Autoencoders and Jet Physics

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Based on: QCD or What? T. Heimel, G. Kasieczka, T. Plehn, **JT**
arXiv:1808.08979

IAS HKUST workshop
11/01/2019

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SEIT 1386

Motivation: New Physics Searches

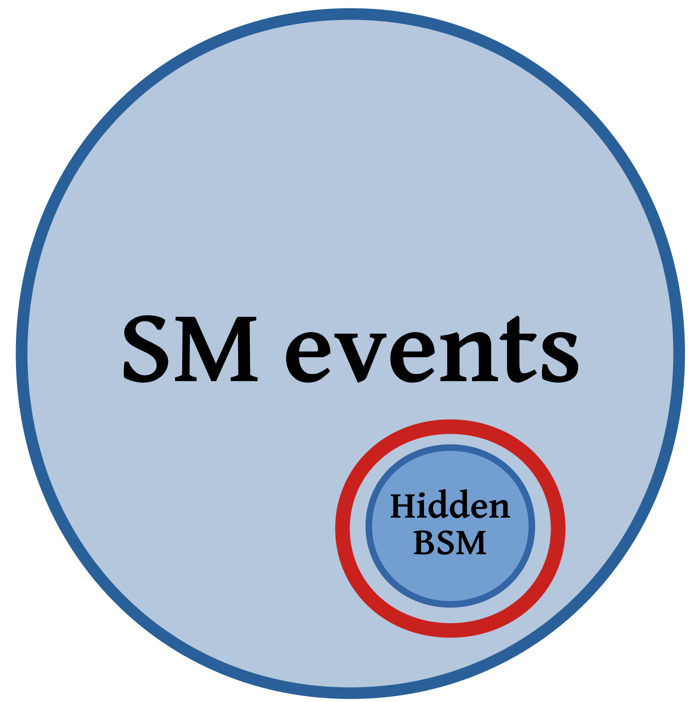
- Particle physics is becoming very data-driven
  - → Even more so at future colliders
- Can make the most of this
  - → With model independent searches
  - → With data driven methods
  - → With **anomaly detection**
- **Unsupervised machine learning**

  arXiv:1808.08979, T. Heimel, G. Kasiecska, T. Plehn, JT

  arXiv:1808.08992, M. Farina, Y. Nakai, D. Shih

  arXiv:1807.10261v2 J. Hajer, Y-Y. Li, T. Liu, H. Wang

  arXiv:1708.0249, E.Metodiev, N. Nachman, J. Thaler
- In this talk: Focus on **autoencoders**



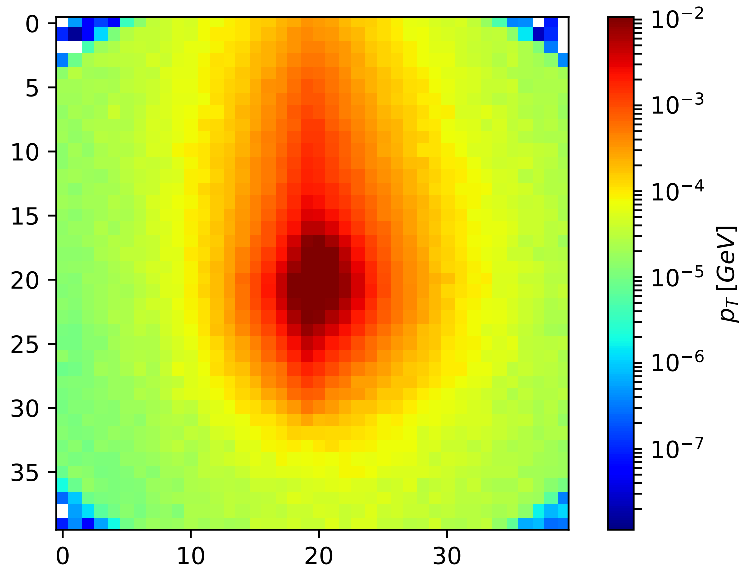
"Background" events

Anomaly detector

Autoencoder Anomaly Search

Idea: Train a network to detect generic anomalies

So it's used to seeing this…



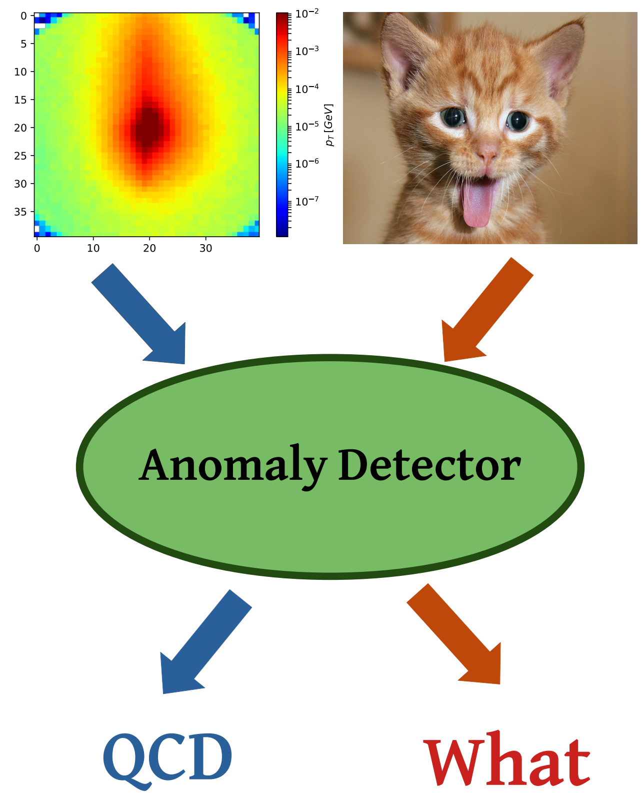
Average QCD image

… but not this

Image credit: Michel Luchman
Preprocessing from arXiv:1803.00107 S. Macaluso and D. Shih

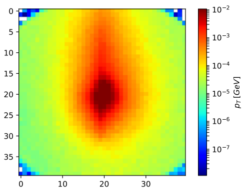
Search Strategy

Idea: Train a network to detect generic anomalies



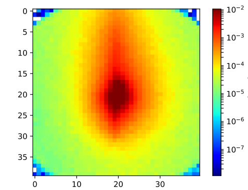
Network Architecture

Train



- Background only
- Compress to latent space
- Learn reconstruction
- Loss $= \sum_{pixels} \left(k_T^{input} - k_T^{out}\right)^2$

