GAN Frontiers/Related Methods

Improving GAN Training

Improved Techniques for Training GANs (Salimans, et. al 2016)

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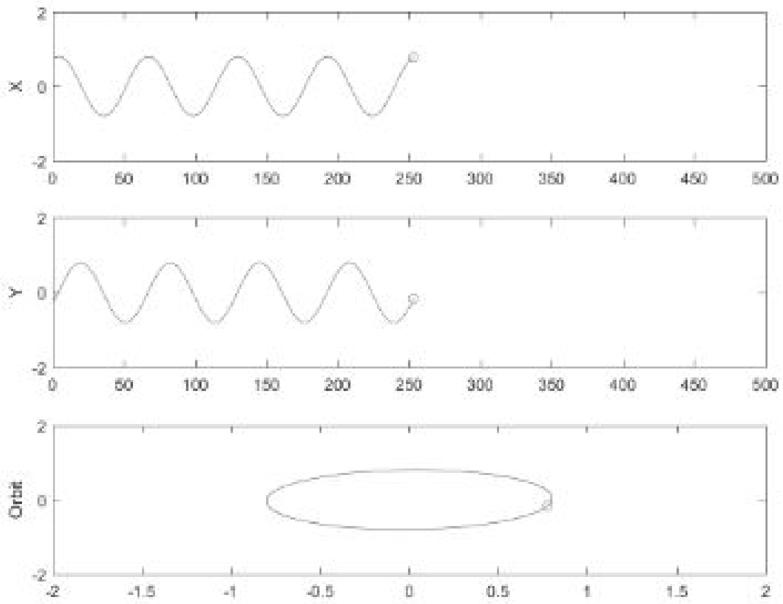
Training GANs is Difficult

- General Case is hard to solve
  - Cost functions are non-convex
  - Parameters are continuous
  - Extreme Dimensionality
- Gradient descent can't solve everything
  - Reducing cost of generator could increase cost of discriminator
  - And vice-versa

Simple Example

- Player 1 minimizes f(x) = xy
- Player 2 minimizes f(y) = -xy
- Gradient descent enters a stable orbit
- Never reaches x = y = 0



(Ian Goodfellow, Yoshua Bengio, and Aaron Courville. Deep Learning. 2016. MIT Press)

Working on Converging

- Feature Mapping
- Minibatch Discrimination
- Historical Averaging
- Label Smoothing
- Virtual Normalization

Feature Matching

- Generate data that matches the statistics of real data
- Train generator to match expected value of intermediate discriminator layer:

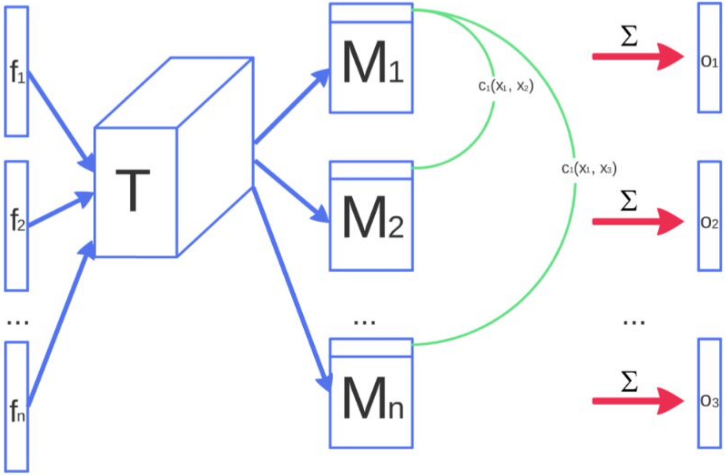
$$||\mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}}\mathbf{f}(\boldsymbol{x}) - \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}\mathbf{f}(G(\boldsymbol{z}))||_2^2$$

(Where f(x) is some activations of an intermediate layer)

- Still no guarantee of reaching G*
- Works well in empirical tests

Minibatch Discrimination

- Discriminator looks at generated examples independently
- Can't discern generator collapse
- Solution: Use other examples as side information
- KL divergence does not change
- JS favours high entropy



(Ferenc Huszár - http://www.inference.vc/understanding-minibatch-discrimination-in-gans/)

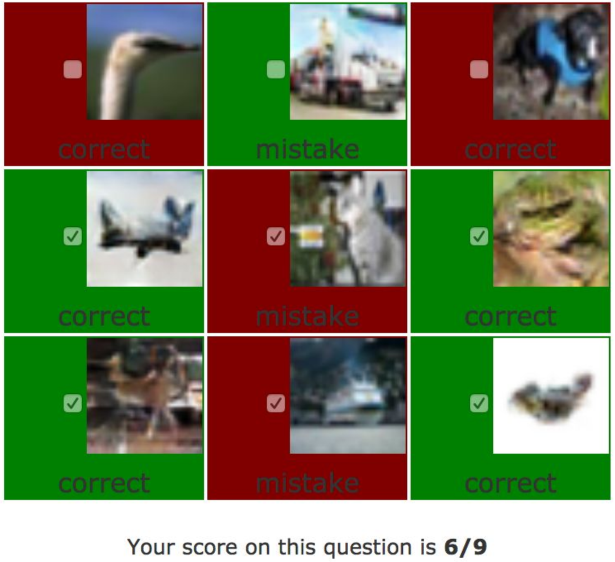
And More...

