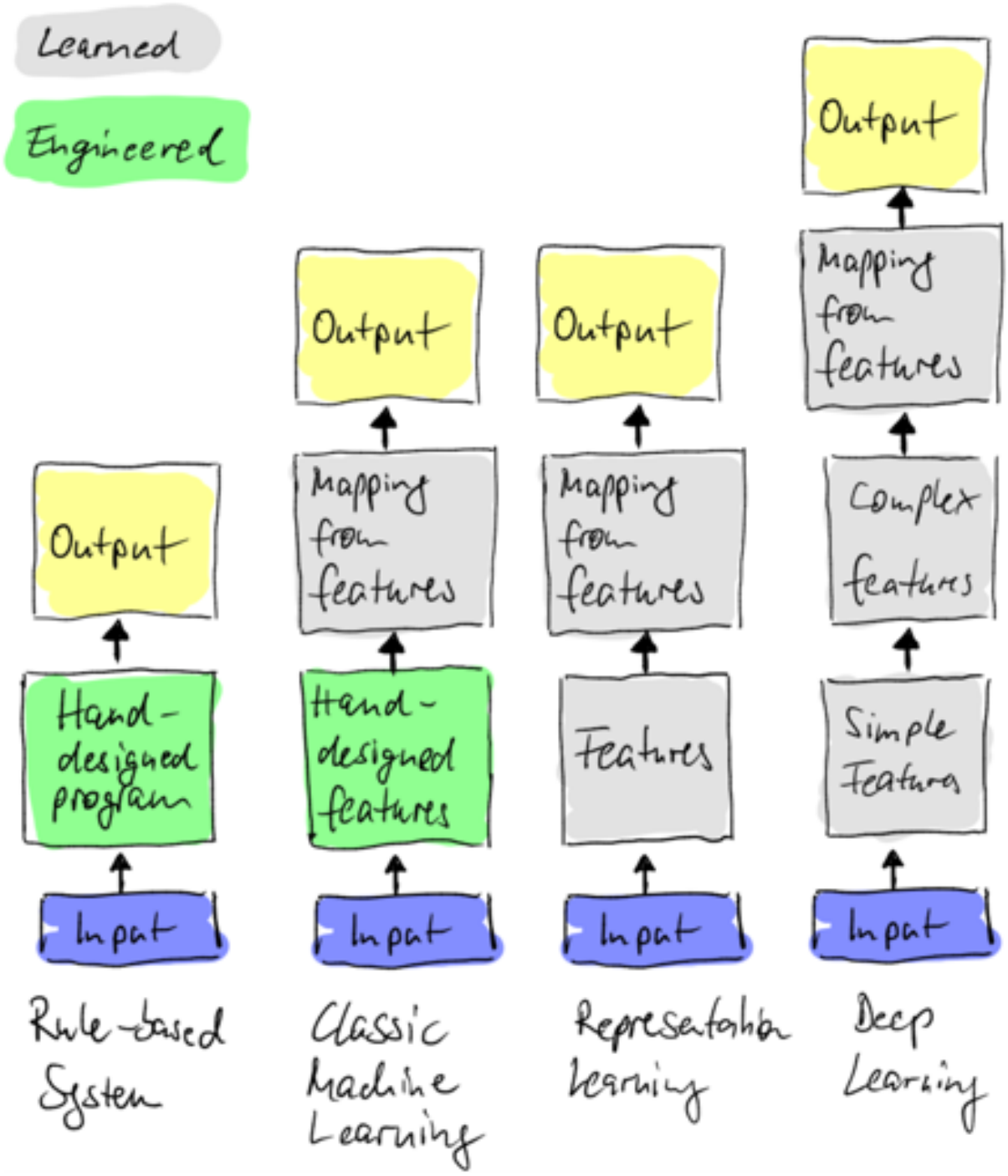
BEUTH HOCHSCHULE FÜR TECHNIK BERLIN
University of Applied Sciences

Learning from Images

Generative Models

Master DataScience
Winter term 2019/20

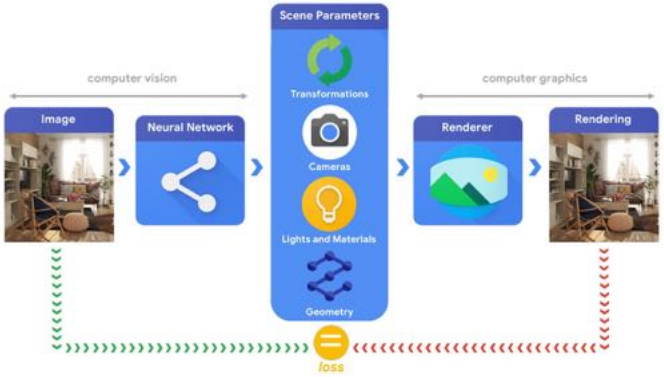
Prof. Dr. Kristian Hildebrand
khildebrand@beuth-hochschule.de


Learned
Engineered
Output
Hand-designed program
Input
Rule-based System
Output
Mapping from features
Hand-designed features
Input
Classic Machine Learning
Output
Mapping from features
Features
Input
Representation learning
Output
Mapping from features
Complex features
Simple Features
Input
Deep Learning

Why do we want to generate Content?

- Learning an understanding of the world

  “What I cannot create, I do not understand.” Richard Feynman



https://github.com/tensorflow/graphics

- Support creative processes
  - Image Denoising, Super Resolution
  - 3D Model generation

- Data Augmentation
- Can benefit Reinforcement Learning exploration strategies

Supervised vs Unsupervised Learning

Supervised Learning	**Unsupervised Learning**
Data: (x,y) X is data, y is label	**Data**: x Just data, no labels
Goal: Learn a function to map x-> y	**Goal**: Learn underlying hidden structure of the data
Examples: Classification, regression, Object detection, Semantics segmentation, image captioning, etc.	**Examples**: Clustering, dimensionality reduction, feature learning, density estimation, etc.

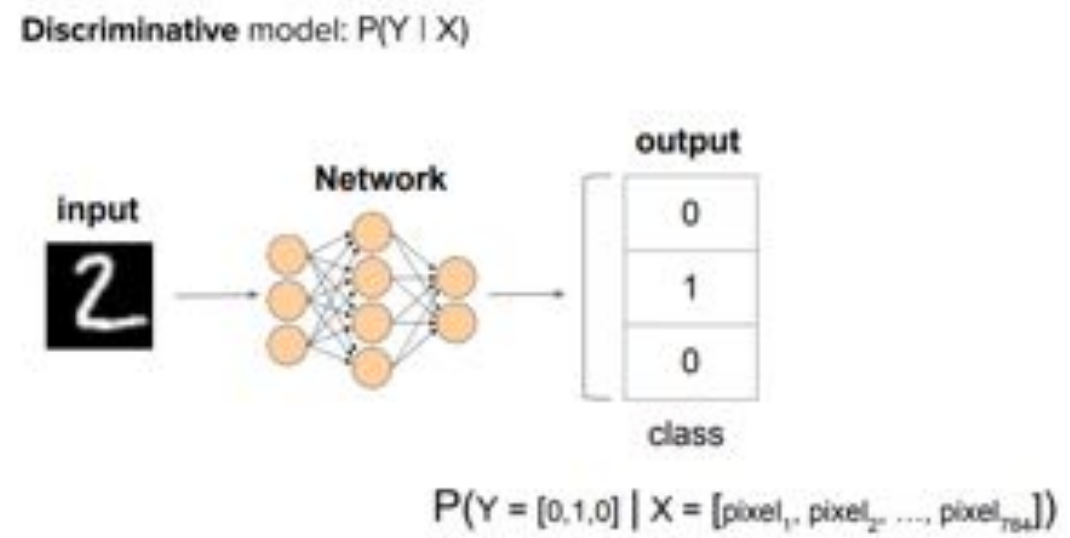
Supervised vs Unsupervised Learning

Supervised Learning

Data: (x,y)
X is data, y is label

Goal:
Learn a function to map x-> y

Examples: Classification, regression,
Object detection, Semantics segmentation, image captioning, etc.



