QCD or What?!?
Deep autoencoder based searches for new physics

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Results based on *QCD or What?* arXiv: 1808.08979

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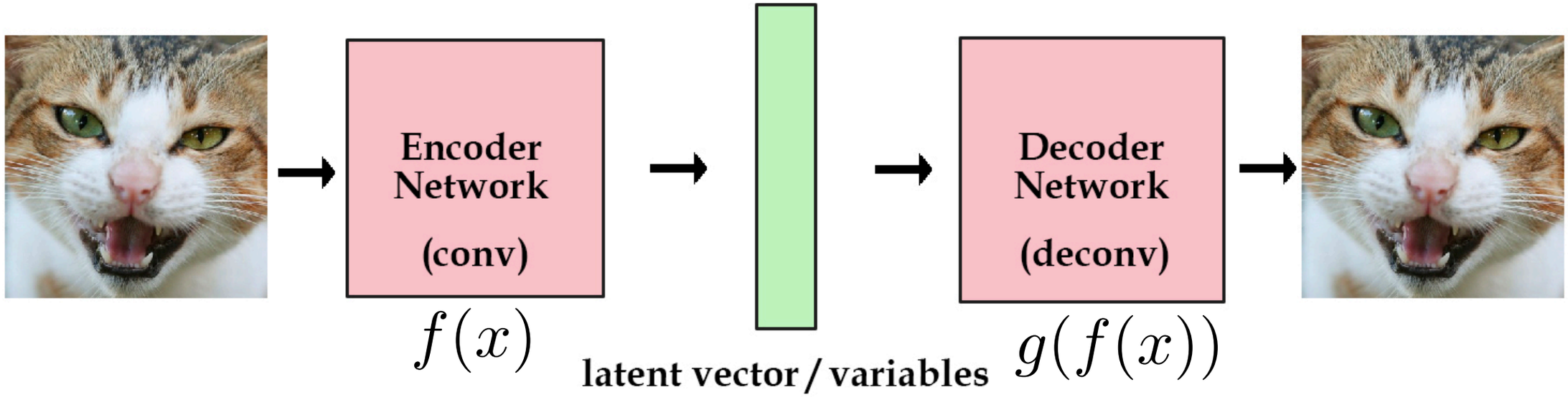
Beyond Classification

- Exhaustive exclusion limits for BSM physics
  - What if it is a model nobody thought of yet (or hides among QCD)
- Machine learning is very powerful for classification
  - Systematic uncertainties when going from simulation to data
- Can we solve both issues at once?

Autoencoders

Autoencoder

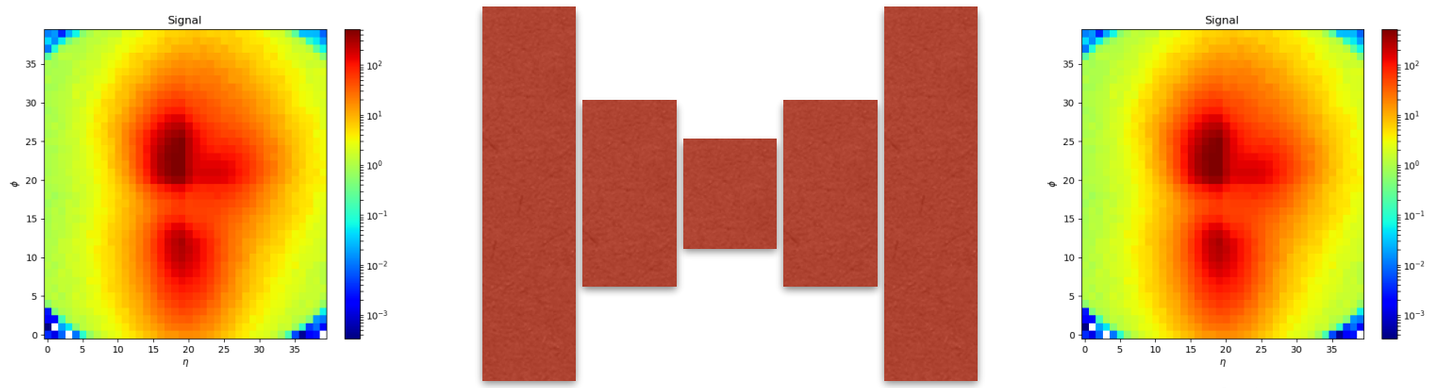


$$L = (\hat{y} - g(f(x)))^2$$

- Unsupervised learning
- *Bottleneck (or latent space)* with compressed representation
- Classical uses:
  - Dimension reduction
  - Denoising

Autoencoder for Physics

Input Autoencoder Output



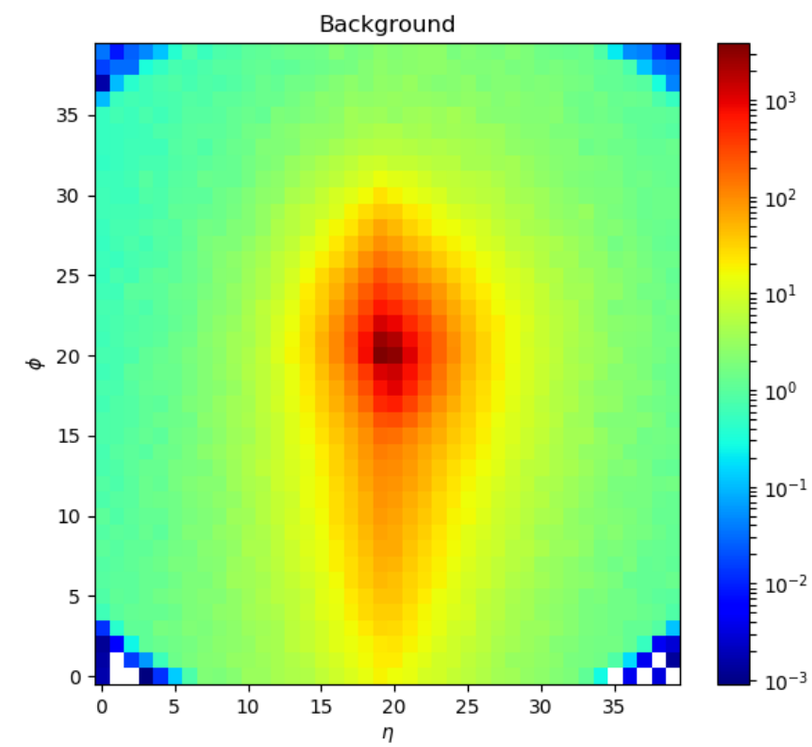
X_{ij} $\widetilde{X}_{ij}$

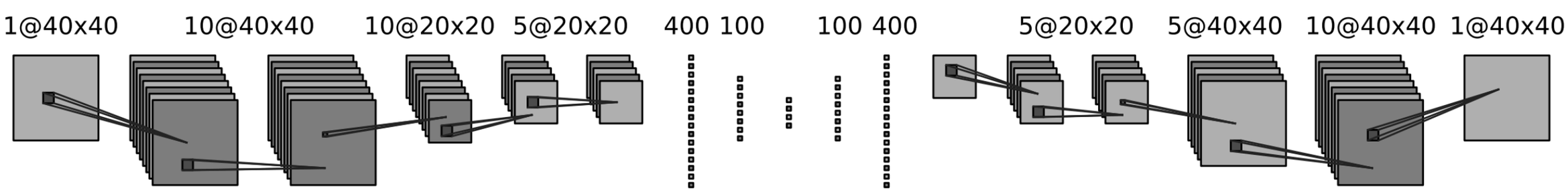
- Train on pure QCD light quark/gluon jets
  - Use top tagging reference sample https://goo.gl/XGYju3
  - Train **only on QCD** events
- New physics identified as anomaly
  - Tail of the loss function

