Unsupervised Learning

BOSTON UNIVERSITY
MACHINE INTELLIGENCE COMMUNITY

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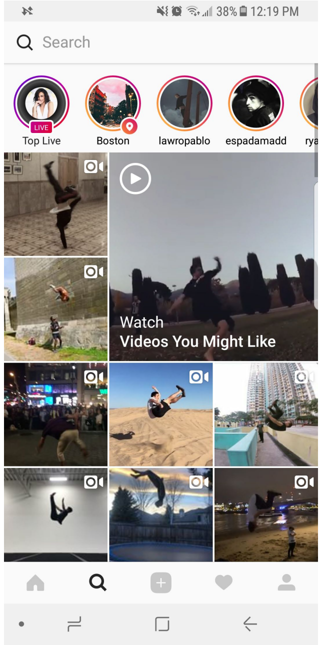
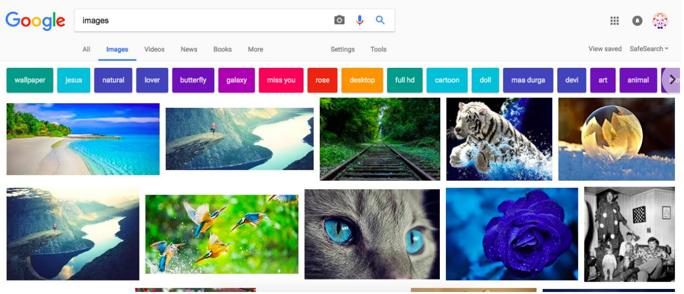
Nov. 28, 2017

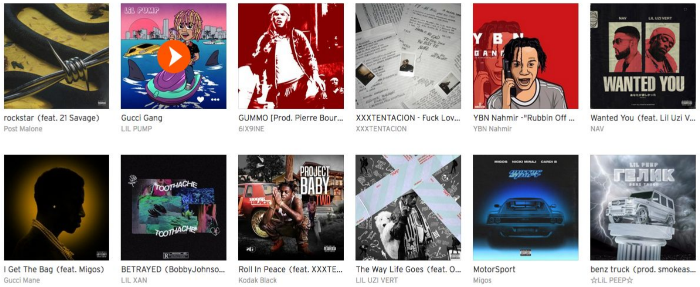
Brief Recap

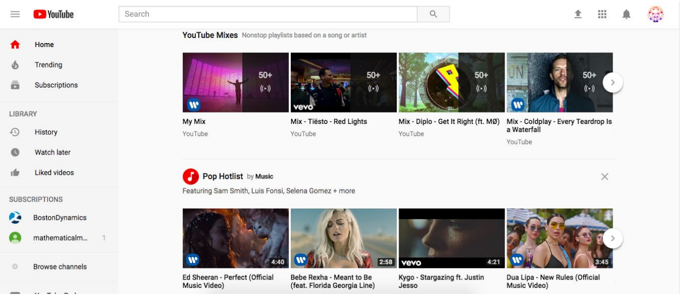
- Supervised Learning
- Reinforcement Learning
- Discriminative models
- Generative models

Motivation: Abundance of Unlabeled Data









Taxonomy of Unsupervised Learning

Unsupervised Learning

- **Non-probabilistic Models**
  e.g. Autoencoders
- **Probabilistic Models**
  - **Explicit Density**
    - **Tractable**
      e.g. Pixel RNN
    - **Intractable**
      e.g. Variational Autoencoders
  - **Implicit Density**
    e.g. Generative Adversarial Networks

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http://www.cs.cmu.edu/~rsalakhu/talk_unsup.pdf

Generative Models

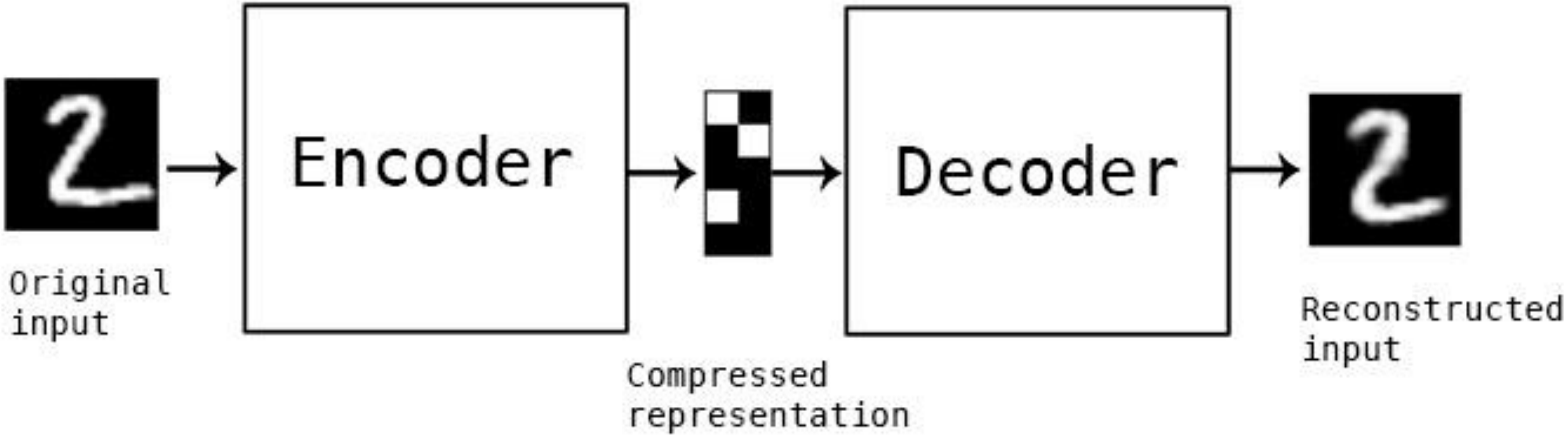
- Models that learn to represent an approximation of a given distribution, given a training set of samples from that distribution
- Examples:
  - Autoencoders
  - Generative Adversarial Networks

Why use generative models?

- Applications in reinforcement learning and semi-supervised learning
- Enable machine learning to adapt to multi-modal outputs
- For tasks that require the generation of good samples

Non-probabilistic Models: Autoencoders

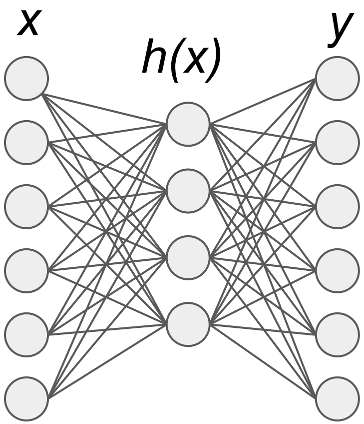
Autoencoders

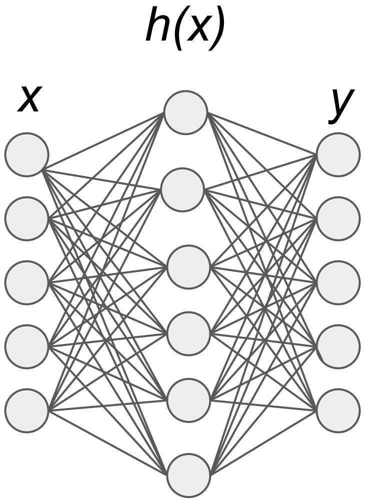


- An autoencoder is a feedforward neural network that outputs a reconstruction of its input

