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New jet tagging techniques at CMS

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on behalf of the CMS Collaboration

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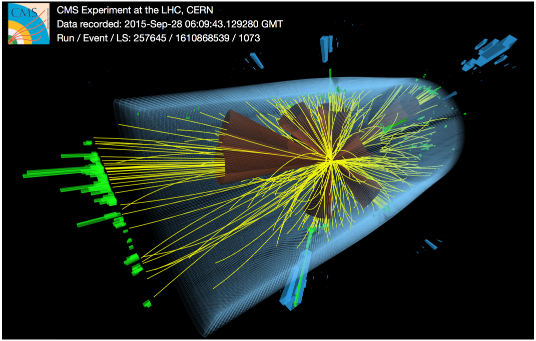
GEFÖRDERT VOM

Bundesministerium für Bildung und Forschung

CLUSTER OF EXCELLENCE
QUANTUM UNIVERSE

Introduction



- Abundant jet production at the LHC with manifold origins:
  - Gluons
  - Light quark flavors
  - Boosted heavy objects (Top, W, Z, Higgs)
  - Pile up
- Many LHC analyses rely on efficient and stable identification

Boosted heavy objects

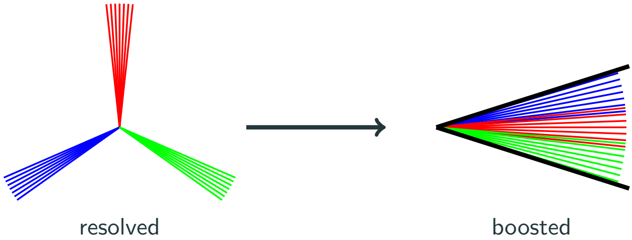
- Search for new heavy particles

→ Decays into high-p_T Top/W/Z/Higgs

→ Boosted decays

→ Reconstruction of hadronic decays in a single jet

Example: top quark



Jet substructure

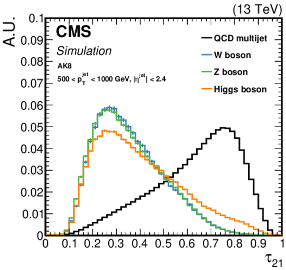
JINST 15 (2020) P06005

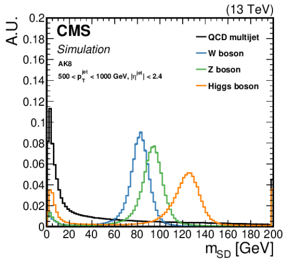
- Identification of jet origin using jet substructure

- N-prong structure of the jet
  $\rightarrow$ Energy distribution functions
  (e.g N-subjettiness ratio τ_{21} or τ_{32})

- Sensitivity to origin particle mass
  $\rightarrow$ Jet mass m_{jet} or m_{SD}

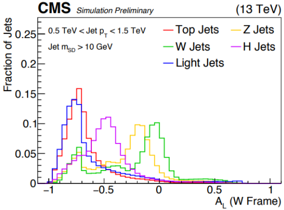
$\rightarrow$ Can we do better?

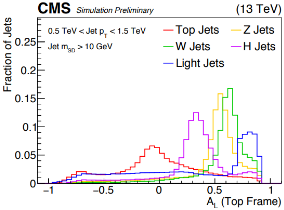




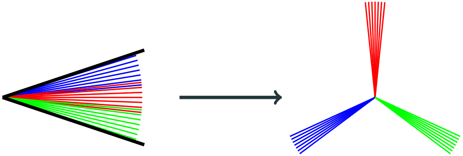
BEST (Boosted Event Shape Tagger)

- Boost jet into rest frame assuming top/W/Z/H mass
- If boost is correct
  - → Isotropic angular distribution
  - → Momentum symmetry in rest frame
- Fully connected neural network with additional jet properties (N-subjettiness, mass, ...)





$$A_L = \frac{\sum_{\text{jet}} p_z^{\text{jet}}}{\sum_{\text{jet}} p^{\text{jet}}}$$

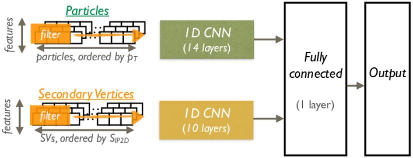


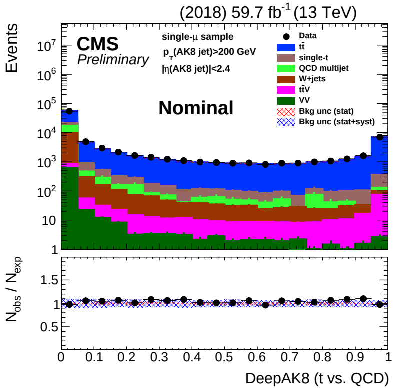
lab frame   rest frame

DeepAK8

CMS DP-2020-025, JINST 15 (2020) P06005

- Multi-class classifier
- Machine learning approach using particle candidates
- Properties of up to 100 jet constituents and 7 secondary vertices
- Two separate networks, later combined with fully connected layer



