# Introduction to Generative Models (and GANs)

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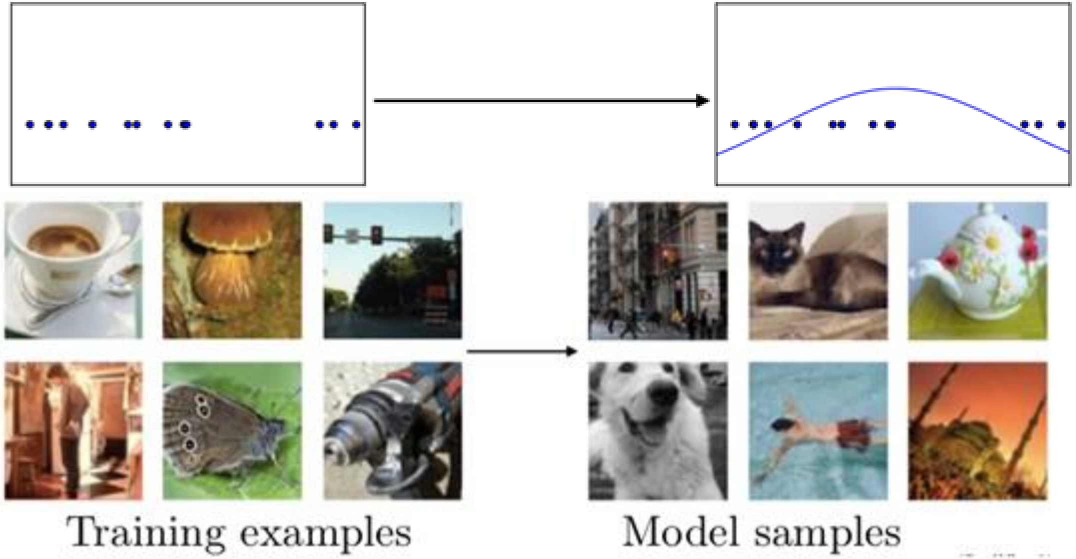
Figures adapted from NIPS 2016 Tutorial Generative Adversarial Networks

# Generative Models: Learning the Distributions

Discriminative: learns the likelihood

Generative: performs Density Estimation (learns the distribution) to allow sampling

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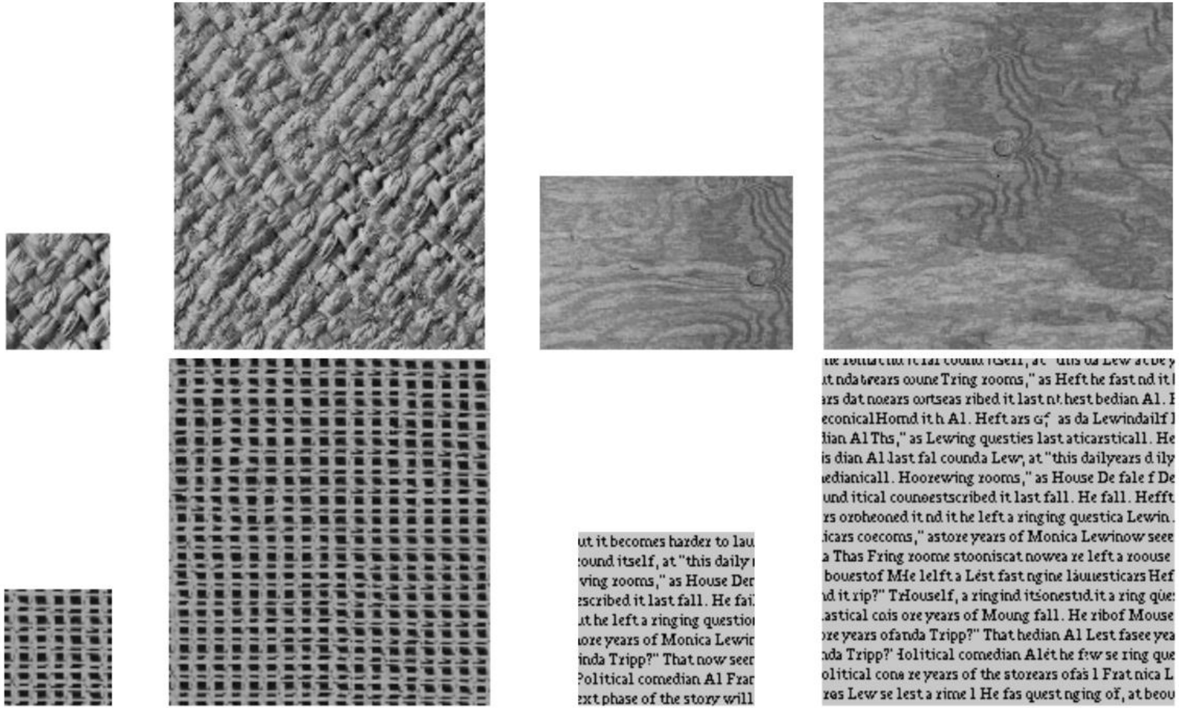
# Texture Synthesis , ICCV 1999

- LUT-based, one pixel at a time.

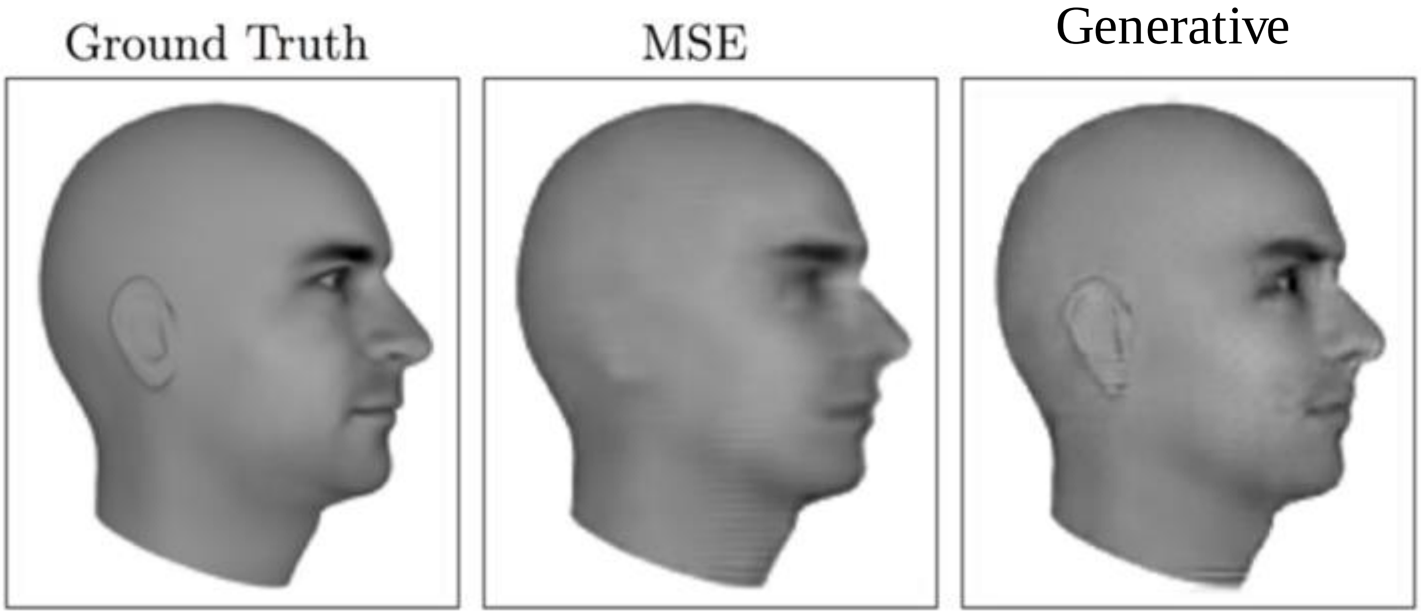


# SinGAN, ICCV 2019

- GAN based, best paper

# Loss function for distribution: Ambiguity and the “blur” effect

MSE: a Discriminative model just smoothes all possibilities.

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# Ambiguity and the "blur" effect

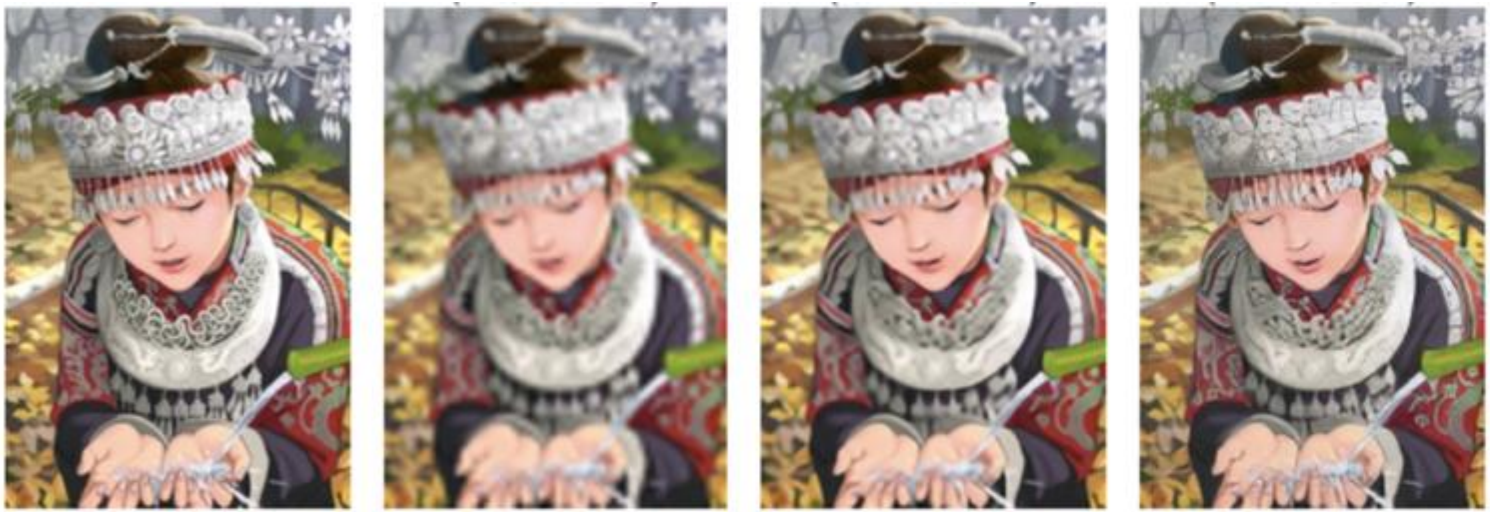

Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network

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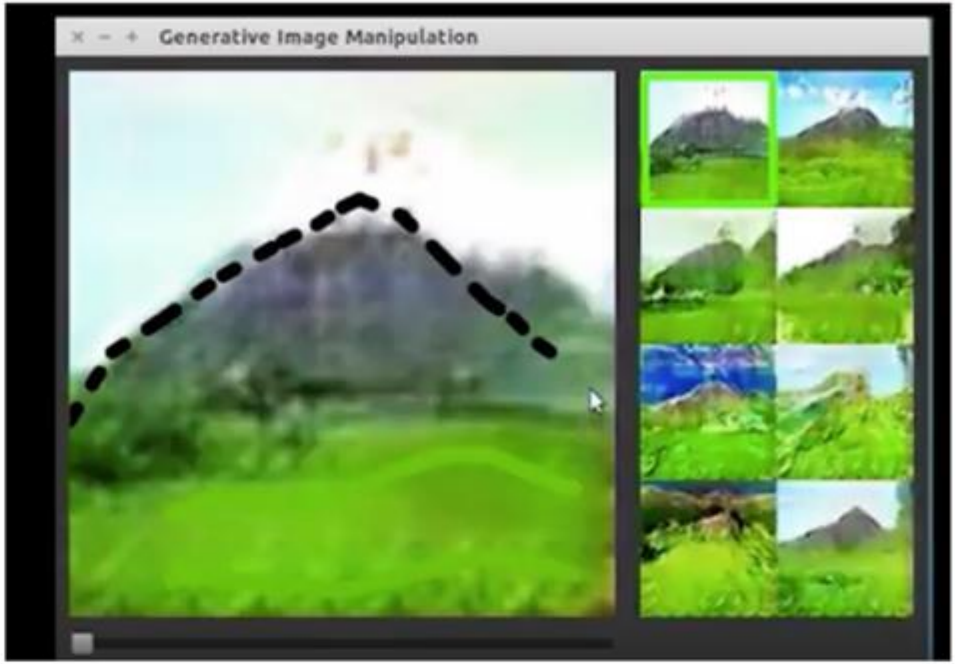
# Example Application of Generative Models