Architecture I

- Reconstruct energy with calorimeter (improve resolution using tracker)
- Cluster energy deposits into jet
- Preprocess:

  - center → rotate → flip (twice) → pixelate → crop → normalise
    - center: centroid is at (0/0)
    - rotate: principal axis is vertical
    - flip: in (x<0, y>0)-plane maximum intensity
    - crop: to nxn images
    - normalise: intensity of each pixel divided by total intensity



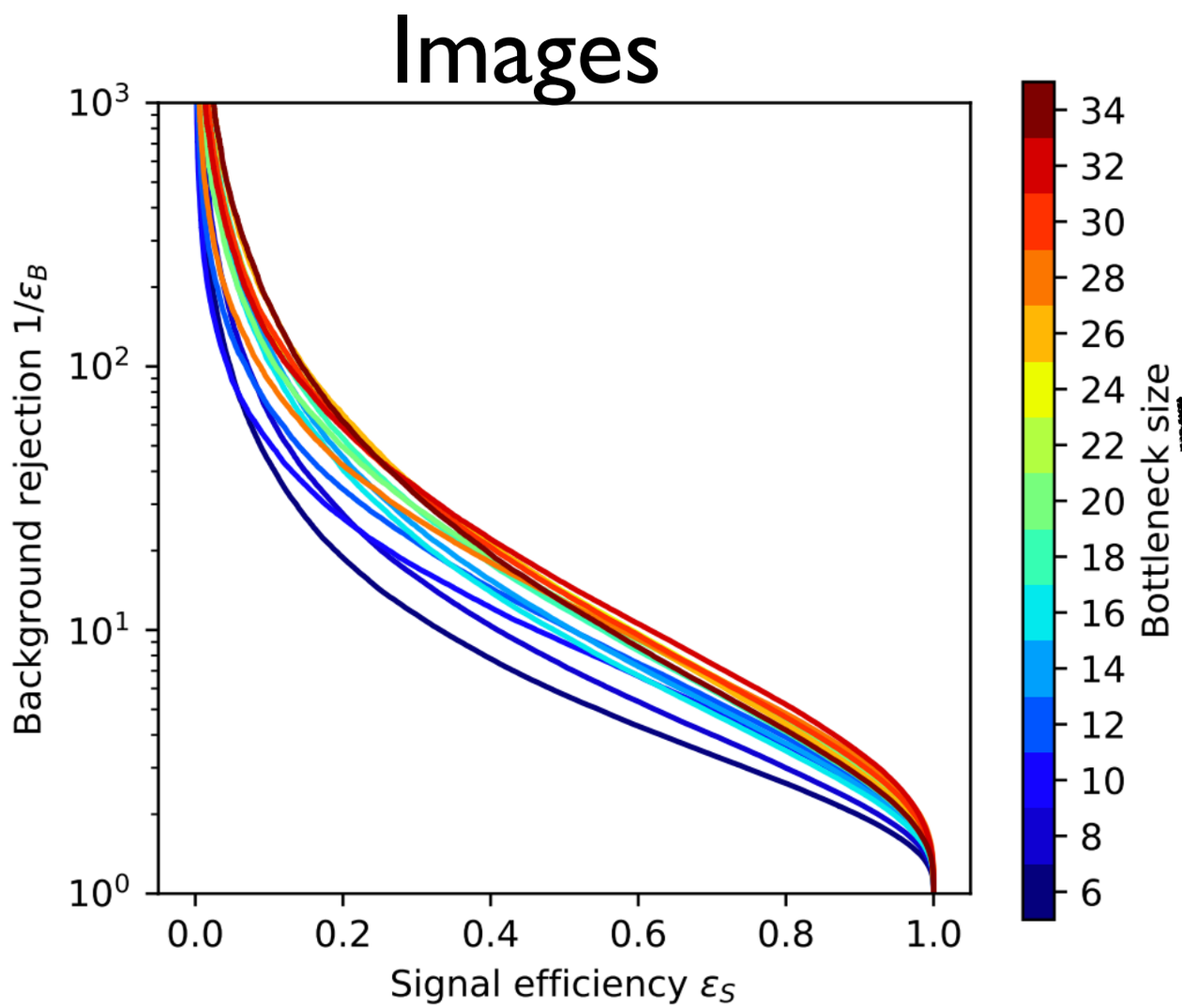


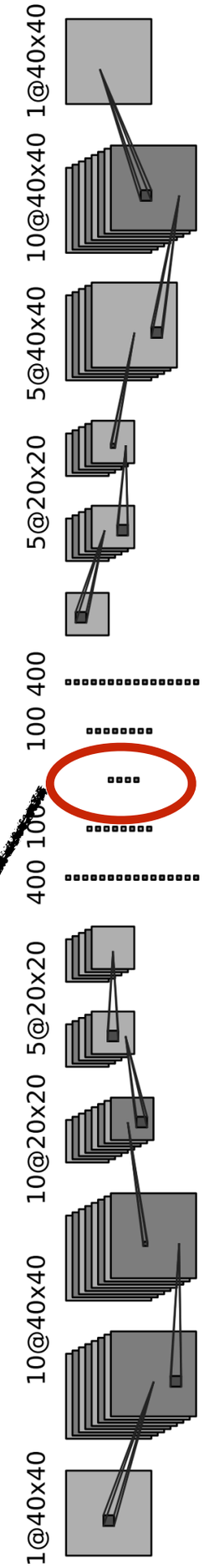
Convolutional network

$$L_{\text{Auto}} = \sum_{\text{Pixels } ij} \left(X_{ij} - \widetilde{X}_{ij} \right)$$

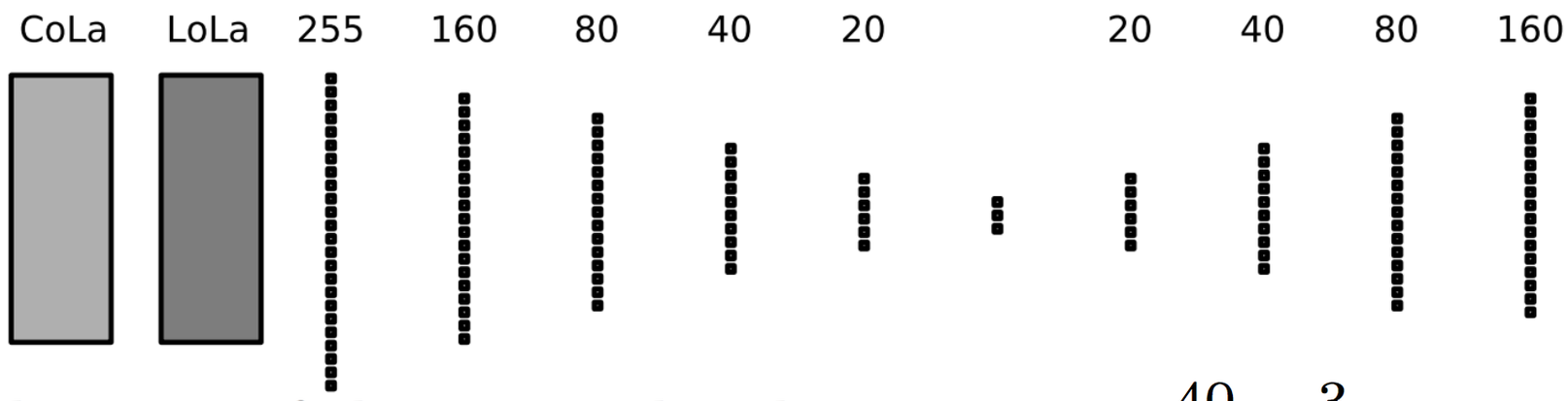
Does it work?

