Machine Learning just because it is Great Fun

Tilman Plehn

Universität Heidelberg

Hamburg 2/2019

Change of title

SciPost Physics — Submission

The Machine Learning Landscape of Top Taggers

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Abstract

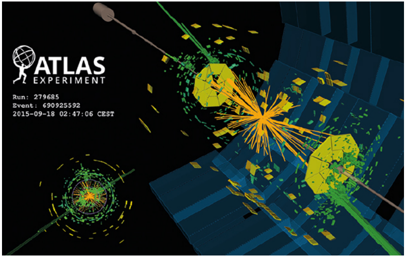
Based on the established task of identifying boosted, hadronically decaying top quarks, we compare a wide range of modern machine learning approaches. We find that they are extremely powerful and great fun.

Why LHC, why jets

Big jet data by ATLAS & CMS

- colliding protons on protons at $E \approx 13000 \times m_p$
- most interactions $q\bar{q}, gg \to q\bar{q}, gg$
- quarks/gluon visible as jets $\quad \sigma_{pp\to jj} \times \mathcal{L} \approx 10^8\text{fb} \times 80/\text{fb} \approx 10^{10}$ events

$\Rightarrow$ It's big data



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Interesting physics in jets

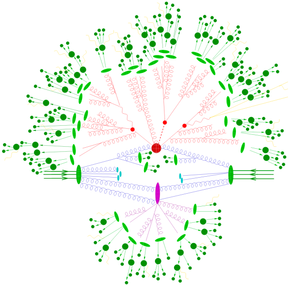
– re-summed perturbative QFT prediction for QCD splittings

– jets as decay products

$67\%\ W \to jj \quad 70\%\ Z \to jj \quad 60\%\ H \to jj \quad 67\%\ t \to jjj \quad 60\%\ \tau \to j$ ...

– new physics in 'dark showers' [Jennifer Thompson's talk]

$\Rightarrow$ It's interesting



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LHC simulations

– QCD simulation: Pythia, Sherpa, Herwig

– fast detector simulation: Delphes

– excellent agreement with data

$\Rightarrow$ We can simulate it

Inside jets

Jets and machine learning from 1990s to 2020s

1991 NN-based quark-gluon tagger [visionary: Lönnblad, Peterson, Rögnvaldsson]

USING NEURAL NETWORKS TO IDENTIFY JETS

Leif LÖNNBLAD*, Carsten PETERSON** and Thorsteinn RÖGNVALDSSON***

Department of Theoretical Physics, University of Lund, Sölvegatan 14A, S-22362 Lund, Sweden

Received 29 June 1990

A neural network method for identifying the ancestor of a hadron jet is presented. The idea is to find an efficient mapping between certain observed hadronic kinematical variables and the quark-gluon identity. This is done with a neuronic expansion in terms of a network of sigmoidal functions using a gradient descent procedure, where the errors are back-propagated through the network. With this method we are able to separate gluon from quark jets originating from Monte Carlo generated e^+e^- events with ~85% approach. The result is independent of the MC model used. This approach for isolating the gluon jet is then used to study the so-called string effect.

Inside jets

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1991 NN-based quark-gluon tagger [visionary: Lönnblad, Peterson, Rögnvaldsson]

1994 jet-algo W/top-tagger for heavy Higgs [Seymour]

2008 jet-algo Higgs tagger [Butterworth, Davison, Rubin, Salam; Kribs, Martin, Spannowsky]

2008 jet-algo top tagger [Kaplan, Rehermann, Schwartz, Tweedie]

2009 jet-algo HEPTopTagger [TP, Salam, Spannowsky; 1st user Gregor Kasieczka]

. . .

2009 template top tagger [Almeida, Lee, Perez, Sterman, Sung, Virzi]

2011 Shower Deconstruction [Soper, Spannowsky]

2015 Multi-variate HEPTopTagger [Kasieczka, TP, Schell, Strebler, Salam]

. . .