DOG, DOG, CAT

Object Detection

A cat sitting on a suitcase on the floor

Image captioning

Supervised vs Unsupervised Learning

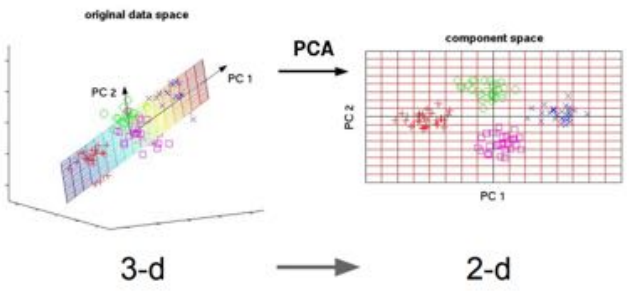
Unsupervised Learning

Data: x

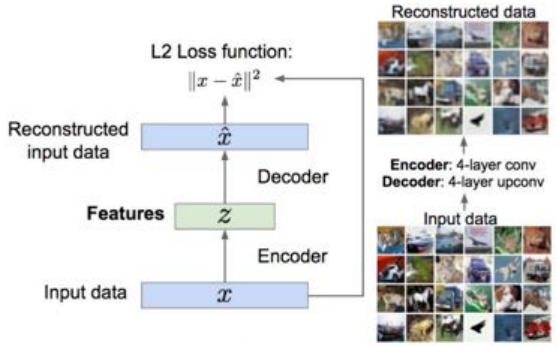
Just data, no labels

Goal: Learn underlying hidden structure of the data

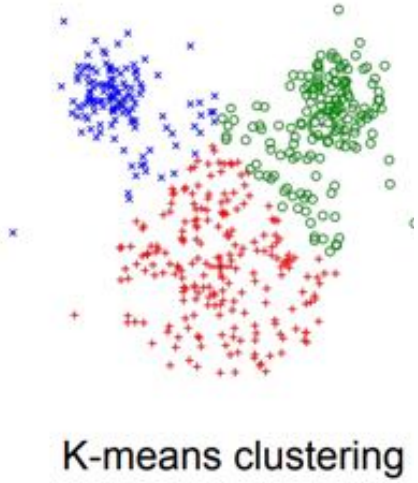
Examples: Clustering, dimensionality reduction, feature learning, density estimation, etc.



Principal Component Analysis
(Dimensionality reduction)

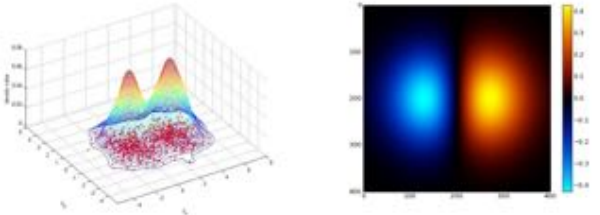


Autoencoders
(Feature learning)



K-means clustering

1-d density estimation



2-d density estimation

Holy Grail: Solve Unsupervised Learning
=> Understand the underlying structure of the visual world

Generative Models

- Given training data, generate new samples from same distribution

Training data ~ $p_{data}(x)$

Generated samples ~ $p_{model}(x)$

Want to learn $p_{model}(x)$ similar to $p_{data}(x)$

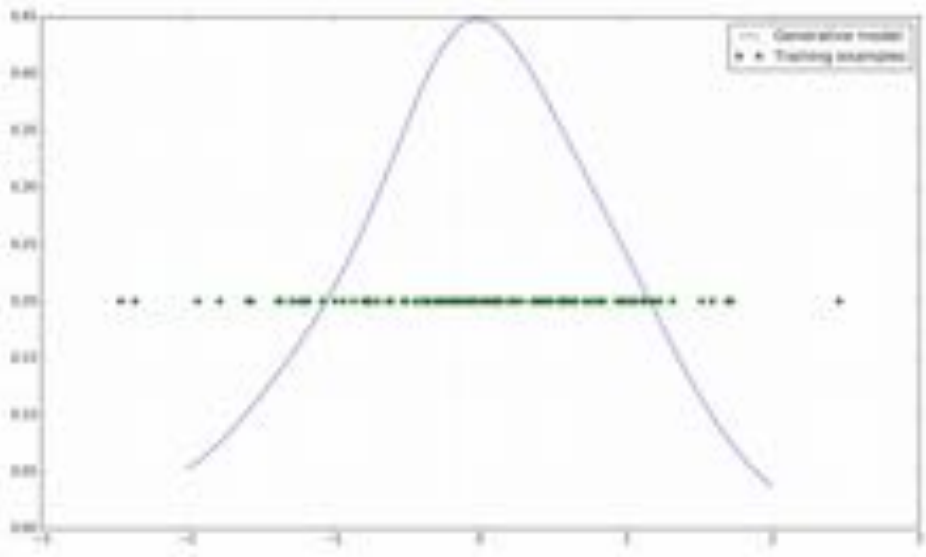
- Addresses density estimation, a core problem in unsupervised learning
- **Several flavors:**
  - Explicit density estimation: explicitly define and solve for $p_{model}(x)$
  - Implicit density estimation: learn model that can sample from $p_{model}(x)$ w/o explicitly defining it

What is a generative model?

We want our model with parameters θ to output samples distributed P_{model}, matching the distribution of our training data P_{data} or P(X).

Example: y = f(x), where y is scalar, make P_{model} similar to P_{data} by training the parameters θ to maximize their similarity

If we have 1-D data that basically following a gaussian distribution (green dots), then a perfectly trained model (P_{model}) need to learn the μ and σ of the data distribution (P_{data})



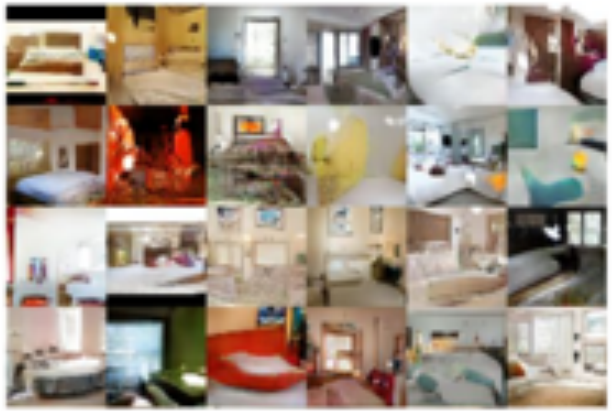
What is a generative model?

- **Key Idea**: our model cares about what distribution generated the input data points, and we want to mimic it with our probabilistic model. **Our learned model should be able to make up new samples from the distribution, not just copy and paste existing samples!**

Figure from NIPS 2016 Tutorial: Generative Adversarial Networks (I. Goodfellow)

Why Generative Models?

- Realistic samples for artwork, super-resolution, colorization, etc.



(1) Alec Radford et al. 2016; (2) David Berthelot et al. 2017; Phillip Isola et al. 2017.

