Jets in the 21st Century

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Mainz 11/2018

Rise of the Machines

Brief history of jets

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

1994 jet-algo top tagger for fun [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]

. . .

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 adversarial autoencoder [Heinel, Kasieczka, Plehn, Thompson; Shi etal]

Jet-level analyses (1990s)

Jets as analysis objects

- jet–parton duality $\Leftrightarrow$ what are partons in detector?
- crucial for any LHC analysis [really???]
- infrared safety the main issue

$\Rightarrow$ any of this true for LHC?

QCD recombination algorithms [FASTJET: Cacciari, Salam, Soyez]

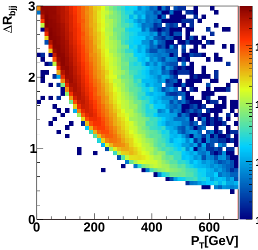
- define jet–jet and jet–beam distances [exclusive with resolution y_{cut}]

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

- (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)

$\Rightarrow$ fat jets/substructure: use clustering history [k_T, C/A only]

Heavy resonance taggers (2000s)



Tagging boosted tops

– hadronic decays vs QCD splittings

– SM sample: semileptonic $t\bar{t}$ events

$\Rightarrow$ substructure playground

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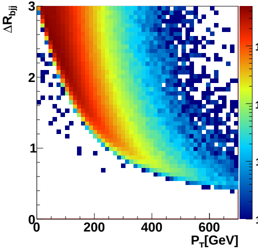


HEPTopTagger [BDRS; TP, Salam, Spannowsky, Takeuchi]

1– C/A fat jet, $R = 1.5$ and $p_T > 200$ GeV [FastJet limitation]

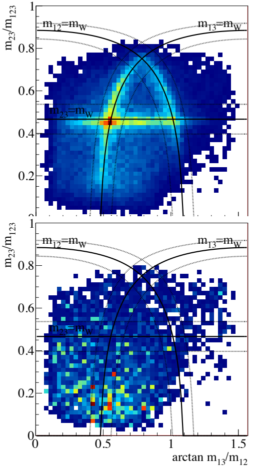
2– mass drop, cutoff $m_{\text{sub}} > 30$ GeV

3– filtering leading to hard substructure triple

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

5– A-shaped mass plane cuts as function of m_W/m_t

6– consistency condition $p_T^{(\text{tag})} > 200$ GeV



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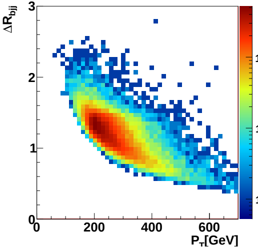

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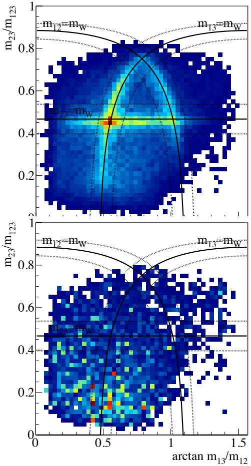
$\Rightarrow$ LHC break-through



N-Subjettiness

N-Jettiness to count subjets inside fat jet [Thaler, van Tilburg]

– how many subjets do the calo entries correspond to?

$$\tau_N = \frac{1}{\sum_{\alpha \in \text{jet}} p_{T,\alpha} R_0^\beta} \sum_{\alpha \in \text{jet}} p_{T,\alpha} \min_{k=1,\dots,N} (\Delta R_{k,\alpha})^\beta$$

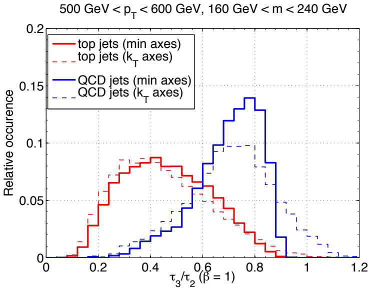
– choice of reference axes

1- from subjet algorithm
2- from minimization of τ_N

– $\tau_N \to 1$ means many calo entries away from N axes
$\tau_N \to 0$ means perfect matching