# Image Generation from Sketch




iGAN: Interactive Image Generation via Generative Adversarial Networks

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# Image to Image Translation



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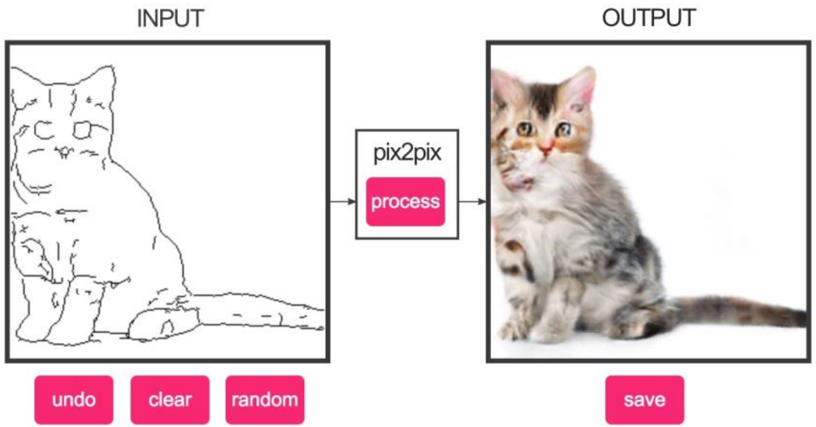
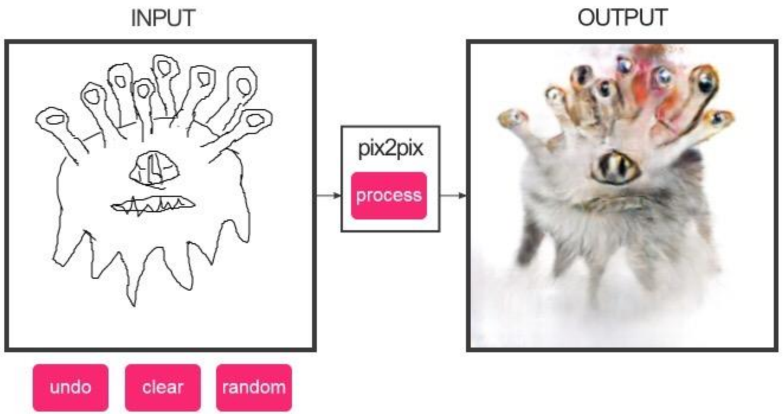
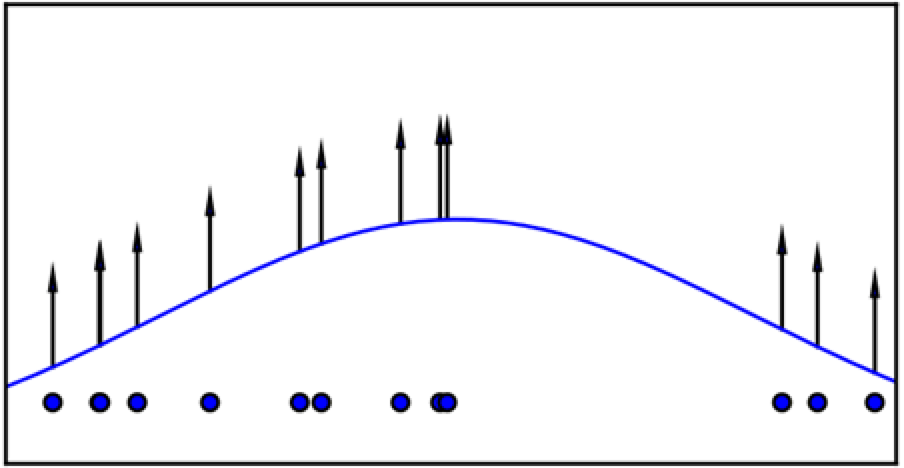

INPUT
OUTPUT
pix2pix
process
undo
clear
random
save


INPUT
OUTPUT
pix2pix
process
undo
clear
random

# How Generative Models are Trained

# Learning Generative Models



$$\boldsymbol{\theta}^* = \arg\max_{\boldsymbol{\theta}} \mathbb{E}_{x\sim p_{\text{data}}} \log p_{\text{model}}(\boldsymbol{x} \mid \boldsymbol{\theta})$$

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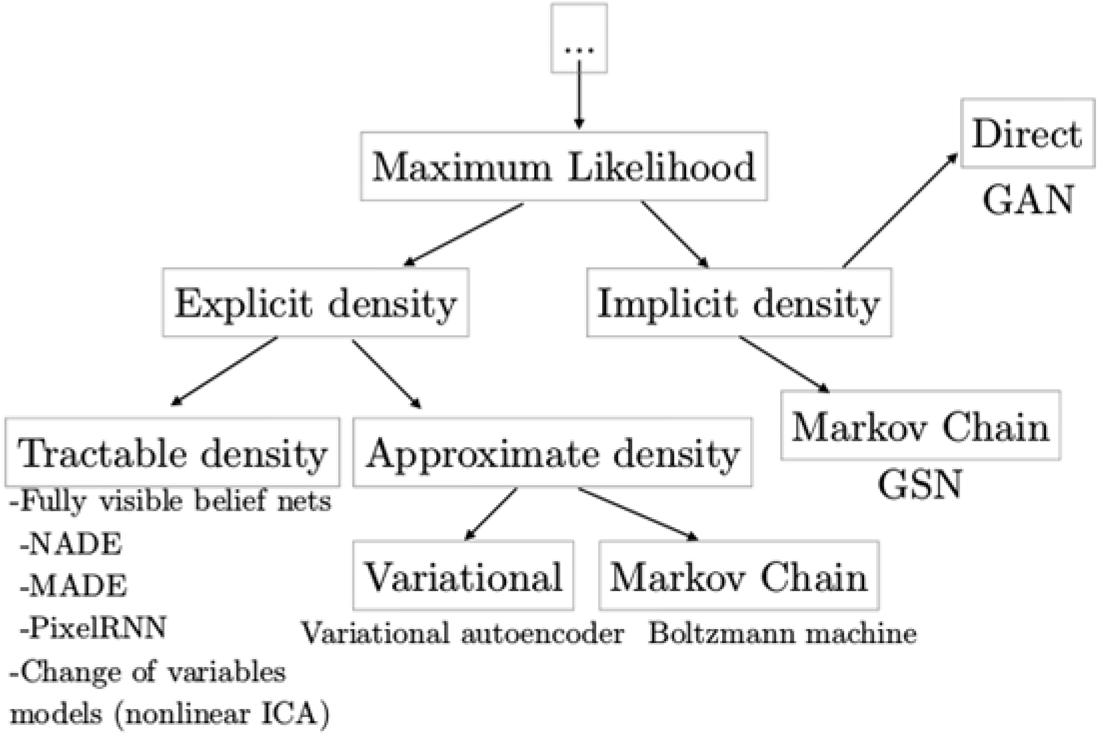
# Taxonomy of Generative Models

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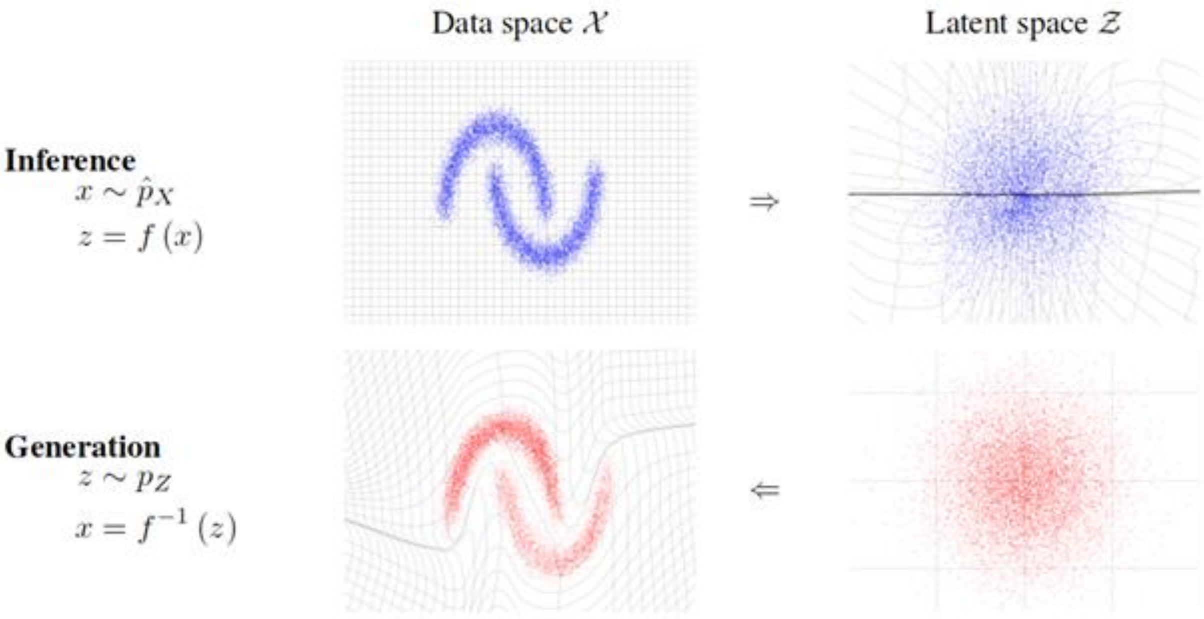
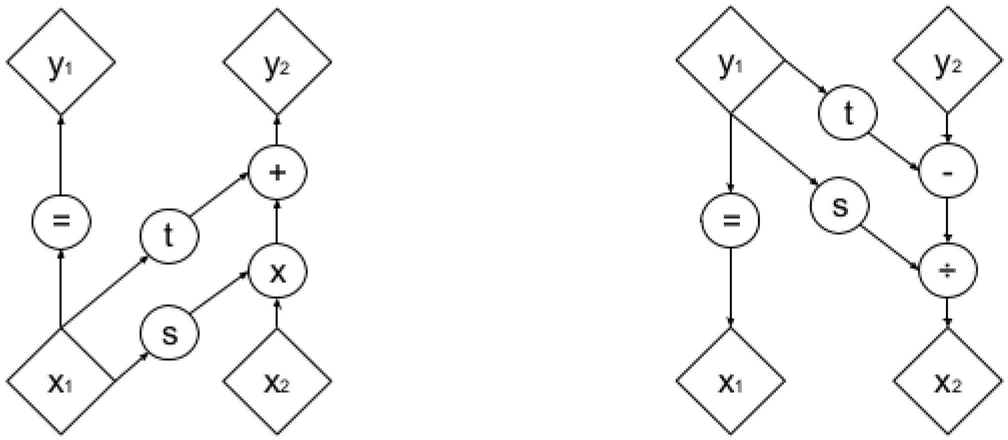
# Exact Model: NVP (non-volume preserving)



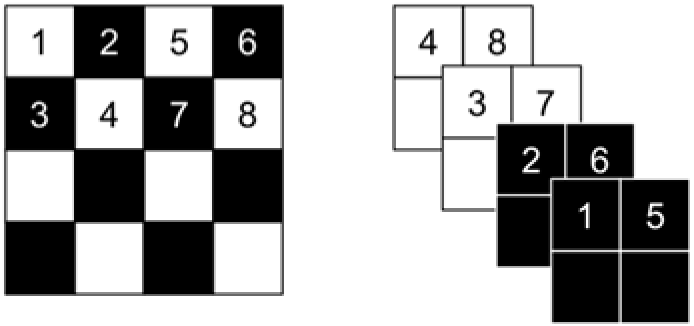

Density estimation using Real NVP https://arxiv.org/abs/1605.08803

# Real NVP: Invertible Non-linear Transforms

$$p_x(\boldsymbol{x}) = p_z(g^{-1}(\boldsymbol{x})) \left| \det \left( \frac{\partial g^{-1}(\boldsymbol{x})}{\partial \boldsymbol{x}} \right) \right| .$$




(a) Forward propagation (b) Inverse propagation




Density estimation using Real NVP

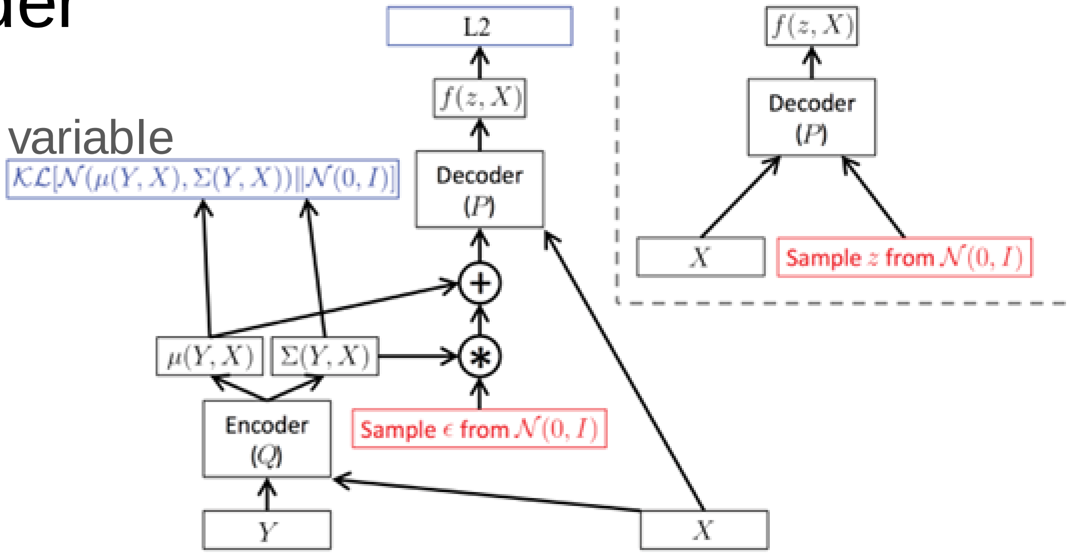
# Real NVP: Examples

# Real NVP

Restriction on the source domain: must be of the same as the target.