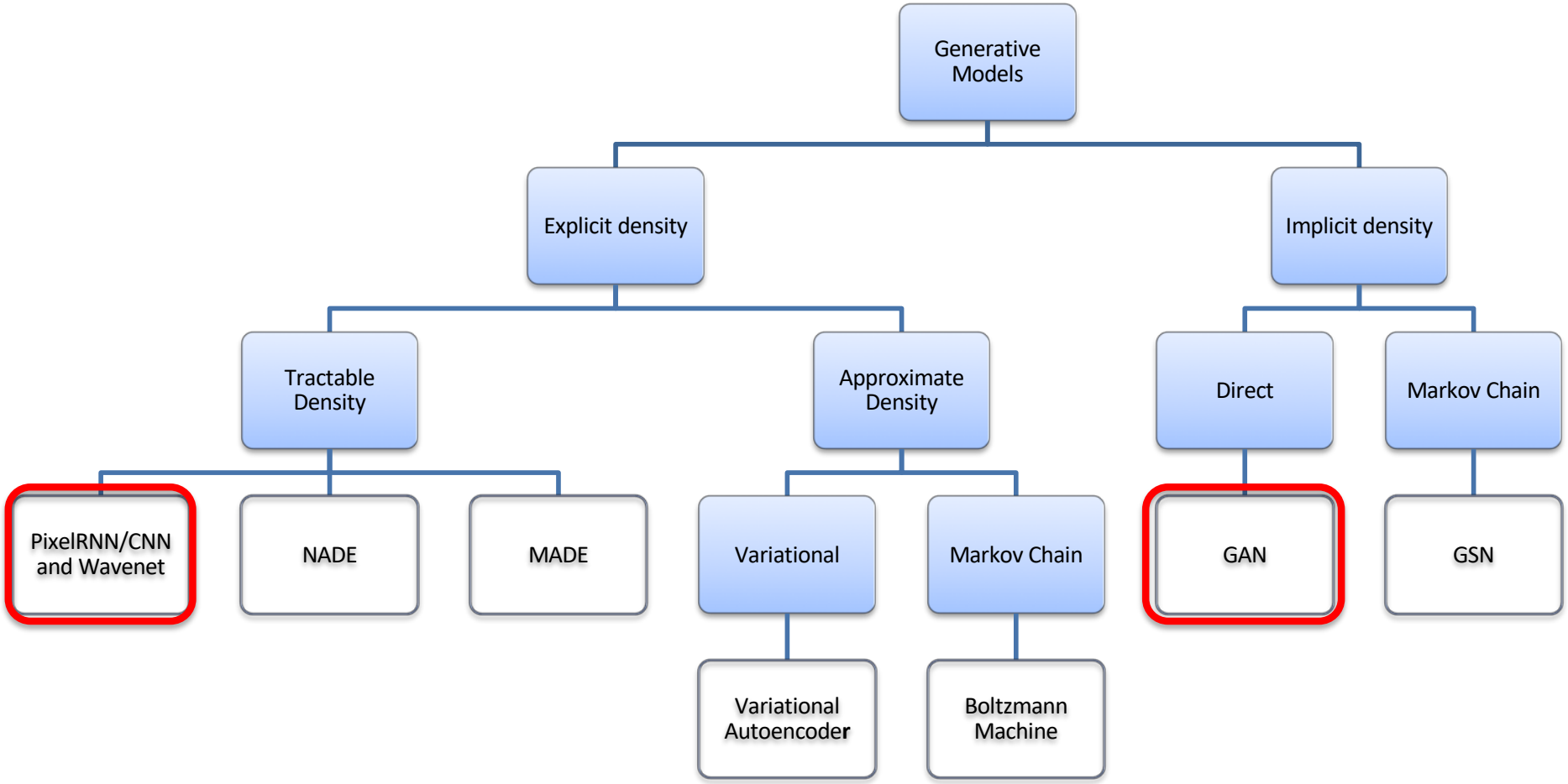
- Generative models of time-series data can be used for simulation and planning (reinforcement learning applications)
- Training generative models can also enable inference of latent representations that can be useful as general features

Why Generative Models?

- Be able to generate realistic synthetic samples
  - Possibly perform data augmentation
  - Simulate possible futures for learning algorithms
- Fill the blanks in the data
- Manipulate real samples with the assistance of the generative model
  - edit pictures with guidance
- GAN quality over the last years

https://pbs.twimg.com/media/Dw6ZIOlX4AMKL9J.jpg:large

Taxonomy of generative models



PixelRNN / PixelCNN

see jupyter notebook
example implementation

Factorizing the joint distribution

- Model explicitly the joint probability distribution of data stream **x** as a product of element-wise conditional distribution for each element x_i in the stream.
  - Example: An image **x** of size (n,n) is decomposed in row by row and pixel by pixel within every row
  - Apply **probability chain rule:** x_i is the i-th pixel in the image.
  - Then maximize the likelihood of training data

Likelihood of image x → $p(x) = \prod_{i=1}^{n^2} p(x_i | x_1, \ldots, x_{i-1})$ ← Probability of i'th pixel value given all previous pixel values

x_1	x_2	...	x_n
x_{n+1}	x_{n+2}	...	x_{n+1}
. . .	. . .		. . .
...			x_{n^2}

→

x_1	x_2	...	x_n	x_{n+1}	x_{n+2}	...	x_{i-1}	x_i	x_{i+1}	...	x_{n^2}

To model highly nonlinear and long-range correlations between pixels and their conditional distributions, we will need a powerful non-linear sequential model.

Question: Which model can we use?
Answer: Recurrent Neural Network.

