

Identification of b-jets using QCD-inspired observables

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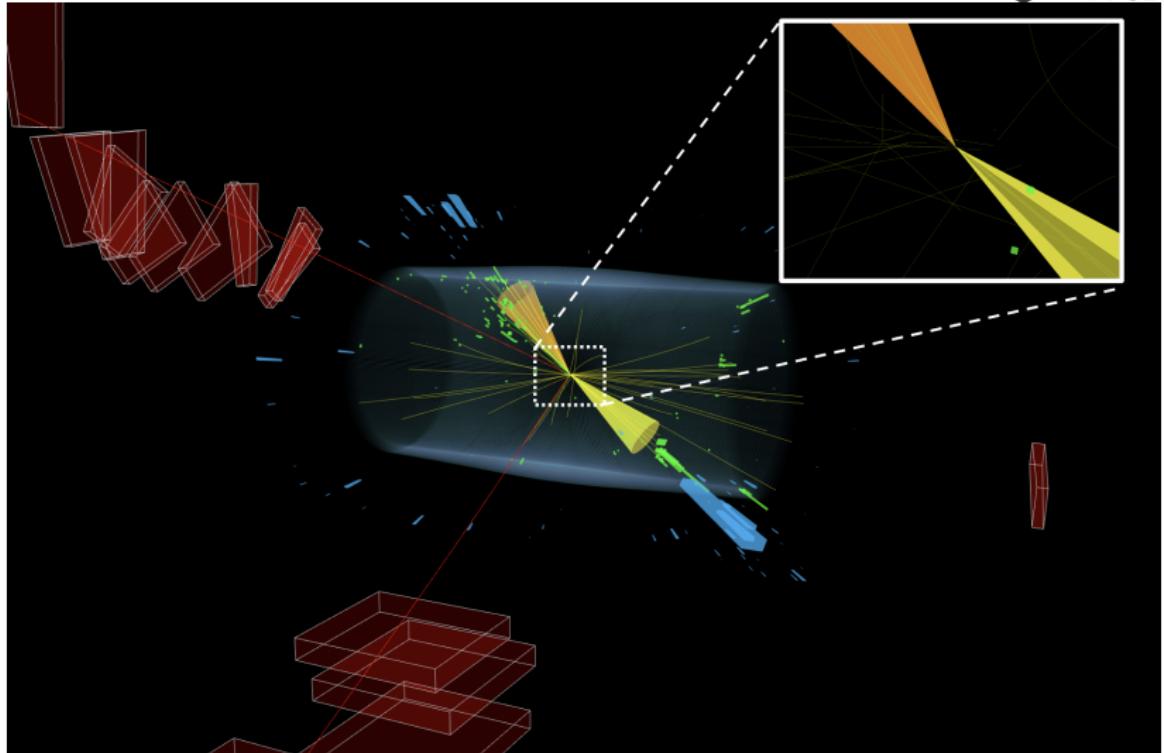
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Why do we study jets?

