Event Generation and Statistical Sampling with Deep Generative Models

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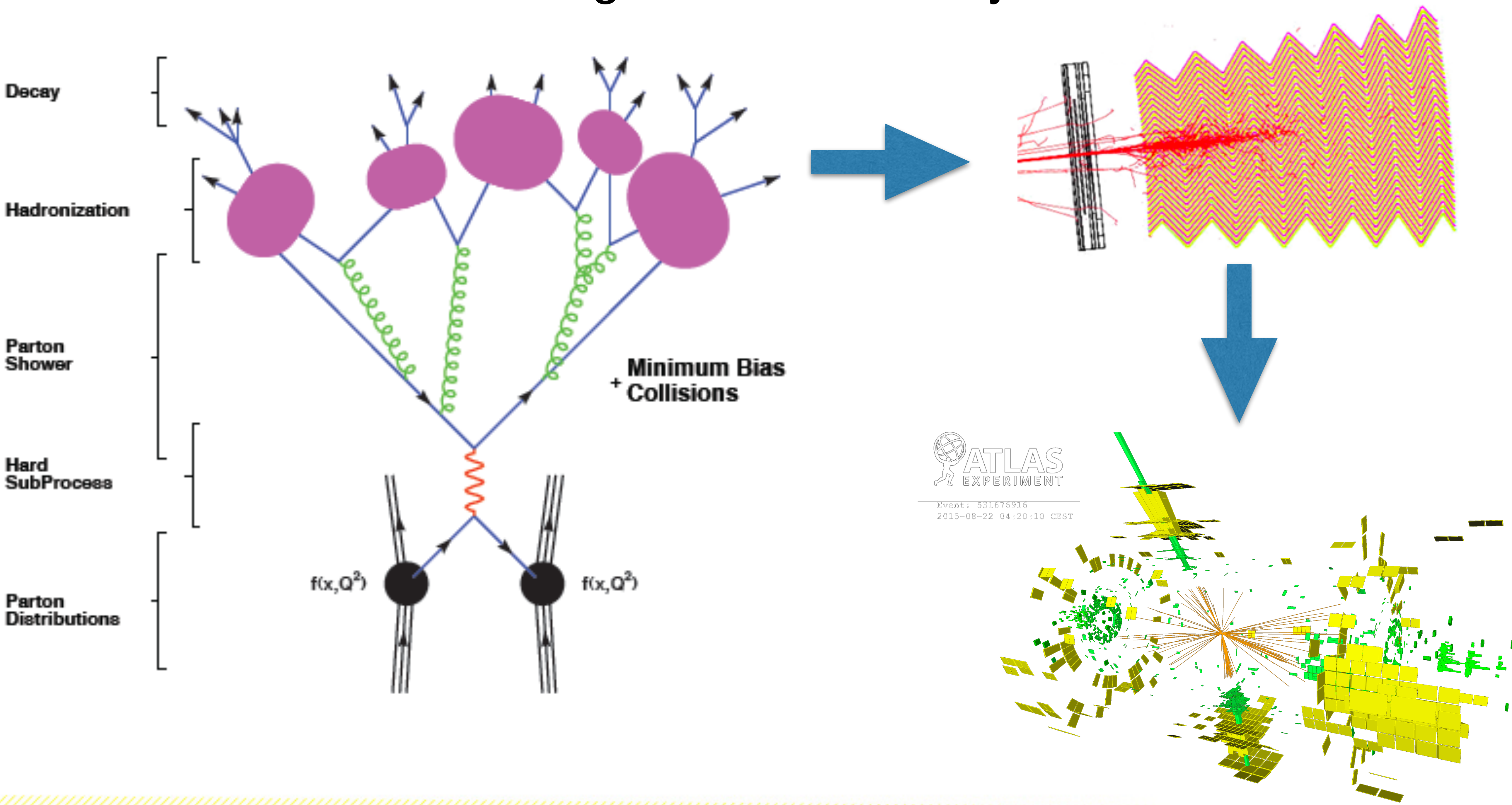
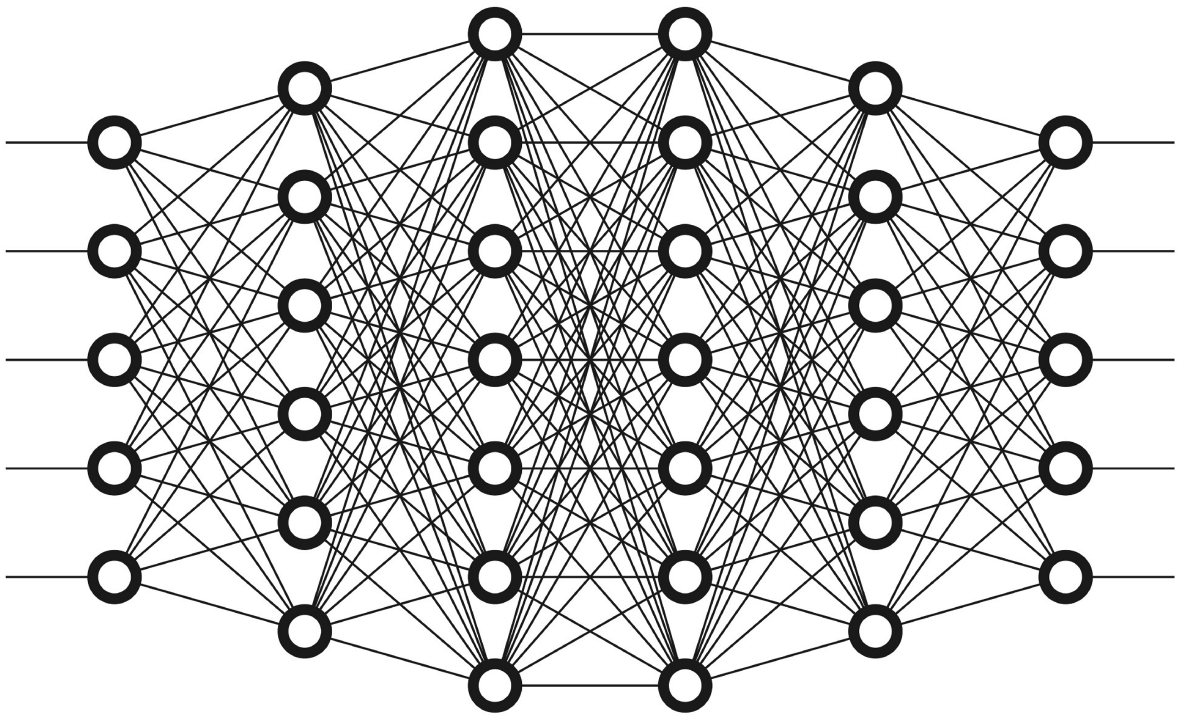
Introduction

Event generation is really hard!



Introduction

Can we use deep neural networks to do event generation?



