CINECA - Practical Quantum Computing School

Quantum Machine Learning for jet tagging @ LHCb

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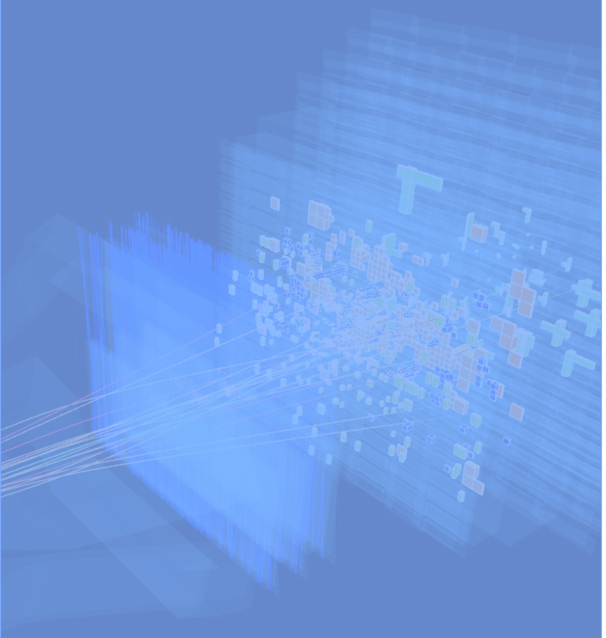


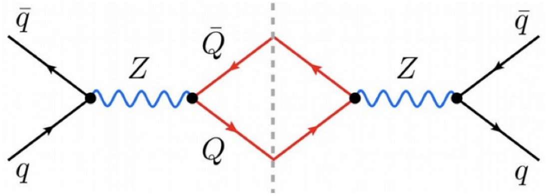
Physics introduction

Physics cases

Jet flavor identification is mandatory for several physics cases

- **b/b-bar charge asymmetry**, interesting for **New Physics** searches (our physics case)

$$A_C^{b\bar{b}} = \frac{N(\Delta y > 0) - N(\Delta y < 0)}{N(\Delta y > 0) + N(\Delta y < 0)} \qquad \Delta y = |y_b| - |y_{\bar{b}}|$$