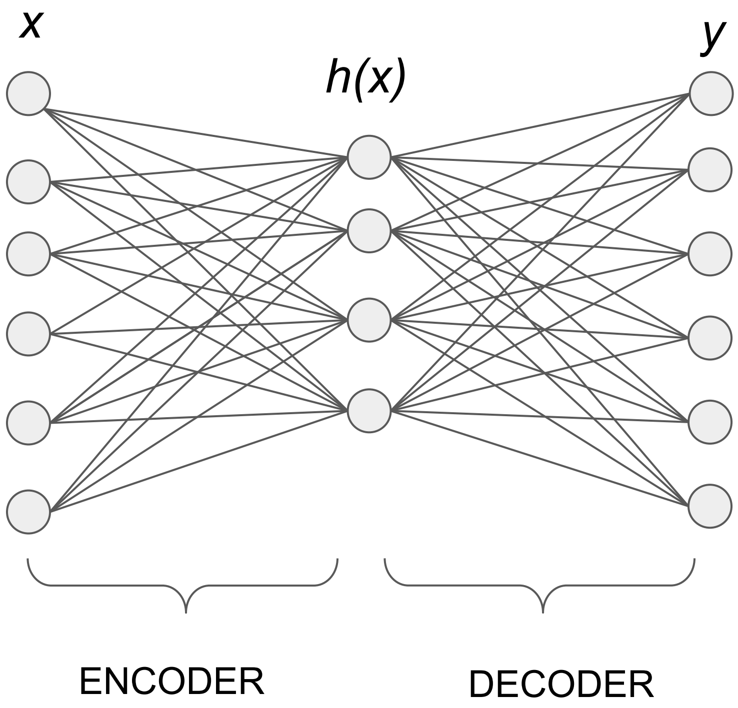
Autoencoders

- Undercomplete: dimensions of *h(x)* are smaller than dimensions of *x*
- Overcomplete: dimensions of *h(x)* are larger than dimensions of x
- Recirculation: alternate method of training autoencoders by comparing activations on original input to activations on reconstructed input



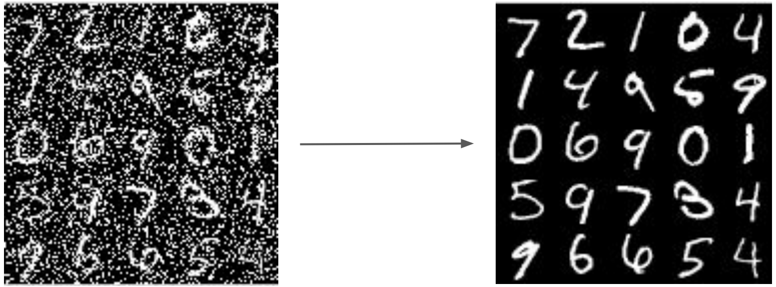


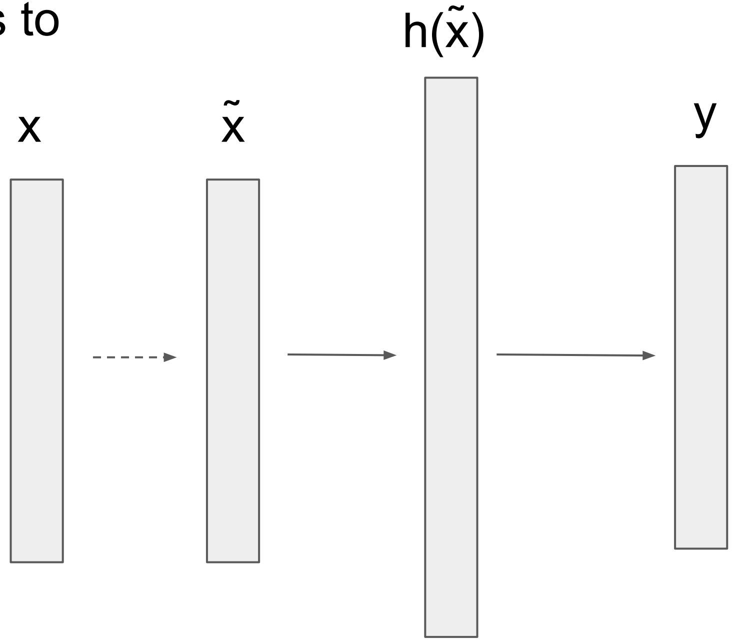
Autoencoders



Denoising Autoencoder

- Given a corrupted dataset, attempts to recover the original data





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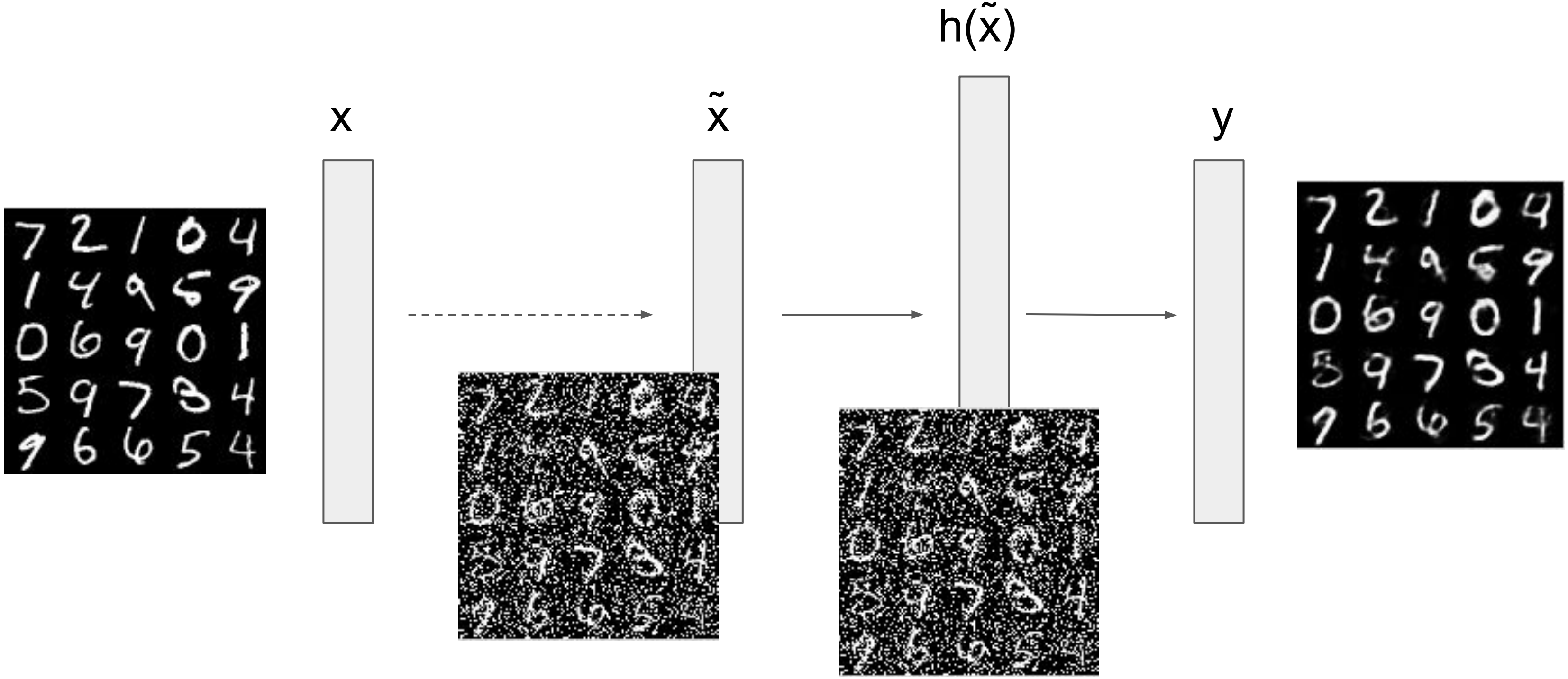
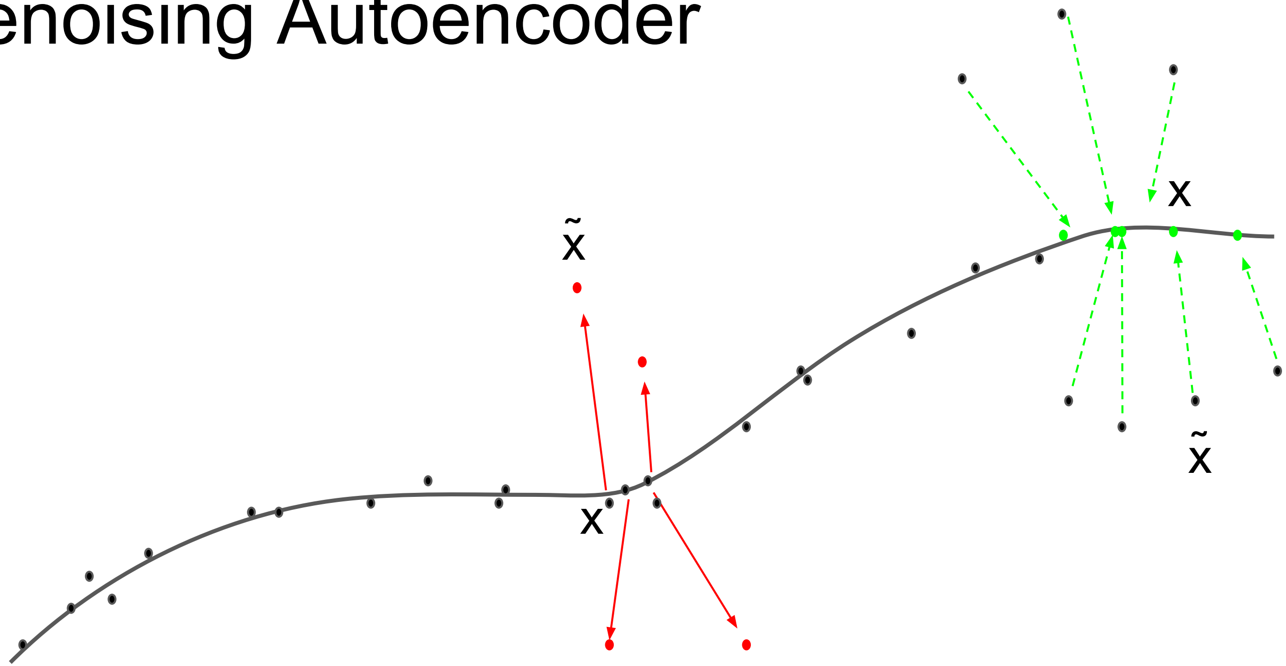
Denoising Autoencoder