# Variational Auto-Encoder

Auto-encoding with noise in hidden variable




$$\log p_{\boldsymbol{\theta}}(\mathbf{x}^{(i)}) = D_{KL}(q_{\boldsymbol{\phi}}(\mathbf{z}|\mathbf{x}^{(i)})||p_{\boldsymbol{\theta}}(\mathbf{z}|\mathbf{x}^{(i)})) + \mathcal{L}(\boldsymbol{\theta}, \phi; \mathbf{x}^{(i)})$$

$$\mathcal{L}(\boldsymbol{\theta}, \phi; \mathbf{x}^{(i)}) \simeq \frac{1}{2}\sum_{j=1}^{J}\left(1 + \log((\sigma_j^{(i)})^2) - (\mu_j^{(i)})^2 - (\sigma_j^{(i)})^2\right) + \frac{1}{L}\sum_{l=1}^{L}\log p_{\boldsymbol{\theta}}(\mathbf{x}^{(i)}|\mathbf{z}^{(i,l)})$$

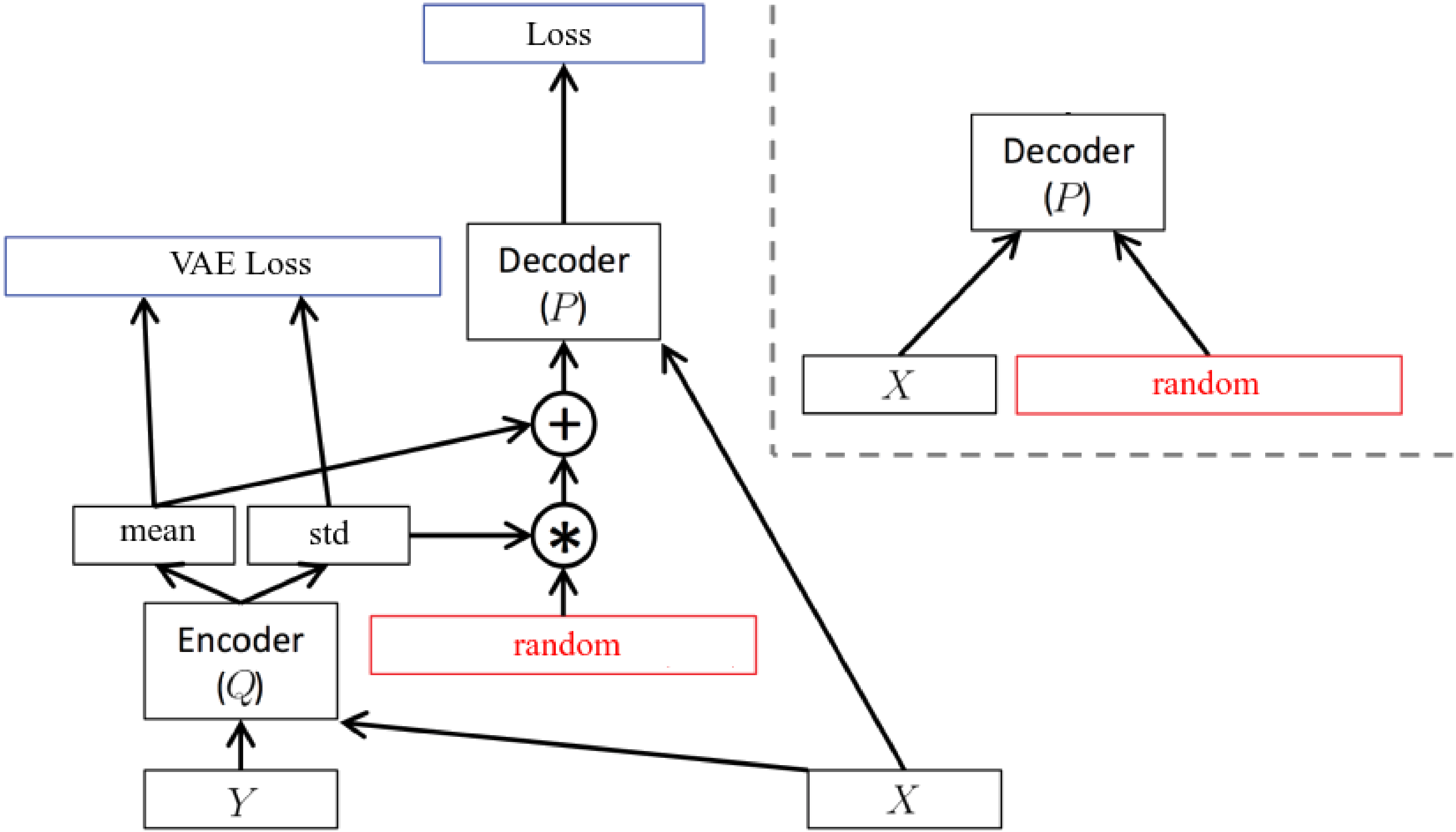
# Variational Auto-Encoder

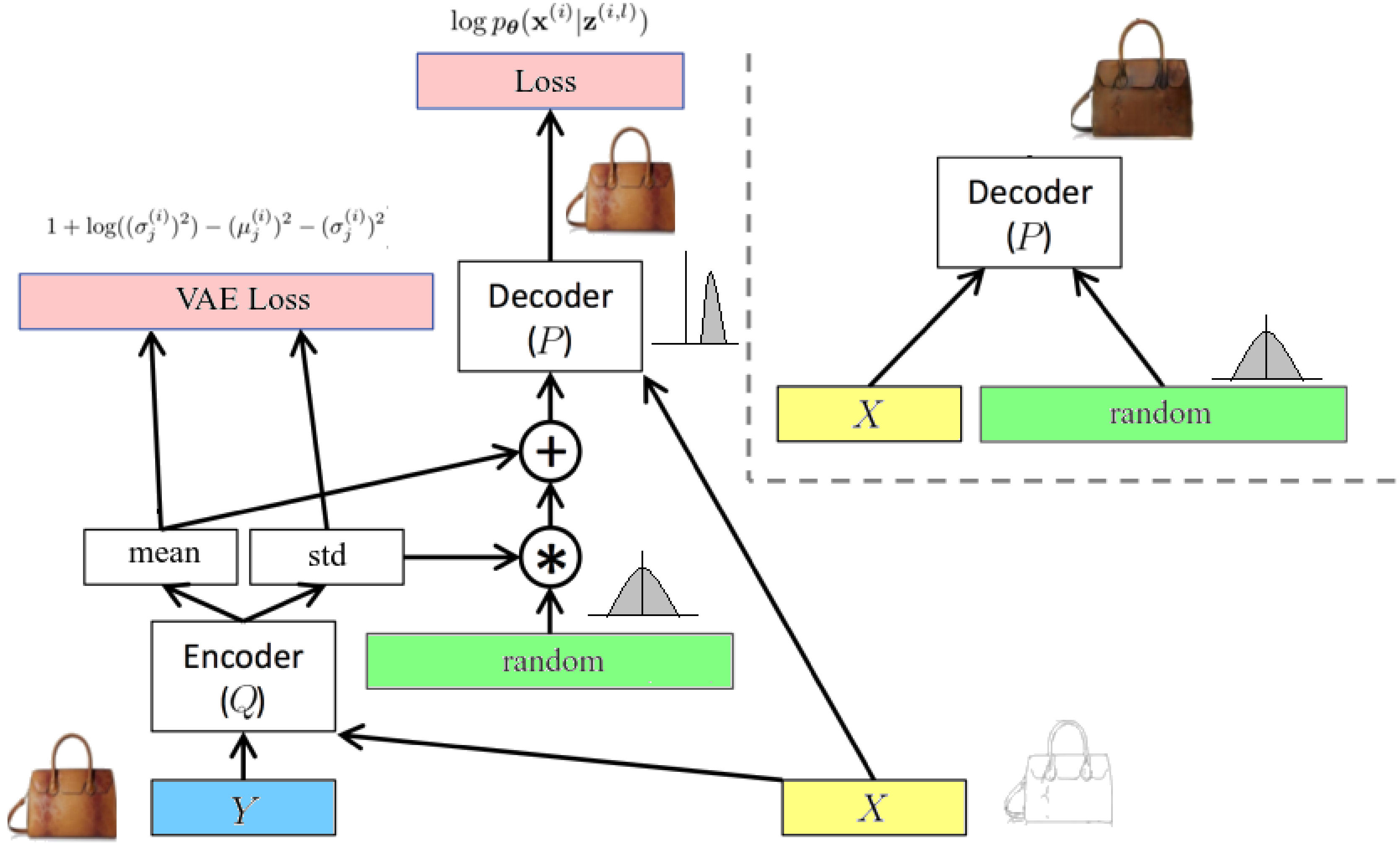
$$\mathcal{D}\left[Q(z)\|P(z|X)\right] = E_{z\sim Q}\left[\log Q(z) - \log P(z|X)\right].$$

$$\mathcal{D}\left[Q(z)\|P(z|X)\right] = E_{z\sim Q}\left[\log Q(z) - \log P(X|z) - \log P(z)\right] + \log P(X).$$

$$\log P(X) - \mathcal{D}\left[Q(z)\|P(z|X)\right] = E_{z\sim Q}\left[\log P(X|z)\right] - \mathcal{D}\left[Q(z)\|P(z)\right]$$

$$\log P(X) - \mathcal{D}\left[Q(z|X)\|P(z|X)\right] = E_{z\sim Q}\left[\log P(X|z)\right] - \mathcal{D}\left[Q(z|X)\|P(z)\right]$$

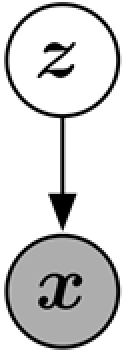

Loss
VAE Loss
Decoder
($P$)
mean
std
Encoder
($Q$)
random
$Y$
$X$
Decoder
($P$)
$X$
random

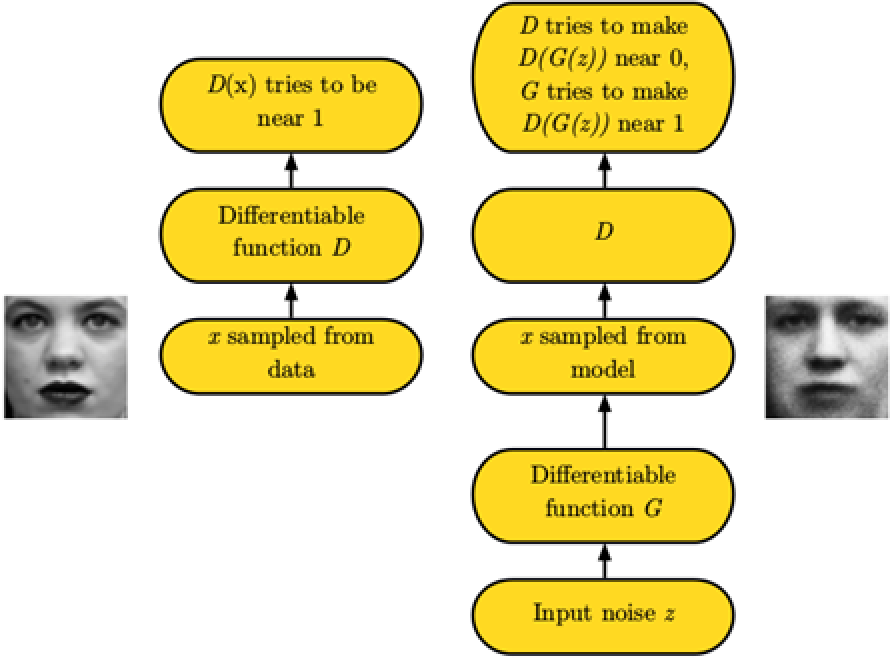


$\log p_{\boldsymbol{\theta}}(\mathbf{x}^{(i)}|\mathbf{z}^{(i,l)})$
Loss
$1 + \log((\sigma_j^{(i)})^2) - (\mu_j^{(i)})^2 - (\sigma_j^{(i)})^2$
VAE Loss
Decoder ($P$)
mean
std
random
Encoder ($Q$)
$Y$
$X$
Decoder ($P$)
$X$
random