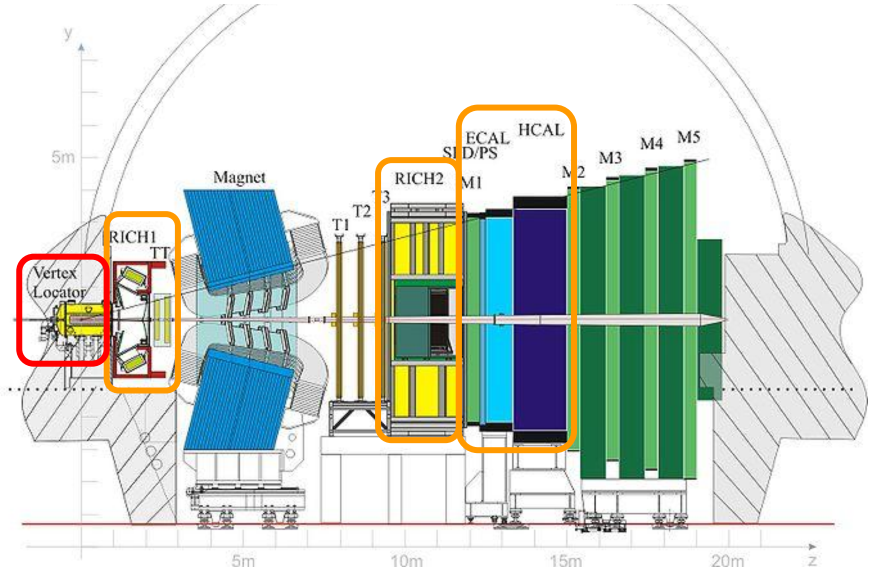


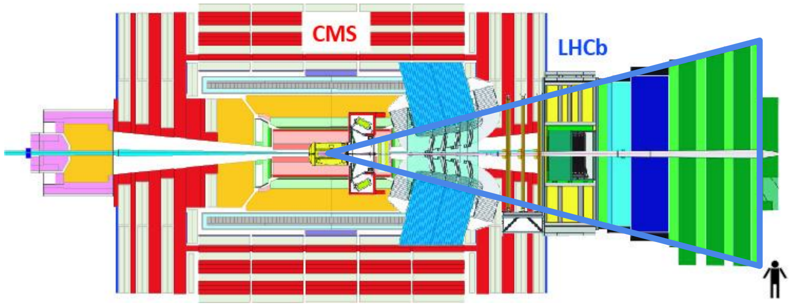
- **identification** of **Higgs boson** decaying to:
  - b b-bar jets (recently observed @ ATLAS & CMS)
  - c c-bar jets (not yet observed)

Final states detected by the experiment → **jets**

LHCb

LHCb is a **forward spectrometer** designed to study **flavour physics**

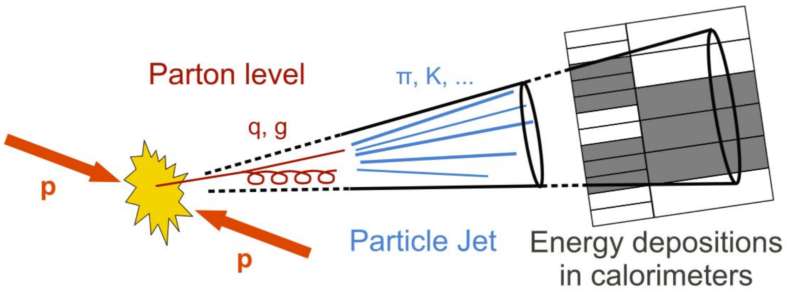


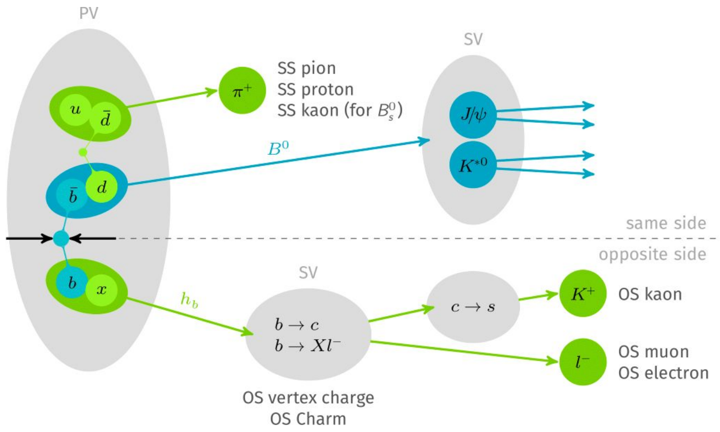


- complementary phase-space region w.r.t. ATLAS & CMS
- excellent vertex reconstruction
- excellent Particle Identification (PID)

b-jet tagging @ LHCb

At LHC is **fundamental** to identify the **flavour** of the quark originating the jet → **jet tagging**





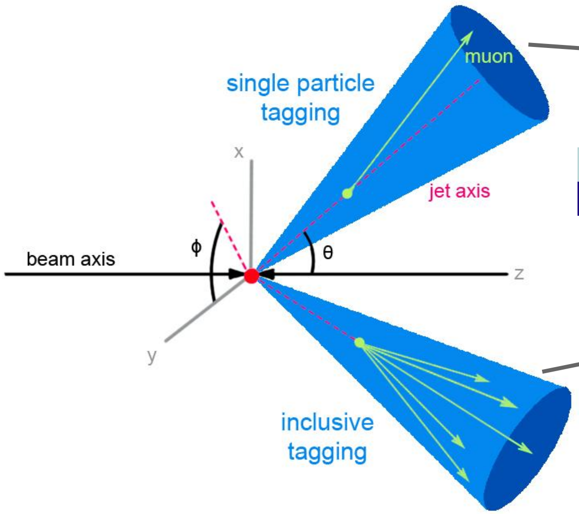
"Jets are streams of particles produced by QCD processes in proton-proton collisions"