- Train on QCD only
- Test on top vs QCD
- Cut on loss function as discriminator
  - Large loss → autoencoding failure → anomaly





Architecture II



*Constituent network**

$$L_{\text{auto}} = \sum_{j=1}^{40} \sum_{i=0}^{3} \left(\tilde{k}^{\text{in}}_{i,j} - \tilde{k}^{\text{auto}}_{i,j} \right)^2$$

$$k_{\mu,i} = \begin{pmatrix} E_0 & E_1 & \dots & E_N \\ p_{x,0} & p_{x,1} & \dots & p_{x,N} \\ p_{y,0} & p_{y,1} & \dots & p_{y,N} \\ p_{z,0} & p_{z,1} & \dots & p_{z,N} \end{pmatrix}$$

Combination Layer (**CoLa**): create linear combinations:

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

Lorentz Layer (**LoLa**): Use resulting matrix to extract physics features.
Main assumption is the Minkowski metric

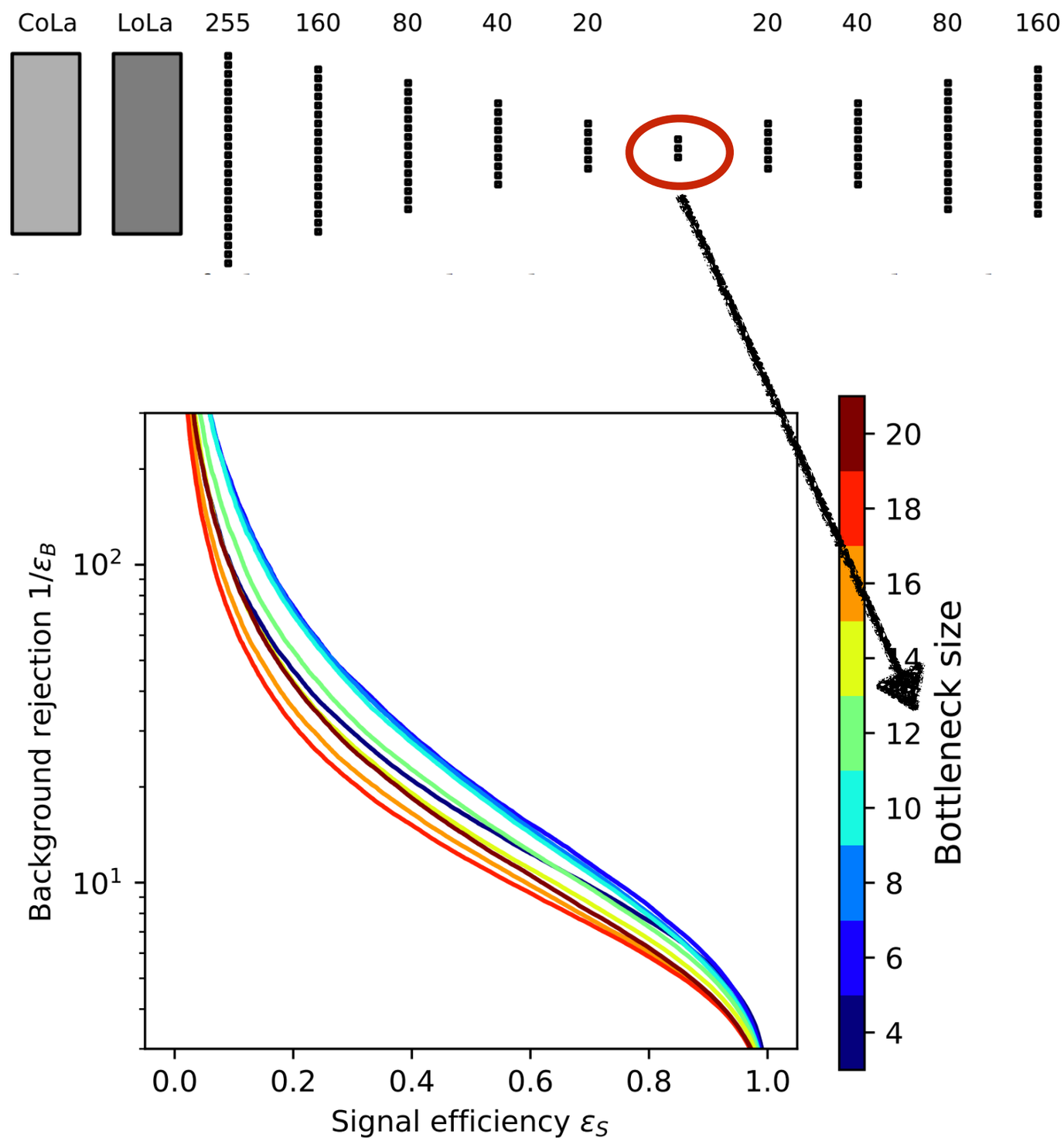
$$\widetilde{k}_{\mu,i} \to \sum_j (\widetilde{k}_i - \widetilde{k}_j)_\mu (\widetilde{k}_i - \widetilde{k}_j)_\nu \eta^{\mu\nu} B_{ij}$$

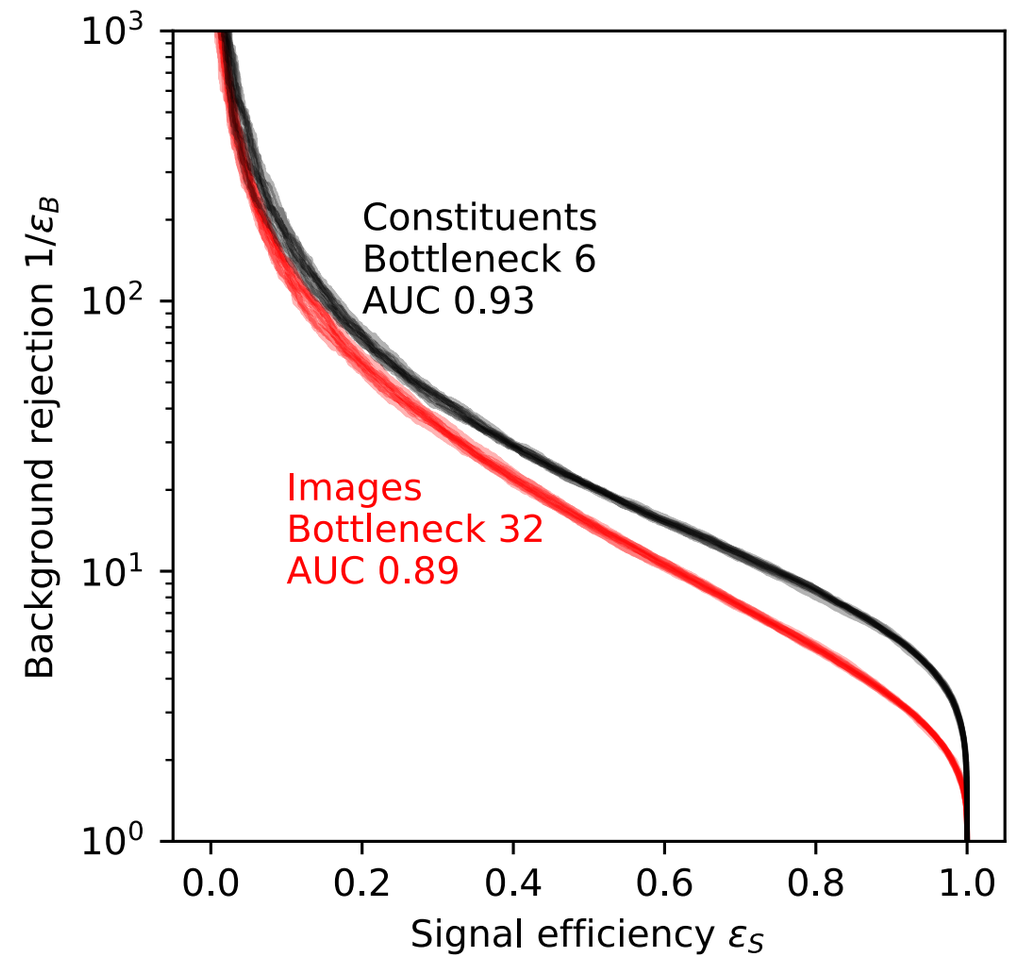
Can implement autoencoders using any architecture!

