Introduction to Generative Adversarial Networks (GANs)

“Adversarial training is the coolest thing since sliced bread.” - Yann LeCun

Jennifer Sleeman

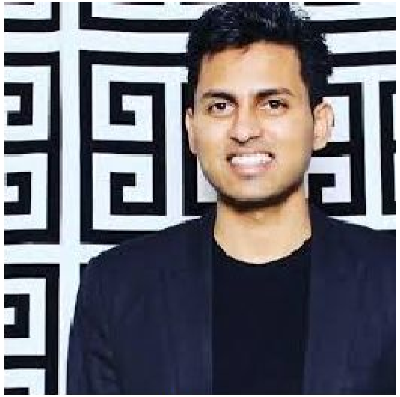
Presented to the DC Data Science Community

February 1, 2017

Special Acknowledgement

Ian Goodfellow

John Kaufhold



Soumith Chintala

Special Acknowledgement

The awesome DLA team!

Special Acknowledgement

the ebiquity lab

Outline of this talk

- Motivation
- Generative Models
- Background of GANs
- Advancements in GANs
- Code Example – Creating your first GAN
- Applications of GANs

Motivation

ImageNet Dataset

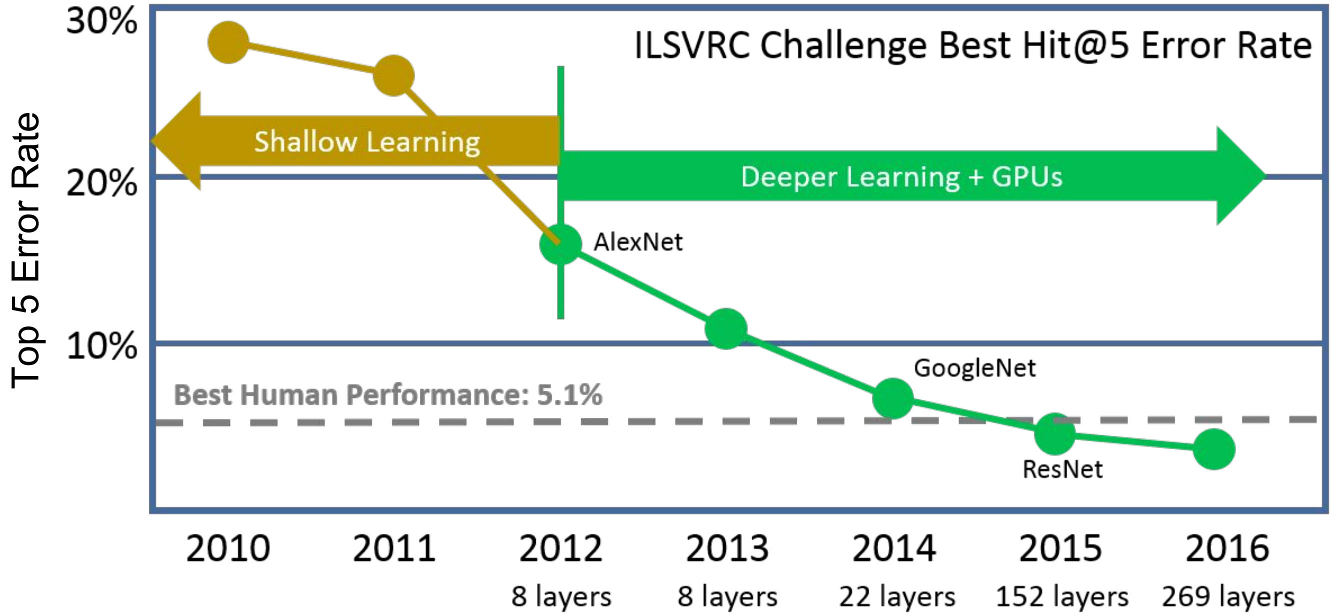
Olga Russakovsky*, Jia Deng*, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg and Li Fei-Fei. (* = equal contribution) **ImageNet Large Scale Visual Recognition Challenge**. *IJCV,* 2015.