# VAE: Examples

# Generative Adversarial Networks (GAN)

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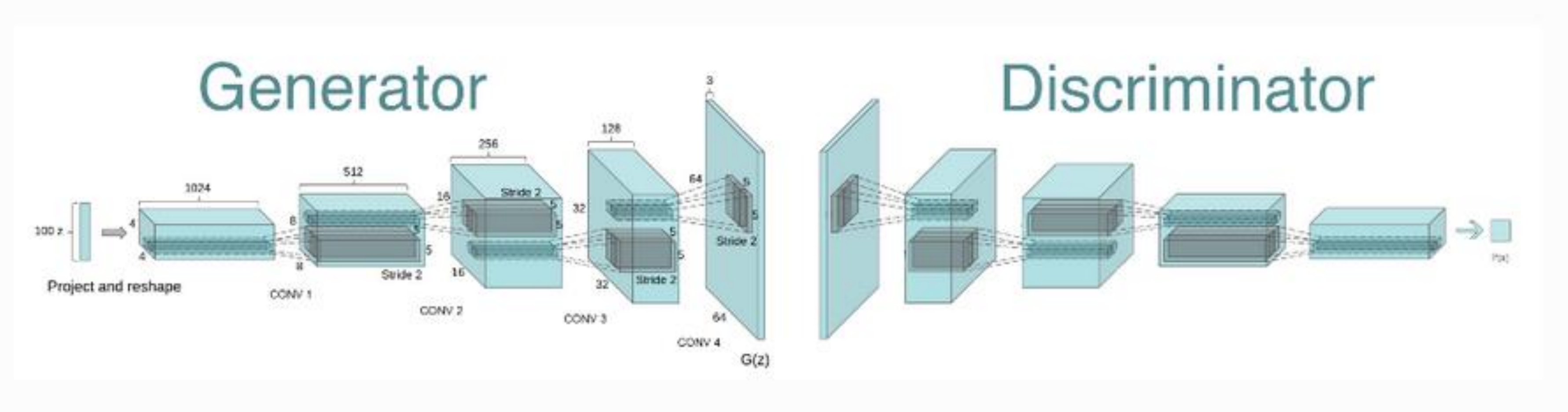
# DCGAN

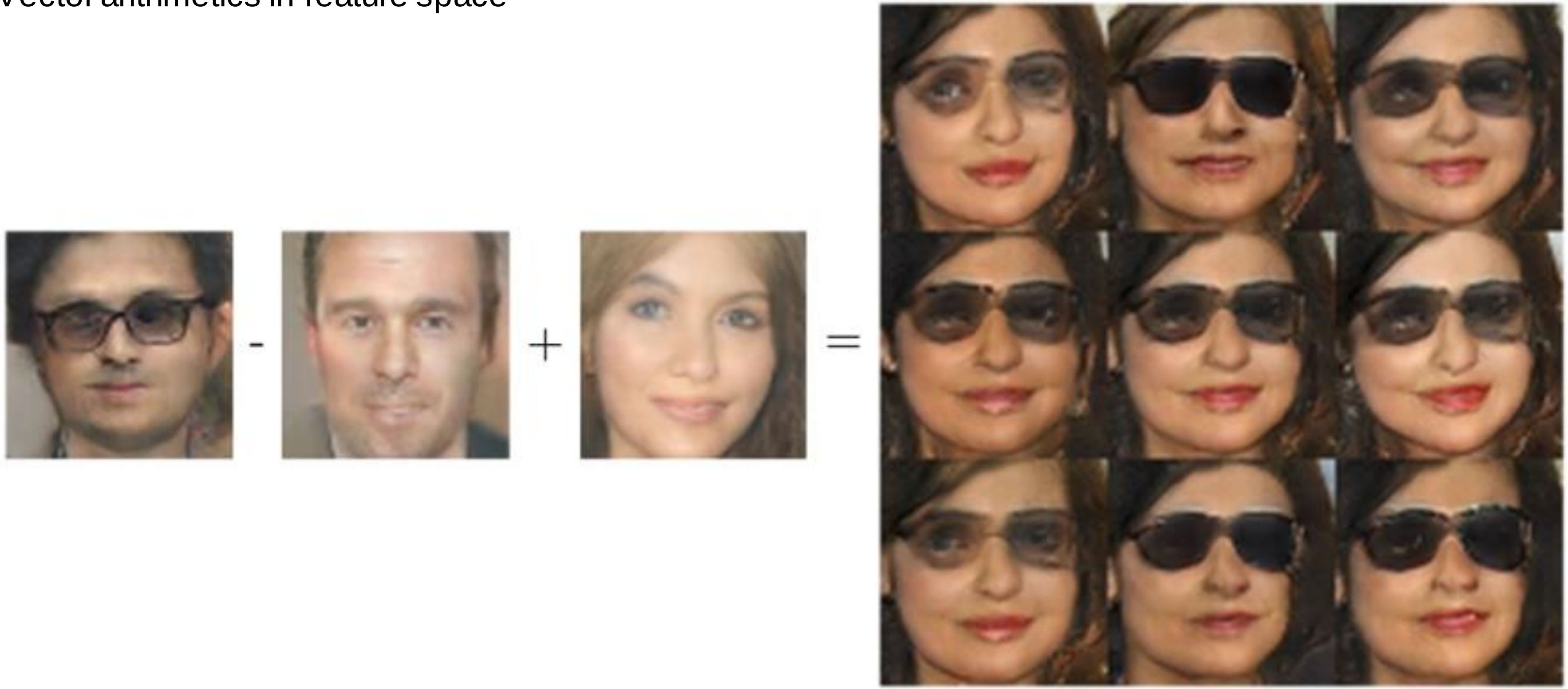



http://gluon.mxnet.io/chapter14_generative-adversarial-networks/dcgan.html

# DCGAN: Examples

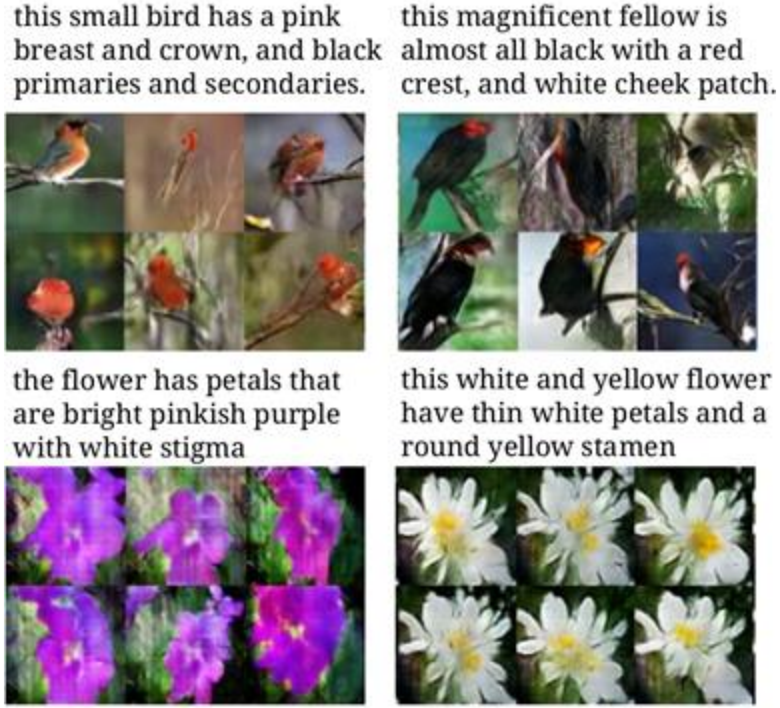
# DCGAN: Example of Feature Manipulation

Vector arithmetics in feature space



# Conditional, Cross-domain Generation

## Generative adversarial text to image synthesis

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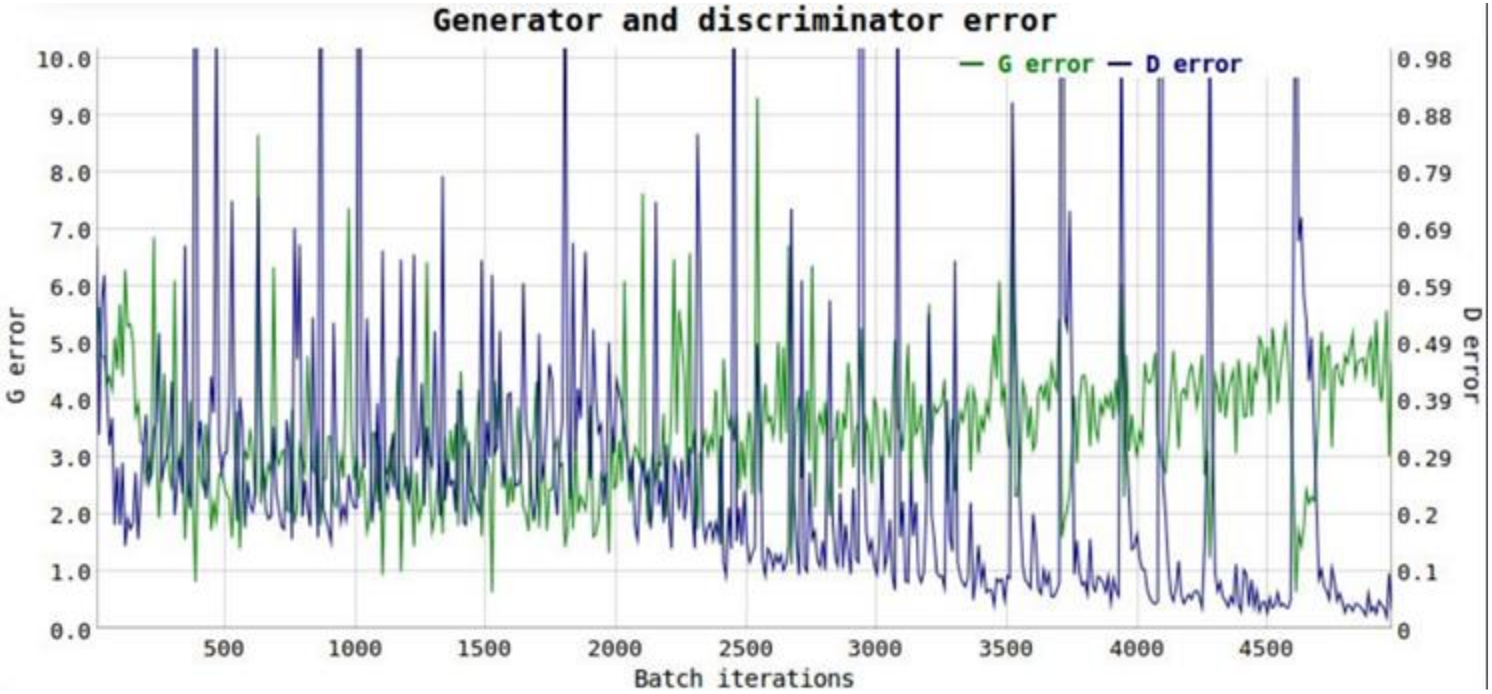
# GAN training problems: unstable losses




http://guimperarnau.com/files/blog/Fantastic-GANs-and-where-to-find-them/crazy_loss_function.jpg

# GAN training problems: Mini-batch Fluctuation

Differs much even between consecutive minibatches.