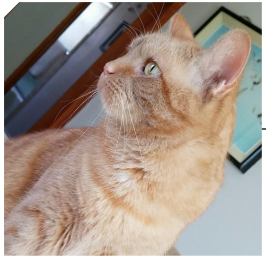


Denoising Autoencoder



Variance Within Datasets

Translation



Rotation

Variance from Transformation

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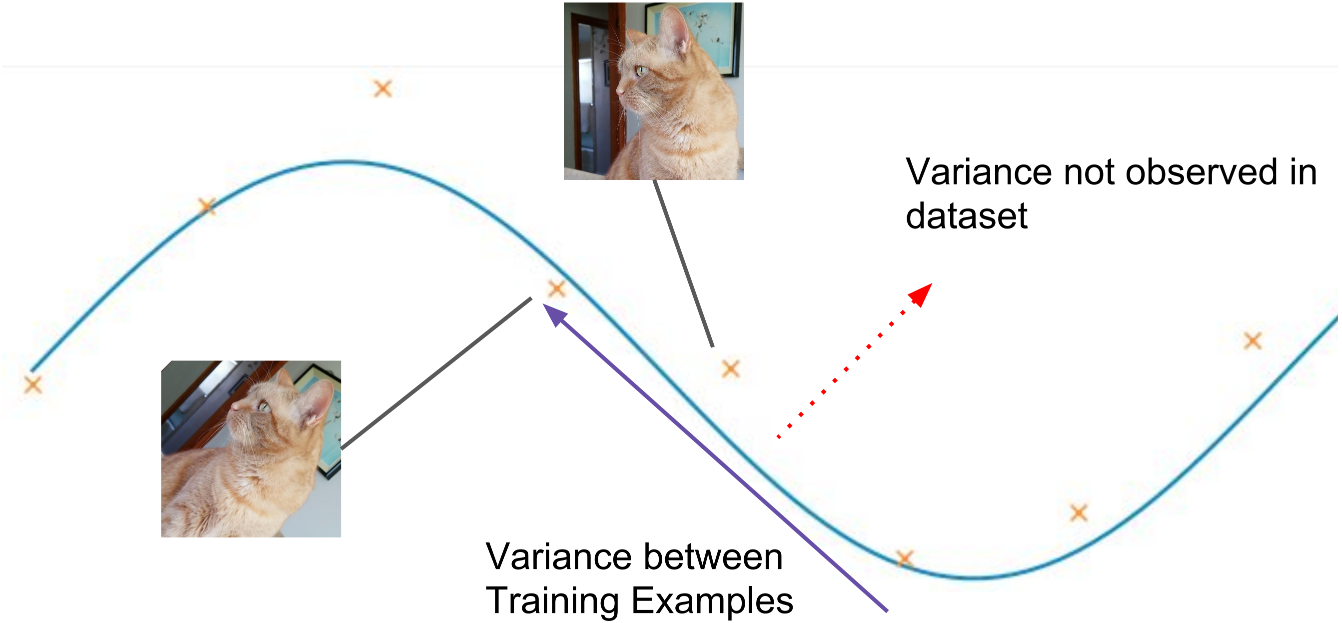
Variance Between Different Features

Contracting Feature Space

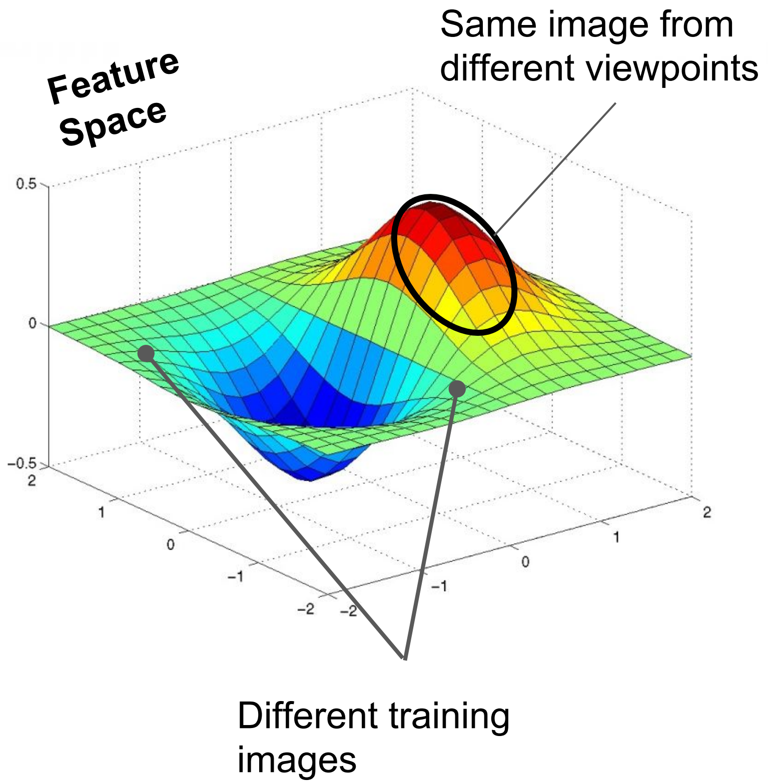


Contractive Autoencoder

Useful Encoder Representation should:

1. Have features **invariant** to small changes around training examples
2. Still be able to **reconstruct** different training examples

*Variation not resulting from training examples will be **contracted** in the feature space*