Motivation

- 1.2 million training samples
- 1000 classes
- ImageNet Large Scale Visual Recognition Challenge (ILSVRC)
- Evaluate object detection and object classification methods

Olga Russakovsky*, Jia Deng*, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg and Li Fei-Fei. (* = equal contribution) **ImageNet Large Scale Visual Recognition Challenge**. *IJCV,* 2015.

Motivation



- Huge improvements since 2012 due to deep learning networks
- Convolutional Networks work well for these tasks
- State of the art based on ‘supervised learning’ approaches

Olga Russakovsky*, Jia Deng*, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg and Li Fei-Fei. (* = equal contribution) **ImageNet Large Scale Visual Recognition Challenge**. *IJCV*, 2015.

Motivation

- SOA convolution network
- “Trick it” into classifying an image incorrectly
- Minor (non-random) perturbations not evident to human eye
- Optimize input to maximize prediction error

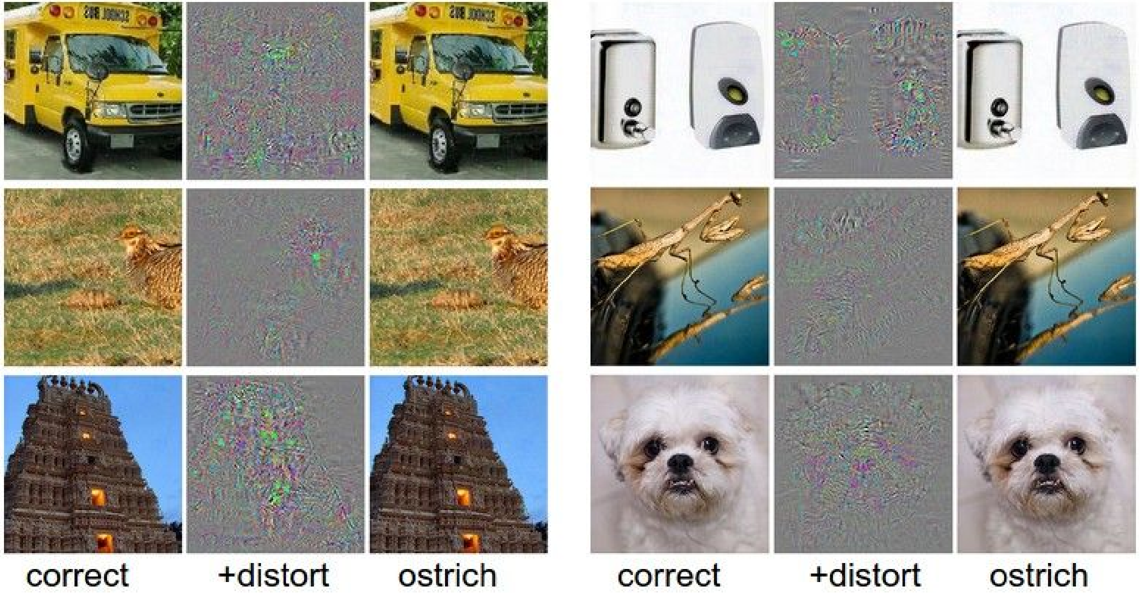


Image and Example Source: “Intriguing properties of neural networks.” by Szegedy et al.
Nice summary also: http://karpathy.github.io/2015/03/30/breaking-convnets/

Motivation

They called these images adversarial examples because they intentionally attempted to trick the convolutional network

These kind of examples don't naturally occur in the wild

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Motivation

- More work shed light on these adversarial examples
- Was not just a weakness with deep learning
- All machine learning methods tested have the same vulnerability

"Panda"
57.7% confidence

"nematode"
8.2% confidence

"gibbon"
99.3% confidence

Image and Example Source: Explaining and Harnessing Adversarial Examples by Goodfellow et al.
Nice summary also: http://karpathy.github.io/2015/03/30/breaking-convnets/

