UNIVERSITÀ DEGLI STUDI DI PADOVA

Istituto Nazionale di Fisica Nucleare

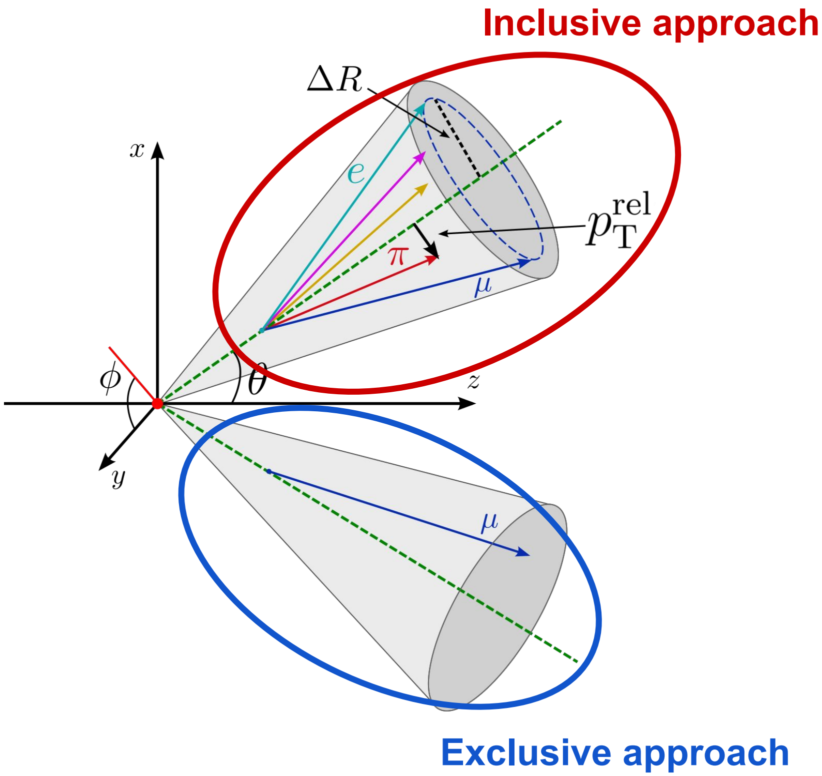
Quantum Machine Learning for b-jet identification

Alessio Gianelle, Donatella Lucchesi, Lorenzo Sestini, Davide Zuliani

https://arxiv.org/abs/2202.13943

Quantum Computing with IBM Q
01/07/2022

b-jet charge identification



Identification of the charge of the b quark

Inclusive algorithms

Use information coming from the **whole jet structure** (e.g. Deep Neural Networks)

Exclusive algorithms

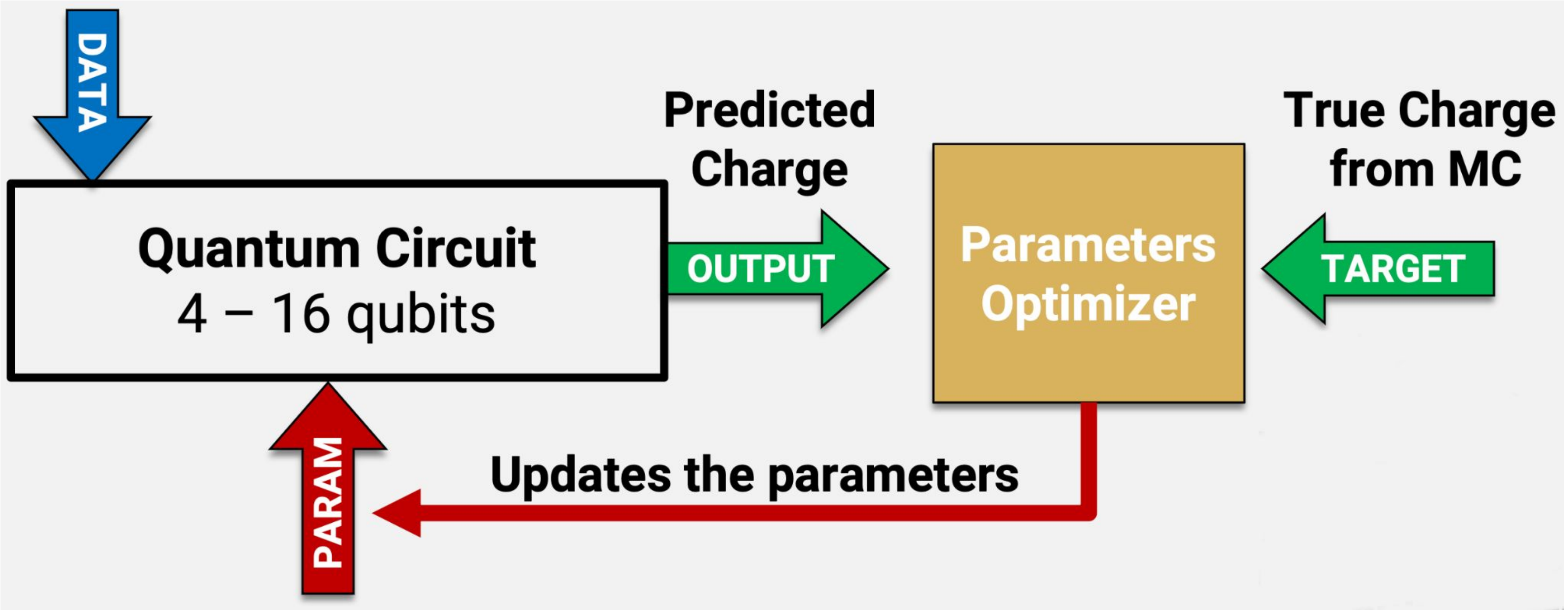
Look for **specific processes** inside the jet

