QCD or What?: Using Autoencoders in HEP

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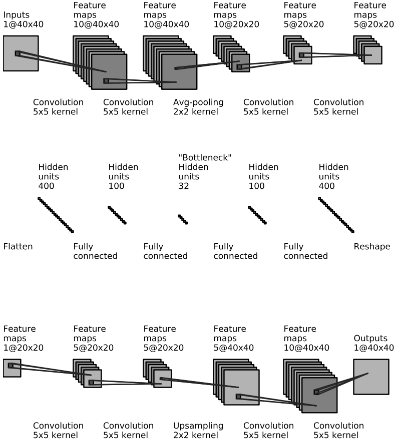
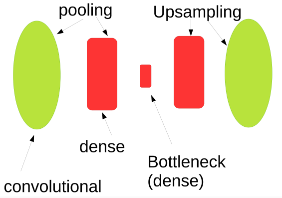
Overview

The Autoencoder

- **Generic anomaly detector**
- Detect non-QCD events
- Entirely data-driven
- Only needs events from a (background-dominated) signal region
- Model-independent



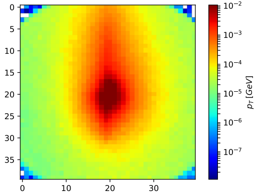
Key Autoencoder Points



- The input data is encoded and compressed
- The reconstruction works for the background, fails for any arbitrary signal
- Minimized at the bottleneck:
  $\longrightarrow$ Needs to be large enough to (completely) encode the background
  $\longrightarrow$ Cannot be so large that it can reconstruct any image

Training

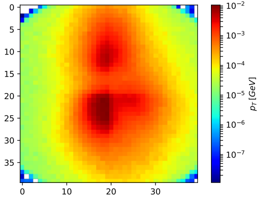
- Train on pure QCD background $\longrightarrow$ **We will consider mixed training samples later**
- Network learns to reconstruct QCD
- Implemented in Keras with TensorFlow and Adam optimiser
- Activation: PReLu, linear final layer
- Loss function: $\sum_{\text{inputs}}(x_{\text{out}} - x_{\text{in}})^2$

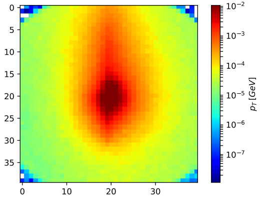


Average QCD image

Testing

- Test on mixed signal+QCD samples
- Network reconstructs QCD, fails for signal
- Signal is flagged as an anomaly
- **Network finds any non-QCD signals: It has only seen QCD**

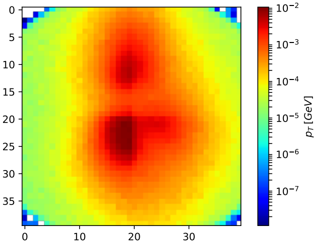




Jet Images (Top vs QCD)

figure credit: Michel Luchmann and Theo Heimel, preprocessing by David Shih

- Create jet images from calorimeter entries
- Preprocess to help discrimination
  - Centre on p_T weighted jet centre
  - Rotate the jet axis to be vertical
  - Flip so 3$^{\text{rd}}$ maximum is on right
  - Pixellate



Average top image

Constituents: Cola and LoLa in Equations

The combination layer (CoLa) acts on 4-momenta $k_{\mu,i}$:

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

and Lorentz layer (LoLa)

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

trainable

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$\longrightarrow$ make d^2_{jm} trainable:

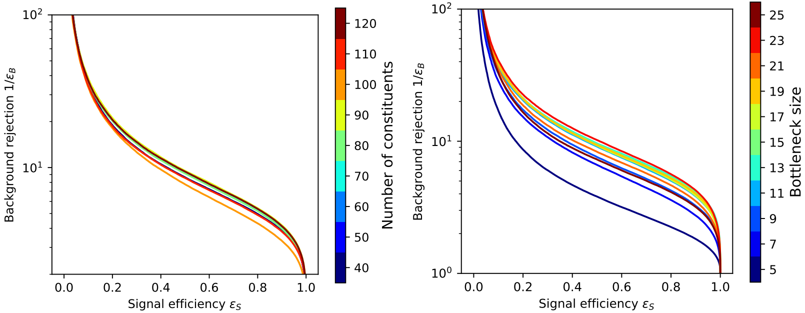
$$g = \mathrm{diag}(0.99 \pm 0.02, -1.01 \pm 0.01, -1.01 \pm 0.02, -0.99 \pm 0.02)$$

$\longrightarrow$ Minkowski metric learnt!

trainable

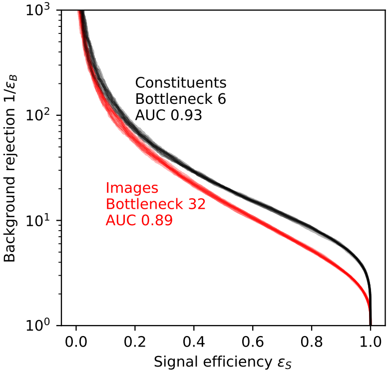
Proof of Concept: Tops vs. QCD

Samples are available: https://goo.gl/XGYju3



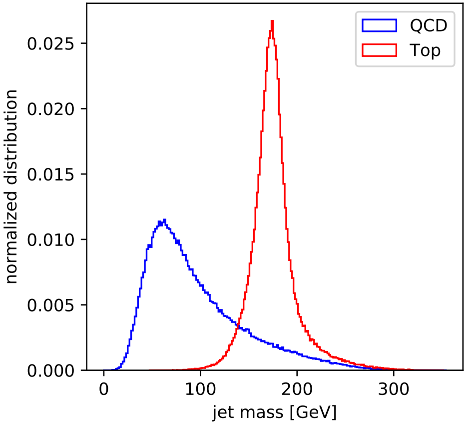
$\longrightarrow$ Training is stable w.r.t. number of constituents
$\longrightarrow$ Loss of information for small bottleneck sizes

Proof of Concept: Tops vs. QCD



- Supervised AUC: 0.98 $\longrightarrow$ **AUC$\sim \mathcal{O}(0.9)$ without knowing what to look for**
- Constituent approach outperforms images

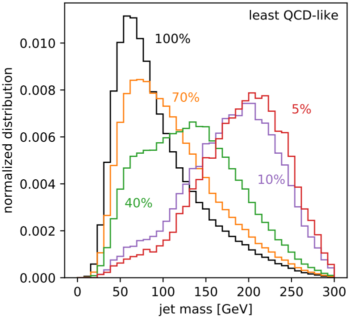
The QCD Jet Mass



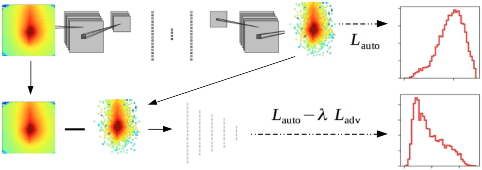
$\longrightarrow$ High-mass jets are less QCD-like, more signal-like

Jet Mass and the Autoencoder

- The autoencoder is sensitive the jet mass.
- It is learning typical signal v background features.
- It is not necessary to use ML tools just for this.

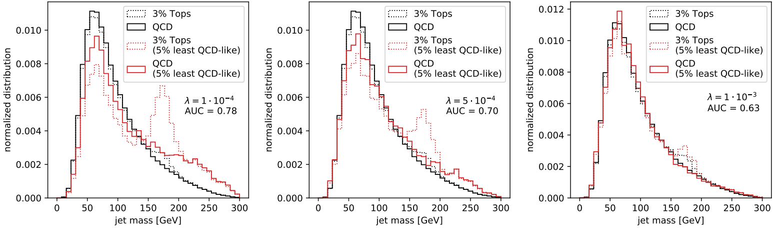


What Else Does the Network Learn?