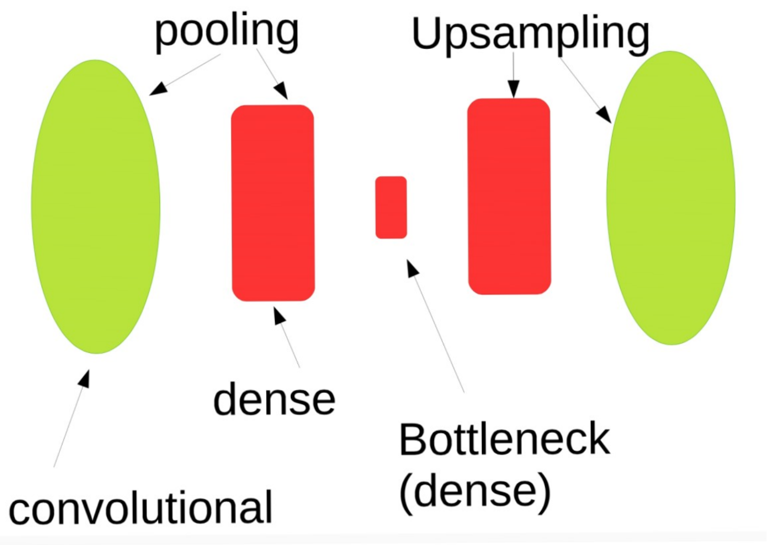
Apply (test)



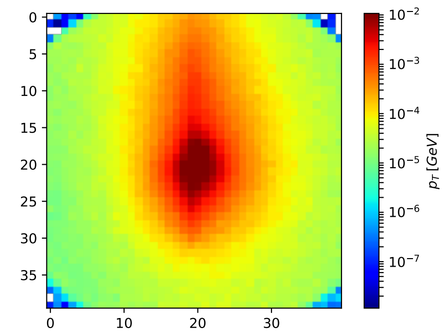
- Background + signal
- Reconstruction

✔ Background

✗ Signal

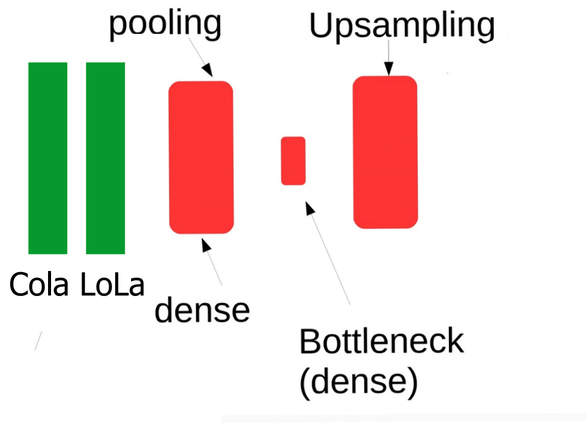


A Note on Data Format



- **So far we have considered images**
- **We also looked at constituent 4-vectors**
  - Implemented in with the **CoLa/LoLa** framework

    arXiv:1707.08966v3 A. Butter, G. Kasieczka, T. Plehn, and M. Russell
  - Different architecture
    - CoLa and LoLa layers at start
    - No convolutional layers



CoLa and LoLa Framework

Traditional

CoLa – simplified jet algorithm, trainable combinations

$$k_{\mu,i} \rightarrow \widetilde{k}_{\mu,i} = k_{\mu,j} C_{ji}$$

LoLa

$$\widetilde{k}_{\mu,j} \rightarrow \hat{k}_{\mu,j} = \begin{pmatrix} m_j^2 \\ p_{T,j} \\ w_{jm}^E E_m \\ w_{jm}^d d_{jm}^2 \end{pmatrix}$$

CoLa and LoLa Framework

~~Traditional~~ For the Autoencoder

Must be invertible

CoLa

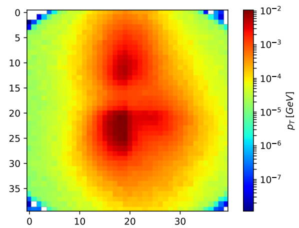
$$k_{\mu,i} \rightarrow \tilde{k}_{\mu,i} = k_{\mu,j} C_{ji}$$

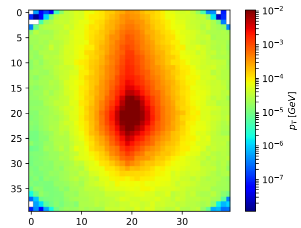
Not invertible

LoLa

$$\cancel{\tilde{k}_{\mu,j} \rightarrow \hat{k}_{\mu,j} = \begin{pmatrix} m_j^2 \\ p_{T,j} \\ w_{jm}^E E_m \\ w_{jm}^d d_{jm}^2 \end{pmatrix}} \Rightarrow \tilde{k}_{\mu,j} = \begin{pmatrix} \tilde{E}_j \\ \tilde{k}_{1j} \\ \tilde{k}_{2j} \\ \tilde{k}_{3j} \end{pmatrix} \rightarrow \begin{pmatrix} \tilde{E}_j \\ \tilde{k}_{1j} \\ \tilde{k}_{2j} \\ \tilde{k}_{3j} \\ \sqrt{m_j^2} \end{pmatrix}$$