2014 image recognition W-tagger [Cogan, Kagan, Strass, Schwartzman]

2015 jet images [de Oliveira, Kagan), Mackey, Nachman, Schwartzman]

2017 image recognition top tagger [Kasieczka, Plehn, Russell, Schell]

2017 language recognition W-tagger [Louppe, Cho, Becot, Cranmer]

2017 4-vector-based top tagger [Butter, Kasieczka, Plehn, Russel]

. . .

2018 jet autoencoder [Heinel, Kasieczka, Plehn, Thompson; Shi etal]

Jet-level analyses (1990s)

Jets as analysis objects

– partonic predictions from QCD $\Leftrightarrow$ jets describing partons in reality
– infrared safety crucial to compare with perturbative QCD rates
– data-to-data analyses more flexible
– data-to-simulation analyses similarly free?

QCD recombination algorithms [FASTJET]

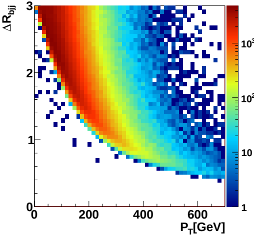
– define jet–jet and jet–beam distances [exclusive with resolution y_{cut}]

$$\begin{array}{llll} k_T & y_{ij} = \dfrac{\Delta R_{ij}}{R} \; \min\left(p_{T,i}, p_{T,j}\right) & & y_{iB} = p_{T,i} \\ \text{C/A} & y_{ij} = \dfrac{\Delta R_{ij}}{R} & & y_{iB} = 1 \\ \text{anti-}k_T & y_{ij} = \dfrac{\Delta R_{ij}}{R} \min\left(p_{T,i}^{-1}, p_{T,j}^{-1}\right) & & y_{iB} = p_{T,i}^{-1} \; . \end{array}$$

– (1) find minimum $y^{\text{min}} = \min_{ij}(y_{ij}, y_{iB})$
(2a) if $y^{\text{min}} = y_{ij}$ merge subjets i and j, back to (1)
(2b) if $y^{\text{min}} = y_{iB}$ remove i from subjets, go to (1)

$\Rightarrow$ clustering history usable?

Fat jet taggers (2000s)



For instance: boosted tops

- hadronic decays vs QCD splittings
- perfectly described by perturbative QCD
- labelled sample: semileptonic $t\bar{t}$ events

$\Rightarrow$ substructure playground

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Simple top tagging [BDRS; TP, Salam, Spannowsky, Takeuchi]

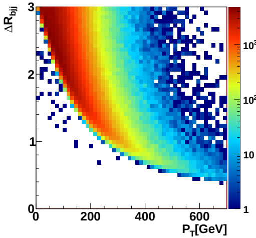
1– C/A fat jet with $p_T > 200$ GeV

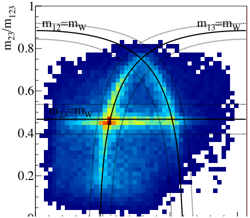
2– filtering defining 3-5 decay jets

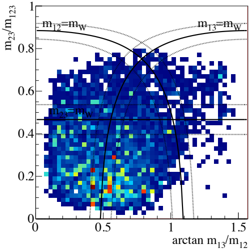
3– top mass window $m_{123} = [150, 200]$ GeV

4– A-shaped mass plane cuts probing m_W

$\Rightarrow$ not rocket science, but experimental break-through







Multi-variate subjet physics (2010s)

OptimalR and N-Subjettiness [Kasieczka, TP, Salam, Schell, Strebler]

– multivariate analysis old idea [Lonnblad, Peterson, Rognvaldsson]
HEPTopTaggerv2 to keep up with shower deconstruction [Soper, Spannowsky]

– optimal fat jet size R_{opt} [large to decay jets, small to avoid combinatorics, compute from kinematics]

$$|m_{123} - m_{123}^{(R_{\text{max}})}| < 0.2\, m_{123}^{(R_{\text{max}})} \quad \Rightarrow \quad R_{\text{opt}}$$

– add N-subjettiness [Thaler, van Tilburg]

– $\{m_{123}, f_W, R_{\text{opt}} - R_{\text{opt}}^{(\text{calc})}, \tau_j, \tau_j^{(\text{filt})}\}$