Loss Function

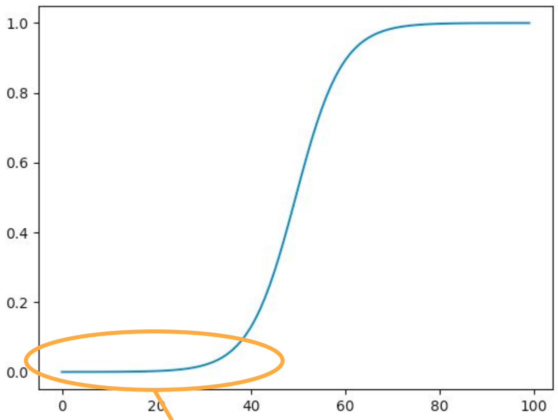
$$\mathcal{J}_{\mathrm{CAE}}(\theta) = \sum_{x \in D_n} \Big(\underbrace{L(x, g(f(x)))}_{\text{Reconstruction Error}} + \overbrace{\lambda}^{\text{Regularization Hyperparameter}} \underbrace{\|J_f(x)\|_F^2}_{\text{Penalizes sensitivity of encoding to input}} \Big)$$

Loss Function

$$\mathcal{J}_{\mathrm{CAE}}(\theta) = \sum_{x \in D_n} \Big(\underbrace{L(x, g(f(x)))}_{\text{Keep useful Information}} + \underbrace{\lambda \|J_f(x)\|_F^2}_{\text{Throw away all information}} \Big)$$

Sparsity and Contraction

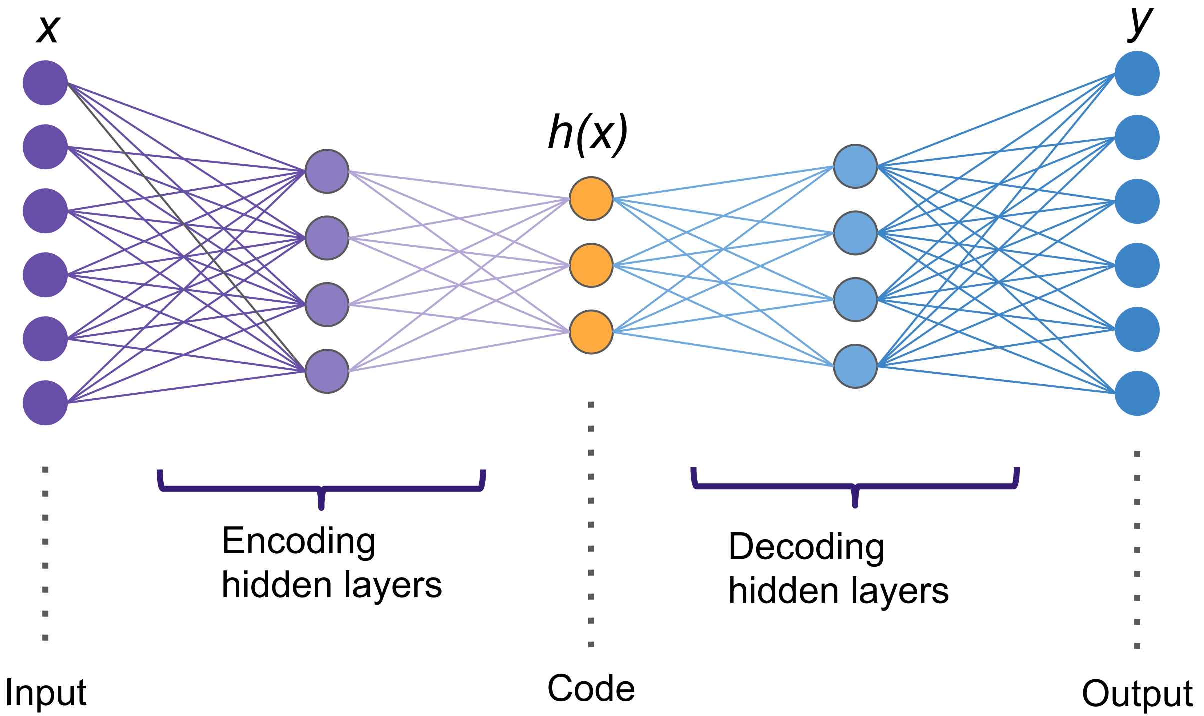
$$\begin{bmatrix} 1 \\ 0 \\ 0 \\ 3.5 \\ 0 \end{bmatrix}$$