– systematics cancelled in ratios
$\tau_{N+1}/\tau_N \to 0$ for $N+1$ subjets

$\Rightarrow$ easily added to any other tagger



Multi-variate top taggers (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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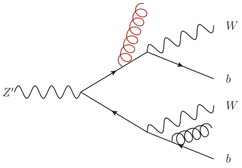
Fat jet and top kinematics

– FSR major problem for Z' search

– tag and reconstruction in each other's way

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



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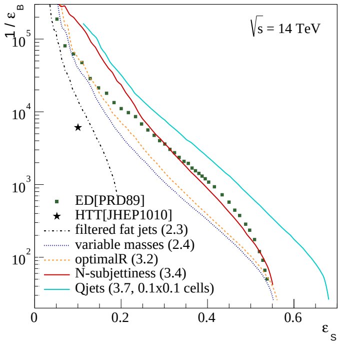
$\Rightarrow$ outperforming deterministic taggers



Jet images (2020s)

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

- why high-level observables as input?
- wavelet transformation [Rentala, Shepherd, Tait; Monk]
- W-tagging with image recognition [Cogan etal, Oliveira etal, Baldi etal]
- top-tagging attempt [Almeida, Backovic, Cliche, Lee, Perelstein]
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$\Rightarrow$ new hammer for jet nails

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Experimental questions

– does it work?
– what is the training sample? [Metodiev, Nachman, Thaler]
– how do we get it past the jets experts?

Theoretical questions

– how much of all this is QCD?
– how can be improve the setup? [the future has not been written]
⇒ what does the network learn?

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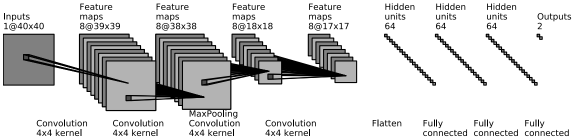
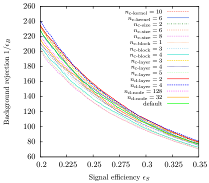
Neural network [Kasieczka, TP, Russell, Schell; Macaluso, Shih]

– colored image as input
– binning through calorimeter resolution [$\Delta\eta = 0.1$ vs $\Delta\phi = 5^\circ$]
– analyze geometric patterns [Facebook: convolutional network]

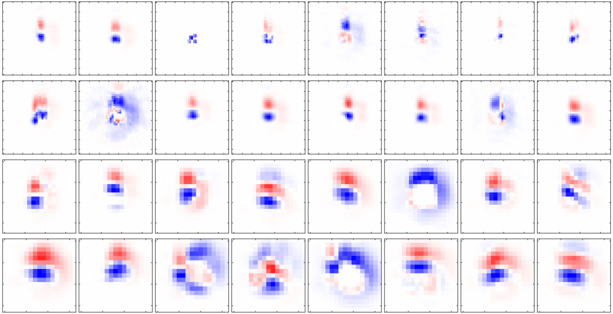


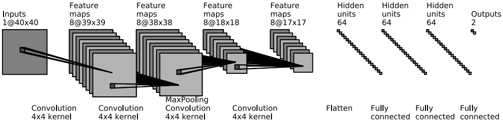


Inside DeepTop

Benchmarking image-based top tagger [Kasieczka, TP, Russell, Schell]

– 2+2 convolutional layers probing 2D structure with kernel matrix





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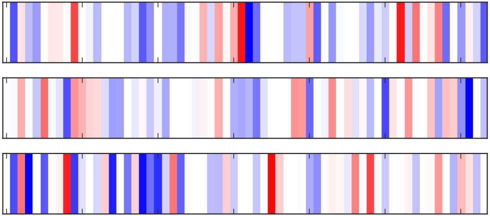
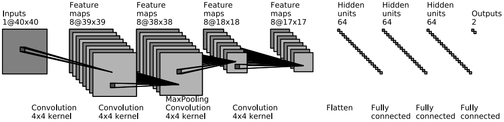
– 2+2 convolutional layers   probing 2D structure with kernel matrix