- **Historical Averaging:** $||\boldsymbol{\theta} - \frac{1}{t}\sum_{i=1}^{t}\boldsymbol{\theta}[i]||^2$
- **Label Smoothing:**
    - e.g., 0.1 or 0.9 instead of 0 or 1
    - Negative values set to zero
- **Virtual Batch Normalization:**
    - Each batch normalized w.r.t a fixed reference
    - Expensive, used only in generator

Assessing Results

Ask Somebody

- Solution: Amazon Mechanical Turk
- Problem:
    - "TASK IS HARD."
    - Humans are slow, and unreliable, and ...
- Annotators learn from mistakes



(http://infinite-chamber-35121.herokuapp.com/cifar-minibatch/)

Inception Score

- Run output through Inception Model
- Images with meaningful objects should have a label distribution (p(y|x)) with low entropy
- Set of output images should be varied
- Proposed score:

$$\exp(\mathbb{E}_{\boldsymbol{x}} \mathrm{KL}(p(y|\boldsymbol{x}) || p(y)))$$

- Requires large data sets (>50,000 images)

Semi-Supervised Learning

Semi-Supervision

- We can incorporate generator output into any classifier
- Include generated samples into data set
- New “generated” label class
    - [Label_1, Label_2, …, Label_n, Generated]
- Classifier can now act as our discriminator

(Odena, “Semi-Supervised Learning with Generative Adversarial Networks” -- https://arxiv.org/pdf/1606.01583v1.pdf)

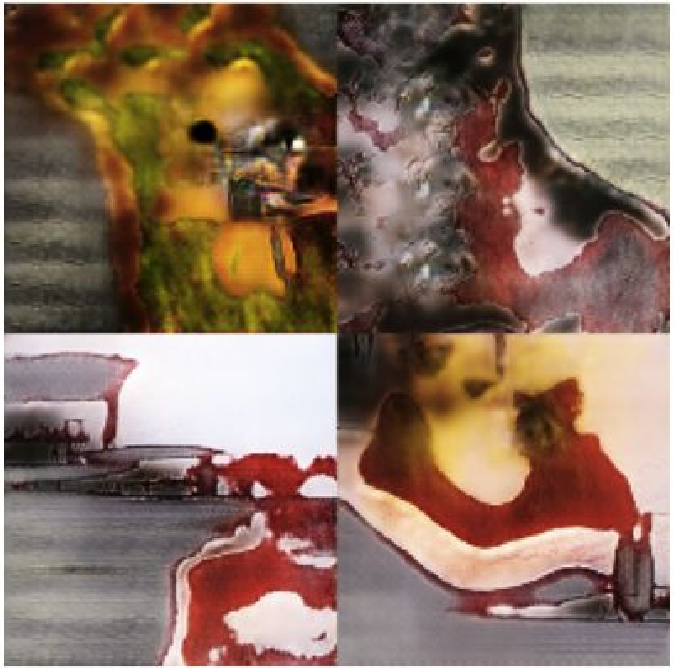
Experimental Results

Generating from MNIST

Semi-Supervised generation without (left) and with (right) minibatch discrimination


Generating from ILSVRC2012

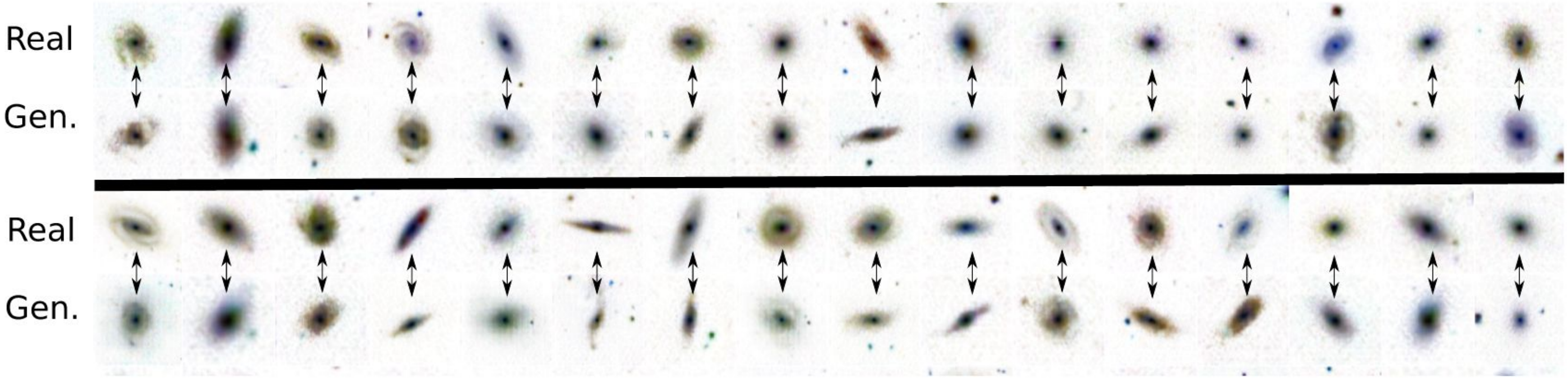
Using DCGAN to generate without (left) and with (right) improvements



Where to go from here

Further Work

- Mini-batch Discrimination in action: https://arxiv.org/pdf/1609.05796v1.pdf
  - Generating realistic images of galaxies for telescope calibration



- MBD for energy based systems:
  - https://arxiv.org/pdf/1609.03126v2.pdf

Adversarial Autoencoders (AAEs)

Adversarial Autoencoders (Makhzani, et. al 2015)

CSC 2541 (07/10/2016)

