

#### Searching for New Physics with Deep Autoencoders

#### Yuichiro Nakai (Rutgers → TDLI)

Based on M. Farina, YN and D. Shih, arXiv:1808.08992 [hep-ph].

**Physics Opportunities and Advanced Tools, HKUST, 2019** 

### **Expected Physics**

Higgs

We have considered many possibilities of BSM physics with <u>top-down</u> theory prejudice.

In particular, many are motivated by the naturalness problem.

Our candidates are :

Supersymmetry, Composite Higgs, Extra dimension, ...



### **Status of Searches**

#### However...

**AT** Julv  $\mathbf{CMS}$ 

July 2018

				-	Γ	Overvi	iew of S	<b>USY</b> results:	gluino pai	ir production
				$\mathbf{C}$	MS	-			July 2018	
					<b>verview of SUSY results:</b> $36 \text{ fb}^{-1}$ (13 TeV)	squark j	pair produ	ction		
				pp	${f p}  ightarrow {f { ilde t}}{f { ilde t}}$					
TLAS SUSY Search	es*	- 95%	6 CL	Lov	wer Limits			ATLAS Preliminary		
Ily 2018 Model e,	μ, τ, γ	Jets	$E_{\mathrm{T}}^{\mathrm{miss}}$	∫£ dt[fb	-1] Mass limit	$\sqrt{s}$ = 7, 8 TeV	$\sqrt{s} = 13 \text{ TeV}$	$\sqrt{s}$ = 7, 8, 13 TeV <b>Reference</b>		
$\tilde{q}\tilde{q},\tilde{q}{ ightarrow}q\tilde{\chi}_1^0$ m	0 ono-jet	2-6 jets 1-3 jets	Yes Yes	36.1 36.1	0.9             0.43         0.71	1.55	$m( ilde{\chi}^0_1) {<} 100  { m GeV} \ m( ilde{q}) {-} m( ilde{\chi}^0_1) {=} 5  { m GeV}$	1712.02332 1711.03301		$= M_t, M_{\tilde{\chi}^0_1} = 400 \text{ GeV}$
$\tilde{g}\tilde{g},  \tilde{g} \! \rightarrow \! q \bar{q} \tilde{\chi}_1^0$	0	2-6 jets	Yes	36.1	ğ ğ Forbidden	2.0 0.95-1.6	m(𝒱̃_1^0)<200 GeV m(𝔅̃_1^0)=900 GeV	1712.02332 1712.02332		, $M_{\tilde{\chi}^0_1} = 400 \text{ GeV}$
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~	o	4 into	-	06.1	×	1 05	( <sup>20</sup> ) 0000 V	1700 00701		M M 400 C M