– 3 fully connected layers   weight function linking input and output





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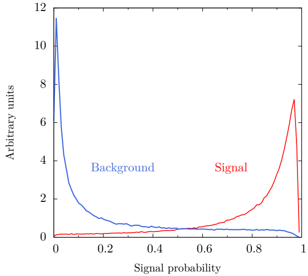
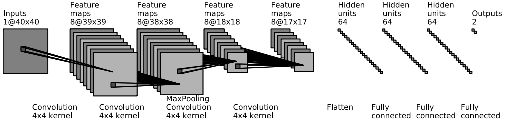
– signal-ness vs background-ness output [probability?]





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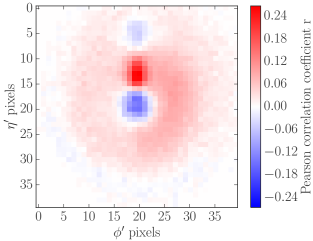
- 2+2 convolutional layers — probing 2D structure with kernel matrix
- 3 fully connected layers — weight function linking input and output
- signal-ness vs background-ness output [probability?]
- Pearson input-output correlation [pixel x vs label y]

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



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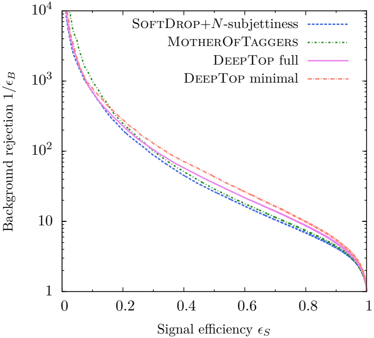
– comparison to MotherOfTaggers

$$\{ m_\text{sd}, m_\text{fat}, m_\text{rec}, f_\text{rec}, \Delta R_\text{opt}, \tau_2, \tau_3, \tau_2^\text{sd}, \tau_3^\text{sd} \}$$

$\Rightarrow$ understandable performance gain



Just a new tool

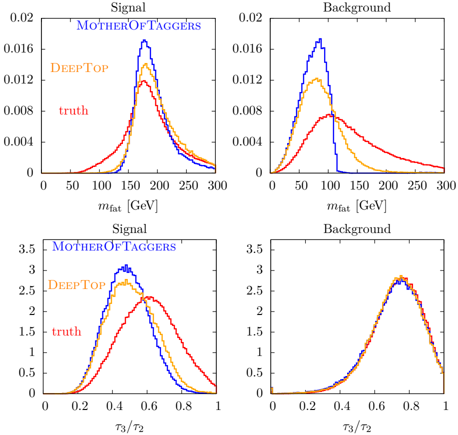
Typical reaction: ‘Fuck you, you fucking machine’

– in principle, full control for fully supervised learning

– lots of events in the grey zone
but checks possible for correctly identified signal/background events

– compare truth vs MotherOfTaggers vs DeepTop

1- fat jet mass and N-subjettiness



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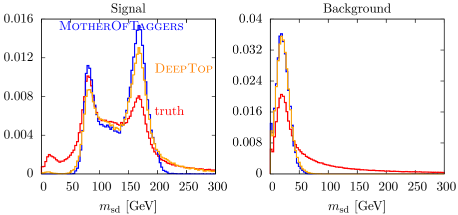
2- soft drop mass



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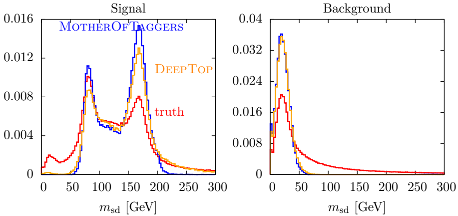
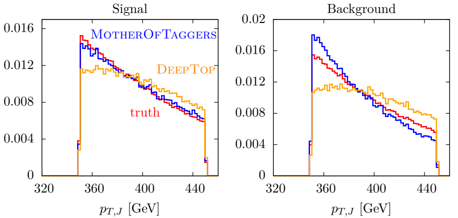
1- fat jet mass and N-subjettiness