Muon tagging algorithm

Look for an high-pt muon from the semileptonic decay of the B-hadron: $\mu^- \rightarrow b \quad \mu^+ \rightarrow \bar{b}$

Efficiency limited by the BR of the decay: ~ 10%

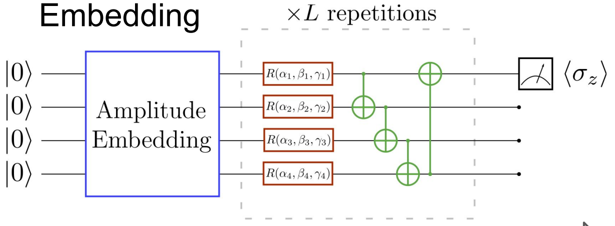
Variational Quantum Classifier



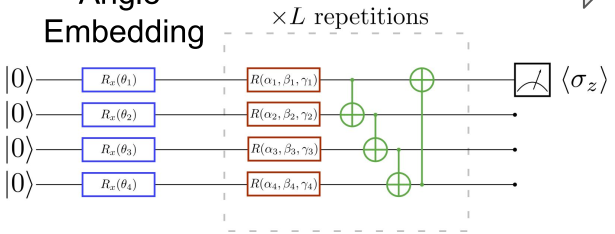
A classical Deep Neural Network was also developed (as a baseline)

