





Let's talk about jets! - Let's talk about (what I think are) the good things and the bad things -

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, 3. 0.4



arxiv:2205.02817



- In the ATLAS TDR 15 top quarks play an important role \rightarrow a lot of them to study
- "largest sample of tt events" consists of six-jet events from the fully hadronic decay mode"
- Reduces combinatorics significantly if large-R jets are considered

talk by Adam

By now precision measurements of boosted top quarks

Differential $t\bar{t}$ cross-section measurements using boosted top quarks in the all-hadronic final state with 139 fb⁻¹ of ATLAS data

Top quark mass measurement with large-R jets



- Measured the top quark mass to 173.06 ± 0.84 GeV → compatible with other measurements (I+jets & all-hadronic resolved)
- Reduced systematic uncertainty by
 - 1. dedicated calibration of the jet mass scale using the W as constrain
 - 2. study of the effects of final state radiation inside large-radius jets

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Improving MC = improving substructure modeling?



- CMS changed their PYTHIA tune from 2016 (CUETP8M1) to 2017 (CP5) which showed improvement in several phase spaces (CMS-GEN-17-001)
- Major change in $\alpha_s^{\text{FSR}}(m_Z^2)$ from 0.1365 to 0.118
- Variables like N-subjettiness very sensitive to these changes

Jet substructure measurements



Jet substructure measurements



4TLAS-CONF-2023-027

- Combination of lepton+jets and all-hadronic final states \rightarrow enable measurements of the substructure of with average p_T > 500 GeV
- Variable defined using charged particles only
- A lot of different substructure variables measured

Let's see more substructure variables in the <u>talk by Adam</u>

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Jet calibration



- The calibration of jets depends on the simulation
- One leading uncertainty at low p_T comes from the MC generators
- At high p_T it is the photon scale \rightarrow we need a good understanding of the detector as well



Jet calibration



- Jet response of quark and gluon jets very different especially at low p_T
- Gluon response depends a lot on the MC generator / tune used
- LEP data tunes like Sherpa ahadic++ help to tune the charged hadron content



Jet mass and energy scale

Future Directions (?)

Combine advantages of PF and TCC in ATLAS

• Single, optimal reconstruction of final state for all use cases

CMS PF developed with low PU in mind

- Fantastic performance, even at Run 2
- Developments needed for HL-LHC
 - Upgraded detectors with longitudinal segmentation, higher granularity, extended η coverage...
 - Improvements can help already now

More consistent treatment of JES, JER, JMS and JMR

- Simultaneous determination
- Factorized approach has advantages, but can introduce doublecounting of uncertainties, unknown correlations





Jet mass and energy scale

CMS DP-2023/044



- Calibration of the jet mass scale in two independent samples
- Correlation between jet energy and mass scale
- Good agreement of jet mass scale also between the samples
- Next step: particle dependent energy scale correlation

Doing the impossible?

CMS-HIG-21-008



- CMS TDR (2006): "The [Higgs] decay modes into cc [..] pairs [..] do not play a relevant role at the LHC."
- The BOOST community made it possible :)

Anna Benecke

[as pointed out by <u>Clemens</u> last year]



Lund Jet Plane tagger



performance



- ML enables us to look into more exotic boosted signatures
- Like $H \rightarrow 4q$

Exotic signatures

https://arxiv.org/abs/2202.03772



- ML enables use to look into more exotic boosted signatures
- Like $\rightarrow 4q$ Anything

Exotic signatures

https://arxiv.org/abs/2202.03772



- ML enables use to look into more exotic boosted signatures
- Like $\checkmark \rightarrow 4$ Specify which quark combination Anything

Is it always useful to go as fine-grained as possible?

Calibrating high-prong jets

What we need to search for BSM

- Data 🗸
- Tools (taggers, new variables) to suppress background and isolate the signal
 - Most ML taggers still trained on MC...
- Background estimate (minimize uncertainty)
 - If dominated by ttbar, W+jets get away with MC...
 - QCD: tricky and messy 🈩 (after lots of work... 🗸)
- Signal efficiency (minimize uncertainty)

 - For exotic signatures ??? X

Petar Maksimovic, Johns Hopkins

Experimental Intro

2022 Beyond the ROC: the mass decorrelation

the model independence

the IRC safety

the p_T stability

the stability with resonance masses

the data/MC (dis-)agreement

the lack of a real proxy in data

the uncertainty on your not-so-real proxy

ALL OF THESE THINGS REALLY MATTER FOR A SEARCH

<u>Boost 2019 -</u> Intro-Talk by <u>Petar</u>

Boost 2022 -Summary-Talk by Cristina

Calibrating high-prong jets



- Construct Lund Jet Plane for subjets of W candidates in data and simulation
- Derive the ratio to construct correction factors for splittings
- Reweight the simulation independent of the tagger/signature targeted
- Still some systematic sources to be studied, but very helpful for exotic signatures!
 Anna Benecke



