

# Searching for new physics with autoencoders

ML4Jets  
November 16, 2018

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Stony Brook University

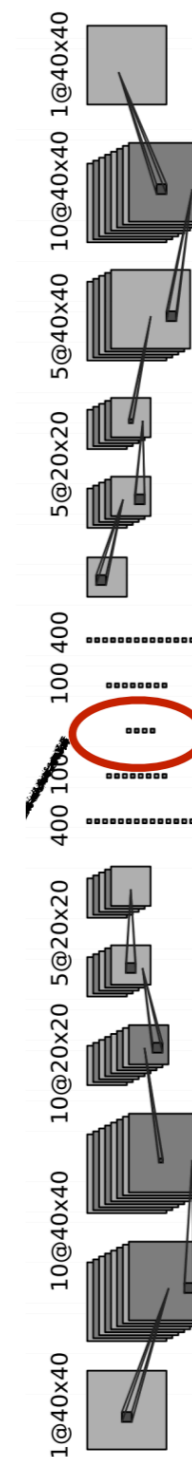
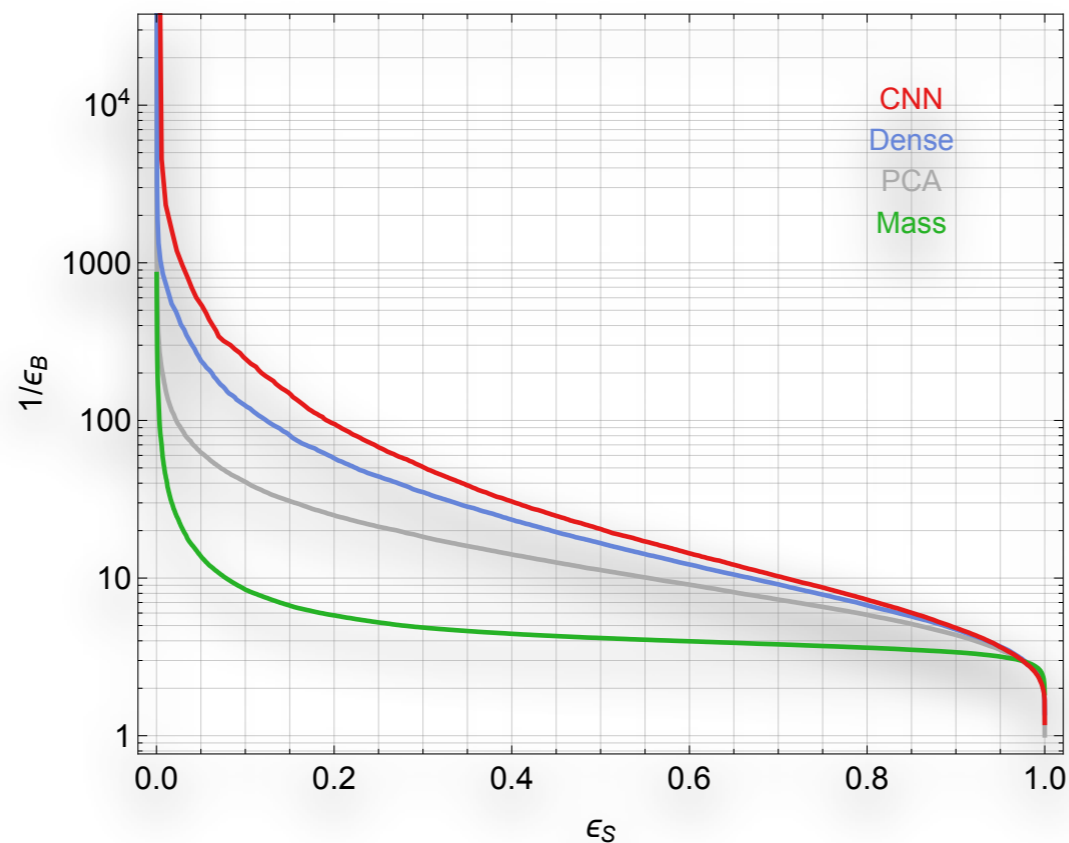


Based on Farina, Nakai, Shih '18

# Thanks Gregor!

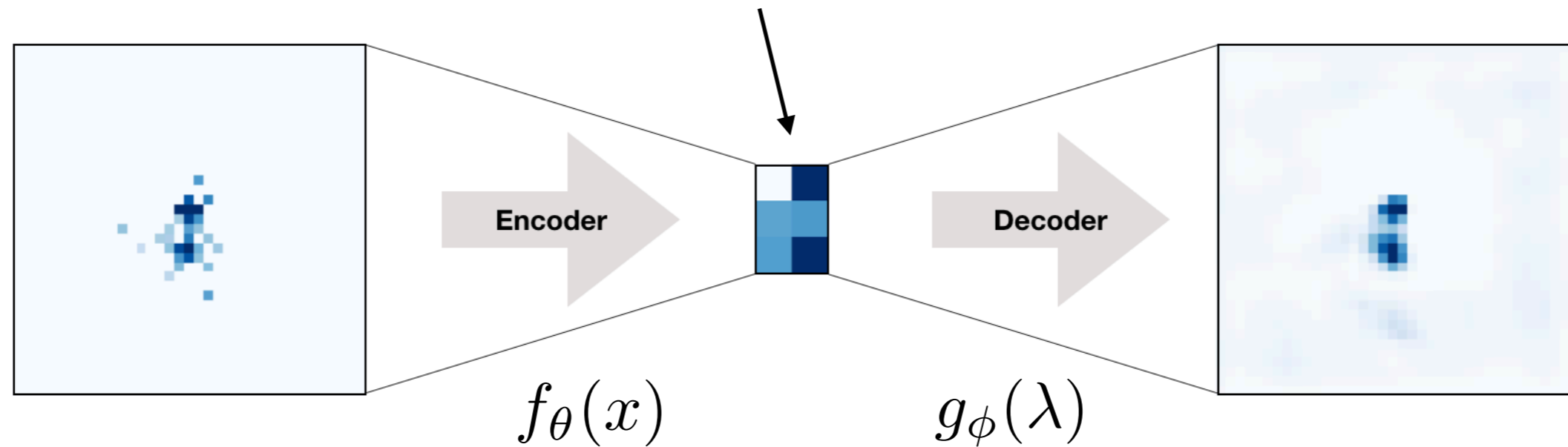
## Does it work?

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



# Autoencoders

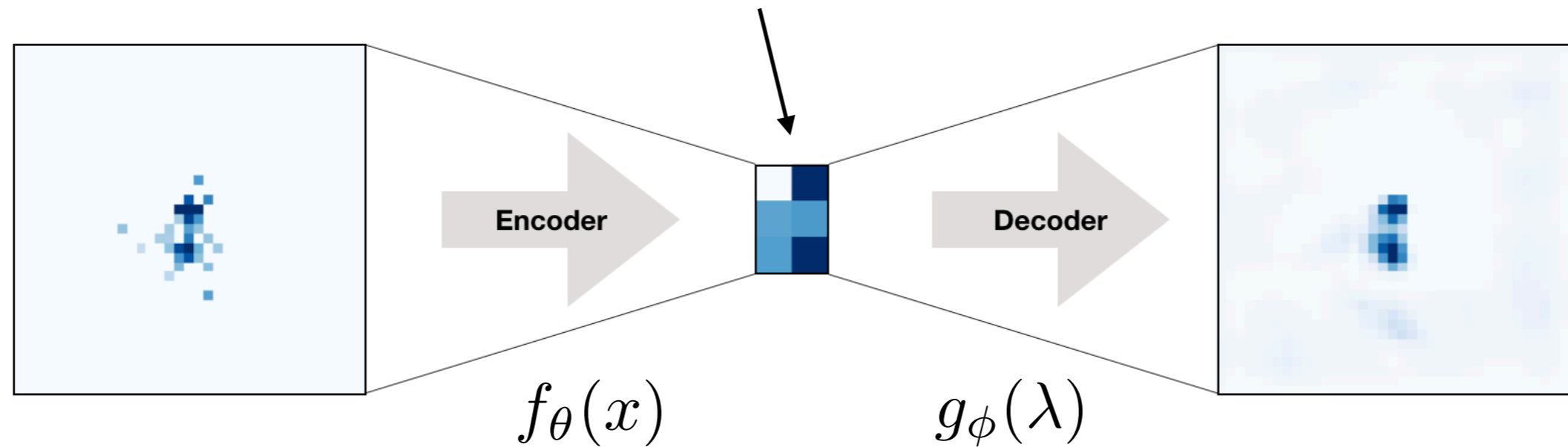
$\lambda$  bottleneck latent dim



$$\ell(\theta, \phi) = |x - g_{\phi}(f_{\theta}(x))|^2$$

# Autoencoders

$\lambda$  bottleneck latent dim



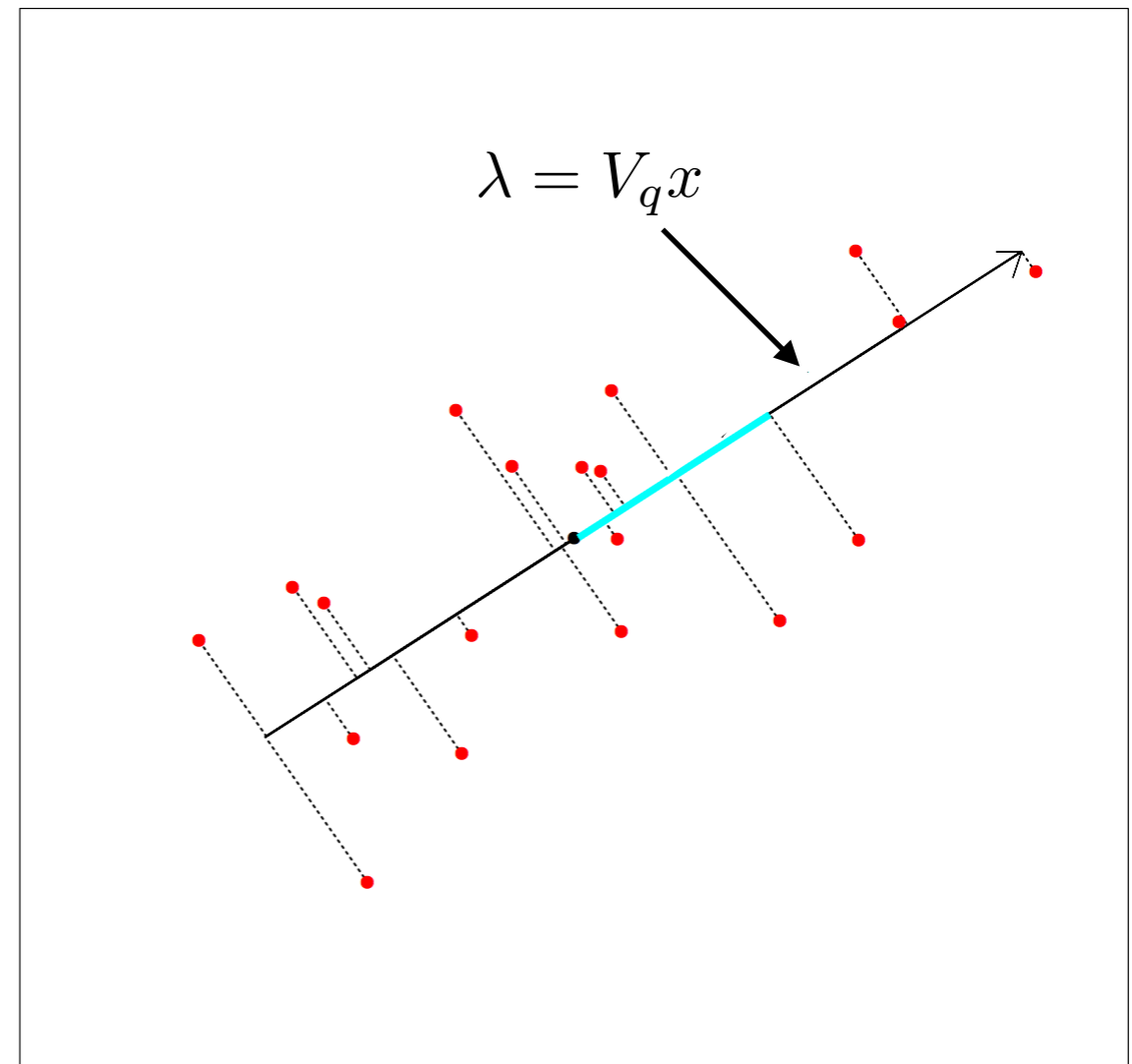
- PCA
- DNN
- CNN

# PCA

Principal component analysis: linear transformation  
Lower dimensional representation of data  $q < n$

$$\ell(V_q) = |x - V_q^T V_q x|^2$$

Find best  $V_q$



Maximum variance  $\longleftrightarrow$  Minimum error

# Data

We generated:

- QCD jets as train/background
- tops and 400 GeV gluinos (with 3j RPV decay) as signal/anomaly

Transformed sample in images

Preprocessing as in Macaluso, Shih '18

	CMS
Jet sample	13 TeV $p_T \in (800, 900)$ GeV, $ \eta  < 1$ PYTHIA 8 and DELPHES particle-flow match: $\Delta R(t, j) < 0.6$ merge: $\Delta R(t, q) < 0.6$ 1.2M + 1.2M
Image	$37 \times 37$ $\Delta\eta = \Delta\phi = 3.2$