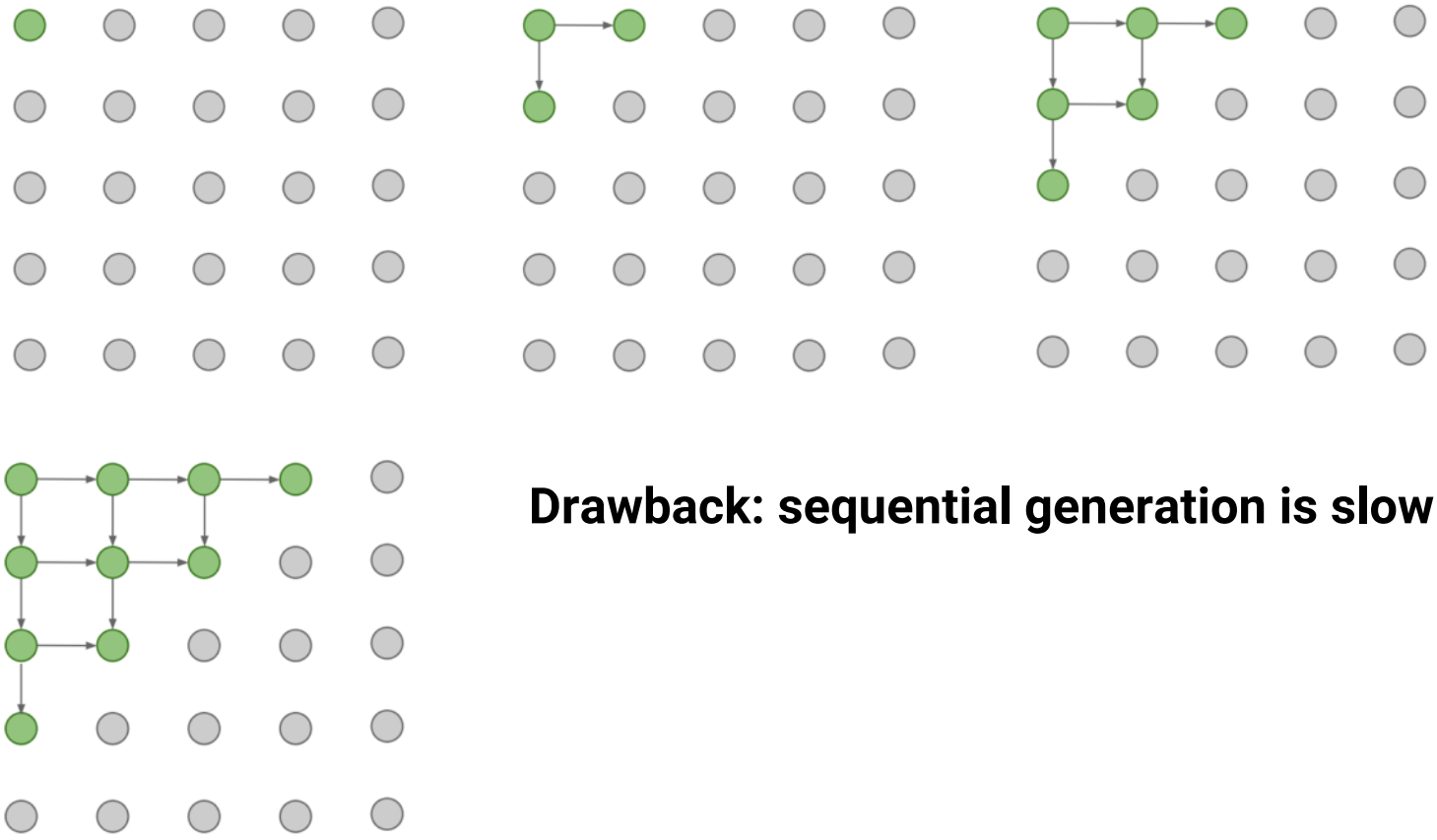
Char-RNN

Training data: Linux Kernel C Code

```
/*
 * Increment the size file of the new incorrect UI_FILTER group information
 * of the size generatively.
 */
static int indicate_policy(void)
{
  int error;
  if (fd == MARN_EPT) {
    /*
     * The kernel blank will coeld it to userspace.
     */
    if (ss->segment < mem_total)
      unblock_graph_and_set_blocked();
    else
      ret = 1;
    goto bail;
  }
  segaddr = in_SB(in.addr);
  selector = seg / 16;
  setup_works = true;
  for (i = 0; i < blocks; i++) {
    seq = buf[i++];
    bpf = bd->bd.next + i * search;
    if (fd) {
      current = blocked;
    }
  }
  rw->name = "Getjbbregs";
  bprm_self_clearl(&iv->version);
  regs->new = blocks[(BPF_STATS << info->historidac)] | PFMR_CLOBATHINC_SECONDS << 12;
  return segtable;
}
```

PixelRNN *[van der Oord et al. 2016]*

- Generate image pixels starting from corner
- Dependency on previous pixels modeled using an RNN (LSTM)



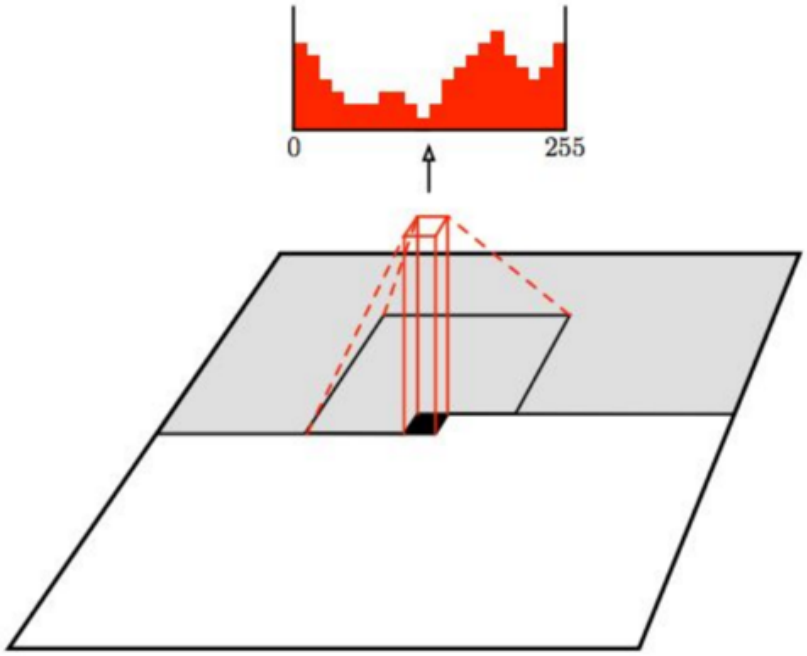
Drawback: sequential generation is slow!

PixelCNN *[van der Oord et al. 2016]*

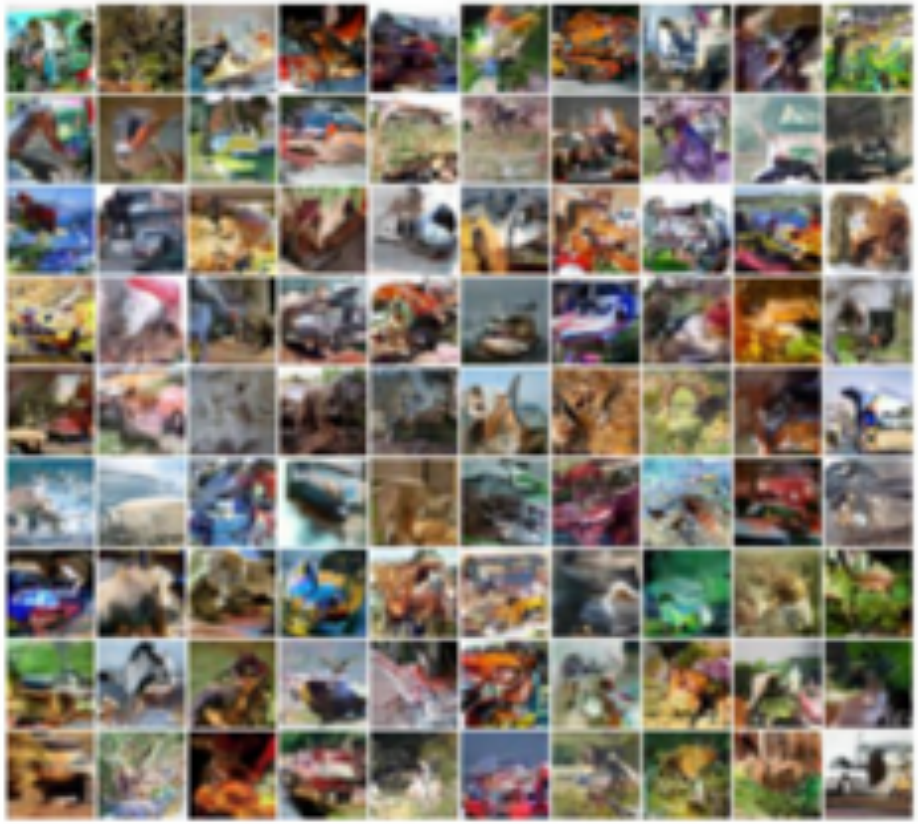
- Still generate image pixels starting from corner
- Dependency on previous pixels now modeled using a CNN over context region
- Training is faster than PixelRNN (can parallelize convolutions since context region values known from training images)