# All the searches for new physics in the expected places have turned up empty.

<del>م</del>	$\tilde{t}_1 \tilde{t}_1, \tilde{t}_1 \rightarrow c \tilde{\chi}_1^0 / \tilde{c} \tilde{c}, \tilde{c} \rightarrow c \tilde{\chi}_1^0$	0 0 n	2c nono-jet	Yes Yes	36.1 36.1	t̃ <sub>1</sub> 0.8           t̃ <sub>1</sub> 0.46           t̃ <sub>1</sub> 0.43	85			$m(\tilde{\chi}_{1}^{0})=0 \text{ GeV}$ $m(\tilde{r}_{1},\tilde{c})-m(\tilde{\chi}_{1}^{0})=50 \text{ GeV}$ $m(\tilde{r}_{1},\tilde{c})-m(\tilde{\chi}_{1}^{0})=5 \text{ GeV}$	1805.01649 1805.01649 1711.03301		2:1, $x = 0.5$
	$\tilde{t}_2\tilde{t}_2, \tilde{t}_2 \rightarrow \tilde{t}_1 + h$	1-2 <i>e</i> , <i>µ</i>	4 <i>b</i>	Yes	36.1	<i>ī</i> <sub>2</sub> 0.32-0.	.88			$m(\tilde{\chi}_1^0)=0$ GeV, $m(\tilde{t}_1)-m(\tilde{\chi}_1^0)=180$ GeV	1706.03986		
	${ ilde \chi}_1^\pm { ilde \chi}_2^0$ via WZ	2-3 e,μ ee,μμ	- ≥ 1	Yes Yes	36.1 36.1	$egin{array}{ccc} & \tilde{\chi}_1^{\pm}/\tilde{\chi}_2^0 & & 0.6 \ & \tilde{\chi}_1^{\pm}/\tilde{\chi}_2^0 & & 0.17 \end{array} \end{array}$				$m(\tilde{\chi}_1^0)=0$ $m(\tilde{\chi}_1^{\pm})-m(\tilde{\chi}_1^0)=10 \text{ GeV}$	1403.5294, 1806.02293 1712.08119	-	x = 0.5
EW direct	$\tilde{\chi}_{1}^{\pm}\tilde{\chi}_{2}^{0} \text{ via } Wh$ $\tilde{\chi}_{1}^{\pm}\tilde{\chi}_{1}^{\mp}/\tilde{\chi}_{2}^{0}, \tilde{\chi}_{1}^{\pm} \rightarrow \tilde{\tau}\nu(\tau\tilde{\nu}), \tilde{\chi}_{2}^{0} \rightarrow \tilde{\tau}\tau(\nu\tilde{\nu})$	<i>ℓℓ/ℓγγ/ℓbb</i> 2 τ		Yes Yes	20.3 36.1	$\begin{array}{c c} \dot{\vec{x}_1^*}/\vec{x}_2^0 & 0.26 \\ \dot{\vec{x}_1^*}/\vec{x}_2^0 & 0.76 \\ \dot{\vec{x}_1^*}/\vec{x}_2^0 & 0.22 \end{array}$		$\begin{split} & m(\tilde{\chi}_{1}^{0}){=}0 \\ & m(\tilde{\chi}_{1}^{0}){=}0, m(\tilde{\tau},\tilde{\nu}){=}0.5(m(\tilde{\chi}_{1}^{+}){+}m(\tilde{\chi}_{1}^{0})) \\ & m(\tilde{\chi}_{1}^{\pm}){-}m(\tilde{\chi}_{1}^{0}){=}100 \text{ GeV}, m(\tilde{\tau},\tilde{\nu}){=}0.5(m(\tilde{\chi}_{1}^{\pm}){+}m(\tilde{\chi}_{1}^{0})) \\ & m(\tilde{\chi}_{1}^{0}){=}0 \\ & m(\tilde{\ell}){-}m(\tilde{\chi}_{1}^{0}){=}5 \text{ GeV} \end{split}$		$m(\tilde{\chi}_{1}^{0})=0, m(\tilde{\tau}, \tilde{\nu})=0.5(m(\tilde{\chi}_{1}^{\pm})+m(\tilde{\chi}_{1}^{0}))$	1501.07110 1708.07875 1708.07875		$_{\rm b}=20~{ m GeV}$
ш i	$\tilde{\ell}_{\mathrm{L,R}}\tilde{\ell}_{\mathrm{L,R}},\tilde{\ell}{\rightarrow}\ell\tilde{\chi}_{1}^{0}$	2 e,μ 2 e,μ	0 ≥ 1	Yes Yes	36.1 36.1	<ul> <li>ℓ</li> <li>0.5</li> <li>ℓ</li> <li>ℓ</li> <li>0.18</li> </ul>				$\mathbf{m}(\tilde{\ell}_{1}^{0})=0$ $\mathbf{m}(\tilde{\ell})-\mathbf{m}(\tilde{\chi}_{1}^{0})=5~\mathrm{GeV}$	1803.02762 1712.08119		
	$\tilde{H}\tilde{H},\tilde{H}{ ightarrow}h\tilde{G}/Z\tilde{G}$	0 4 <i>e</i> , µ	$\geq 3b$ 0	Yes Yes	36.1 36.1	Ĥ         0.13-0.23         0.29-0.3           Ĥ         0.3         0.3	.88			$\begin{array}{l} BR(\tilde{\chi}_1^0 \to h\tilde{G}) {=} 1 \\ BR(\tilde{\chi}_1^0 \to Z\tilde{G}) {=} 1 \end{array}$	1806.04030 1804.03602		
pe	Direct $\tilde{\chi}_1^+ \tilde{\chi}_1^-$ prod., long-lived $\tilde{\chi}_1^\pm$	Disapp. trk	1 jet	Yes	36.1	$egin{array}{ccc} { ilde \chi}^{\pm}_1 & 0.46 \ { ilde \chi}^{\pm}_1 & 0.15 \end{array}$				Pure Wino Pure Higgsino	1712.02118 ATL-PHYS-PUB-2017-019		BF = 50%
Long-live particle	Stable $\tilde{g}$ R-hadron Metastable $\tilde{g}$ R-hadron, $\tilde{g} \rightarrow qq \tilde{\chi}_{1}^{0}$ GMSB, $\tilde{\chi}_{1}^{0} \rightarrow \gamma \tilde{G}$ , long-lived $\tilde{\chi}_{1}^{0}$ $\tilde{g}\tilde{g}, \tilde{\chi}_{1}^{0} \rightarrow eev/e\mu v/\mu\mu v$	SMP 2 γ displ. ee/eμ/μμ	- Multiple - -	- Yes -	3.2 32.8 20.3 20.3	$\tilde{g} = [\pi(\tilde{g}) = 100 \text{ ns}, 0.2 \text{ ns}]$ $\tilde{X}_{1}^{0} = 0.44$ $\tilde{g} = 0.44$		1. 1. 1.3	.6 .6 2	.4 m( $\tilde{\chi}_1^0$ )=100 GeV 1<τ( $\tilde{\chi}_1^0$ )<3 ns, SPS8 model 6 <cτ(<math>\tilde{\chi}_1^0)&lt; 1000 mm, m(<math>\tilde{\chi}_1^0</math>)=1 TeV</cτ(<math>	1606.05129 1710.04901, 1604.04520 1409.5542 1504.05162		1750 2000 Ps unless stated otherwise.
RPV	$ \begin{array}{c} LFV pp \! \rightarrow \! \tilde{v}_{\tau} + X, \tilde{v}_{\tau} \! \rightarrow \! e\mu/e\tau/\mu\tau \\ \tilde{\chi}_{1}^{+} \tilde{\chi}_{1}^{+} / \tilde{\chi}_{2}^{0} \rightarrow WW/Z\ell\ell\ell\ell\nu\nu \\ \tilde{g}\tilde{g}, \tilde{g} \rightarrow \! qq \tilde{\chi}_{1}^{0}, \tilde{\chi}_{1}^{0} \rightarrow qqq \end{array} $	Ν	0 large- <i>R</i> je Multiple	- Yes ts -	3.2 36.1 36.1 36.1	$ \begin{array}{ccc} \bar{y}_{\tau} \\ \bar{X}_{1}^{0} / \bar{X}_{2}^{0} & [l_{d33} \neq 0, l_{12k} \neq 0] \\ \bar{g} & [m(\bar{X}_{1}^{0}) = 200 \text{ GeV}, 1100 \text{ GeV}] \\ \bar{g} & [M_{112}^{2} = 2e-4, 2e-5] \end{array} $	2 1.05	1.33 1.3	1.9 1.9 2.0	$\begin{array}{l} \lambda_{311}'=\!0.11,\;\lambda_{132/133/233}\!=\!0.07\\ m(\tilde{\xi}_1^0)\!=\!100\;\text{GeV}\\ \text{Large}\;\lambda_{112}''\\ m(\tilde{\xi}_1^0)\!=\!200\;\text{GeV},\;\text{bino-like} \end{array}$	1607.08079 1804.03602 1804.03568 ATLAS-CONF-2018-003	$ ilde{q}_R+ ilde{q}_L( ilde{u}, ilde{d}, ilde{c}, ilde{s})$	between the intermediate
R	$\begin{array}{l} \tilde{g}\tilde{g}, \tilde{g} \rightarrow tbs / \tilde{g} \rightarrow tt \tilde{\chi}_{1}^{0}, \tilde{\chi}_{1}^{0} \rightarrow tbs \\ \tilde{t}\tilde{t}, \tilde{t} \rightarrow t \tilde{\chi}_{1}^{0}, \tilde{\chi}_{1}^{0} \rightarrow tbs \\ \tilde{t}_{1}\tilde{t}_{1}, \tilde{t}_{1} \rightarrow bs \\ \tilde{t}_{1}\tilde{t}_{1}, \tilde{t}_{1} \rightarrow b\ell \end{array}$	Ν	Multiple Multiple jets + 2 b 2 b	-	36.1 36.1 36.7 36.1	$ \begin{array}{c} \tilde{g} & [\mathcal{A}'_{333}=1, 1e-2] \\ \tilde{g} & [\mathcal{A}'_{333}=2e-4, 1e-2] \\ \tilde{f}_1 & [qq, bs] \\ \end{array} \begin{array}{c} \textbf{0.55} \\ \textbf{0.61} \\ \tilde{f}_1 \end{array} $	1.05	0.4-1.45	1.8 2.1	m $(\tilde{\chi}_1^0)$ =200 GeV, bino-like m $(\tilde{\chi}_1^0)$ =200 GeV, bino-like BR $(\tilde{\iota}_1 \rightarrow be/b\mu)$ >20%	ATLAS-CONF-2018-003 ATLAS-CONF-2018-003 1710.07171 1710.05544	1400 1600	)
*Only	y a selection of the available ma	ass limits on ne	w states	s or	1	0 <sup>-1</sup>	I 1			Mass scale [TeV]		-	

\*Only a selection of the available mass limits on new states of phenomena is shown. Many of the limits are based on simplified models, c.f. refs. for the assumptions made.

### **Unexpected Physics**

We may need to prepare well for unexpected physics.

# UNEXPECTED RD

## Can we find new physics without knowing what we're looking for ??

#### Machine Learning can help !

### **ML Algorithms**

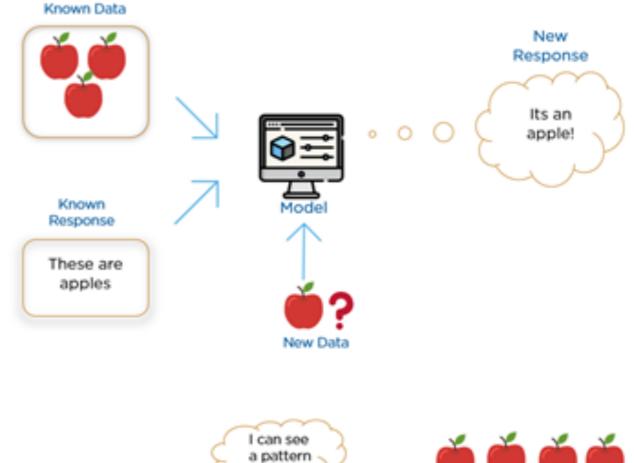
Machine learning algorithms can be classified into :

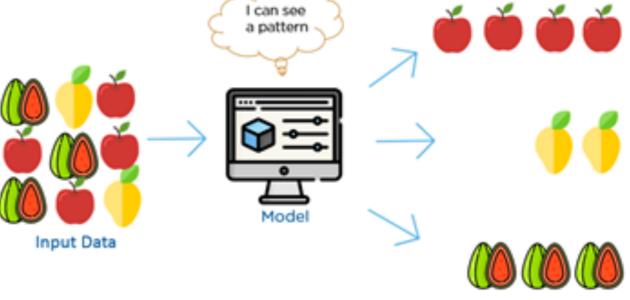
#### Supervised learning

- ✓ Learn from <u>labeled</u> data.
- ✓ Machine can answer if <u>new</u> <u>data</u> is an apple or not.

#### Unsupervised learning

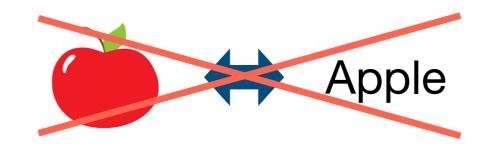
- ✓ Learn from <u>unlabeled</u> data.
- ✓ Machine looks for patterns and extracts <u>features in data</u>.