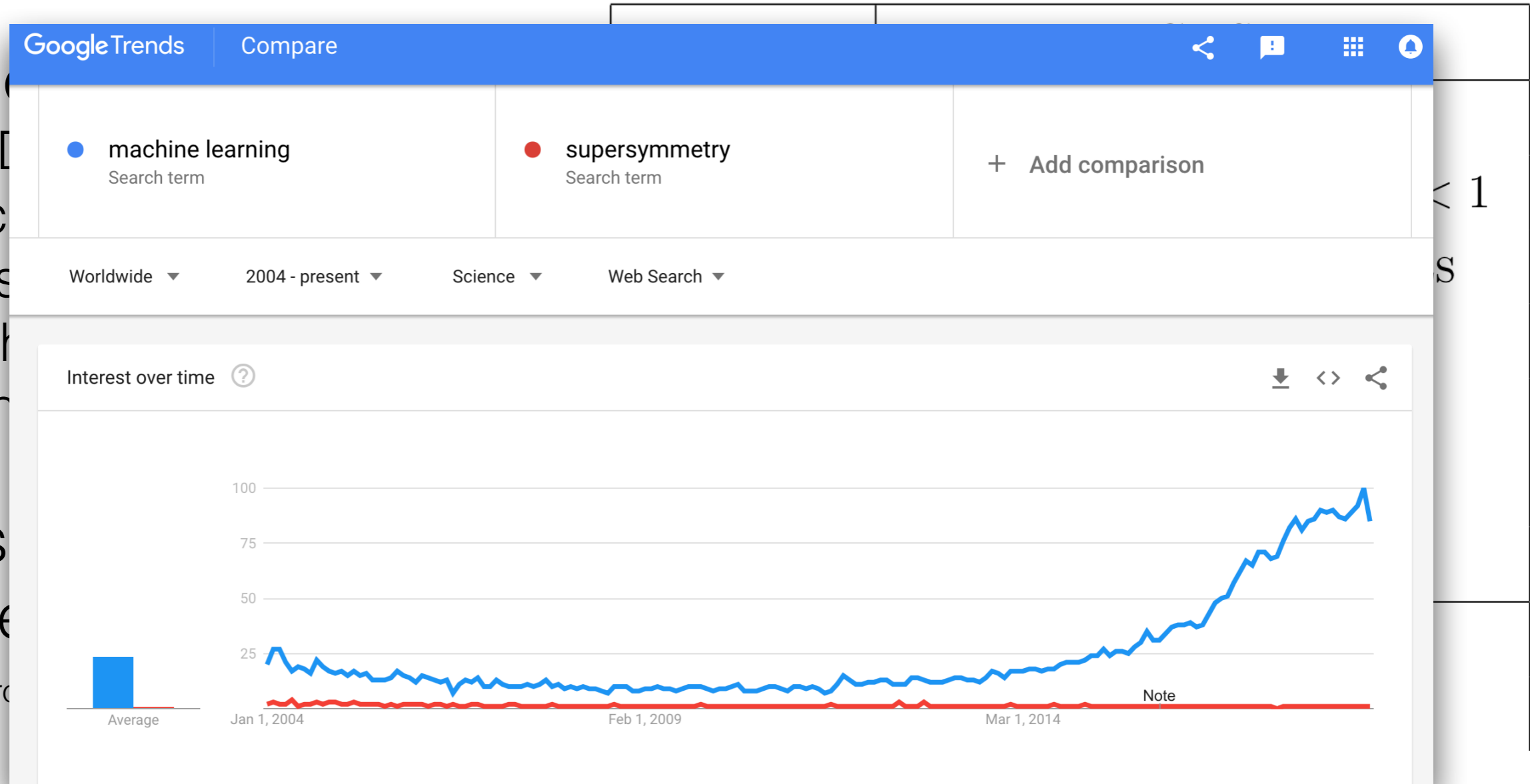
# Data

We go

- QCD  
back
- tops  
(with  
sign

Trans  
image

Prepr



> 1  
S

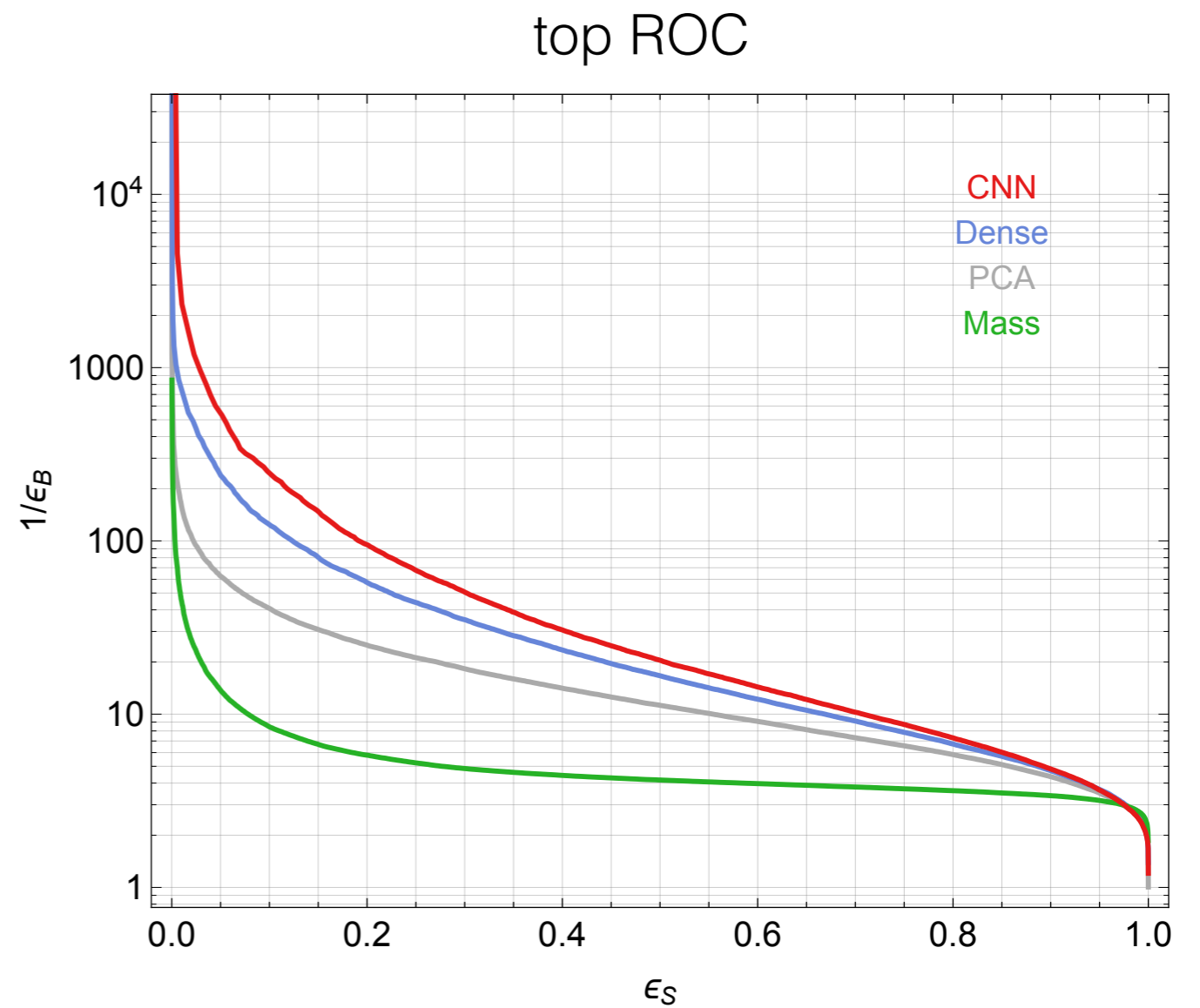
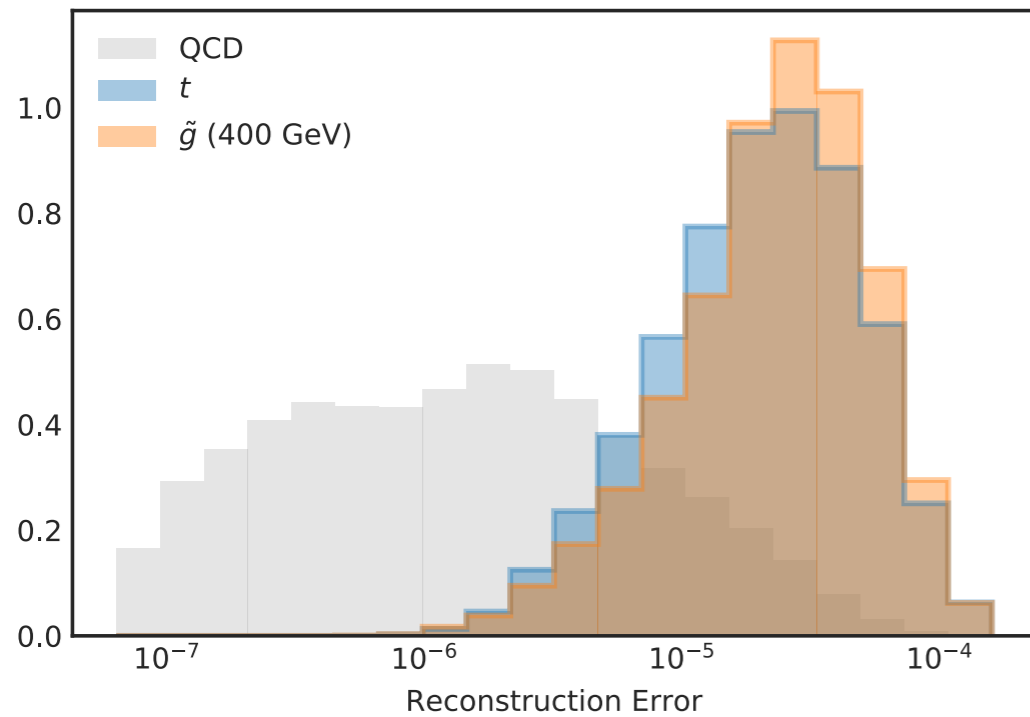
# Anomalous jets detection

After training on QCD jets...



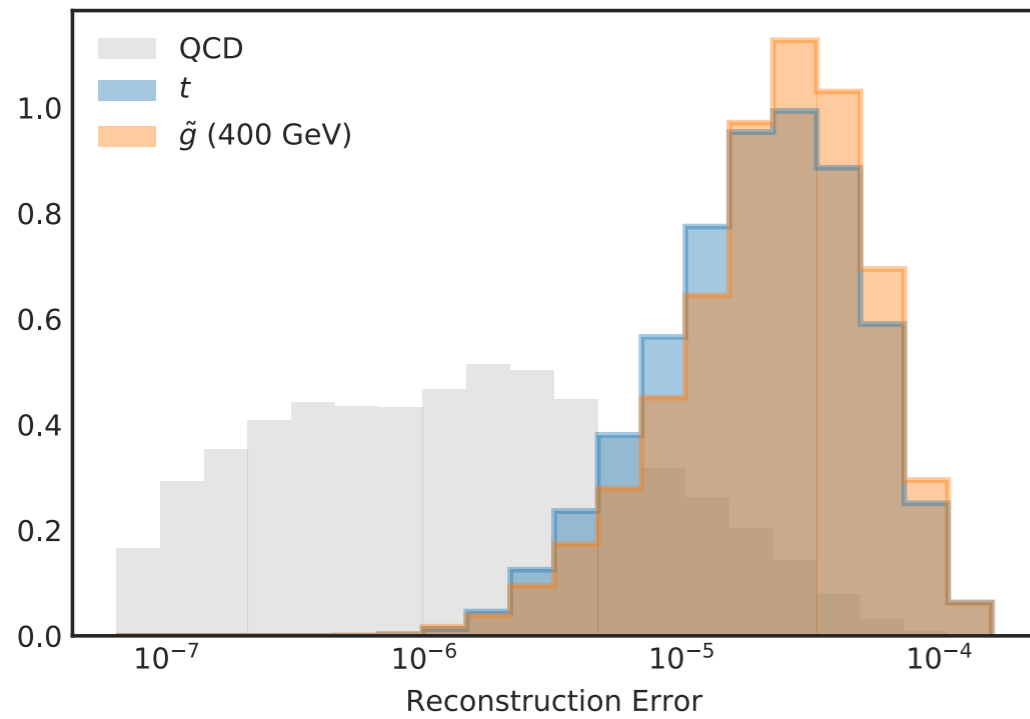


# Anomalous jets detection



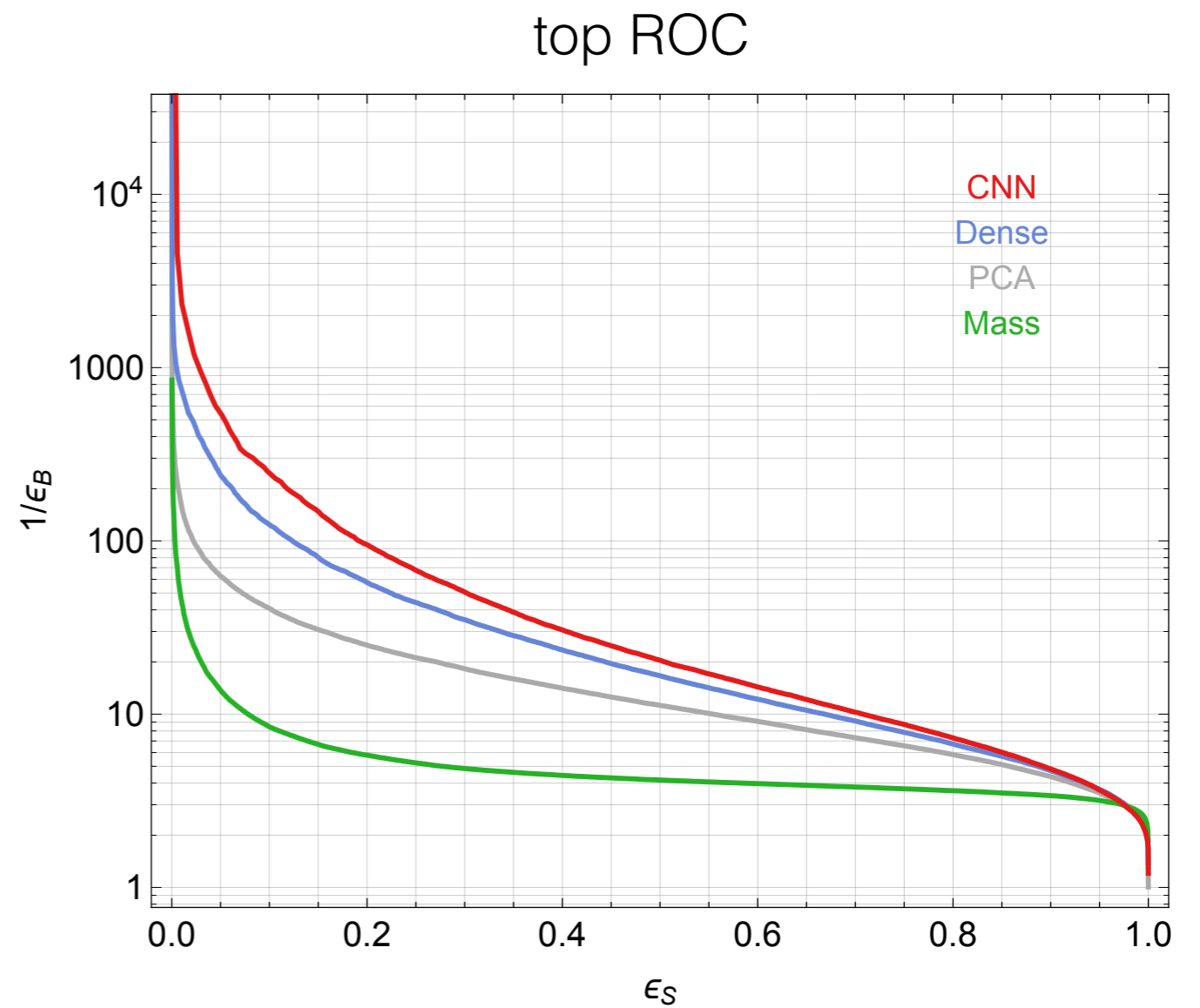
Tag anomaly using cut on reconstruction error

# Anomalous jets detection



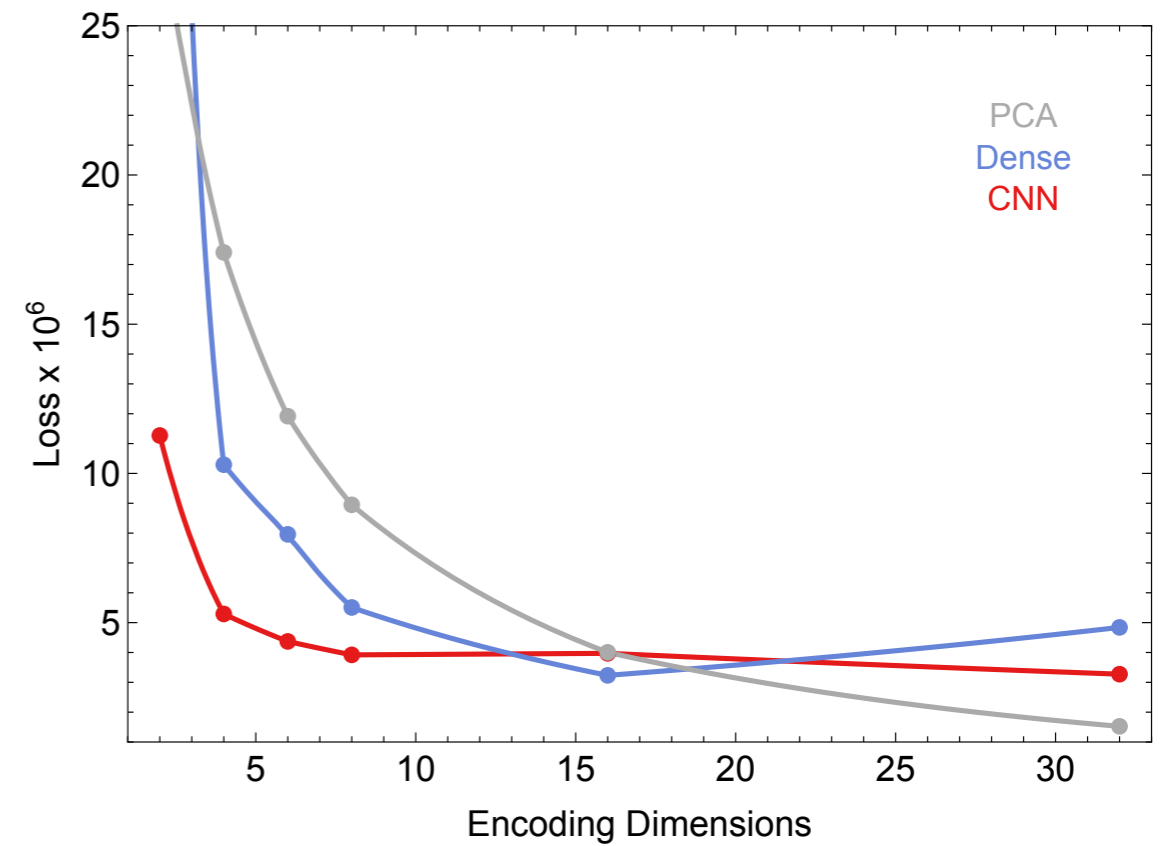
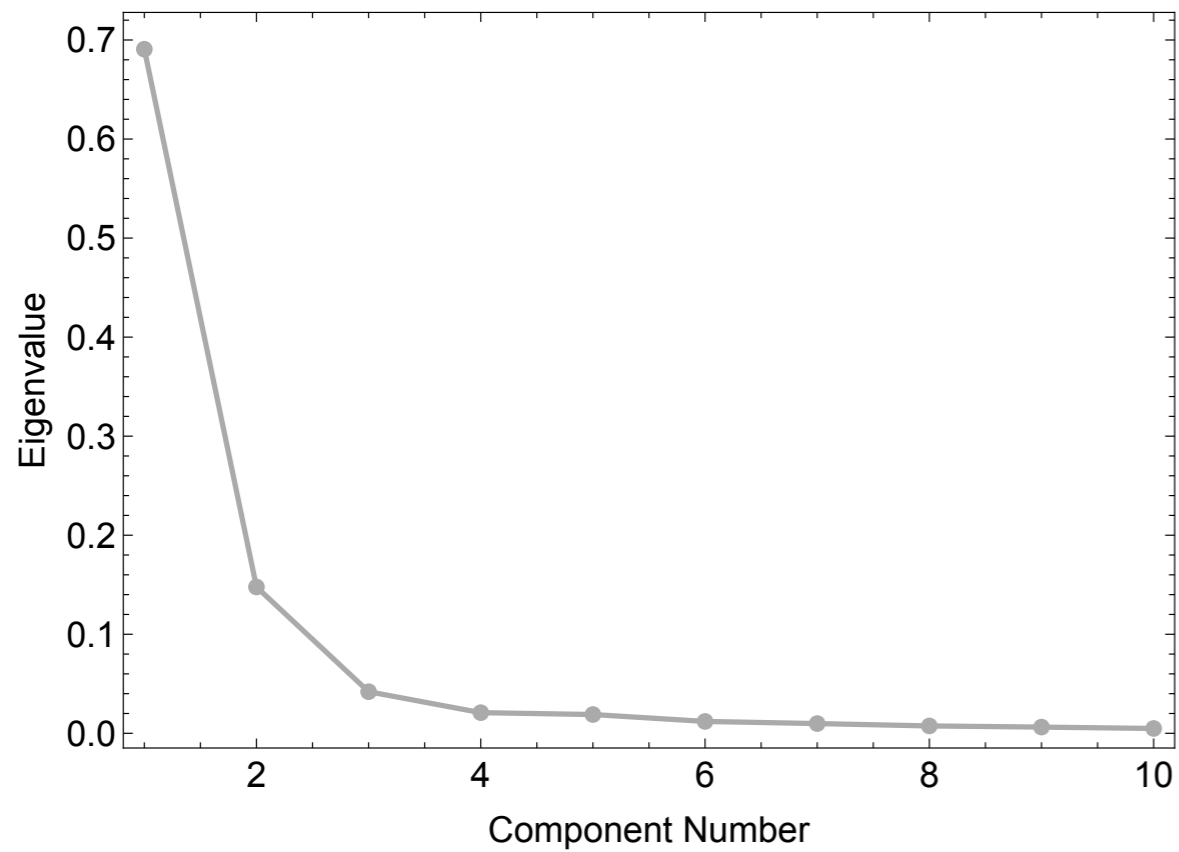
$$E_{10} \sim 0.7$$