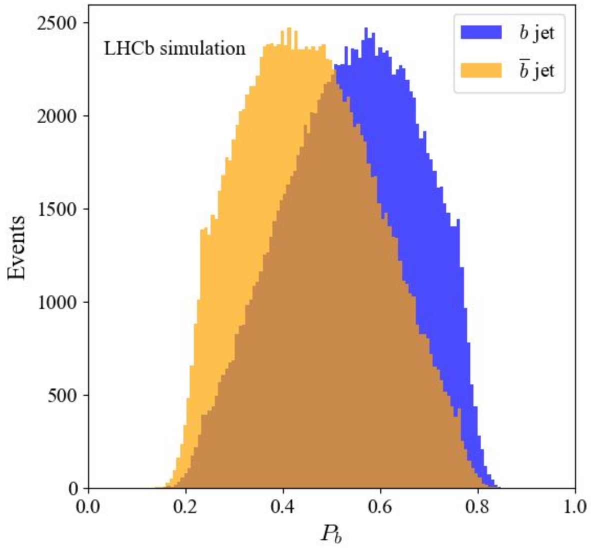
Training results

Amplitude Embedding

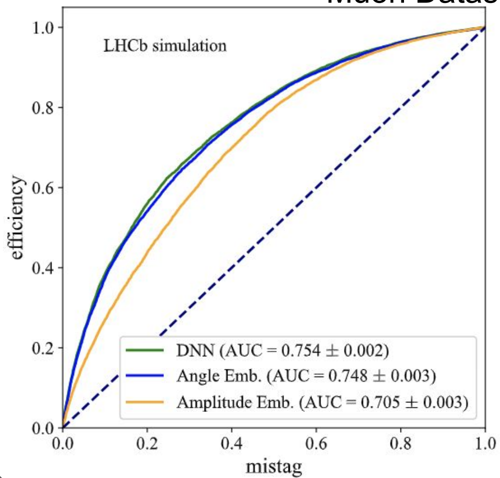


Angle Embedding

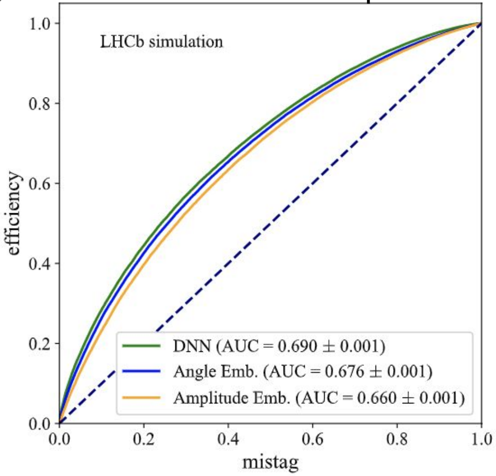




Muon Dataset



Complete Dataset

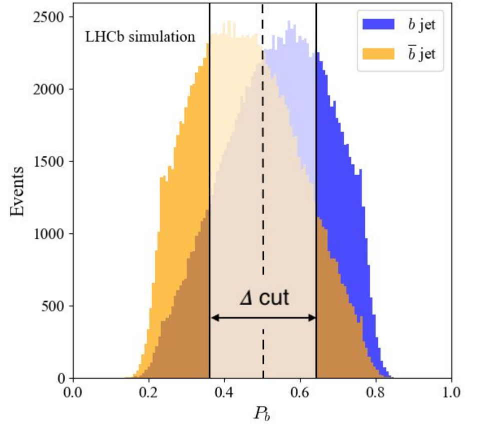


- The Angle Embedding circuit performs better than the Amplitude Embedding circuit, for both the Muon and the Complete dataset
- For the Muon dataset the Angle Emb. circuit performs as good as the DNN

Results on Tagging Power

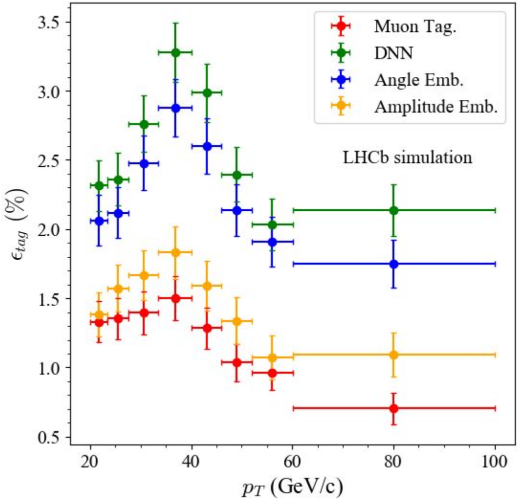
$$\epsilon_{\text{tag}} = \epsilon_{\text{eff}}(1-2\omega)^2$$

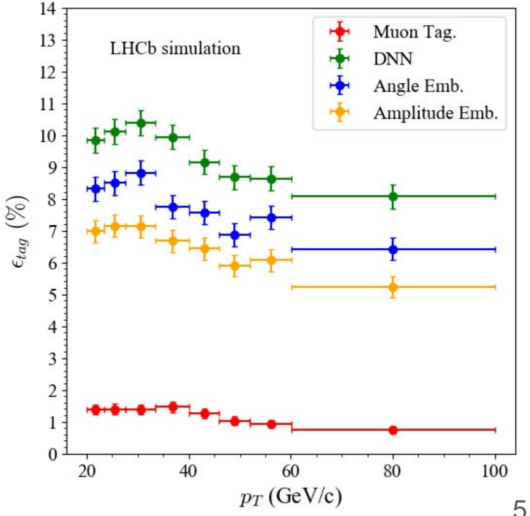
$$\epsilon_{\text{eff}} = \frac{\text{n. of tagged jets}}{\text{total n. of jets}} \quad \omega = \frac{\text{n. of wrongly tagged jets}}{\text{n. of tagged jets}}$$