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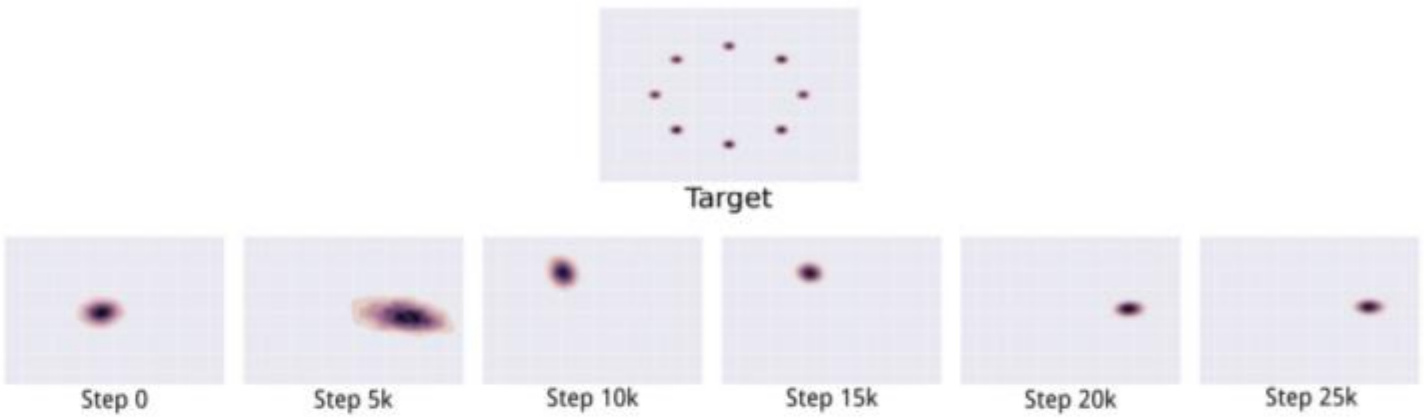
# GAN training problems: Mode Collapse

Lack of diversity in generated results.

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# Improve GAN training: Label Smoothing

Improves stability of training

```
d_on_data = discriminator_logits(data_minibatch)
d_on_samples = discriminator_logits(samples_minibatch)

loss = tf.nn.sigmoid_cross_entropy_with_logits(d_on_data, .9) + \
       tf.nn.sigmoid_cross_entropy_with_logits(d_on_samples, 0.)
```

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# The (once) break-through: WGAN

- The *Earth-Mover* (EM) distance or Wasserstein-1

$$W(\mathbb{P}_r, \mathbb{P}_g) = \inf_{\gamma \in \Pi(\mathbb{P}_r, \mathbb{P}_g)} \mathbb{E}_{(x,y)\sim\gamma}\big[\, \|x - y\| \,\big] \;, \tag{1}$$

  where $\Pi(\mathbb{P}_r, \mathbb{P}_g)$ denotes the set of all joint distributions $\gamma(x, y)$ whose marginals are respectively $\mathbb{P}_r$ and $\mathbb{P}_g$. Intuitively, $\gamma(x, y)$ indicates how much "mass" must be transported from $x$ to $y$ in order to transform the distributions $\mathbb{P}_r$ into the distribution $\mathbb{P}_g$. The EM distance then is the "cost" of the optimal transport plan.

# Duality

Again, Theorem 2 points to the fact that $W(\mathbb{P}_r, \mathbb{P}_\theta)$ might have nicer properties when optimized than $JS(\mathbb{P}_r, \mathbb{P}_\theta)$. However, the infimum in (1) is highly intractable. On the other hand, the Kantorovich-Rubinstein duality [21] tells us that

$$W(\mathbb{P}_r, \mathbb{P}_\theta) = \sup_{\|f\|_L \leq 1} \mathbb{E}_{x\sim\mathbb{P}_r}[f(x)] - \mathbb{E}_{x\sim\mathbb{P}_\theta}[f(x)] \tag{2}$$

# Improve GAN training: Wasserstein GAN

Use linear instead of log

$$W(\mathbb{P}_r, \mathbb{P}_\theta) = \sup_{\|f\|_L \leq 1} \mathbb{E}_{x\sim\mathbb{P}_r}[f(x)] - \mathbb{E}_{x\sim\mathbb{P}_\theta}[f(x)]$$

**for** $t = 0, ..., n_{\text{critic}}$ **do**

Sample $\{x^{(i)}\}_{i=1}^m \sim \mathbb{P}_r$ a batch from the real data.

Sample $\{z^{(i)}\}_{i=1}^m \sim p(z)$ a batch of prior samples.

$g_w \leftarrow \nabla_w \left[\frac{1}{m}\sum_{i=1}^m f_w(x^{(i)}) - \frac{1}{m}\sum_{i=1}^m f_w(g_\theta(z^{(i)}))\right]$

$w \leftarrow w + \alpha \cdot \text{RMSProp}(w, g_w)$

$w \leftarrow \text{clip}(w, -c, c)$

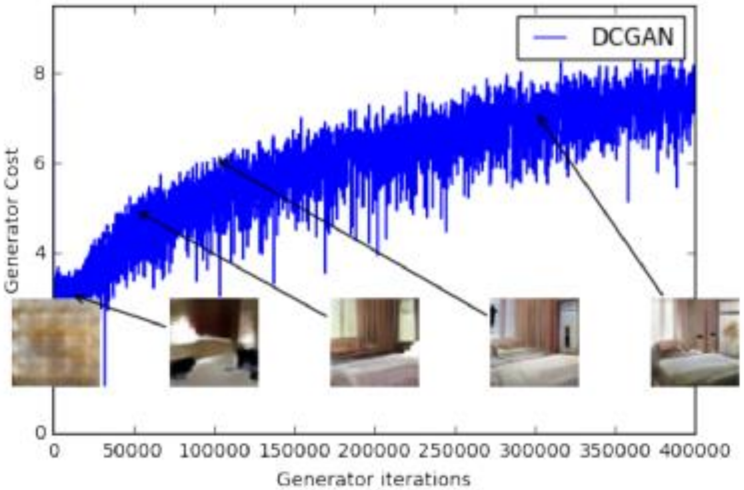
**end for**

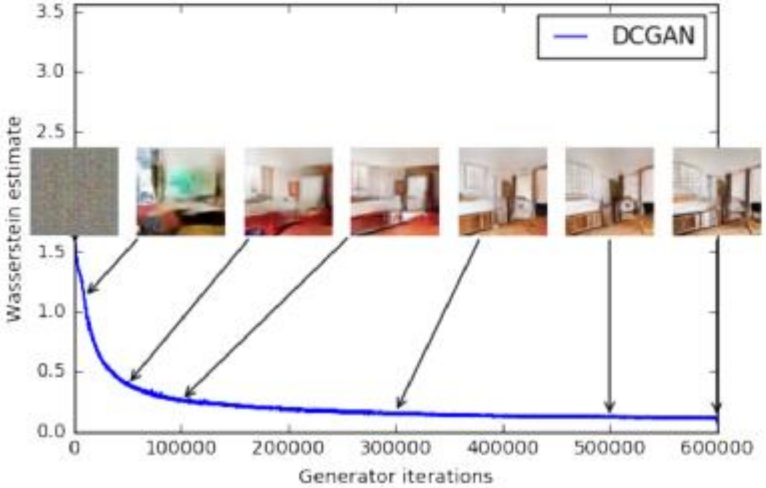
Sample $\{z^{(i)}\}_{i=1}^m \sim p(z)$ a batch of prior samples.

$g_\theta \leftarrow -\nabla_\theta \frac{1}{m}\sum_{i=1}^m f_w(g_\theta(z^{(i)}))$

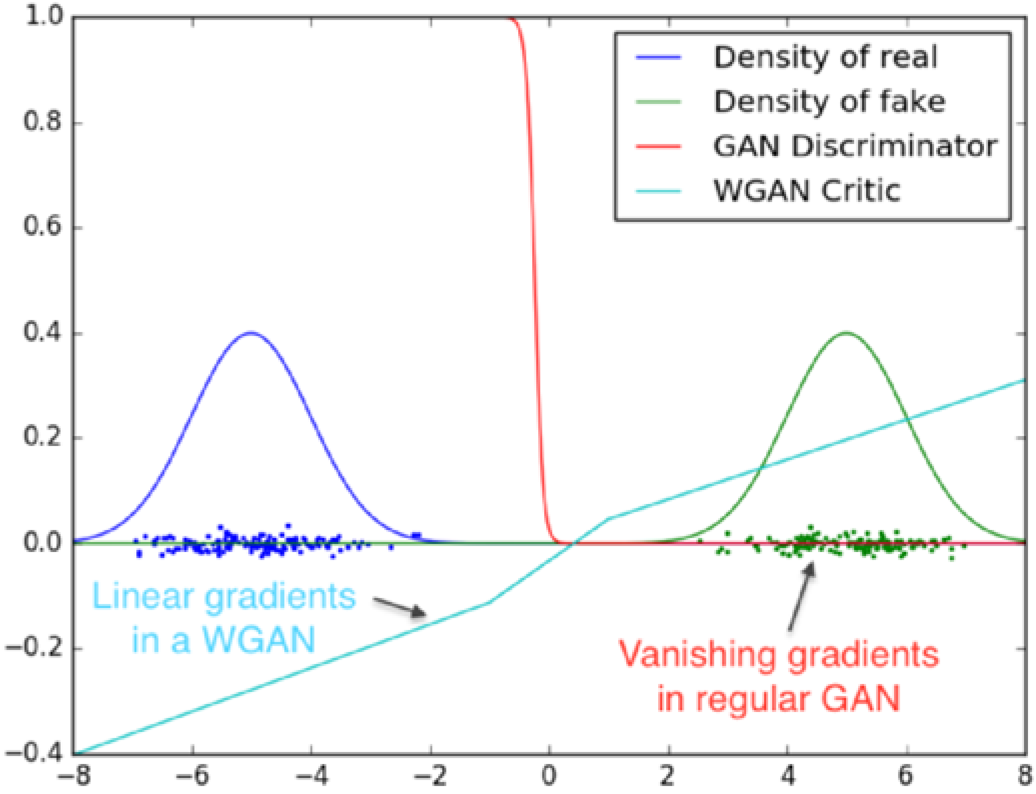
$\theta \leftarrow \theta - \alpha \cdot \text{RMSProp}(\theta, g_\theta)$

# WGAN: Stabilized Training Curve



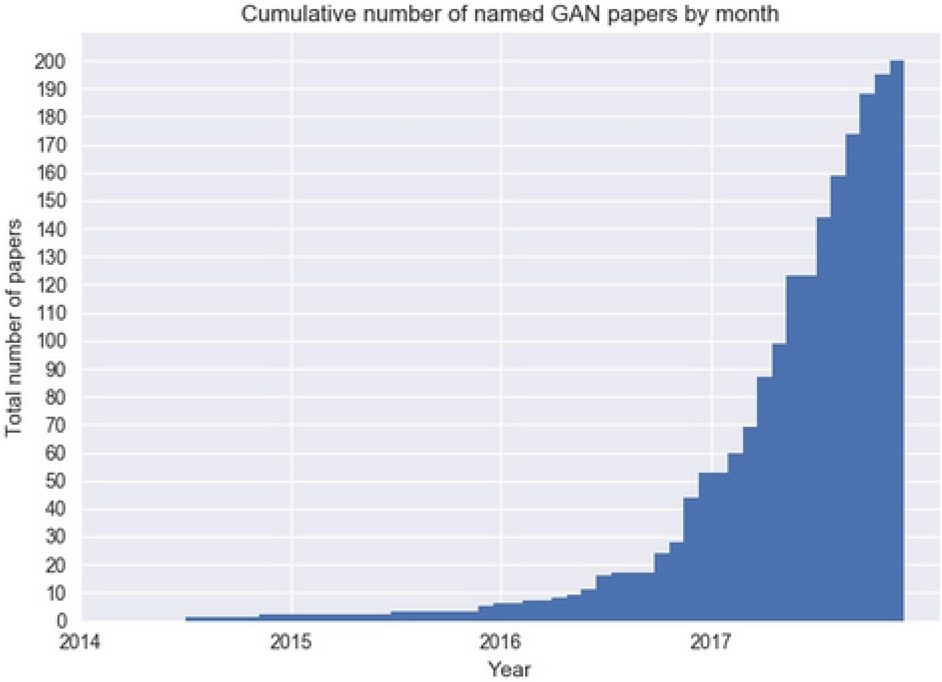



# WGAN: Non-vanishing Gradient



# The GAN Zoo

https://github.com/hindupuravinash/the-gan-zoo



- 3D-GAN - Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling (github)
- 3D-IWGAN - Improved Adversarial Systems for 3D Object Generation and Reconstruction (github)
- 3D-RecGAN - 3D Object Reconstruction from a Single Depth View with Adversarial Learning (github)
- ABC-GAN - ABC-GAN: Adaptive Blur and Control for improved training stability of Generative Adversarial Networks (github)
- AC-GAN - Conditional Image Synthesis With Auxiliary Classifier GANs
- acGAN - Face Aging With Conditional Generative Adversarial Networks
- AdaGAN - AdaGAN: Boosting Generative Models
- AE-GAN - AE-GAN: adversarial eliminating with GAN
- AEGAN - Learning Inverse Mapping by Autoencoder based Generative Adversarial Nets
- AffGAN - Amortised MAP Inference for Image Super-resolution
- AL-CGAN - Learning to Generate Images of Outdoor Scenes from Attributes and Semantic Layouts
- ALI - Adversarially Learned Inference
- AlignGAN - AlignGAN: Learning to Align Cross-Domain Images with Conditional Generative Adversarial Networks
- AM-GAN - Activation Maximization Generative Adversarial Nets
- AnoGAN - Unsupervised Anomaly Detection with Generative Adversarial Networks to Guide Marker Discovery
- ARAE - Adversarially Regularized Autoencoders for Generating Discrete Structures (github)
- ARDA - Adversarial Representation Learning for Domain Adaptation
- ARIGAN - ARIGAN: Synthetic Arabidopsis Plants using Generative Adversarial Network
- ArtGAN - ArtGAN: Artwork Synthesis with Conditional Categorial GANs
- b-GAN - Generative Adversarial Nets from a Density Ratio Estimation Perspective
- Bayesian GAN - Deep and Hierarchical Implicit Models
- Bayesian GAN - Bayesian GAN
- BCGAN - Bayesian Conditional Generative Adverserial Networks
- BEGAN - BEGAN: Boundary Equilibrium Generative Adversarial Networks
- BGAN - Binary Generative Adversarial Networks for Image Retrieval (github)