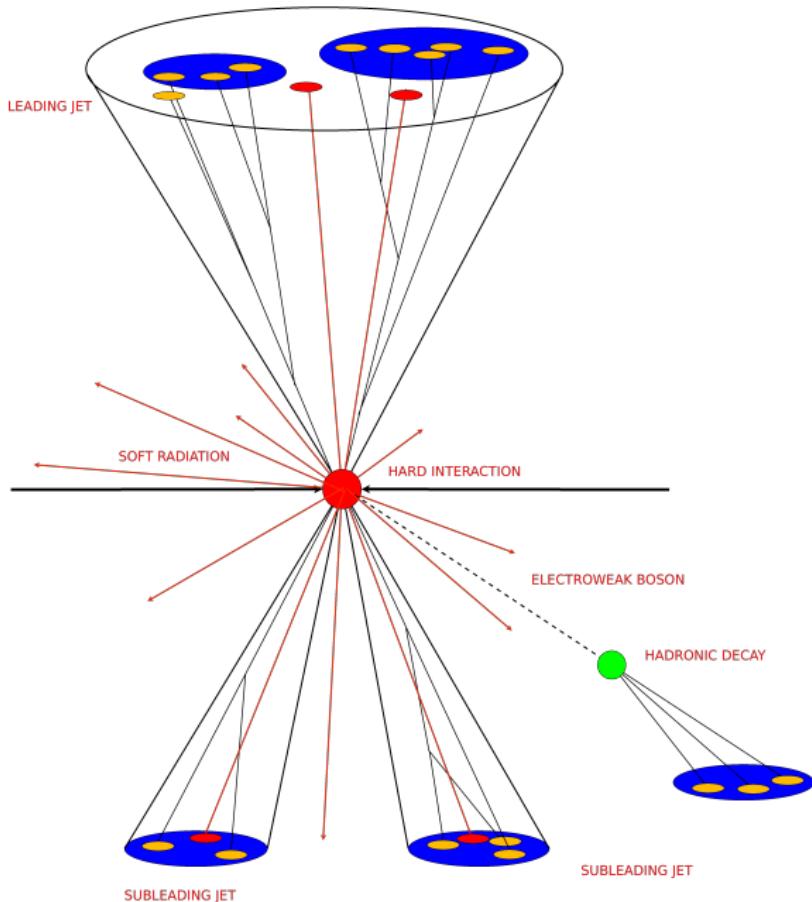


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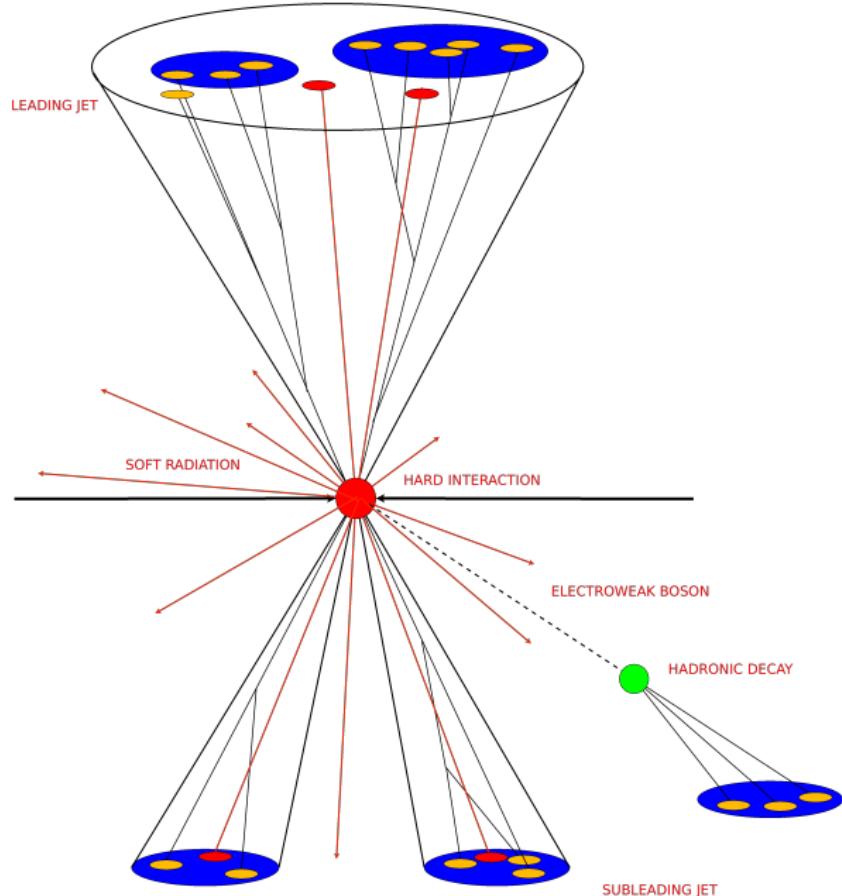


A $Z+b$ event candidate recorded by CMS collaboration (credits: [CERN](#))