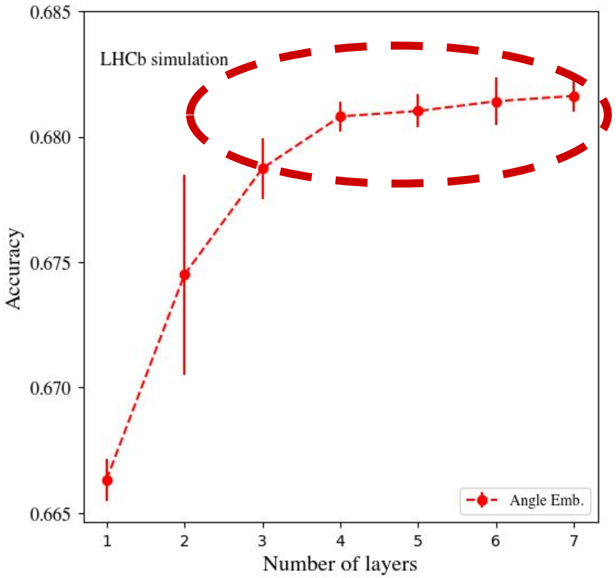
- It can be interpreted as the **effective fraction** of jets that contribute to a b-bbar asymmetry measurement

- An optimal cut on the probability distribution is used to maximise ϵ_{tag}



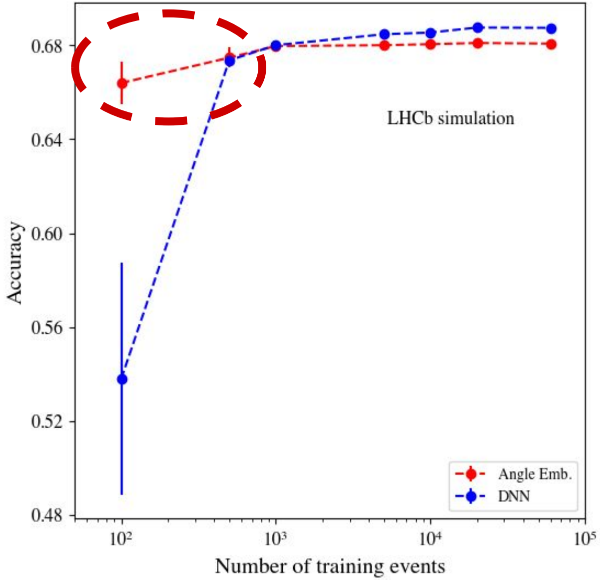


Accessing performance



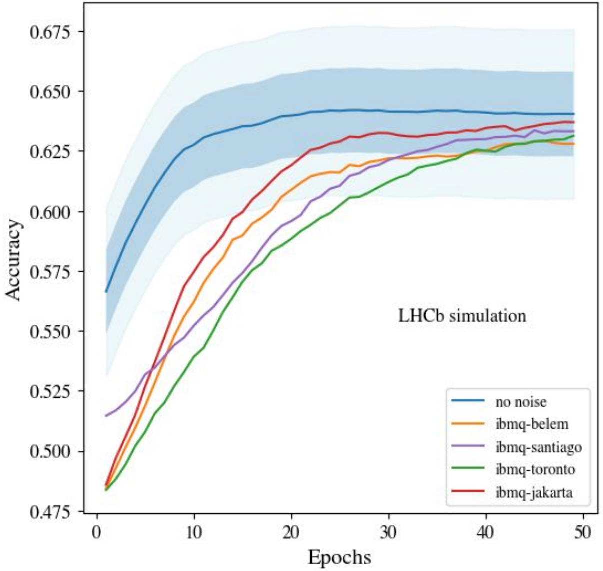
Accuracy vs.

number of layers



Accuracy vs. number

of training events



Simulation with noise

from ibm QC backend

Overview and future perspectives

- **Paper accepted for publication in JHEP**
- **First QC application developed within a LHC collaboration**
- **First QML application to LHC detector simulations**

EUROPEAN ORGANIZATION FOR NUCLEAR RESEARCH (CERN)

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Quantum Machine Learning for *b*-jet identification

Alessio Gianelle[1], Patrick Koppenburg[2], Donatella Lucchesi[1,3], Davide Nicotra[3,4], Eduardo Rodrigues[5], Lorenzo Sestini[1], Jacco de Vries[4], Davide Zuliani[1,3,6]