Saturation Region

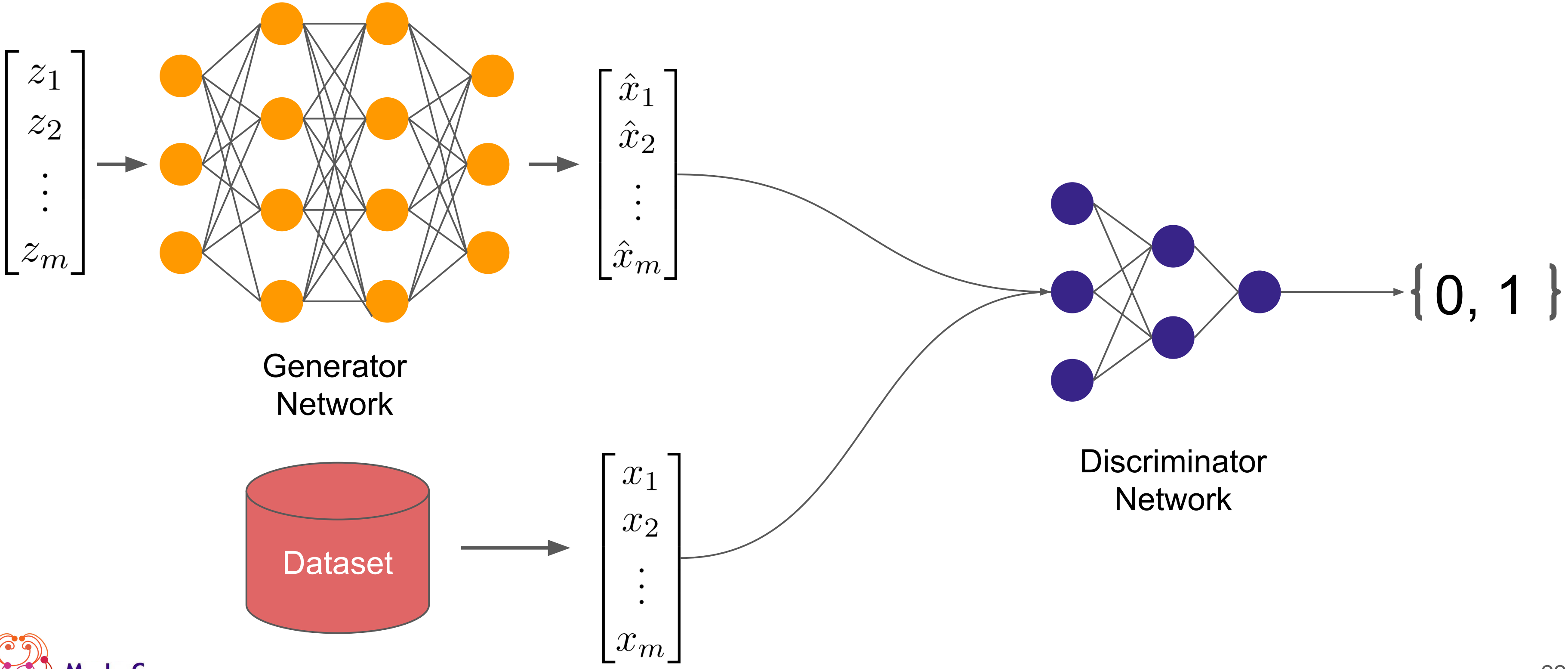
Low values in the Jacobian Matrix

Deep Autoencoders



Probabilistic Models: Generative Adversarial Networks

Generative Adversarial Networks (GAN) Framework



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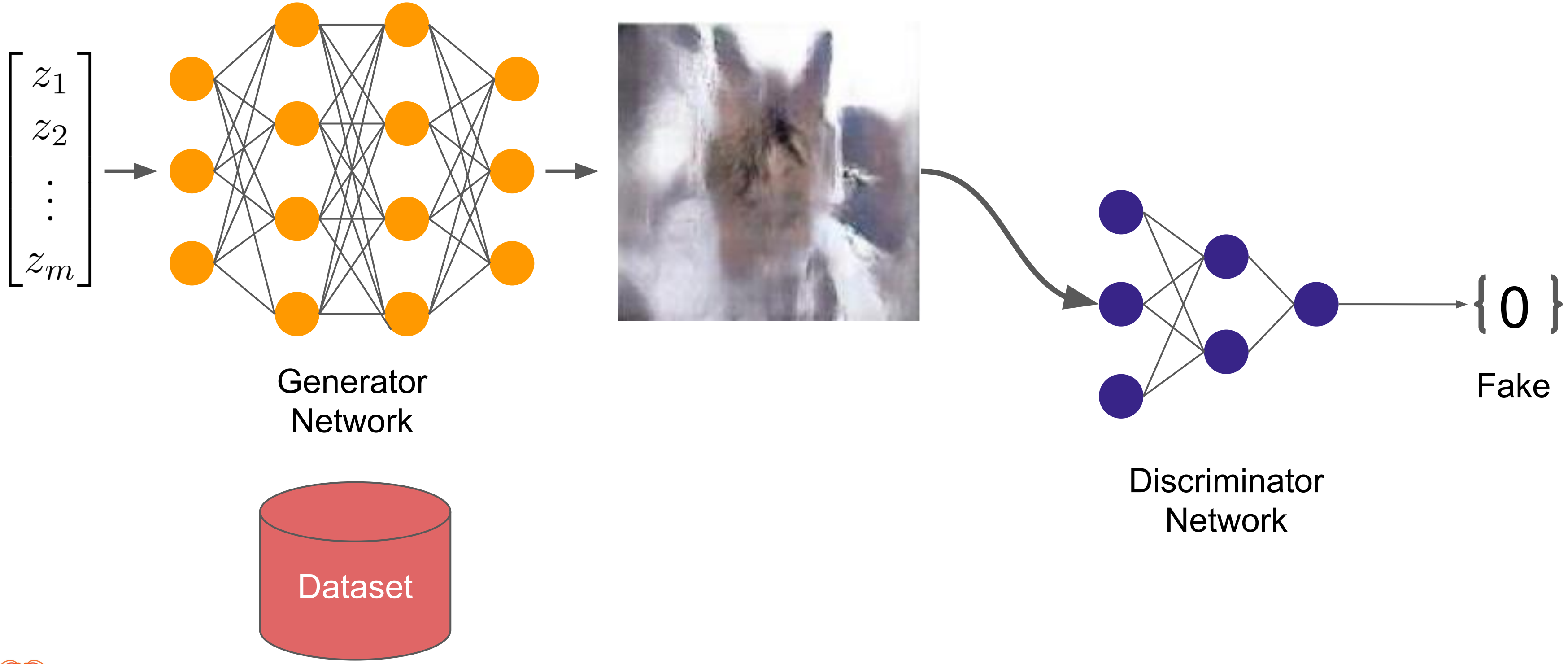
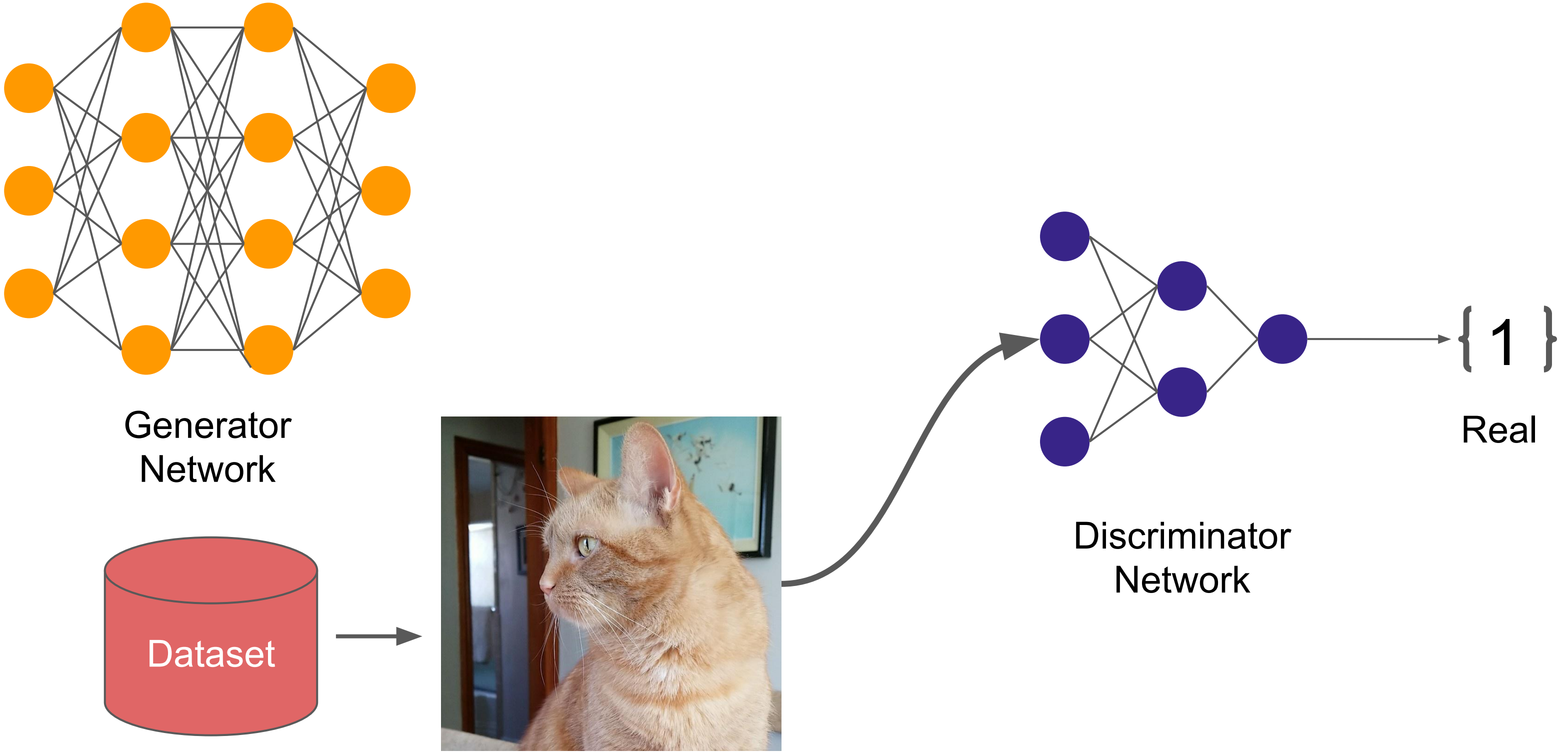
GAN Framework



GAN Framework



GAN Value Function

$$\underbrace{\min_{G} \max_{D}}_{\text{Minimize generator, Maximize discriminator}} V(D,G) = \overbrace{\mathrm{E}_{\underbrace{x\sim p_{data}(x)}_{\text{x distributed according to the data-generating distribution}}}[\log D(x)]}^{\text{Probability that x comes from the data-generating distribution}} + \overbrace{\mathbf{E}_{\underbrace{z\sim p_z(z)}_{\text{z distributed according to the noise distribution}}}[\underbrace{\log}_{\text{Measuring function}}(1 - D(G(z)))]}^{\text{Probability that x comes from the generator's distribution}}$$

