The Rise of the Tagging Machines

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Generation One to Three

From deterministic taggers to deep networks

1994 QCD-algorithm W-tagger for heavy Higgs [Seymour]

1994 QCD-algorithm top tagger for fun [Seymour]

2008 QCD-algorithm BDRS Higgs tagger [Butterworth, Davison, Rubin, Salam]

2008 QCD-algorithm JH/CMS top tagger [Kaplan, Rehermann, Schwartz, Tweedie]

2009 QCD-algorithm HEPTopTagger [TP, Salam, Spannowsky]

...

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

2011 N-Subjettiness [Thaler, van Tilburg]

2011 Shower Deconstruction [Soper, Spannowsky]

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

...

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

Jet algorithms

Jets

– jet–parton duality $\Leftrightarrow$ what are partons in detector? [IR save recombination algos]

– crucial for any LHC analysis [actually???]

– quarks vs gluons tricky in perturbative QCD [looking well-definď in Pythia]

– extension to b and t perturbative QCD problem

– top tagging: easy and well-defined

Recombination algorithms [FASTJET: Cacciari, Salam, Soyez]

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

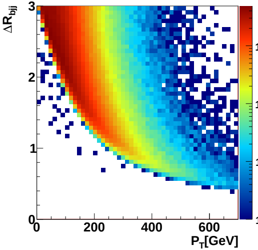
$$\begin{aligned}
&k_T && y_{ij} = \frac{\Delta R_{ij}}{R} \, \min\left(p_{T,i}, p_{T,j}\right) && y_{iB} = p_{T,i} \\
&\text{C/A} && y_{ij} = \frac{\Delta R_{ij}}{R} && y_{iB} = 1 \\
&\text{anti-}k_T && y_{ij} = \frac{\Delta R_{ij}}{R} \, \min\left(p_{T,i}^{-1}, p_{T,j}^{-1}\right) && y_{iB} = p_{T,i}^{-1}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

– (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)

– theoretical and experimental trade-off decisions

– fat jets/substructure: use clustering history

Hadronic $t\bar{t}$ resonances



Sub-jet top tagging

- hadronic top identification and reconstruction
- hadronic decays vs QCD splittings
- SM sample: semileptonic $t\bar{t}$ events

$\Rightarrow$ *t*-tagging the new *b*-tagging?

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

– algorithm based on QCD-controlled variables

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

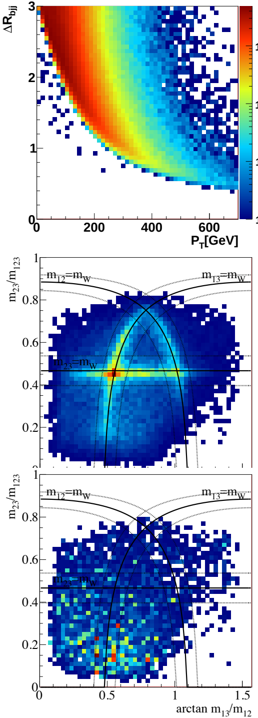
2– mass drop, cutoff $m_{\text{sub}} > 30$ GeV

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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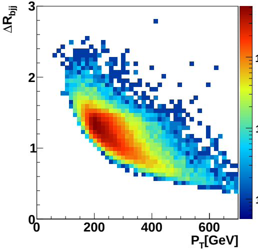
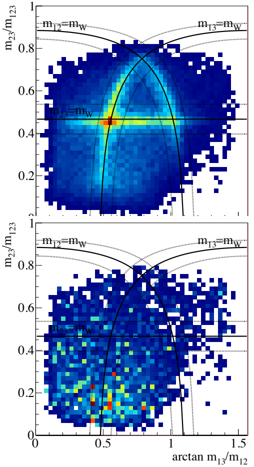
$\Rightarrow$ G1: experimental break-through





N-Subjettiness

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

– how many subjets do the calo entries correspond to?