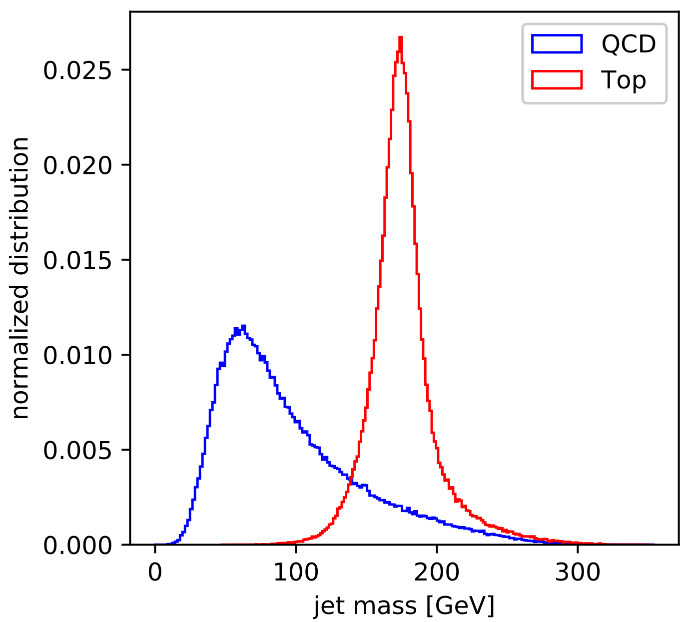
Tops vs QCD

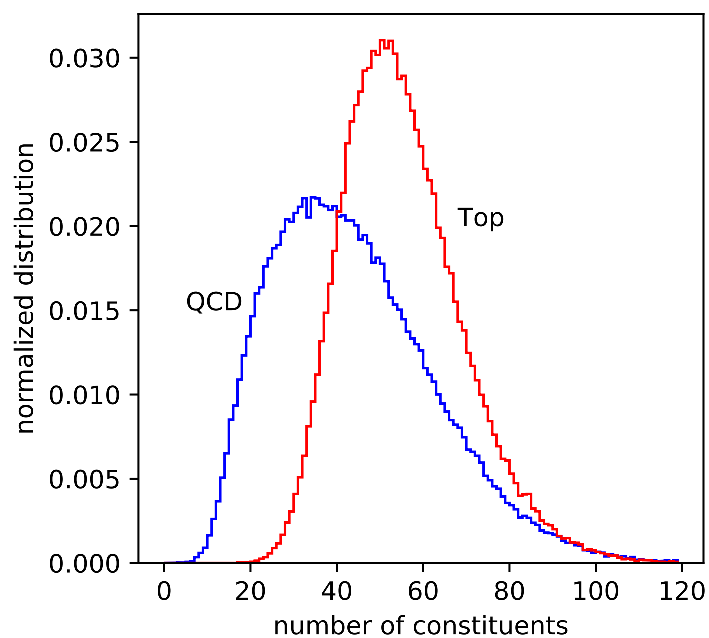




Use public data set for tops vs QCD

https://goo.gl/XGYju3

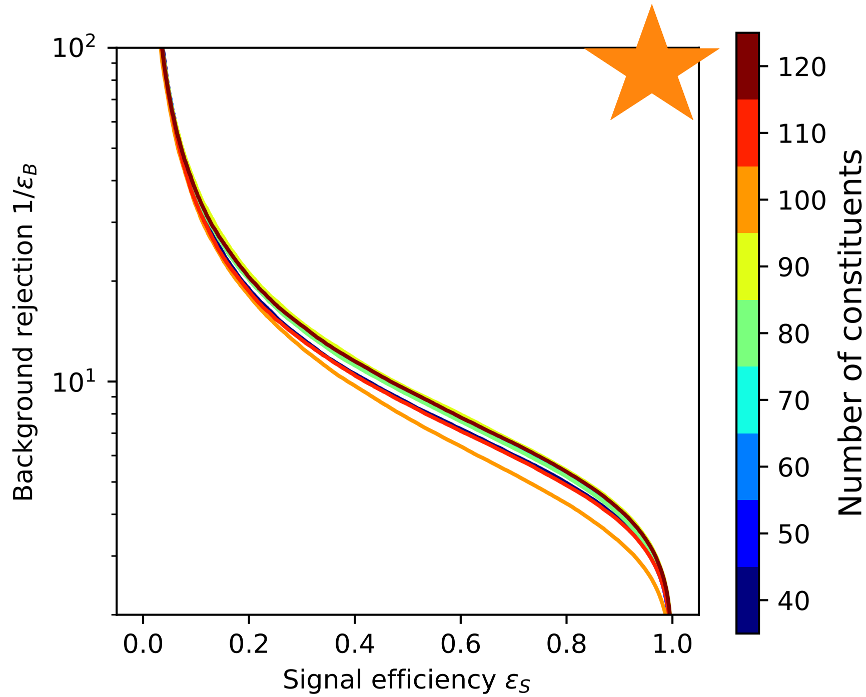


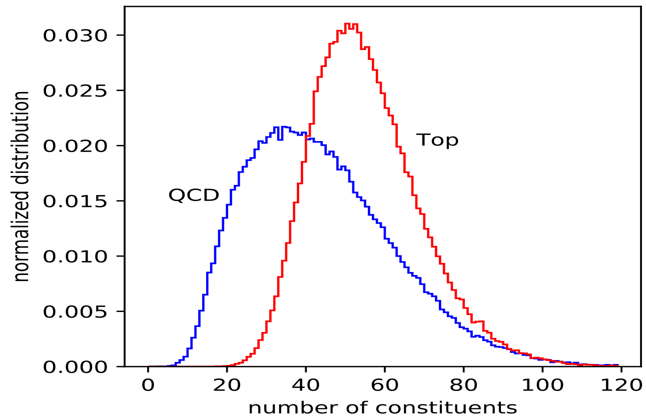


- Pythia sample with Delphes detector simulation 14 TeV
- 14 TeV hadronic tops
- $550\,GeV < p_{T,j} < 650\,GeV$

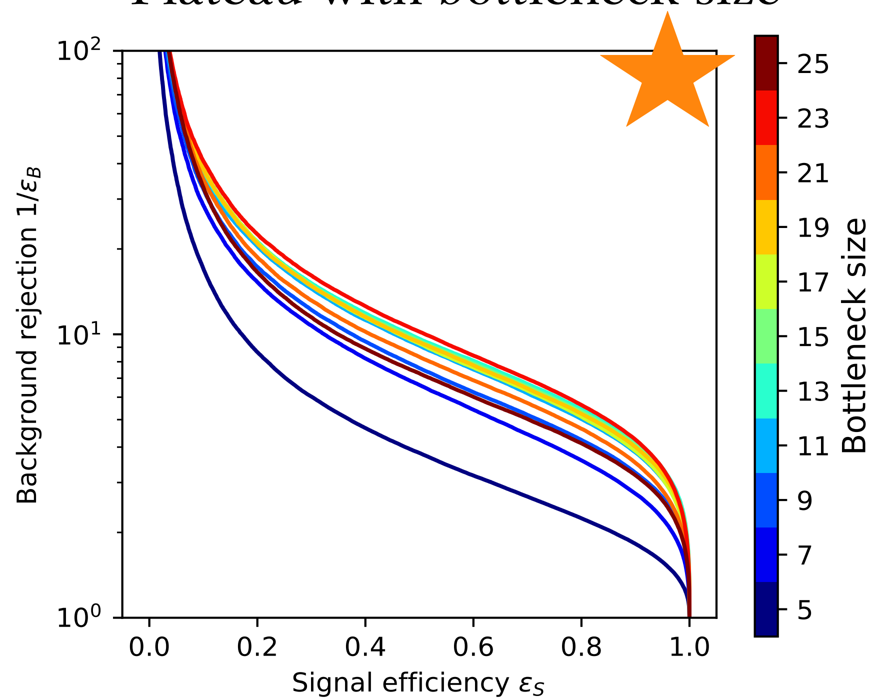
The Latent Space

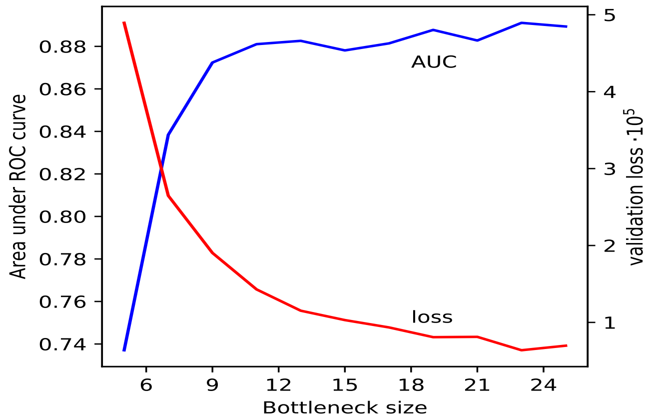
Very stable w.r.t number of constituents