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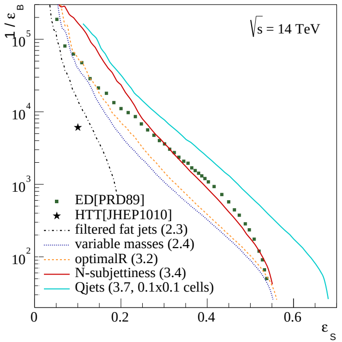
Fat jet and top kinematics

– FSR major problem for Z' search

– tag and reconstruction in each other's way

$\Rightarrow$ $\{ ..., m_{tt}, p_{T,t}, m_{jj}^\text{(filt)}, p_{T,j}^\text{(filt)} \}$

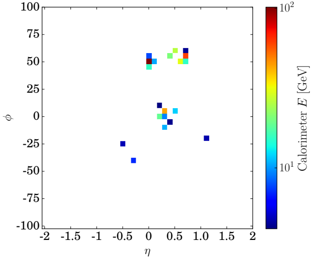
$\Rightarrow$ expected performance increase



Jet images (2020s)

'Deep learning' = modern architectures on low-level observables

- wavelet transformation [Rentala, Shepherd, Tait; Monk]
- *W*-tagging with image recognition [Cogan etal, Oliveira etal, Baldi etal]
- impact of shower? [Barnard etal]
- combining calorimeter and tracking? [Komiske etal]
- understanding additional information? [Datta & Larkosky]
- link to infrared safety? [Choi, Lee, Perelstein; Friday speakers]



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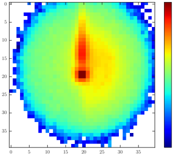
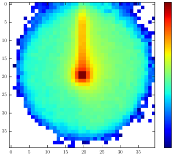


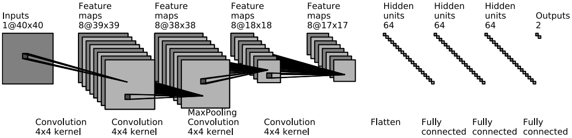


Convolutional network [Kasieczka, TP, Russell, Schell; Macaluso, Shih]

– run on 2-D jet images [$p_T = 350, \dots, 450$ GeV]

– colored image as input

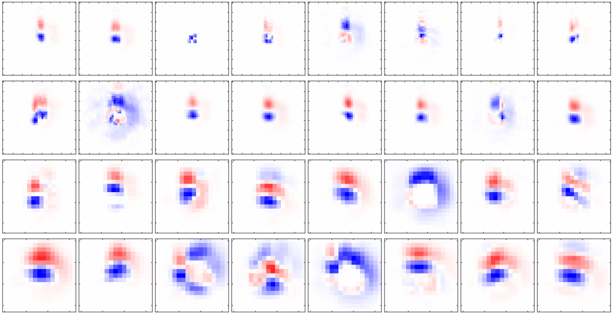
– binning through calorimeter resolution [$\Delta\eta = 0.1$ vs $\Delta\phi = 5^\circ$]

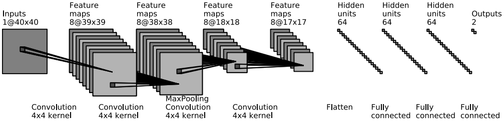


Inside DeepTop

Benchmarking image-based top tagger [Kasieczka, TP, Russell, Schell; Macaluso & Shih]

– 2+2 convolutional layers





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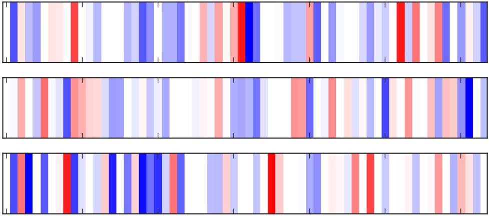
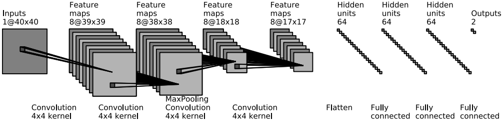
Benchmarking image-based top tagger [Kasieczka, TP, Russell, Schell; Macaluso & Shih]