[1] *INFN Sezione di Padova, Padova, Italy*
[2] *Nikhef National Institute for Subatomic Physics, Amsterdam, Netherlands*
[3] *Università degli Studi di Padova, Padova, Italy*
[4] *Universiteit Maastricht, Maastricht, Netherlands*
[5] *University of Liverpool, Liverpool, United Kingdom*
[6] *European Organization for Nuclear Research (CERN), Geneva, Switzerland*

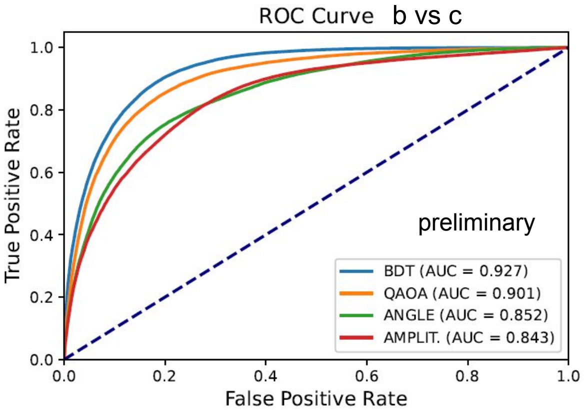
Abstract

Machine Learning algorithms have played an important role in hadronic jet classification problems. The large variety of models applied to Large Hadron Collider data has demonstrated that there is still room for improvement. In this context Quantum Machine Learning is a new and almost unexplored methodology, where the intrinsic properties of quantum computation could be used to exploit particles correlations for improving the jet classification performance. In this paper, we present a brand new approach to identify if a jet contains a hadron formed by a b or $\bar{b}$ quark at the moment of production, based on a Variational Quantum Classifier applied to simulated data of the LHCb experiment. Quantum models are trained and evaluated using LHCb simulation. The jet identification performance is compared with a Deep Neural Network model to assess which method gives the better performance.

Submitted to JHEP

Future perspectives:

1. Application to the **b- vs c-jet tagging** for Higgs identification
2. Running of **IBM Quantum hardware** (mainly testing pretrained configurations)
3. **Physics insights** from correlations encoded in **entanglement**



Thank you for the attention

BACKUP

Software libraries and Hardware resources

- The algorithms were tested on **noiseless** and **noisy** quantum simulations

PENNYLANE

- Library designed for Quantum ML
- Automatic calculation of the **gradients** of quantum circuits
- **Exploits GPUs!**

Qiskit

- Supported by **IBM Quantum**
- Noisy simulations emulate IBM Quantum hardware
- Run on IBM Q Hardware

CINECA

MARCONI100

CPU	**GPU**
2x16 cores IBM POWER9 AC922	4 x NVIDIA Volta V100 GPUs

Dataset

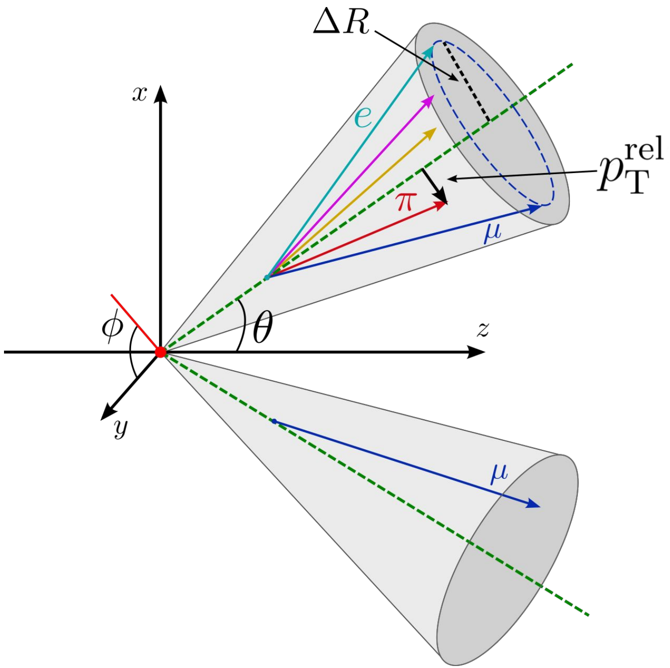
- Simulations sample of di-jets generated by b and b-bar quarks @ Run 2 condition
- ~ 700.000 jets (60% training, 40% testing)
- Inside each jet we consider 5 types of particles

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 in the (η,φ) plane
- q : charge of the particle