### Search for Unexpected

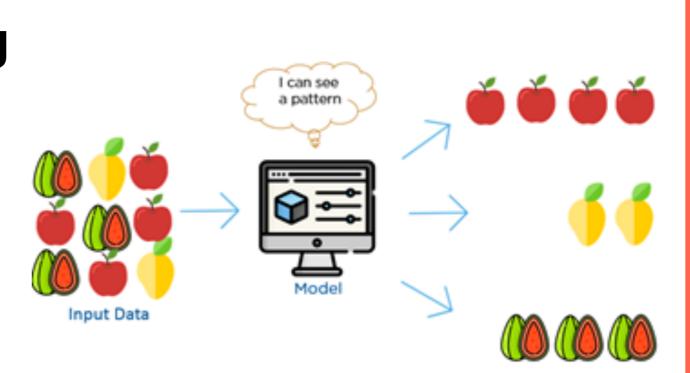
We don't know what we're looking for and cannot attach a label to new physics.



Unsupervised learning comes into play !

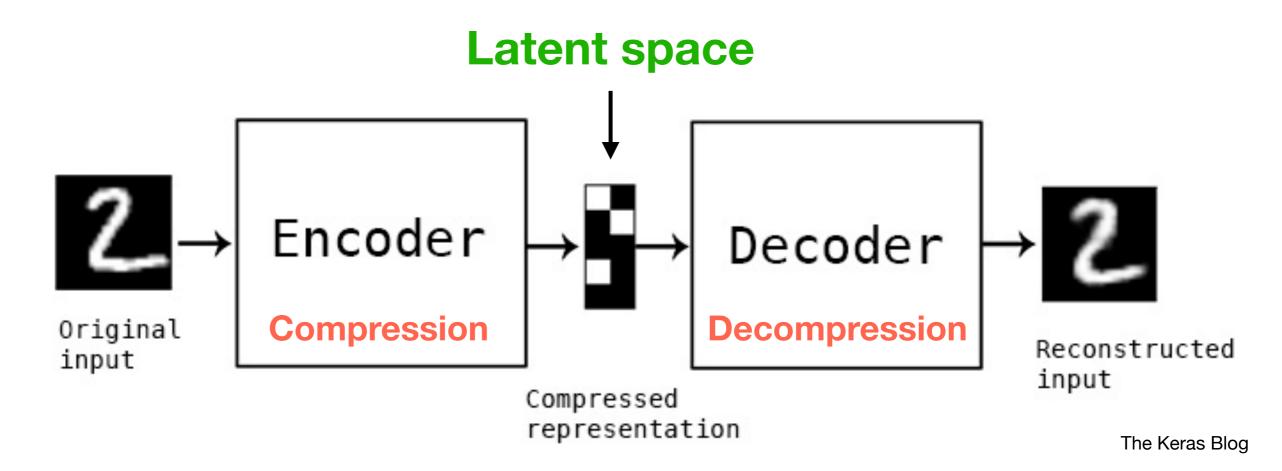
#### Unsupervised learning

- $\checkmark$  Learn from <u>unlabeled</u> data.
- ✓ Machine looks for patterns and extracts <u>features in data</u>.



### Autoencoder

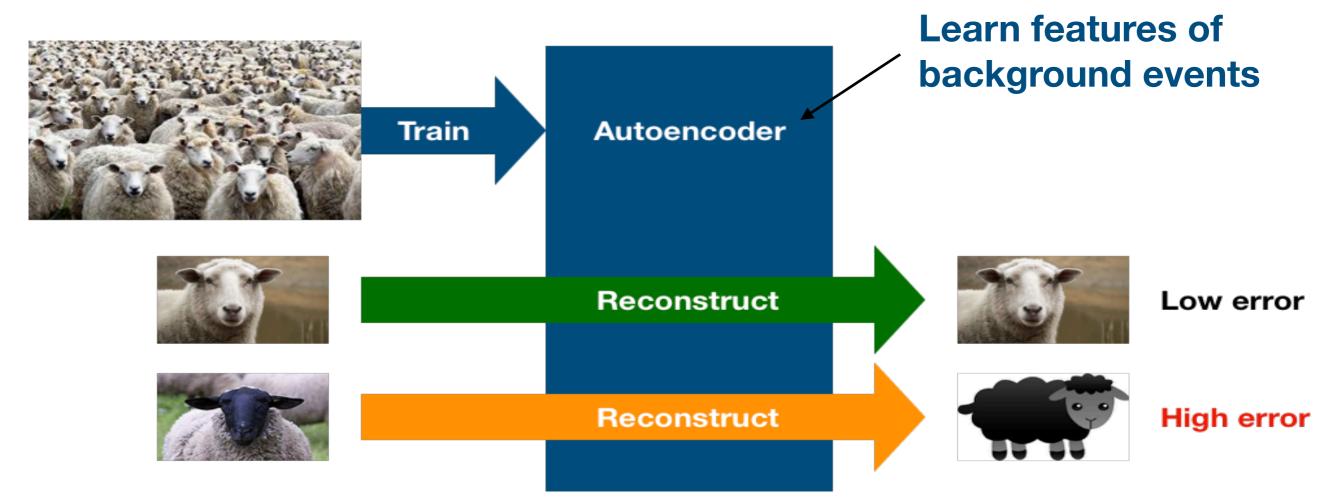
Autoencoder is an unsupervised learning algorithm that maps an input to <u>a latent compressed representation</u> and then <u>back to itself</u>.



By learning how to reproduce original input, autoencoder <u>extracts features of input data</u>.

### **Anomaly Detection**

Autoencoder learns to map background events back to themselves.

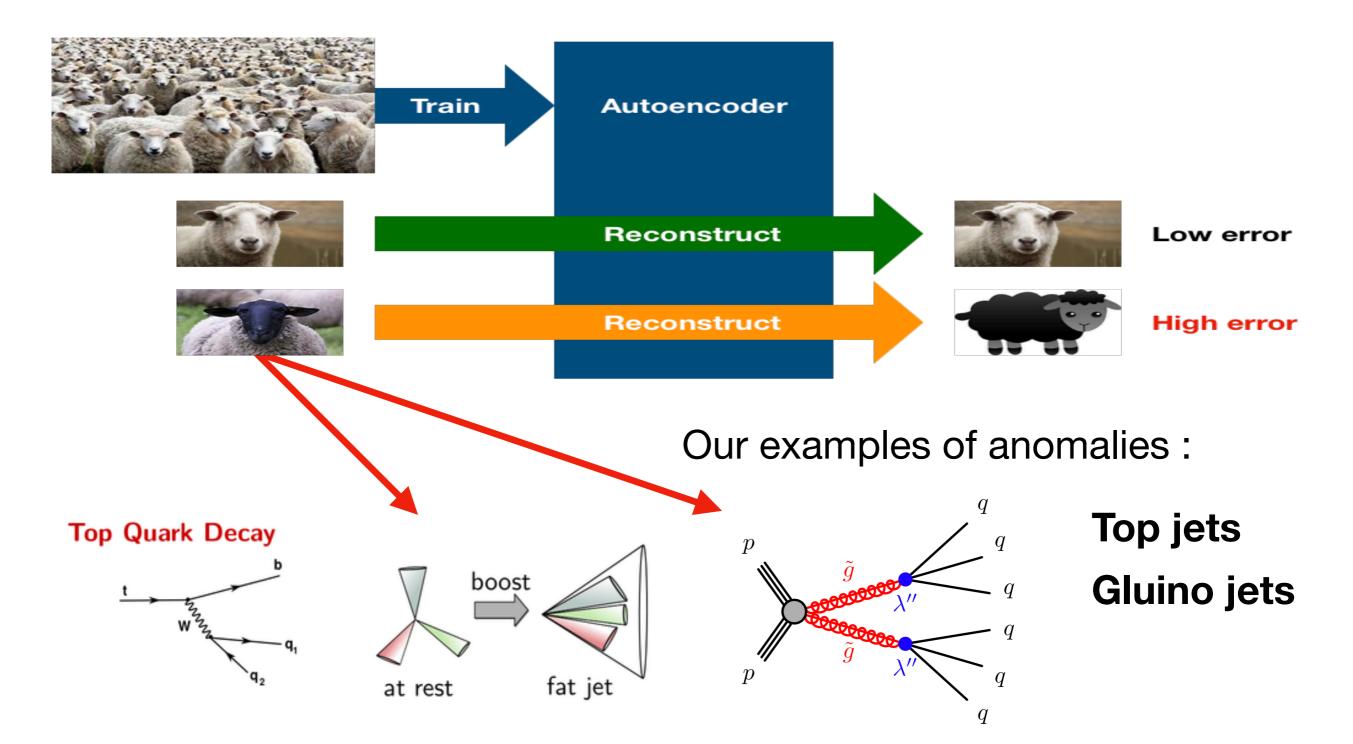


Autoencoder fails to reconstruct anomalous events that it has never encountered.

