b-Jet and c-Jet Identification at LHCb Using Deep Learning Techniques

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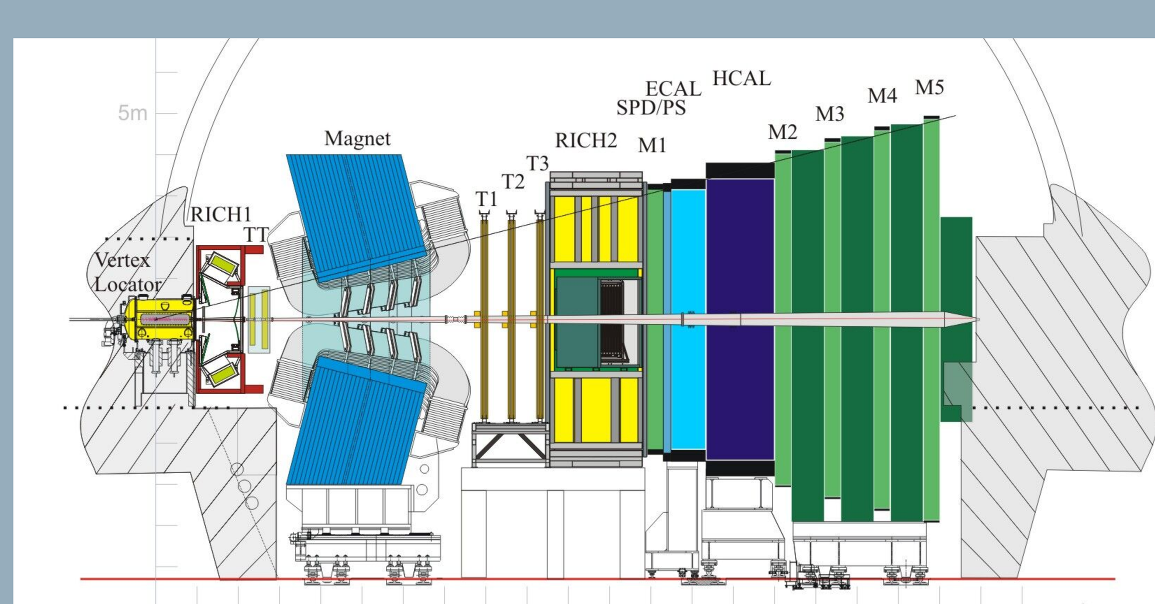
Abstract

The LHCb experiment at CERN is capable of performing measurements with jets of particles generated by beauty (b) quarks, as the measurement of the Z–>bb-bar production cross section. Due to an upgraded detector that will be ready in 2021, the experiment will collect a large sample of jets, therefore the identification of the quarks that initiated the jets will be of great importance as well as the reduction of the background generated by light quarks and gluons. Identification of jets that originate from the hadronisation of b and charm (c) quarks is important for studying the Standard Model processes and for searching for new physics. We identify these jets with deep learning algorithms developed to select the b and c quarks. We aim to improve the jet tagging by using Deep Neural Network (DNN) algorithms, which uses several observables to differentiate between b, c and light quarks.

Introduction

The indication of a b or c jet is the presence of a long lived b or c hadron that carries an ample fraction of the jet energy. Jets are showers of particles generated from energetic quarks or gluons, produced during a collision. They are an excellent tool to study fragmentation and hadronisation in proton-proton collisions. The LHCb was designed to identify b and c hadrons covering the pseudorapidity range $2<\eta<5$, so it is expected to perform well at identifying, or tagging, these jets.

