Classification Networks in Particle Physics

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Physics story: Nothing is ever new

LHC visionaries

– 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 $\sim 85\%$ 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.

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- 1994: jet-algorithm *W*/top-tagger [Seymour]

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Searches for new particles using cone and cluster jet algorithms: a comparative study

Michael H. Seymour

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

Received 18 June 1993; in revised form 16 September 1993

Abstract. We discuss the reconstruction of the hadronic decays of heavy particles using jet algorithms. The ability to reconstruct the mass of the decaying particle is compared between a traditional cone-type algorithm and a recently proposed cluster-type algorithm. The specific examples considered are the semileptonic decays of a heavy Higgs boson at $\sqrt{s}=16$ TeV, and of top quark–antiquark pairs at $\sqrt{s}=1.8$ TeV. We find that the cluster algorithm offers considerable advantages in the former case, and a slight advantage in the latter. We briefly discuss the effects of calorimeter energy resolution, and show that a typical resolution dilutes these advantages, but does not remove them entirely.

except that the invariant mass of a pair is replaced by the transverse momentum of the softer particle relative to the other.

More recently, this algorithm was extended to collisions with incoming hadrons [5], and a longitudinally-invariant $k_\perp$-clustering algorithm for hadron-hadron collisions was proposed [6]. This algorithm has been compared with the more commonly used cone algorithm from the viewpoints of a parton-shower Monte Carlo program [6, 7], and a fixed-order matrix lation [8], and advantages of the cluster reported in both cases. This paper is a comparison between the algorithms reconstructing the hadronic decays of which was also studied in a preliminary

The only as-yet unobserved particles Standard Model are the top quark and H search for, and study of, these particles most important goals of current and p hadron collider experiments. In both cas

∼ 1970: *People with visions should see a doctor* [Helmut Schmidt, wrong for once]

Fat jet taggers

Look what makes jets [Pre-LHC, jets were just annoying]

– top jets from $t \to bq\bar{q}'$ vs QCD jets

– top decays well-defined in theory

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

$\Rightarrow$ Fat jets as LHC physics playground

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

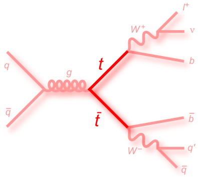
1– fat jet with $p_T > 200$ GeV

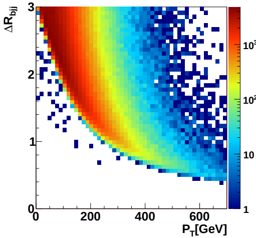
2– filtering defining 3-5 decay jets

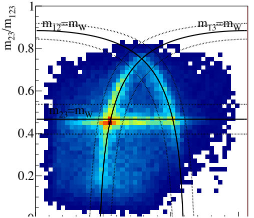
3– top mass window $m_{123} = [150, 200]$ GeV

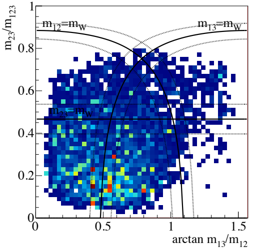
4– mass plane cuts extracting $m_{ij} \approx m_W$

$\Rightarrow$ Not rocket science, but crucial to build trust









Multi-variate taggers

Developing the benchmark

- multivariate analysis generally old news
  multivariate tagger 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]

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

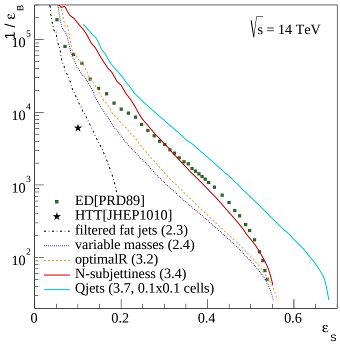
- add N-subjettiness [Thaler, van Tilburg]
- $\{m_{123}, f_W, R_{\text{opt}} - R_{\text{opt}}^{(\text{calc})}, \tau_j, \tau_j^{(\text{filt})}\}$

$\Rightarrow$ Theory all but precision

Fat jet and top kinematics

- jet radiation major problem for Z' search
- tag and reconstruction in each other's way
- $\{\dots, m_{tt}, p_{T,t}, m_{jj}^{(\text{filt})}, p_{T,j}^{(\text{filt})}\}$

$\Rightarrow$ Best we can do?