Signal the existence of anomaly !

### **Anomalous Jet Detection**

The idea is general, but concentrate on detection of <u>anomalous jets</u> as the first baby step.



### **Sample Generation**

Generate jet samples by using PYTHIA for hadronization and Delphes for detector simulation.

Background : <u>QCD jets</u>  $p_T \in [800, 900]$  GeV  $|\eta| < 1$ 

Signal jets: top jets, RPV gluino jets  $m_{\tilde{g}} = 400 \text{ GeV}$ (decay to 3 light quark jets)

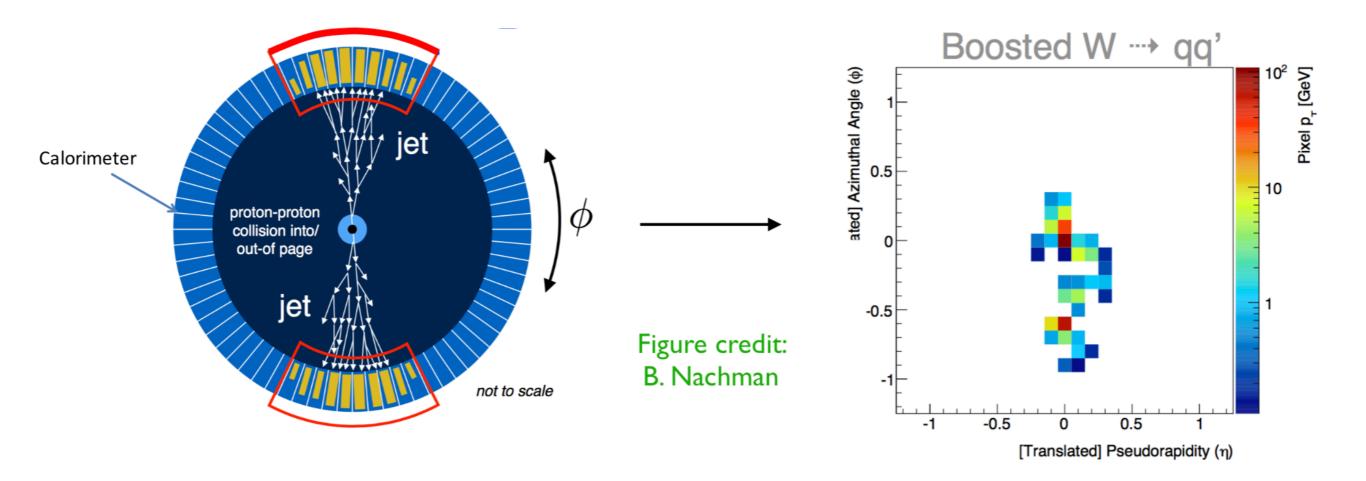
Match requirement : heavy resonance is within the fat jet,  $\Delta R < 0.6$ 

Merge requirement : the partonic daughters of heavy resonance is within the fat jet,  $\Delta R < 0.6$ 

We use sample sizes of 100k events for training and testing. (The performance seems to saturate.)

### Jet Images

Focus on jet images (2D of eta and phi) as inputs to autoencoder.



✓ Pixelation is provided by <u>calorimeter towers</u>.

✓ Pixel intensity is <u>pT recorded by each tower</u>.

### Jet Images

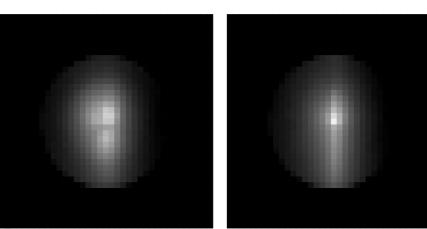
#### To improve performance...

Image pre-processing

- 1. Shift an image so that the centroid is at the origin
- 2. Rotate the image so that the major principal axis is vertical
- 3. Flip the image so that the maximum intensity is in the upper right region
- 4. Normalize the image to unit total intensity
- 5. Pixelate the image :  $\Delta \eta = \Delta \phi = 3.2$  (37 x 37 pixels)

#### **Average images**

Left : top jets Right : QCD jets



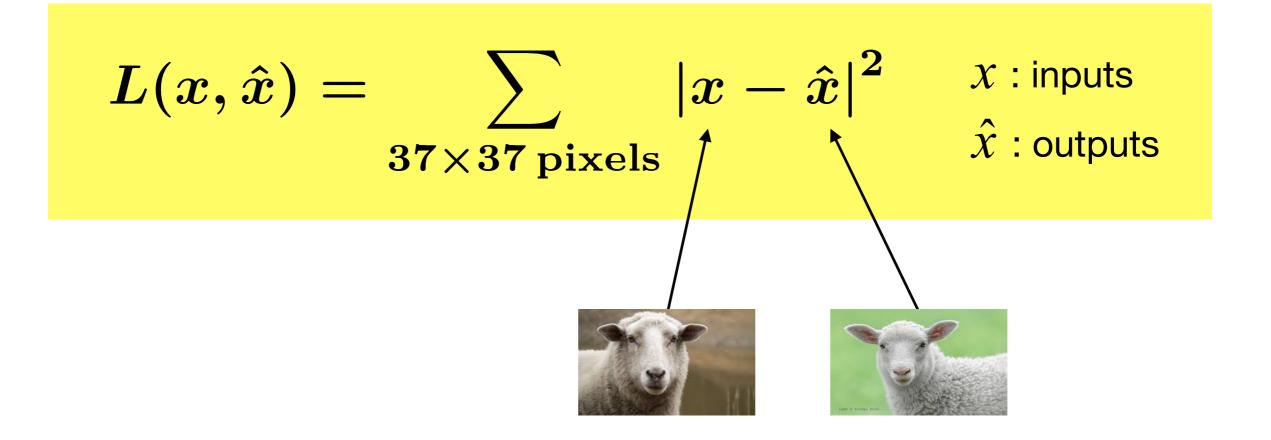






#### **Reconstruction Error**

**Reconstruction error**: a measure for how well autoencoder reproduce the original input.

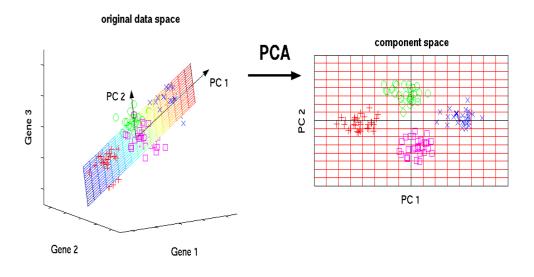


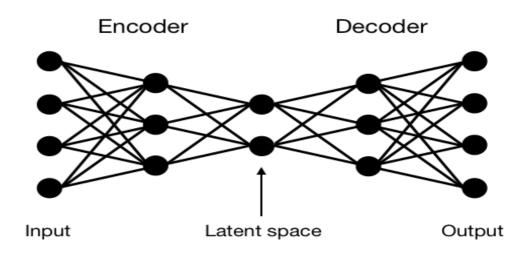
Train autoencoder to minimize reconstruction error on background events.