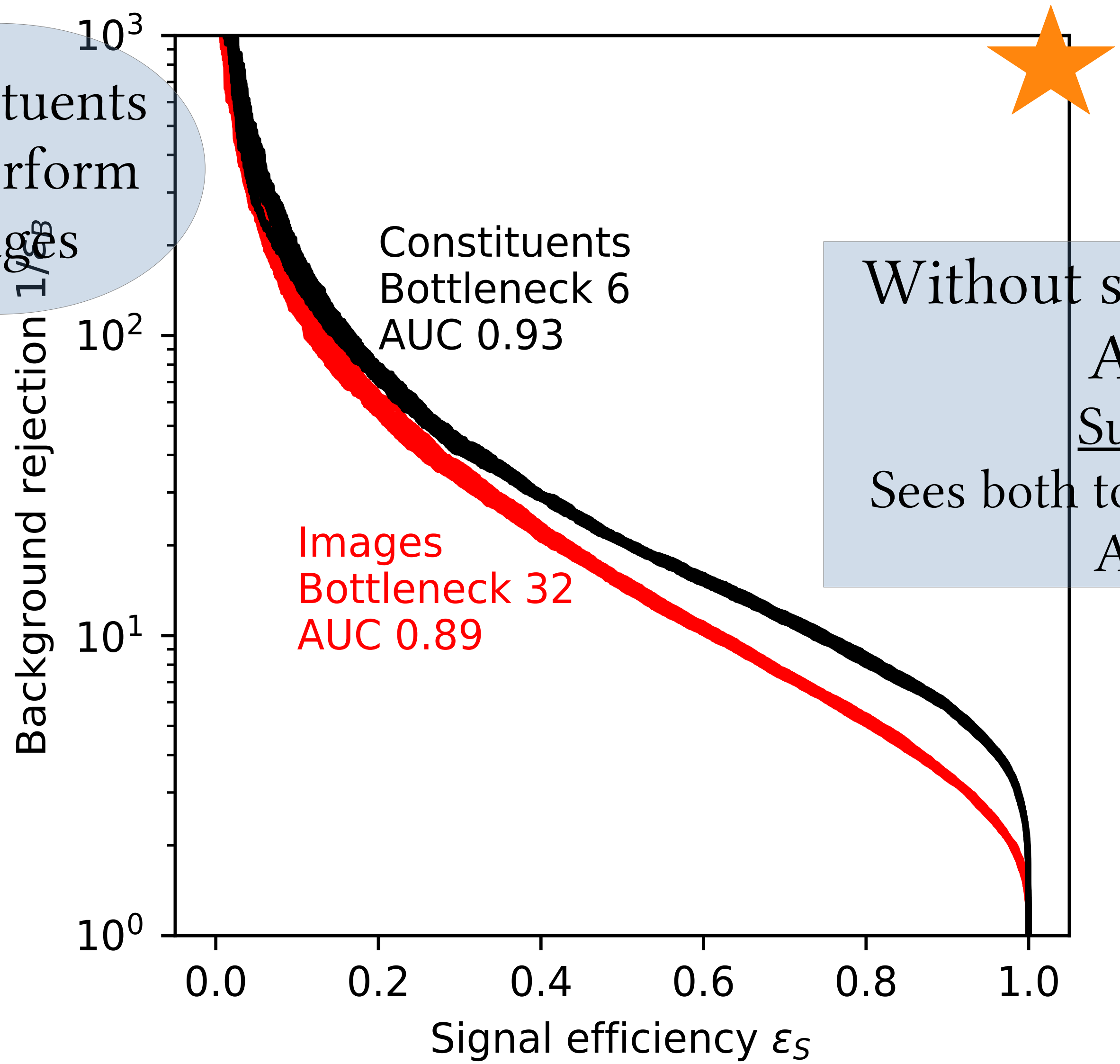
Plateau with bottleneck size





Test application: Tops vs QCD

Constituents outperform images

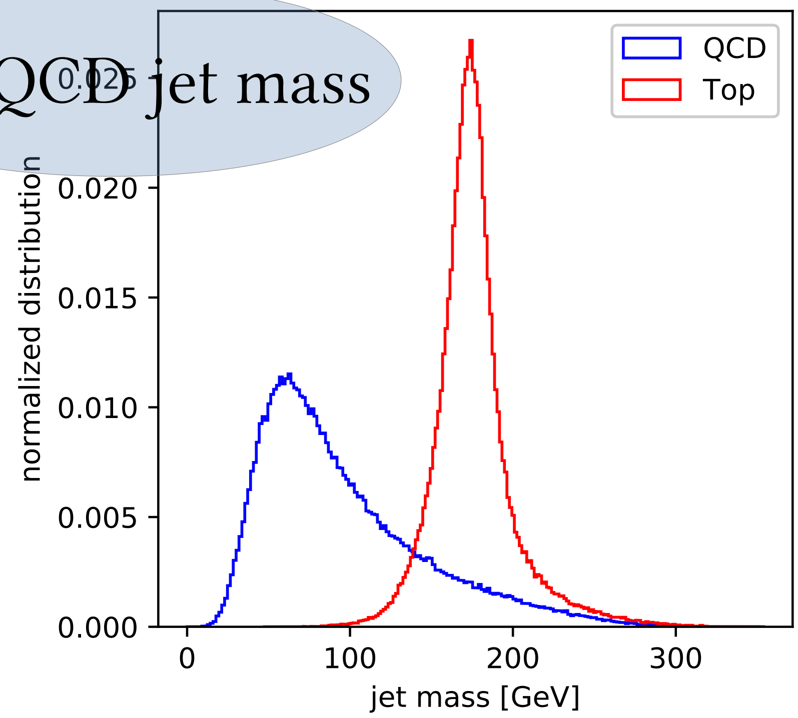


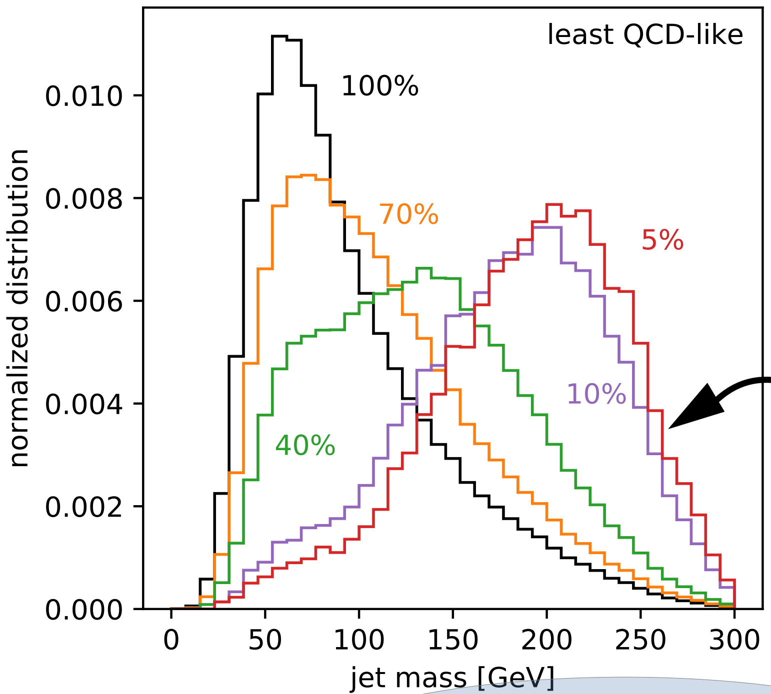
Without seeing top events
AUC~0.9

<u>Supervised</u>
Sees both top and QCD events
AUC~0.98

Does the Network use Mass?