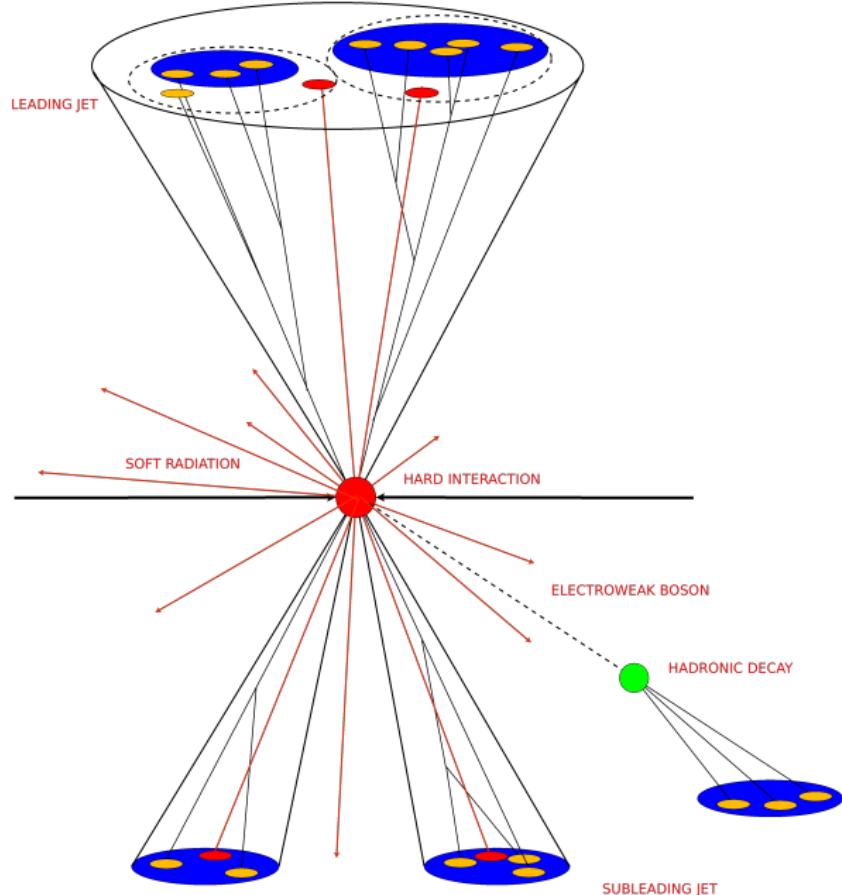
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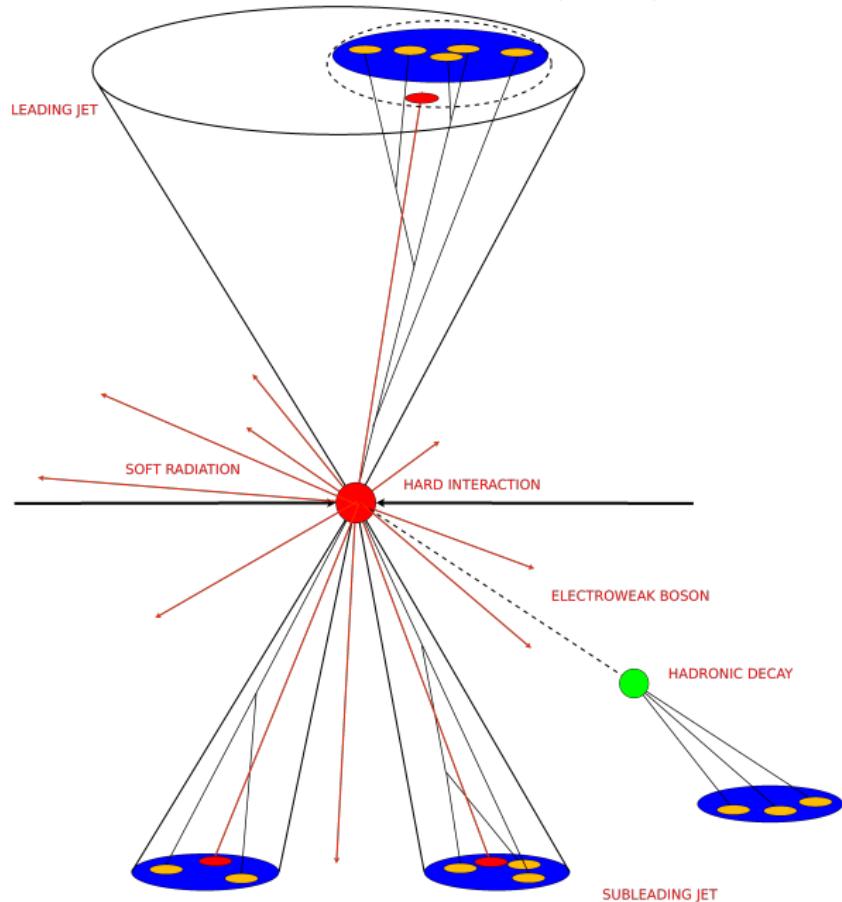
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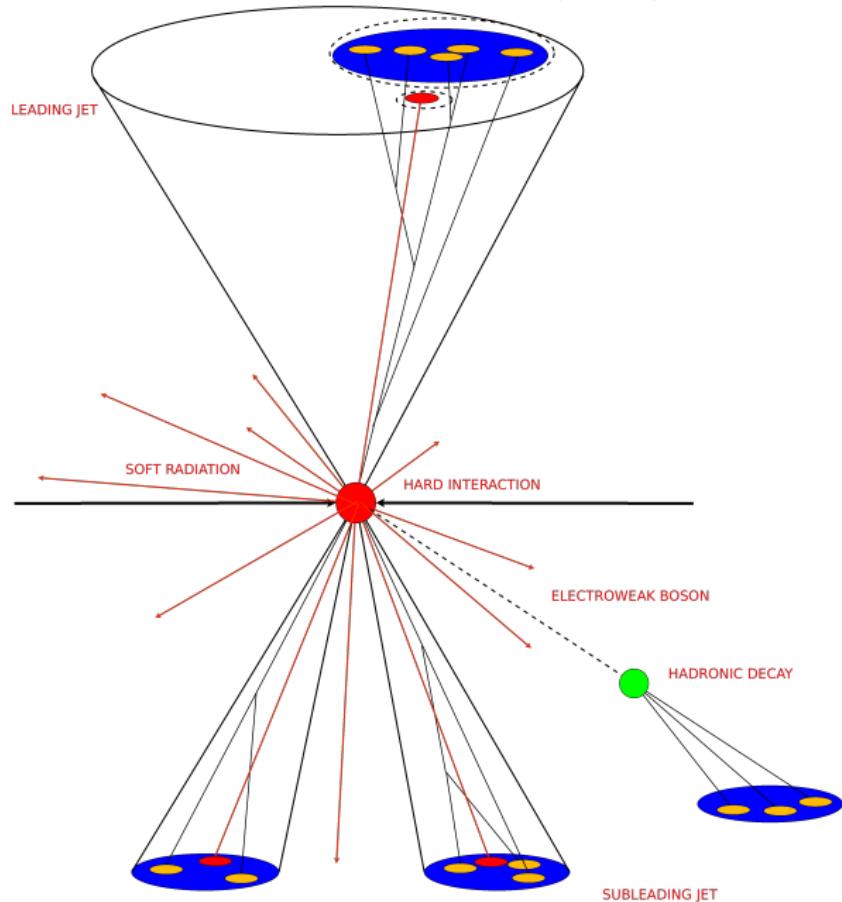