2- soft drop mass

3- transverse momenta

$\Rightarrow$ it works and we know why

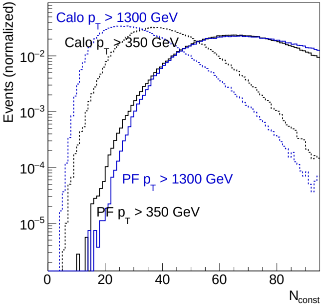




DeepTopLoLa

Our version of graph network [Butter, Kasieczka, TP, Russell; see also Louppe etal, Pearkes etal]

- 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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- 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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– on-shell conditions for top tag

– combined 4-vectors

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

$$C = \begin{pmatrix} 1 & 0 & \cdots & 0 & C_{1,N+2} & \cdots & C_{1,M} \\ 0 & 1 & & \vdots & C_{2,N+2} & \cdots & C_{2,M} \\ \vdots & \vdots & \ddots & 0 & \vdots & & \vdots \\ 0 & 0 & \cdots & 1 & C_{N,N+2} & \cdots & C_{N,M} \end{pmatrix}$$

– 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

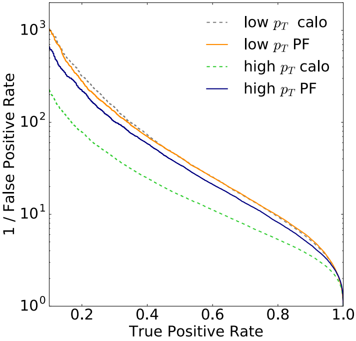
$$\tilde{k}_j \xrightarrow{\text{LoLa}} \hat{k}_j = \begin{pmatrix} m^2(\tilde{k}_j) \\ p_T(\tilde{k}_j) \\ w_{jm}^{(E)} \, E(\tilde{k}_m) \\ w_{jm}^{(d)} \, d_{jm}^2 \end{pmatrix}$$

– fun: measure Minkowski metric

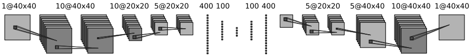
$g = \text{diag}(0.99 \pm 0.02,$
$\quad -1.01 \pm 0.01, -1.01 \pm 0.02, -0.99 \pm 0.02)$

– extend to particle flow

– network with little but Lorentz invariance



Getting inspired



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

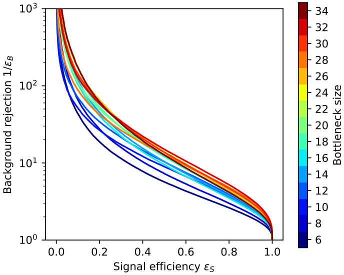
– established concept: autoencoder

– 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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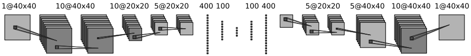

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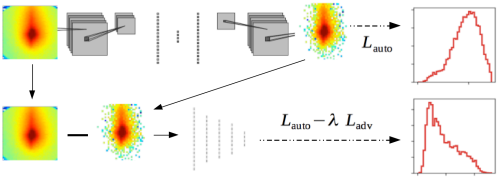
De-correlate background shaping

– established concept: adversary [Google Go]



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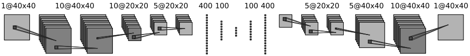

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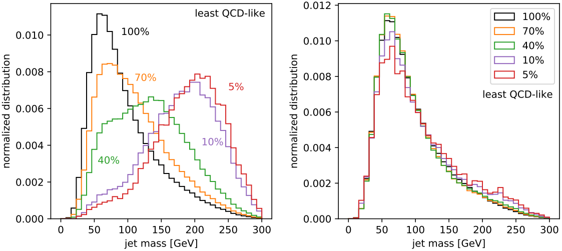
De-correlate background shaping

- established concept: adversary [Google Go]
- 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 established/old/boring [was 2000s]

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

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

...DeepTop is not a black box

...DeepTopLoLa took Jackson

...Autoencoders really change analyses

Join the fun!