* from: *Deep-learning Top Taggers & No End to QCD*
A Butter, GK, T Plehn, M Russell
1707.08966

Does it work?

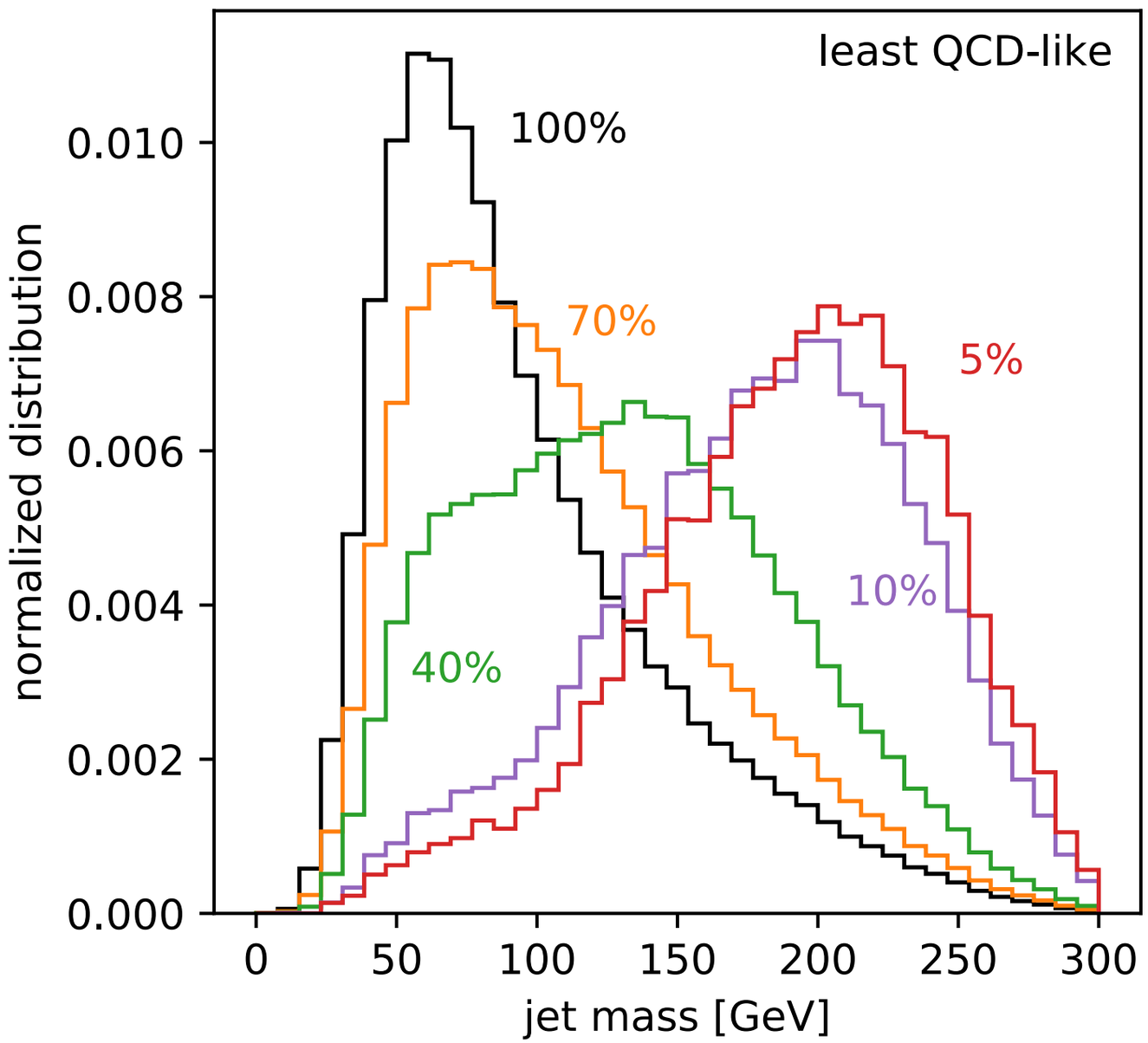
LoLa





Different ROC curve as well as bottleneck size preferred by different architectures