Probability that x comes from the data-generating distribution

Probability that x comes from the generator's distribution

Minimize generator
Maximize discriminator

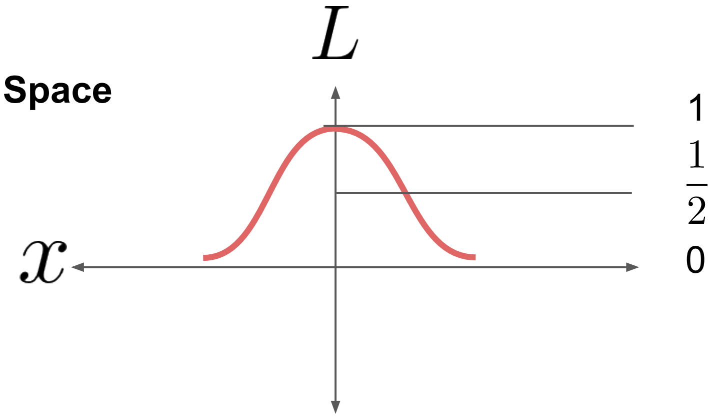
x distributed according to the data-generating distribution

z distributed according to the noise distribution

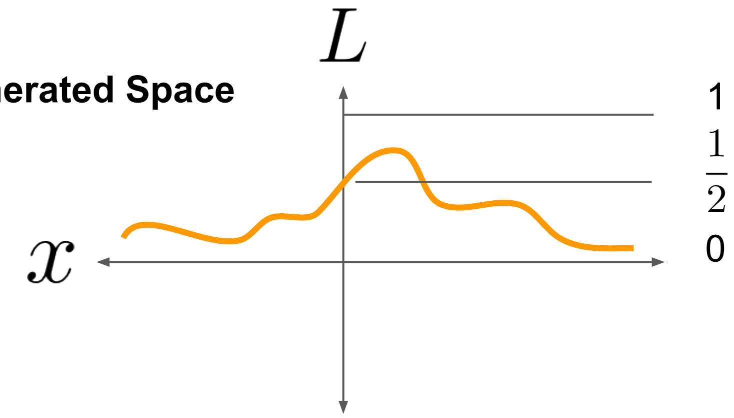
Measuring function - monotonic function that assigns importance to different samples

Conceptual Spaces

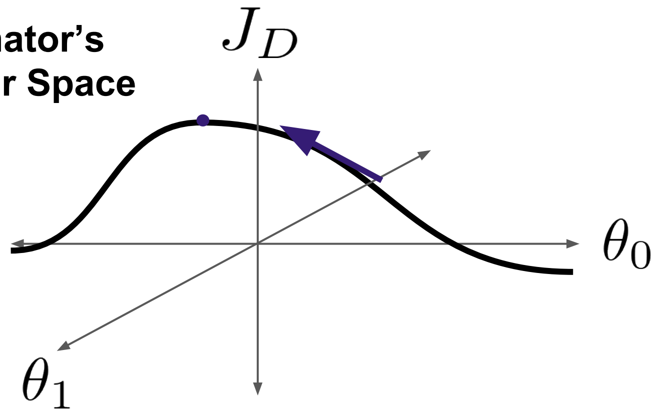
Data Space



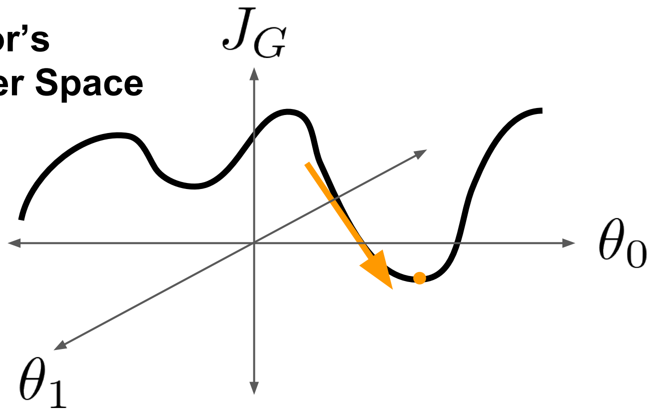
Generated Space



Discriminator's Parameter Space



Generator's Parameter Space



Discriminator Loss

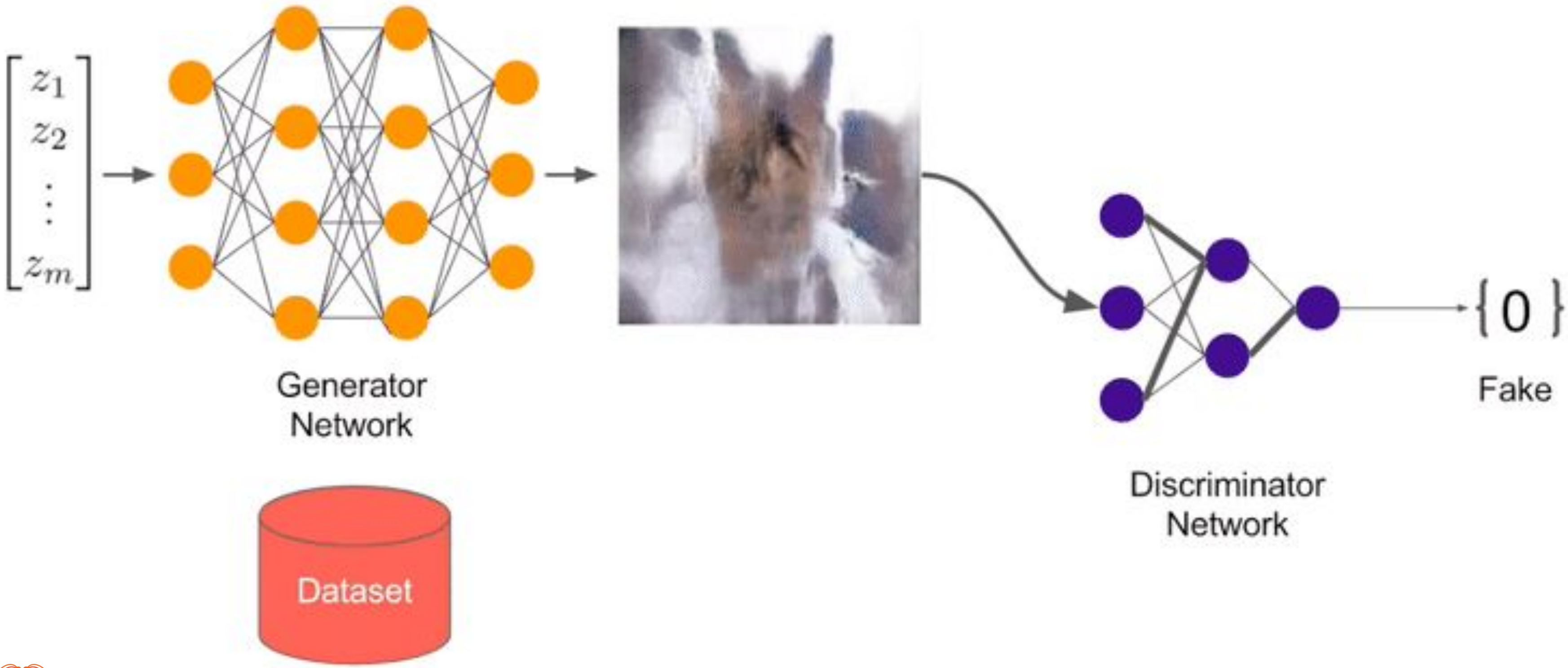
Binary Cross Entropy (BCE) Loss

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} [\underbrace{log\ D(x^{(i)})} + \underbrace{log(1 - D(G(z^{(i)})))}]$$