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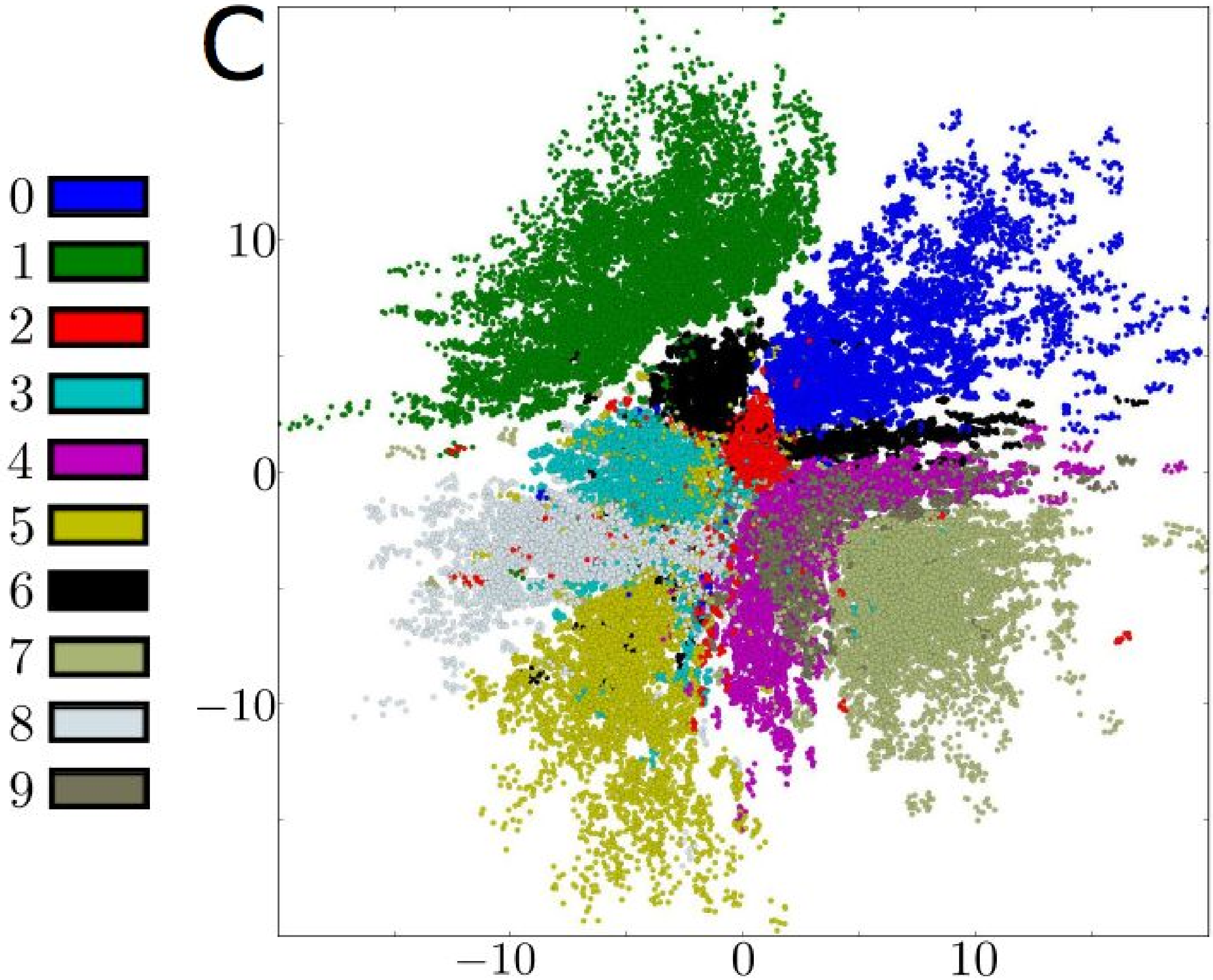
Variational Autoencoders (VAEs)

- Maximize the variational lower bound (ELBO) of $\log p(x)$:

$$\mathcal{L}(\phi, \theta, \mathbf{x}) = -D_{KL}\left(\underbrace{q_\phi(\mathbf{z}|\mathbf{x})||p_\theta(\mathbf{z})}_{\substack{\text{Divergence of } q \text{ from prior} \\ \text{(regularization)}}}\right) + \mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x})}\left(\underbrace{\log p_\theta(\mathbf{x}|\mathbf{z})}_{\text{Reconstruction quality}}\right)$$