– event shape using N subjet directions $\hat{n}_j$ [$\beta > 0$]

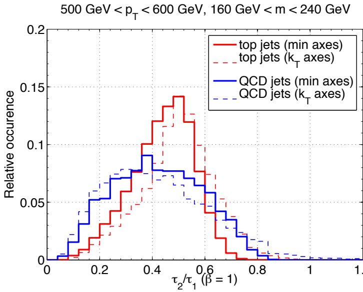
$$\tau_N = \frac{1}{\sum_{\alpha \in \text{jet}} p_{T,\alpha} R_0^\beta} \sum_{\alpha \in \text{jet}} p_{T,\alpha} \min_{k=1,\ldots,N} (\Delta R_{k,\alpha})^\beta$$

– 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



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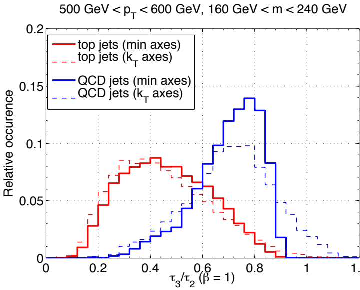

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Tagger

- simple selection

$$m_\text{fat jet} = 160...240 \;\; \text{GeV} \qquad\qquad \frac{\tau_3}{\tau_2} < 0.6$$

- multi-variate in N and β with some improvement

$\Rightarrow$ easily added to any other tagger

Multi-variate top taggers

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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Qjets [Ellis, Hornig, Roy, Krohn, Schwartz]

– tagger problem: wrong ‘best’ option

– more than one clustering history, weighted by

$$\omega_{ij} = \exp\left[-\alpha \frac{y_{ij} - y_{ij}^{\min}}{y_{ij}^{\min}}\right]$$

then using distributions like $\langle m^2 \rangle - \langle m \rangle^2$

– $\{\ldots, \{m_{123}^{\text{Qjets}}\}\}$

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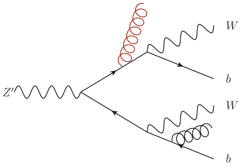
Fat jet and top kinematics

– 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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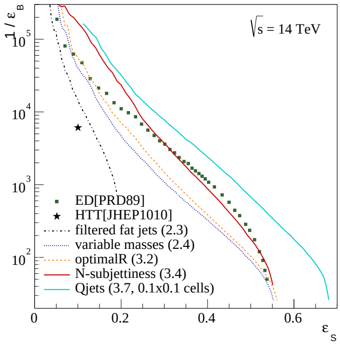
$\Rightarrow$ G2: deterministic taggers terminated!



Jet images

Image regognition for jets [template tagger, shower deconstruction]

- 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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$\Rightarrow$ G3: new avenue in jet physics

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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 people?

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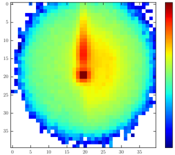
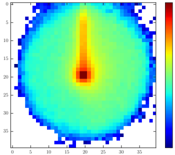
Theoretical questions

– what does the neutal network learn?
– how much of it is hard QCD?
– how can be improve the setup? [the future has not been written]
⇒ Benchmarks crucial

Jet images





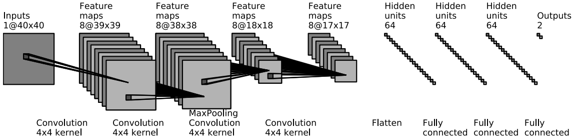
Start with anti-k_T fat jet [$p_T = 350\dots450$ GeV, $R = 1.5$]

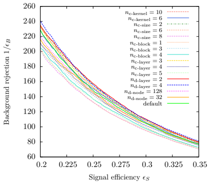
- shift move image to center the global maximum
- rotation rotate the second maximum to 12 o'clock
- flip ensure third maximum is in the right half-plane
- crop crop the image to 40×40 pixels
- decide on E vs E_T for rapidities $\eta \gtrsim 2$

$\Rightarrow$ pre-processing only for illustration

Set up network [Kasieczka, TP, Russell, Schell]

- run on 2-D jet images [$p_T = 350, \dots, 450$ GeV]
- binning through calorimeter resolution [$\Delta\eta = 0.1$ vs $\Delta\phi = 5^\circ$]
- 150k events for training
- analyze geometric patterns [convolutional network]

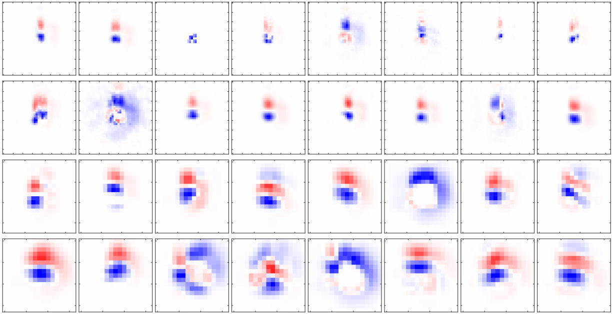




DeepTop tagger

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

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



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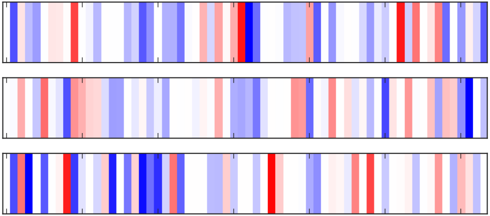
$$y_i = \max\left(0, \sum_{j=1}^{n^2} W_{ij} x_j + b_i\right)$$