$$E_{100} \sim 0.15$$



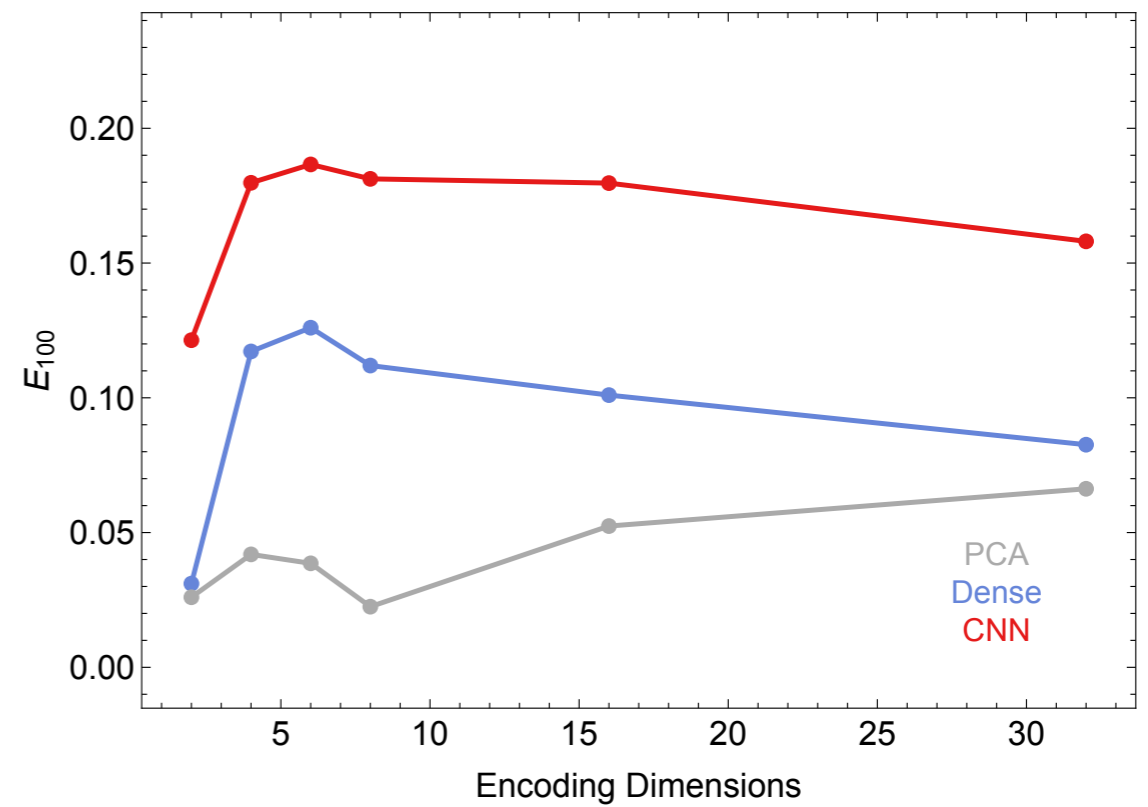
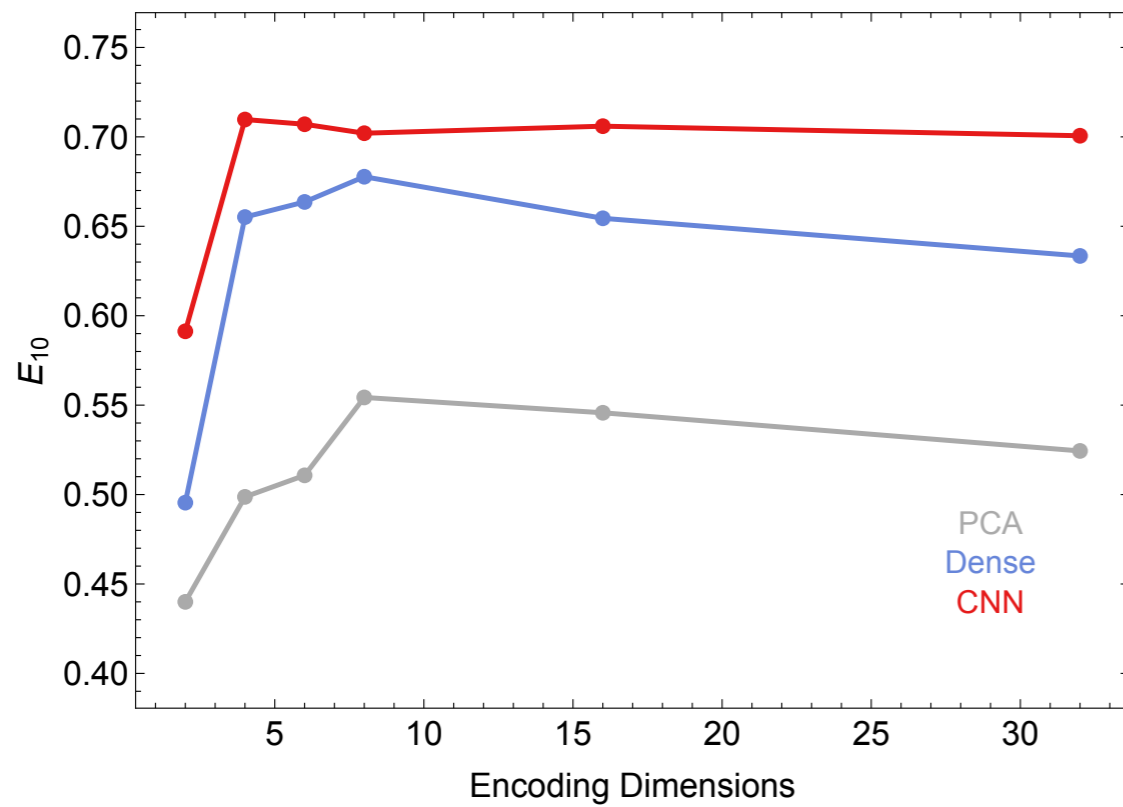
# Encoding dim

## Expressivity vs Triviality



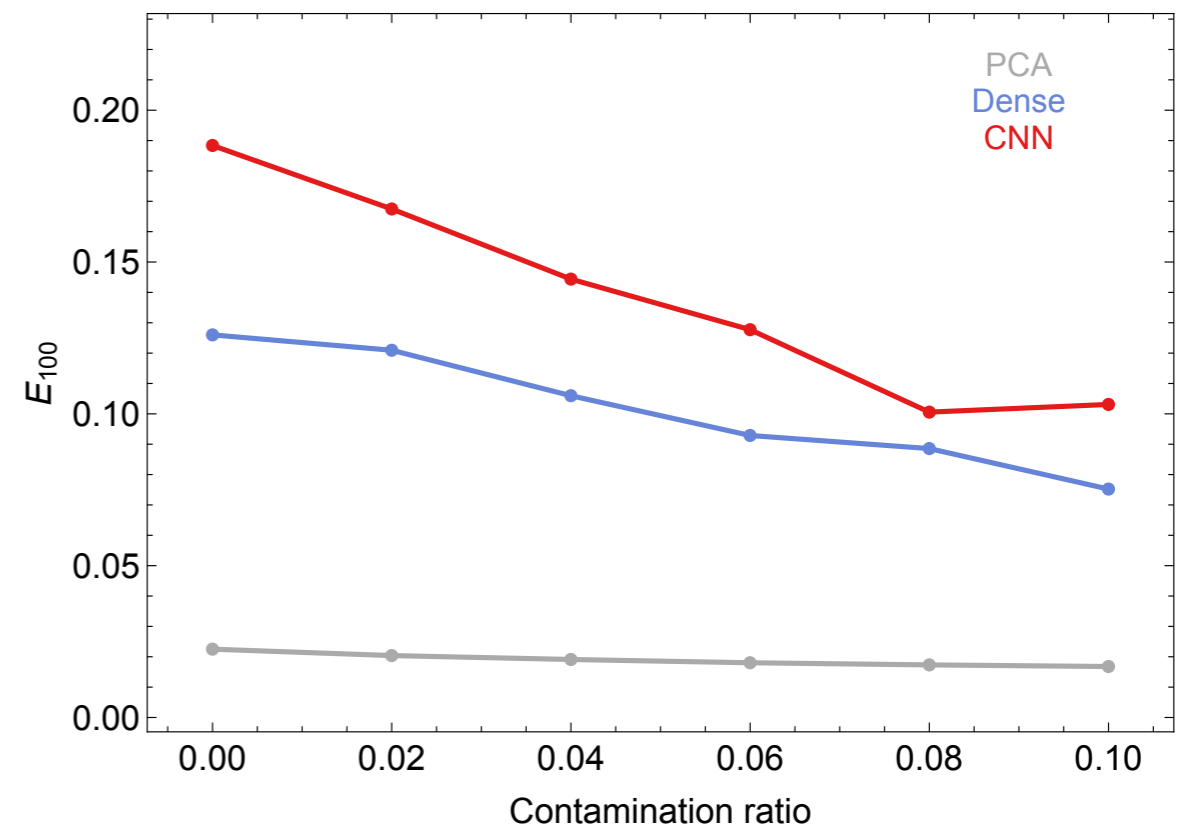
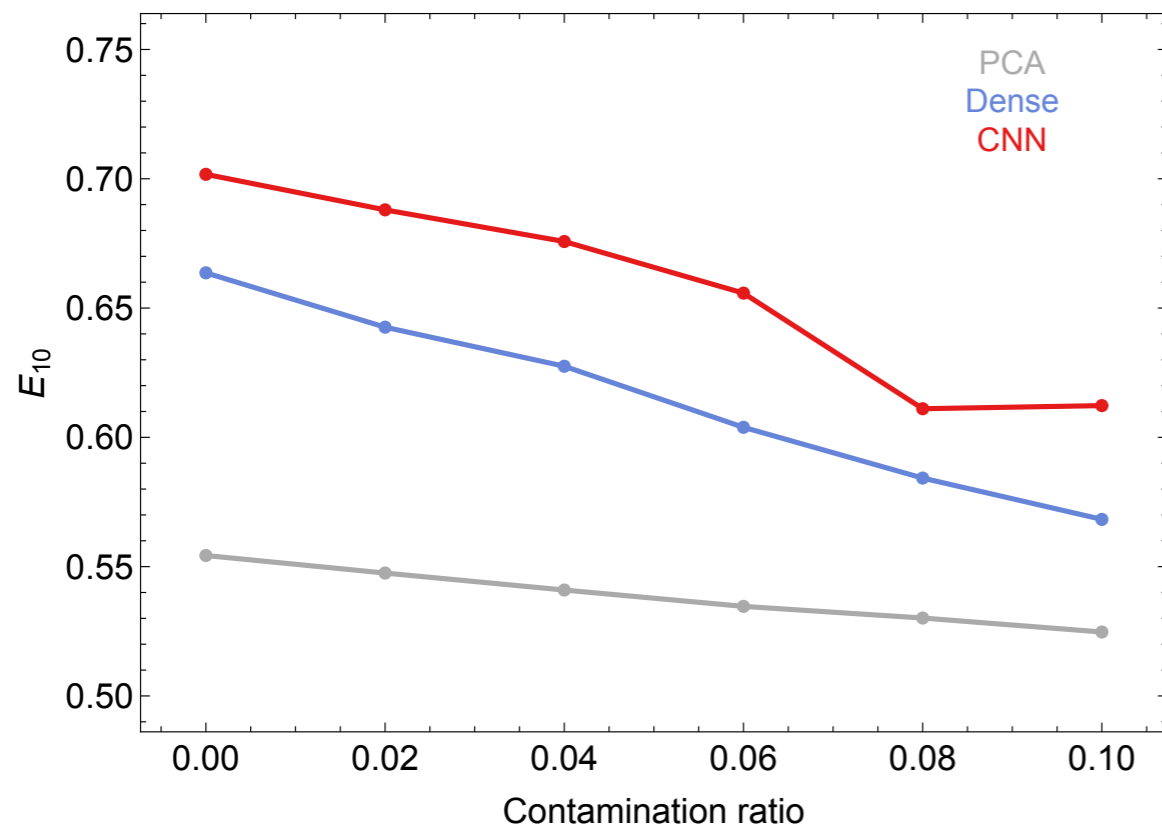
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## Expressivity vs Triviality