– 2+2 convolutional layers

– 3 fully connected layers





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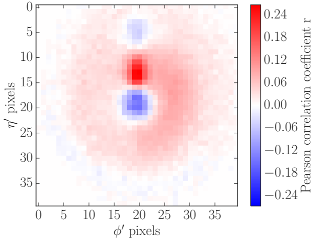
– Pearson input-output correlation [pixel x vs label y]

$$r_{ij} \approx \sum_{\text{images}} \left(x_{ij} - \bar{x}_{ij} \right) \left(y - \bar{y} \right)$$



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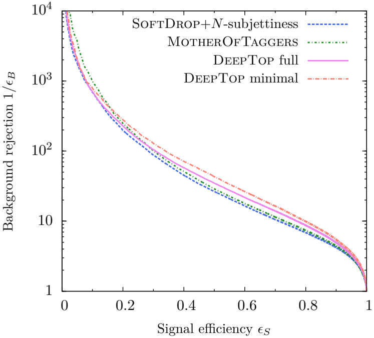
– comparison to MotherOfTaggers BDT

$\Rightarrow$ understandable performance gain



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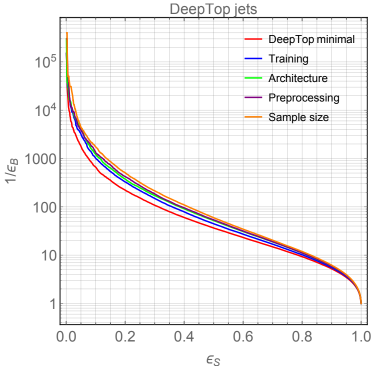

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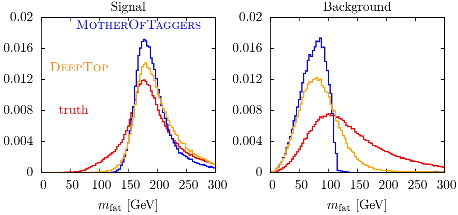
⇒ understandable performance gain

Typical reaction: ‘Fuck you, you fucking machine’

– full control for supervised learning
easy checks for correctly identified signal/background events

– MC truth vs MotherOfTaggers vs DeepTop

fat jet mass



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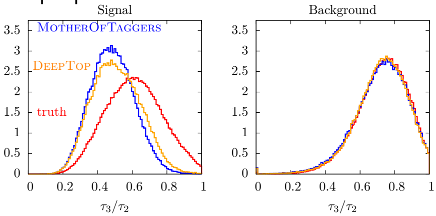

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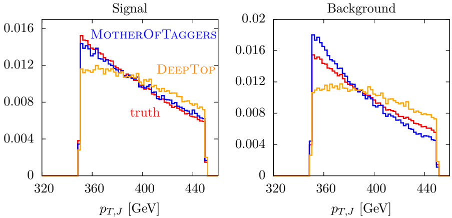
- full control for supervised learning
  easy checks for correctly identified signal/background events
- MC truth vs MotherOfTaggers vs DeepTop
  fat jet mass
  N-subjettiness
  transverse momenta

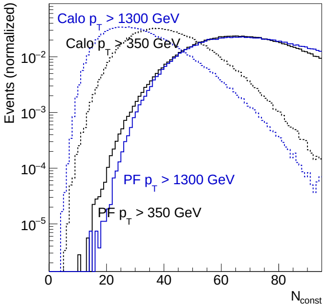
⇒ it works and we know why



DeepTopLoLa

Our version of graph network [Butter, Kasieczka, TP, Russell; many more by now]

- sparsely filled picture: graph CNN
- physics objects from calorimeter and tracker
- distance measure known from e&m



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Inspired by jet algorithm — combination layer

– input 4-vectors

$$(k_{\mu,i}) = \begin{pmatrix} k_{0,1} & k_{0,2} & \cdots & k_{0,N} \\ k_{1,1} & k_{1,2} & \cdots & k_{1,N} \\ k_{2,1} & k_{2,2} & \cdots & k_{2,N} \\ k_{3,1} & k_{3,2} & \cdots & k_{3,N} \end{pmatrix}$$