Possible applications:

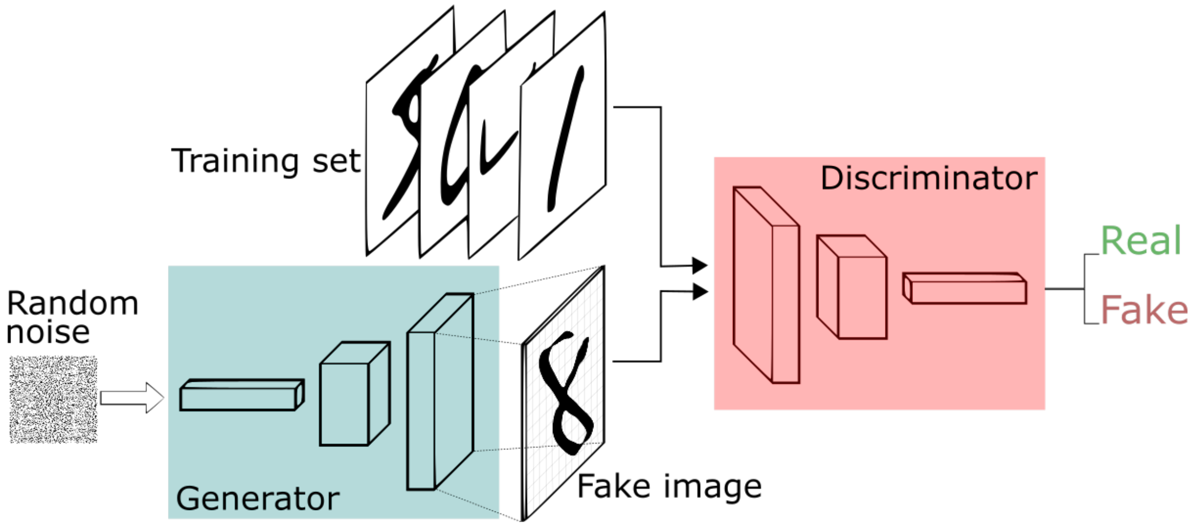
- Faster
- Data driven generators
- Targeted event generation

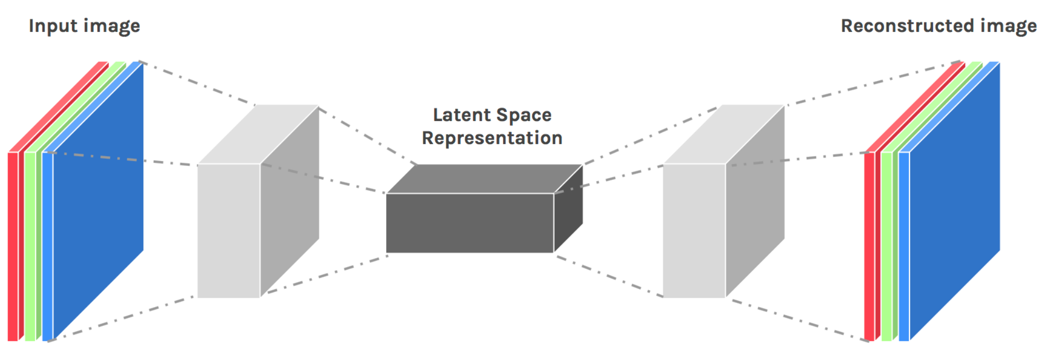
Introduction

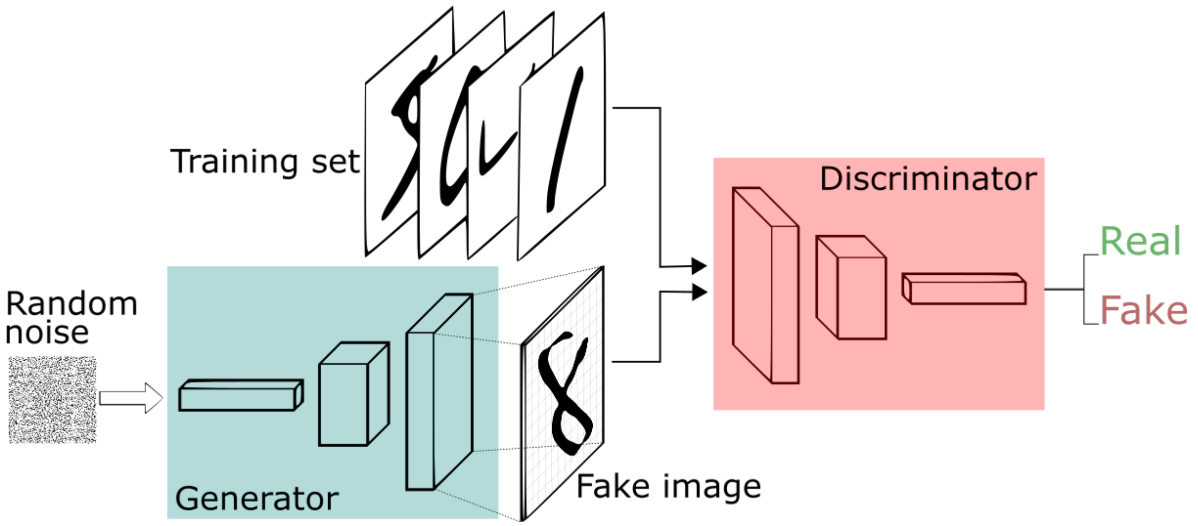
Study of different types of unsupervised generative models

- Generative Adversarial Networks
- Variational Autoencoders
- Buffer Variational Autoencoder

Can these networks be used to sample probability distributions?