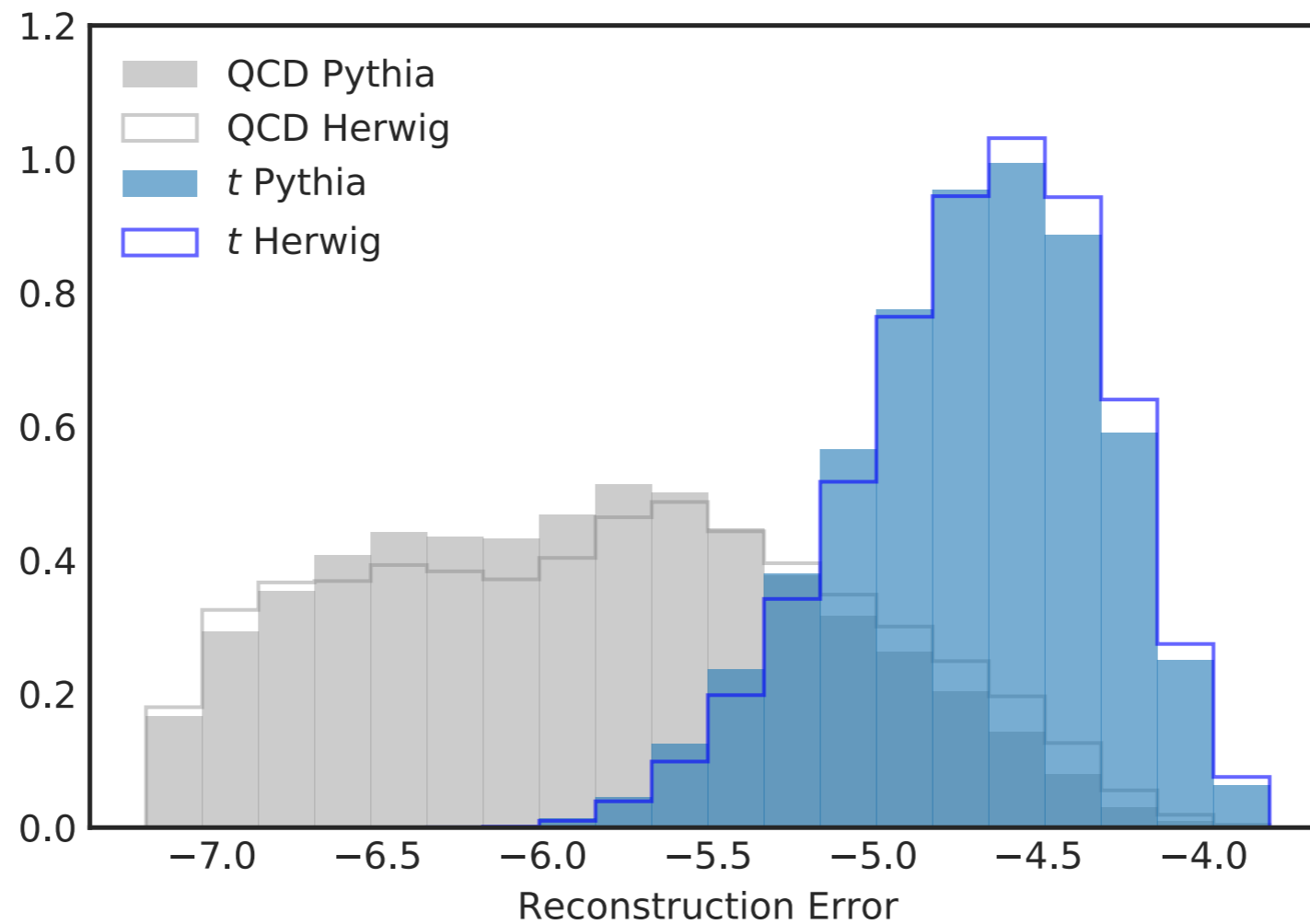


# Train set contamination

Cheating so far: weakly supervised vs unsupervised



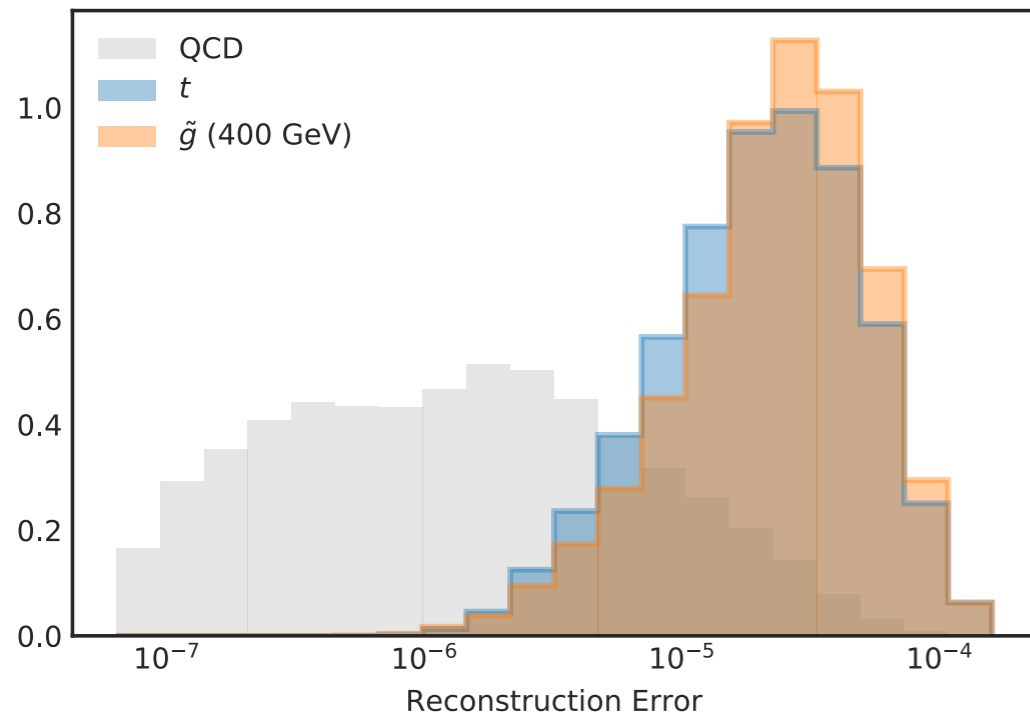
# Robustness?



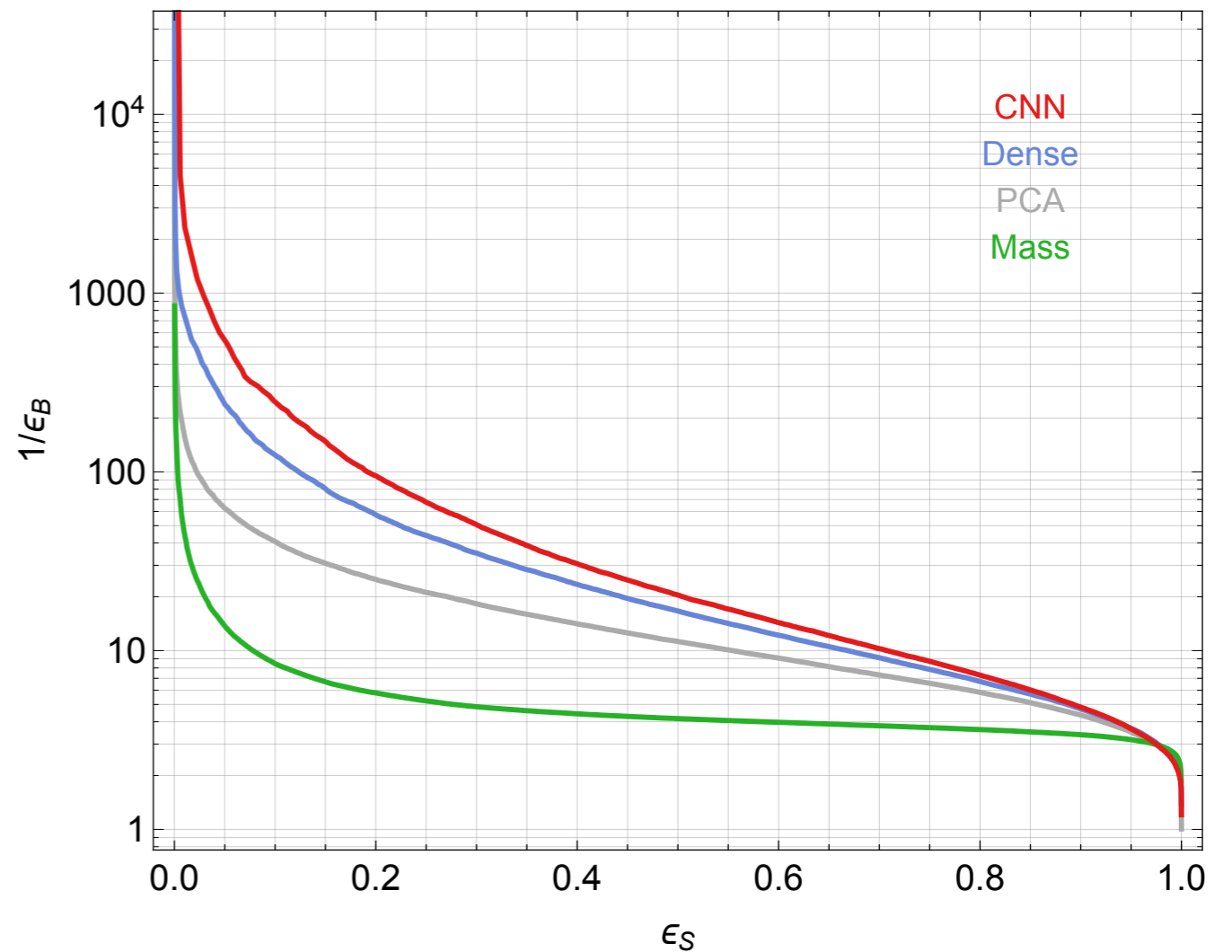
Different generators, as a proxy for training on simulation vs real data

Very qualitative...

# Anomalous jets detection



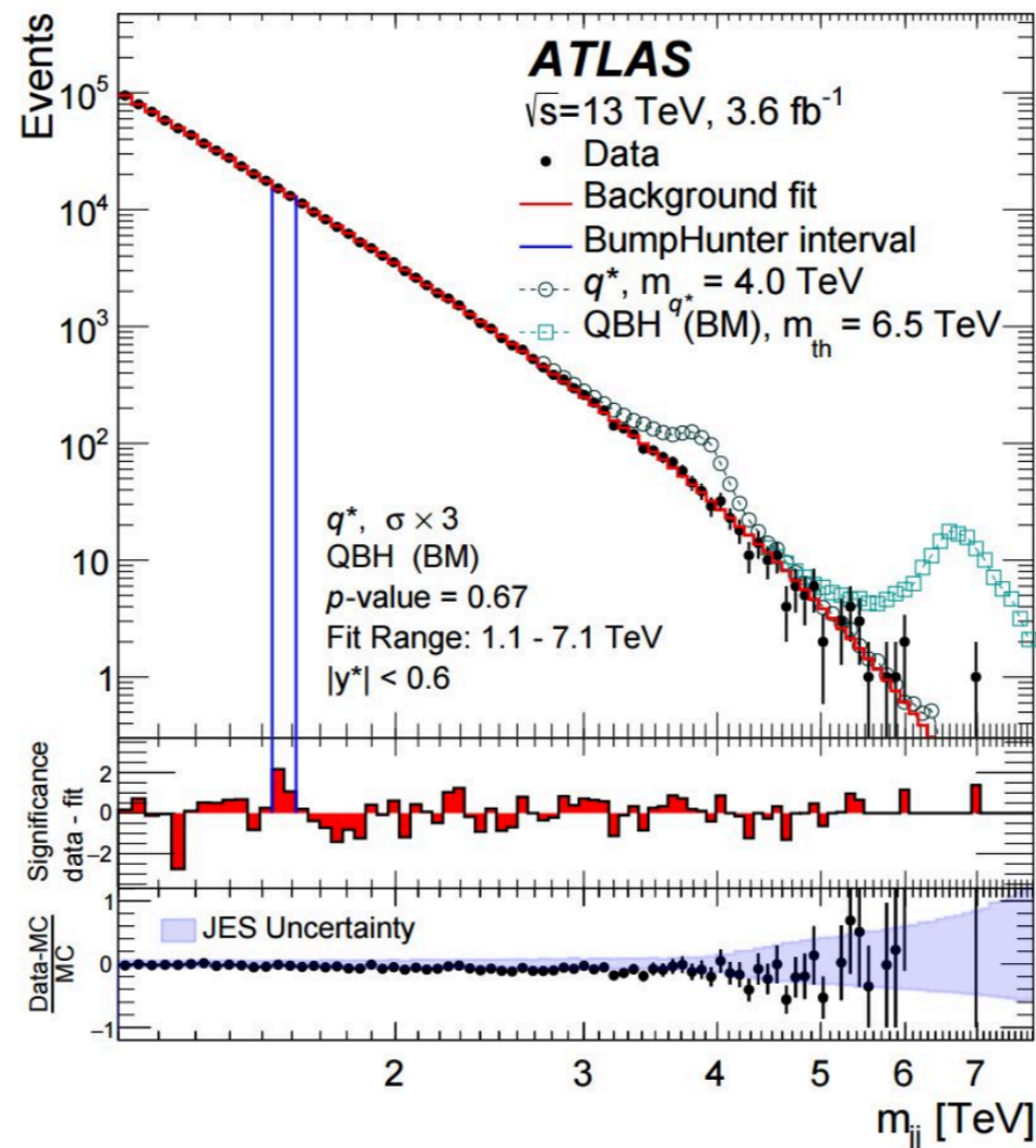
	$t$	$\tilde{g}$
PCA	0.51 / 0.04	0.98 / 0.36
Dense	0.66 / 0.13	0.90 / 0.39
CNN	0.70 / 0.19	0.77 / 0.23



Build test statistic given expected number of events passing the cut or...

# Enhanced bump hunt?

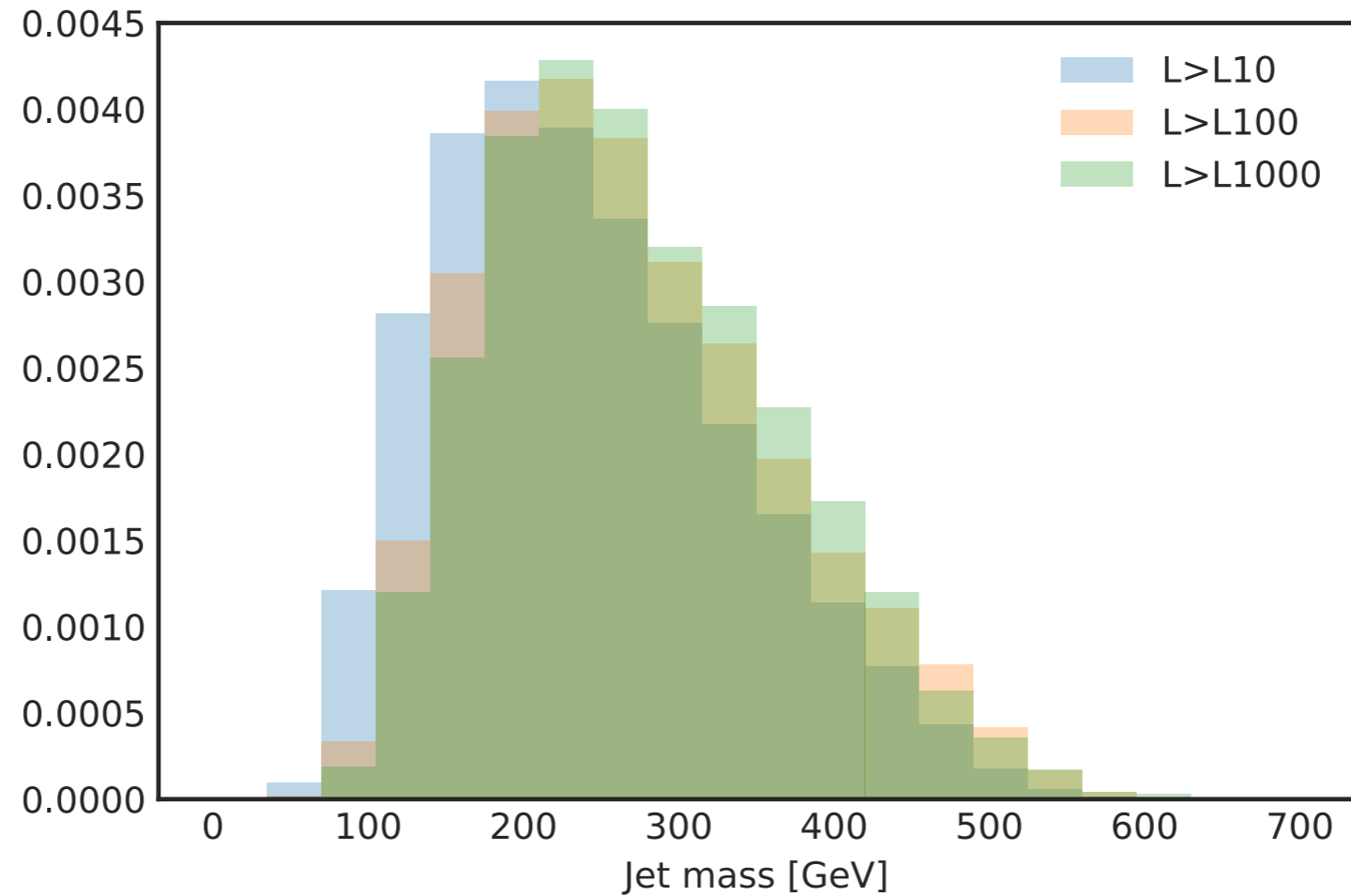
Use AE to reduce background in conventional searches