Motivation

- Nguyen et al. took one step further
- Fooled ConvNets into classifying images from noise
- And other strangely generated images
- >99.6% confidence classification

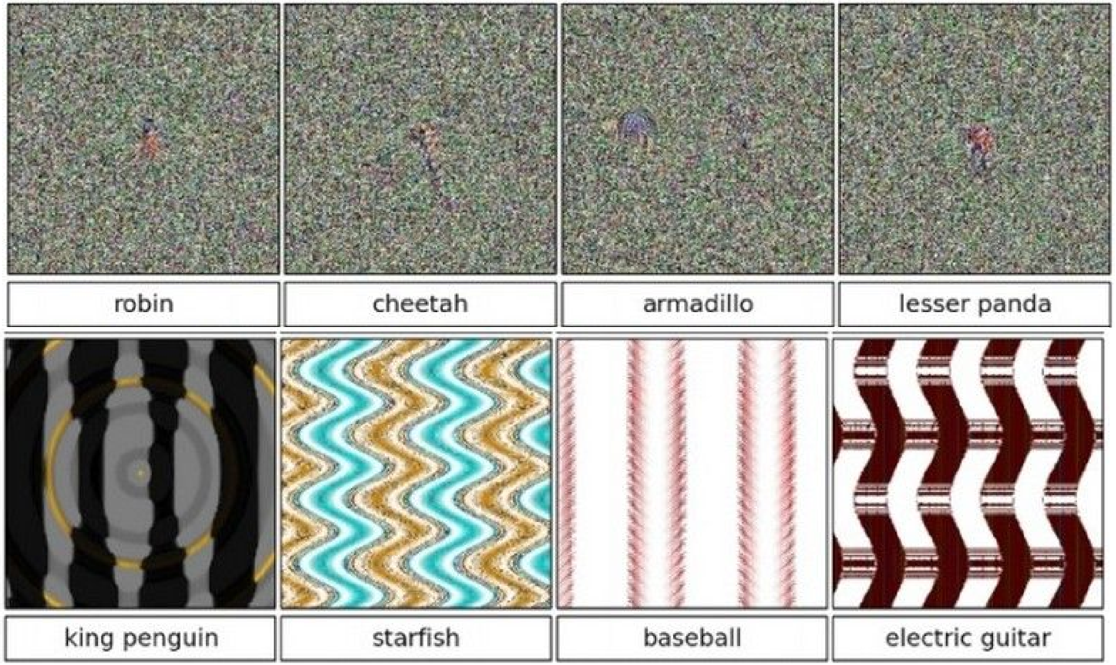

Image and Example Source: “Deep neural networks are easily fooled: High confidence predictions for unrecognizable images." by Nguyen et al.
Nice summary also: http://karpathy.github.io/2015/03/30/breaking-convnets/

Motivation

Generative Adversarial Networks were born.

Generative Models

Discriminative vs. Generative Models

- Discriminative:
  - Map inputs X to outputs y (classes)
  - Goal is to classify or categorize
  - Discrete or continuous
  - Supervised
  - Examples: SVMs and Logistic Regression
- Generative:
  - Models how data was generated
  - Models underlying data distribution
  - Can be used to generate, classify or categorize
  - Unsupervised
  - Examples: LDA and HMMs