In particular @ LHCb we are interested in studying jets generated by b and b-bar quarks

b-jet tagging

Classical tagging methods

There are two possible approaches to achieve this task: **exclusive** and **inclusive** algorithms



exclusive algorithms use information from a specific process to infer the quark flavour

muon tagging: a μ coming from the b (or b-bar) semileptonic decay (P =10%) is used to tag the jet (μ and b charges are correlated)

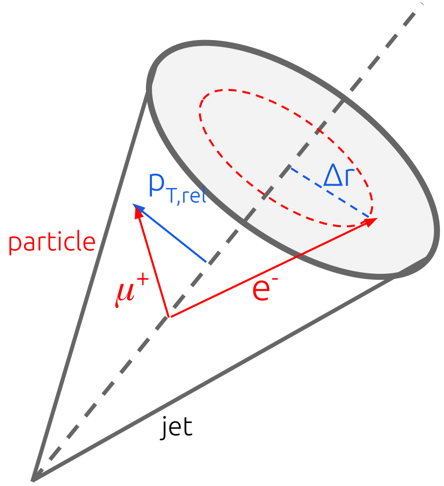
inclusive algorithms use information from the whole jet substructure

Machine Learning (ML) algorithms such as **Deep Neural Networks** (DNN)

LHCb Open Data - https://opendata.cern.ch/record/4910

Dataset

LHCb detailed simulation of di-jet generated by b and b-bar quarks @ E_{cm} = 13 TeV (Run 2 condition) → ~ 700.000 jets (60% training, 40% testing & evaluation)



Inside each jet we consider 5 types of particles

muon electron pion kaon proton

and for each type we select 3 variables:

- $p_{T,rel}$: transverse momentum relative to the jet axis
- Δr: distance relative to jet axis
- q: charge of the particle

\+ 1 global variable → total jet charge

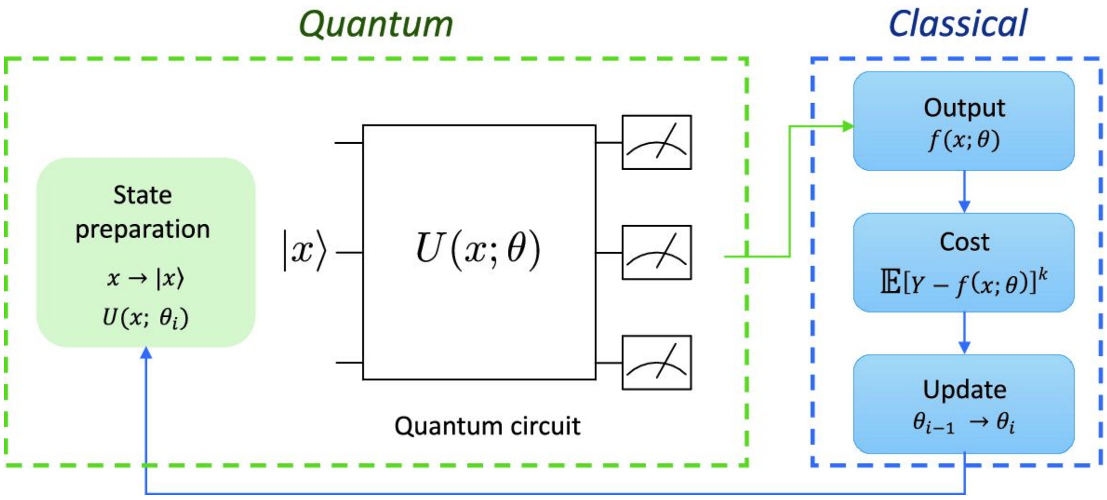
for a total of 16 input variables

the LHCb detailed simulation resembles LHCb data

A quantum approach

Going to quantum...

classification problem = **Variational Quantum Classifier**



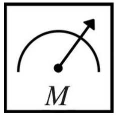
Data are fed into variational quantum circuit.

Measurements of qubits are mapped to probabilities for labels.