Mass regression & decorrelation

CMS Simulation Preliminary **CMS Simulation Preliminary** E 0.7 - 0.65 (μ)^{μθ} 0.55 - 0.55 event fraction 0.1 anti-k ₊ jets $H \rightarrow cc$ (soft drop) H -> bb (soft drop) anti-k₊ jets H -> cc (regression) H -> bb (regression) R = 0.80.12 R = 0.8 $H \rightarrow cc$ (soft drop) p > 400 GeV p_ > 400 GeV 0.5 H -> cc (regression) Fraction of jets 0.1 0.45 $H \rightarrow qq$ (soft drop) 0.4 0.08 H -> qq (regression) 0.35 0.3 0.06 0.25 0.2 0.04 0.15 0.02 0.1 0.05 0<u></u>0 08 80 100 120 140 0.5 1.5 2 160 180 200 220 1 M_{reco} / M_{target} M_{target} [GeV/c²]

CNAC DD 2021 017

W jets Multijets Tagged multijets: D_2 10 10^{-2} 10^{-3} 10^{-4} Tagged multijets: 30 10⁻¹ $Z_{\rm NN}$ $Z_{ANN}^{(\lambda=10)}$ 10⁻² 10^{-3} 10^{-4} 150 300 200 250 50 100 Large-R jet mass [GeV] ATL-PHYS-PUB-2018-014

ATLAS Simulation Preliminary

 $\sqrt{s} = 13 \text{ TeV}, W$ jet tagging

Cuts at $\varepsilon_{sig}^{rel} = 50\%$

Inclusive selection:

- ML does more than "just" tagging \rightarrow reconstruction of specific quantities
- Better decorrelation of tagger output and mass
- Better mass resolution
- Next: p_T regression for AK4 jets!

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M_t

Towards jet p_T regression



- Jet p_T response depends on the flavor and the MC generator used
- Additional correction step to improve the jet resolution by 6 different (mostly) uncorrelated variables
- With ML you can take correlated varaibles and improve the performance further!

Let's find out more about the advantages of ML in jet calibration talk by Margherita

Model-independent searches with ML

arxiv:2307.01612



- So many different BSM models on the market
- Model-independent searches interesting approaches to "scan" bigger phase space
- AutoEncoders is a good way to detect anomalies
- 9 different invariant mass regions to detect new physics



ML for data certification



First Run3 cross section results

ATLAS-CONF-2023-006



<u>CMS-TOP-22-012</u>



- We have first Run3 results!
- In good agreement with the SM
- No substructure yet \rightarrow too complicated?

New data - Calibration at the start of Run3



- We are collected new exciting data, however, not well calibrated nor understood YET
- Jets are complex objects involving a lot of detector subsystems
- First jet energy calibrations of Run3 are very sensitive to detector effects

Summary

An exiting week ahead with new results about

- Jet substructure measurements
- New jet calibration techniques
- New tagger ideas to improve data-to-simulation agreement
- New calibration techniques of the more fine-grained taggers
- ML application in various areas

First Run3 results available

- Calibration of the detector and objects ongoing
- Jet substructure affected by many detector subsystems

My wish: Let's boost together to calibrate Run3 data from the detector subsystems to jet substructure at least as good as in Run2! And get amazing results from combinations!



AutoEncoders

AutoEncoder-based Anomaly Detection Tool

 The model is trained on non-anomalous data from GOOD runs: histograms of specific MEs are fed to the model with an LS granularity to allow the AE to learn a «normal» nonanomalous behavior of that specific ME. The training is performed via the minimization of the reconstruction loss, a measure of the distance between the input and output of the AE. In this case the reconstruction loss is the mean squared error:

MSE =
$$\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

where y and \hat{y} are respectively the input and the output of the AE and n is the bin number.

- Possibly anomalous runs under investigation are tested by looking again at the reconstruction loss: peaks in this function indicate LSs containing histograms that deviate from the learned behavior.
- The comparison between the reconstruction losses of the three runs under study is on the right.





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2022 (13.6 TeV)

Lund Plane tagger



Data-to-simulation agreement



- We know that in general new simulation tunes improve the description of data
- However, sometimes worsening other phase spaces like jet substructure variables
- Also visible in the correction factors for W-tagging with τ_{21}

<u>CMS-DP-2020-025</u>

- CUETP8M1: 0.99 ± 0.11
- CP5: 0.957 ± 0.074 (2017), 0.964 ± 0.032 (2018)

FSR study



- Same selection but AK8 jets instead of XCone jets which are more sensitive to FSR
- Matching between XCone and AK8 jets
- $\alpha_S^{\text{FSR}}(m_Z^2) = 0.1373^{+0.0017}_{-0.0018}$ for 2016
- $\alpha_S^{\mathsf{FSR}}(m_Z^2) = 0.1416^{+0.0019}_{-0.0018}$ for 2016