

Quark vs Gluon Jet Tagging

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q/g discrimination

- For background (gluon) suppression - e.g. VBF, SUSY, ...
- For final state reconstruction e.g hadronic top or W
- Requires detailed understanding of jet fragmentation properties
- Probes generator PS/tunes

hep-ph/1106.3076

Gluon Rejection

10°



Many observables exploiting different fragmentation properties are useful for q/q discrimination



group of 5

girth R=0.5 optimal kernel 1st subjet R=0.5

charged mult R=0.5 subjet mult R_{sub}=0.1

best pair charge * girth

q/g tagging with jet images







 Performance and uncertainties for quark/gluon tagging with charged particle multiplicity

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 First look quark/gluon tagging with ATLAS jet images <u>ATL-PHYS-PUB-2017-017</u>

- A simple observable: number of tracks ghost-matched to the jet (n_{track})
- Proxy for charged multiplicity (n_{charged}) in quark/gluon fragmentation



- Particle multiplicity scales with the color charge (C_F/C_A)
- —> powerful q/g discriminant

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- A simple observable: number of tracks ghost-matched to the jet (n_{track})
- Proxy for charged multiplicity (n_{charged}) in quark/gluon fragmentation



n_{charged} modeling

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- Eur. Phys. J. C76(6), 1-23 (2016) 30 < n charged , ATLAS $L dt = 20.3 \text{ fb}^{-1}$ vs = 8 TeV 25 $p_{\tau}^{track} > 0.5 \text{ GeV}$ $|\eta_{\tau}^{jet}| < 2.1$ 20 15 Data (with stat. uncertainty) Data stat. ⊕ syst. uncert. Herwig++ 2.6.3 EE3 CTEQ6L1 Herwig++ 2.7.1 EE5 CTEQ6L1 10 Pythia 8.175 AU2 CT10 Pythia 8.186 A14 NNPDF2.3 Pythia 8.186 Monash NNPDF2.3 5 Pythia 6.428 P2012 CTEQ6L1 Pythia 6.428 P2012 RadHi Pythia 6.428 P2012 RadLo 1.2 Data/Model 0.8^{1} 500 1000 1500 Jet p_{T} [GeV]
- The challenge is assessing the modeling of the discrimination performance in MC
- Run 1 n_{charged} measurement shows large data/MC discrepancies depending on generator and tuning choices

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Recasting Run 1 measurement for Run 2 tagger

• Fragmentation modeling uncertainties from Run 1 charged multiplicity measurement.

• Experimental uncertainties from track reconstruction uncertainties at 13 TeV (Run 2).

n_{charged} for quark and gluon jets

 Extract n_{charged} separately for quarks and gluons by exploiting rapidity difference in dijet events (mostly qg—>qg)











1500



Excellent closure in wide kinematic range

Contamination from gg and qq events at low and high p_T, respectively 11





- Unfolded measurement of ⟨n_{charged}⟩ separately for quark and gluon jets as a function of jet p_T
- Uncertainties from
 - ME and PDF used to estimate quark/gluon fractions from MC
 - detector/physics objects (through unfolding)

From Run 1 measurement to Run 2 tagger



Overall uncertainties

- ~5% overall uncertainties across a wide range of p_T
- Precision limited by statistics and gg(qq) contamination at low and high p_T



• Caveat: small(*) additional uncertainties for topologies other than dijet

(*) to be assessed case-by-case with MC comparisons

First look quark/gluon tagging with ATLAS jet images

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- Boost and rotate jets so that η , $\phi = 0,0$
- Different types of constituents:
 - truth-particles
 - charged particle tracks
 - topological calorimeter clusters
 - calorimeter towers
- Build 16x16 pixel image so that the intensity (I) of a pixel is the sum of the p_T of the constituents within the pixel
- Normalize each image so that Σ_{pixels} I = 1



-0.2

-0.4

-0.4

-0.2

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0.05

0.4

0.2

0

The CNN tagger

ATLAS Simulation Preliminary ATL-PHYS-PUB-2017-017 convolutional filters Dixel Intensity 0.4 0.2 Translated Pseudorapidity η Max-pooling dense layer 0.2 quark jet n 0.1 -0.2 0.05 gluon jet -0.4-0.4 -0.2 0 0.2 0.4 Translated Azimuthal Angle ϕ **3**x

- Convolutional neural network (CNN) learns non-linear representations of the input image with the goal of discriminating between quark and gluon jet images.
- Similar network architecture as in Komiske et al., hep-ph/1612.01551

Input for jet images

 Comparison of CNN tagger performance with different input images (network retrained for each input type)



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Low p_T:

Gluon Jet Rejection

- Calo+tracks tagger performs as well as truth-particle one.

High pt:

- Gap wrt truth-particle image.
- Some differences from treatment of calo information (towers vs clusters).

CNN tagger vs high-level observables

 Comparison of CNN tagger performance wrt single observables (n_{track}, jet width) and their combination (likelihood ratio).



CNN tagger performs at least as well as n_{track}+width

At high p_T, CNN tagger performs better/worse than n_{track}+width depending on quark efficiency working point

MC generators

- Comparison of CNN tagger performance vs fragmentation modeling
- Similar performance when comparing Sherpa and Pythia (for either training or testing)
- Moderate difference in performance between taggers trained on Pythia vs Herwig and tested on Pythia
- Large difference in performance when testing on Pythia vs Herwig (irrespective of training)



 Difference in fragmentation modeling plays a role, but features learned by network only partially sensitive to it.