Motivation: an issue with VAEs

- After training a VAE, we can feed samples from the latent prior ($p(z)$) to the decoder ($p(x|z)$) to generate data points
- Unfortunately, in practice, VAEs often leave “holes” in the prior’s space which don’t map to realistic data samples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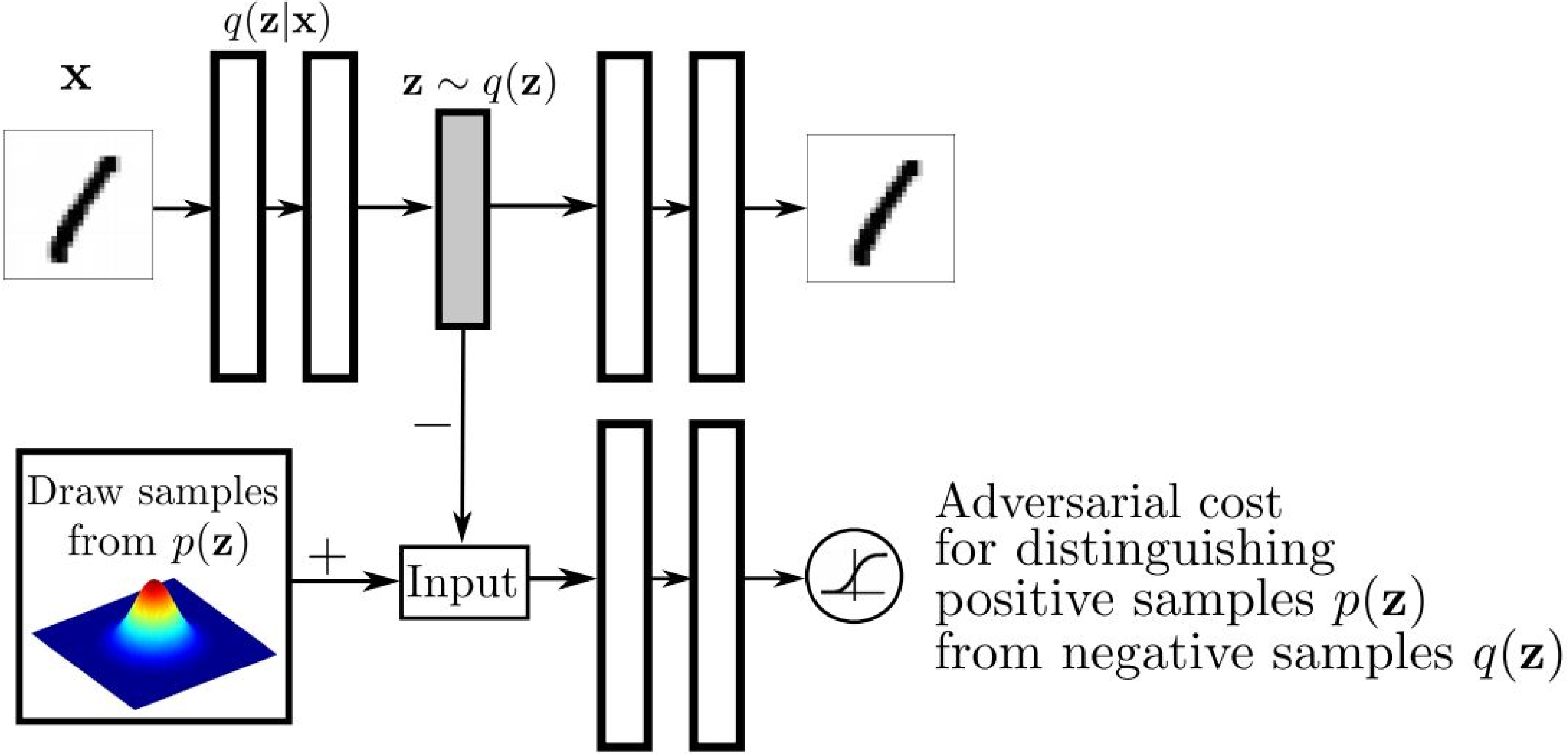
From VAEs to Adversarial Autoencoders (AAEs)

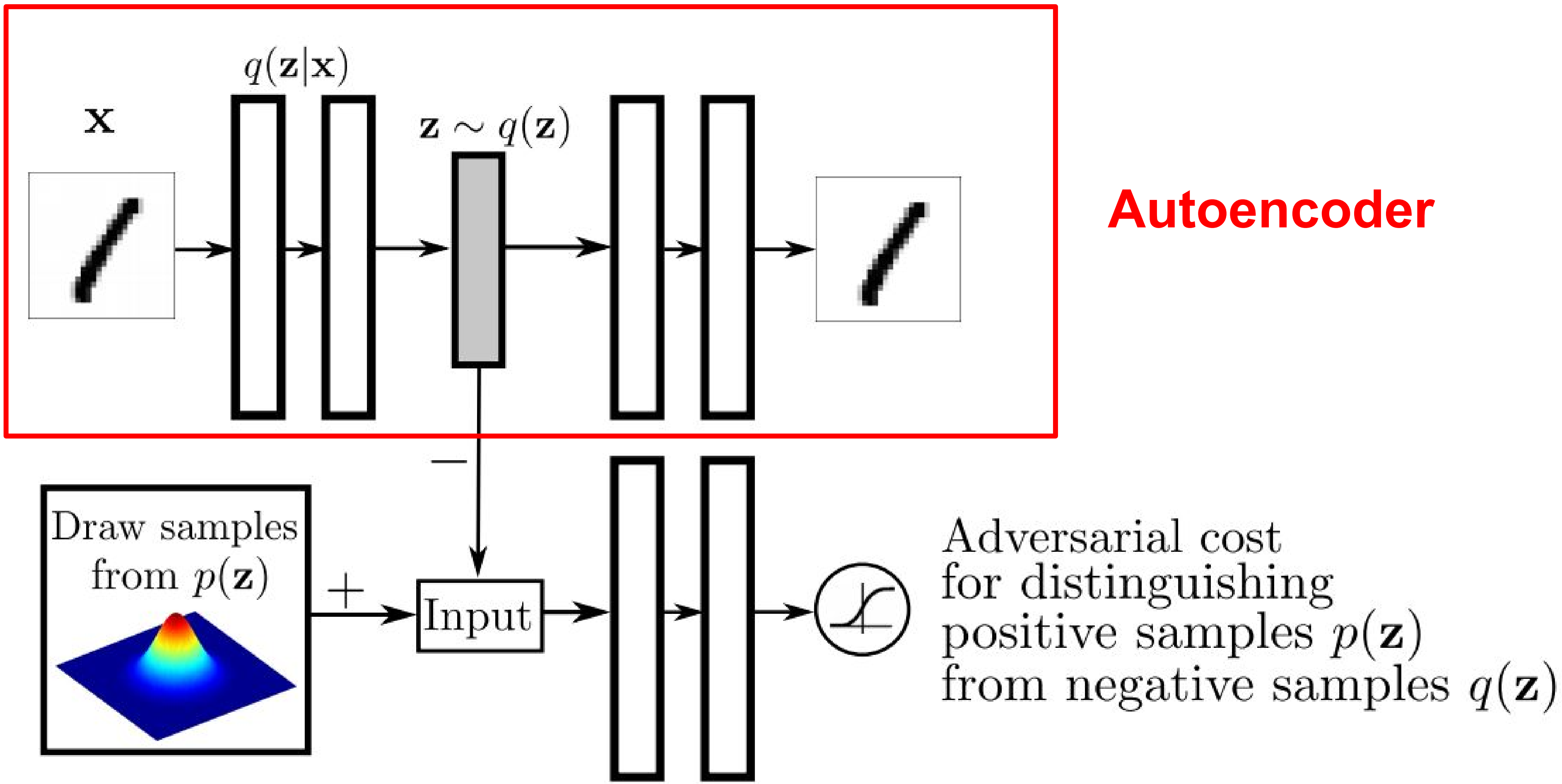
- Both turn autoencoders into generative models
- Both try to minimize reconstruction error
- A prior distribution $p(z)$ is imposed on the encoder ($q(z)$) in both cases, but in different ways:
  - VAEs: Minimizes $KL(q(z)||p(z))$
  - AAEs: Uses adversarial training (GAN framework)