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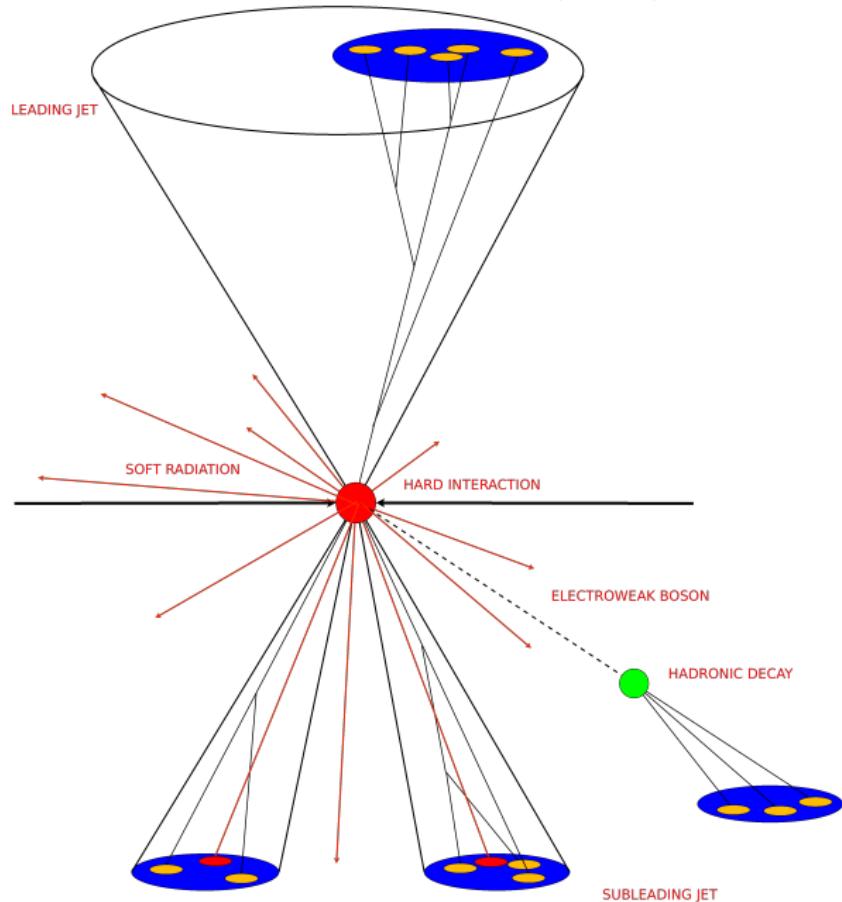
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We study jet angularities in Z +jet production