Low QCD jet mass





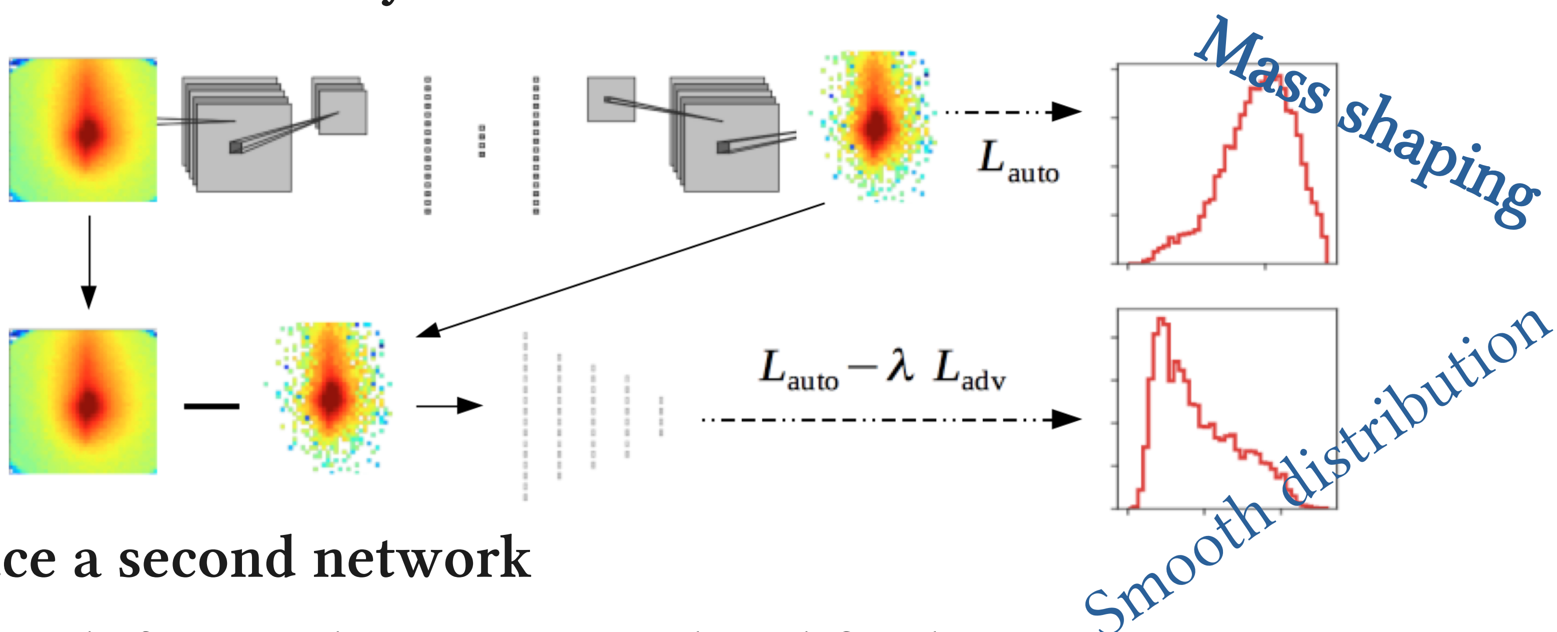
The higher the jet mass, the less QCD-like

✔ QCD jet-mass spectrum learnt

✗ Want to learn more than jet mass

Decorrelating from the Jet Mass

We can use an adversary to decorrelate



- **Introduce a second network**
  - Input = difference between initial and final image
  - Predict the (binned) jet mass
  - $L_{adv} = \left(\widetilde{M} \left(|k_{T,i}^{adv} - k_{T,i}^{auto}| \right) - M \right)^2$

True mass

Reconstructed mass

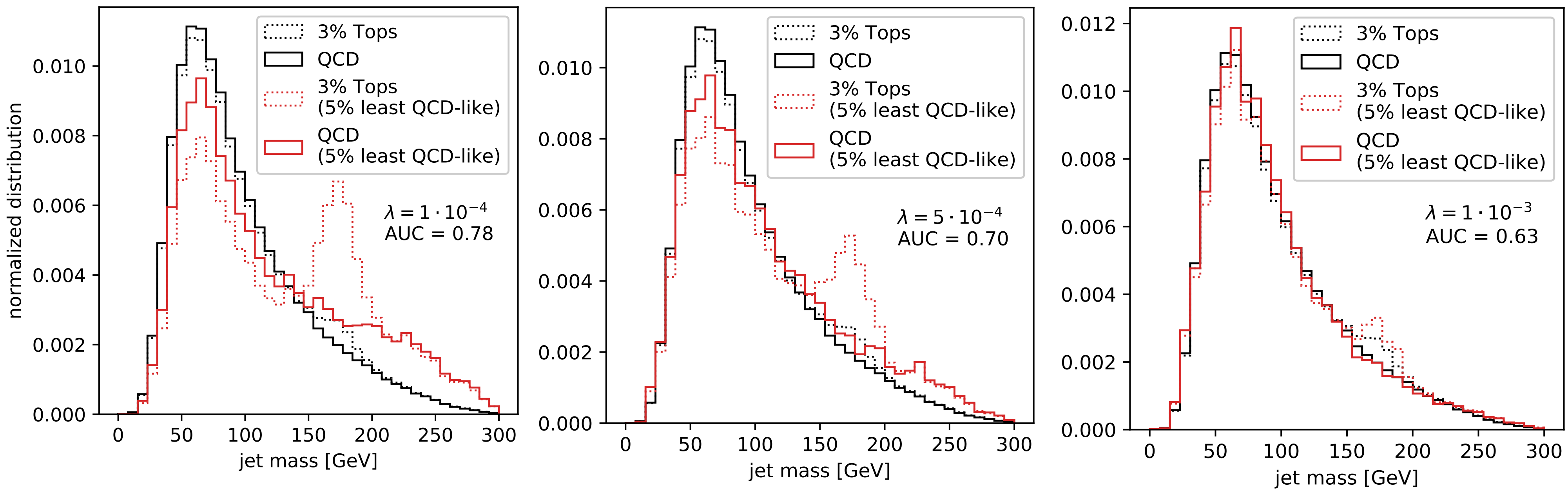
More adversarial training in particle physocs
arXiv:1807.08763 C. Englert, P, Galler, P. Harris, M. Spannowsky

Balancing Loss Functions

Loss = $L_{auto} - \lambda\, L_{adv}$: How do we set λ?