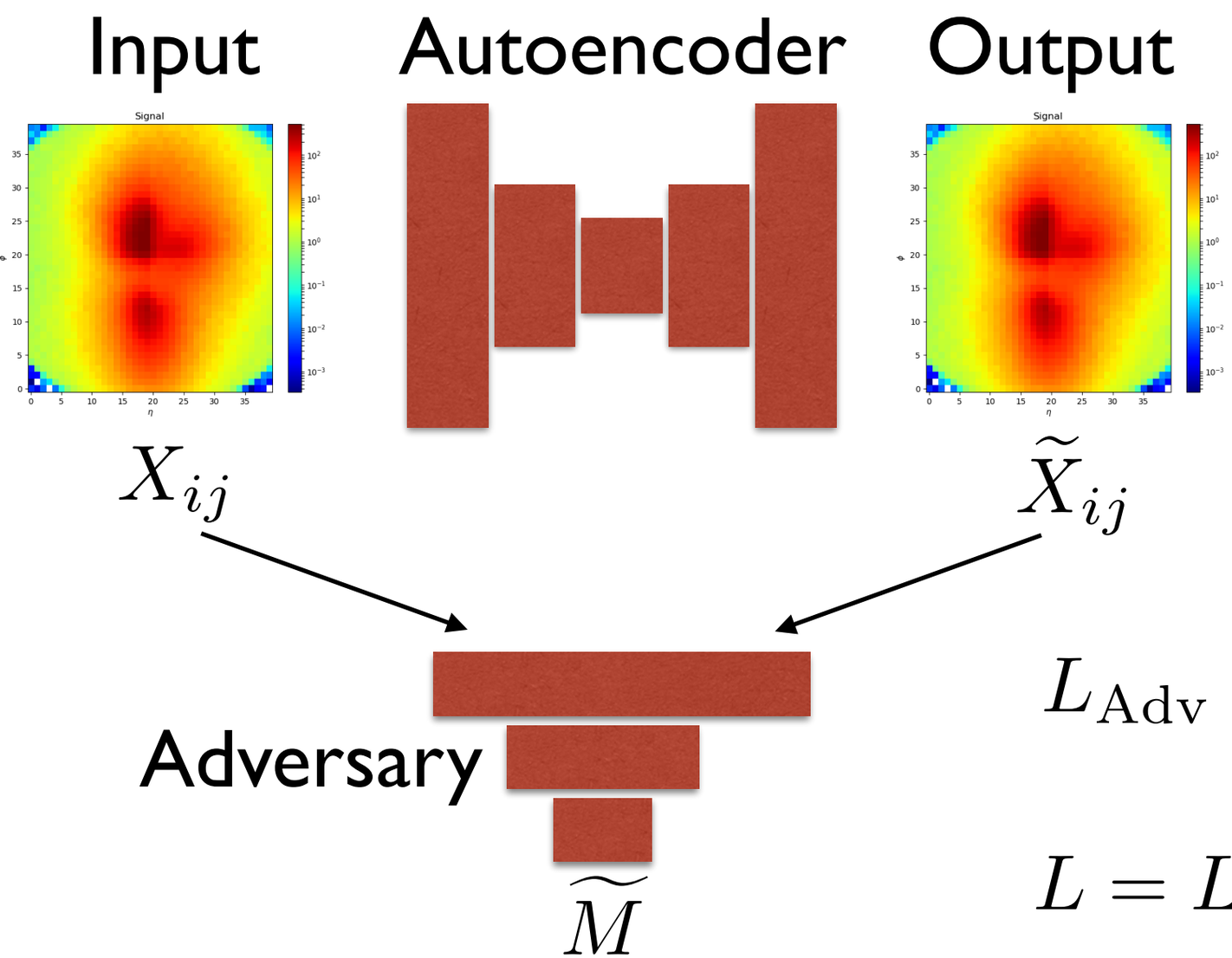
What about mass?



- Without additional constraints the autoencoder also learns the kinematics of the training sample
- How to avoid?

Adversarial Training

Combined Setup



$$L_{\text{Auto}} = \sum_{\text{Pixels } ij} \left(X_{ij} - \widetilde{X}_{ij} \right)$$

$$L_{\text{Adv}} = \text{CCE}\left(M, \widetilde{M}(X_{ij} - \widetilde{X}_{ij}) \right)$$

$$L = L_{\text{Auto}} - \lambda L_{\text{Adv}}$$

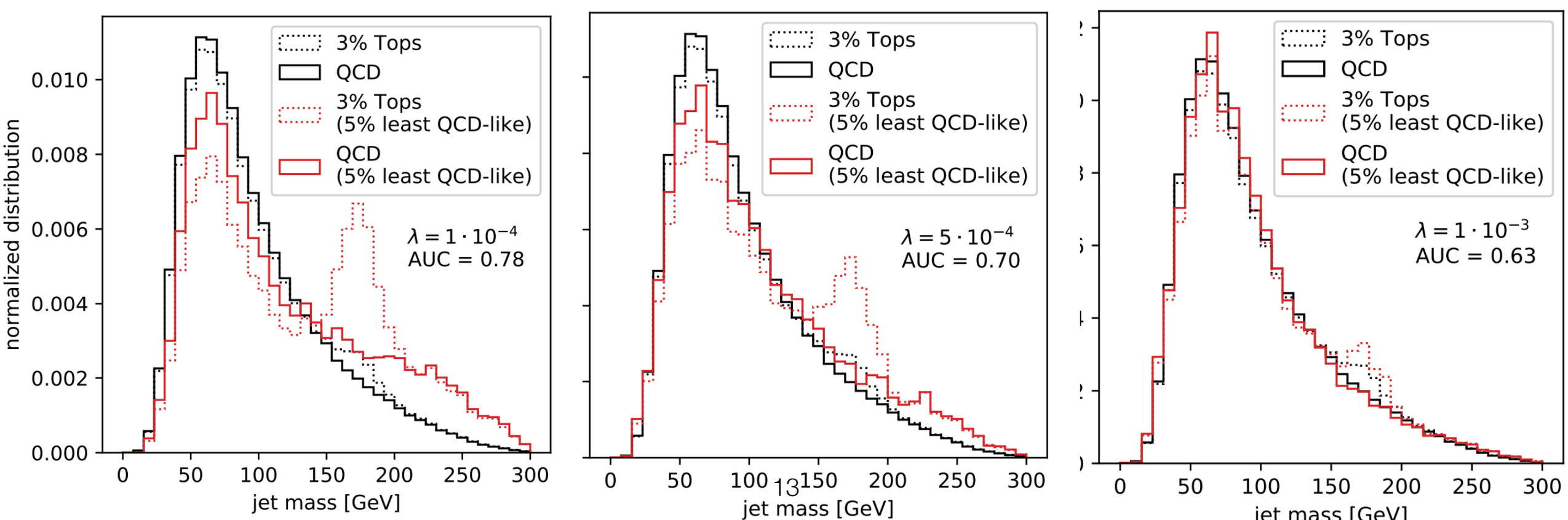
Decorrelated Jet Substructure Tagging using Adversarial Neural Networks
C Shimmin, P Sadowski, P Baldi, E Weik, D Whiteson, E Goul, A Søgaard 1703.03507

Mass Sculpting

- Counteract with adversary:

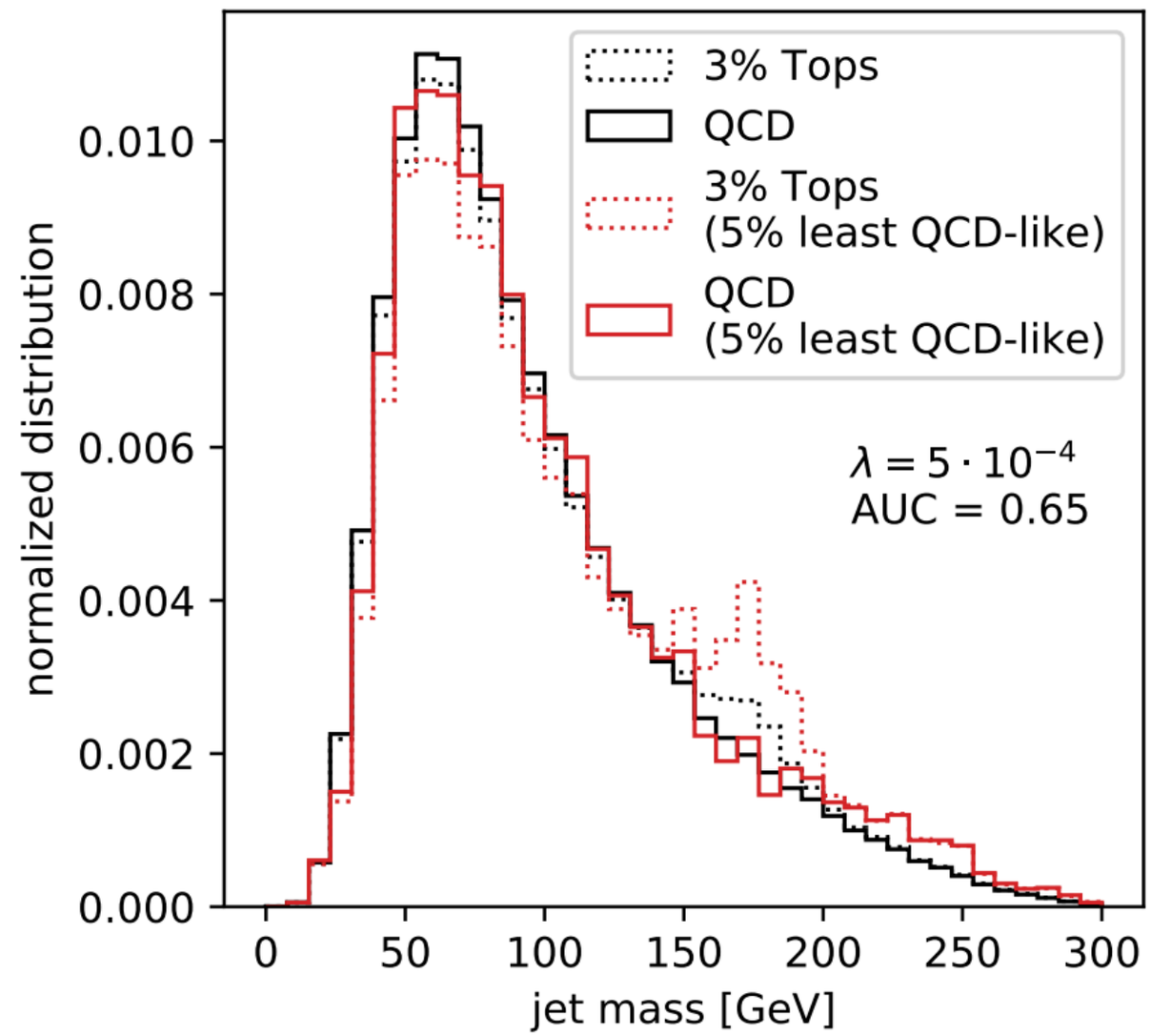
$$L = L_{\mathrm{Auto}} - \lambda L_{\mathrm{Adv}}$$