Loss term for how well D does at determining the positive class

Loss term for how well D does at determining the positive class

Discriminator Training



Generator Loss

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} log(1 - D(G(z^{(i)})))$$

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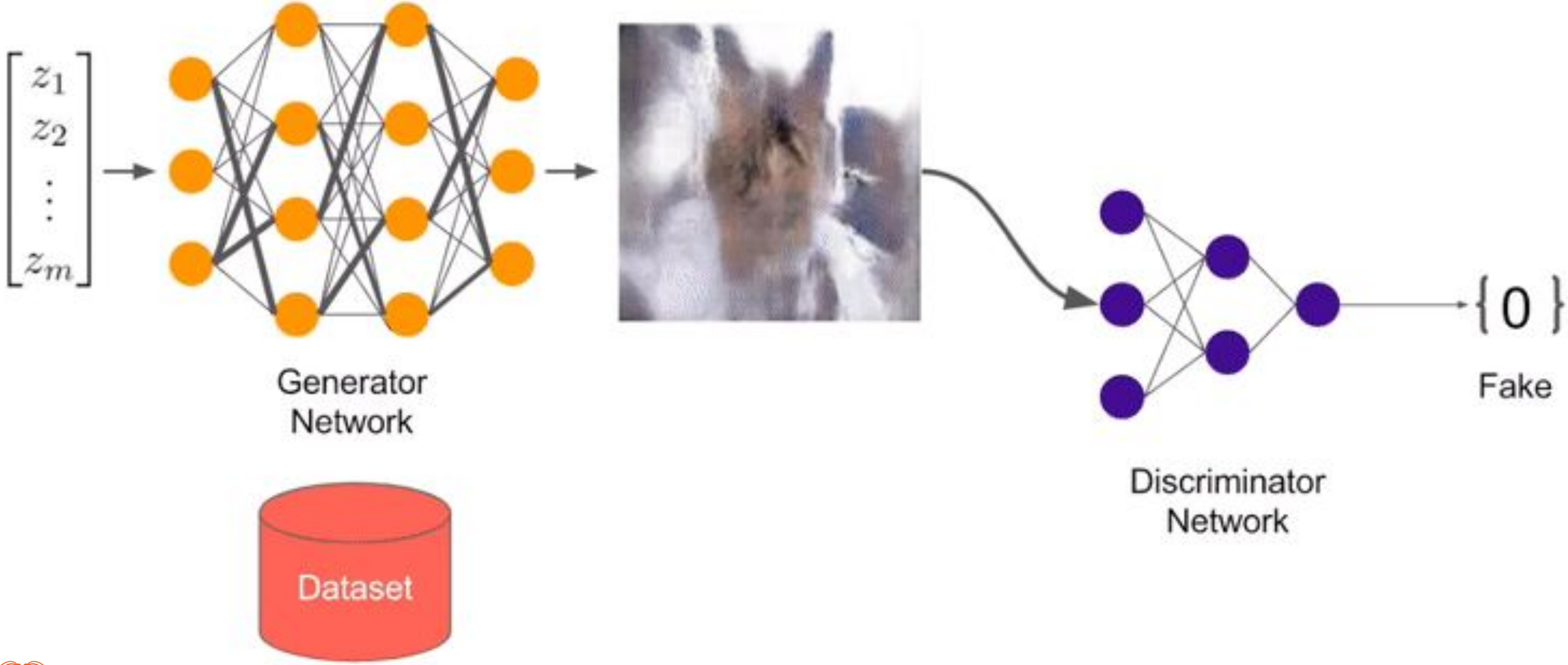
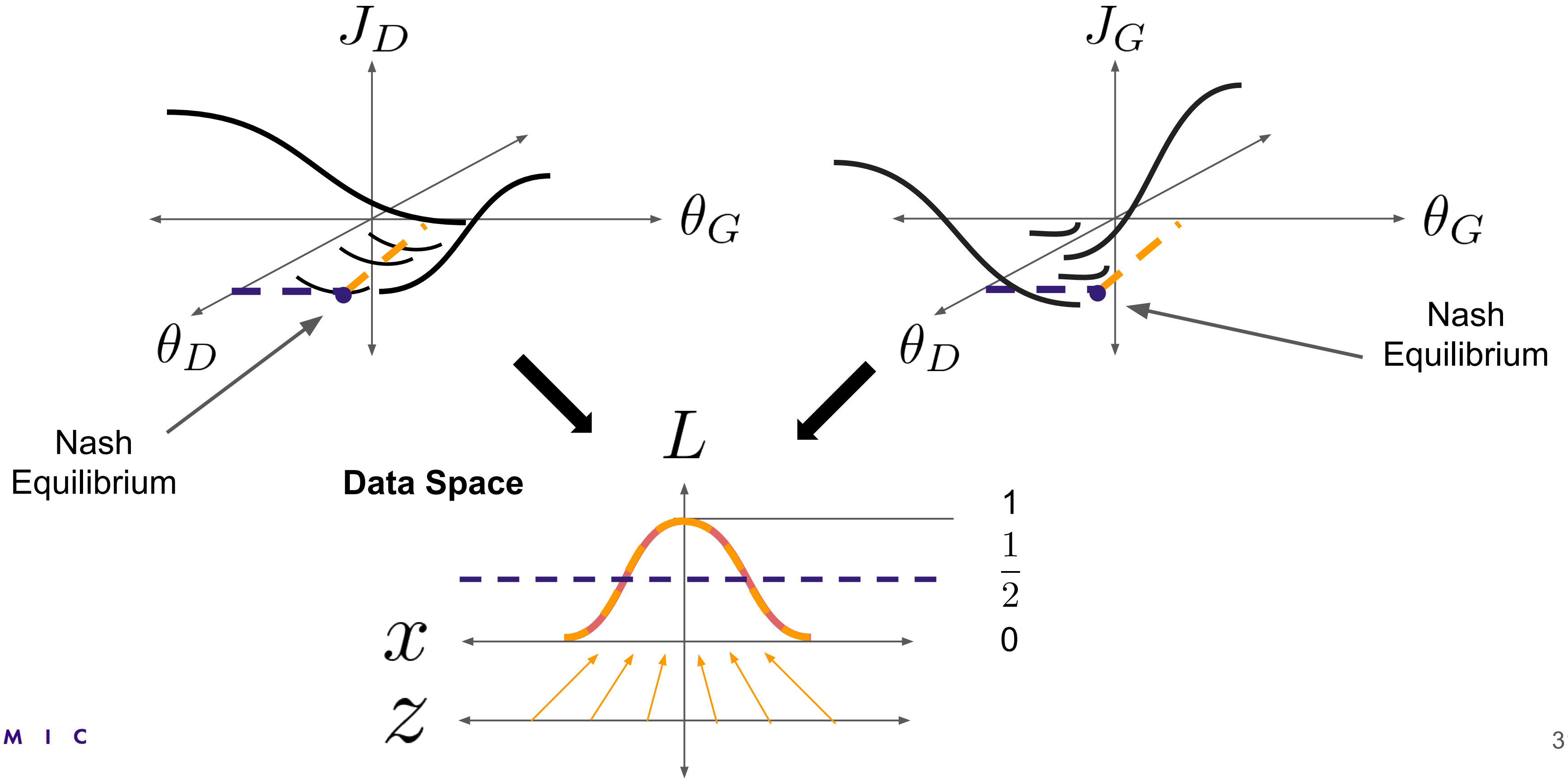
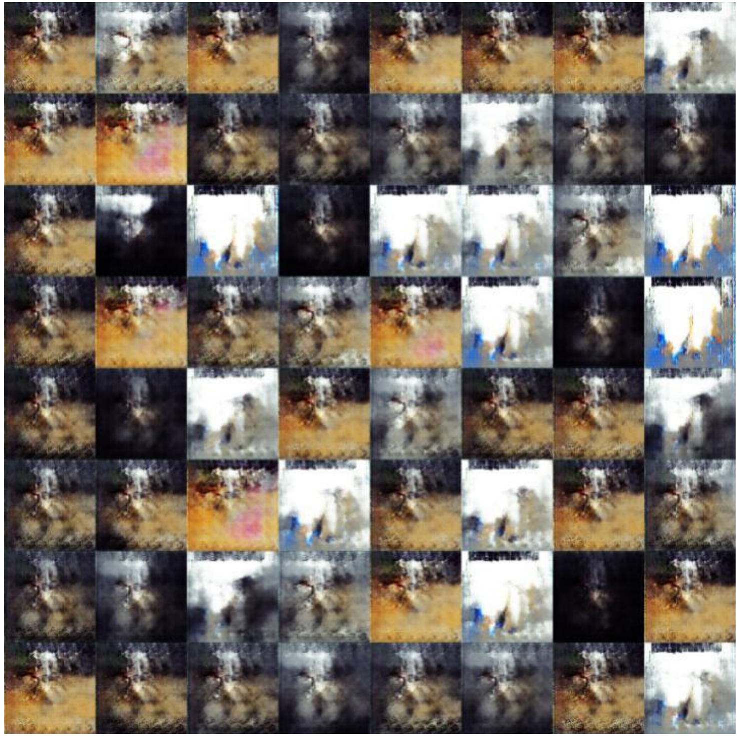
Generator Training