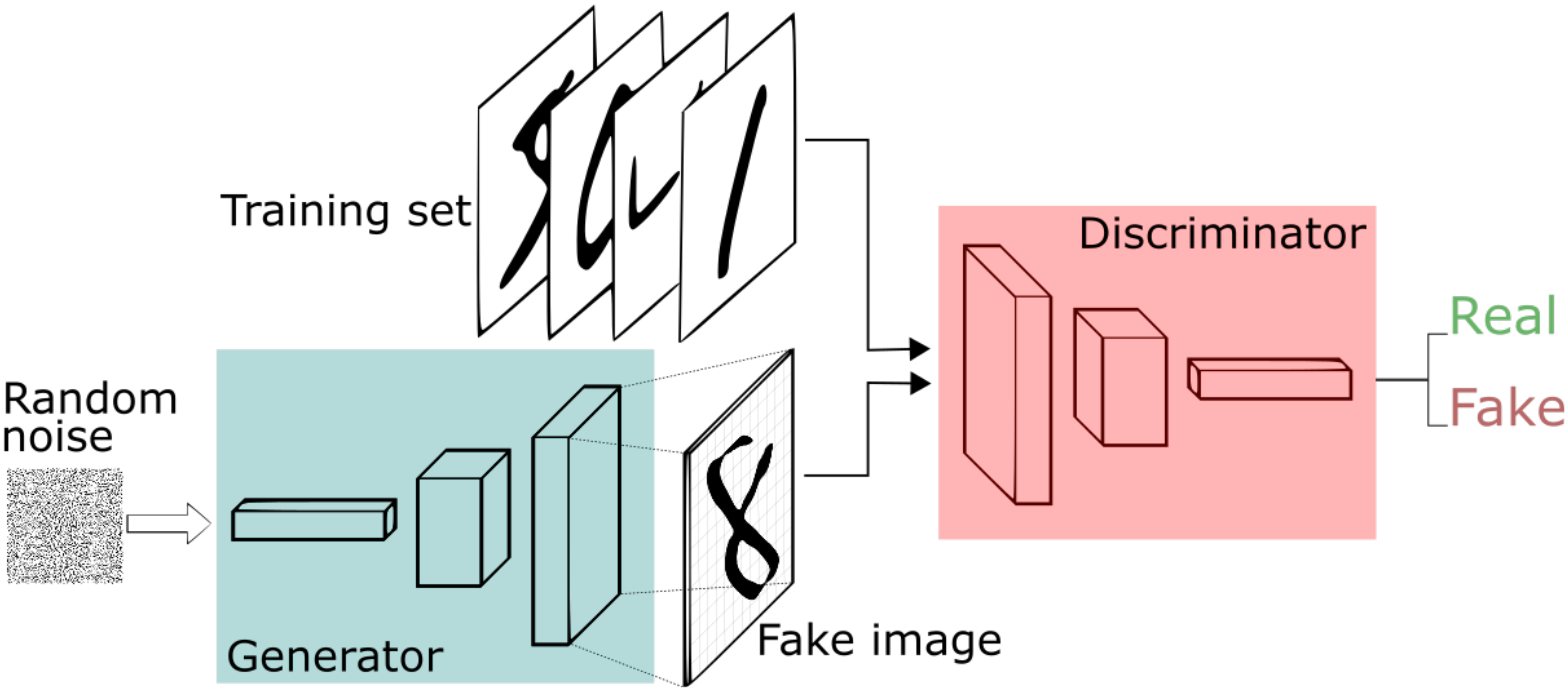




Generative Adversarial Networks (GANs)

Generative Adversarial Networks

Two networks (Generator & Discriminator) that play a game against each other



Generative Adversarial Networks

Loss function:

$$\min_G \max_D V(G, D) = \mathbb{E}_{x \sim p_{data}(x)} \log[D(x)] + \mathbb{E}_{z \sim p_z(z)} \log[1 - D(G(z))]$$

Nash equilibrium:

$$p_{data}(x) = p_{gen}(x)$$

$$D(x) = \frac{1}{2}$$

Generative Adversarial Networks

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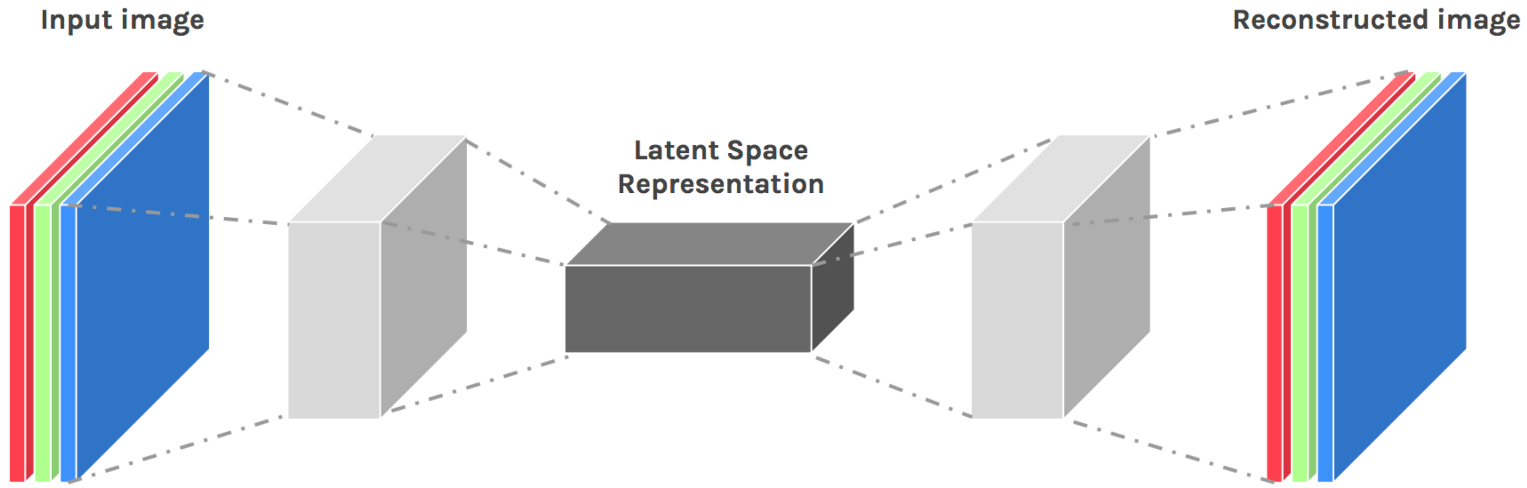
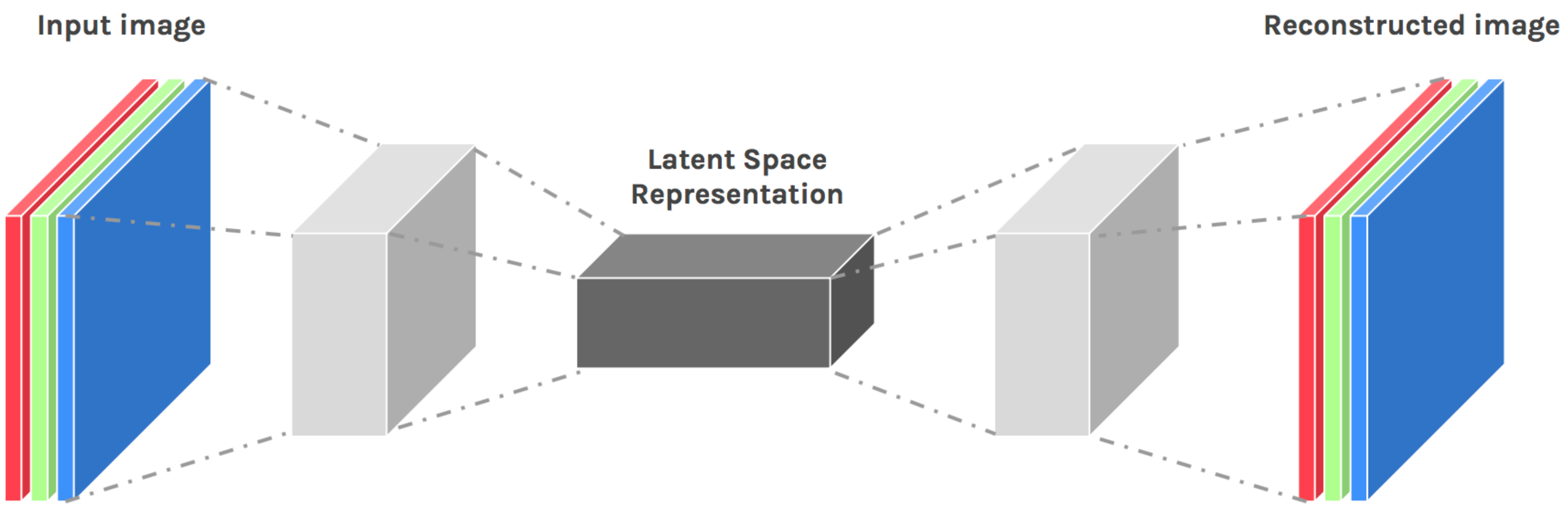