- Scan with the background-only hypothesis

- Want both loss functions to be of a similar size



Trade off between performance and mass-shaping

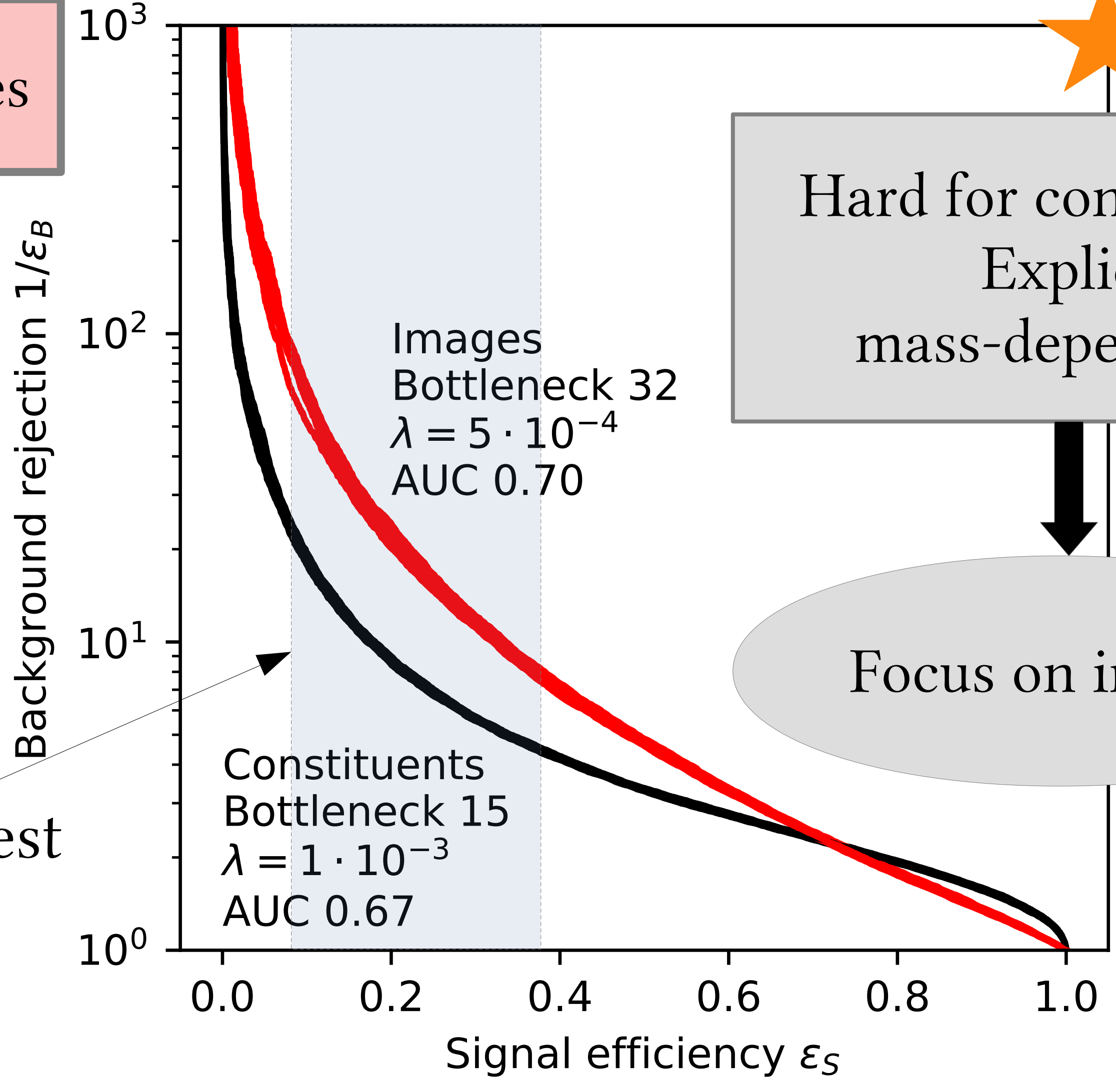
Adversarial Autoencoder

Works well for images

Hard for constituents: Explicit mass-dependence

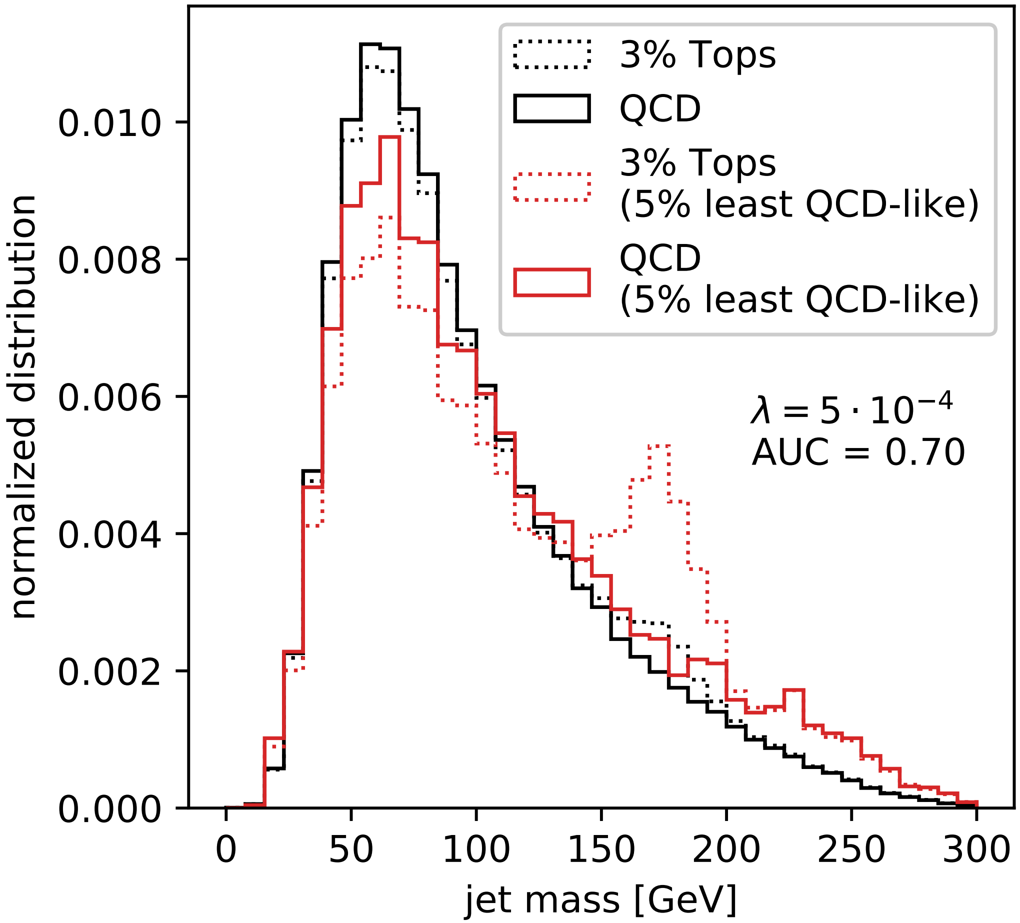
Focus on images

Typical area of interest



The Adversarial Autoencoder in a Bump Hunt

1) **Train on background**
   - Monte Carlo
   - Data
     - ➔ Background region
2) **Decorrelate from jet mass**
3) **Bump hunt in jet mass**