- BiGAN - Adversarial Feature Learning
- BS-GAN - Boundary-Seeking Generative Adversarial Networks
- C-RNN-GAN - C-RNN-GAN: Continuous recurrent neural networks with adversarial training (github)
- CaloGAN - CaloGAN: Simulating 3D High Energy Particle Showers in Multi-Layer Electromagnetic Calorimeters with Generative Adversarial Networks (github)
- CAN - CAN: Creative Adversarial Networks, Generating Art by Learning About Styles and Deviating from Style Norms
- CatGAN - Unsupervised and Semi-supervised Learning with Categorical Generative Adversarial Networks
- CausalGAN - CausalGAN: Learning Causal Implicit Generative Models with Adversarial Training
- CC-GAN - Semi-Supervised Learning with Context-Conditional Generative Adversarial Networks (github)
- CDcGAN - Simultaneously Color-Depth Super-Resolution with Conditional Generative Adversarial Network
- CGAN - Conditional Generative Adversarial Nets
- CGAN - Controllable Generative Adversarial Network
- Chekhov GAN - An Online Learning Approach to Generative Adversarial Networks
- CM-GAN - CM-GANs: Cross-modal Generative Adversarial Networks for Common Representation Learning
- CoGAN - Coupled Generative Adversarial Networks
- Conditional cycleGAN - Conditional CycleGAN for Attribute Guided Face Image Generation
- constrast-GAN - Generative Semantic Manipulation with Contrasting GAN
- Context-RNN-GAN - Contextual RNN-GANs for Abstract Reasoning Diagram Generation
- Coulomb GAN - Coulomb GANs: Provably Optimal Nash Equilibria via Potential Fields
- Cramèr GAN - The Cramer Distance as a Solution to Biased Wasserstein Gradients
- crVAE-GAN - Channel-Recurrent Variational Autoencoders
- CS-GAN - Improving Neural Machine Translation with Conditional Sequence Generative Adversarial Nets
- CVAE-GAN - CVAE-GAN: Fine-Grained Image Generation through Asymmetric Training
- CycleGAN - Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks (github)
- D2GAN - Dual Discriminator Generative Adversarial Nets

- DAN - Distributional Adversarial Networks
- DCGAN - Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks (github)
- DeliGAN - DeLiGAN : Generative Adversarial Networks for Diverse and Limited Data (github)
- DiscoGAN - Learning to Discover Cross-Domain Relations with Generative Adversarial Networks
- DistanceGAN - One-Sided Unsupervised Domain Mapping
- DM-GAN - Dual Motion GAN for Future-Flow Embedded Video Prediction
- DR-GAN - Representation Learning by Rotating Your Faces
- DRAGAN - How to Train Your DRAGAN (github)
- DSP-GAN - Depth Structure Preserving Scene Image Generation
- DTN - Unsupervised Cross-Domain Image Generation
- DualGAN - DualGAN: Unsupervised Dual Learning for Image-to-Image Translation
- Dualing GAN - Dualing GANs
- EBGAN - Energy-based Generative Adversarial Network
- ED//GAN - Stabilizing Training of Generative Adversarial Networks through Regularization
- EGAN - Enhanced Experience Replay Generation for Efficient Reinforcement Learning
- ExprGAN - ExprGAN: Facial Expression Editing with Controllable Expression Intensity
- f-GAN - f-GAN: Training Generative Neural Samplers using Variational Divergence Minimization
- FF-GAN - Towards Large-Pose Face Frontalization in the Wild
- Fila-GAN - Synthesizing Filamentary Structured Images with GANs
- Fisher GAN - Fisher GAN
- Flow-GAN - Flow-GAN: Bridging implicit and prescribed learning in generative models
- GAMN - Generative Adversarial Mapping Networks
- GAN - Generative Adversarial Networks (github)
- GAN-ATV - A Novel Approach to Artistic Textual Visualization via GAN
- GAN-CLS - Generative Adversarial Text to Image Synthesis (github)
- GAN-sep - GANs for Biological Image Synthesis (github)

- GAN-VFS - Generative Adversarial Network-based Synthesis of Visible Faces from Polarimetric Thermal Faces
- GANCS - Deep Generative Adversarial Networks for Compressed Sensing Automates MRI
- GANDI - Guiding the search in continuous state-action spaces by learning an action sampling distribution from off-target samples
- GAP - Context-Aware Generative Adversarial Privacy
- GAWWN - Learning What and Where to Draw (github)
- GeneGAN - GeneGAN: Learning Object Transfiguration and Attribute Subspace from Unpaired Data (github)
- Geometric GAN - Geometric GAN
- GMAN - Generative Multi-Adversarial Networks
- GMM-GAN - Towards Understanding the Dynamics of Generative Adversarial Networks
- GoGAN - Gang of GANs: Generative Adversarial Networks with Maximum Margin Ranking
- GP-GAN - GP-GAN: Towards Realistic High-Resolution Image Blending (github)
- GP-GAN - GP-GAN: Gender Preserving GAN for Synthesizing Faces from Landmarks
- GRAN - Generating images with recurrent adversarial networks (github)
- IAN - Neural Photo Editing with Introspective Adversarial Networks (github)
- IcGAN - Invertible Conditional GANs for image editing (github)
- ID-CGAN - Image De-raining Using a Conditional Generative Adversarial Network
- iGAN - Generative Visual Manipulation on the Natural Image Manifold (github)
- Improved GAN - Improved Techniques for Training GANs (github)
- InfoGAN - InfoGAN: Interpretable Representation Learning by Information Maximizing Generative Adversarial Nets (github)
- IRGAN - IRGAN: A Minimax Game for Unifying Generative and Discriminative Information Retrieval models
- IWGAN - On Unifying Deep Generative Models
- KGAN - KGAN: How to Break The Minimax Game in GAN
- l-GAN - Representation Learning and Adversarial Generation of 3D Point Clouds
- LAGAN - Learning Particle Physics by Example: Location-Aware Generative Adversarial Networks for Physics Synthesis

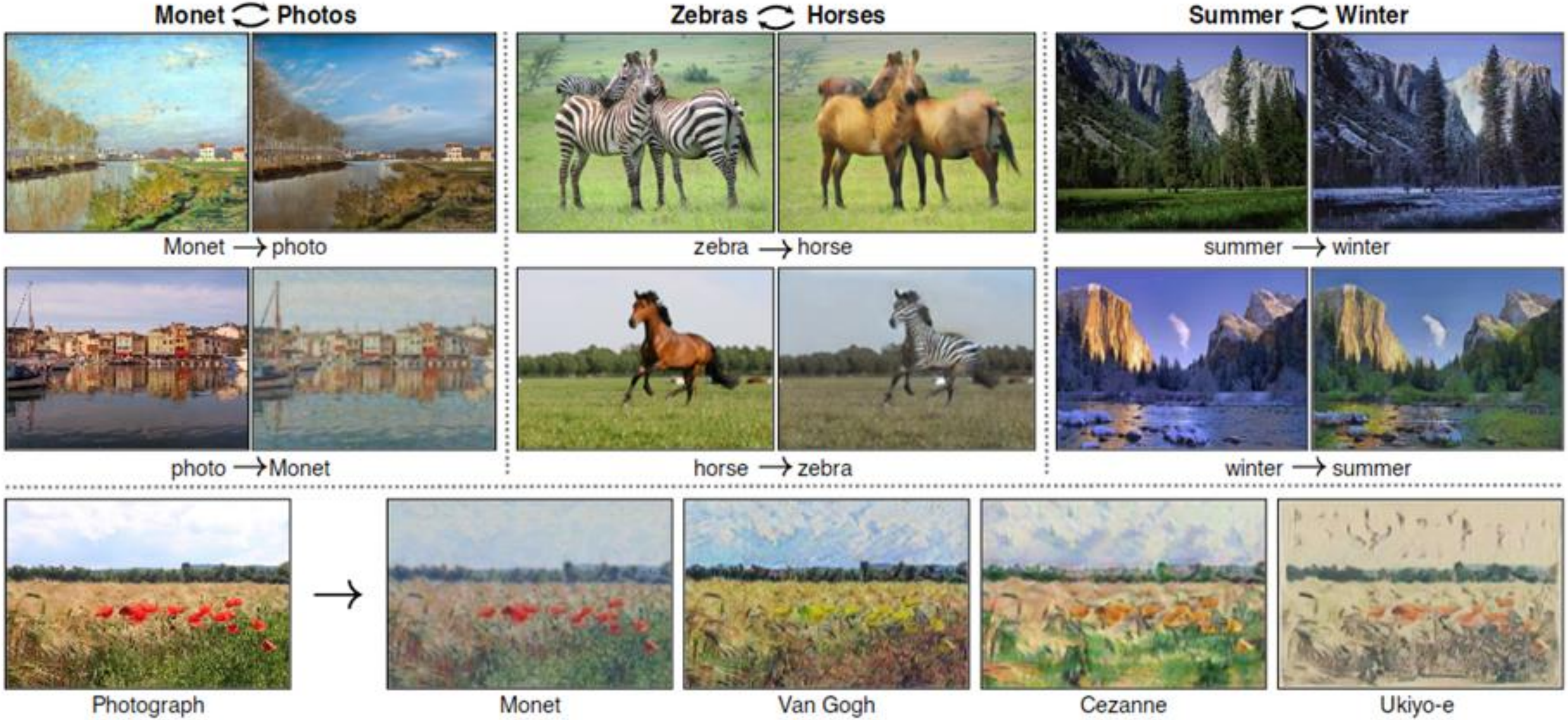
- LAPGAN - Deep Generative Image Models using a Laplacian Pyramid of Adversarial Networks (github)
- LD-GAN - Linear Discriminant Generative Adversarial Networks
- LDAN - Label Denoising Adversarial Network (LDAN) for Inverse Lighting of Face Images
- LeakGAN - Long Text Generation via Adversarial Training with Leaked Information
- LeGAN - Likelihood Estimation for Generative Adversarial Networks
- LR-GAN - LR-GAN: Layered Recursive Generative Adversarial Networks for Image Generation
- LS-GAN - Loss-Sensitive Generative Adversarial Networks on Lipschitz Densities
- LSGAN - Least Squares Generative Adversarial Networks
- MAD-GAN - Multi-Agent Diverse Generative Adversarial Networks
- MAGAN - MAGAN: Margin Adaptation for Generative Adversarial Networks
- MalGAN - Generating Adversarial Malware Examples for Black-Box Attacks Based on GAN
- MaliGAN - Maximum-Likelihood Augmented Discrete Generative Adversarial Networks
- MARTA-GAN - Deep Unsupervised Representation Learning for Remote Sensing Images
- McGAN - McGan: Mean and Covariance Feature Matching GAN
- MD-GAN - Learning to Generate Time-Lapse Videos Using Multi-Stage Dynamic Generative Adversarial Networks
- MDGAN - Mode Regularized Generative Adversarial Networks
- MedGAN - Generating Multi-label Discrete Electronic Health Records using Generative Adversarial Networks
- MGAN - Precomputed Real-Time Texture Synthesis with Markovian Generative Adversarial Networks (github)
- MGGAN - Multi-Generator Generative Adversarial Nets
- MIX+GAN - Generalization and Equilibrium in Generative Adversarial Nets (GANs)
- MLGAN - Metric Learning-based Generative Adversarial Network
- MMD-GAN - MMD GAN: Towards Deeper Understanding of Moment Matching Network (github)
- MMGAN - MMGAN: Manifold Matching Generative Adversarial Network for Generating Images
- MoCoGAN - MoCoGAN: Decomposing Motion and Content for Video Generation (github)
- MPM-GAN - Message Passing Multi-Agent GANs
- MuseGAN - MuseGAN: Symbolic-domain Music Generation and Accompaniment with Multi-track Sequential Generative Adversarial Networks
- MV-BiGAN - Multi-view Generative Adversarial Networks