Adversarial Autoencoders (AAEs)

- Combine an autocoder with a GAN
  - Encoder is the generator, $G(x)$
  - Discriminator, $D(z)$, trained to differentiate between samples from prior $p(z)$ and encoder output ($q(z)$)
- Autoencoder portion attempts to minimize reconstruction error
- Adversarial network guides $q(z)$ to match prior $p(z)$



$q(\mathbf{z}|\mathbf{x})$
$\mathbf{x}$
$\mathbf{z} \sim q(\mathbf{z})$
$-$
Draw samples from $p(\mathbf{z})$
$+$
Input
Adversarial cost for distinguishing positive samples $p(\mathbf{z})$ from negative samples $q(\mathbf{z})$


$q(\mathbf{z}|\mathbf{x})$
$\mathbf{x}$
$\mathbf{z} \sim q(\mathbf{z})$
Autoencoder
$-$
Draw samples from $p(\mathbf{z})$
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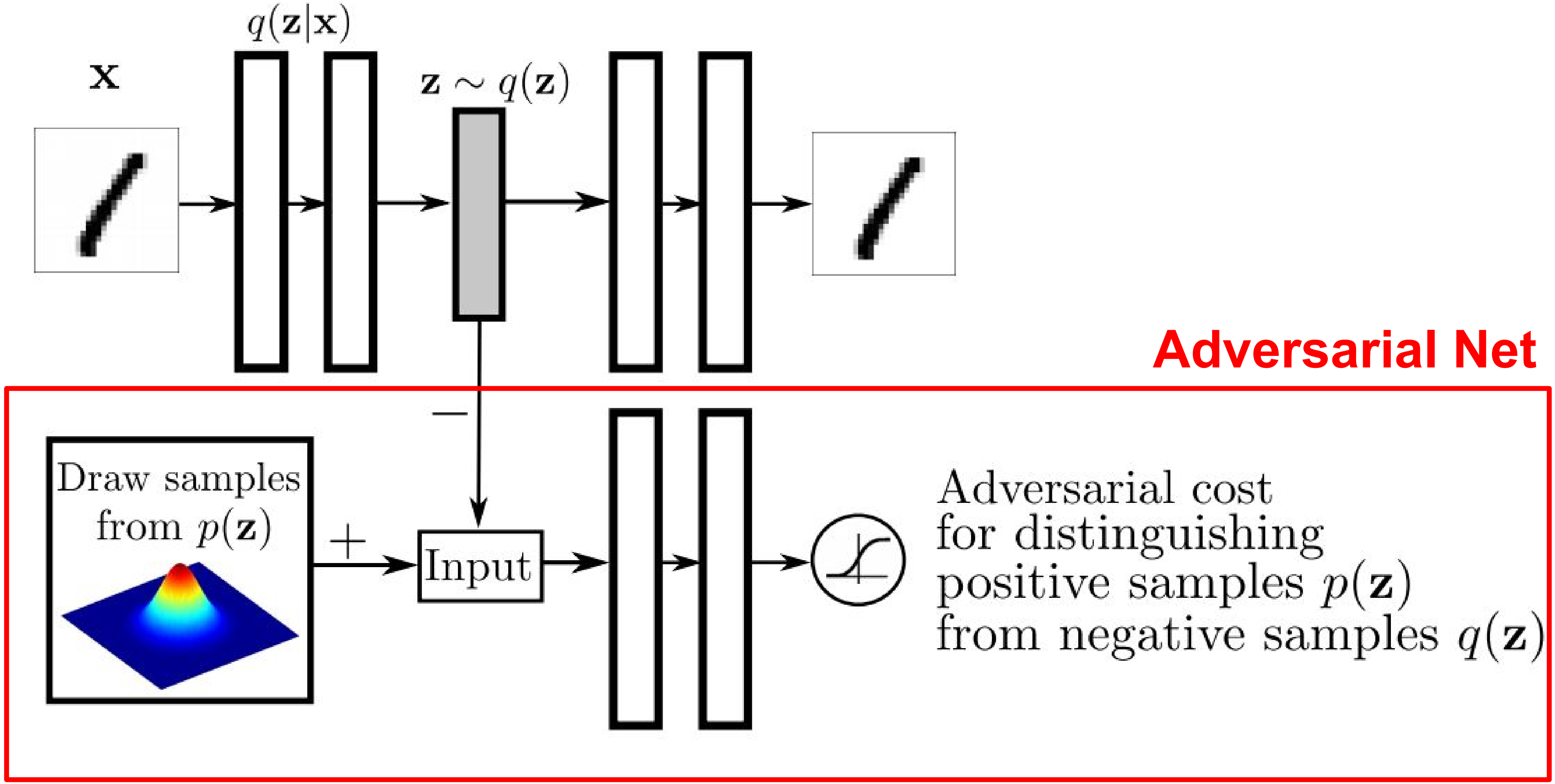
Input
Adversarial cost for distinguishing positive samples $p(\mathbf{z})$ from negative samples $q(\mathbf{z})$