Crucial to avoid distortions of the spectrum

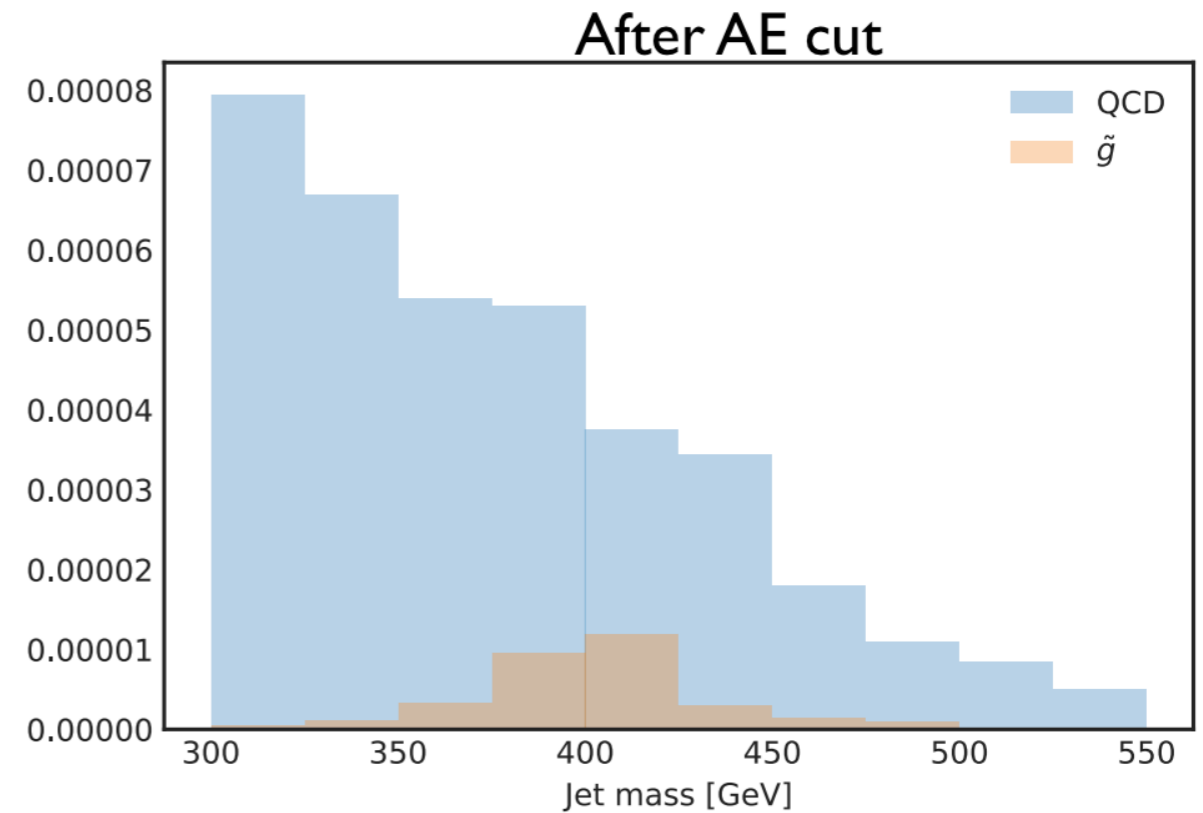
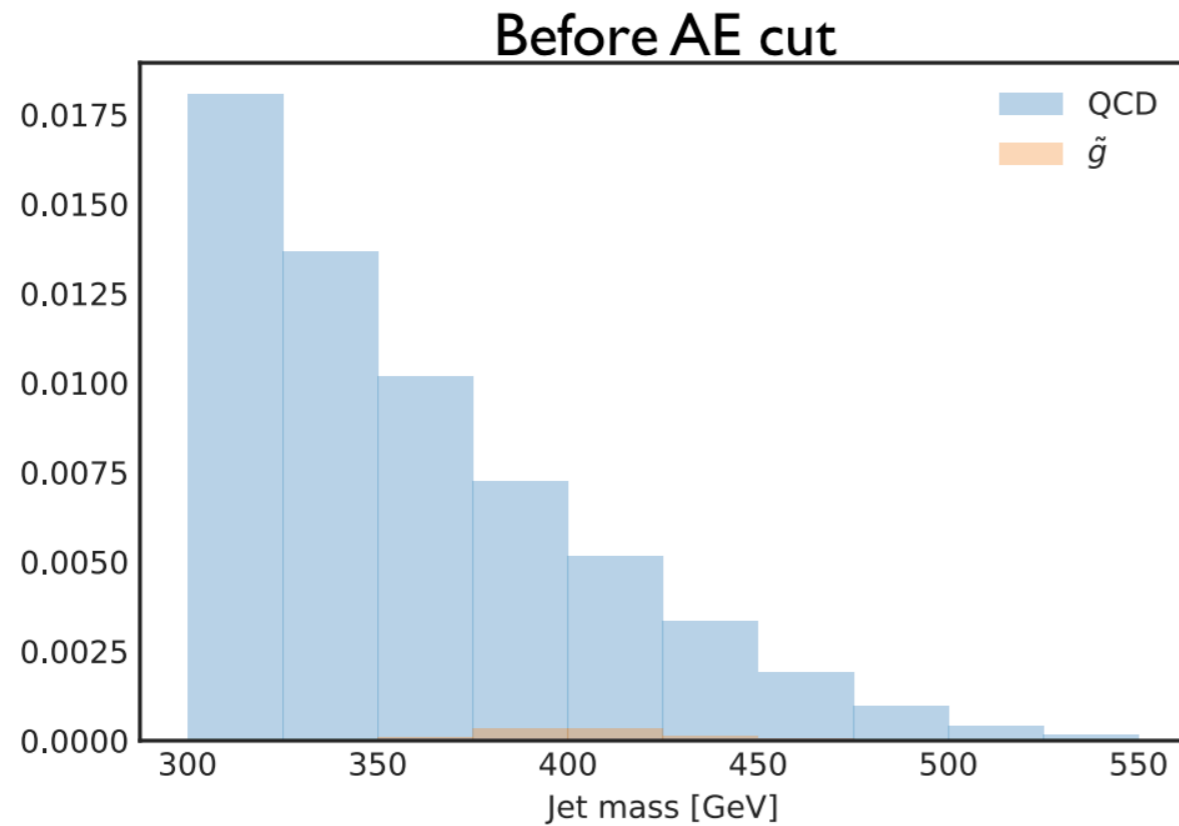


# Enhanced bump hunt?



Mass distribution stable against reconstruction error cuts

# Enhanced bump hunt?

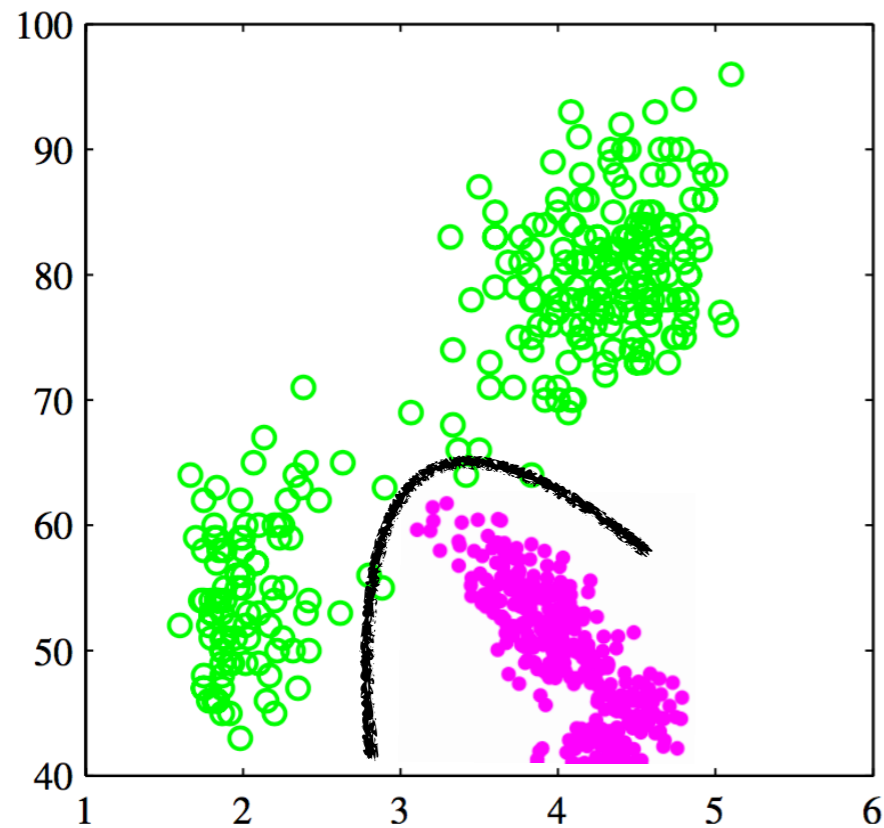


Use AE to deplete data from bkg events.  
Followed by bump hunt? Other techniques?