- OptionGAN - OptionGAN: Learning Joint Reward-Policy Options using Generative Adversarial Inverse Reinforcement Learning
- ORGAN - Objective-Reinforced Generative Adversarial Networks (ORGAN) for Sequence Generation Models
- PAN - Perceptual Adversarial Networks for Image-to-Image Transformation
- PassGAN - PassGAN: A Deep Learning Approach for Password Guessing
- Perceptual GAN - Perceptual Generative Adversarial Networks for Small Object Detection
- PGAN - Probabilistic Generative Adversarial Networks
- pix2pix - Image-to-Image Translation with Conditional Adversarial Networks (github)
- PixelGAN - PixelGAN Autoencoders
- Pose-GAN - The Pose Knows: Video Forecasting by Generating Pose Futures
- PPGN - Plug & Play Generative Networks: Conditional Iterative Generation of Images in Latent Space
- PrGAN - 3D Shape Induction from 2D Views of Multiple Objects
- PSGAN - Learning Texture Manifolds with the Periodic Spatial GAN
- PS$^2$-GAN - High-Quality Facial Photo-Sketch Synthesis Using Multi-Adversarial Networks
- RankGAN - Adversarial Ranking for Language Generation
- RCGAN - Real-valued (Medical) Time Series Generation with Recurrent Conditional GANs
- RefineGAN - Compressed Sensing MRI Reconstruction with Cyclic Loss in Generative Adversarial Networks
- RenderGAN - RenderGAN: Generating Realistic Labeled Data
- ResGAN - Generative Adversarial Network based on Resnet for Conditional Image Restoration
- RNN-WGAN - Language Generation with Recurrent Generative Adversarial Networks without Pre-training (github)
- RPGAN - Stabilizing GAN Training with Multiple Random Projections (github)
- RTT-GAN - Recurrent Topic-Transition GAN for Visual Paragraph Generation
- RWGAN - Relaxed Wasserstein with Applications to GANs
- SAD-GAN - SAD-GAN: Synthetic Autonomous Driving using Generative Adversarial Networks
- SalGAN - SalGAN: Visual Saliency Prediction with Generative Adversarial Networks (github)
- SBADA-GAN - From source to target and back: symmetric bi-directional adaptive GAN
- SD-GAN - Semantically Decomposing the Latent Spaces of Generative Adversarial Networks
- SEGAN - SEGAN: Speech Enhancement Generative Adversarial Network

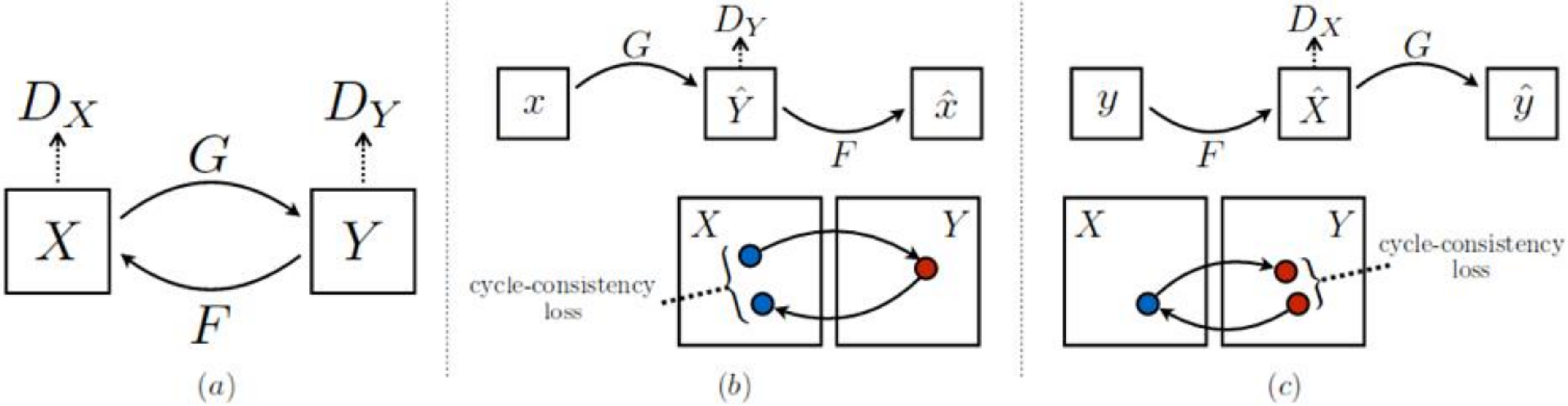
- SeGAN - SeGAN: Segmenting and Generating the Invisible
- SegAN - SegAN: Adversarial Network with Multi-scale L1 Loss for Medical Image Segmentation
- SeqGAN - SeqGAN: Sequence Generative Adversarial Nets with Policy Gradient (github)
- SGAN - Texture Synthesis with Spatial Generative Adversarial Networks
- SGAN - Stacked Generative Adversarial Networks (github)
- SGAN - Steganographic Generative Adversarial Networks
- SimGAN - Learning from Simulated and Unsupervised Images through Adversarial Training
- SketchGAN - Adversarial Training For Sketch Retrieval
- SL-GAN - Semi-Latent GAN: Learning to generate and modify facial images from attributes
- SN-GAN - Spectral Normalization for Generative Adversarial Networks (github)
- Softmax-GAN - Softmax GAN
- Splitting GAN - Class-Splitting Generative Adversarial Networks
- SRGAN - Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network
- SS-GAN - Semi-supervised Conditional GANs
- ss-InfoGAN - Guiding InfoGAN with Semi-Supervision
- SSGAN - SSGAN: Secure Steganography Based on Generative Adversarial Networks
- SSL-GAN - Semi-Supervised Learning with Context-Conditional Generative Adversarial Networks
- ST-GAN - Style Transfer Generative Adversarial Networks: Learning to Play Chess Differently
- StackGAN - StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks
- SteinGAN - Learning Deep Energy Models: Contrastive Divergence vs. Amortized MLE
- SVSGAN - SVSGAN: Singing Voice Separation via Generative Adversarial Network
- S^2GAN - Generative Image Modeling using Style and Structure Adversarial Networks
- TAC-GAN - TAC-GAN - Text Conditioned Auxiliary Classifier Generative Adversarial Network (github)
- TAN - Outline Colorization through Tandem Adversarial Networks
- TextureGAN - TextureGAN: Controlling Deep Image Synthesis with Texture Patches
- TGAN - Temporal Generative Adversarial Nets
- TGAN - Tensorizing Generative Adversarial Nets

- TGAN - Tensor-Generative Adversarial Network with Two-dimensional Sparse Coding: Application to Real-time Indoor Localization
- TP-GAN - Beyond Face Rotation: Global and Local Perception GAN for Photorealistic and Identity Preserving Frontal View Synthesis
- Triple-GAN - Triple Generative Adversarial Nets
- Unrolled GAN - Unrolled Generative Adversarial Networks (github)
- VAE-GAN - Autoencoding beyond pixels using a learned similarity metric
- VariGAN - Multi-View Image Generation from a Single-View
- VAW-GAN - Voice Conversion from Unaligned Corpora using Variational Autoencoding Wasserstein Generative Adversarial Networks
- VEEGAN - VEEGAN: Reducing Mode Collapse in GANs using Implicit Variational Learning (github)
- VGAN - Generating Videos with Scene Dynamics (github)
- VGAN - Generative Adversarial Networks as Variational Training of Energy Based Models (github)
- ViGAN - Image Generation and Editing with Variational Info Generative Adversarial Networks
- VIGAN - VIGAN: Missing View Imputation with Generative Adversarial Networks
- VRAL - Variance Regularizing Adversarial Learning
- WaterGAN - WaterGAN: Unsupervised Generative Network to Enable Real-time Color Correction of Monocular Underwater Images
- WGAN - Wasserstein GAN (github)
- WGAN-GP - Improved Training of Wasserstein GANs (github)
- WS-GAN - Weakly Supervised Generative Adversarial Networks for 3D Reconstruction
- ZipNet-GAN - ZipNet-GAN: Inferring Fine-grained Mobile Traffic Patterns via a Generative Adversarial Neural Network
- $\alpha$-GAN - Variational Approaches for Auto-Encoding Generative Adversarial Networks (github)
- $\Delta$-GAN - Triangle Generative Adversarial Networks

# Cycle GAN: Correspondence from Unpaired Data



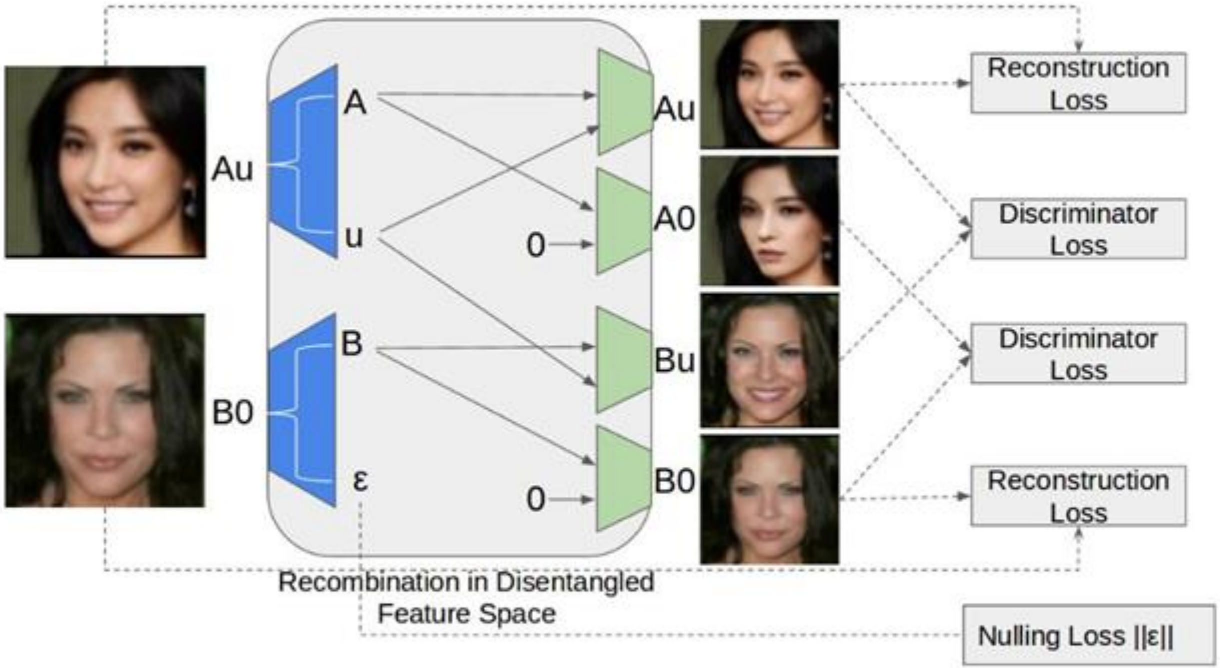
# Cycle GAN



$D_X$
$D_Y$
$G$
$X$
$Y$
$F$
(a)
$D_Y$
$G$
$x$
$\hat{Y}$
$\hat{x}$
$F$
$X$
$Y$
cycle-consistency loss
(b)
$D_X$
$G$
$y$
$\hat{X}$
$\hat{y}$
$F$
$X$
$Y$
cycle-consistency loss
(c)

# GeneGAN: shorter pathway improves training

Cross breeds and reproductions



# GeneGAN: Object Transfiguration

Transfer ***"my"*** hairstyle to him, not just ***a*** hairstyle.