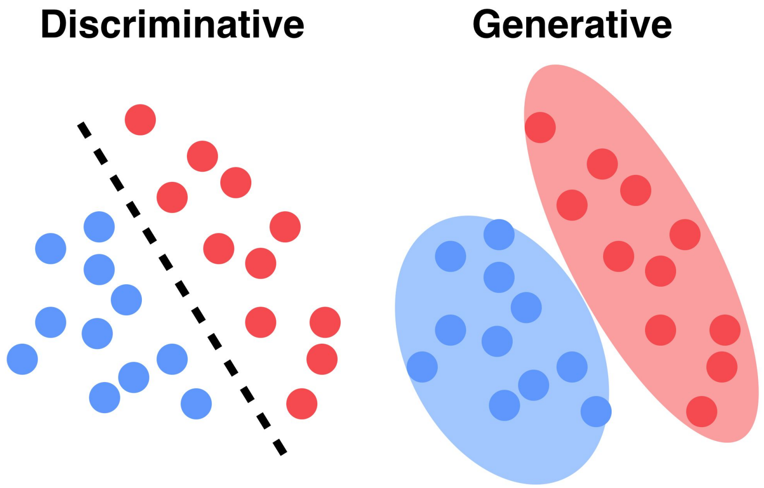

Image source: http://joelouismarino.github.io/blog_posts/blog_VAE.html

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Examples of Generative Models

Latent Dirichlet Allocation (LDA)

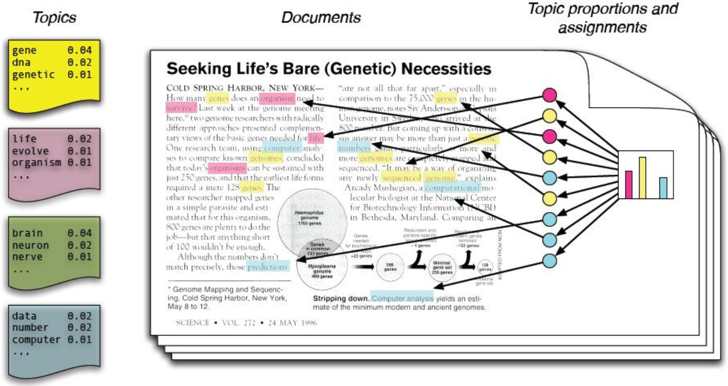

Image source: http://deeplearning.net/tutorial/rbm.html

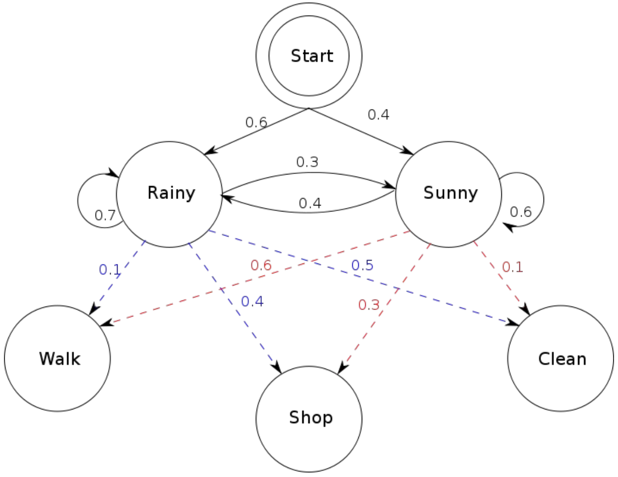

Image source: http://deeplearning.net/tutorial/rbm.html

Hidden Markov Models (HMM)

Restricted Boltzmann Machines (RBM)

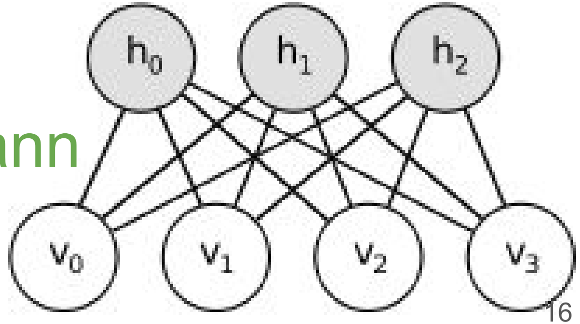

Image credit: http://deeplearning.net/tutorial/rbm.html

The important take away is that generative model will potentially give us the ability to “automatically learn the natural features of a dataset”.