# Very different tasks

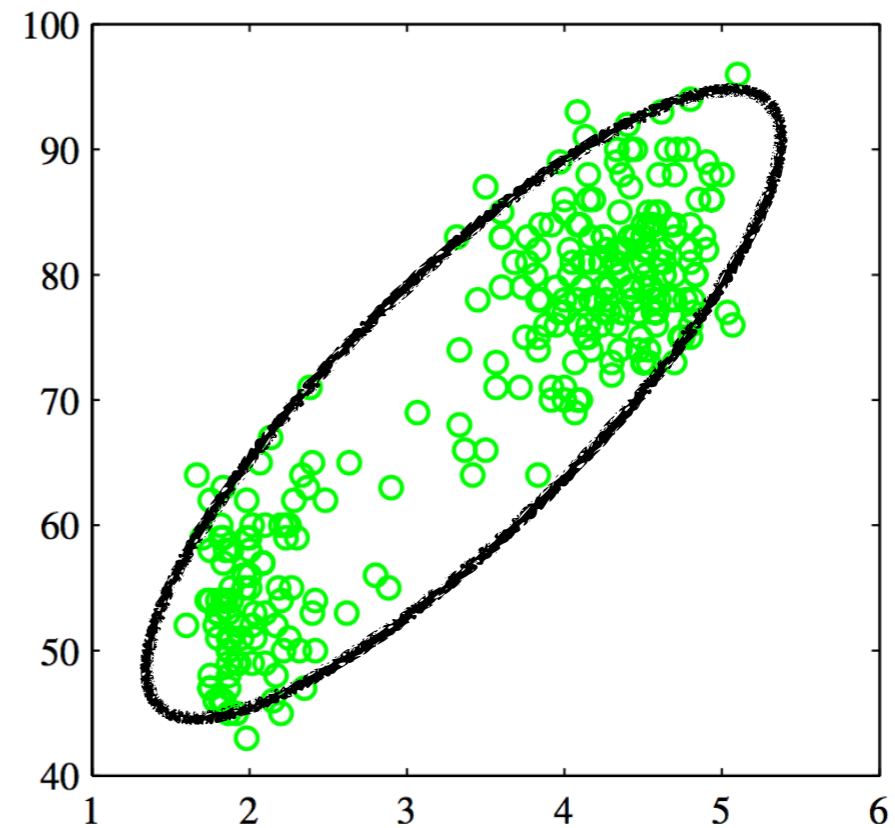
Training

Supervised



Optimized decision boundary

Unsupervised



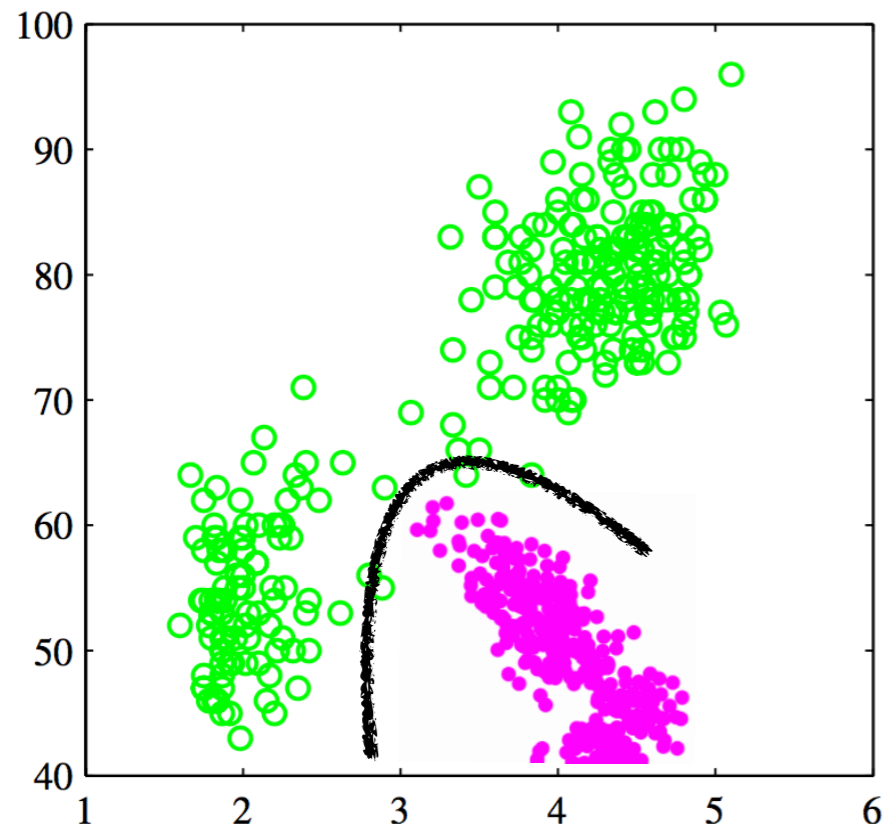
Optimized modeling of input data

VS

# Very different tasks

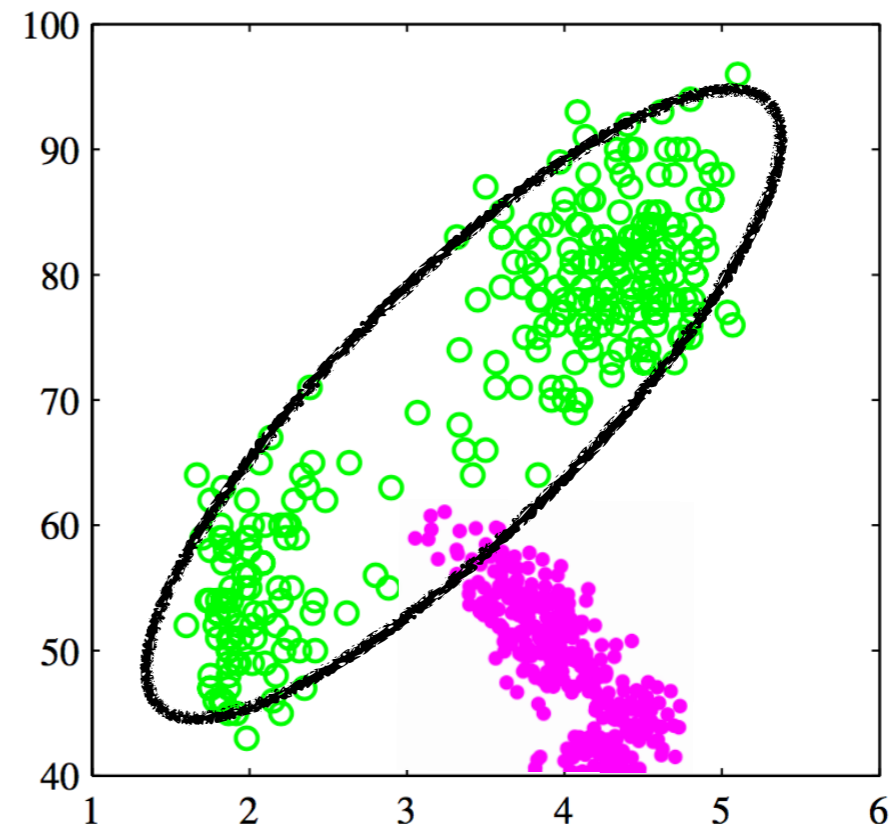
Inference

Supervised



Optimized decision boundary

Unsupervised



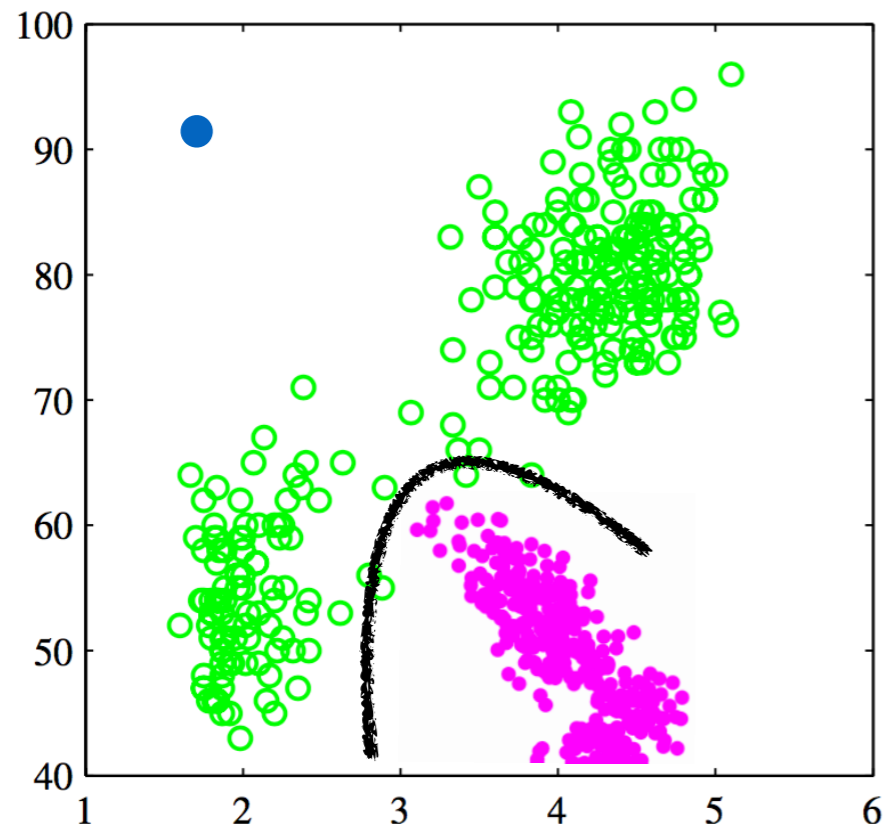
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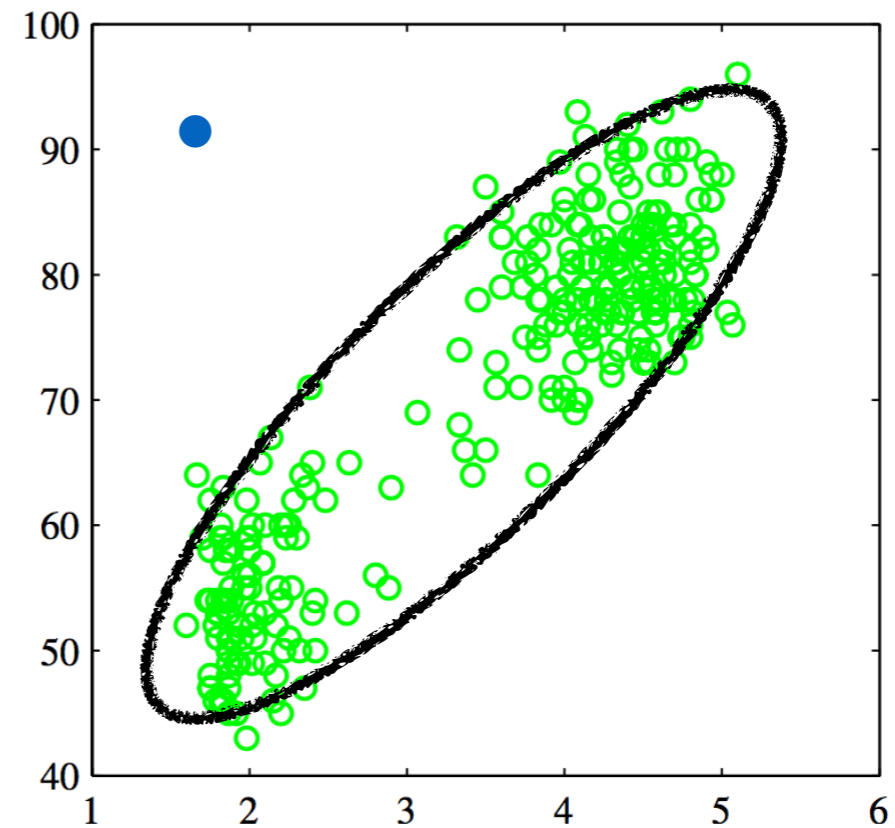
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Supervised



Optimized decision boundary

Unsupervised

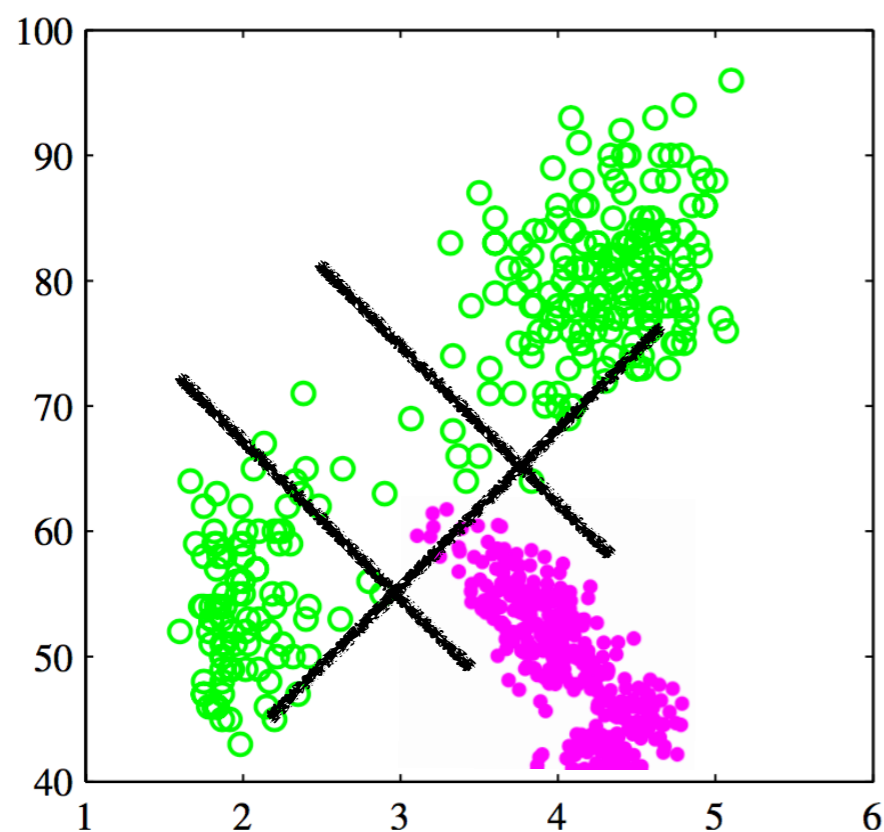


Optimized modeling of input data

VS

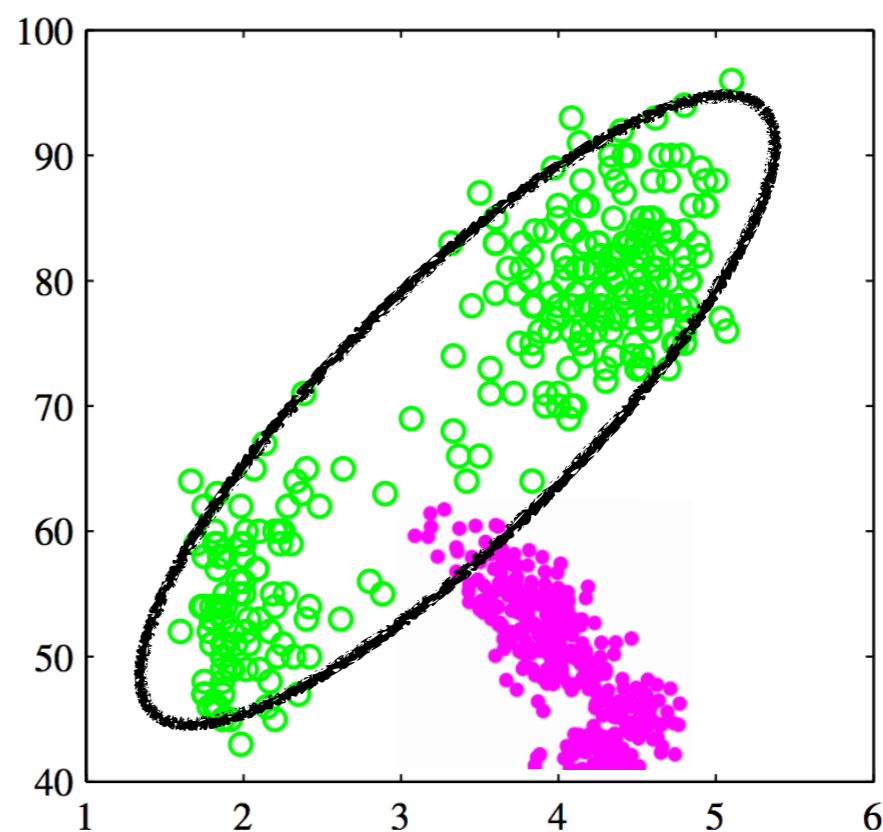
# Very different tasks

CWoLa hunting



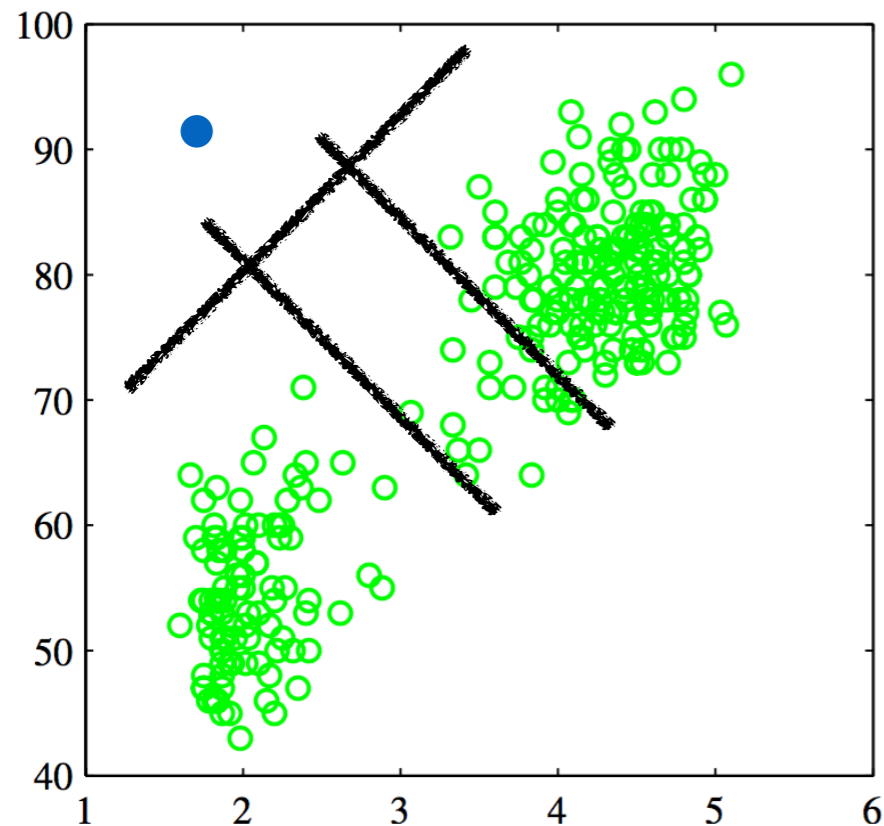
VS

Autoencoders



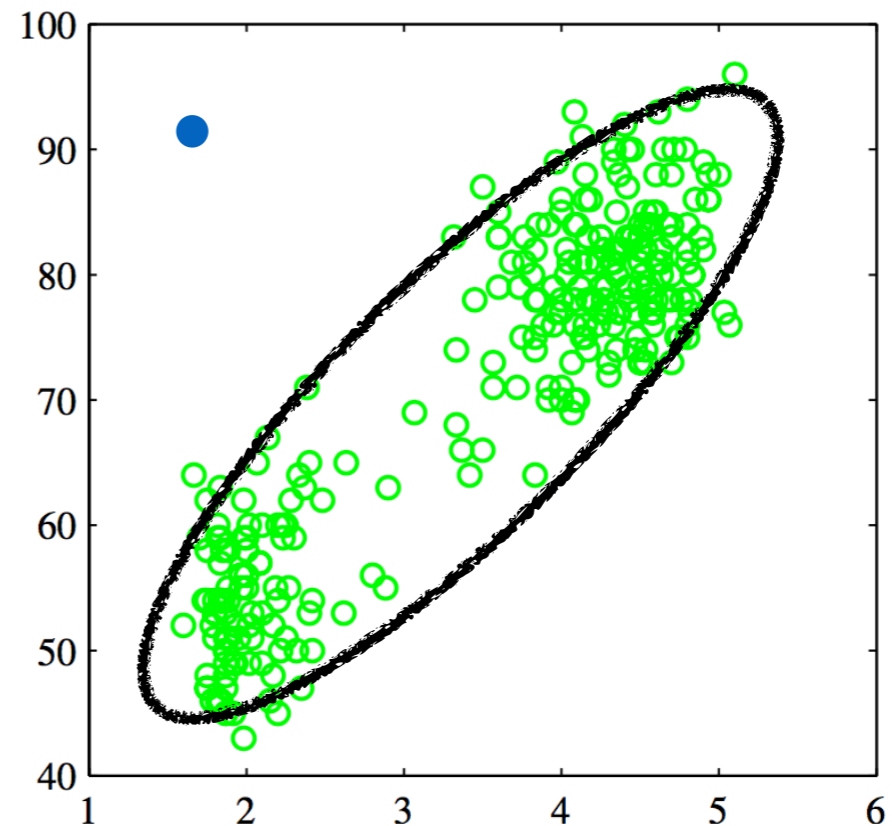
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CWoLa hunting



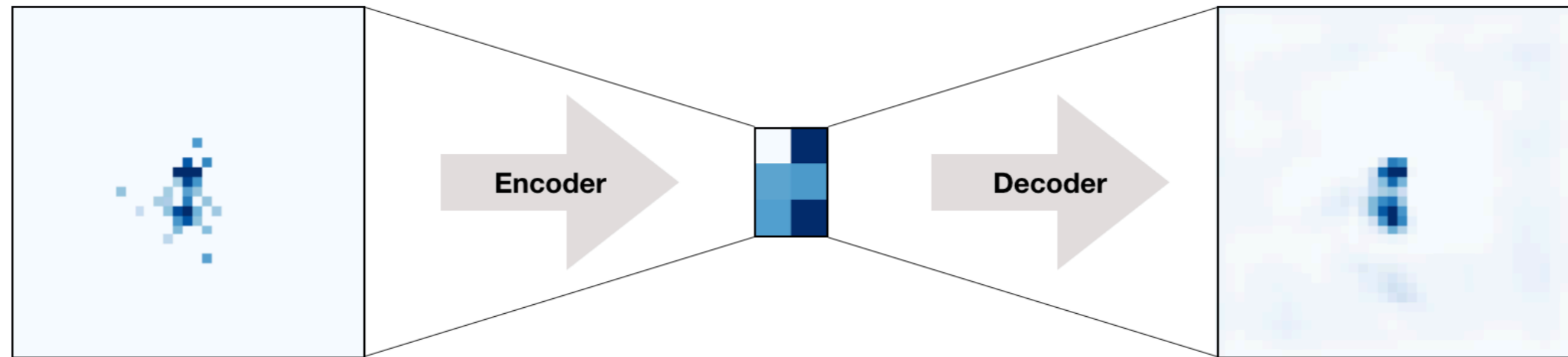
VS

Autoencoders



Which one is better? When? Can they be combined?

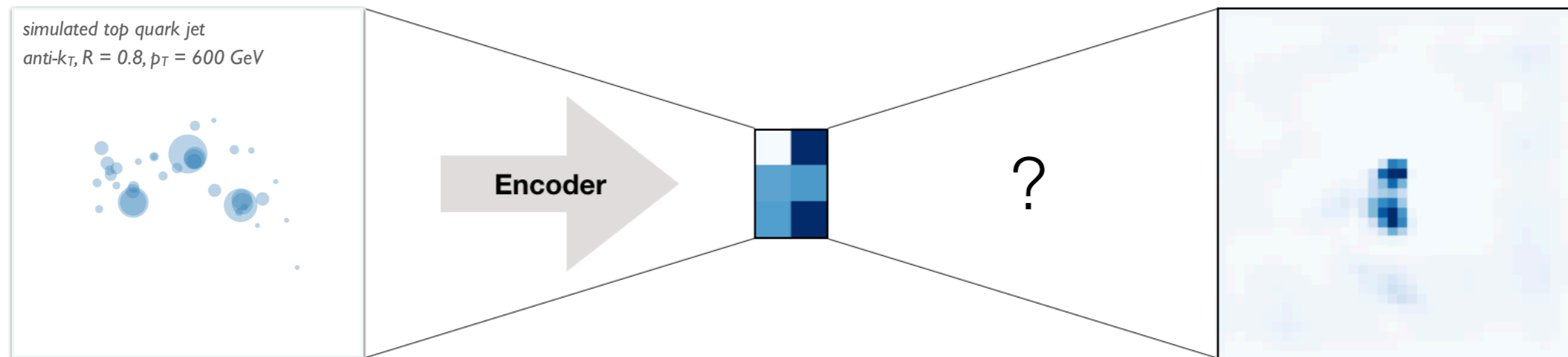
# Other jet representations?



- 4-vectors matrix (see Gregor's talk)
- sequence (RNN/seq2seq)



# Other jet representations?



Huilin's talk

- 4-vectors matrix (see Gregor's talk)
- sequence (RNN/seq2seq)
- binary tree (?)
- point cloud
- ...

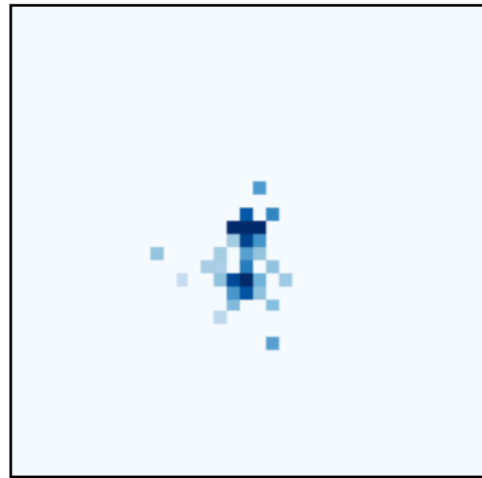
Is it really useful/relevant?