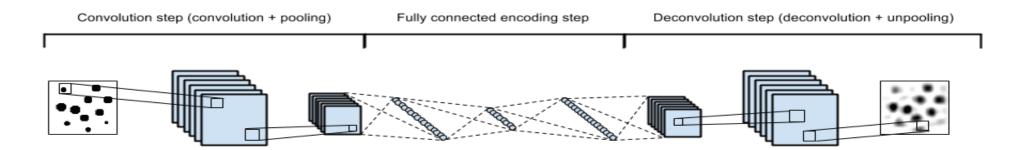
#### **Our Autoencoders**

We consider the following architectures :

- ✓ Principal Component Analysis (PCA)
- ✓ Simple (dense) autoencoder
- Convolutional autoencoder

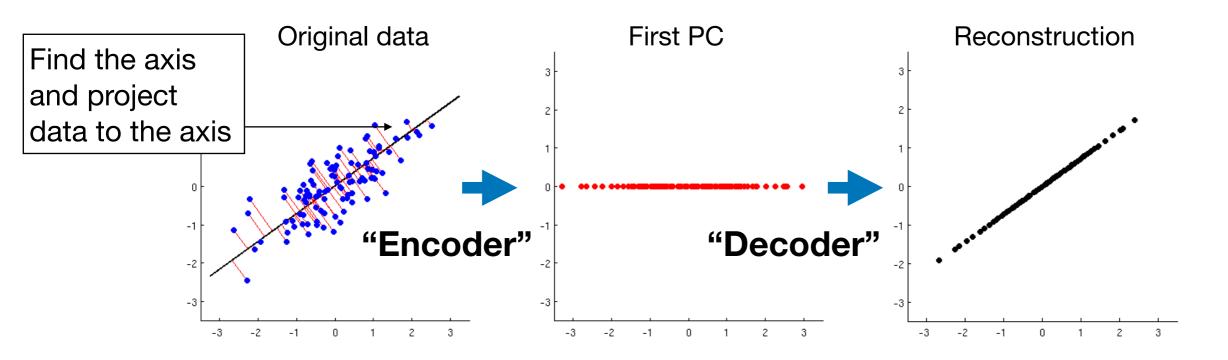






#### **Principal Component Analysis**

### PCA is a technique to drop the least important variables by focusing on variance of data.



Eigenvectors of covariance matrix of  $\boldsymbol{x}_n - \boldsymbol{c}_0$  ( $\boldsymbol{c}_0 = \sum_n \boldsymbol{x}_n / N$ ) give desired axes.

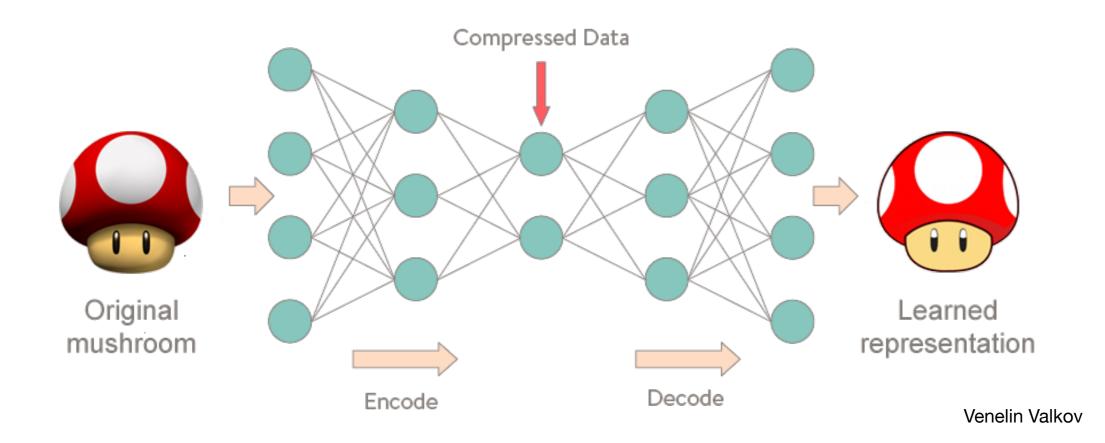
 $\rightarrow \Gamma = (\boldsymbol{e}_1 \ \boldsymbol{e}_2 \ \dots \ \boldsymbol{e}_d) \quad d$ : the number of principal components (d < D)

"PCA autoencoder"  
"Encoder": 
$$\tilde{\boldsymbol{x}}_n = (\boldsymbol{x}_n - \boldsymbol{c}_0)\Gamma$$
 "Decoder":  $\boldsymbol{x}'_n = \tilde{\boldsymbol{x}}_n\Gamma^T + \boldsymbol{c}_0$ 

### Simple Autoencoder

Autoencoder with a single dense (fully-connected) layer as encoder and as decoder.

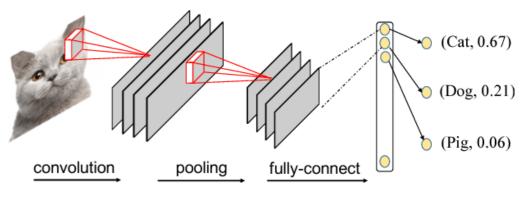
- $\checkmark$  Encoder and decoder are <u>symmetric</u> (weights are not the same).
- ✓ The number of neurons in a hidden layer = 32.
- $\checkmark$  Flatten a jet image into <u>a single column vector</u> for input.



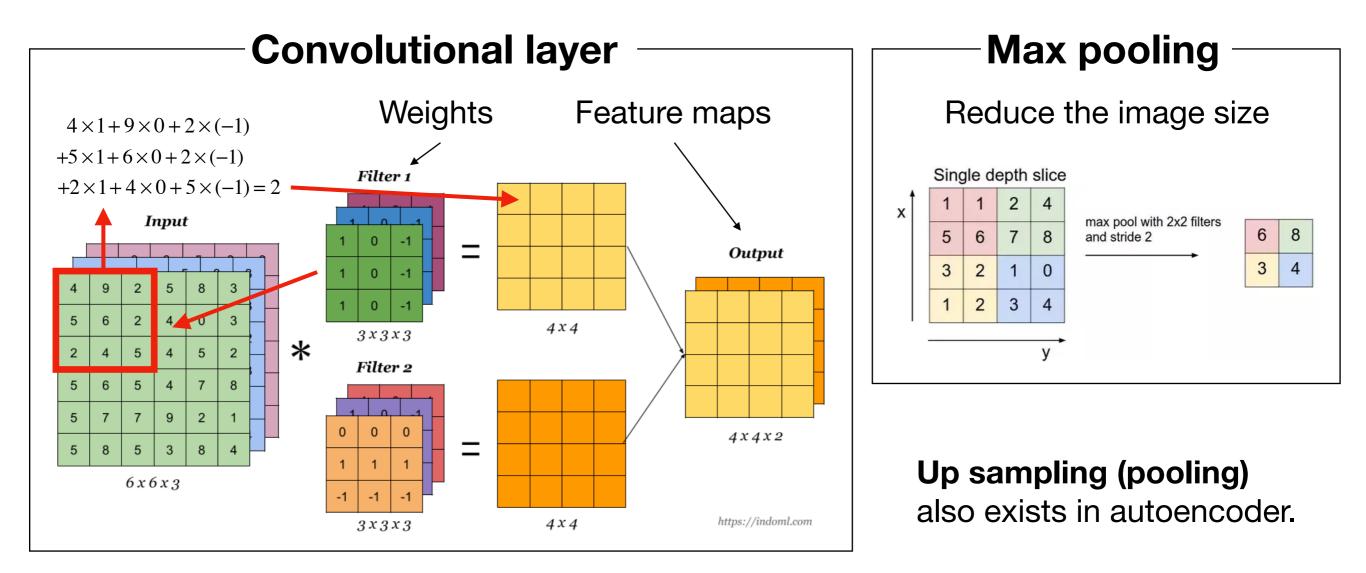
### **Convolutional Autoencoder**

#### **Convolutional Neural Network (CNN)**

- ✓ Show high performance for <u>image recognitions</u>
- ✓ Maintain the <u>spacial information</u> of images

