Jet flavour tagging using Deep Learning in the CMS experiment

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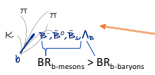
on behalf of the CMS Collaboration

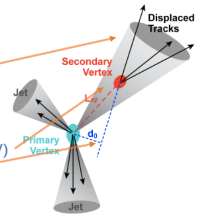
1. Motivation

The identification of jets originating from heavy flavour quarks (b/c 'tagging') is crucial in various studies at the Large Hadron Collider, in both New Physics searches and Standard Model processes.

2. Key features of b jets



b quarks typically hadronise in B hadrons forming the b jets



b hadrons: distinctive features with detectable particularities:

- Long lifetime ⟹ large displacement of Secondary Vertex (SV)
- Mass of 5–10 GeV ⟹ large decay angle ⟹ large d_0
- Possible decay to leptons [BR ≈ 42%]
- ~5 charged tracks per decay

3. b and c taggers

CSVv2: 'Combined* SV, version 2' [updated CSV for Run2]

- Neural Network (NN) instead of likelihood ratio
- Input: info on tracks & SV (='combined')

cMVAv2: 'combined* Multivariate Algorithm, version 2'

- Boosted Decision Tree (BDT)
- Input: info on tracks, SV (combined) & soft leptons in the jet as the output of the taggers:
  - → Jet Probability (JP), Jet B Probability (JBP)
  - → CSVv2
  - → Soft Electron (SE), Soft Muon (SM)

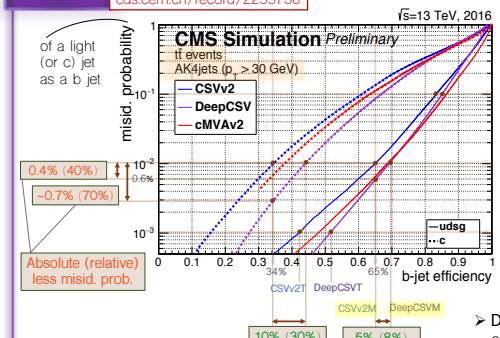
ctagger: c jet identification algorithm against b (CvsB) and light (CvsL) jets

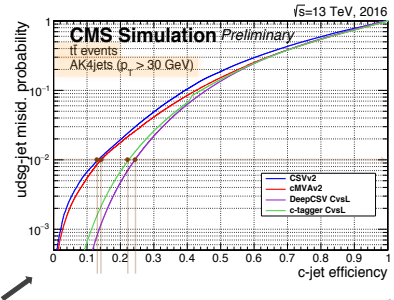
- Gradient Boosting Classifier (GBC)
- Input: info on tracks, SV (combined) & soft leptons in the jet

Same input as CSVv2 but based on more tracks, deep NN, multi-classification

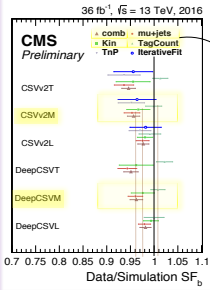
DeepCSV

CMS DP 2017-005
cds.cern.ch/record/2255736





- DeepCSV significantly better than CSVv2 in ~every b jet efficiency value, vs both light and c jet misid. (as b jet) prob.
- DeepCSV efficiency equal or better than (i) cMVAv2 and (ii) ctagger (in most cases), despite not containing lepton info. (ii) also shows DeepCSV as a multi-classifier

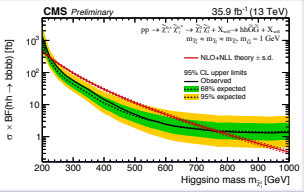


Methods for the b tagging efficiency measurement

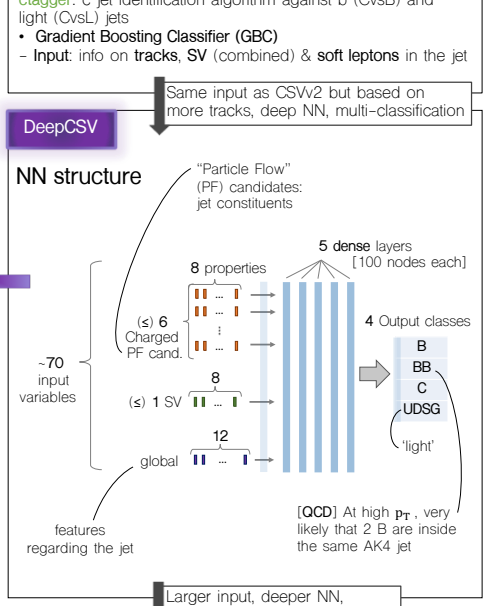
- Similar Scale Factors between CSVv2 and DeepCSV ⇒ better performance for DeepCSV in data too