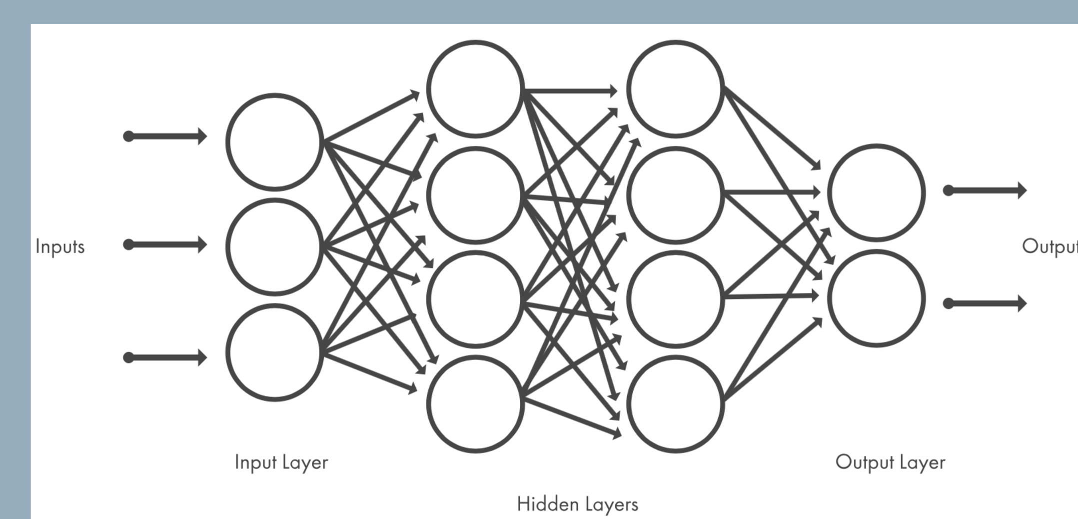


LHCb Detector Diagram; Protons collide in the precise vertex detector on the left. The RICH detectors are essential for particle identification, and the tracking detectors provide information to reconstruct the jets. The magnetic field allows for the measurement of momentum by the particles deflection. On the right are the electromagnetic, hadron calorimeters, and muon chambers.

Deep Learning Technique

Deep Neural Network

- signals travel between 'neurons' and the network assigns weights to various neurons
- A neuron weighted more heavily than another will exert more of an effect on the next layer of neurons.
- The final layer puts together the weighted inputs to come up with an answer.

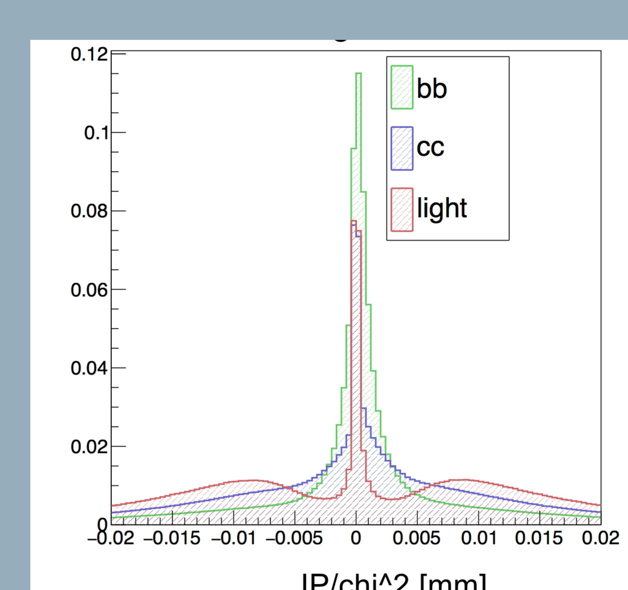


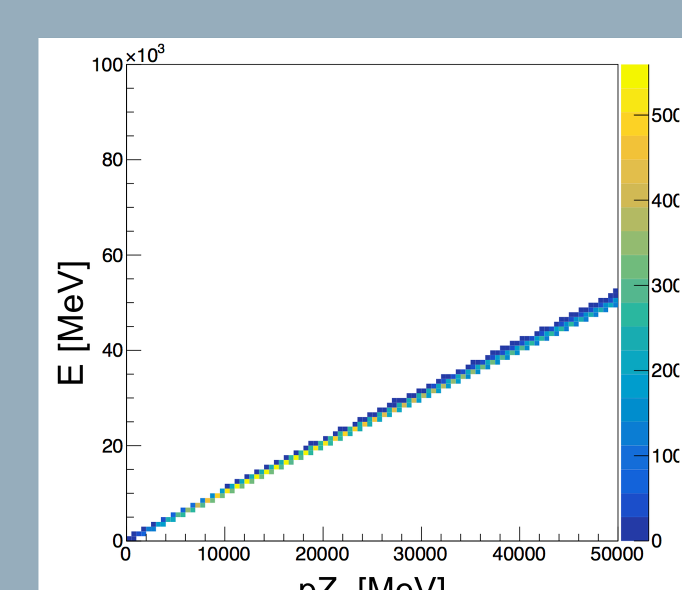
DNN illustration: Increasing the number of layers in DNN produces an algorithm that works better compared to one layer. A shallow network may perform as good, but it may require an immense amount of neurons.

Procedure

Analyze Simulated LHCb Data

- analyze distribution of observables such as momentum, energy, impact parameter
- interested in distributions that are most distinguishable between b, c, and light jets
- remove correlated observables to optimize DNN