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Inspired by jet algorithm — combination layer

- input 4-vectors
- on-shell conditions for top tag

$$\tilde{k}^2_{\mu,1} = (k_{\mu,1} + k_{\mu,2} + k_{\mu,3})^2 \stackrel{!}{=} m_t^2$$

$$\tilde{k}^2_{\mu,2} = (k_{\mu,1} + k_{\mu,2})^2 \stackrel{!}{=} m_W^2$$

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Inspired by jet algorithm — combination layer

– input 4-vectors
– on-shell conditions for top tag
– combined 4-vectors

$$k_{\mu,i} \xrightarrow{\text{CoLa}} \widetilde{k}_{\mu,j} = k_{\mu,i} \; C_{ij} \qquad C = \begin{pmatrix} 1 & 0 & \cdots & 0 & C_{1,N+2} & \cdots & C_{1,M} \\ 0 & 1 & & \vdots & C_{2,N+2} & \cdots & C_{2,M} \\ \vdots & \vdots & \ddots & 0 & \vdots & & \vdots \\ 0 & 0 & \cdots & 1 & C_{N,N+2} & \cdots & C_{N,M} \end{pmatrix}$$

– after combination of input 4-vectors

original momenta k_i
$M - N$ trainable linear combinations [M-N=15]

$\Rightarrow$ physics step, easy to interpret

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Inspired by jet algorithm — combination layer

- combined 4-vectors $k_{\mu,i} \xrightarrow{\text{CoLa}} \widetilde{k}_{\mu,j} = k_{\mu,i}\, C_{ij}$

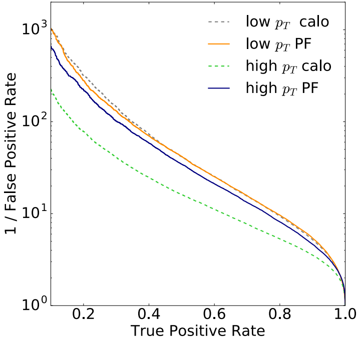
Inspired by Jackson — Lorentz layer

- DNN on Lorentz scalars

$$\tilde{k}_j \xrightarrow{\text{LoLa}} \hat{k}_j = \begin{pmatrix} m^2(\tilde{k}_j) \\ p_T(\tilde{k}_j) \\ w_{jm}^{(E)}\, E(\tilde{k}_m) \\ w_{jm}^{(d)}\, d_{jm}^2 \end{pmatrix}$$

- learn Minkowski metric

$g = \text{diag}(0.99 \pm 0.02,$
$-1.01 \pm 0.01, -1.01 \pm 0.02, -0.99 \pm 0.02)$



Moving on

Simple questions

– ML4Jets 2017: what architecture?

– ML4Jets 2018: top tagging study

SciPost Physics Submission

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February 26, 2019

Abstract

Based on the established task of identifying boosted, hadronically decaying top quarks, we compare a wide range of modern machine learning approaches. We find that they are extremely powerful and great fun.

Content

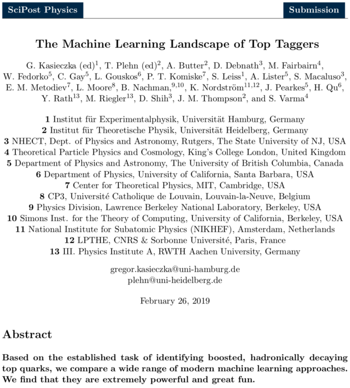
Moving on

Simple questions

– ML4Jets 2017: what architecture?