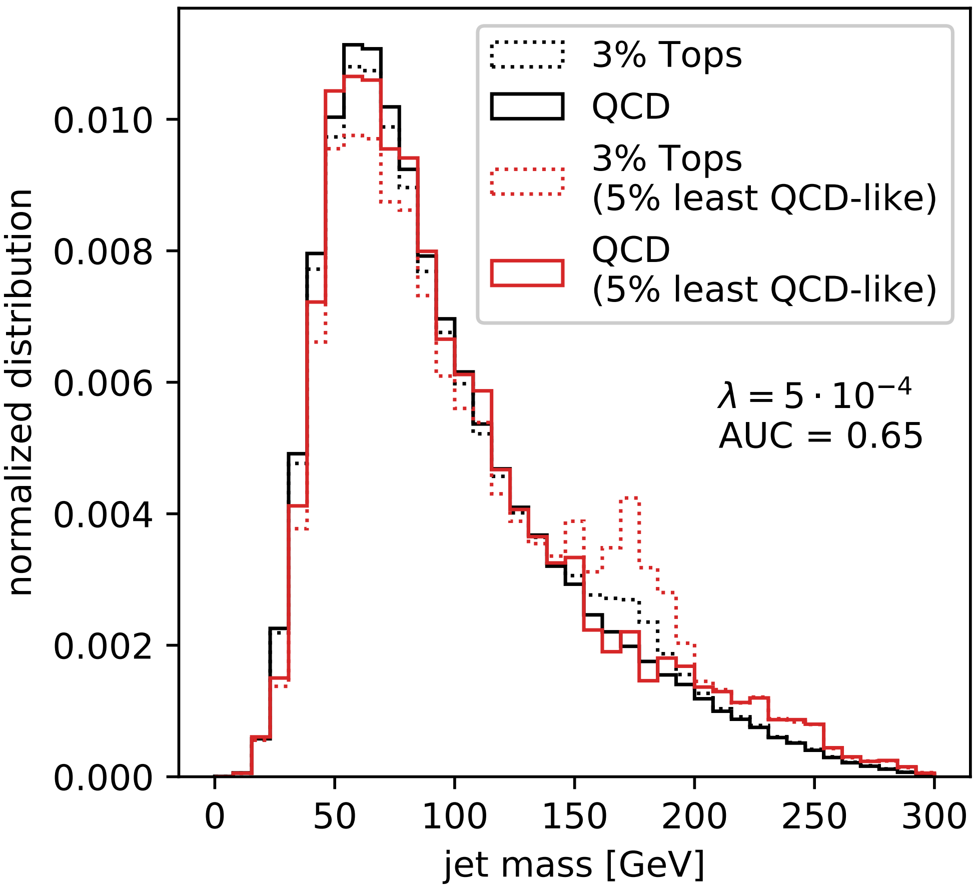


Question: can we train in the signal region?

Training on the Signal Region

Train on 97% QCD, 3% tops

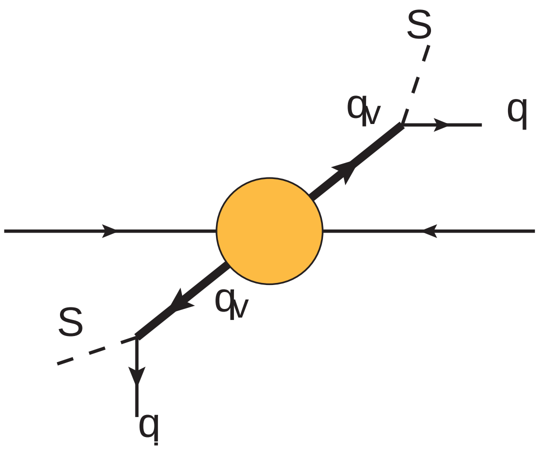
- **Not all events encoded**
  - ➔ Bottleneck too small
- **Network learns QCD**
  - ➔ Dominant component
- **Still see emergent peak**



Train on any background-dominated region

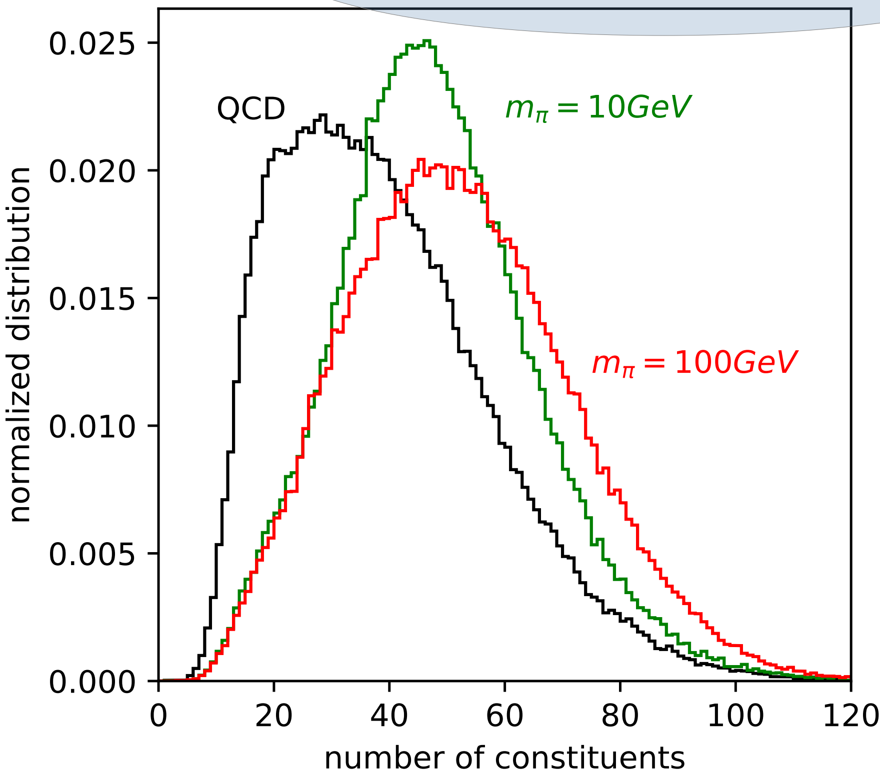
Dark Showers

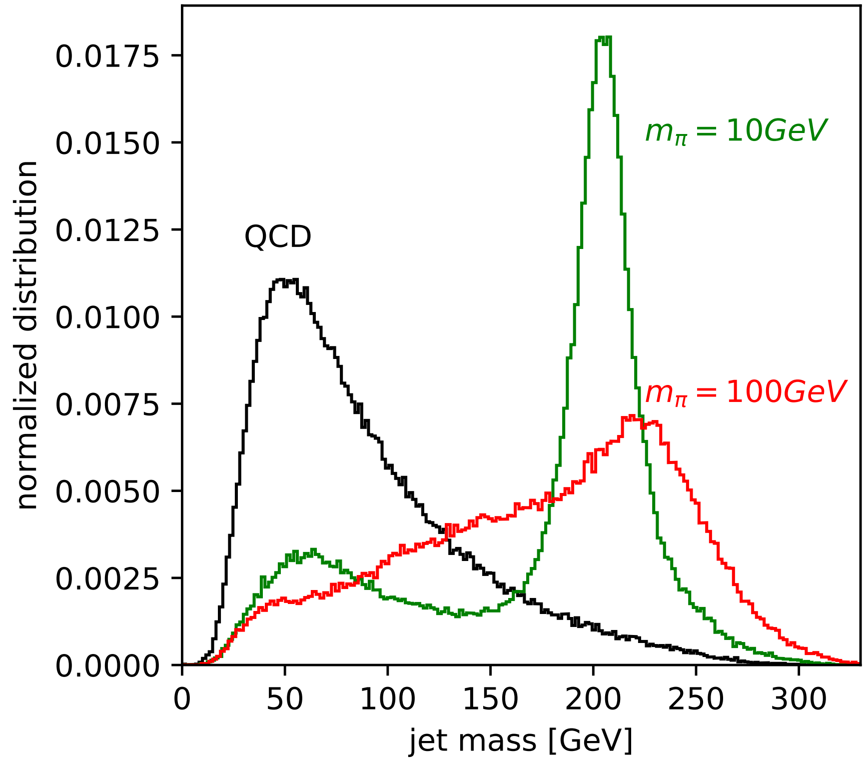
- **Dark showers have many possible collider signatures**
  - ➔ Increased hadronic activity, displaced vertices, E_T^{miss}
- **We consider a dark SU(3) symmetry**
  - ➔ Implemented in Pythia
- **2 benchmark points (fixed 200 GeV dark quark mass)**
  - ➔ 100 GeV dark meson mass
  - ➔ 10 GeV dark meson mass
- **Dark meson able to decay back to SM**
- $575\,GeV < p_{T,j} < 625\,GeV$