- Tune mass dependency with Lagrange multiplier
  - Defines control regions in data



Signal contamination

- Procedure works also when signal is present in training data
- This means a search for exotic new physics with unknown shower patterns (dark showers) could be done using data-only training



Dark Showers

Recap

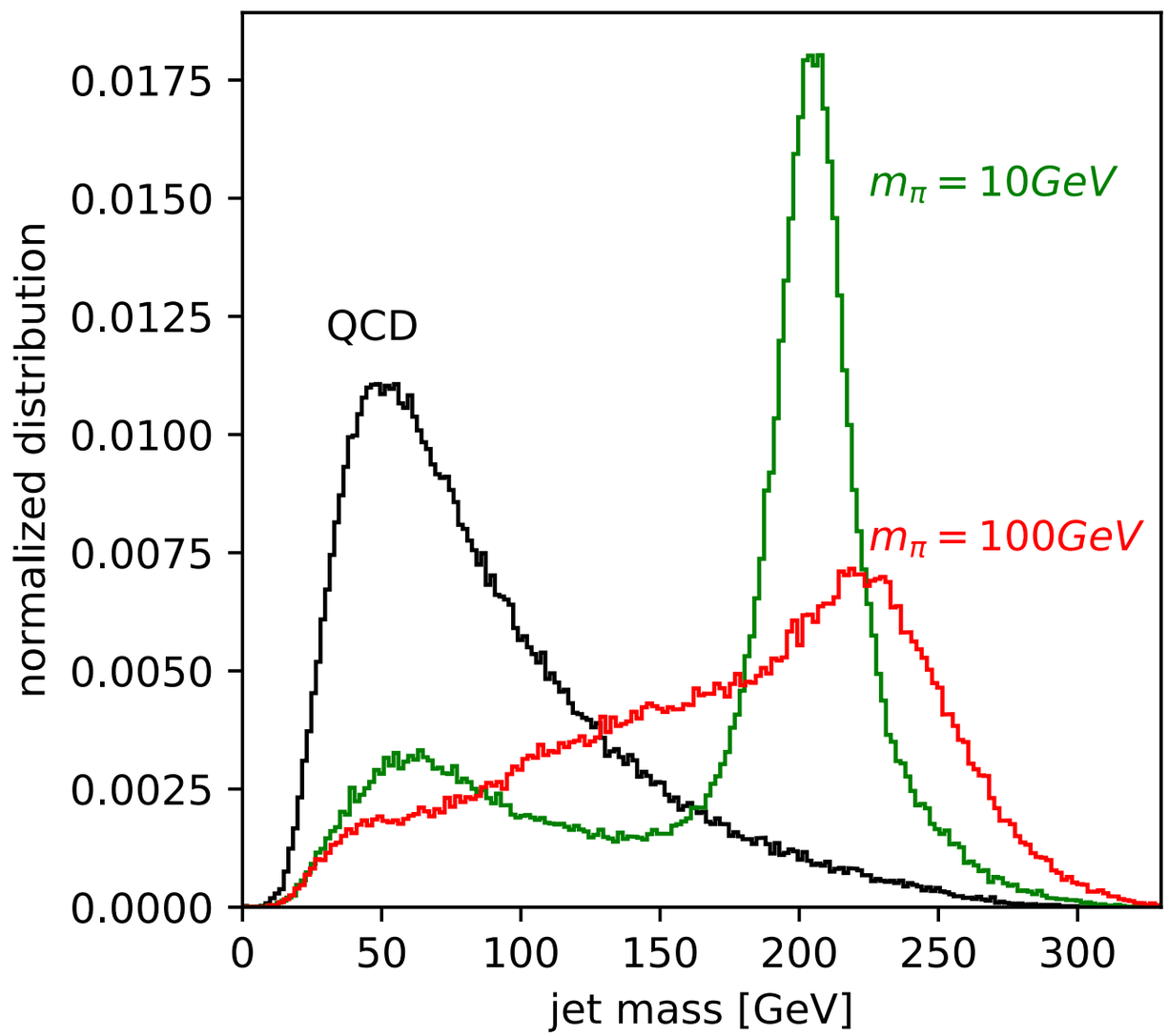
- We now have a tool that can identify anomalous jets..
  - ..purely **trained on data** in an unsupervised way
  - ..**decorrelated** from arbitrary variables (like mass)
- Potential usecase:
  - **Dark shower jets**