- DeepCSV already been applied and improved sensitivity in the analysis on the search for: $\tilde{H} \to h\,(\to b\bar{b}) + |\vec{p}_T^{\,miss}|$, 4 b jets in the final state

CMS PAS SUS-16-044
cds.cern.ch/record/2256648



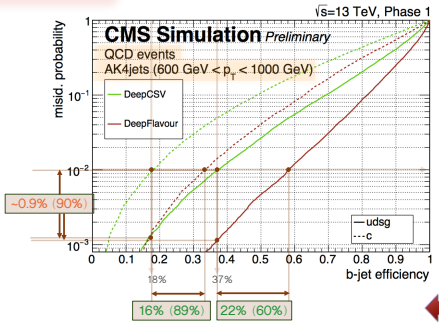
DeepCSV — NN structure



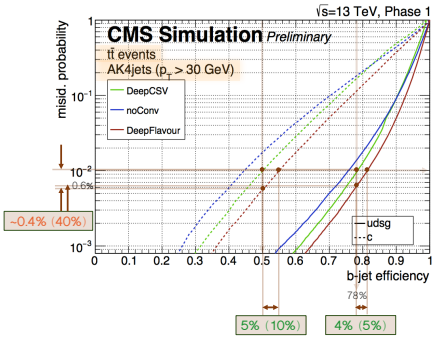
Larger input, deeper NN, +convolutional, recurrent layers

DeepFlavour

CMS DP 2017-013
cds.cern.ch/record/2263802



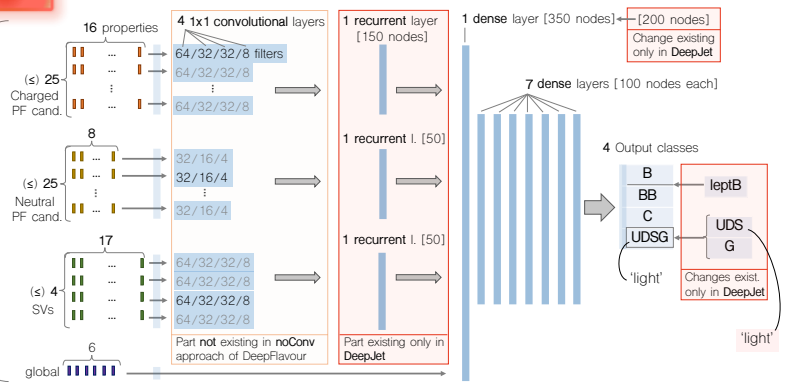
- Significant gain in efficiency of DeepFlavour w.r.t DeepCSV in all p_T regions, especially in high p_T
  ⇒ can lead to improved sensitivity for analyses with highly energetic b jets in the final state



- Removing the convolutional layers degrades performance, even with larger input and deeper NN
- Improvement w.r.t. DeepCSV comes from both larger input and a better NN model (i.e. exploiting input structure)

DeepFlavour — DeepJet

NN structure



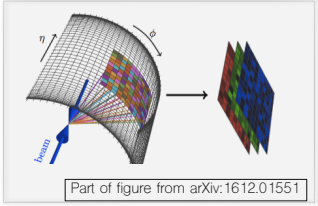
DeepJet

CMS DP 2017-027
cds.cern.ch/record/2275226

NN approaches compared to DeepJet in Quark/Gluon discrimination [Quark:'light']:

recurrent [inspired by arXiv:1702.00748]: Input: relative $p_T/\eta/\varphi$, and PUPPI (Pileup Per Particle Identification) weight (arXiv:1407.6013) of charged (fed to one recurrent layer of 100 nodes – LSTM) and neutral PF cand. (fed to identical layer). LSTM output then merged with global* variables in a dense NN [1 layer of 200 nodes, 5 of 100].

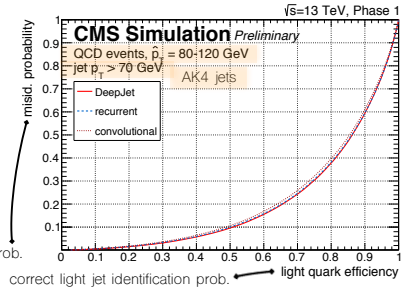
convolutional: Jet treated as image on $\eta - \varphi$ plane. 3rd dimension – color: (separate study for charged and neutral PF cand.) relative p_T and particle multiplicity within the pixel. This input info fed to a CNN (Convolutional NN) [as in arXiv:1612.01551], then merged with the global* variables in a dense layer of 128 nodes.



Part of figure from arXiv:1612.01551

*Jet variables:
jet p_T/η,
#(charged PF cand.),
#(neutral PF cand.),
#(SV within the jet)

[Jets originating from gluon splitting to bb or cc not considered as gluon jets]



- Similar performance among DeepJet and 2 alternative approaches

This Report is part of a project that has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N° 675440