Jet image machines

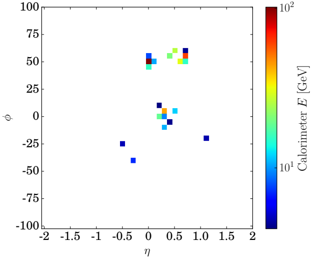
Natural next step [Cogan etal, Oliveira, Nachman etal, Baldi, Whiteson etal (2014/15)]

– why intermediate high-level variables?

– as much data as possible

– calorimeter output as image

$\Rightarrow$ Deep learning = modern networks on low-level observables



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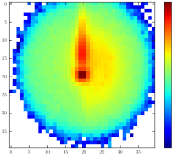
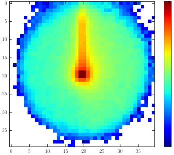




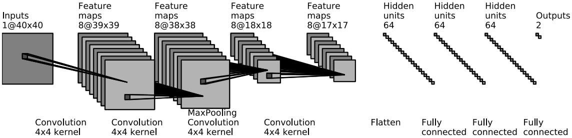
Convolutional network [Kasieczka, TP, Russell, Schell; Macaluso, Shih]

– image recognition standard ML task

– rapidity vs azimuthal angle, colored by energy deposition

– top tagging on 2D jet images

– 40×40 bins through calorimeter resolution



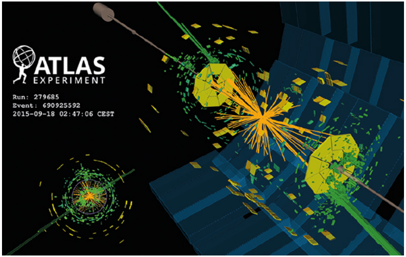
Why LHC? Why jets?

Data from ATLAS & CMS

– most LHC 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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Physics in jets

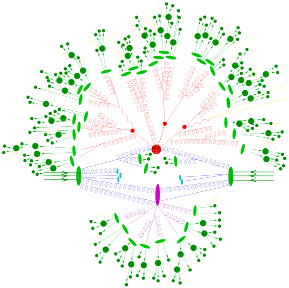
– re-summed perturbative QFT prediction from QCD

– jets as decay products

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

– new physics in 'dark showers'

$\Rightarrow$ It's fundamentally interesting



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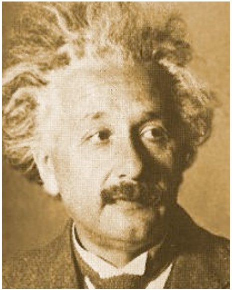
Monte Carlo data

– QCD simulation: Sherpa, Pythia, Herwig [Madgraph]

– fast detector simulation: Delphes

– data-to-data comparison: MC vs LHC

$\Rightarrow$ We can simulate it



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Why not LHC?

ATLAS & CMS

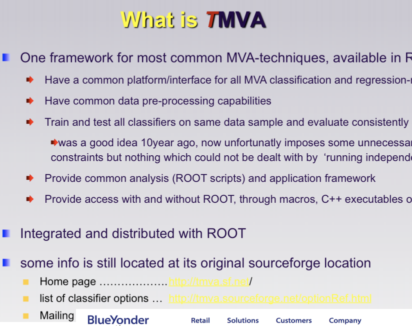
– 3000 know-it-alls per experiment
– strong top-down structures
– strongly organized analysis groups
$\Rightarrow$ Incentive for innovation?