# Choice of loss?

What's a good "distance" between two jets?

E.g.

1)



$$\ell = |p_T^{(\text{pred})} - p_T^{(\text{true})}|^2 \quad \longrightarrow \quad \ell = \log \left( \frac{p_T^{(\text{pred})} + \bar{p}}{p_T^{(\text{true})} + \bar{p}} \right)^2$$

Kominske, Metodiev, Nachman, Schwartz '17

2)

$$\tilde{k}_j = \begin{pmatrix} \tilde{k}_{0,j} \\ \tilde{k}_{1,j} \\ \tilde{k}_{2,j} \\ \tilde{k}_{3,j} \\ \sqrt{\tilde{k}_j^2} \end{pmatrix} \xrightarrow{\text{LoLa}}$$

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

# Jet (binary) classification

Muffin or chihuahua?



$$p(\text{dog}|x) = f(x)$$

# Jet anomaly detection

Given data from  $p(x)$ . Can I tell if  $\hat{x}$  comes from the same distribution?

Train set



$$p(\text{muffin}|\hat{x}) > \epsilon$$

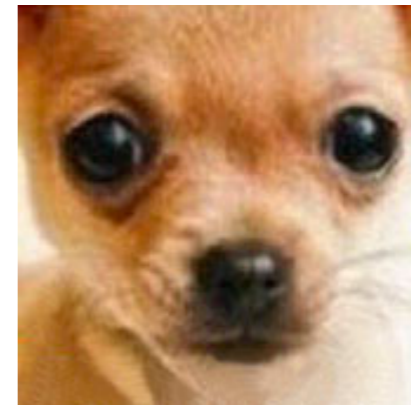
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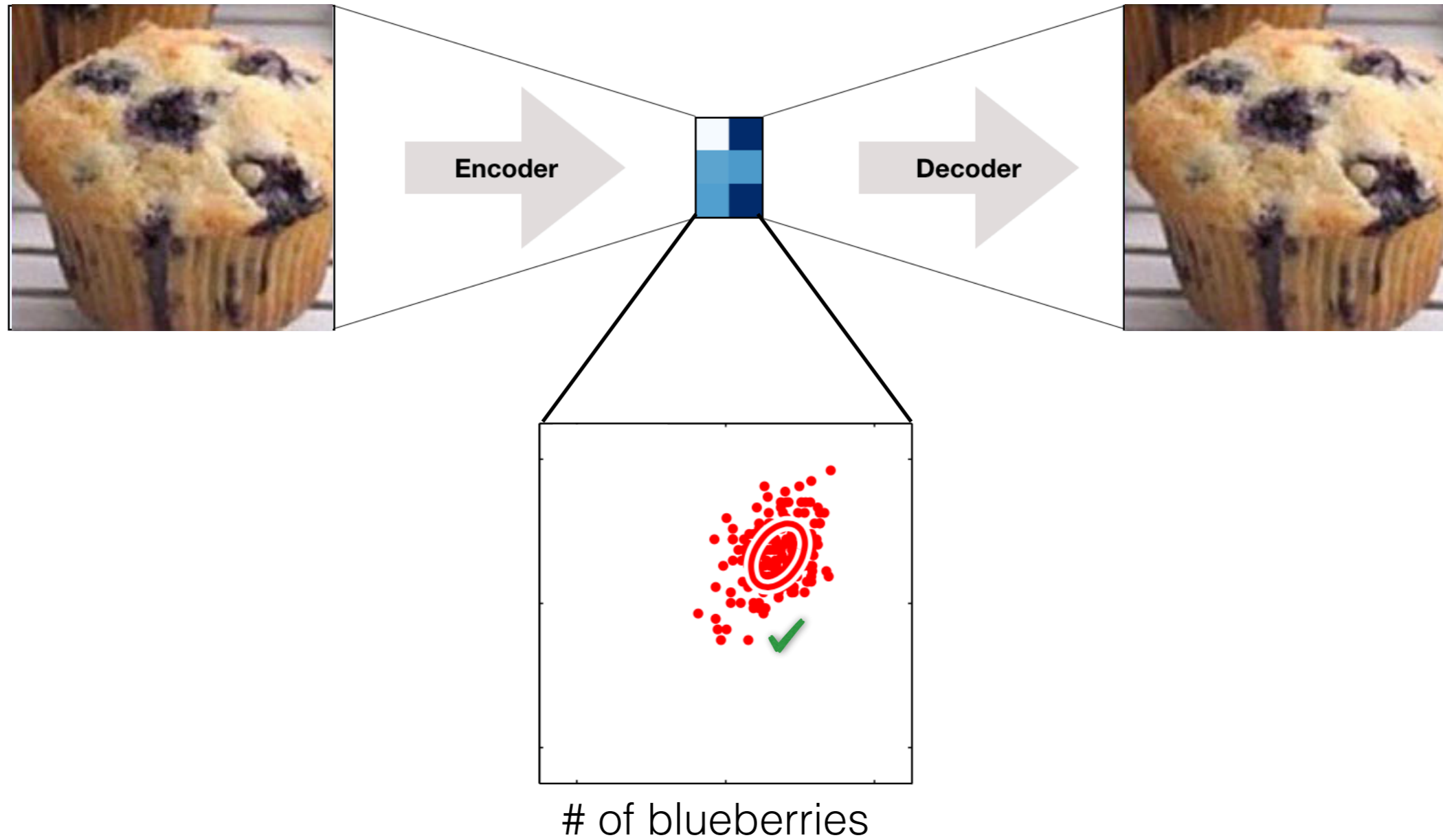
Train set



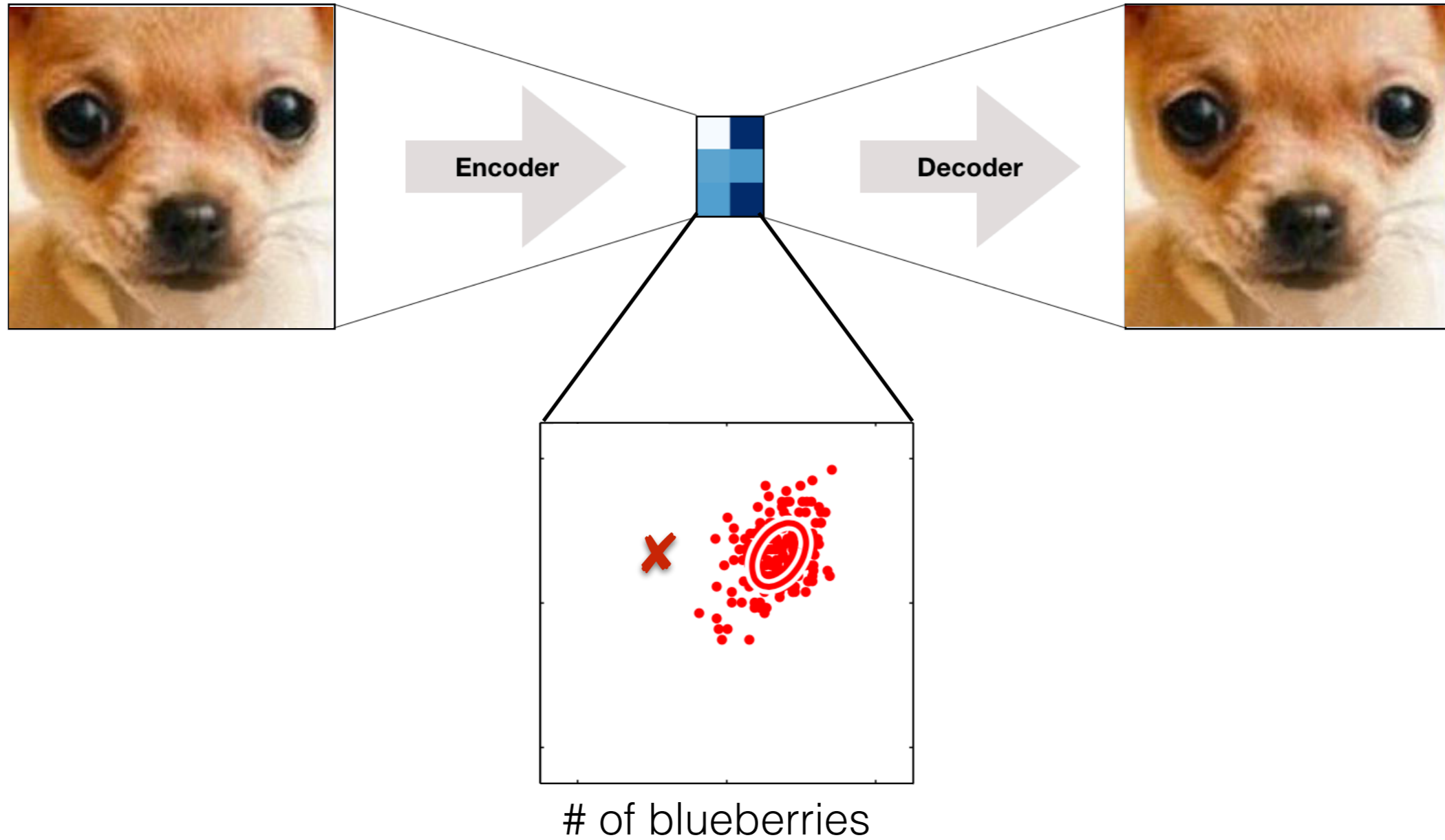
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# Future directions?



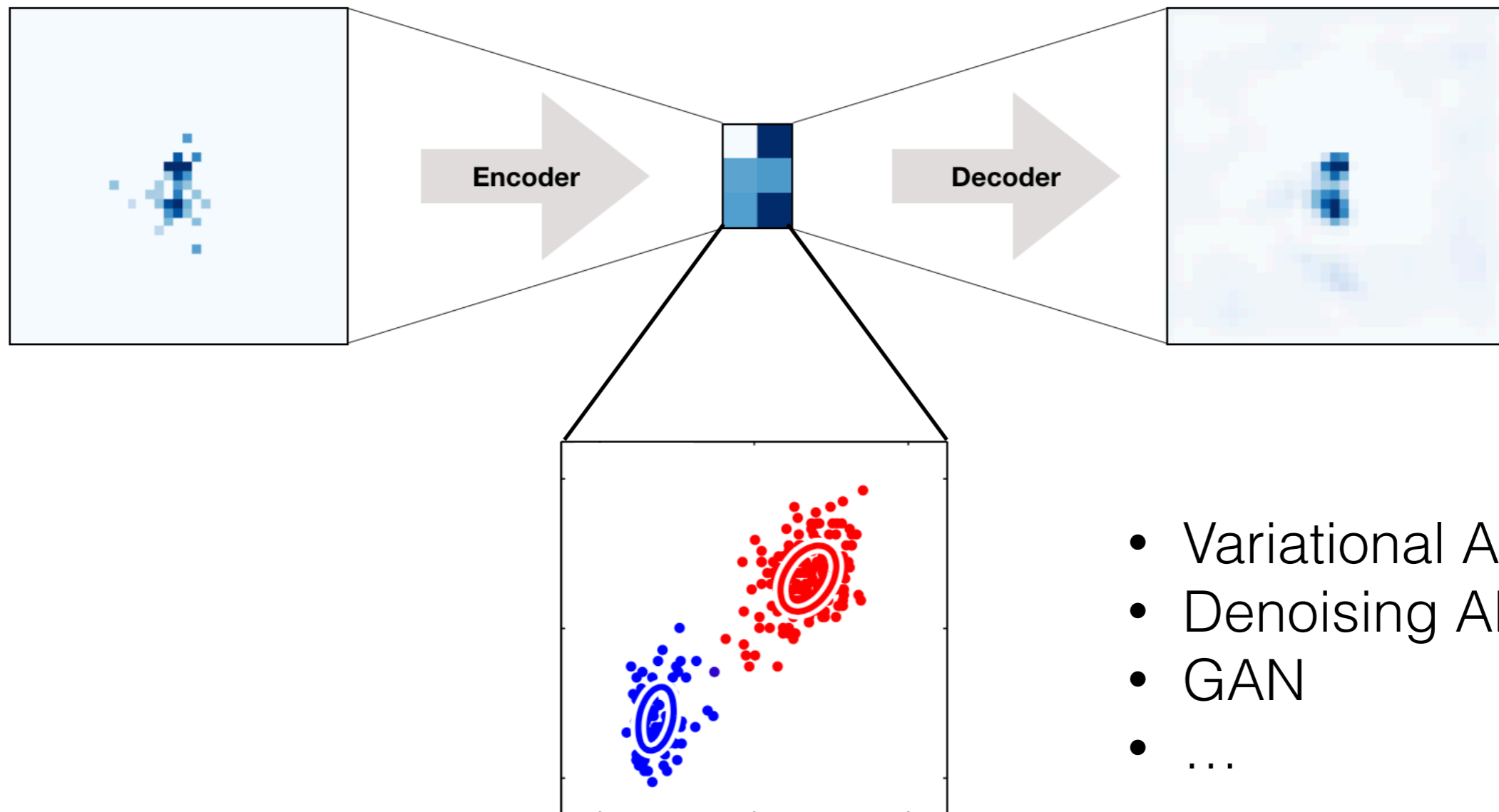
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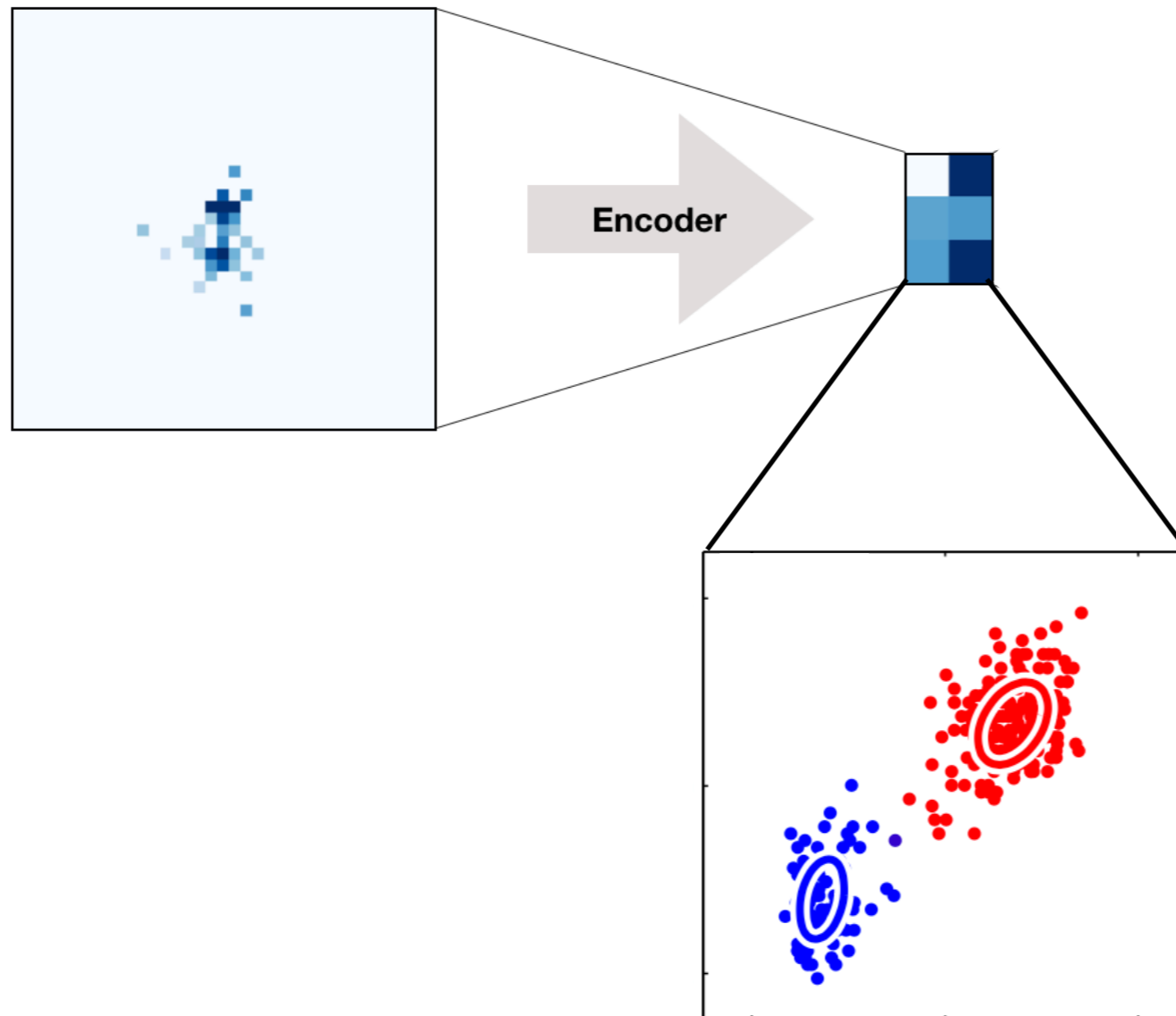
For now we have abandoned all probabilistic interpretation and discarded latent space information



- Variational AE
- Denoising AE
- GAN
- ...