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), λ_1^1 (Width) and λ_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 $p_{T,\mu} > 26 \text{ GeV}$, and $|\eta_\mu| < 2.4$
- ▶ The lepton pair has to pass the additional conditions $70 \text{ GeV} < m_{\mu^+\mu^-} < 110 \text{ GeV}$, and $p_{T,\mu^+\mu^-} > 30 \text{ GeV}$
- ▶ The leading AK8 (AK4) jet has to satisfy $|y_{\text{jet}}| < 1.7$ and $p_{TJ} \in [50, 1500] \text{ GeV}$

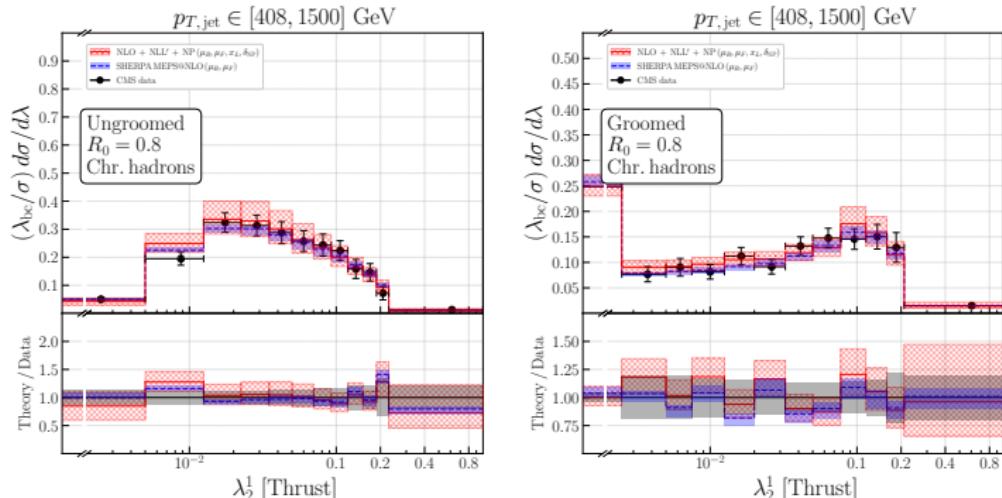
Additionally, we impose the constraint

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

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

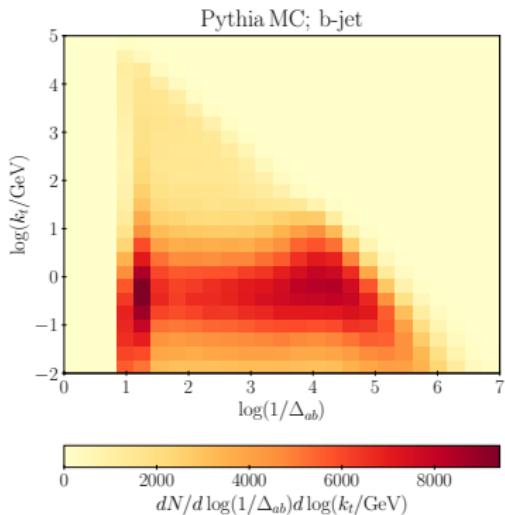
$$\Delta_{Z,\text{jet}}^\phi \equiv |\phi_Z - \phi_{\text{jet}}| > 2.$$

Theory vs. CMS data



Comparison against recent CMS data for the Jet Thrust angularity,
 $p_{T,\text{jet}} \in [408, 1500]$ GeV.