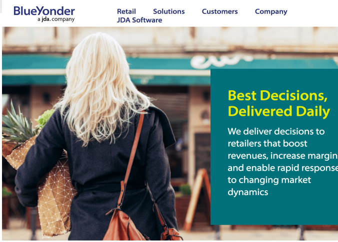
Expertize

– LHC data format: ROOT
– multi-variate analyses tool: TMVA
– Tensorflow from TMVA/ROOT
– ML challenges running
$\Rightarrow$ Little sense of ML-urgency

Help from theory

– theorists linked to lack of team compatibility
– simulated data as good as actual data
– excellent personal ex-th connections
$\Rightarrow$ Theory driving non-theory developments





Networks for LHC

Neural networks in particle physics

– classification — signal extraction
generative — help with Monte Carlo [ask Anja & Ramon]

– deep network: many layers/weights

– cross-entropy loss function: probability output

⇒ Network just a learned function $p(\vec{x})$

Need to focus

– not: understand neural networks using physics

– not: improve standard analyses by 10%

– not: tackle detector-limited problems

– not: cats-dogs-icecream cones

⇒ New analysis tools

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LHC physicist's perspective

– find architectures suitable for input

– avoid re-learning known physics

– control what network learns

– ensure network is stable

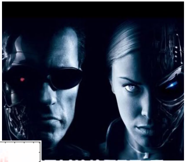
– assign error bars

– find things to play with

...

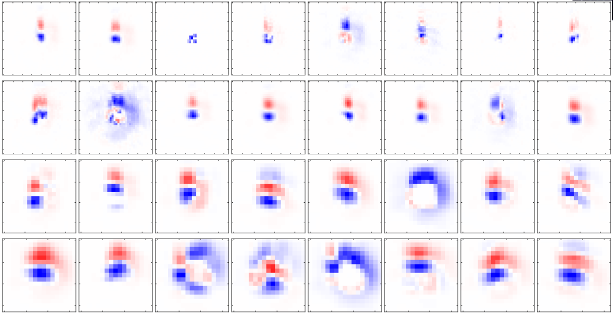
⇒ If you have the source code there is no black box!

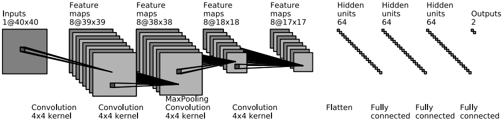
Inside DeepTop



Particle physicists as ‘users’ [Kasieczka, TP, Russell, Schell; Macaluso & Shih]

– 2+2 convolutional layers





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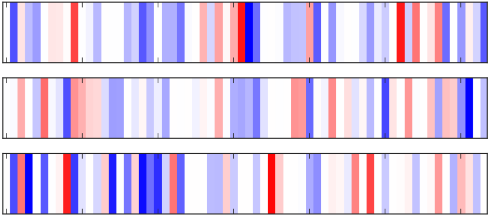
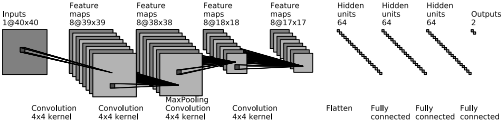
– 3 fully connected layers





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– 2+2 convolutional layers

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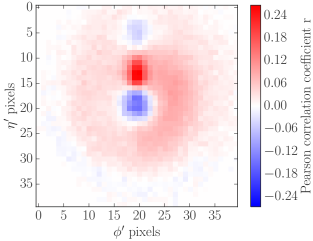
– Pearson input-output correlation [pixel x vs label y]

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



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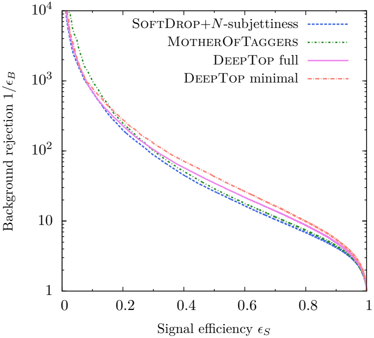
– comparison to MotherOfTaggers BDT

$\Rightarrow$ Understandable performance gain



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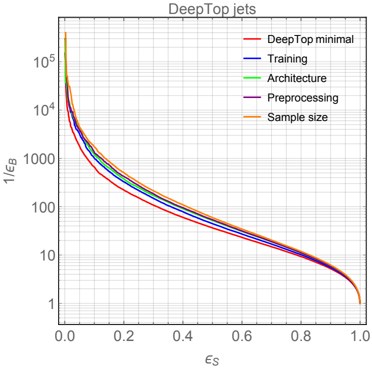