\+ 1 global variable → weighted jet charge



Complete dataset
15 variables + jet charge

Muon dataset
3 muon variables + jet charge

Jet reconstruction

1. **Particle Flow** : tracks and calorimeter clusters are selected

2. **Anti-kt** : inputs are clustered to form jets of a given cone radius

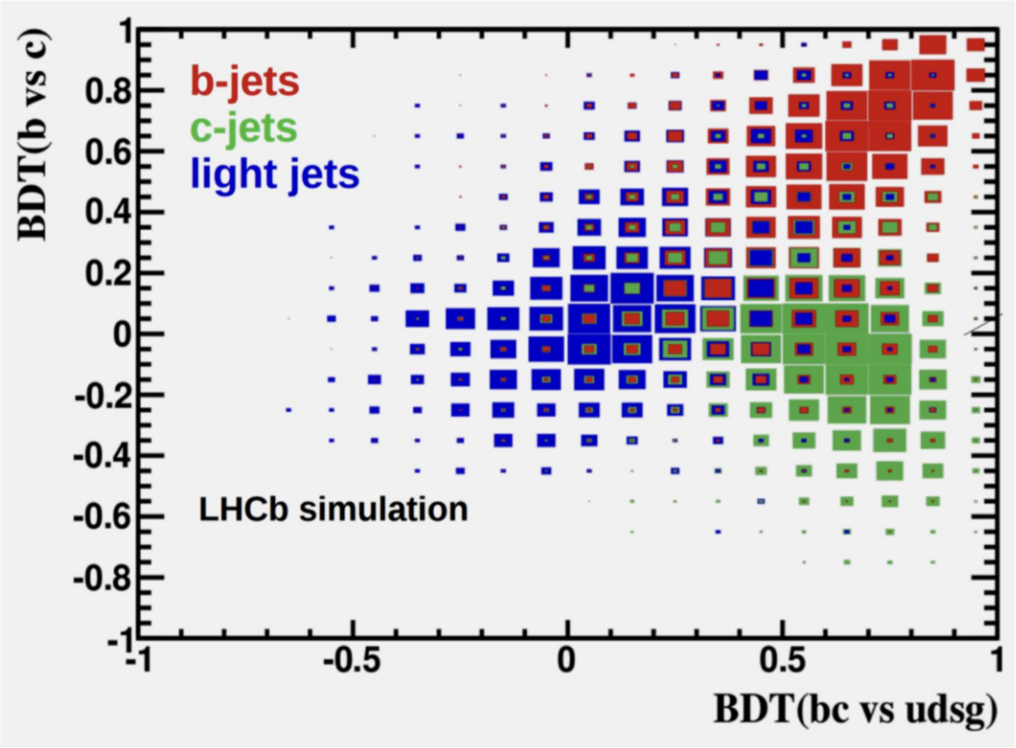
3. **Jet 4-momentum** is defined (sum of particles 4-momenta)