Probabilities are used to estimate a cost function which is optimized through a classical optimizer

Loss function and Optimizer

Measurement



$$\mathbb{E}(\sigma_z) = M \quad M \in [-1, 1]$$

Tagging probabilities

$$P_b = \frac{M+1}{2}$$

$$P_{\bar{b}} = 1 - P_b$$

Cost function

$$MSE(\theta_i) = \frac{1}{N} \sum_{dataset} (M - M_{true})^2$$

$$CE(\theta_i) = -\frac{1}{N} \sum_{dataset} \sum_{i \in \{b, \bar{b}\}} p_i \log q_i$$

Classical optimization

Gradient-Free optimizers.
e.g.

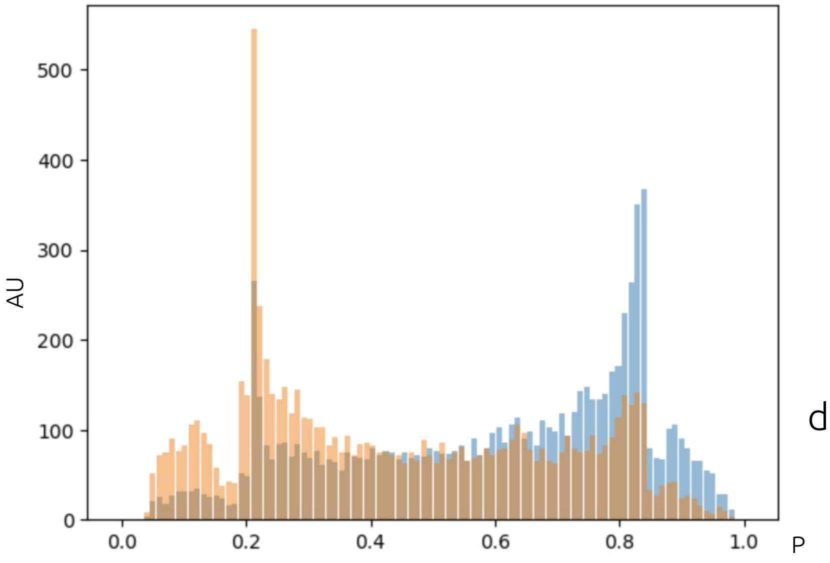
- COBYLA
- SPSA

Gradient Descent optimizers:
e.g.

- ADAM
- RMSProp

Tagging Performance

The figure of merit for this task is the **tagging power**



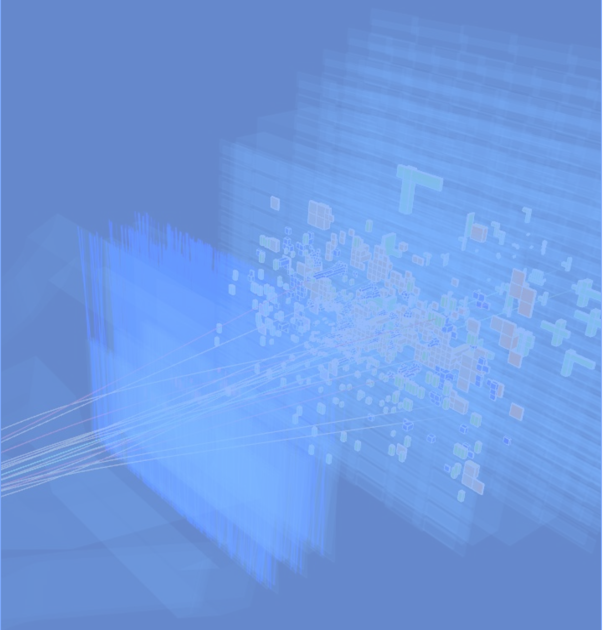
$$\varepsilon_{tag} = \varepsilon_{eff} \cdot (1 - 2\omega)^2$$

$\frac{N_{tagged}}{N_{tot}}$ ***"efficiency"***

$\frac{N_{wrong}}{N_{tagged}}$ ***"mistag"***

It is possible to put some cuts on the probability distribution in order to maximize the tagging power

reduce efficiency, increase accuracy
→ increase tagging power



A look at the code!

https://doi.org/10.5281/zenodo.5707435