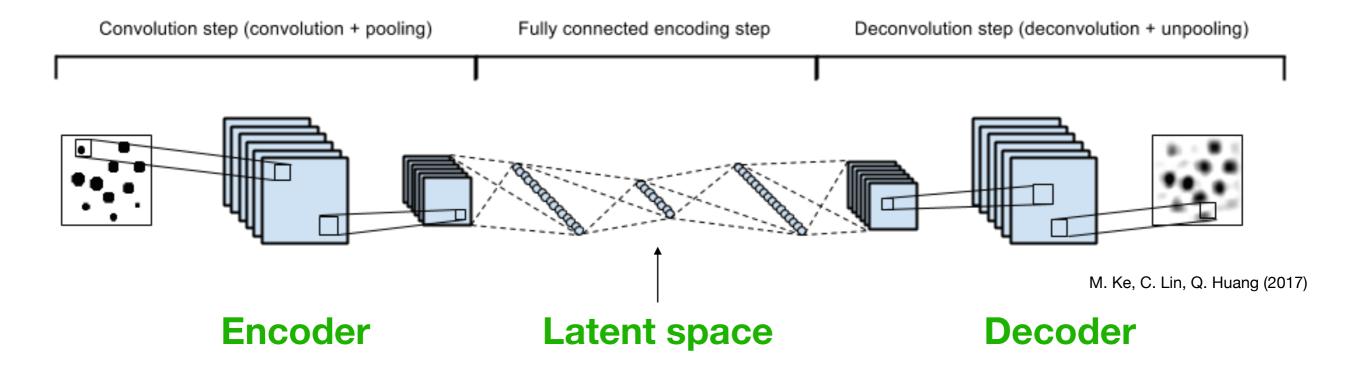


arXiv:1712.01670



#### **Convolutional Autoencoder**

#### Autoencoder architecture :



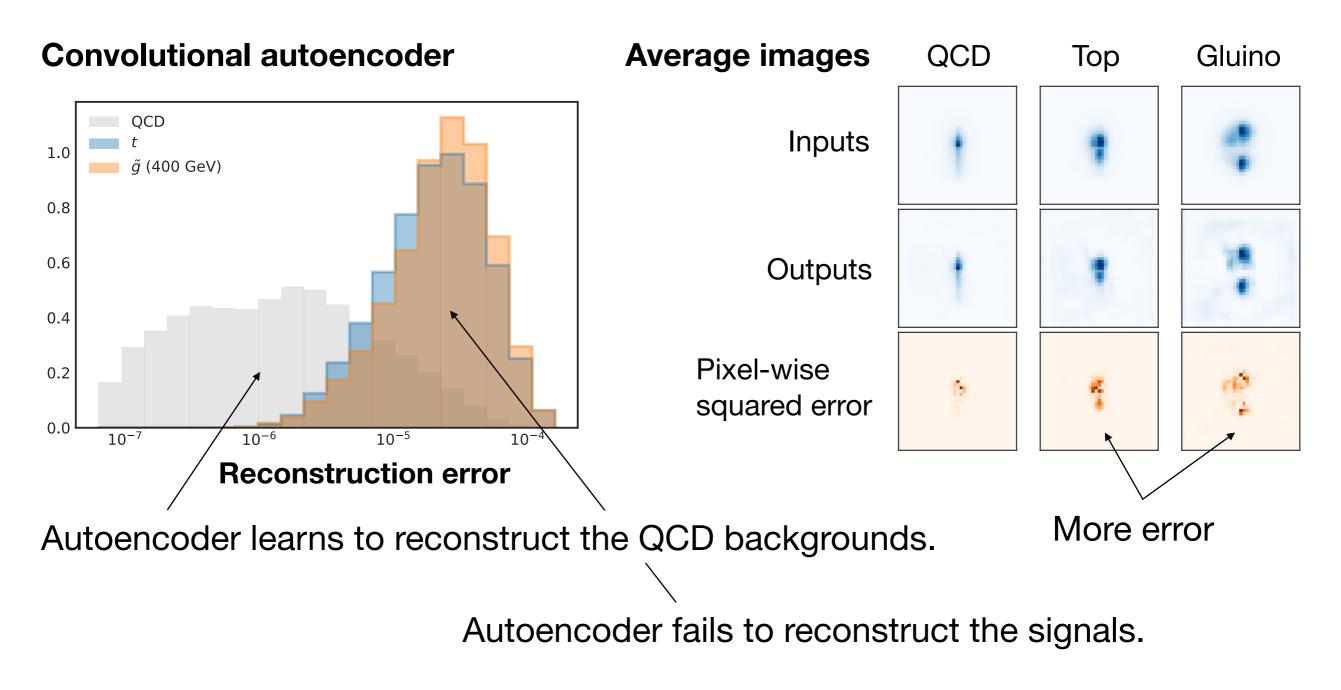
128C3-MP2-128C3-MP2-128C3-32N-6N-32N-12800N-128C3-US2-128C3-US2-1C3

128C3 : 128 filters with a 3x3 kernel 32N : a fully-connected layer with 32 neurons MP2 : max pooling with a 2x2 reduction factor

US2 : up sampling with a 2x2 expansion factor

### Weakly-supervised mode

Weakly-supervised case with pure background events for training.

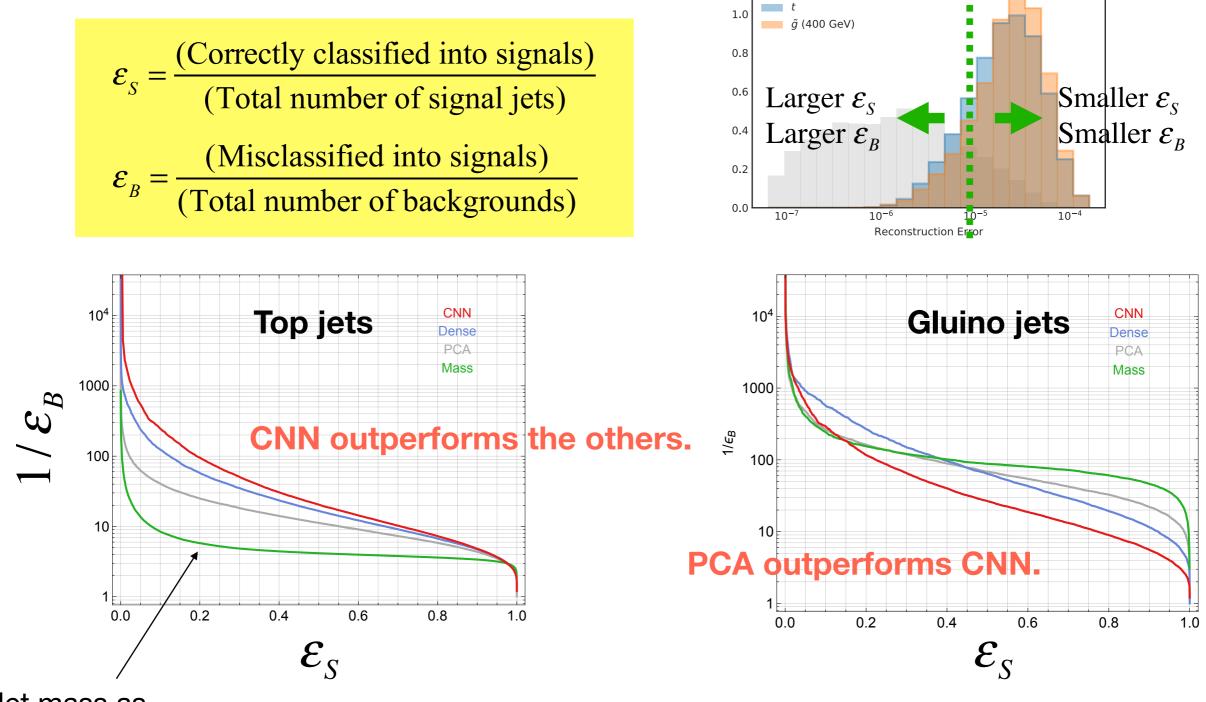


#### **Reconstruction error is used as an anomaly threshold.**

#### Autoencoder Performance

OCD

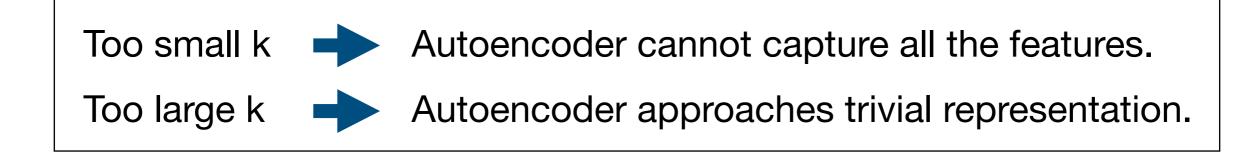
#### Performance measure :



