Identification of b-jets using QCD-inspired observables

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Why do we study jets?

A $Z+b$ event candidate recorded by CMS collaboration (credits: CERN)
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We study jet angularities in $Z+$jet production

The jet angularities are defined as

$$\lambda_{\alpha}^\kappa = \sum_{i \in \text{jet}} \left( \frac{p_{T,i}}{\sum_{j \in \text{jet}} p_{T,j}} \right)^\kappa \left( \frac{\Delta_i}{R_0} \right)^\alpha,$$

where

$$\Delta_i = \sqrt{(y_i - y_{\text{jet}})^2 + (\phi_i - \phi_{\text{jet}})^2},$$

is the Euclidean azimuth-rapidity distance of particle $i$ from the jet axis.

- The concept of infrared and collinear (IRC) safety requires $\kappa = 1$ and $\alpha > 0$.
- We consider $\lambda_{1/2}^1$ (LHA), $\lambda_1^1$ (Width) and $\lambda_2^1$ (Thrust) cases.
- For the grooming we use SoftDrop with $\beta = 0$ and $z_{\text{cut}} = 0.1$. 
We study jet angularities in $Z$+jet production

We use the selection cuts from the recent CMS measurements:

- We require all final state particles to have pseudo-rapidity $|\eta| < 5$
- $Z$-boson decays into muons. For both muon candidates we require $p_T,\mu > 26$ GeV, and $|\eta_\mu| < 2.4$
- The lepton pair has to pass the additional conditions $70$ GeV $< m_{\mu^+\mu^-} < 110$ GeV, and $p_T,\mu^+\mu^- > 30$ GeV
- The leading AK8 (AK4) jet has to satisfy $y_{\text{jet}} < 1.7$ and $p_T,\text{jet} \in [50, 1500]$ GeV

Additionally, we impose the constraint

$$\Delta p_T \equiv \left| \frac{p_T,\text{jet} - p_T,\mu^+\mu^-}{p_T,\text{jet} + p_T,\mu^+\mu^-} \right| < 0.3.$$ 

and require the $Z$-boson and the leading jet to be well separated in azimuthal angle

$$\Delta \phi \equiv |\phi_Z - \phi_{\text{jet}}| > 2.$$
Comparison against recent CMS data for the Jet Thrust angularity, $p_{T,\text{jet}} \in [408, 1500]$ GeV.

Theory: JHEP 07 (2021) 076, CMS data: JHEP 01 (2022) 188
To build a Lund plane:

- Recluster your jet using CA algorithm
- Then compute:
  \[
  \Delta_{ab} \equiv \sqrt{(y_a - y_b)^2 + (\phi_a - \phi_b)^2},
  \]
  \[
  k_t \equiv p_T b \Delta_{ab}.
  \]
- Discard softest branch and repeat.
Training input

Jet flavour

- Jets are labelled as $b$-jets if they are matched to at least one weakly decaying $b$-hadron having $p_T \geq 5$ GeV within a cone of size $\Delta R = 0.3$ around the jet axis.
- Similarly, a jet matched to a $c$-hadron is labelled as a $c$-jet.
- After assigning $b$- and $c$-jet labels we dub the remaining jets as light-jets.
- The training and validation samples are produced using PYTHIA LO MC simulations.
- To check a stability of our results against different MC models we also produce a control data set using HERWIG LO MC simulations.
- We use $\lambda_{1/2}^1$, $\lambda_1^1$ and $\lambda_2^1$ to train our DNN and Lund plane projection to train our CNN.
- We consider ungroomed and groomed distributions separately.
An example of observables we consider as an input for our DNN / CNN taggers.
The ROC curves obtained for one-dimensional angularity distributions, multivariable DNN classification and Lund plane CNN classification.

The ROC curves obtained for one-dimensional angularity distributions, multivariable DNN classification and Lund plane CNN classification.

Summary

- We found that one can use jet angularities and Lund plane projection as an input for DNN / CNN discriminators.
- Our DNN/CNN discriminators show performance compatible to JetFitter and IP3D taggers used by ATLAS.
- The discriminating features we use can be added to a list of already considered ones and, therefore, can be used to improve performance of e.g. DL1 tagger (which is NL trained upon multiple variables).
Thank you for your attention!

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