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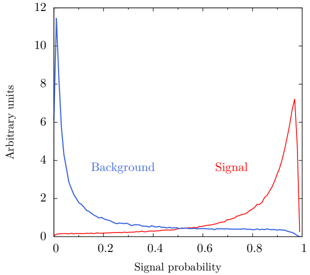

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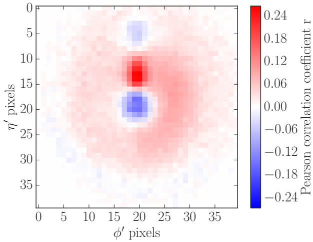
$$r_{ij} \approx \sum_{\text{images}} \left(x_{ij} - \bar{x}_{ij}\right)\left(y - \bar{y}\right)$$



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– comparison to G2 MotherOfTaggers

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

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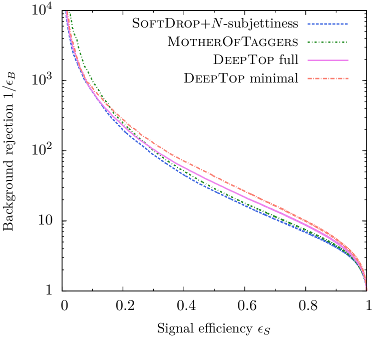
⇒ slight performance gain for CNN



Checking physics

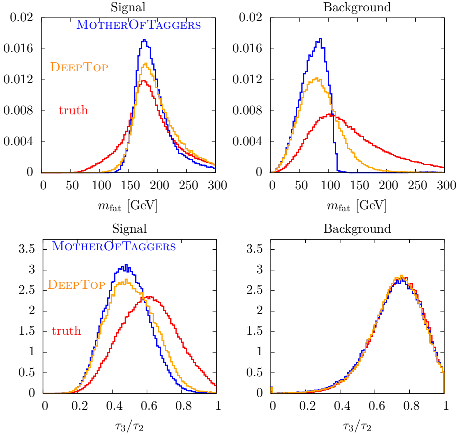
Typical reaction: ‘fuck you, you fucking machine’

– 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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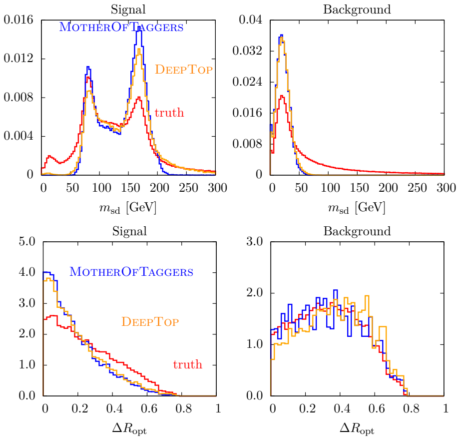

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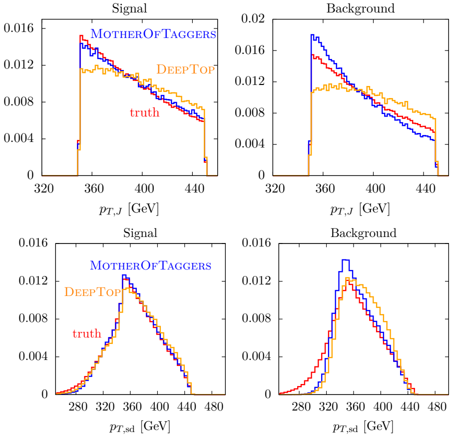

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4- any other suggestions?

⇒ Machine learning works and we know why

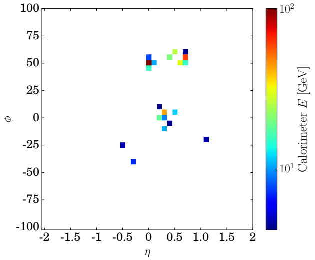
DeepTop using Lorentz Layer

Why standard software? [Butter, Kasieczka, TP, Russell; see also Louppe etal, Pearkes etal]

1 appropriate physics objects known

2 tracking+calorimeter pictures?