Dark multi-jet shower

Model

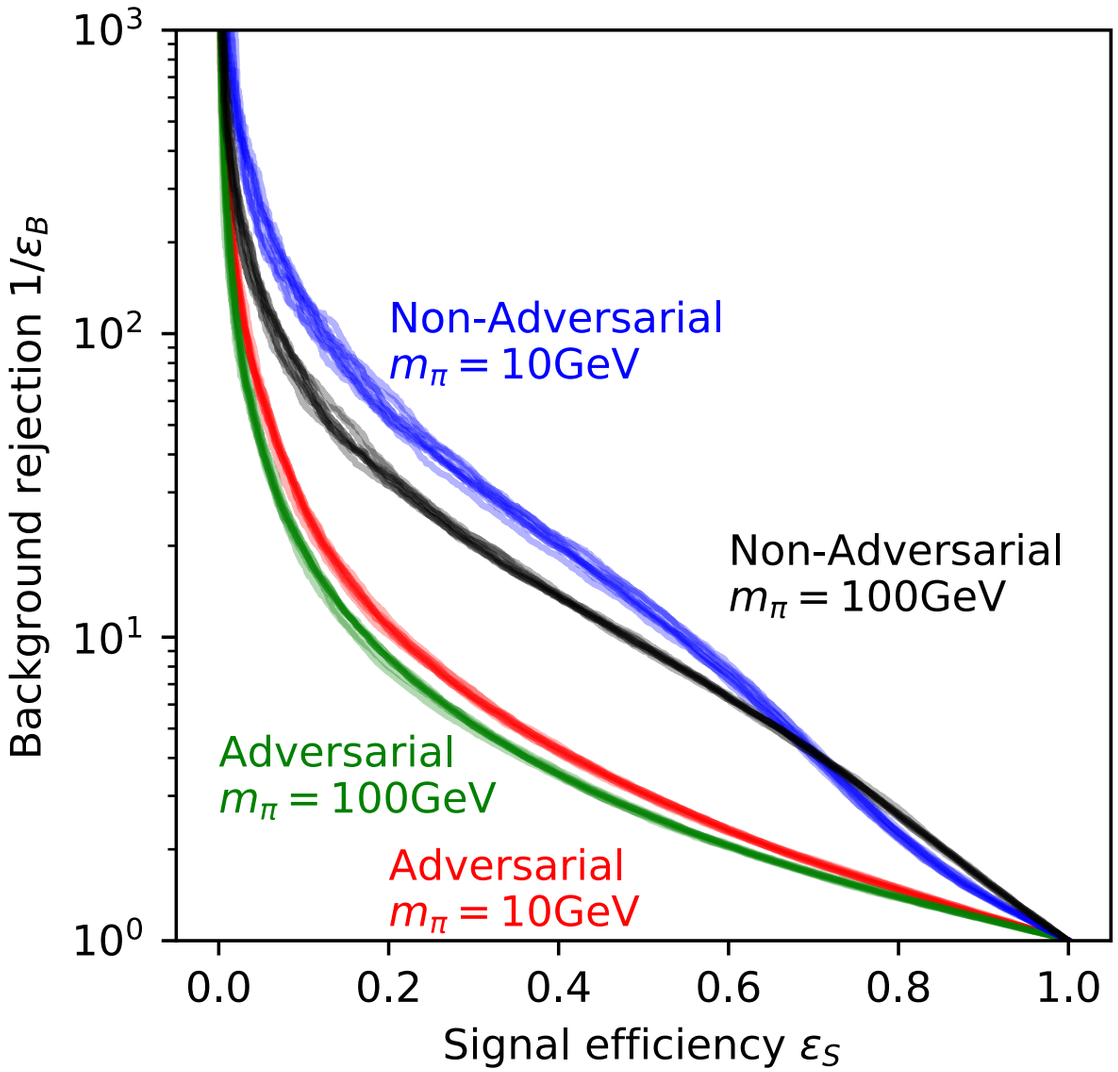
$$pp \to q_v \bar{q}_v \to q\bar{q} + \not{E}_T$$

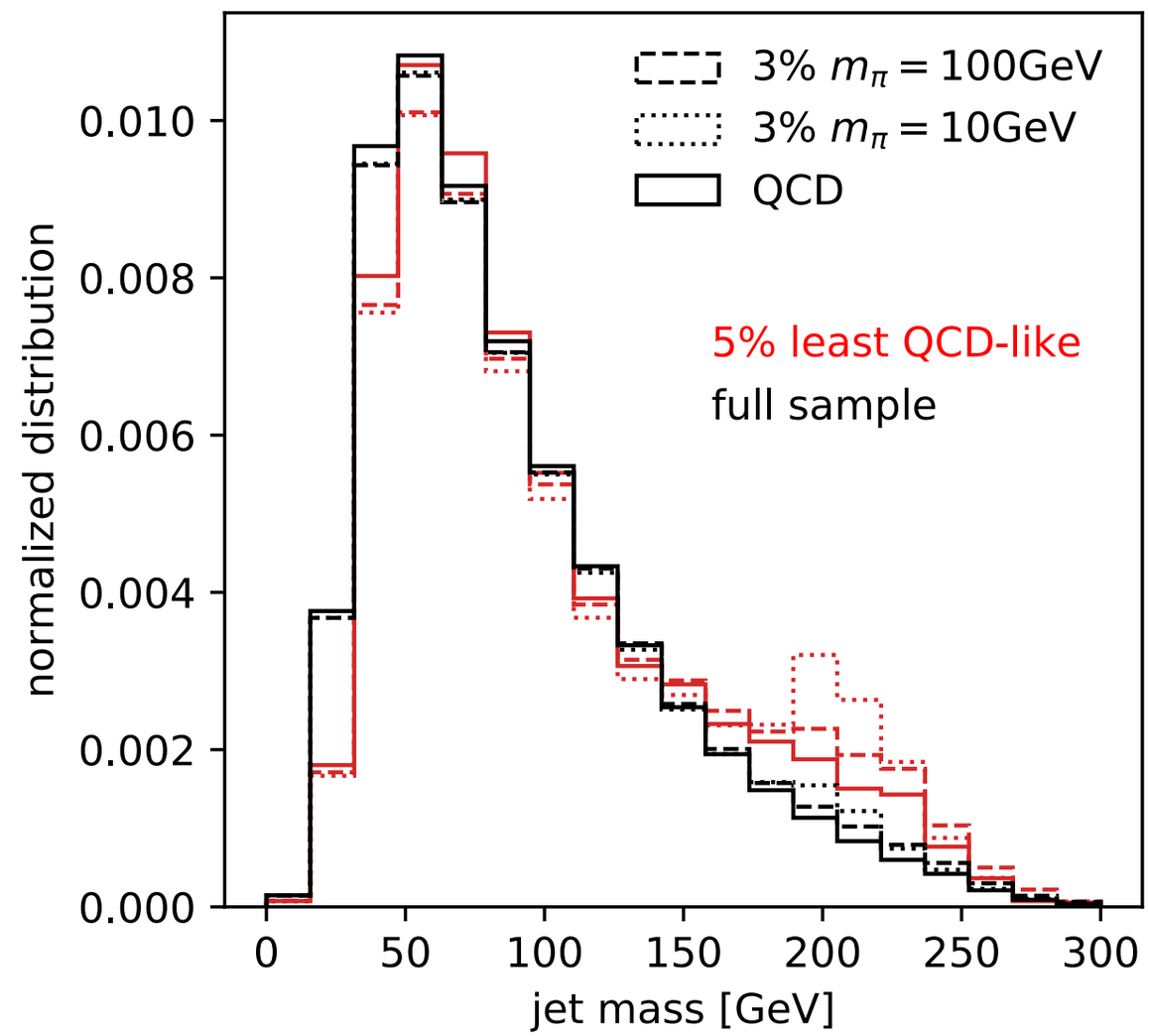
- Heavy quark q_v pair-produced
- Decay to SM partner + dark boson b
- Hadronise into dark mesons π (stable or not)
- Assume:
  - Dark SU(3)$_C$, α=0.1
  - $m_\pi = 2m_b$
  - m_q = 200 GeV



Visible Effects of Invisible Hidden Valley Radiation
L Carloni, T Sjostrand, JHEP 1009 (2010)
Discerning Secluded Sector gauge structures
L Carloni, J Rathsman, T Sjostrand, JHEP 1104 (2011)

Results





- Identify dark showers vs QCD
- Sensitivity will depend on model parameters

Closing

Spectrum of MC Reliance

Fully Supervised Learning

Fully Supervision, Mixed signals

Weak Supervision

CWoLa

Autoencoder

Dependence on Simulation

Assumes a classifier trained on MC will be correct on data as well

Assume MC gets the fractions of different classes right on average

Assume that we can tune the adversarial setup such that an anomaly based on data is credible.