And that is powerful.

https://openai.com/blog/generative-models/

Examples of Generative Models

Generative Adversarial Networks

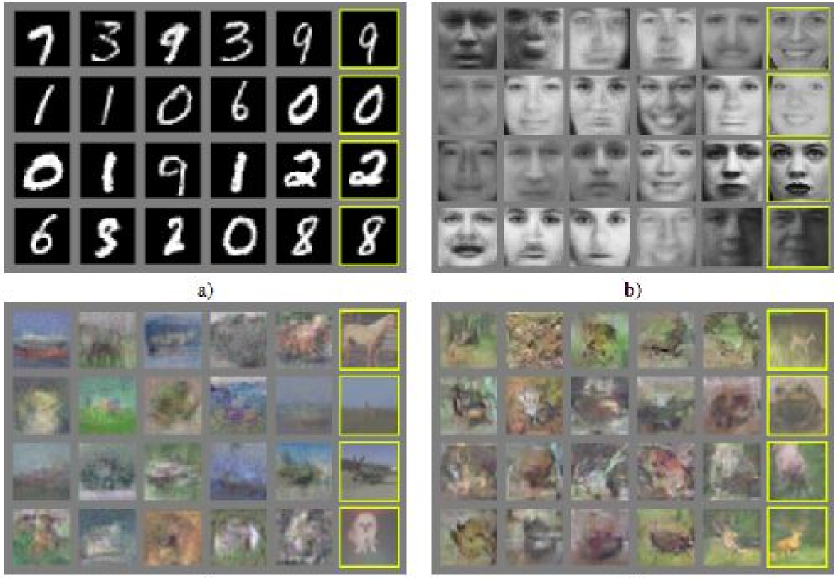

Image generation from Goodfellow et al. 2014 paper which introduced Generative Adversarial Networks

Ian Goodfellow
Research Scientist, OpenAI

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Generative Adversarial Networks

- Imagine looking at training samples in an embedded space
- Similar pictures cluster closer together given their features

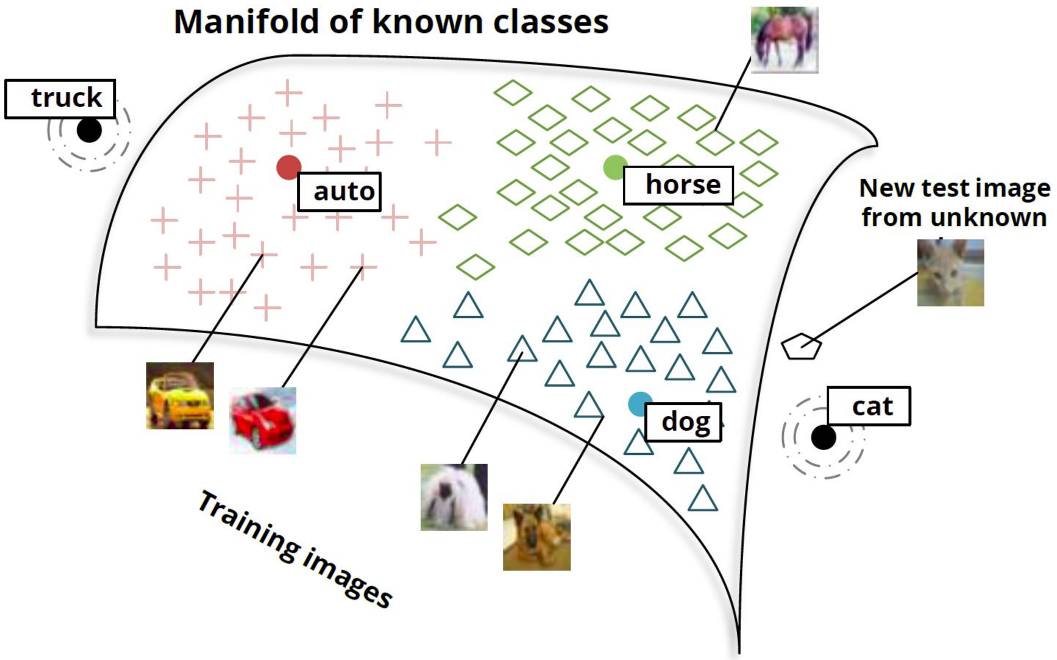

Image source: Socher, Richard, et al. "Zero-shot learning through cross-modal transfer." Advances in neural information processing systems. 2013.