- Generation must still proceed sequentially => still slow

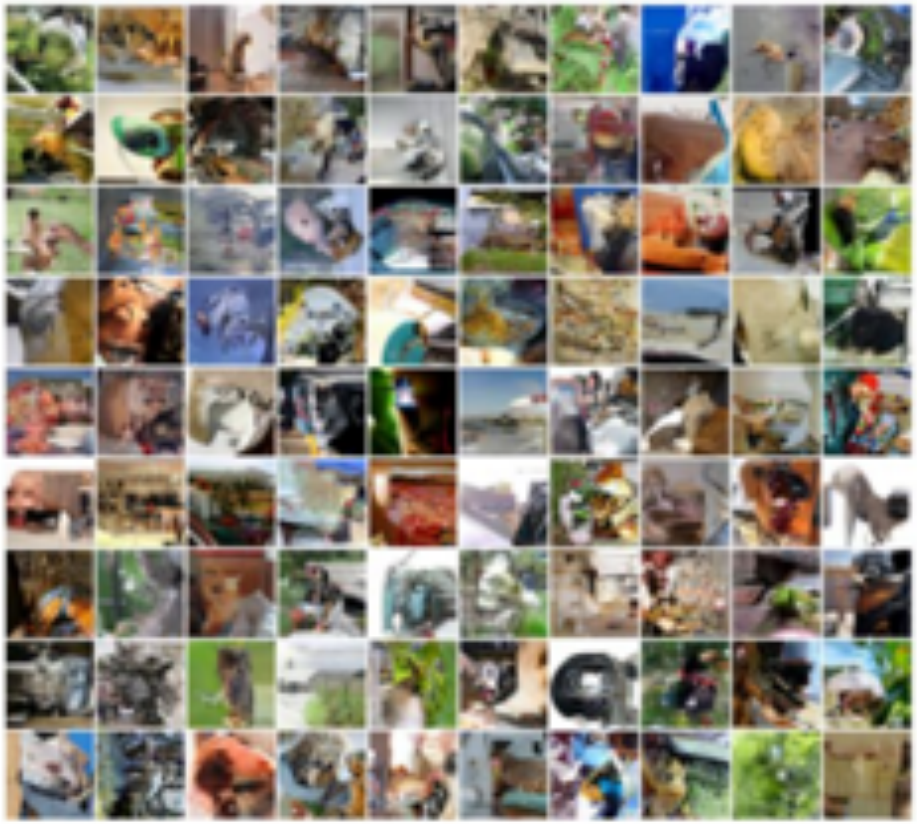
Softmax loss at each pixel



PixelRNN / PixelCNN generation samples



32x32 CIFAR-10



32x32 ImageNet

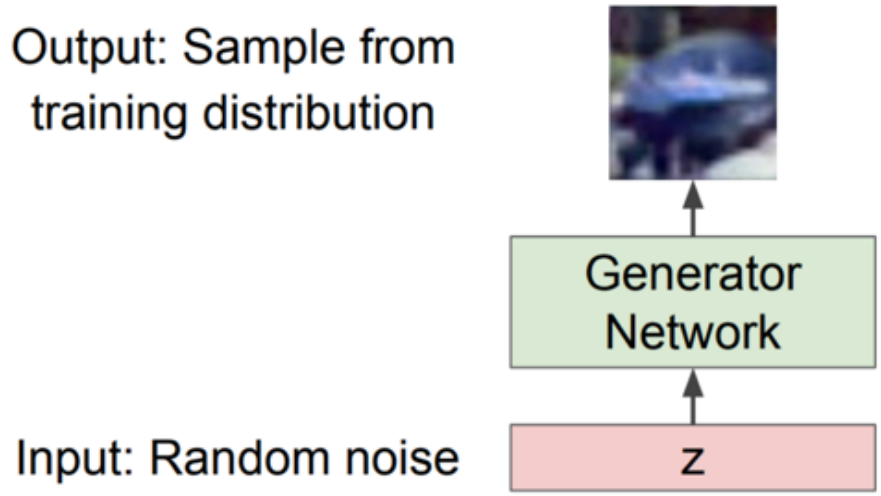
Generative Adversarial Networks (GAN)

Learn the structure of the world

https://www.youtube.com/embed/kSLJriaOumA?start=335

Generative Adversarial Networks

- **Problem:** Want to sample from complex, high-dimensional training distribution. No direct way to do this!
- **Solution:** Sample from a simple distribution, e.g. random noise. Learn transformation to training distribution.
- **Question:** What can we use t transformation?
- **Answer:** A neural network!



Training GANs: Two-player game (Counterfeit example)

[Goodfellow et al., "Generative Adversarial Nets", NIPS 2014]