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Typical reaction: ‘F*** you, you f***ing machine’

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

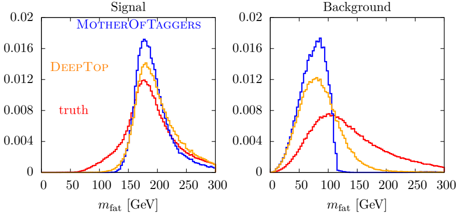
– MC truth vs MotherOfTaggers vs DeepTop

fat jet mass

N-subjettiness

transverse momenta

⇒ The box is not black



Grand theory ideas

Networks with 4-vector input [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 [alternatively: Erdmann, Rath, Rieger]

Inspired by jet algorithm — combination layer

- input 4-vectors

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

- combining them

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

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

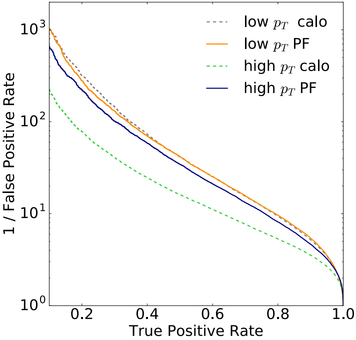
Inspired by Jackson — Lorentz layer

- DNN on Lorentz scalars

$$\tilde{k}_j \xrightarrow{\text{LoLa}} \hat{k}_j = \begin{pmatrix} m^2(\tilde{k}_j) \\ p_T(\tilde{k}_j) \\ \vdots \end{pmatrix}$$

$\Rightarrow$ Learn Minkowski metric

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



Meet the professionals

A brief history of achievement

- 2014/15: first jet image papers
- 2017: first (working) ML top tagger
- ML4Jets 2017: What architecture works best?
- ML4Jets 2018: Lots of architectures work [1902.09914]

⇒ Jet classification understood and done

SciPost Physics Submission

The Machine Learning Landscape of Top Taggers

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5 Theoretical Particle Physics and Cosmology, King's College London, United Kingdom
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April 12, 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

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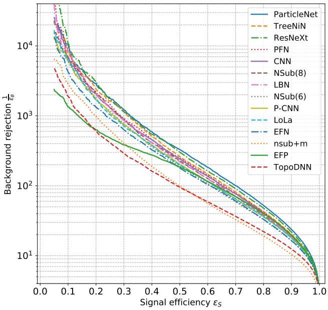
Abstract

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.



Meet the professionals

A brief history of achievement

– 2014/15: first jet image papers

– 2017: first (working) ML top tagger

– ML4Jets 2017: What architecture works best?

– ML4Jets 2018: Lots of architectures work [1902.09914]

⇒ Jet classification understood and done

⇒ **What's new and cool?**

When reality hits

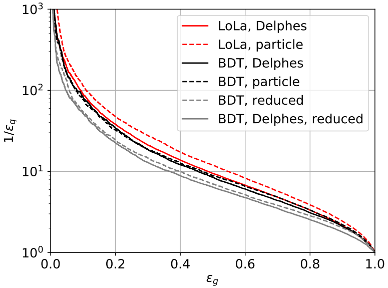
ML-Life is not always nice to us [Kasieczka, Kiefer, TP, Thompson]

– quark-gluon tagging a problem since 1991

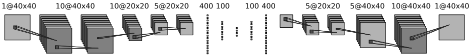
– quark jets typical for resonance searches
gluon jets typical as dark matter recoil
...

– BDT/NN on high-level variables established

$\Rightarrow$ deep-learning advantage gone after detector simulation, REALLY???