Variational Autoencoders (VAEs)

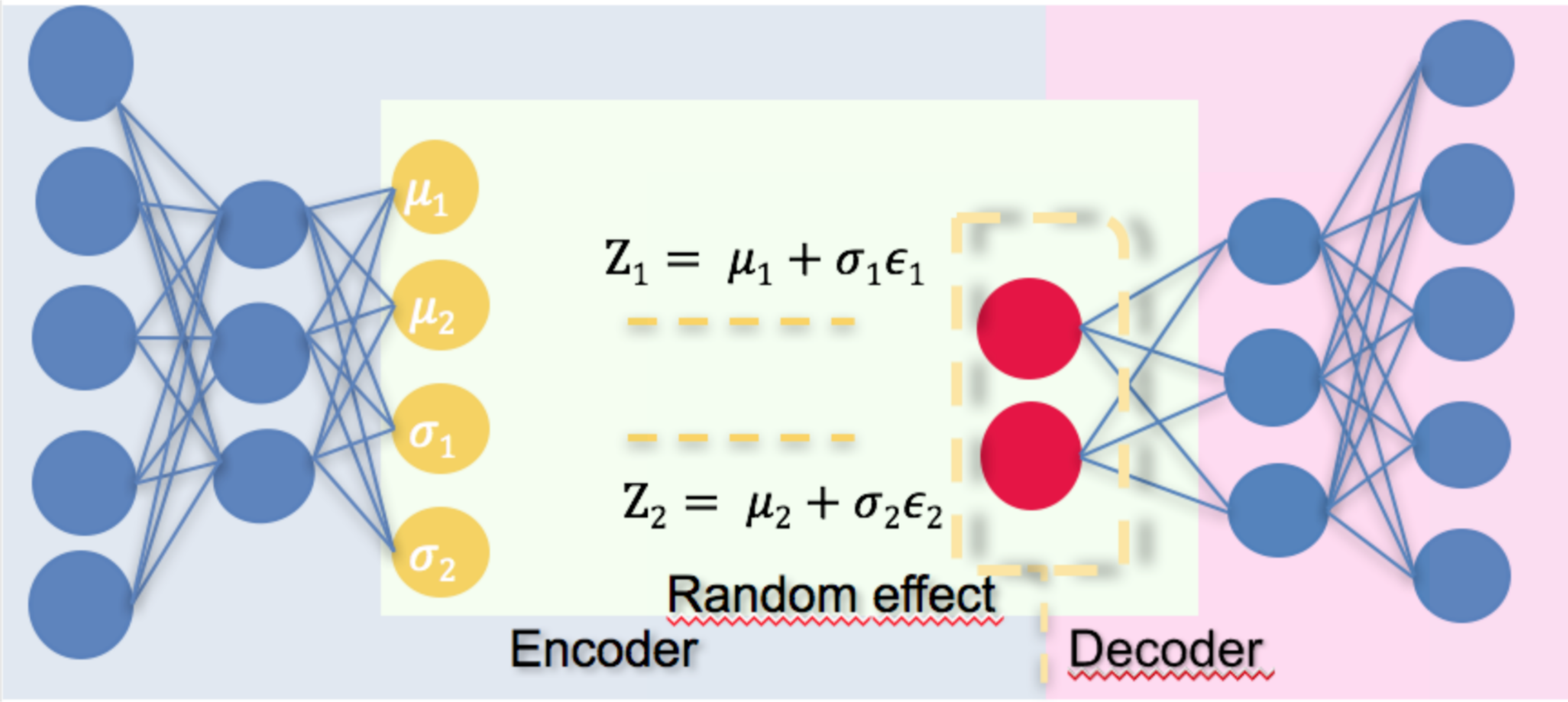
Autoencoders



- Data is encoded into latent space
- Dim of latent space is often lower than dim of data

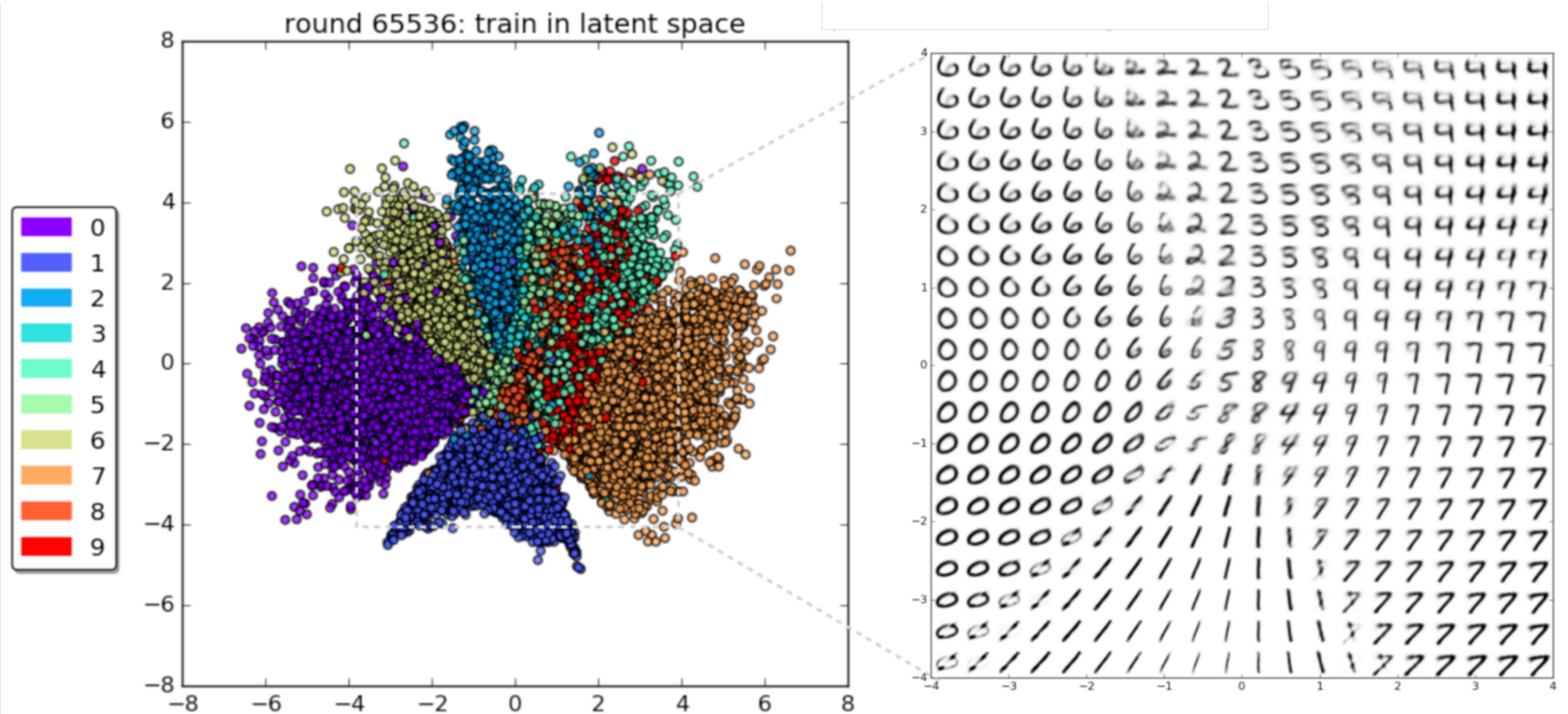
Variational Autoencoders

Add degree of randomness to training procedure



Variational Autoencoders

Points in latent space are ordered



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Variational Autoencoders

Loss function

$$\mathcal{L}_{\mathrm{VAE}} = (1-\beta)\frac{1}{N}(\vec{x}_i - \vec{y}_i)^2 + \beta D_{\mathrm{KL}}(\mathcal{N}(\mu_i, \sigma_i), \mathcal{N}(0,1))$$