Generator

Counterfeiter

Discriminator

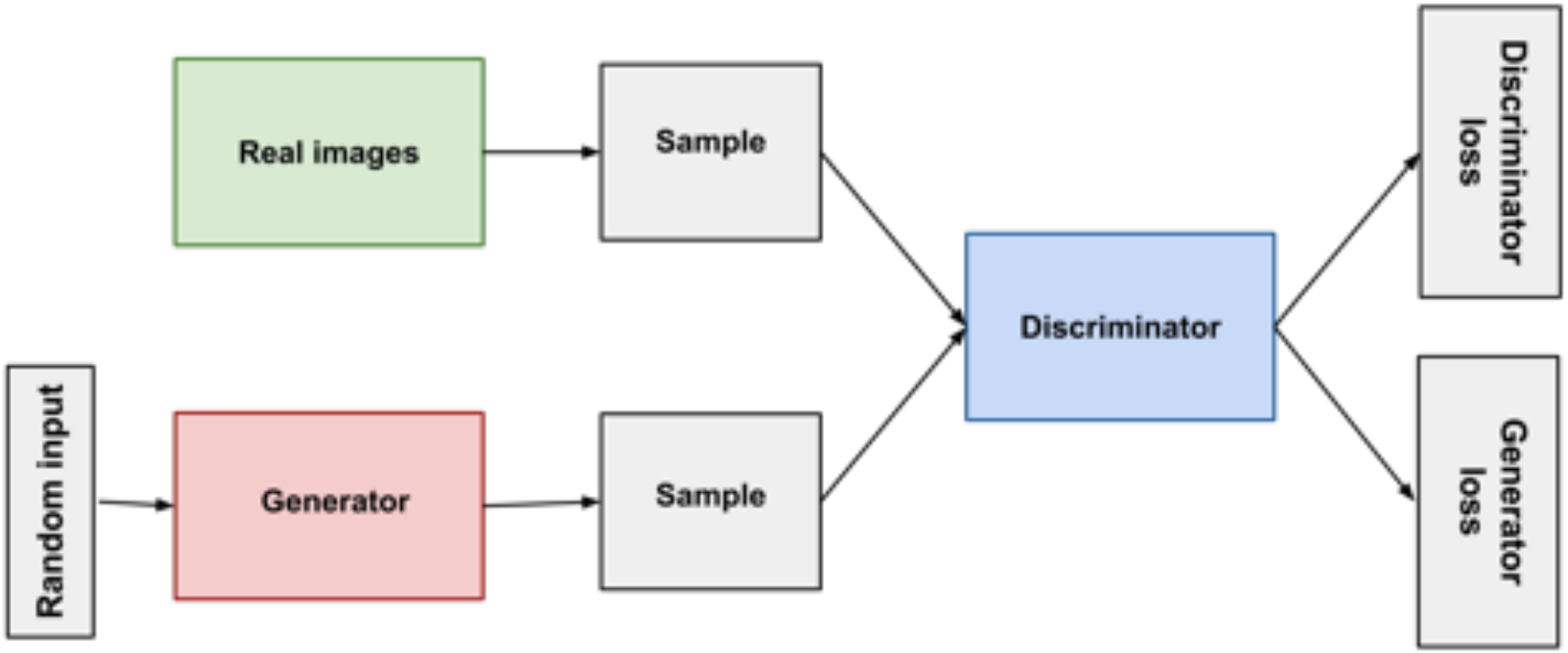
FBI

Fake

Real

Training GANs: Two-player game

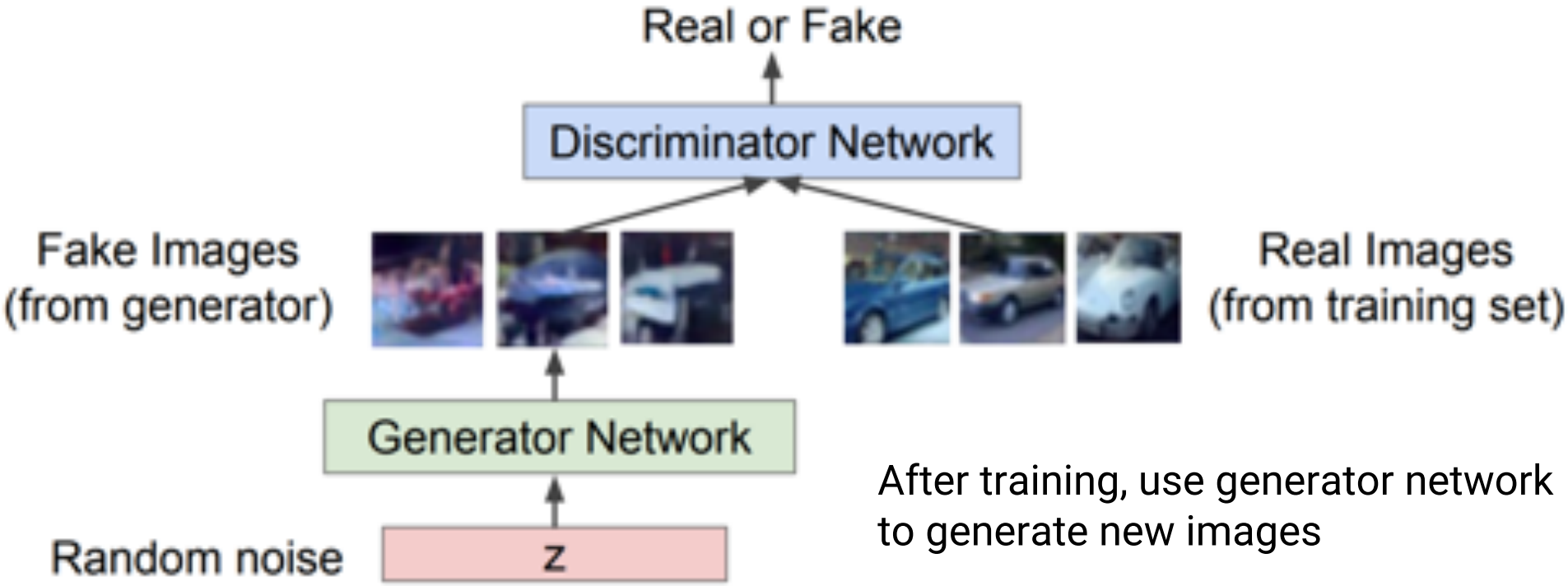
[Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014]



Training GANs: Two-player game

[Goodfellow et al., "Generative Adversarial Nets", NIPS 2014]

- **Generator network:** try to fool the discriminator by generating real-looking images
- **Discriminator network:** try to distinguish between real and fake images



After training, use generator network to generate new images

Training GANs: Two-player game

[Goodfellow et al., "Generative Adversarial Nets", NIPS 2014]

- **Generator network:** try to fool the discriminator by generating real-looking images
- **Discriminator network:** try to distinguish between real and fake images

Minimax objective function:

Discriminator outputs likelihood in (0,1) of real image

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

Discriminator output for real data x

Discriminator output for generated fake data G(z)

- Discriminator $D_{\theta d}$ wants to maximize objective such that D(x) is close to 1 (real) and D(G(z)) is close to 0 (fake)
- Generator $G_{\theta g}$ wants to minimize objective such that D(G(z)) is close to 1 (discriminator is fooled into thinking generated G(z) is real)

Training GANs: Two-player game

D(x) tries to be near 1

Differentiable function D

X sampled from data

D tries to make D(G(z)) near 0, G tries to make D(G(z) near 1

D

X sampled from model

Differentiable function G

Input noise z

$$J^{(D)} = -\frac{1}{2}\mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}} \log D(\boldsymbol{x}) - \frac{1}{2}\mathbb{E}_{\boldsymbol{z}} \log\left(1 - D\left(G(\boldsymbol{z})\right)\right)$$

$$J^{(G)} = -\frac{1}{2}\mathbb{E}_{\boldsymbol{z}} \log D\left(G(\boldsymbol{z})\right)$$

GAN Training algorithm

Lets code a GAN

for number of training iterations **do**

for k steps **do**

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
- Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D_{\theta_d}(x^{(i)}) + \log(1 - D_{\theta_d}(G_{\theta_g}(z^{(i)}))) \right]$$