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Generative Adversarial Networks

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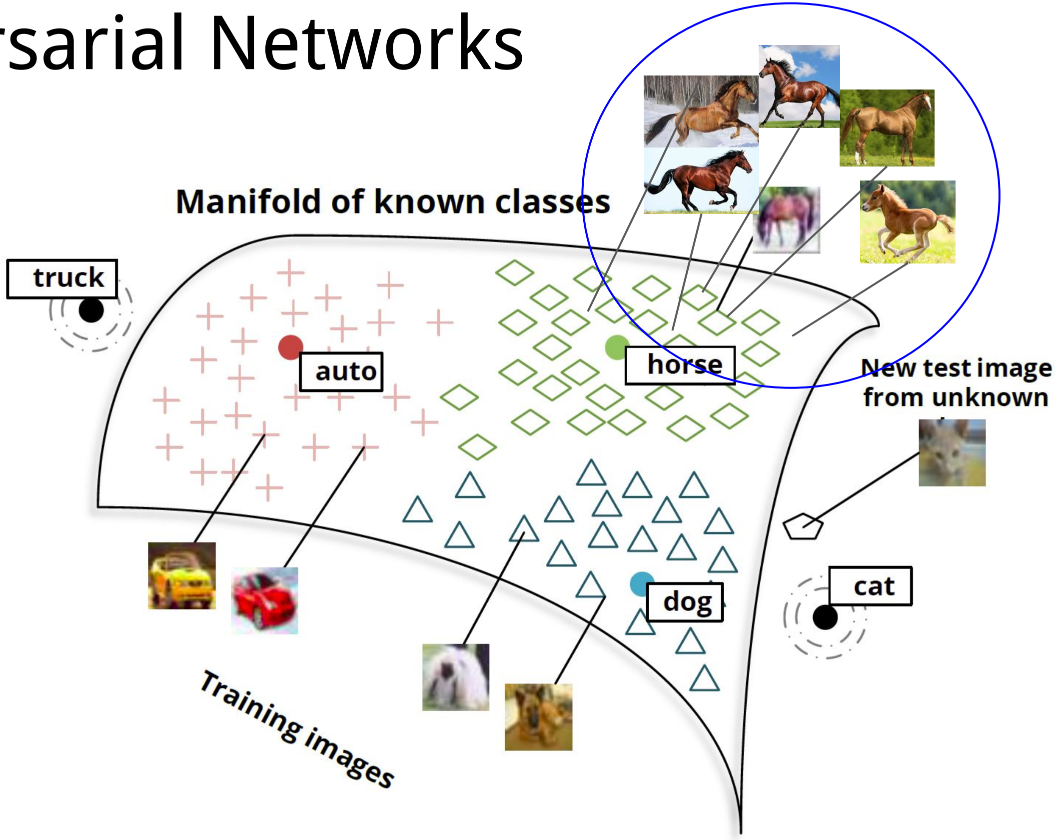


Image source: Socher, Richard, et al. "Zero-shot learning through cross-modal transfer." Advances in neural information processing systems. 2013.