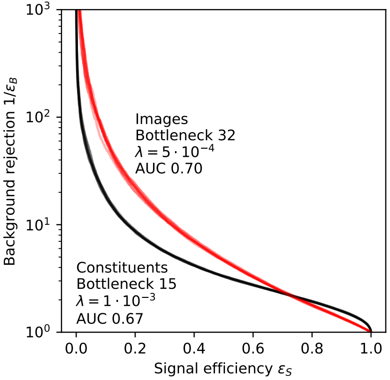
- We want to stop the network from learning the jet mass.
- Adversarial training:
  $\longrightarrow$ adversary (lower) predicts the jet mass from the autoencoder output.
- Need to balance learning rates/relative contributions to total loss.
  $\longrightarrow$ Best parameter choice depends on QCD p_T slice.
  $\longrightarrow$ But only dependent on the background.

Proof of Concept: Tops vs. QCD



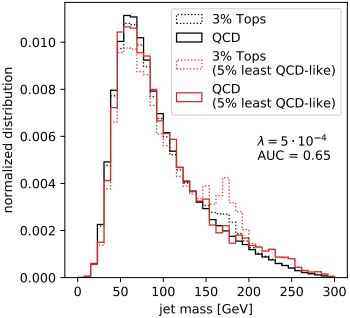
$\longrightarrow$ Tradeoff: more mass shaping $\leftrightarrow$ better performance

Proof of Adversarial Concept: Tops vs. QCD



- Still see discrimination power
  $\longrightarrow$ The network learns more than the jet mass.
- Images now outperform constituents
  $\longrightarrow$ CoLa/LoLa approach explictly encodes the mass.
- Move to jet images for the adversarial autoencoder.

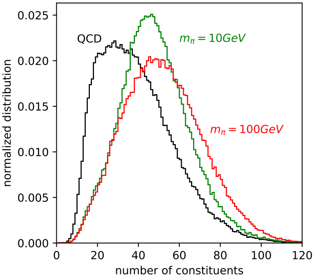
Training on Mixed Samples



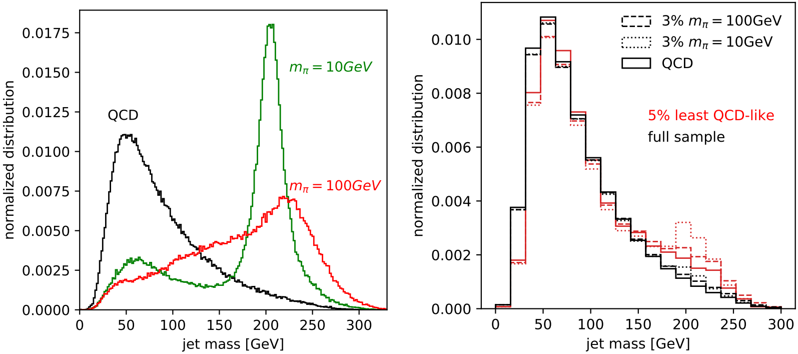
- Train on sample with signal+background
- For background dominated, the autoencoder still picks out only QCD features
- Bottleneck does not have enough information for both tops and QCD
- **Can train and test on same region of phase space**

Dark Showers

- Dark showers have a wide variety of possible collider signatures $\longrightarrow E_T^{\text{miss}}$, displaced vertices, increased hadronic activity
- We consider a dark SU(3) symmetry
- 2 points chosen for 200GeV dark quark mass
  $\longrightarrow$ 100GeV dark meson mass
  $\longrightarrow$ 10GeV dark meson mass
- Dark meson can decay to SM via inverted production mechanism



Dark Showers



$\longrightarrow$ The adversarial autoencoder has discrimination power for a QCD-like signature

Conclusions

https://goo.gl/XGYju3

- Autoencoders are a powerful ML tool to reconstruct images.
- They allow for a generic new physics search.
- They can be trained in a signal region.
- Adversarial autoencoders can be used to decorrelate from the jet-mass (or other observable).