Mean squared error

Kullback–Leibler divergence

MSE : Gaussians prefer being very narrow
KL Div: Gaussians prefer being close to $\mathcal{N}(0,1)$

β is a hyperparameter: tune by hand

Information Buffer

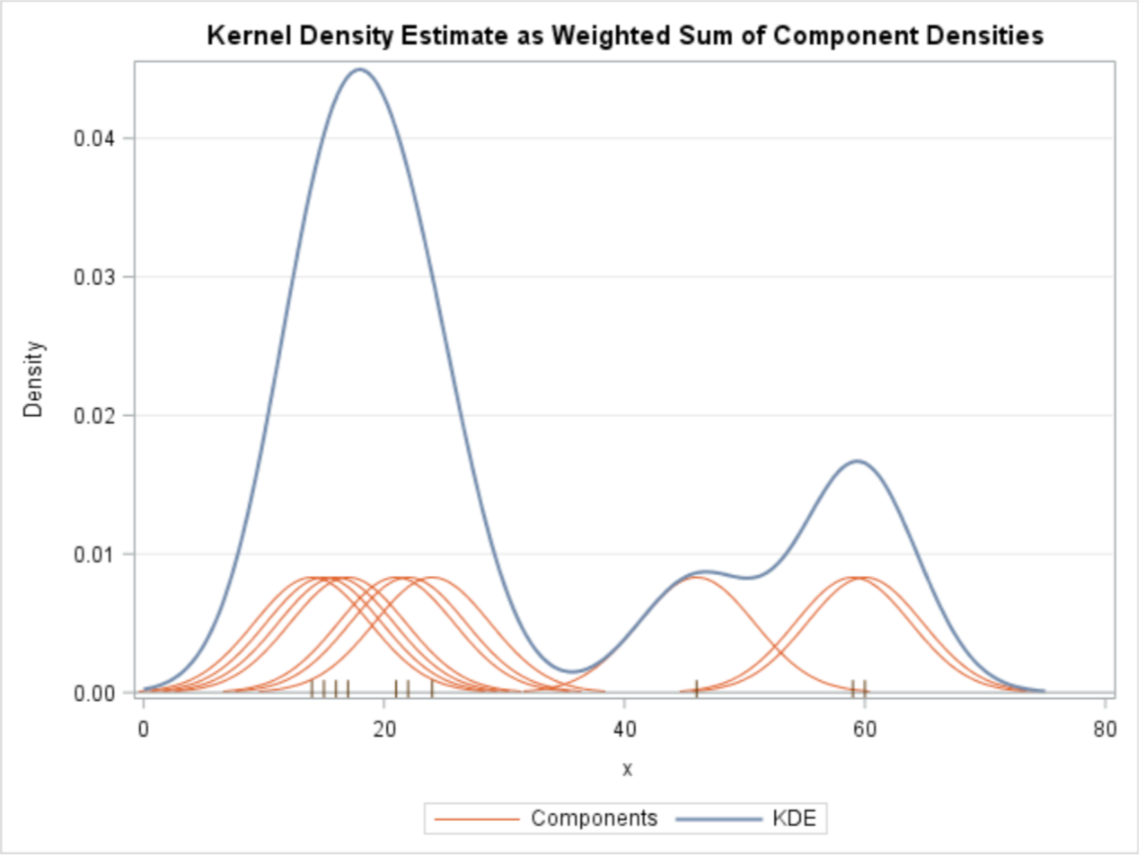
The latent space representation of our datapoints are now ordered

Normally, one would now sample from $\mathcal{N}(0,1)$ in latent space

But we can do better: Create information buffer

$$p(z) = \frac{1}{n}\sum_{i}^{n}\mathcal{N}(\mu_i, \sigma_i)$$

Representation of distribution of training data in latent space



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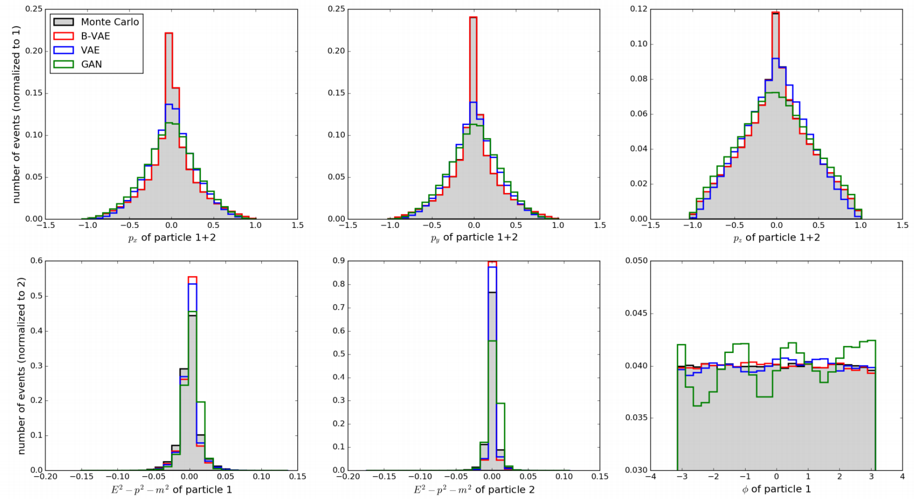