Assume simulation is good. Do not depend on specific model (but still limited by which models are in the mix)

Assume interpolation between phases spaces in data.

And now for something completely different

“Greatest Of All Taggers”



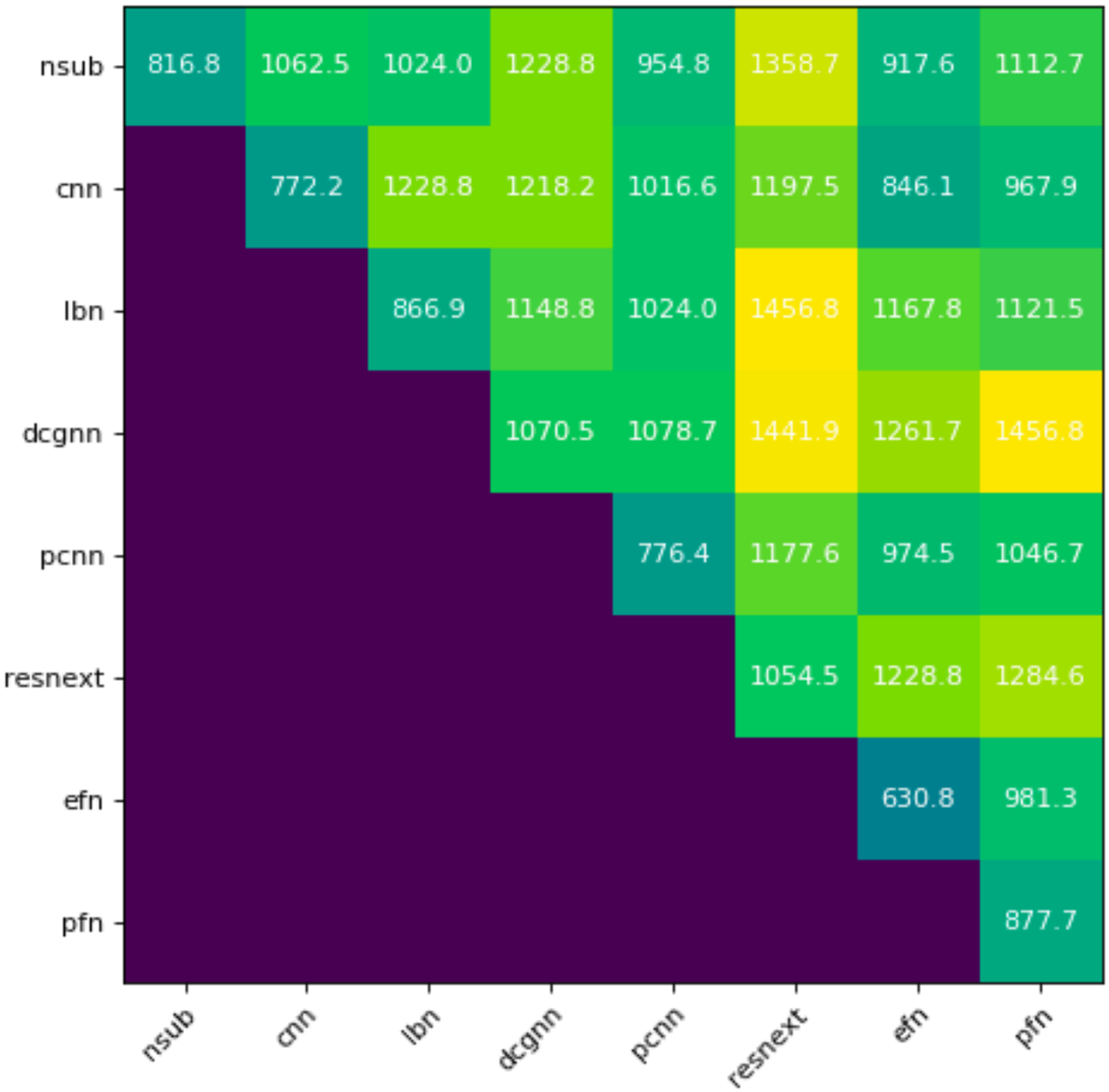





Approach	AUC	Acc.	1/eB (@ eS=0.3)	Contact	Comments
LoLa	0.980	0.928	680	GK / SImon Leiss	Preliminary number, based on LoLa
LBN	0.981	0.931	863	Marcel Rieger	Preliminary number
CNN	0.981	0.93	780	David Shih	Model from *Pulling Out All the Tops with Computer Vision and Deep Learning (1803.00107)*
P-CNN (1D CNN)	0.980	0.930	782	Huilin Qu, Loukas Gouskos	Preliminary, use kinematic info only (https://indico.physics.lbl.gov/indico/event/546/contributions/1270/)
6-body N-subjettiness (+mass and pT) NN	0.979	0.922	856	Karl Nordstrom	Based on 1807.04769 (*Reports of My Demise Are Greatly Exaggerated: N-subjettiness Taggers Take On Jet Images*)
8-body N-subjettiness (+mass and pT) NN	0.980	0.928	795	Karl Nordstrom	Based on 1807.04769 (*Reports of My Demise Are Greatly Exaggerated: N-subjettiness Taggers Take On Jet Images*)
Linear EFPs	0.980	0.932	380	Patrick Komiske, Eric Metodiev	d<= 7, chi <= 3 EFPs with FLD. Based on 1712.07124: *Energy Flow Polynomials: A complete linear basis for jet substructure.*
Particle Flow Network (PFN)	0.982	0.932	888	Patrick Komiske, Eric Metodiev	Median over ten trainings. Based on Table 5 in 1810.05165: *Energy Flow Networks: Deep Sets for Particle Jets.*
Energy Flow Network (EFN)	0.979	0.927	619	Patrick Komiske, Eric Metodiev	Median over ten trainings. Based on Table 5 in 1810.05165: *Energy Flow Networks: Deep Sets for Particle Jets.*
2D CNN [ResNeXt50]	0.984	0.936	1086	Huilin Qu, Loukas Gouskos	Preliminary from indico.cern.ch/event/745718/contributions/3202526
DGCNN	0.984	0.937	1160	Huilin Qu, Loukas Gouskos	Preliminary from indico.cern.ch/event/745718/contributions/3202526

- Based on top tagging reference
- Train a fully connected network (100x3-20-2) on output of existing classifiers
- Use *testing* sample (20% for training, 10% for early stopping, 70% for testing)
- GOAT (Meta Tagger):
  - **AUC**: ~0.985
  - **1/eB**: 1390 +-100 (unstable, too low statistics!)

“Correlations”



- Train DNN on pairs of taggers
- Strongest combinations:
  - *Physics* + *Facebook*
- Will be interesting to explore orthogonalities

Conclusions

- Propose a new method based on unsupervised deep networks find non-SM physics as anomaly
  - Orthogonal approach to dedicated searches
  - Can be trained from data and made independent of mass
  - Shown for images and LoLa, but can work with any neural network architecture
- Top tagging classification has not saturated
  - "Improve" by ~60% in a day
  - Can a non-Frankenstein tagger capture this?
- Challenges for ML4Jets 2019:
  - Understand stability & error bars
  - New ideas hitting data
  - Go beyond jets

Thank you!