– ML4Jets 2018: top tagging study

⇒ lots of architectures work



SciPost Physics Submission

The Machine Learning Landscape of Top Taggers

G. Kasieczka (ed)[1], T. Plehn (ed)[2], A. Butter[2], D. Debnath[3], M. Fairbairn[4], W. Fedorko[5], C. Gay[5], L. Gouskos[6], P. T. Komiske[7], S. Leiss[1], A. Lister[5], S. Macaluso[3], E. M. Metodiev[7], L. Moore[8], B. Nachman,[9,10], K. Nordström[11,12], J. Pearkes[5], H. Qu[6], Y. Rath[13], M. Rieger[13], D. Shih[3], J. M. Thompson[2], and S. Varma[4]

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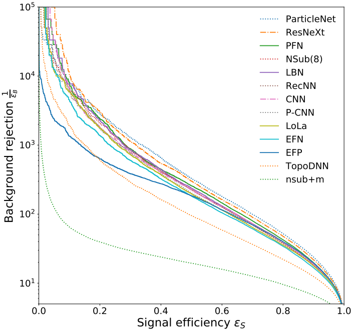


Moving on

Simple questions

– ML4Jets 2017: what architecture?

– ML4Jets 2018: top tagging study

$\Rightarrow$ lots of architectures work

More questions

– what about uncertainties?

– how stable are taggers in experimental reality?

– can we go beyond fully supervised learning?

– how do we go beyond jets?

– is classification all we can use ML for?

– are there analyses only ML will allow us to do?

– what is the particle nature of dark matter?

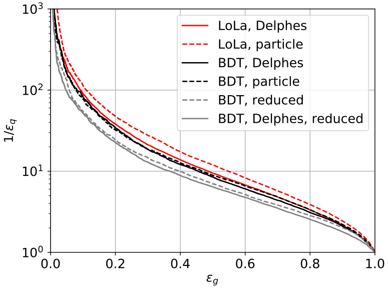
etc

When reality hits

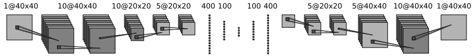
ML-Life is not always nice to us [Kasieczka, Kiefer, TP, Thompson]

- Quark-gluon tagging a problem since 1991
- quark jets typical for resonance searches
  gluon jets typical as dark matter recoil
- BDT/NN on high-level variables established

⇒ deep-learning advantage gone after detector simulation, REALLY???



Getting seriously inspired



Anomaly search only trained on background [Heimel, Kasieczka, TP, Thompson; Farina, Macari, Shih]

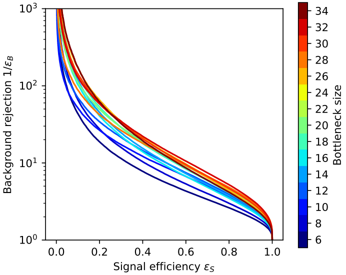
– established ML concept: autoencoder

– reconstruct typical QCD jet image from many QCD jets

– reduce weights in central layer
  compress information on 'typical'

– search for outliers hard to describe

– benchmark on top jets, search for Higgs or dark showers



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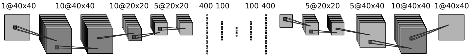

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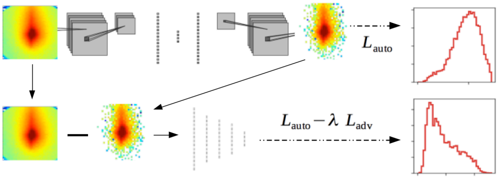
De-correlate background shaping

– established concept: adversary



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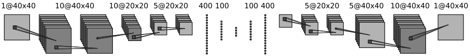

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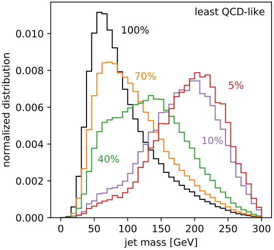
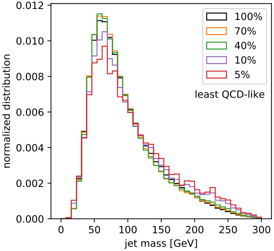
De-correlate background shaping

- established concept: adversary
- atypical QCD jets typially with large jet mass
  remove jet mass from network training





The future

Times are moving fast...

...jets are containers for subjet physics [was 1990s]

...deterministic taggers are established/old/boring [was 2000s]

...multi-variate taggers are an intermediate step [dying with the 2010s]

...imagine recognition is a starting point [will be 2020s]

...deep learning is not just classification

Join the fun!