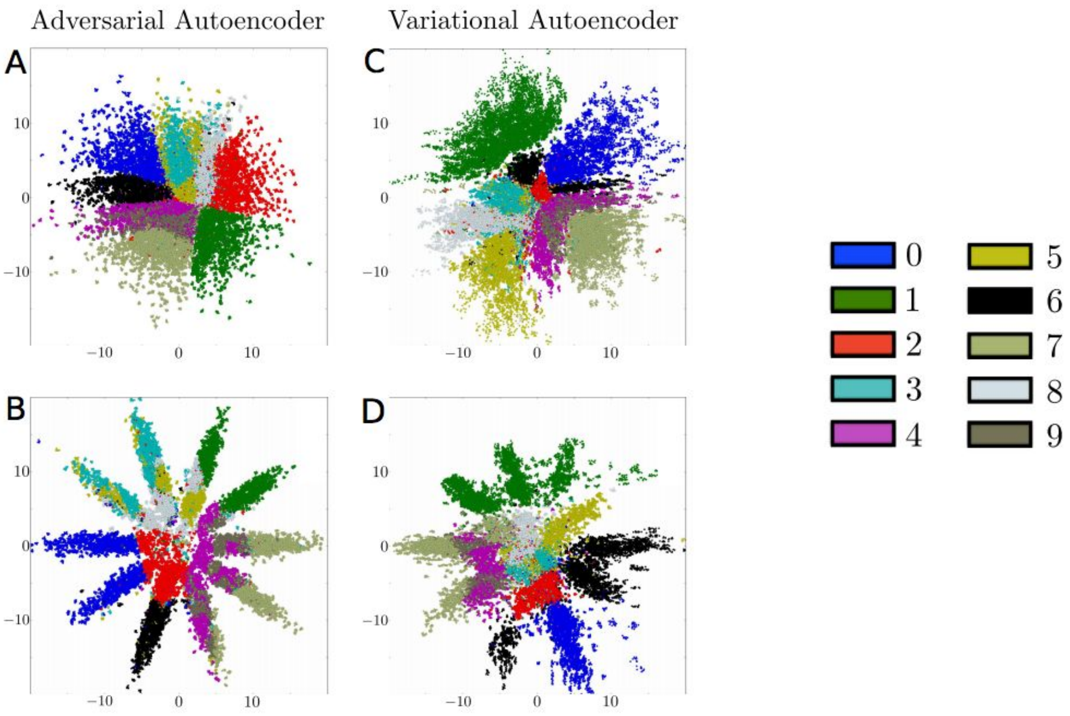


$q(\mathbf{z}|\mathbf{x})$
$\mathbf{x}$
$\mathbf{z} \sim q(\mathbf{z})$
Adversarial Net
$-$
Draw samples from $p(\mathbf{z})$
$+$
Input
Adversarial cost for distinguishing positive samples $p(\mathbf{z})$ from negative samples $q(\mathbf{z})$

Training

- Train jointly with SGD in two phases
- "*Reconstruction*" phase (autoencoder):
    - Run data through encoder and decoder, update both based on reconstruction loss
- "*Regularization*" phase (adversarial net):
    - Run data through encoder to "generate" codes in the latent space
        - Update $D(z)$ based on its ability to distinguish between samples from prior and encoder output
        - Then update $G(x)$ based on its ability to fool $D(z)$ into thinking codes came from the prior, $p(z)$