Learning background only



Fully supervised classification boring [Heimel, Kasieczka, TP, Thompson; Farina, Macari, Shih]

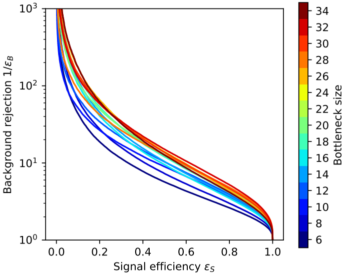
– anomaly searches, only training on ‘background’

– established ML concept: autoencoder

– reconstruct typical QCD jet image from many QCD jets
reduce weights in central layer, compress information to ‘typical’

– search for outliers hard to describe

⇒ Making an okay tagger



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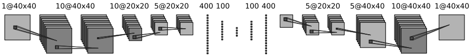

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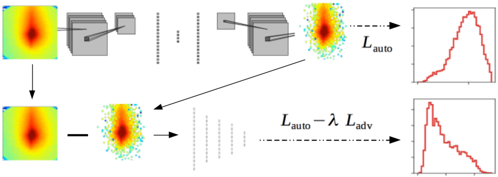
De-correlate background shaping

– established concept: adversary [Shimmin,...]



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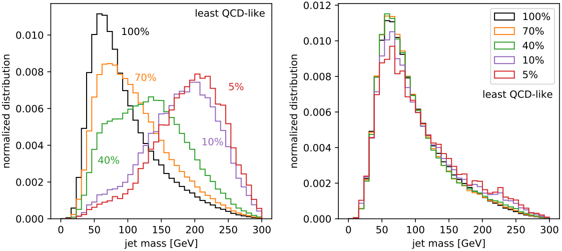
De-correlate background shaping

– established concept: adversary [Shimmin,...]

– atypical QCD jets typially with large jet mass
remove jet mass from network training



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⇒ Making an okay tagger

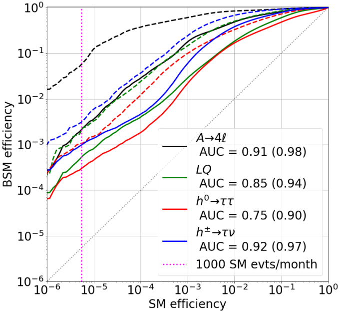
The whole thing on anomalous LHC events [Cerri, Nguyen, Pierini, Spiropulu, Vlimant]

– same thing on full events

– training data a problem

– variational autoencoder more powerful

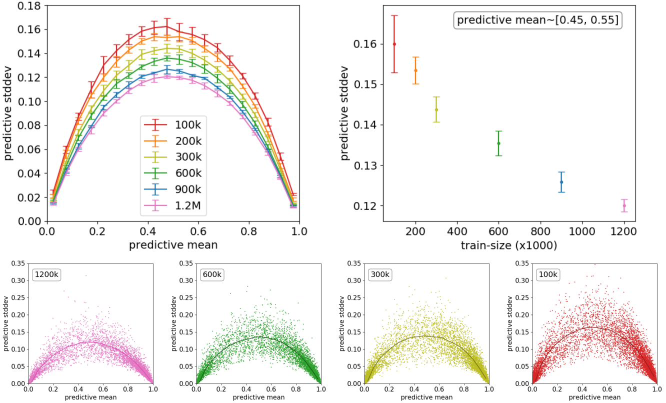
⇒ Proof of concept...



B****ian networks

Simply better networks [Bollweg, Haussmann, Kasieczka, Luchmann, TP, Thompson]

- learn classification output and uncertainty [(60 $\pm$ 0)% top different from (60 $\pm$ 1)% top]
- error bars: limited training statistics



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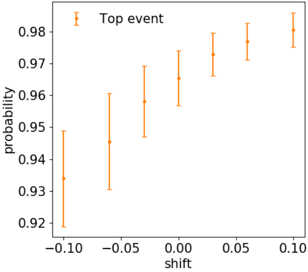
– error bars: jet energy scale (correlated)



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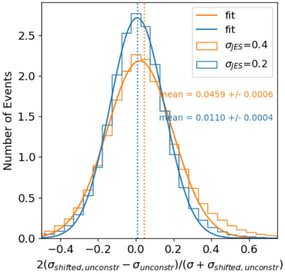