Jet mass as anomaly threshold

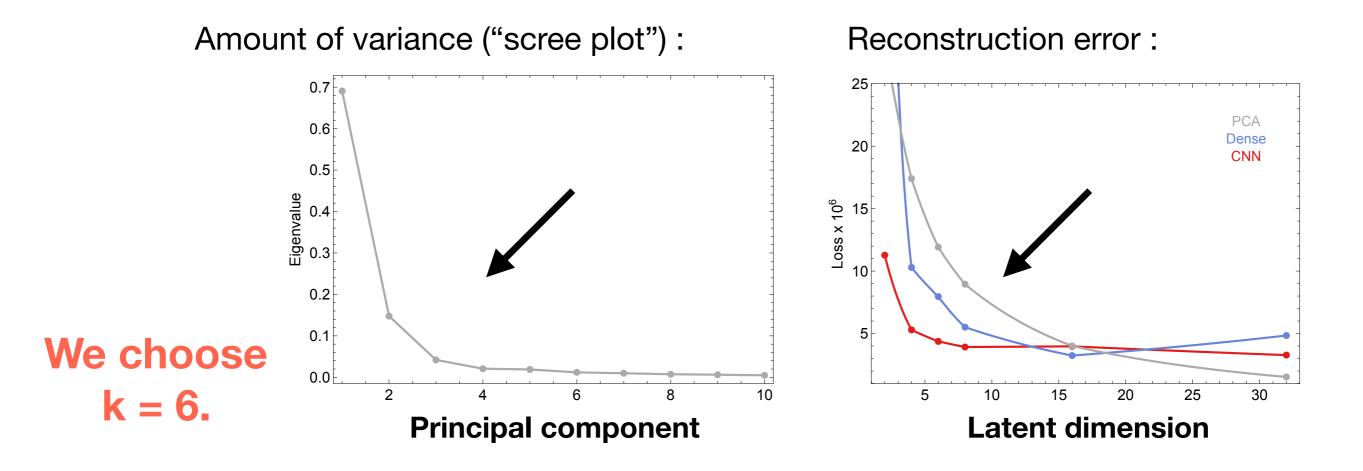
PCA and Dense curves approach jet mass curve, suggesting their reconstruction errors are highly correlated with jet mass.

#### **Choosing Latent Dimension k**



Optimizing latent dimension using a specific signal is **NOT** a good idea.

Instead, we examine <u>PCA eigenvalues</u> or <u>reconstruction error</u> vs latent dimension and look at where they are saturated.

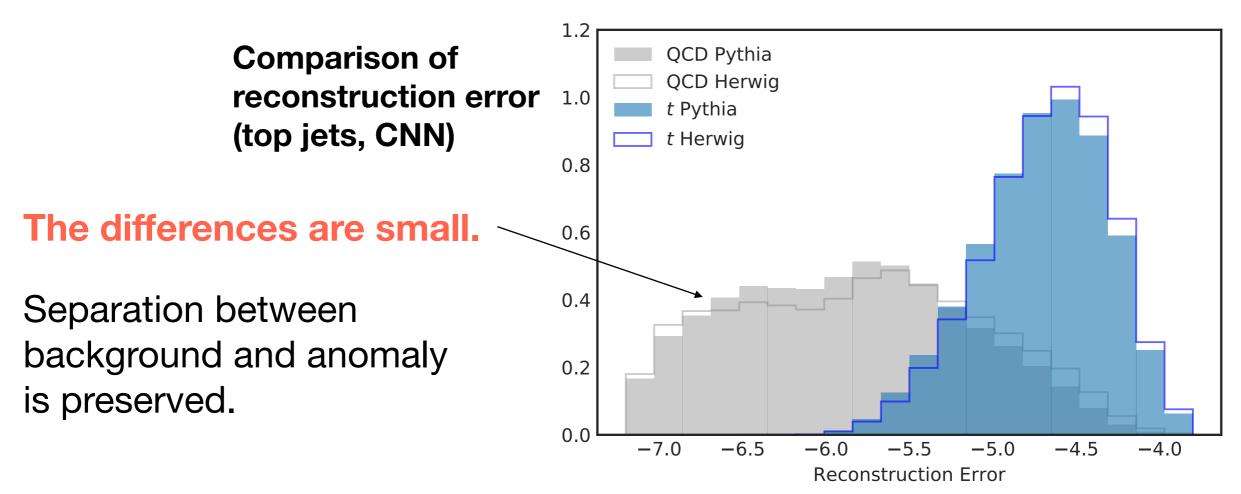


#### **Robustness with Other Monte Carlo**

Autoencoder really does not learn artifacts special to a Monte Carlo?

One possible check :

Evaluate autoencoder (trained on PYTHIA samples) on jet samples produced with HERWIG.



Autoencoder probably learns fundamental jet features.

#### **Unsupervised Mode**

A much more exciting possibility is...

#### Train autoencoder on actual data !



#### Actual data may contain some amount of signals.



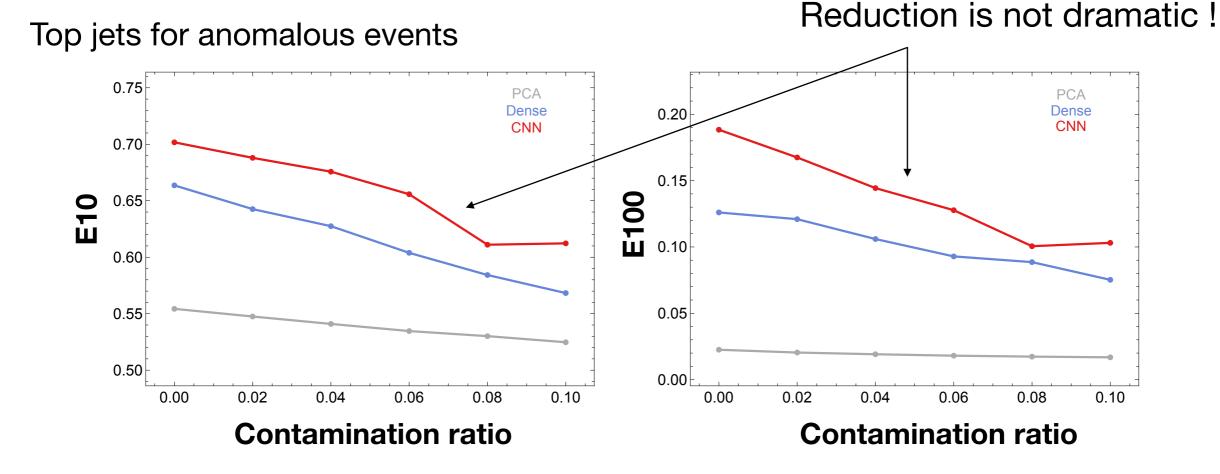
### **Unsupervised Mode**

Train autoencoder on a sample of backgrounds <u>contaminated by a small fraction of signal events</u>.