Lund plane projection



To build a Lund plane:

- ▶ Recluster your jet using CA algorithm
- ▶ Then compute:

$$\Delta_{ab} \equiv \sqrt{(y_a - y_b)^2 + (\phi_a - \phi_b)^2},$$
$$k_t \equiv p_{Tb} \Delta_{ab}.$$

- ▶ Discard softest branch and repeat.

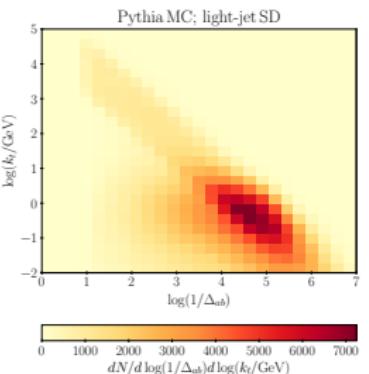
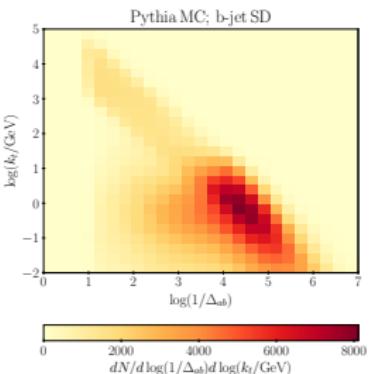
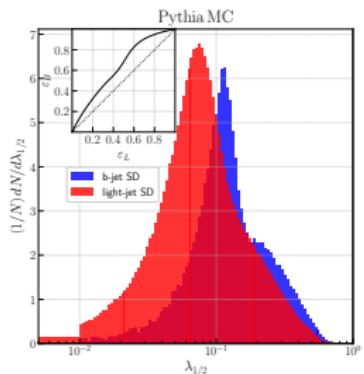
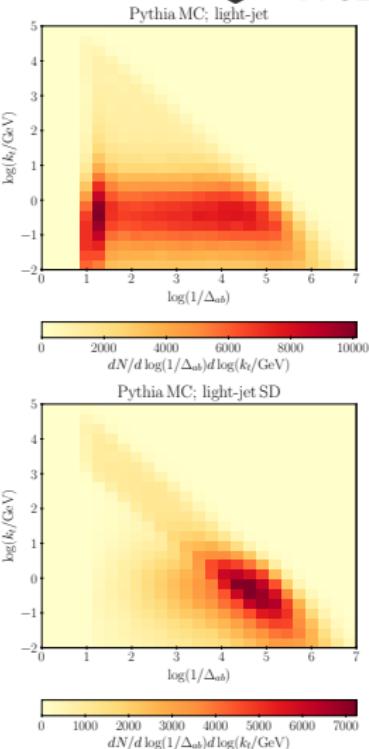
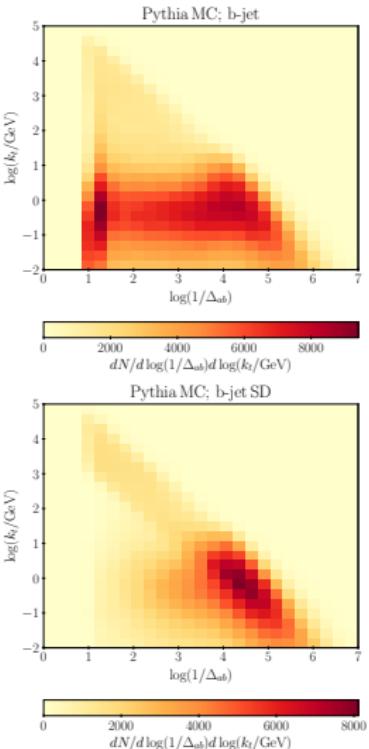
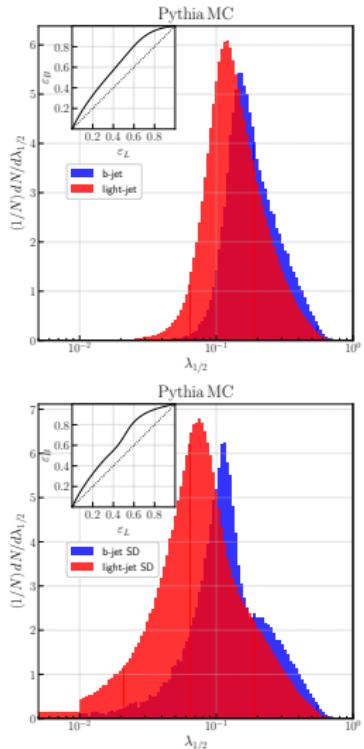