Resulting latent spaces of AAEs vs VAEs

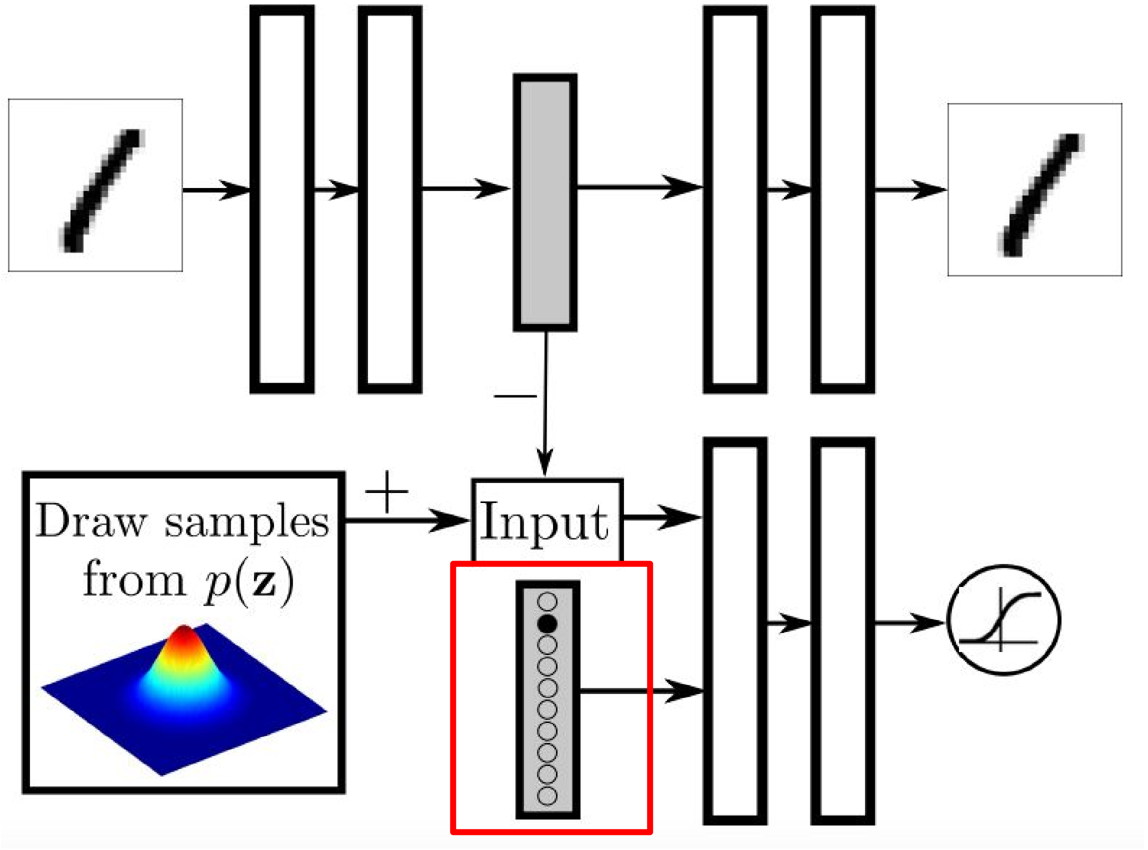


AAE vs VAE on MNIST (held out images in latent space)

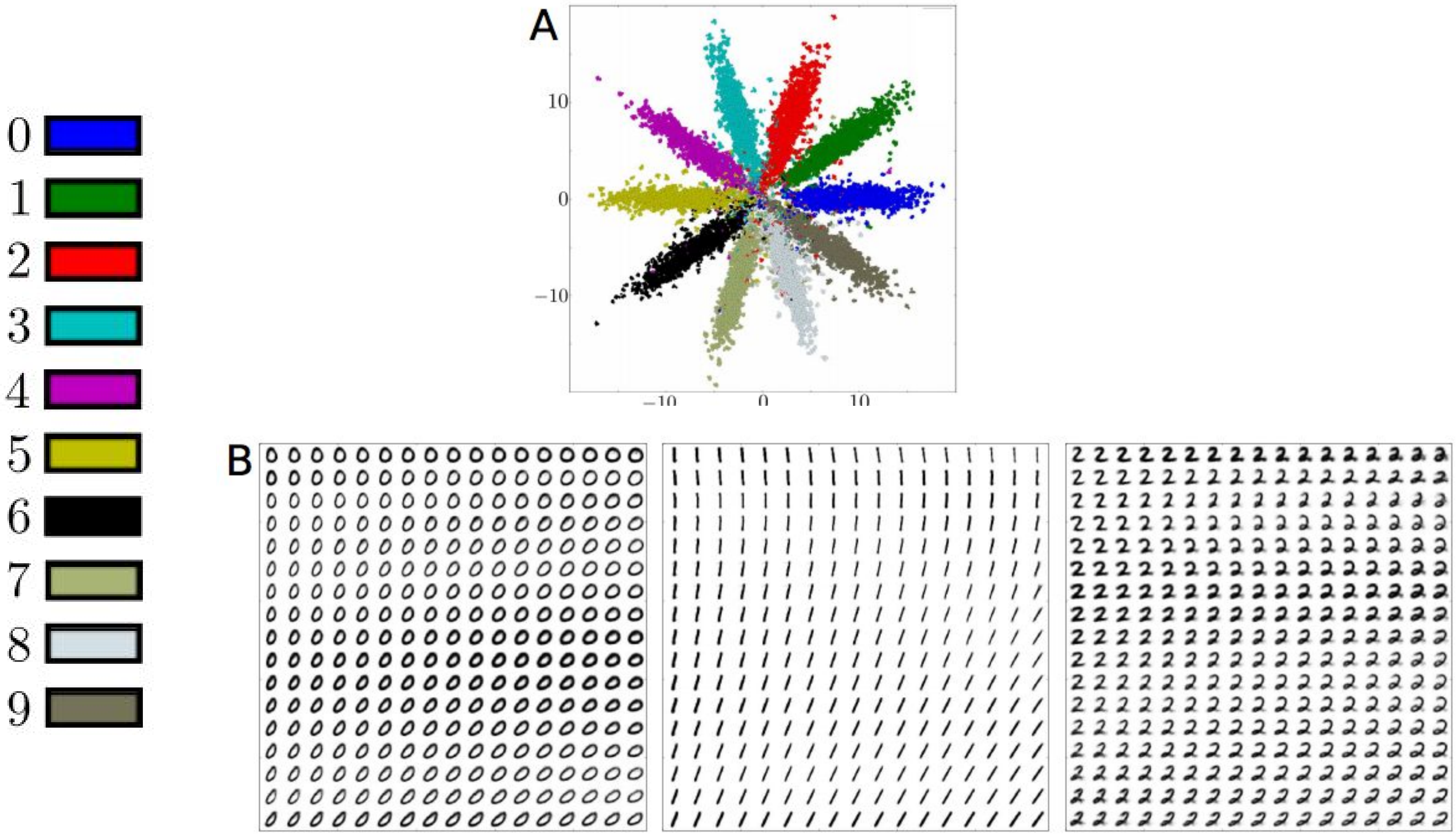
- First row: Spherical 2-D Gaussian prior
- Second row: MoG prior (10 components)

Possible Modifications

Incorporating Label Info



Incorporating Label Info



Possible Applications

Example Samples

(a) MNIST samples (8-D Gaussian)