# Future directions?

For now we have abandoned all probabilistic interpretation and discarded latent space information



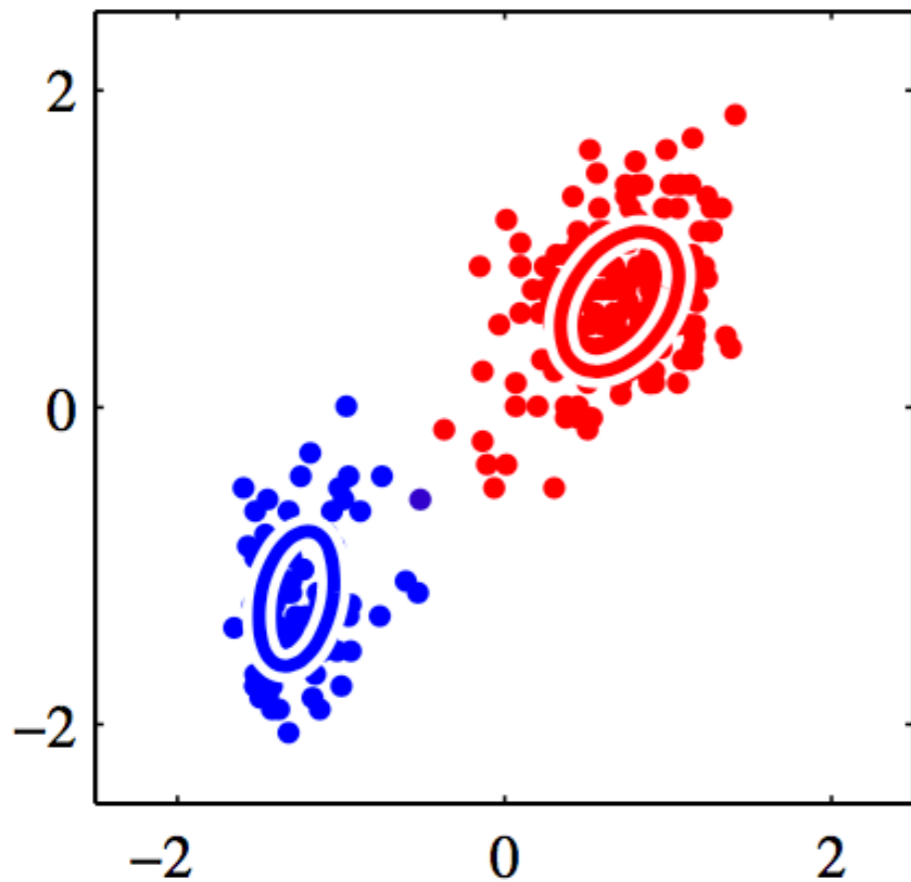
# Conclusion

Autoencoders can be powerful tools for anomaly searches in jet physics

First baby steps in unsupervised territory

# One example

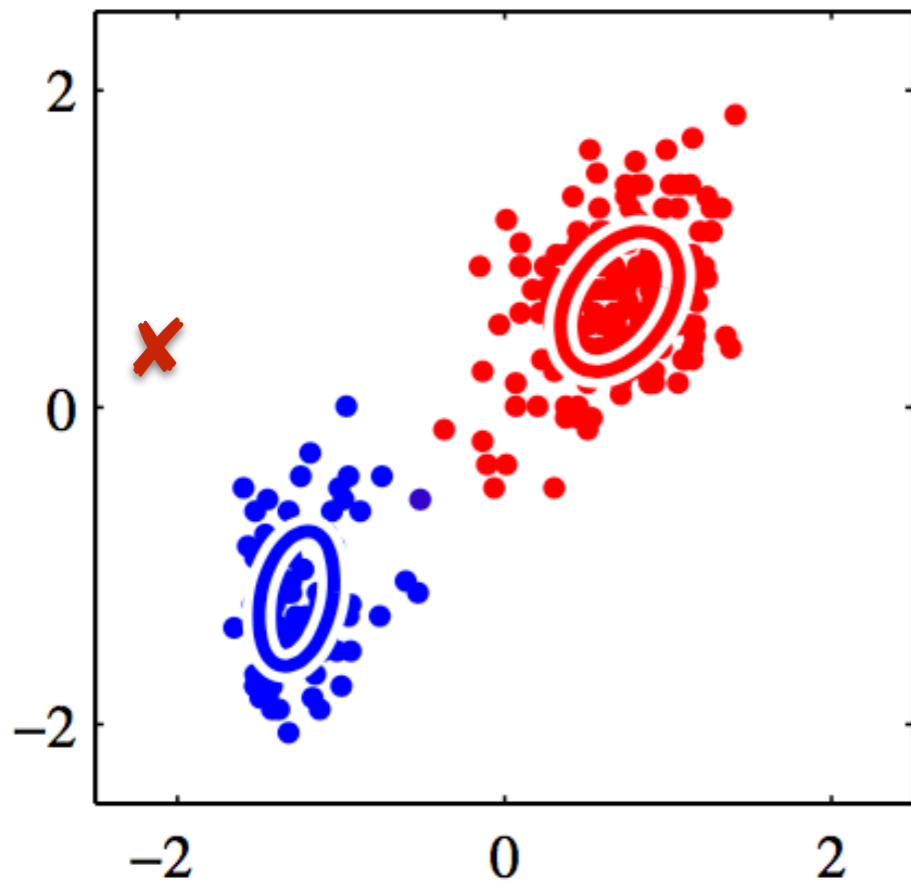
Model distribution in some way, e.g. as a mixture (of gaussians). Maximum likelihood parameter estimation.



$$p(\mathbf{x}) = \sum_{k=1}^K \pi_k \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k).$$

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Model distribution in some way, e.g. as a mixture (of gaussians). Maximum likelihood parameter estimation.

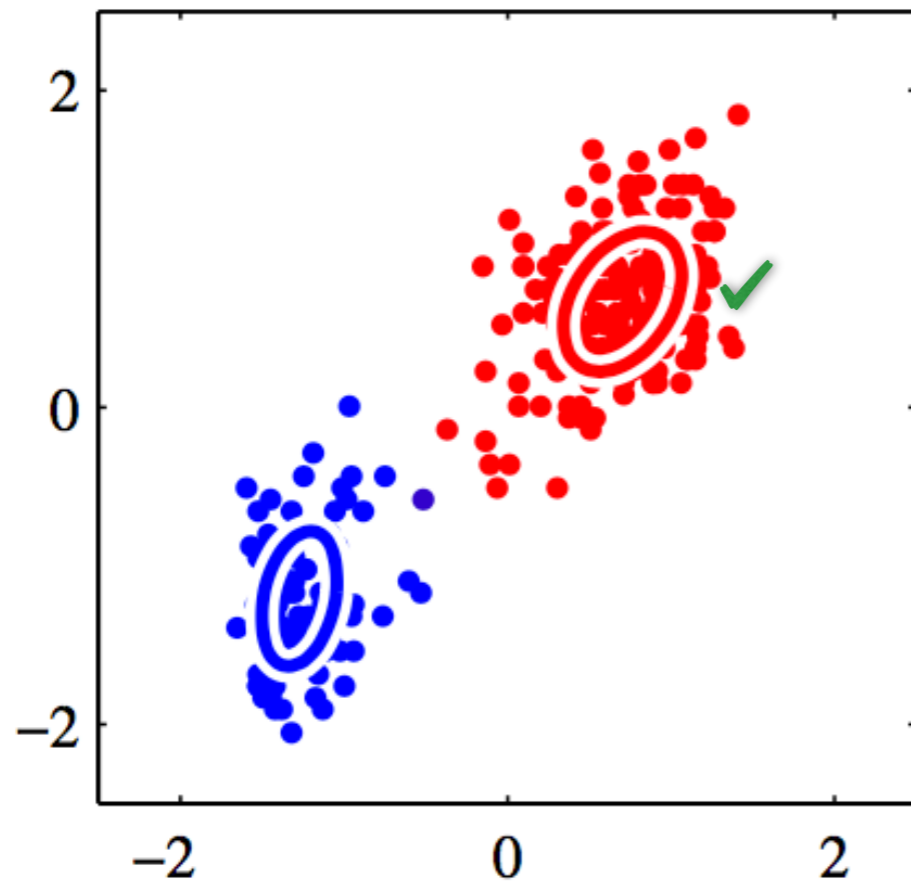


$$p(\mathbf{x}) = \sum_{k=1}^K \pi_k \mathcal{N}(\mathbf{x} | \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k).$$

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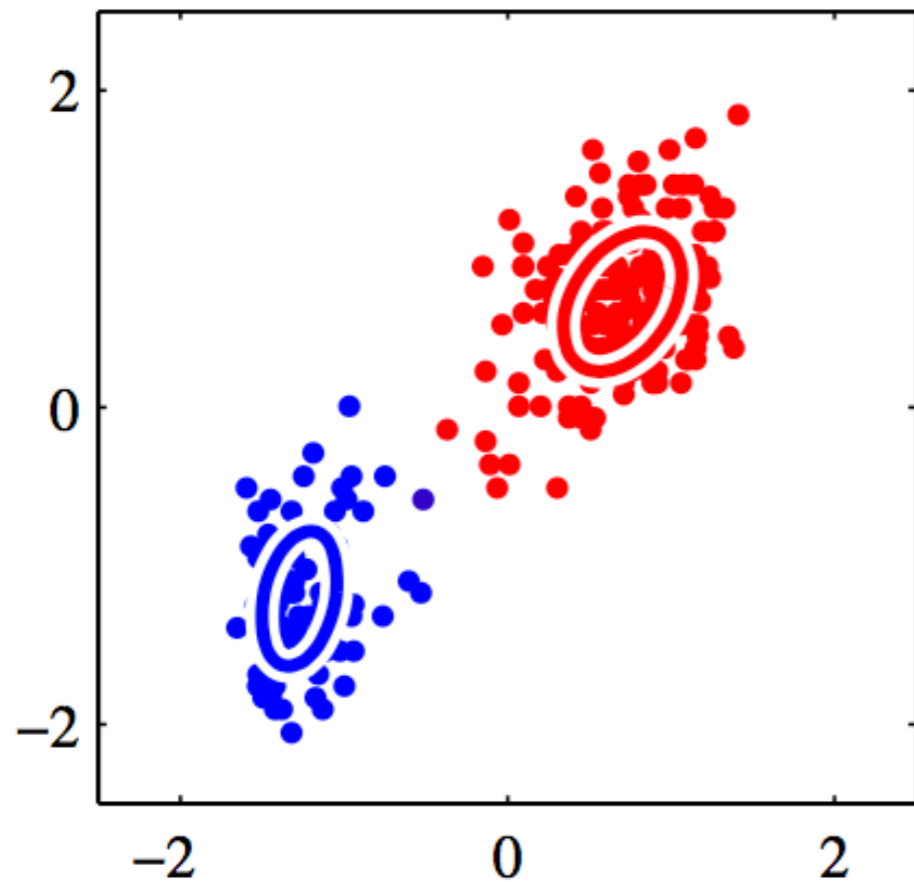


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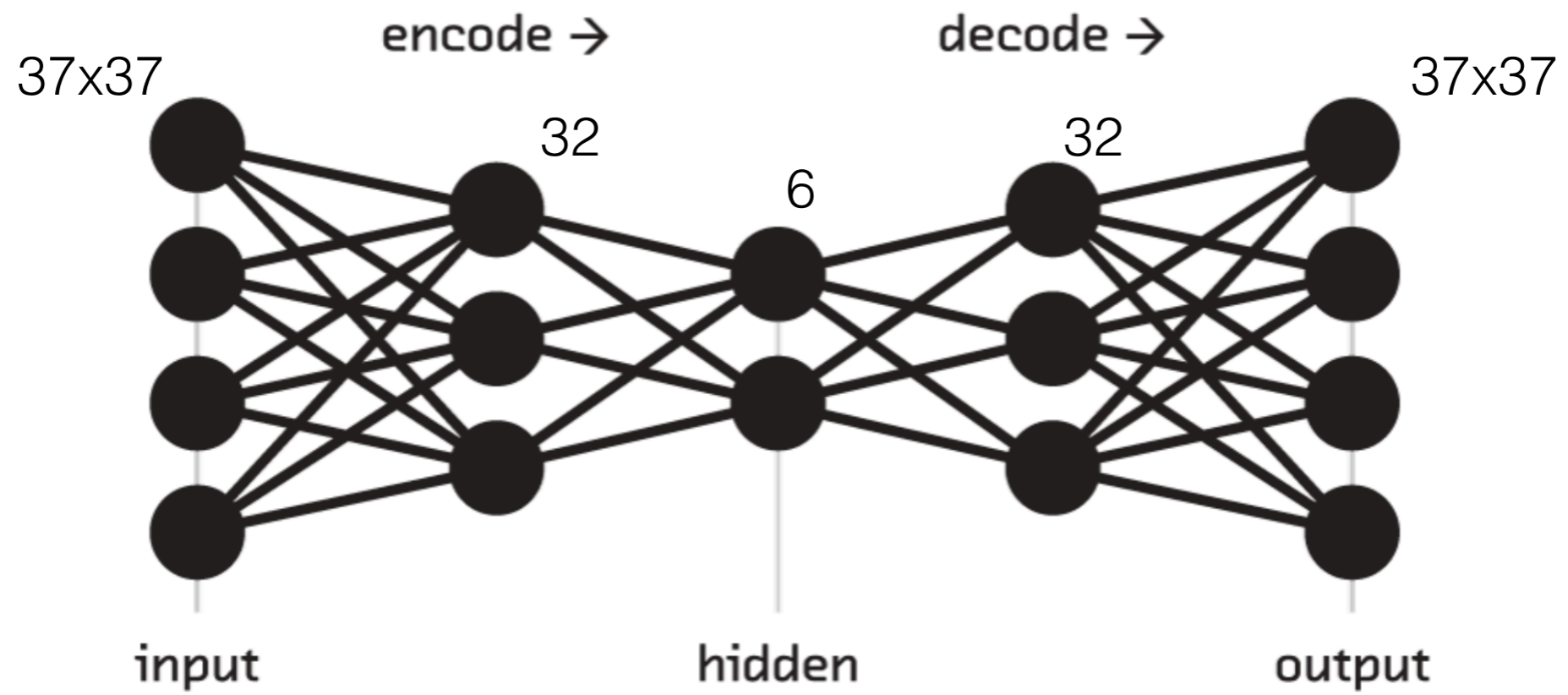
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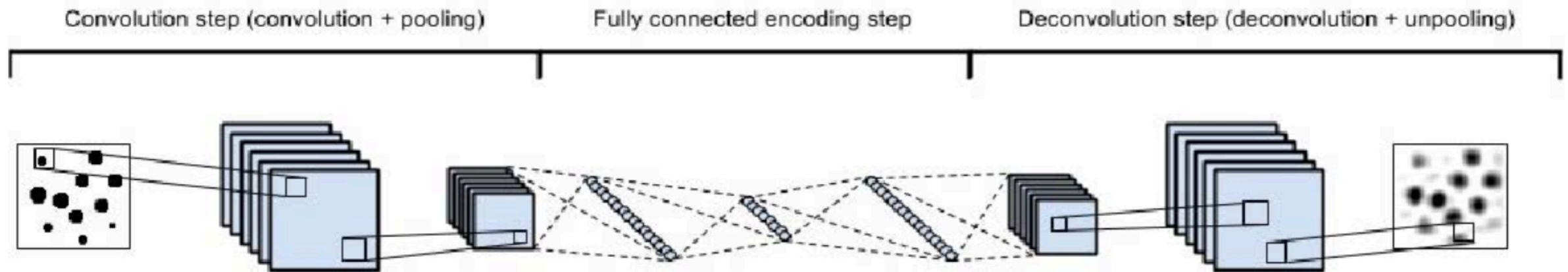
Not feasible for large dimensionality data

# DNN





# CNN



Ke, Lin, Huang '17

```
layer=Conv2D(128, kernel_size=(3, 3),
            activation='relu',padding='same')(layer)
layer=MaxPooling2D(pool_size=(2, 2),padding='same')(layer)
layer=Conv2D(128, kernel_size=(3, 3),
            activation='relu',padding='same')(layer)
layer=MaxPooling2D(pool_size=(2, 2),padding='same')(layer)
layer=Conv2D(128, kernel_size=(3, 3),
            activation='relu',padding='same')(layer)
layer=Flatten()(layer)
layer=Dense(32, activation='relu')(layer)
layer=Dense(6)(layer)
encoded=layer
```

# Gluino ROC