3 link to G1 and G2 taggers? [Larkoski etal]



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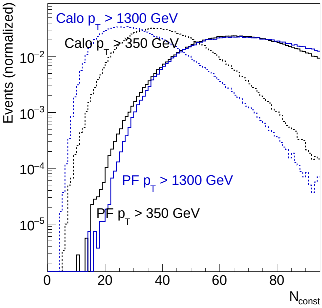

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Inspired by jet algorithm — combination layer

– 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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– input 4-vectors

– on-shell conditions for top tag

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

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

DeepTop using Lorentz Layer

Why standard software? [Butter, Kasieczka, TP, Russell; see also Louppe etal, Pearkes etal]

1 appropriate physics objects known

2 tracking+calorimeter pictures?

3 link to G1 and G2 taggers? [Larkoski etal]

⇒ Start from leading 4-vectors [N=40]

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

sum of all momenta, fat jet momentum [only in v1]
original momenta k_i
$M - N$ trainable linear combinations [M-N=15]

⇒ Physics step, easy to interpret

DeepTop using Lorentz Layer

Inspired by jet algorithm — combination layer

– input 4-vectors $k_{\mu,i}$

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

Remember e&m — Lorentz layer

– DNN on Lorentz scalars

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

– measurement-inspired individual $m_j, p_{T,j}$

trainable correlations: energy, metric

[1+4 copies, sum,max]

DeepTop using Lorentz Layer

Inspired by jet algorithm — combination layer

– input 4-vectors $k_{\mu,i}$

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

Remember e&m — Lorentz layer

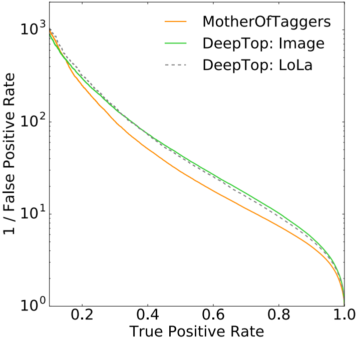
– DNN on Lorentz scalars $\tilde{k}_j \xrightarrow{\text{LoLa}} \hat{k}_j$

– measurement-inspired individual $m_j, p_{T,j}$

trainable correlations: energy, metric

[1+4 copies, sum,max]

– comparison to G2, images



DeepTop using Lorentz Layer

Inspired by jet algorithm — combination layer

– input 4-vectors $k_{\mu,i}$

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

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– comparison to G2, images

– fun: measure Minkowski metric

$g =$diag$(0.99\pm0.02,$

$-1.01\pm0.01, -1.01\pm0.02, -0.99\pm0.02)$

DeepTop using Lorentz Layer

Inspired by jet algorithm — combination layer

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

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– running on particle flow

[$p_T = 350, \ldots, 450$ GeV and $1300, \ldots, 1400$ GeV]

– 180k training events, 15 GPU minutes

DeepTop using Lorentz Layer

Inspired by jet algorithm — combination layer

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

Remember e&m — Lorentz layer

- DNN on Lorentz scalars $\quad \tilde{k}_j \xrightarrow{\text{LoLa}} \hat{k}_j$
- measurement-inspired individual $m_j, p_{T,j}$

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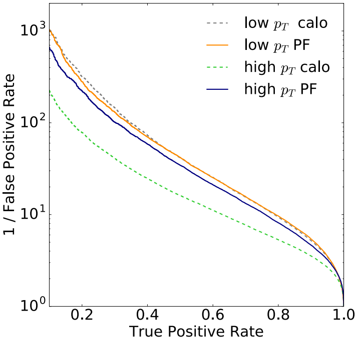
  $\quad -1.01 \pm 0.01, -1.01 \pm 0.02, -0.99 \pm 0.02)$
- running on particle flow

  [$p_T = 350, \ldots, 450$ GeV and $1300, \ldots, 1400$ GeV]
- 180k training events, 15 GPU minutes
- G3 with little but Lorentz invariance



The future

Times are moving fast...