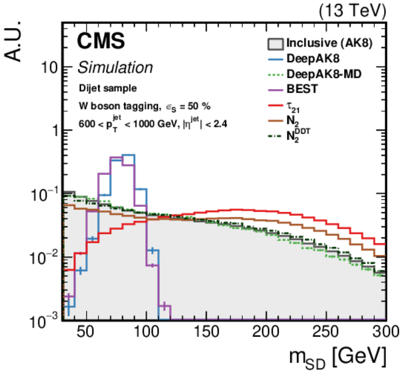


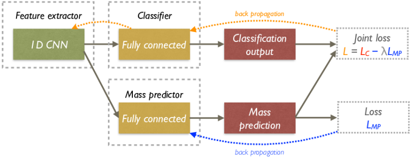
Stability against m_{jet}

JINST 15 (2020) P06005

- DeepAK8 learns jet mass as feature
  - → Sculpts m_{jet} distribution
  - → Complicates background estimation
- De-correlation with mass predictor network
  - → Penalty if outputs largely correlated with mass

→ Efficiency stable against jet mass after de-correlation

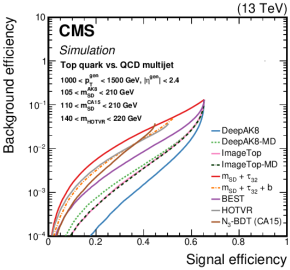


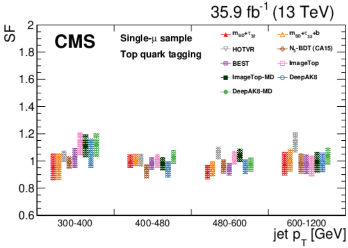


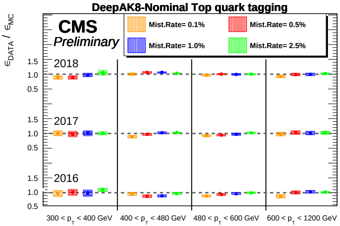
Performance and validation

JINST 15 (2020) P06005, CMS DP-2020-025

- Large machinery validates tagger performance in CMS
- Machine learning approaches already outperform classical taggers
- Correction factors are derived via tag and probe method



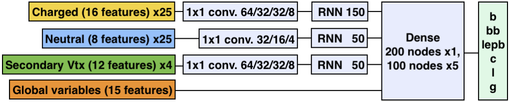


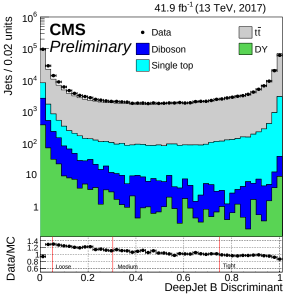


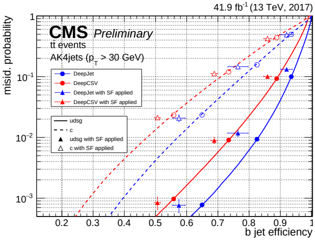
DeepJet

CMS DP-2018-058

- Identification of small radius jets (AK4)
- Distinguish quark flavors and gluons
- Deep neural network approach
- Inputs: Charged, neutrals, secondary vertices, global jet variables



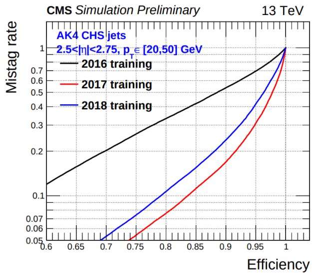


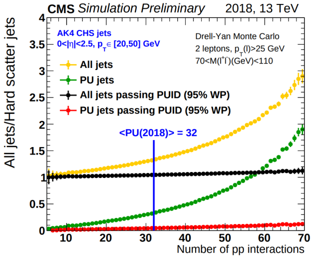


Pile up mitigation

CMS DP-2020-020

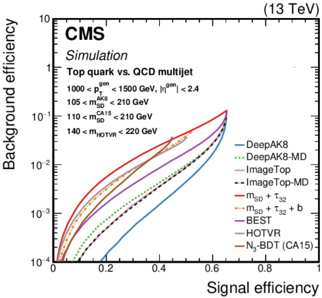
- Pile up jet identification (PU ID)
- Boosted decision tree
- Jet and event variables
- Huge improvement in $2.5 < |\eta| < 2.75$ region with new pixel layer!





Summary

- Jet identification crucial for LHC analyses
- Large machinery within CMS validates performance
- Categorization of jets profits from machine learning techniques and lots of new taggers are developed



And there is more:

- ImageTop [JINST 15 (2020) P06005]
- Particle Net [Phys. Rev. D 101, 056019 (2020), CMS DP-2020-002]
- ...