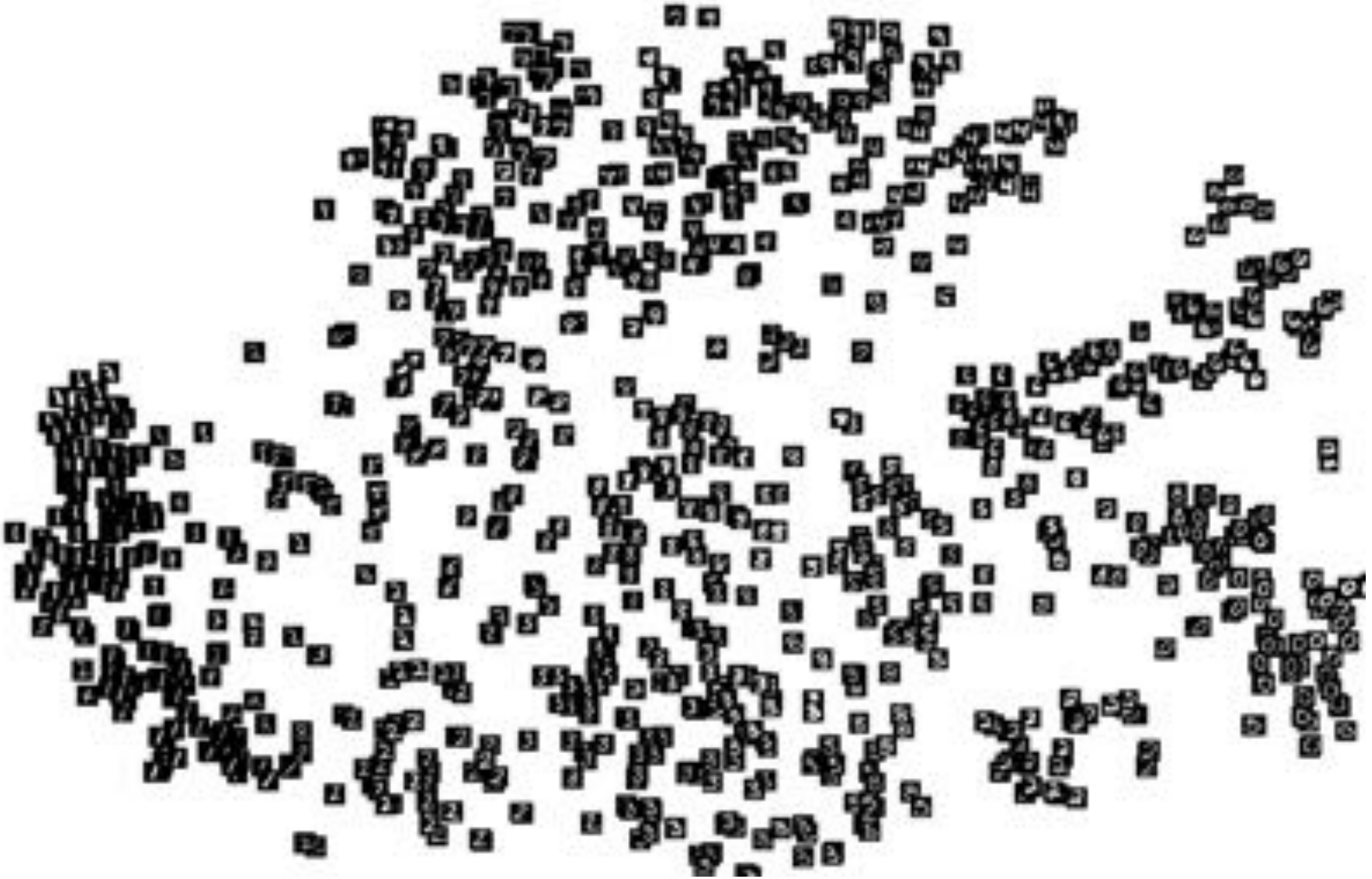
end for

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Update the generator by ascending its stochastic gradient (improved objective):

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log(D_{\theta_d}(G_{\theta_g}(z^{(i)})))$$

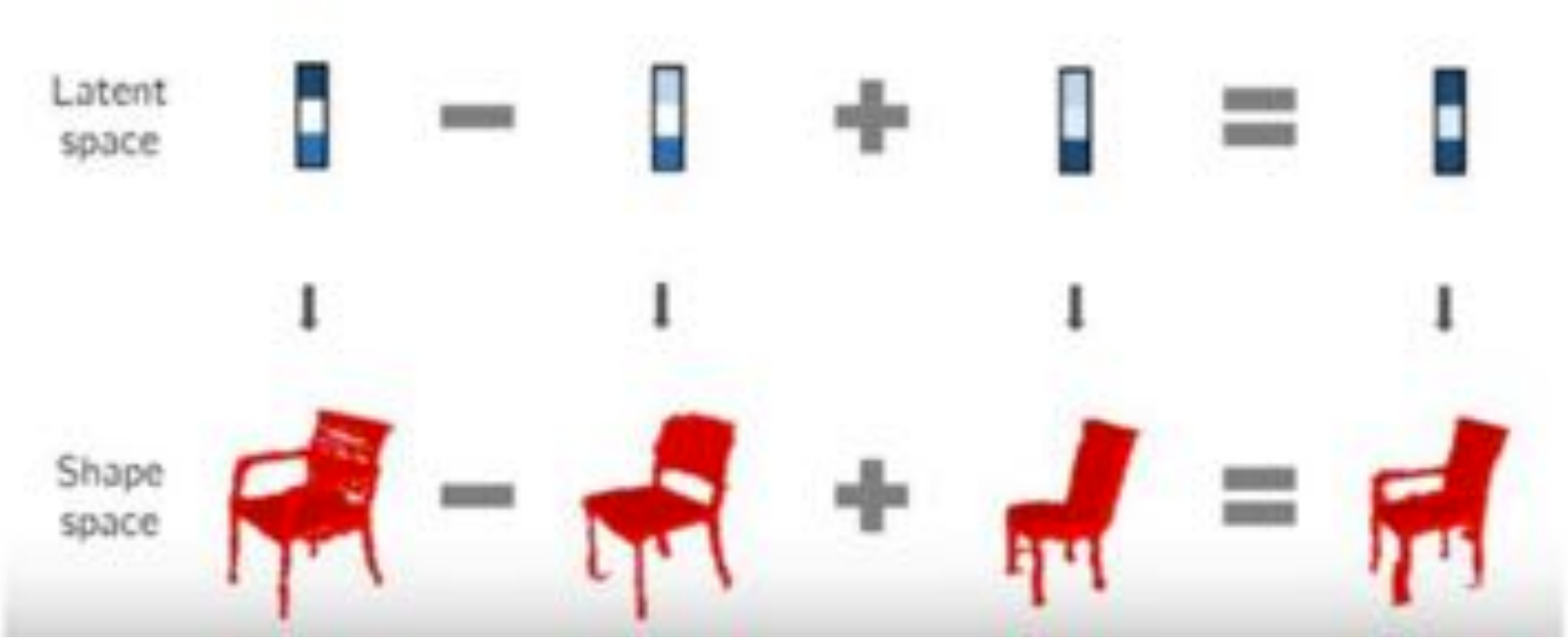
end for

GAN Training algorithm



https://medium.com/intel-student-ambassadors/reducing-mode-collapse-in-gans-using-guided-latent-spaces-36f52a08a668

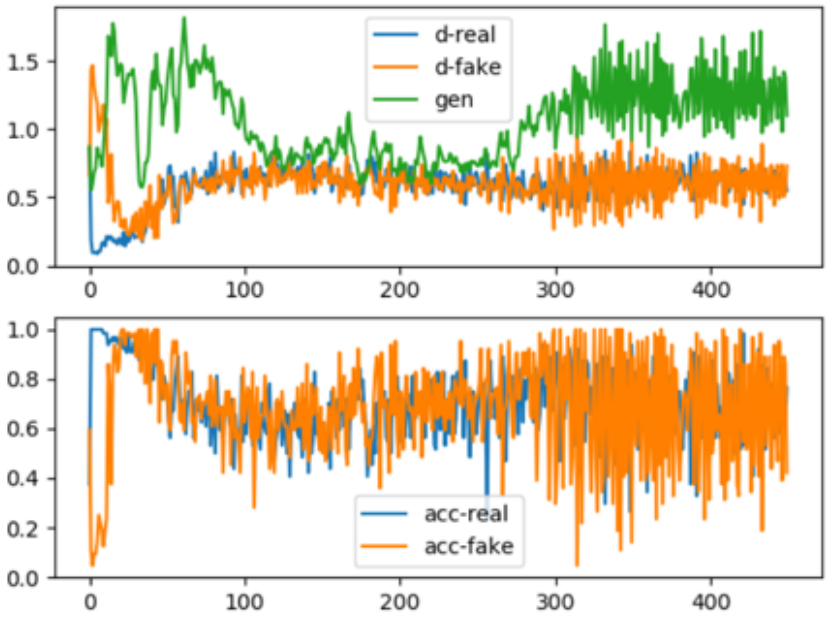
GAN Training algorithm



https://medium.com/intel-student-ambassadors/reducing-mode-collapse-in-gans-using-guided-latent-spaces-36f52a08a668

GAN Mode Collapse / Convergence Failure

1. **GANs are difficult to train**
2. Stable GAN
    - Discriminator loss 0.5 – 0.8 (acc ~50% for fake images, ~70-80% real images)
    - Generator loss higher 1.0 - 2.0 or even higher.