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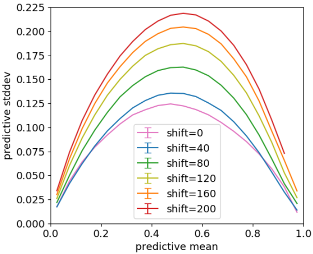
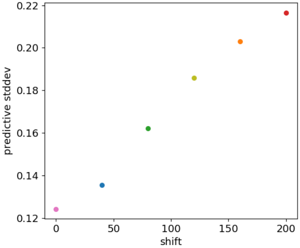
– stability detection: pile-up





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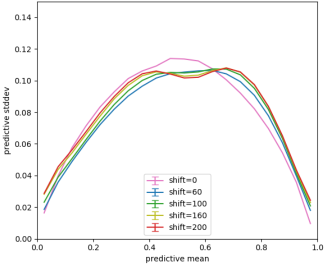

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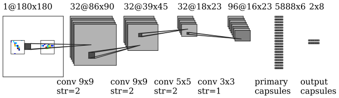
– error bars: limited training statistics
– error bars: jet energy scale (correlated)
– error bars: jet energy scale (uncorrelated)
– stability detection: pile-up
– tagger calibration part of the training
– systematic approach to regularization and drop-out
– performance just like usual taggers

....

– Lots of conceptual and practical advantages at no cost

Capsules vs CNN



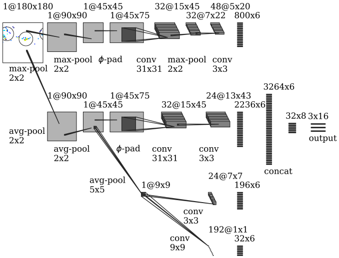
Calorimeter images too big for CNN

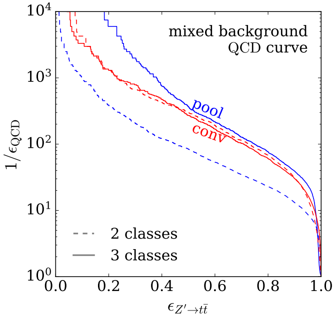
- full detector instead of fat jet [forget training for now]
- sparse in objects with sparse objects
- multi-label for different backgrounds

Capsule networks [Diefenbacher, Frost, Kasieczka, TP, Thompson]

- vector output instead of scalar classification
- agreement by parallel vectors in feature space
- vector components for properties and geometry [eyes, nose, mouth]
- pooling vs stride convolutions?

⇒ boosted tops from Z' resonance





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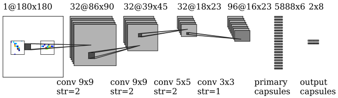

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Visualization

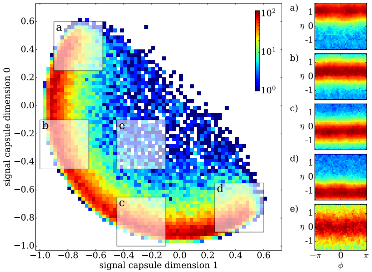
– signal capsule for signal events

– two components distinctive through radius

– rotation remaining symmetric

– average event per region

signal identifying η_j
azimuthal angle insensitive



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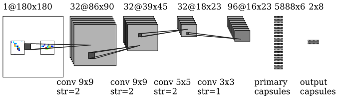

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Visualization

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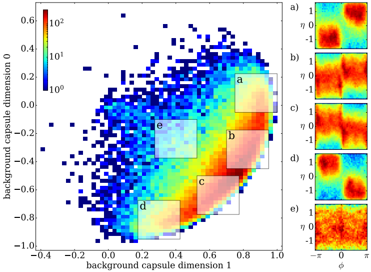
signal identifying η_j
azimuthal angle insensitive

background identifying back-to-back

– and we can also do $t\bar{t}H_{bb}$...



The future

Machine learning is an amazing tool box...

...LHC physics really is big data

...imagine recognition is a starting point

...deep learning is not just classification

...jets are not the only interesting objects at LHC

...Bayesian networks are extremely likable

...capsule networks useful for full events

Let's find some really cool applications!