(b) TFD samples (15-D Gaussian)

Unsupervised Clustering

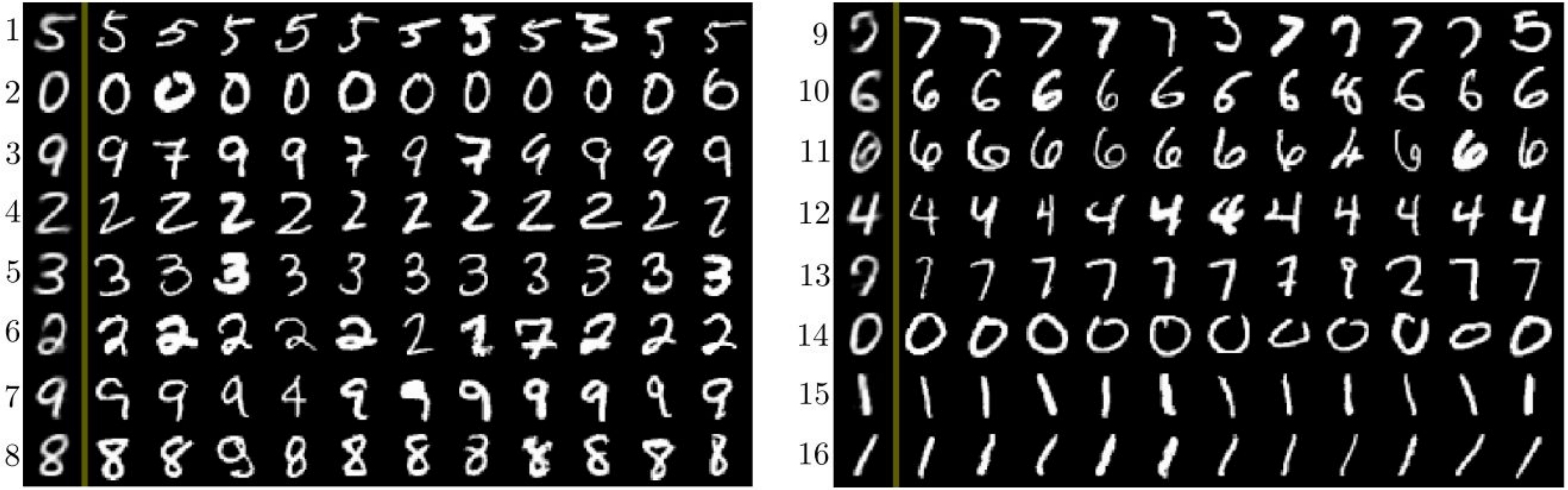
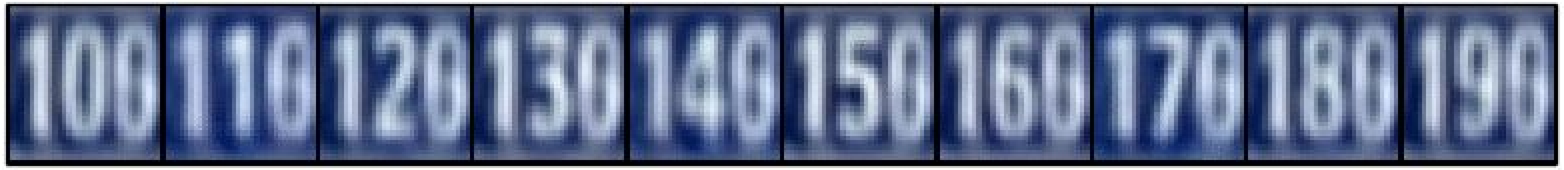
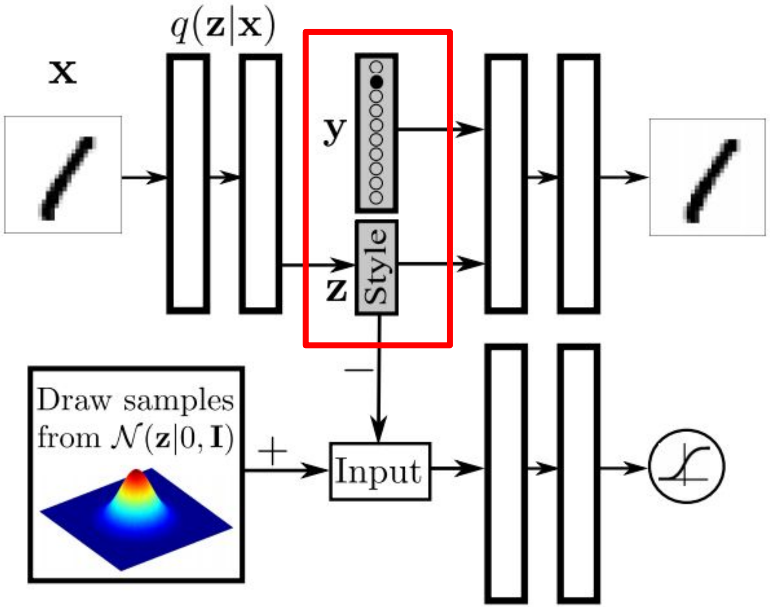


Figure 9: Unsupervised clustering of MNIST using the AAE with 16 clusters. Each row corresponds to one cluster with the first image being the cluster head. (see text)

Disentangling Style/Content



http://www.comm.utoronto.ca/~makhzani/adv_ae/svhn.gif



More Applications...

- Dimensionality reduction
- Data visualization
- …
  (see paper for more)

Further reading

Nice blog post on AAEs: http://hjweide.github.io/adversarial-autoencoders

Thanks!