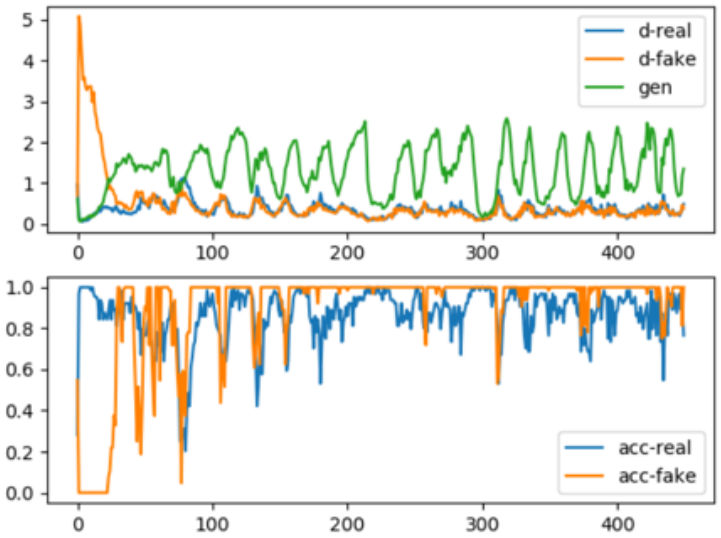


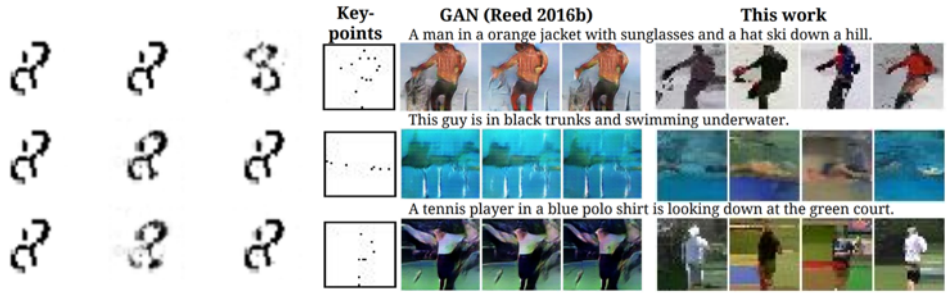
https://machinelearningmastery.com/practical-guide-to-gan-failure-modes/

GAN Mode Collapse / Convergence Failure

3. Mode Collapse

- Generator model **only capable of generating one or a small subset of different outcomes** – modes
- Generated **images show low diversity**, with identical image or same small subset of identical images
- **Oscillating loss in generator** (jumps from generating one mode to another model that has different loss)
- Solution (sometimes) **increase latent space**



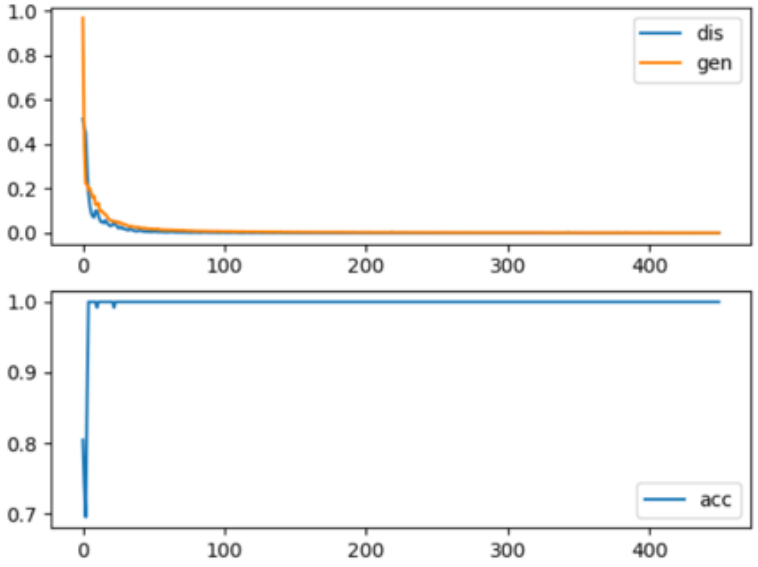


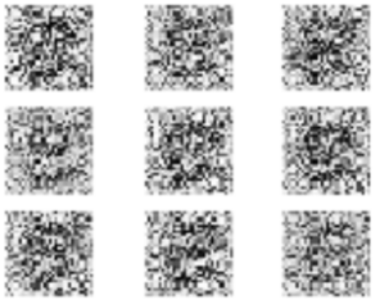
„Mode collapse, also known as the scenario, is a problem that occurs when the generator learns to map several different input z values to the same output point.“ - Goodfellow

GAN Mode Collapse / Convergence Failure

4. Convergence Failure

- NN fails to converge - not finding an (Nash) equilibrium between the discriminator and the generator
- Loss for the discriminator goes to zero, sometimes loss of generator rises
- Generator outputting garbage images





GAN Examples

DCGAN
11/2015

EBGAN-PT
9/2016

BEGAN
3/2017
128 × 128

Progressive GAN
10/2017
1024 x 1024

202x

Figure 7: Generated samples

“The GAN Zoo”

- GAN - Generative Adversarial Networks
- 3D-GAN - Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling
- acGAN - Face Aging With Conditional Generative Adversarial Networks
- AC-GAN - Conditional Image Synthesis With Auxiliary Classifier GANs
- AdaGAN - AdaGAN: Boosting Generative Models
- 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
- AM-GAN - Generative Adversarial Nets with Labeled Data by Activation Maximization
- AnoGAN - Unsupervised Anomaly Detection with Generative Adversarial Networks to Guide Marker Discovery
- ArtGAN - ArtGAN: Artwork Synthesis with Conditional Categorial GANs
- b-GAN - b-GAN: Unified Framework of Generative Adversarial Networks
- Bayesian GAN - Deep and Hierarchical Implicit Models
- BEGAN - BEGAN: Boundary Equilibrium Generative Adversarial Networks
- BiGAN - Adversarial Feature Learning
- BS-GAN - Boundary-Seeking Generative Adversarial Networks
- CGAN - Conditional Generative Adversarial Nets
- CaloGAN - CaloGAN: Simulating 3D High Energy Particle Showers in Multi-Layer Electromagnetic Calorimeters with Generative Adversarial Networks
- CCGAN - Semi-Supervised Learning with Context-Conditional Generative Adversarial Networks
- CatGAN - Unsupervised and Semi-supervised Learning with Categorical Generative Adversarial Networks
- CoGAN - Coupled Generative Adversarial Networks
- Context-RNN-GAN - Contextual RNN-GANs for Abstract Reasoning Diagram Generation
- C-RNN-GAN - C-RNN-GAN: Continuous recurrent neural networks with adversarial training
- 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
- DTN - Unsupervised Cross-Domain Image Generation
- DCGAN - Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks
- DiscoGAN - Learning to Discover Cross-Domain Relations with Generative Adversarial Networks
- DR-GAN - Disentangled Representation Learning GAN for Pose-Invariant Face Recognition
- DualGAN - DualGAN: Unsupervised Dual Learning for Image-to-Image Translation
- EBGAN - Energy-based Generative Adversarial Network
- f-GAN - f-GAN: Training Generative Neural Samplers using Variational Divergence Minimization
- FF-GAN - Towards Large-Pose Face Frontalization in the Wild
- GAWWN - Learning What and Where to Draw
- GeneGAN - GeneGAN: Learning Object Transfiguration and Attribute Subspace from Unpaired Data
- Geometric GAN - Geometric GAN
- GoGAN - Gang of GANs: Generative Adversarial Networks with Maximum Margin Ranking
- GP-GAN - GP-GAN: Towards Realistic High-Resolution Image Blending
- IAN - Neural Photo Editing with Introspective Adversarial Networks
- iGAN - Generative Visual Manipulation on the Natural Image Manifold
- IcGAN - Invertible Conditional GANs for image editing
- ID-CGAN - Image De-raining Using a Conditional Generative Adversarial Network
- Improved GAN - Improved Techniques for Training GANs
- InfoGAN - InfoGAN: Interpretable Representation Learning by Information Maximizing Generative Adversarial Nets
- 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

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