Dark Shower vs QCD

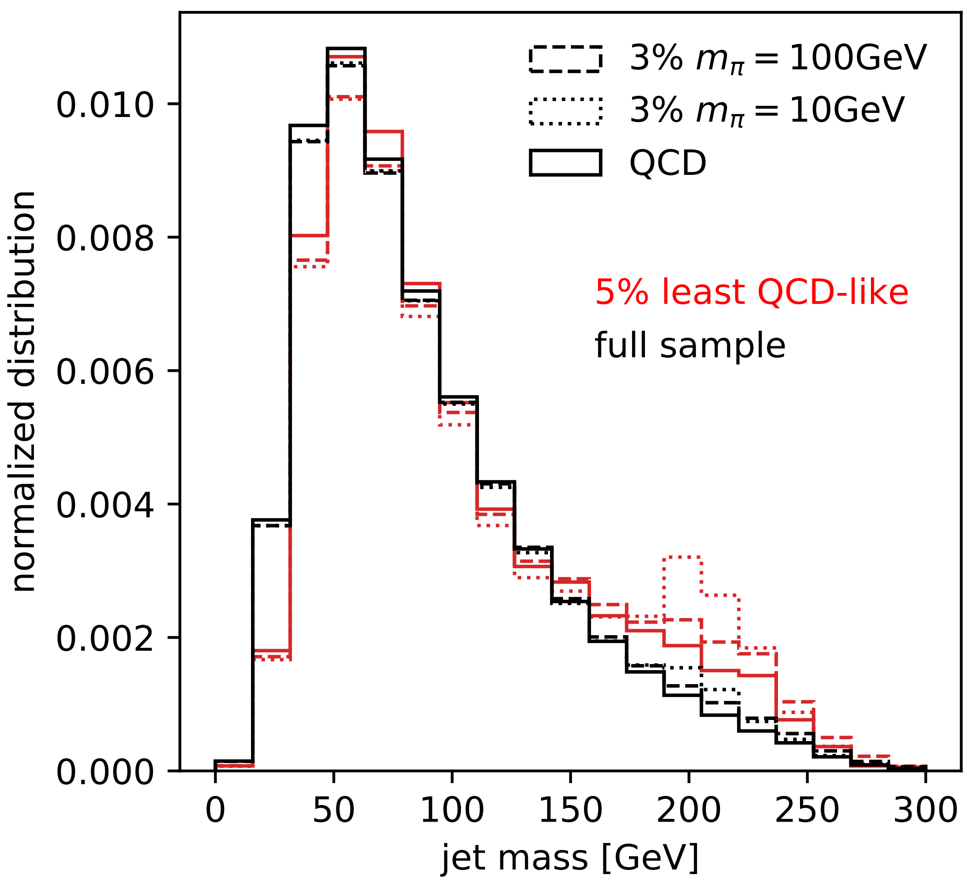
Similar to QCD

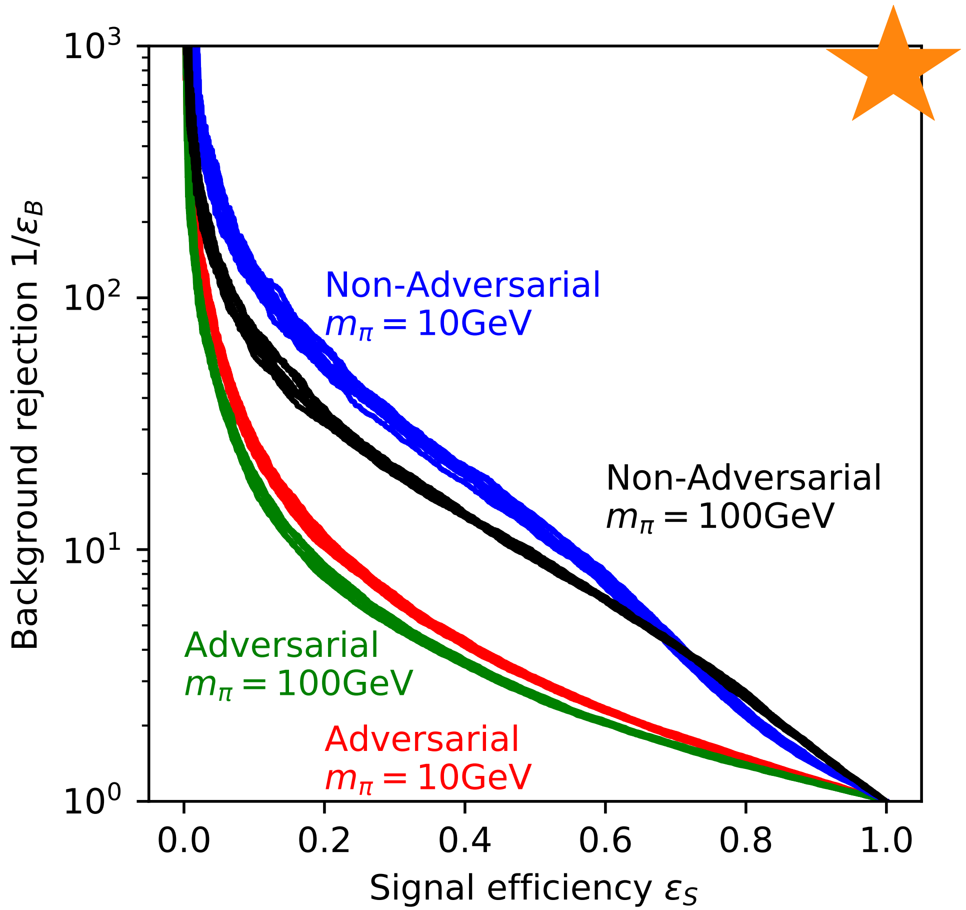




100 GeV meson mass = small mass peak

Dark Shower Results





Discrimination power in challenging processes

Conclusions

- **Autoencoders allow for**
  - model-independent searches
  - training entirely on data
- **Adversarial autoencoders allow jet mass-decorrelation**
  - Bump hunt in jet mass
- **See discrimination power in**
  - Tops vs QCD
  - Dark showers