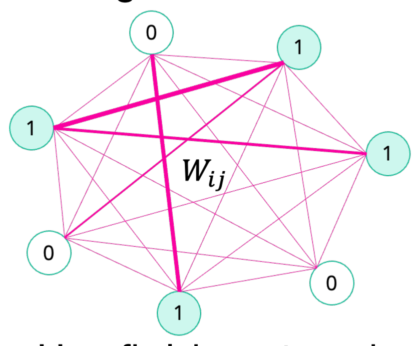


*Figure 9: a Hopfield network is a set of **densely, not self-connected binary neurons**. The **coupling** between neurons is described in the W_{ij} matrix. The optimisation is done updating one neuron at the time until a stable state is reached. **Tracking** applications, a neuron is associated to each candidate segment. The couplings are determined according to the DP Hamiltonian*

- Hopfield networks have been used in tracking applications at **LHCb, ALICE, ALEPH** and **HERA-B**
- *Rebentrost et al.* have developed a **quantum algorithm** to optimise an Hopfield network.

Network embedded in the amplitude of a **quantum state**

$$|x\rangle = \frac{1}{\||x\|\|_2}\sum_i x_i|i\rangle$$

Optimisation using the **quantum algorithm for linear systems of equations** with a **exponential advantage** over classical algorithms for events with a large number of hits.

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- *Zlokapa A. et al. Charged particle tracking with quantum annealing optimization. Quantum Mach. Intell. 3, 27 (**2021**).*
- Rebentrost P. *et al.* Quantum Hopfield neural network. Phys.Rev.A 98 (**2018**)
- Peterson C. Track Finding With Neural Networks Nucl.Instrum.Meth.A 279 (**1989**)
- Denby B. The Use of Neural Networks in High-Energy Physics. Neural Computation, vol. 5, no. 4 (**1993**)

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