Results

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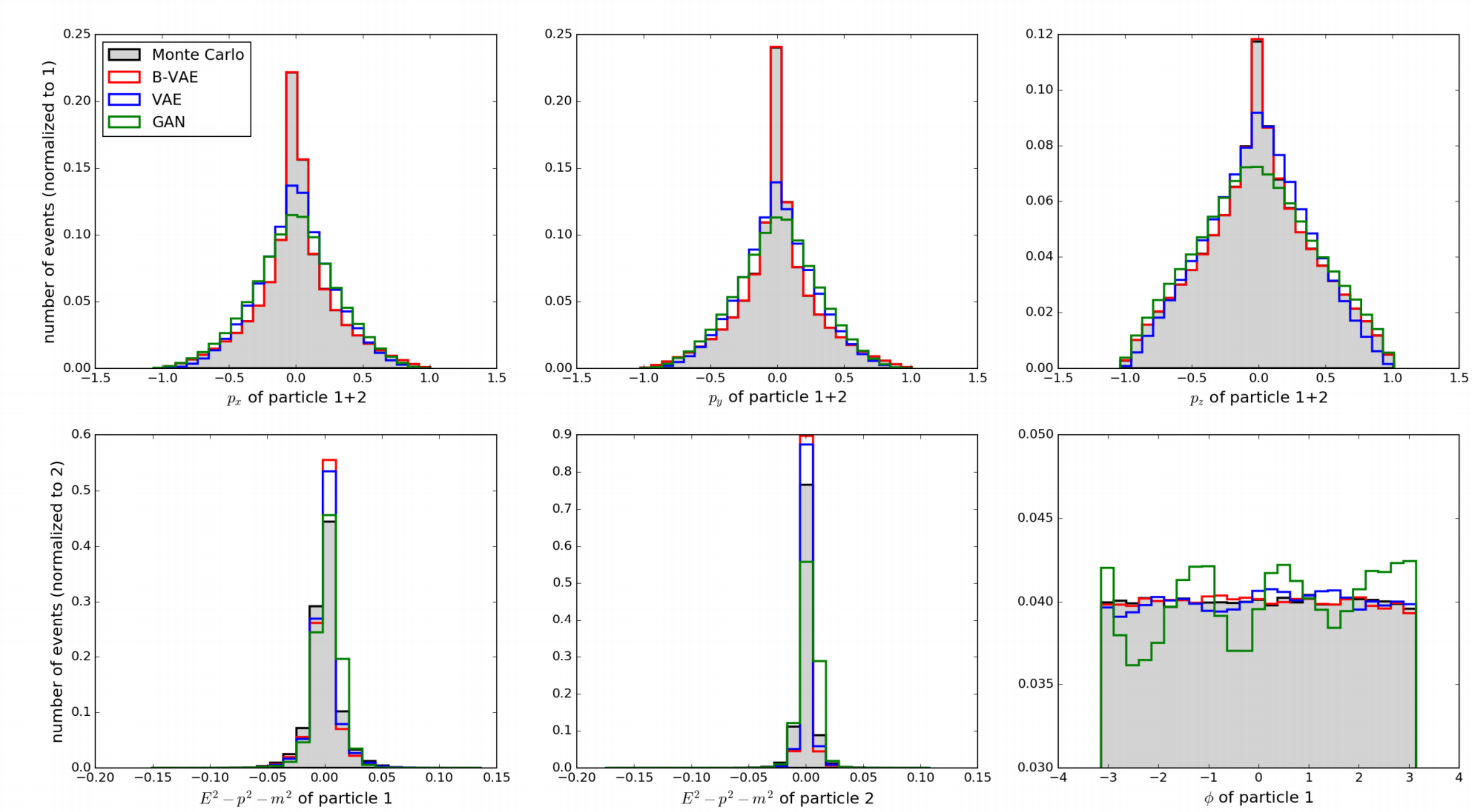
Toy Model

$1 \to 2$ decay with uniform angles and no exact momentum conservation



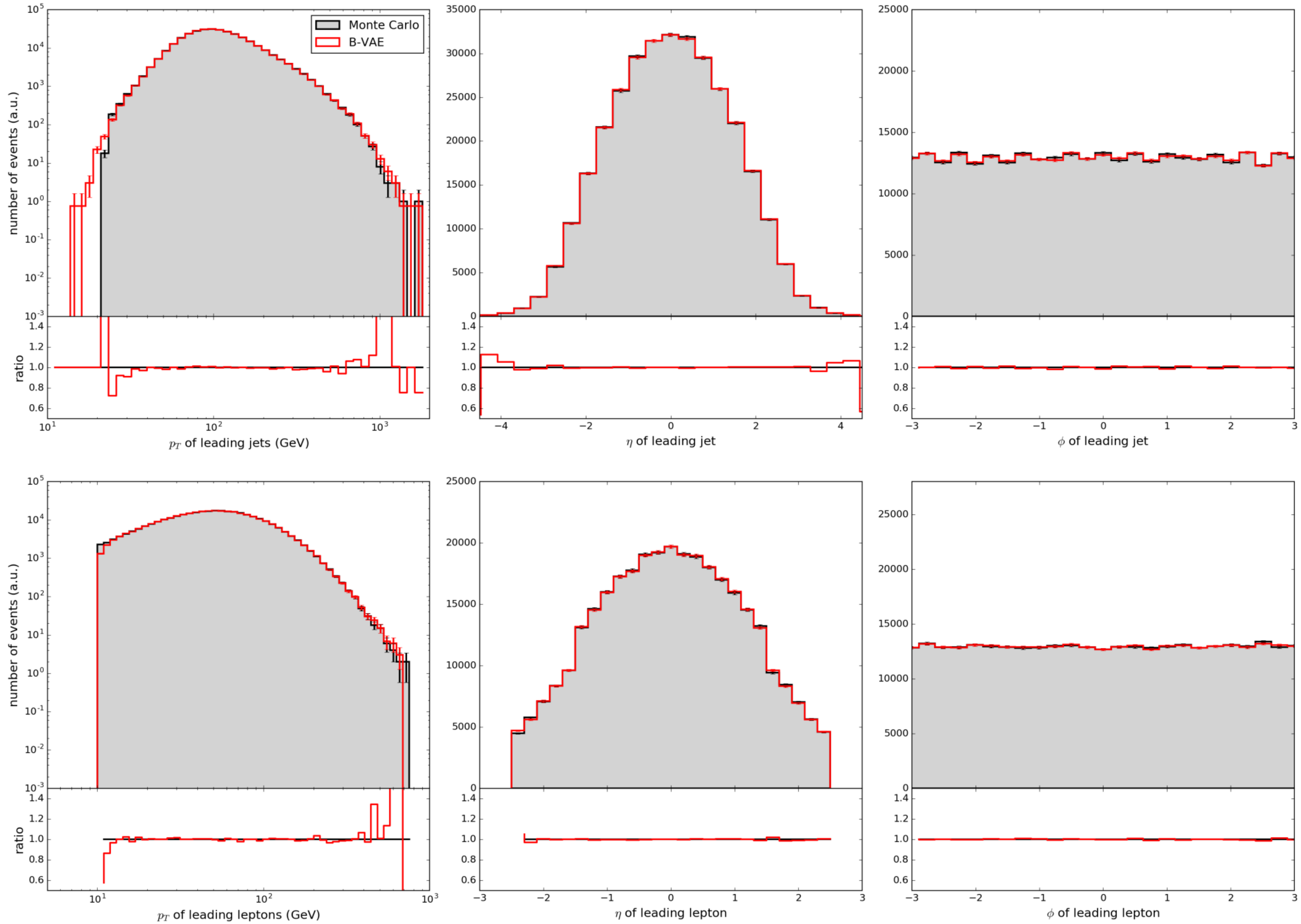
Trained on four-vectors

Top pair production

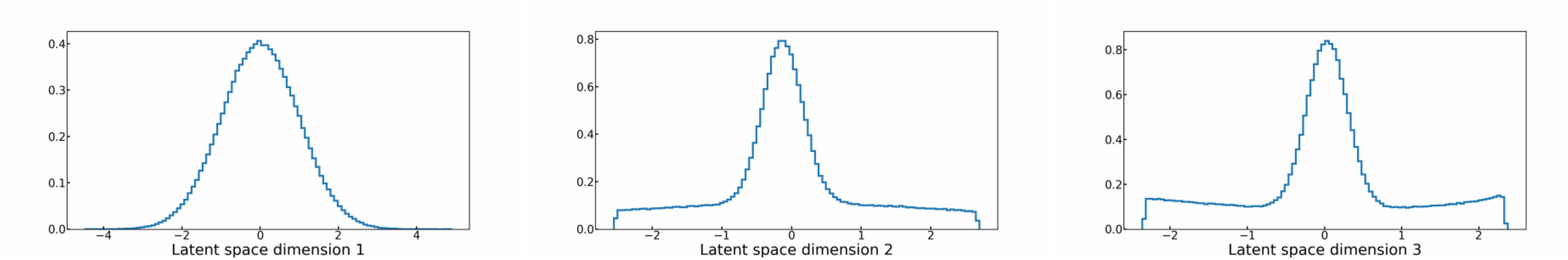
- One top required to decay leptonically
- Number of training points 5×10^5
- MG5 aMC@NLO 6.3.2 + Pythia 8.2 + Delphes 3
- Jets with $p_T > 20 \text{ GeV}$

Event generation with the B-VAE is $\mathcal{O}(10^8)$ faster!