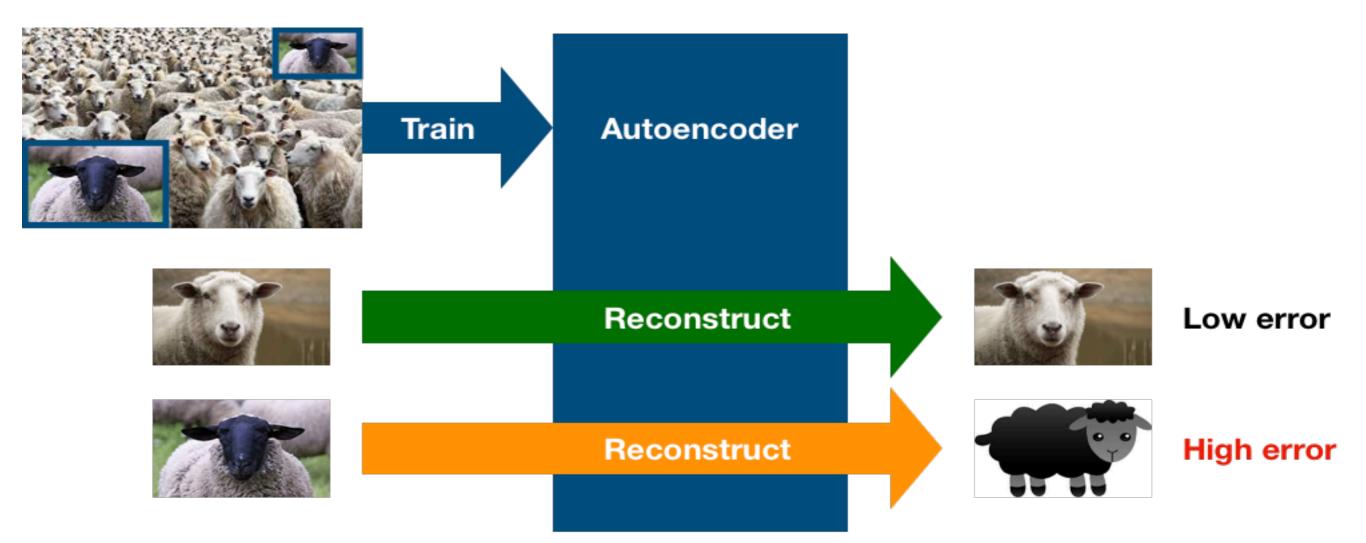
### Autoencoder performance is remarkably stable against signal contamination.

 $E_{\rm 10,\ 100}$  : the signal efficiency at 90% and 99% background rejection



#### **Unsupervised Mode**

Autoencoder learns to preferentially reconstruct backgrounds and still poorly reconstructs signals.



Autoencoder could be trained directly on data and then could potentially discover anomalies in backgrounds.

### **Correlation with Jet Mass**

#### In actual new physics searches, we look for subtle signals...



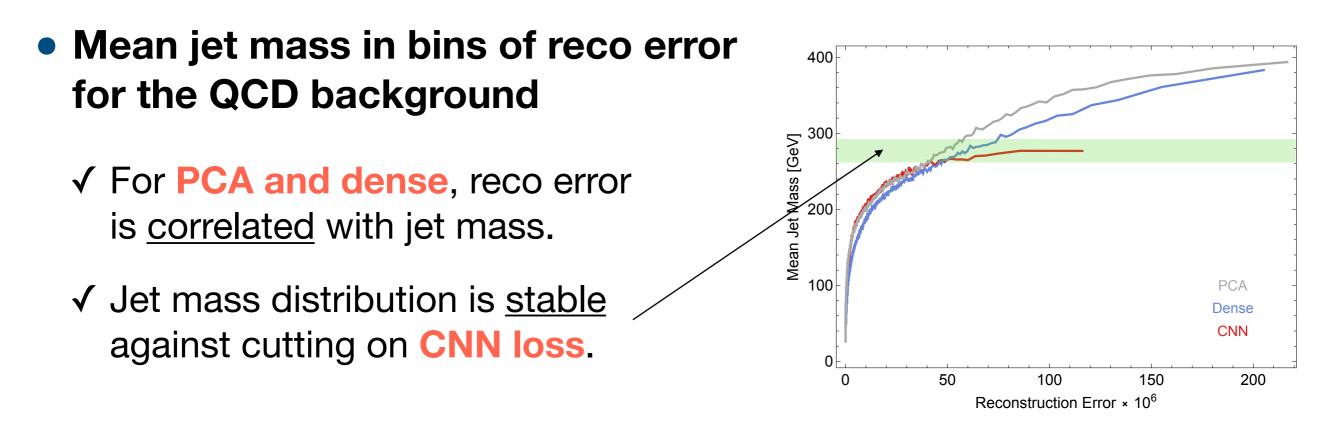
It's more powerful to combine autoencoder with another variable such as jet mass.

Cut hard on reconstruction error to clean out the QCD background and look for a bump in jet mass distribution.

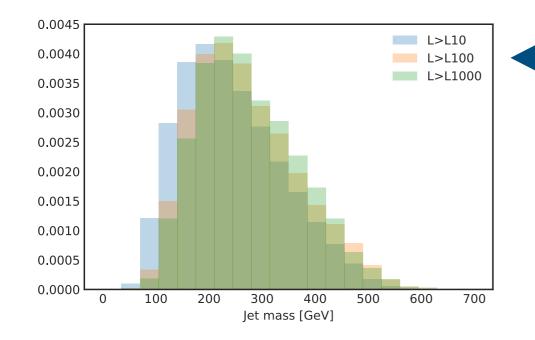


Reconstruction error should not be correlated with jet mass.

#### **Correlation with Jet Mass**



#### Jet mass distributions after cuts on CNN loss



Reduce the QCD background by a factor of 10, 100 and 1000.

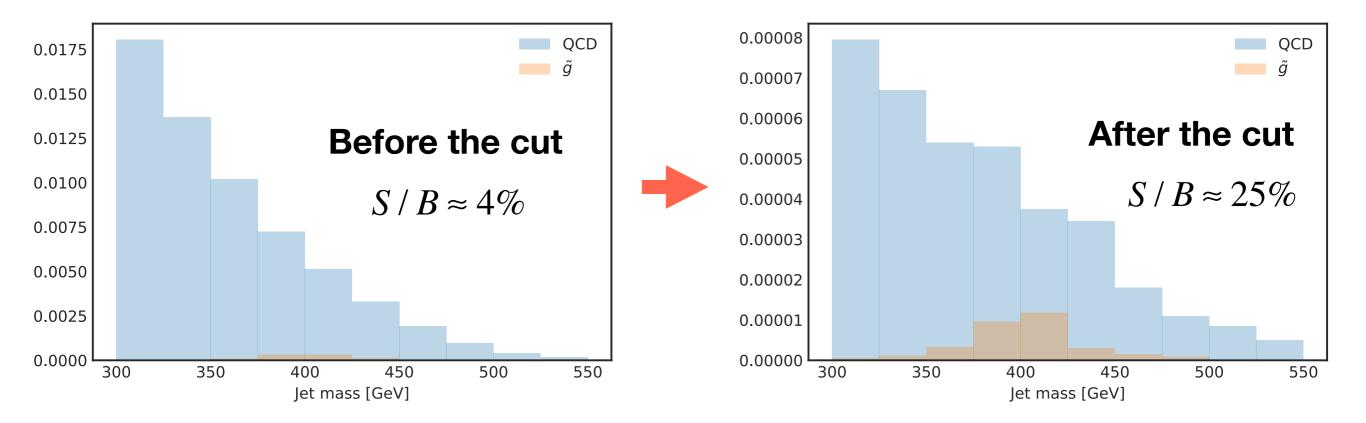
**Convolutional autoencoder is useful for a bump hunt in jet mass above 300 GeV.** 

#### **Bump Hunt**

### Thresholding on reconstruction error gives a significant improvement of S/B.

#### Jet mass histograms

(normalized to LO gluino and QCD cross sections)



One could plausibly discover new physics this way !

### Summary

- ✓ Autoencoder learns to map background events back to themselves but <u>fails to reconstruct signals</u> that it has never encountered before.
- $\checkmark$  Reconstruction error is used as an anomaly threshold.
- ✓ Autoencoder performance is <u>stable against signal contamination</u> which enables us to <u>train autoencoder on actual data</u>.
- ✓ Jet mass distribution is stable against cutting on CNN loss and <u>convolutional autoencoder is useful for a bump hunt in jet mass</u>.
- ✓ Thresholding on reco error gives <u>a significant improvement of S/B</u>.

Thank you.