...deterministic taggers estalished/old/boring

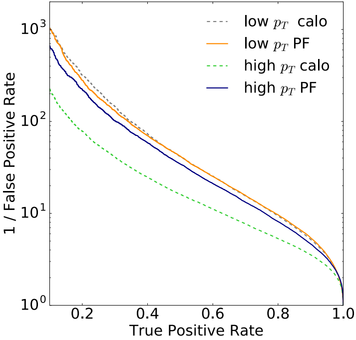
...information beyond clustering history helps

...imagine recognition for subjets as starting point

...DeepTop is not a black box

...back to physics with DeepTopLoLa

ML taggers ready, perfect career launcher



Backup: non-improvements

Tagging without fat jets [Lapsien, Kogler, Haller; FastJetContrib]

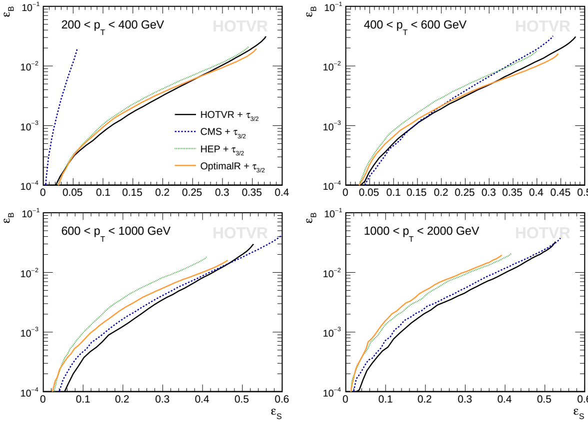
1– variable-R: jet size depending on p_T [Krohn, Thaler, Wang]

2– mass jump: jet mass condition in C-A jet algorithm [Stoll]
specifically $m_{ij} \lesssim 30$ GeV and $m_{ij} \gtrsim 1.4 \max(m_{ij})$

– possible advantage: not relying on fixed fat jet

– comparison with HEPTopTagger, CMSTagger in working points
pseudo-ROC curve by adding $\tau_{2,3}$ [why???]

– improvement?



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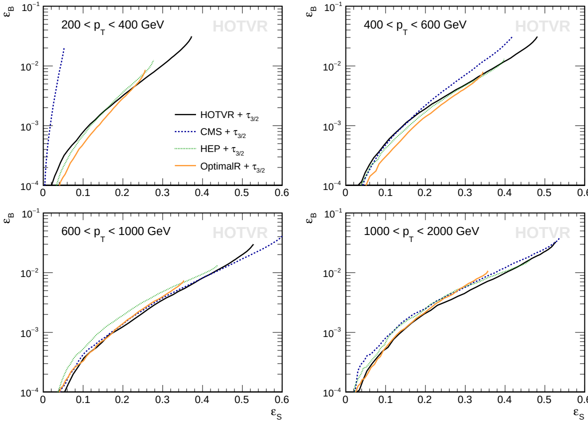
– not in v2!



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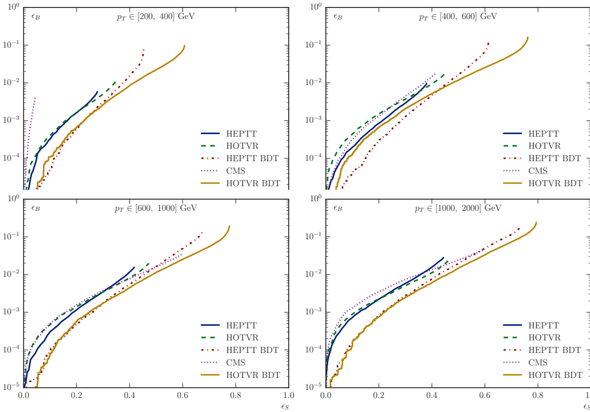
– comparison with HEPTopTagger, CMSTagger in working points
pseudo-ROC curve by adding $\tau_{2,3}$ [why???]

– proper job

[no Qjets, $p_T > 30$ GeV]



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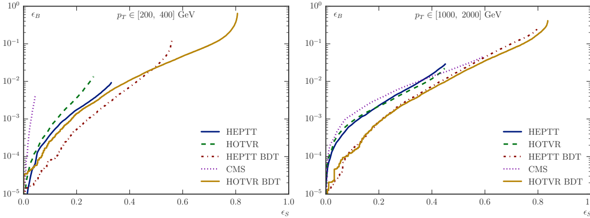
– proper job

[no Qjets, all p_T]



⇒ tagger performance stable and plateau'd

⇒ find other ways to improve?