Top pair production



Latent space distributions

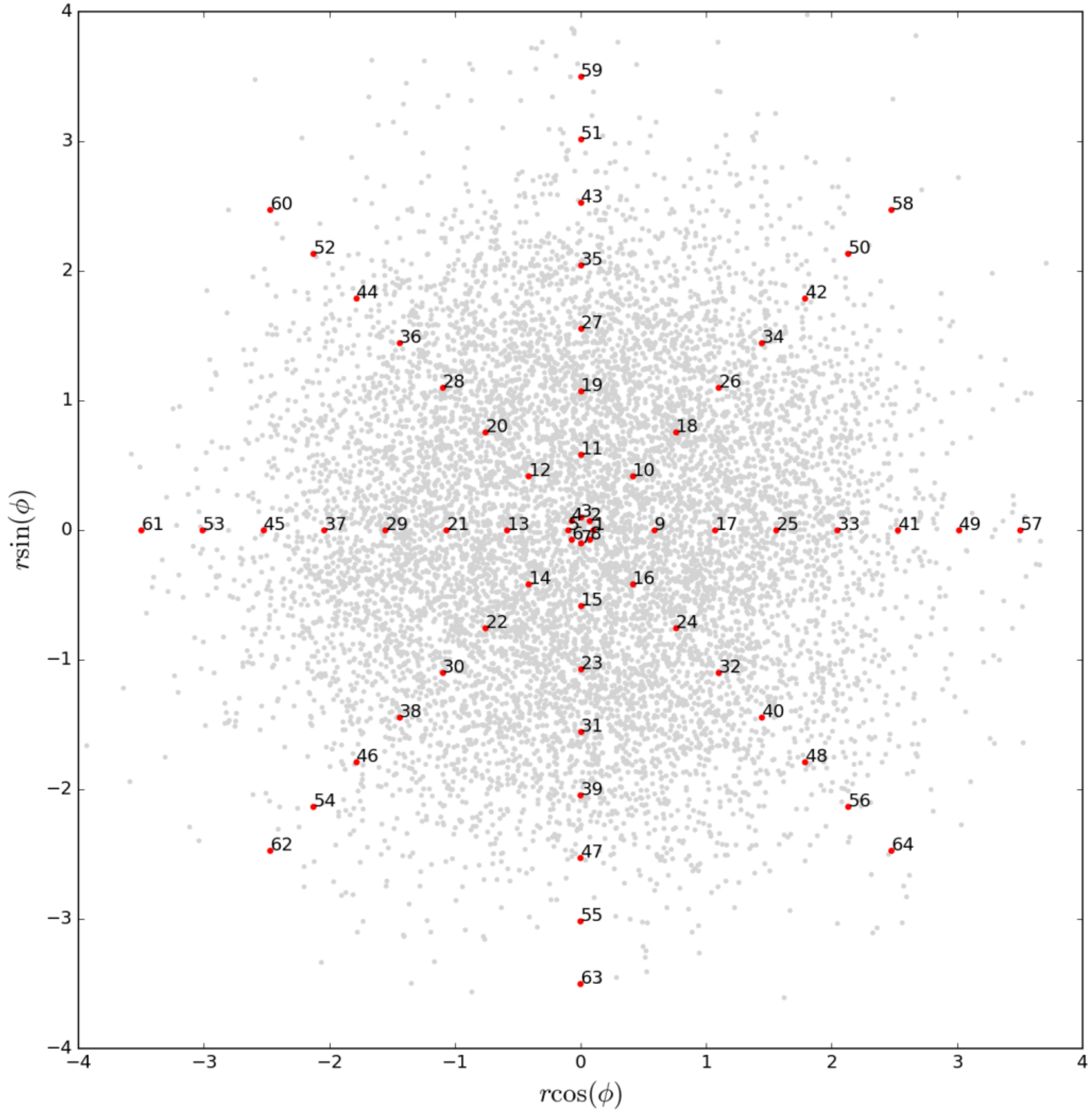


Distributions are still Gaussian-like

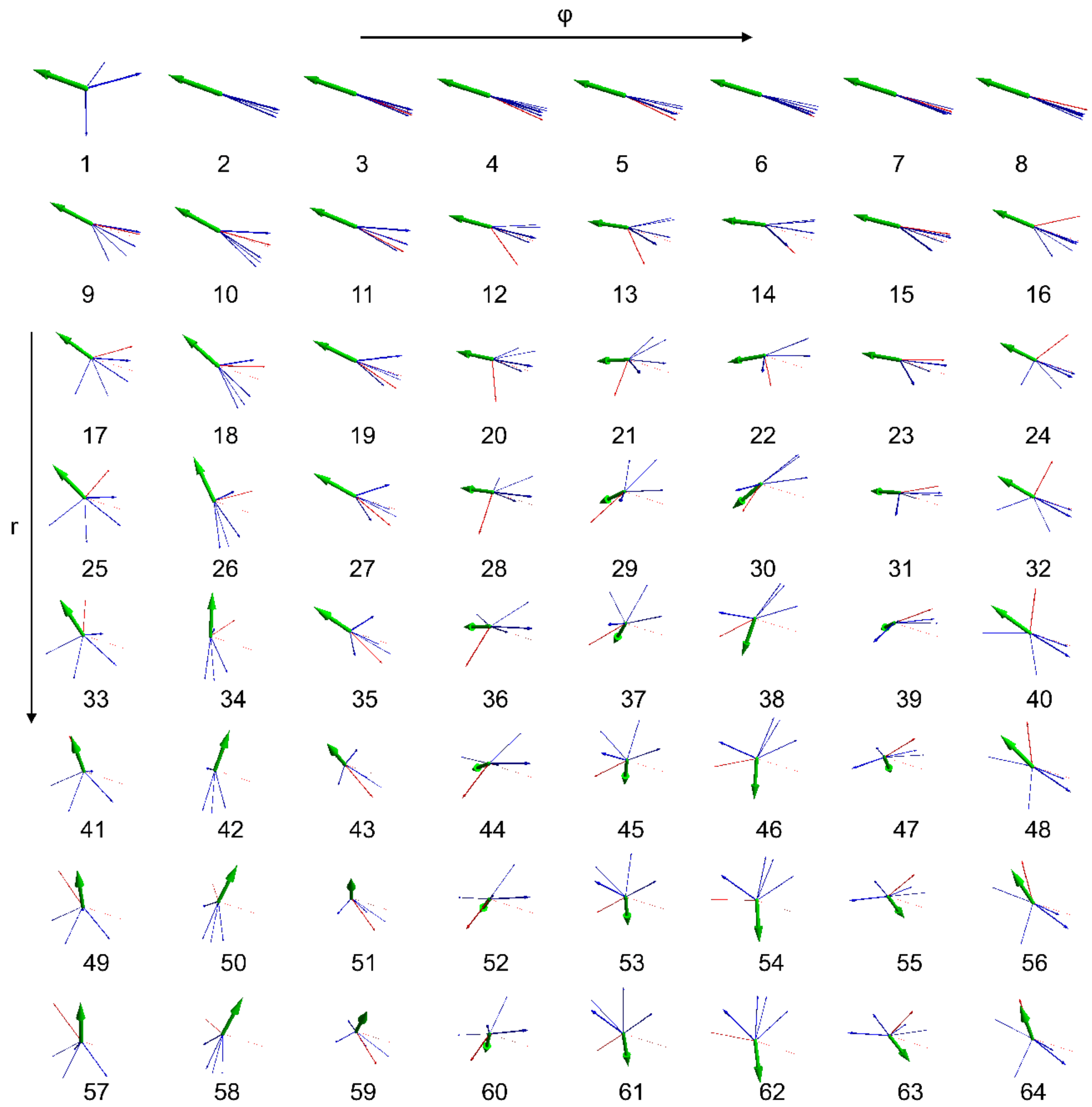
Some have sharp cutoffs: Unphysical events outside