- Established strategy for calibrating and deriving uncertainties for q/g tagging observables using dijet events
- ~5% uncertainties for tagger based on charged particle multiplicity
- Begun exploration of q/g tagging using jet images and convolutional neural networks
 - Next steps: understand differences between input objects and what is learnt (e.g. compared with high-level observables).



- Measurement of the charged-particle multiplicity inside jets from sqrt(s) = 8 TeV pp collisions with the ATLAS detector <u>Eur. Phys. J. C76(6), 1-23 (2016)</u>
- Quark versus Gluon Jet Tagging Using Charged Particle Multiplicity with the ATLAS Detector <u>ATL-PHYS-PUB-2017-009</u>
- Quark versus Gluon Jet Tagging Using Jet Images with the ATLAS Detector

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ntrack - Run 2 tunes





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Gluon $\langle n_{\text{charged}} \rangle$	Jet $p_{\rm T}$ Range [100 GeV]									
Systematic	[0.5, 1]	[1,2]	[2,3]	[3, 4]	[4, 5]	$[5,\!6]$	[6, 8]	[8,10]	[10, 12]	[12, 15]
Total exp. ME PDF	$^{+0.44}_{-0.34}$ 0.04 $^{+0.01}_{-0.01}$	$^{+0.29}_{-0.24}$ 0.06 $^{+0.06}_{-0.05}$	$^{+0.15}_{-0.24}$ 0.05 $^{+0.11}_{-0.10}$	$^{+0.24}_{-0.17}$ 0.12 $^{+0.18}_{-0.19}$	$^{+0.21}_{-0.33}$ 0.14 $^{+0.22}_{-0.27}$	$^{+0.37}_{-0.43}$ 0.16 $^{+0.25}_{-0.34}$	$^{+0.48}_{-0.58}$ 0.06 $^{+0.30}_{-0.48}$	$^{+1.01}_{-1.03}$ 0.01 $^{+0.30}_{-0.60}$	$^{+2.20}_{-2.39}$ 0.05 $^{+0.41}_{-1.01}$	$^{+6.09}_{-6.16}$ 0.22 $^{+0.23}_{-0.81}$
PDF comparison Half cone HS Label	$0.03 \\ 0.01 \\ 0.06$	$0.09 \\ 0.03 \\ 0.03$	$0.00 \\ 0.03 \\ 0.04$	$0.04 \\ 0.04 \\ 0.05$	$0.01 \\ 0.03 \\ 0.04$	$0.10 \\ 0.03 \\ 0.03$	$\begin{array}{c} 0.33 \\ 0.03 \\ 0.01 \end{array}$	$0.84 \\ 0.02 \\ 0.01$	$1.76 \\ 0.03 \\ 0.04$	$1.69 \\ 0.01 \\ 0.05$
Quark $\langle n_{\rm charged} \rangle$	Jet $p_{\rm T}$ Range [100 GeV]									
Systematic	[0.5, 1]	[1,2]	[2,3]	[3, 4]	[4, 5]	$[5,\!6]$	[6, 8]	[8,10]	[10, 12]	[12, 15]
Total exp. ME PDF	$^{+0.82}_{-1.16}$ 0.06 $^{+0.02}_{-0.02}$	$^{+0.36}_{-0.41}$ $^{-0.41}_{0.23}$ $^{+0.11}_{-0.10}$	$^{+0.26}_{-0.28}$ 0.19 $^{+0.17}_{-0.16}$	$^{+0.22}_{-0.30}$ 0.23 $^{+0.27}_{-0.24}$	$^{+0.25}_{-0.32}$ 0.22 $^{+0.33}_{-0.27}$	$^{+0.30}_{-0.35}$ $^{-0.25}_{+0.38}$ $^{+0.38}_{-0.28}$	$^{+0.32}_{-0.36}$ 0.26 $^{+0.44}_{-0.30}$	$^{+0.41}_{-0.47}$ 0.22 $^{+0.47}_{-0.28}$	$^{+0.69}_{-0.67}$ 0.23 $^{+0.62}_{-0.33}$	$^{+1.42}_{-1.70}$ 0.16 $^{+0.45}_{-0.21}$
PDF comparison Half cone HS Label	$0.04 \\ 0.01 \\ 0.07$	$0.01 \\ 0.02 \\ 0.03$	$0.17 \\ 0.02 \\ 0.01$	$0.23 \\ 0.02 \\ 0.01$	$0.17 \\ 0.02 \\ 0.01$	$0.10 \\ 0.01 \\ 0.01$	$0.01 \\ 0.01 \\ 0.02$	$0.21 \\ 0.01 \\ 0.02$	$0.44 \\ 0.01 \\ 0.02$	$0.39 \\ 0.00 \\ 0.02$

ntrack - uncertainties

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CNN - track-truth and η range

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Figure 7: Gluon jet rejection as a function of the quark jet efficiency using the CNN tagger for jets with $150 < p_T < 200$ GeV. (a) Comparison between using track images and truth charge particle images as input. (b) Comparison between different $|\eta|$ ranges. The full $|\eta|$ range ($|\eta| < 2.1$) is used for training.

CNN - pileup

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Figure 8: Gluon jet rejection as a function of the quark jet efficiency evaluated at different pileup conditions, quantified by the number of reconstructed primary vertices (N_{PV}).

CNN - fragmentation modeling

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Figure 11: Gluon jet rejection as a function of the quark jet efficiency comparing Pythia to (a) Sherpa and (b) Herwig for jets with $150 < p_T < 200$ GeV.

CNN - fragmentation modeling



CNN - average convolution differences



(a)

Figure 13: Average convolved filter differences for jet images (same color scheme as left plot; red is more quarklike). The filters of the first convolutional layer are considered.

CNN - correlation

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