Slide

Github

# Math behind Generative Models

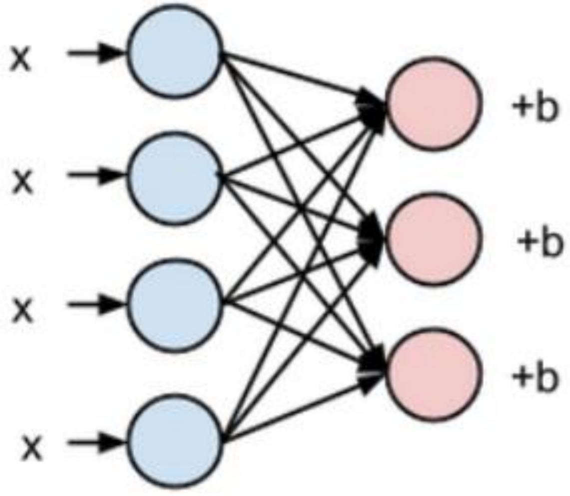
Those who don’t care about math or theory can open their PyTorch now...

# Formulation of Generative Models

sampling v.s. density estimation

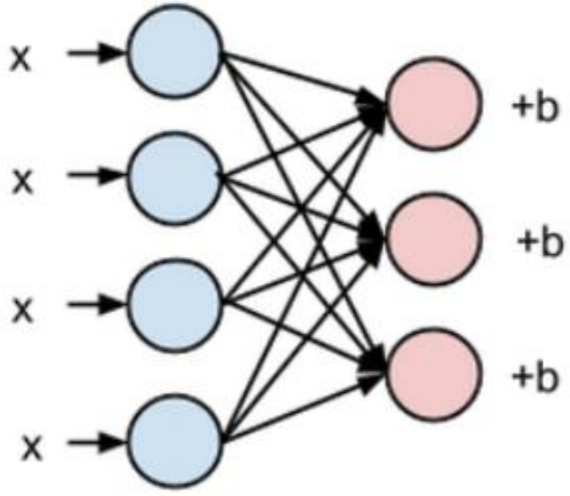
# RBM

$$p(x) = \frac{1}{Z} \sum_{y \in \{0,1\}^n} e^{x^T A y + x^T b + y^T c}$$



# RBM

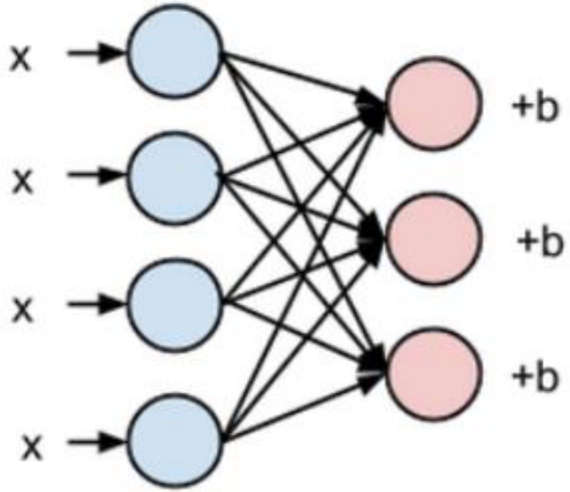
$$p(x) = \frac{1}{Z} \sum_{y \in \{0,1\}^n} e^{x^T A y + x^T b + y^T c}$$




It is NP-Hard to estimate Z

# RBM

$$p(x) = \frac{1}{Z} \sum_{y \in \{0,1\}^n} e^{x^T A y + x^T b + y^T c}$$




It is NP-Hard to sample from P

# Score Matching

Let L be the likelihood function, score V is:

$$V \equiv V(\theta, X) = \frac{\partial}{\partial \theta} \log \mathcal{L}(\theta; X) = \frac{1}{\mathcal{L}(\theta; X)} \frac{\partial \mathcal{L}(\theta; X)}{\partial \theta}$$

If two distribution's scores match, they also match.

A Connection Between Score Matching and Denoising Autoencoders

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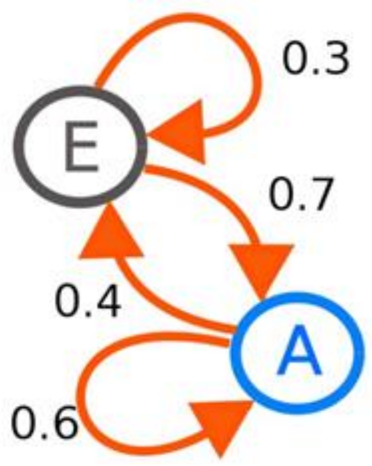
# Markov Chain Monte Carlo

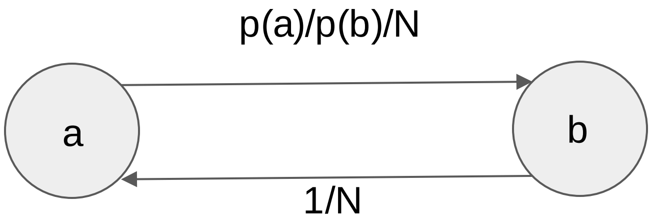
From each node a,

walk to “neighbor” b with probability **proportional** to p(b).

Neighbors must be reciprocal: a <->b

Walk for long enough time to reach equilibrium



# MCMC in RBM

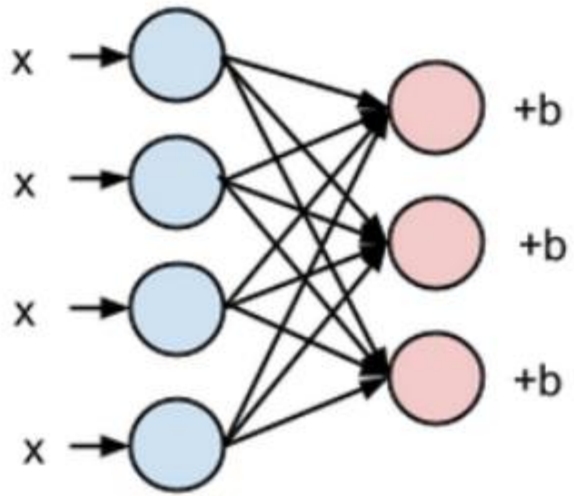
$$p(x) = \frac{1}{Z} \sum_{y \in \{0,1\}^n} e^{x^T A y + x^T b + y^T c}$$

Sample x given y

Sample y given x

Sample x given y

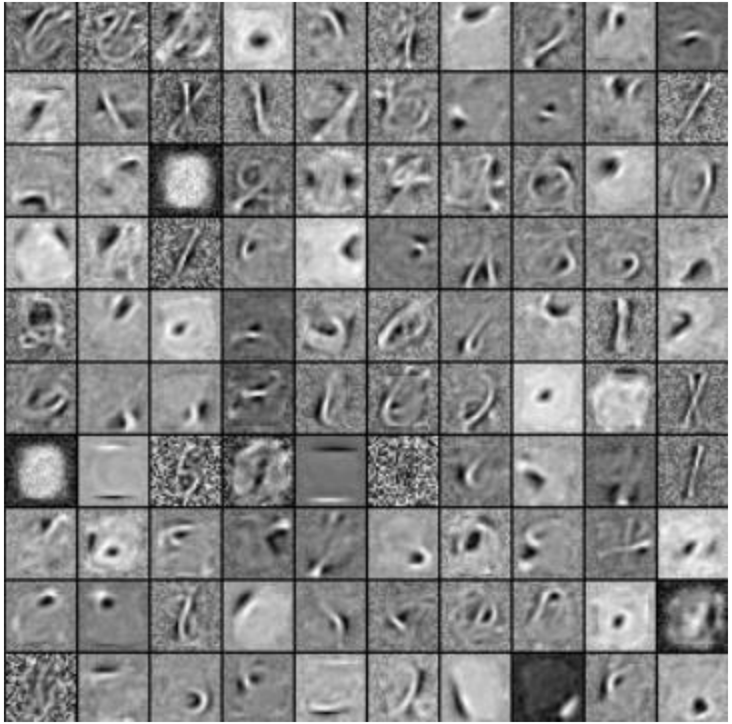
…..




In theory, repeat for long enough time.

In practice, repeat a few times. ("burnin")

# RBM: Learned “Filters”



# From Density to Sample

Given density function $p(x)$, can we efficiently black-box sample from it?

No! $p(x) = \mathrm{MD5}(x) == 0$

Unless query $\Omega(N)$ samples, it is hard to determine.

# From Sample to Density

Given black-box sampler G, can we efficiently estimate the density (frequency) of x?

Naive bound: $\Omega(\varepsilon^{-2})$ absolute, $\Omega(1/p(x)\ \varepsilon^{-2})$ relative

Cannot essentially do better.

Example: Sample x randomly. Retry iff x=0.

# What can be done if only samples are available?

Problem: Given black box sampler G, decide if:

(1) it is uniform
(2) it is <u>ε-far</u> from uniform

How to define distance between distributions?

Statistical distance: $\frac{1}{2} \sum |p(x)-q(x)|$ p:G q:Uniform

L2 distance: $\sum (p(x)-q(x))^2$

KL divergence: $\sum q(x)\log(q(x)/p(x))$

# Uniformity Check using $q(x)\log(q(x)/p(x))$

Impossible to check unless $\Omega(N)$ samples are obtained.

Consider $\{1,2,\ldots,N\}^T$ and $\{1,2,\ldots,N-1\}^T$. Unbound KL.

Statistical distance = sum $\max(p(x)-q(x),0)$

$((N-1)/N)^T = 1-o(1)$ if $T=o(N)$

**Statistical distance is the best distinguisher's advantage over random guess!**

advantage = 2*|Pr(guess correct)-0.5|

# Uniformity Check using L2 Distance

sum $(p(x)-q(x))^2$ = sum $p(x)^2+q(x)^2-2p(x)q(x)$ = sum $p(x)^2$ - $1/N$

$p(x)^2$ : seeing two x in a row

sum $p(x)^2$: counting collisions

Algorithm: Get T samples, count the number of x[i]==x[j] for i<j, divide by C(T,2)

variance calculation: $O(\varepsilon^2)$ is enough!

# Uniformity Check using L1 Distance

Estimate collision probability to $1 \pm O(\varepsilon^2)$

$O(\varepsilon^{-4}\mathrm{sqrt}(N))$ samples are enough.

# Lessons Learned: What We Can Get From Samples

Given samples, some properties of the distribution can be learned, while others cannot.

# Discriminator based distances

$\max_D E(D(x))_{x \sim p} - E(D(y))_{y \sim q}$

0<=D<=1 : Statistical Distance

D is Lipschitz Continuous: Wasserstein Distance

# Wasserstein Distance

Duality

Earth Mover Distance:

$$W_p(\mu,\nu) := \left( \inf_{\gamma\in\Gamma(\mu,\nu)} \int_{M\times M} d(x,y)^p \,\mathrm{d}\gamma(x,y) \right)^{1/p}$$

Definition using Discriminator:

$$W_1(\mu,\nu) = \sup\left\{ \int_M f(x)\,\mathrm{d}(\mu-\nu)(x) \,\middle|\, \text{continuous } f : M \to \mathbb{R}, \mathrm{Lip}(f) \le 1 \right\}$$

# Estimating Wasserstein Distance in High Dimension

The curse of dimensionality

There is no algorithm that, for any two distributions P and Q in an n-dimensional space with radius r,

takes poly(n) samples from P and Q and estimates W(P,Q) to precision o(1)*r w.h.p.

# Finite Sample Version of EMD

Let $W_N(P,Q)$ be the expected EMD between N samples from P and Q.

$W_N(P,Q) >= W(P,Q)$

$W(P,Q) \geq W_N(P,Q) - \min(W_N(P,P), W_N(Q,Q))$

# Projected Wasserstein Distance

The k-dimensional projected EMD: let σ be a random k-dim subspace

$$W^k(P,Q) = \mathrm{E}_\sigma W(\sigma(P), \sigma(Q))$$

As a lower bounding approach

$$W(P,Q) \geq \sqrt{n} W^1(P,Q) \geq \sqrt{n}(W^1_N(P,Q) - W^1_N(P,P))$$

# Application

Texture Synthesis by matching deep learning features.

source | previous work | our method

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Texture Synthesis by matching deep learning features.

source

previous work

our method

# Application

## GAN Evaluation

radius of space 90

uncertainty caused by sampling 38

$W_1(P, Q)$ 3.1

$W_{\mathrm{WGAN}}(P, Q)$ ≤ 0.26