4. **Jet energy correction**: jet energy is corrected by detector efficiencies

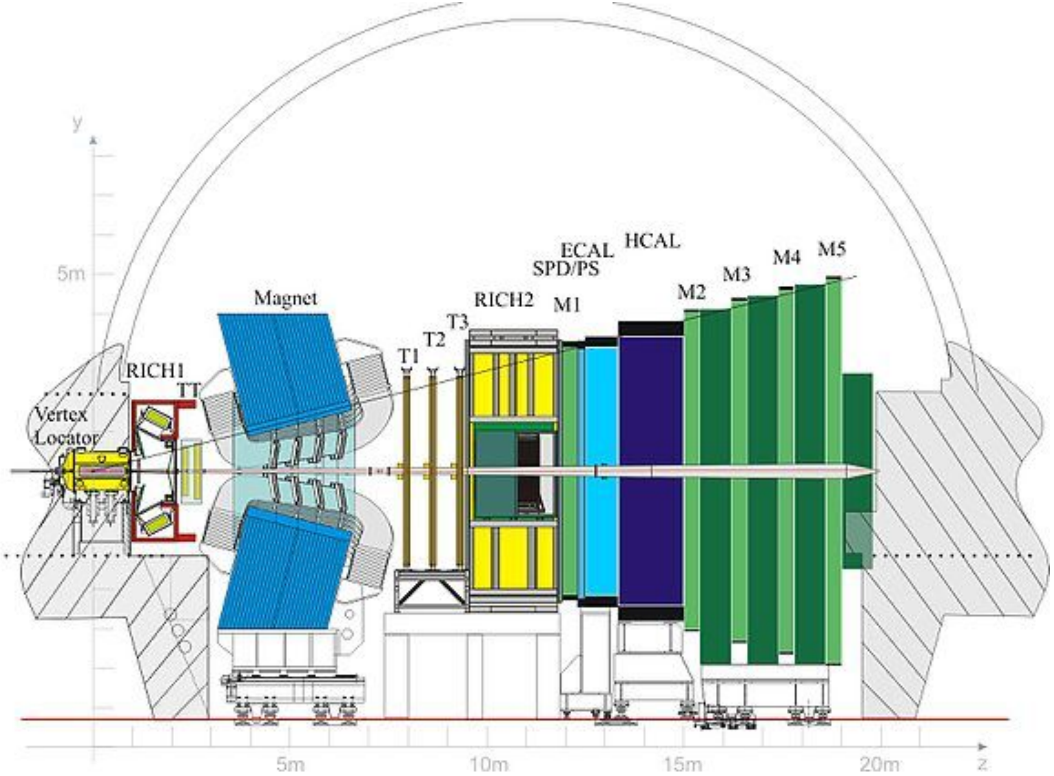
b vs c vs light

1. Secondary Vertex

2. BDTs

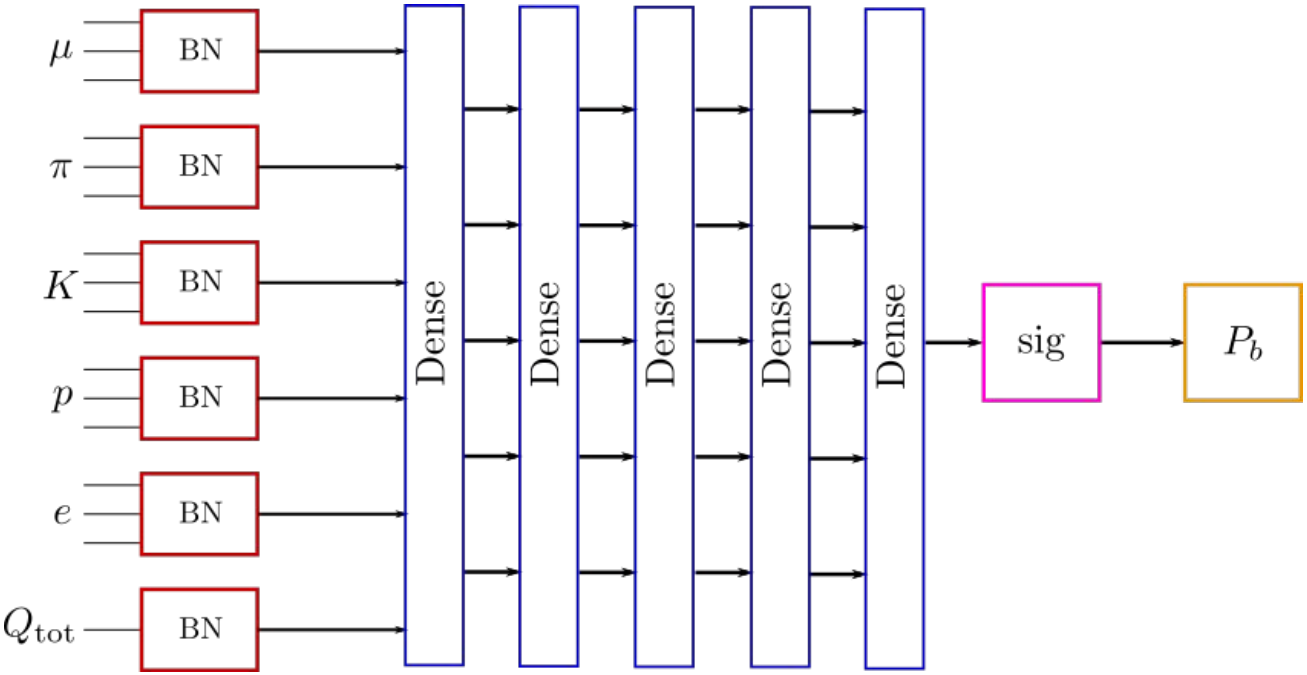


Detector



y
5m
Magnet
RICH1
TT
Vertex
Locator
T1
T2
T3
RICH2
SPD/PS
ECAL
HCAL
M1
M2
M3
M4
M5
5m
10m
15m
20m
z

DNN



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Dense
Dense
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