Information buffer very important!

Latent Space Principal Component Analysis



Latent Space Principal Component Analysis

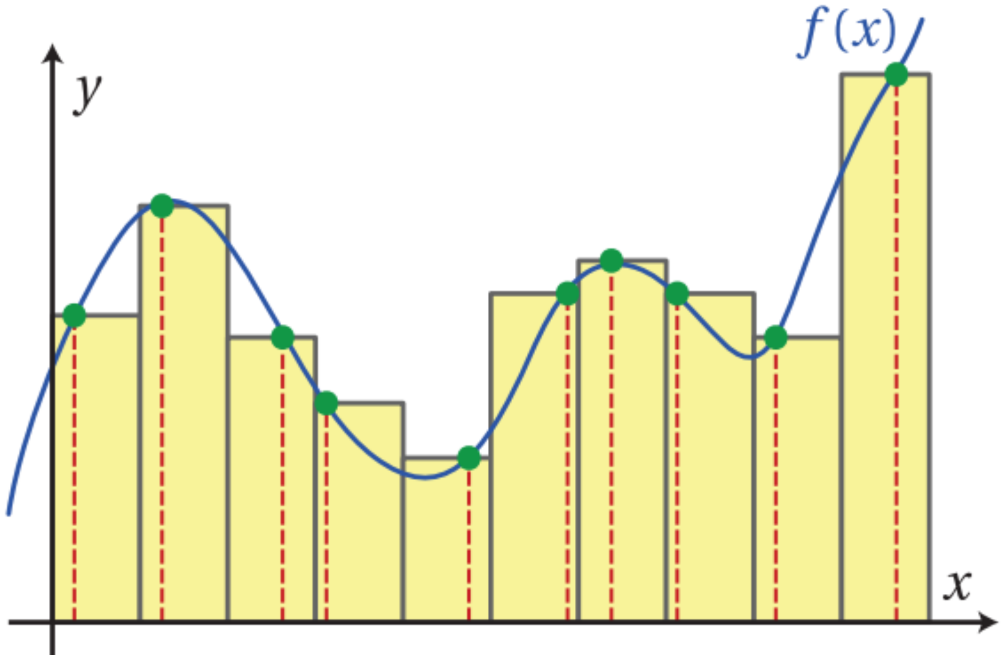


Possible Applications

Most direct application: Importance sampling for ME generation

$$\sigma \propto \int d\Phi |M(\Phi)|^2 = \int d\Phi\, p(\Phi) \frac{|M(\Phi)|^2}{p(\Phi)}$$

Current methods: VEGAS



Recent ML techniques:
Latent variable models
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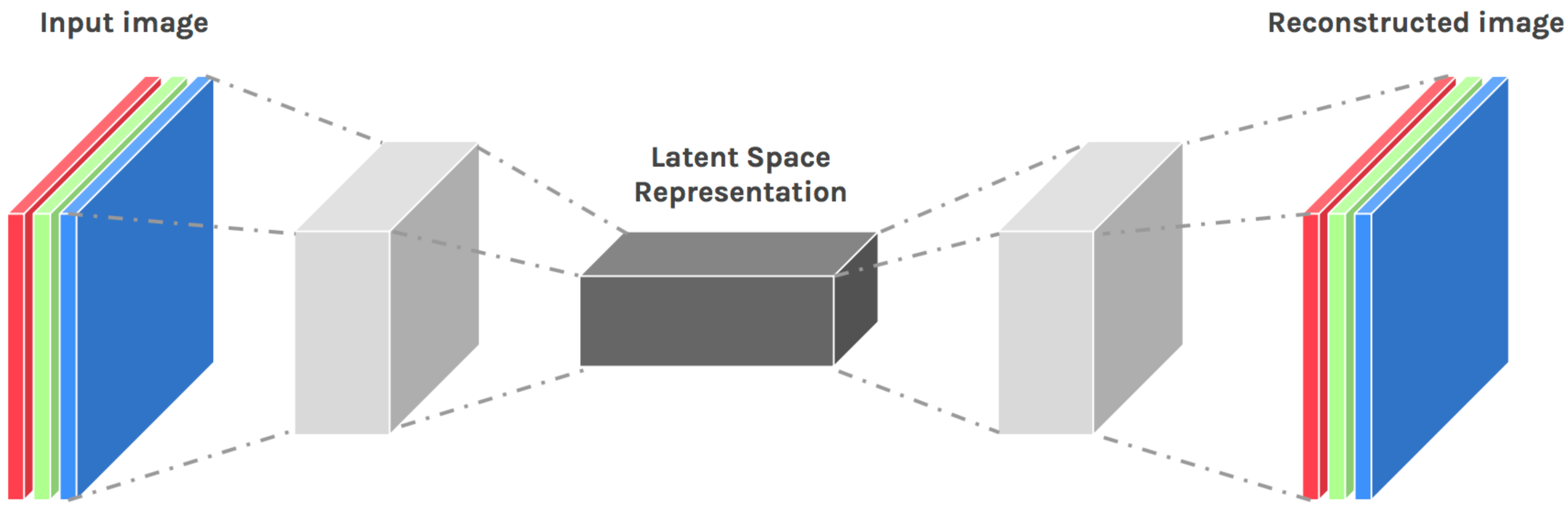
$e^+e^- \to qg\bar{q}$ efficiency:

- VEGAS: ~4%
- LVM: ~ 65%
- B-VAE: ???

Applications & Conclusion

- Data-driven event generators
- Targeted event generation
- Applications outside High Energy Physics?
- ???

Deep neural networks can be used as event generators



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