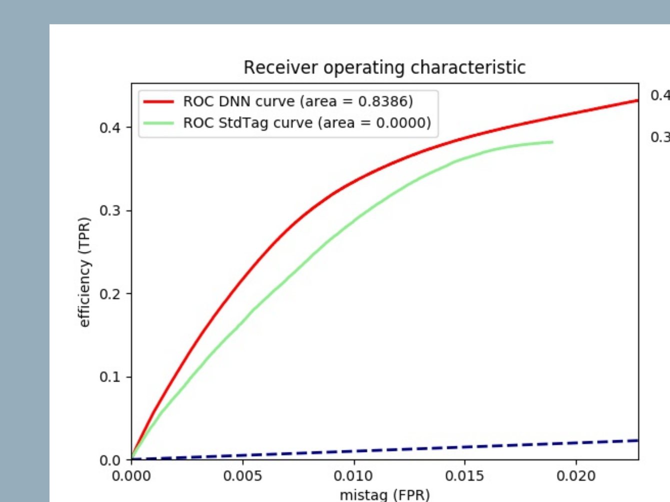




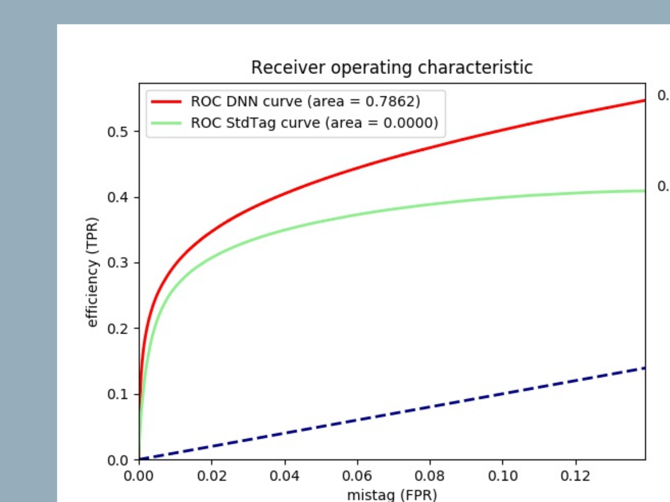
Observables: (left) Distribution of impact parameter divided by X^2 (right) correlation of z momentum and energy for charged particles

Preliminary Results

- Tested 8 different DNN configurations
- All performed better than the previous BDT algorithm
- performance is determined by ROC curves
- best performing DNN model uses 100 % of the data for testing, 38 observables



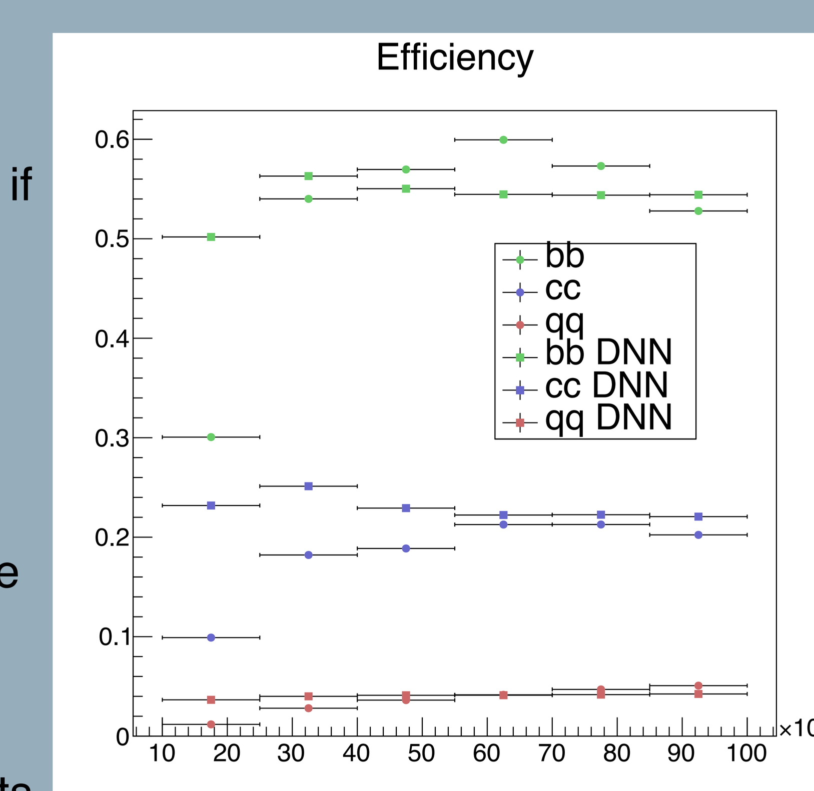
b vs c ROC: DNN algorithm (red) and BDT algorithm (green)



b vs q ROC: DNN algorithm (red) andBDT algorithm (green)

Efficiency Curve

Efficiency as a function of transverse momentum to see if biases are introduced in the spectrum. We determine efficiency with the DNN output: probabilities of b, c, and light quarks to be b, c, and light quarks. The number of tagged yields for the DNN algorithm are obtained requiring a probability of tagging a light quark < 0.15. We always see a greater efficiency for b jets, but not c jets



Further Analysis

- Continue to optimize algorithm by testing various configuration
  - change the number of layers of the DNN
- Study the correlation between charged and neutral particle observables
- More CPU or GPU for computation might improve results

References and Acknowledgements:

The LHCb Collaboration; JINST 10 (2015) P06013, Int. J. Mod. Phys. A 30, 1530022 (2015)
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