Local Differentiable Nash Equilibria (LDNE)



Mode Collapse (the Helvetica scenario)



Complete Collapse

Partial Collapse

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iGAN

https://www.youtube.com/watch?v=5jfViPdYLic

Progressive Growing of GANs for Improved Quality, Stability, and Variation

https://www.youtube.com/watch?v=XOxxPcy5Gr4

GAN Zoo

3D-GAN
3D-IWGAN
3D-RecGAN
ABC-GAN
AC-GAN
acGAN
AdaGAN
AE-GAN
AEGAN
AffGAN
AL-CGAN
ALI
AlignGAN
AM-GAN
AnoGAN
ARAE
ARDA
ARIGAN
ArtGAN
b-GAN
Bayesian
GAN
Bayesian
GAN
BCGAN
BEGAN
BGAN
BiGAN
BS-GAN
C-RNN-GAN
CaloGAN
CAN
CatGAN
CausalGAN
CC-GAN
CDcGAN
CGAN

CGAN
Chekhov GAN
CM-GAN
CoGAN
Conditional
cycleGAN
constrast-GAN
Context-RNN-GAN
Coulomb GAN
Cramèr GAN
crVAE-GAN
CS-GAN
CVAE-GAN
CycleGAN
D2GAN
DAN
DCGAN
DeliGAN
DiscoGAN
DistanceGAN
DM-GAN
DR-GAN
DRAGAN
DSP-GAN
DTN
DualGAN
Dualing GAN
EBGAN
ED//GAN
EGAN
ExprGAN
f-GAN
FF-GAN
Fila-GAN
Fisher GAN
Flow-GAN
GAMN

GAN
GAN-CLS
GAN-sep
GAN-VFS
GANCS
GAP
GAWWN
GeneGAN
Geometric
GAN
GMAN
GMM-GAN
GoGAN
GP-GAN
GP-GAN
GRAN
IAN
IcGAN
ID-CGAN
iGAN
Improved
GAN
InfoGAN
IRGAN
IWGAN
l-GAN
LAGAN
LAPGAN
LD-GAN
LDAN
LeakGAN
LeGAN
LR-GAN
LS-GAN
LSGAN
MAD-GAN
MAD-GAN

MAGAN
MalGAN
MaliGAN
MARTA-GAN
McGAN
MD-GAN
MDGAN
MedGAN
MGAN
MGGAN
MIX+GAN
MMD-GAN
MMGAN
MoCoGAN
MPM-GAN
MuseGAN
MV-BiGAN
OptionGAN
ORGAN
PAN
PassGAN
Perceptual GAN
PGAN
pix2pix
PixelGAN
Pose-GAN
PPGN
PrGAN
PSGAN
RankGAN
RCGAN
RefineGAN
RenderGAN
ResGAN
RNN-WGAN
RPGAN
RTT-GAN

RWGAN
SAD-GAN
SalGAN
SBADA-GAN
SD-GAN
SEGAN
SeGAN
SegAN
SeqGAN
SGAN
SGAN
SGAN
SimGAN
SketchGAN
SL-GAN
SN-GAN
Softmax-GAN
Splitting GAN
SRGAN
SS-GAN
ss-InfoGAN
SSGAN
SSL-GAN
ST-GAN
StackGAN
SteinGAN
S^2GAN
TAC-GAN
TAN
TextureGAN
TGAN
TP-GAN
Triple-GAN
Unrolled GAN
VAE-GAN
VariGAN
VAW-GAN

VEEGAN
VGAN
VGAN
ViGAN
VIGAN
VRAL
WaterGAN
WGAN
WGAN-GP
WS-GAN
α-GAN
Δ-GAN

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https://deephunt.in/the-gan-zoo-79597dc8c347

References & Further Reading

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2. Radford, Alec, Luke Metz, and Soumith Chintala. "**Unsupervised representation learning with deep convolutional generative adversarial networks**." arXiv preprint arXiv:1511.06434 (2015).
3. Shrivastava, Ashish, et al. "**Learning from simulated and unsupervised images through adversarial training**." arXiv preprint arXiv:1612.07828 (2016).
4. Arjovsky, Martin, Soumith Chintala, and Léon Bottou. "**Wasserstein generative adversarial networks**." International Conference on Machine Learning. 2017.
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7. Salah Rifai, Pascal Vincent, Xavier Muller, Xavier Glorot, Yoshua Bengio. “**Contractive Auto-Encoders: Explicit Invariance During Feature Extraction.**” ICML 2011.
8. Larochelle, Hugo. “**Neural networks [6.7] : Autoencoder - contractive autoencoder.**” https://www.youtube.com/watch?v=79sYlJ8Cvlc.

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Upcoming Events

MIC Paper signup: https://goo.gl/iAm6TL
BUMIC Projects signup: https://goo.gl/GmP9oK

BUMIC paper discussion:

Paper: CryptoNets: Applying Neural Networks to Encrypted Data with High Throughput and Accuracy
Location: Fishbowl Conference Room
Date: 12.4.17 Time: 7 PM

Next workshop:

Topic: Neural Style Transfer
Location: BU Hariri Seminar Room
Date: 12.12.17 Time: 7 PM

Learning to Learn by Discoursing Discourse

Location: Pavement Coffee on Commonwealth Ave

Time: 10 AM

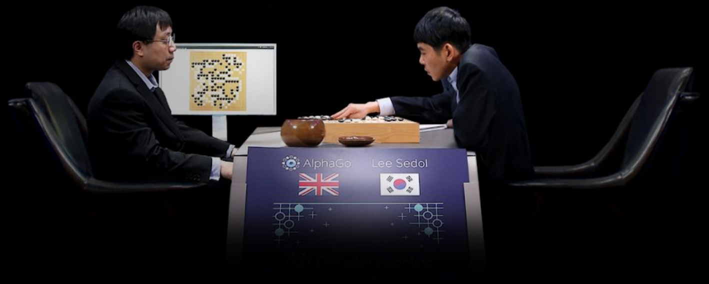
A chill session where we read short and light papers together and trade thought processes for reading papers, develop intuition, and discourse research ideas. A meta exercise in learning to learn by discoursing discourse!

MACHINE INTELLIGENCE COMMUNITY

BU SED 2 Silber Way, Boston, MA, Room 130

Dec. 1st, 2017 7 - 9 PM

https://goo.gl/yNKMhH



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