Training input

Jet flavour

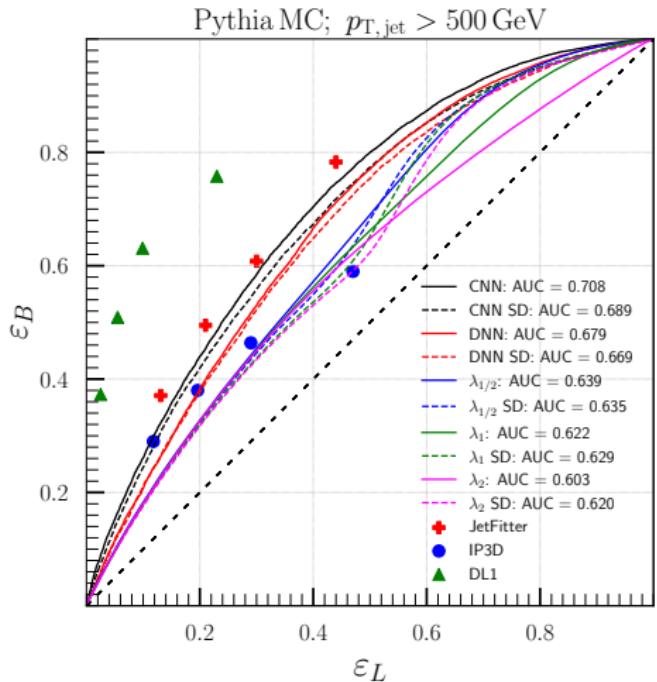
- ▶ Jets are labelled as b -jets if they are matched to at least one weakly decaying b -hadron having $p_T \geq 5$ GeV within a cone of size $\Delta R = 0.3$ around the jet axis.
- ▶ Similarly, a jet matched to a c -hadron is labelled as a c -jet.
- ▶ After assigning b - and c -jet labels we dub the 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 $\lambda_{1/2}^1$, λ_1^1 and λ_2^1 to train our DNN and Lund plane projection to train our CNN.
- ▶ We consider ungroomed and groomed distributions separately.

Training input



An example of observables we consider as an input for our DNN / CNN taggers.

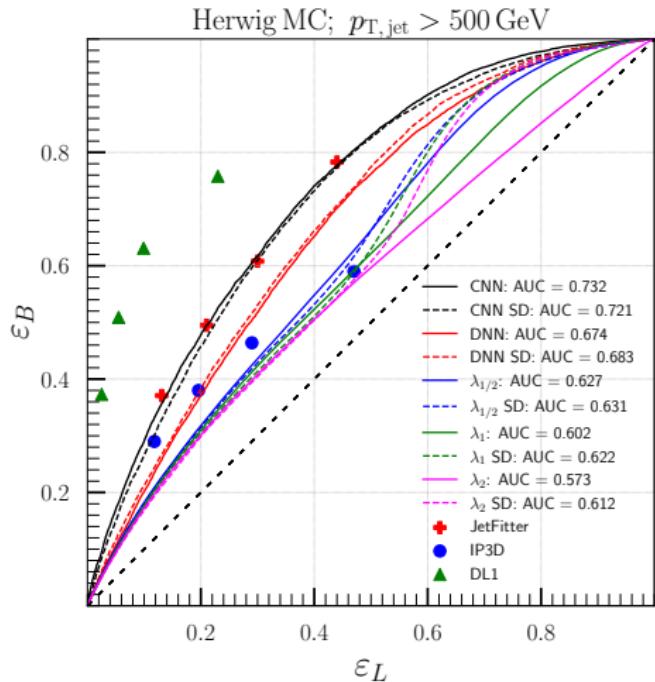
Performance of our CNN / DNN taggers



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

The single points correspond to ATLAS JetFitter, IP3D and DL1 b -tagging performance from [CERN-EP-2019-132](#)

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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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