Generative Adversarial Networks

- Using t-distributed Stochastic Neighbor Embedding (t-SNE) view images of cats in an embedded space
    - t-SNE is a technique for visualizing high dimensional data
    - two or three-dimensional data
- In this picture, two distinct groupings are box bounded
    - Grey cats
    - Black cats

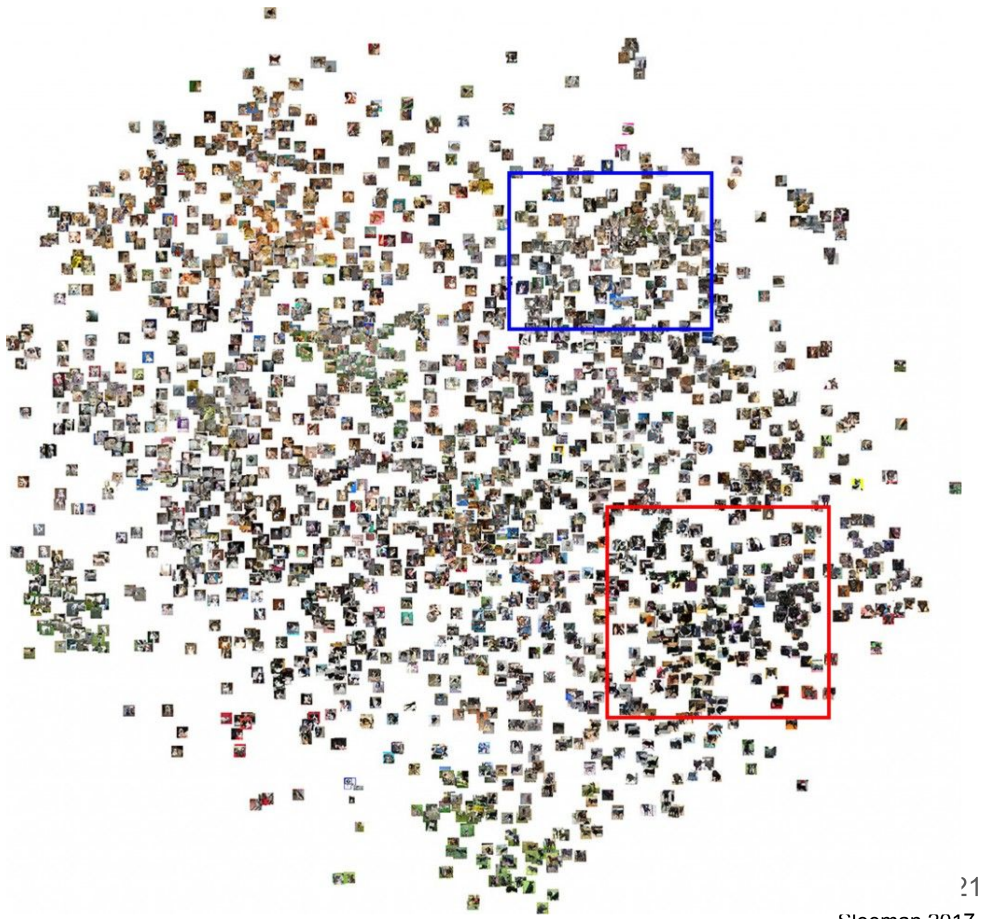


Image source: https://indico.io/blog/visualizing-with-t-sne/
More on t-sne: https://lvdmaaten.github.io/tsne/

Generative Adversarial Networks

- Zooming into the gray cat cluster
- Further grouped by various features such as color, orientation, etc.

Image source: https://indico.io/blog/visualizing-with-t-sne/

Generative Adversarial Networks (GANs)

A tale of a dog and his owner….

I’m a dog.

D = dog

They call me D.

D = dog

D loves yummy treats.

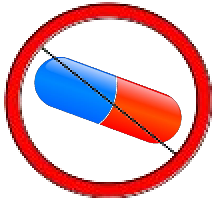
D

All shapes and sizes of yummy treats.

D

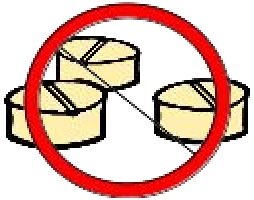
D is not feeling well.

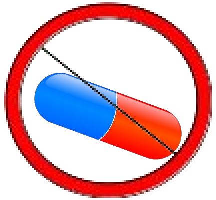
D



But D does not like medicine.

D

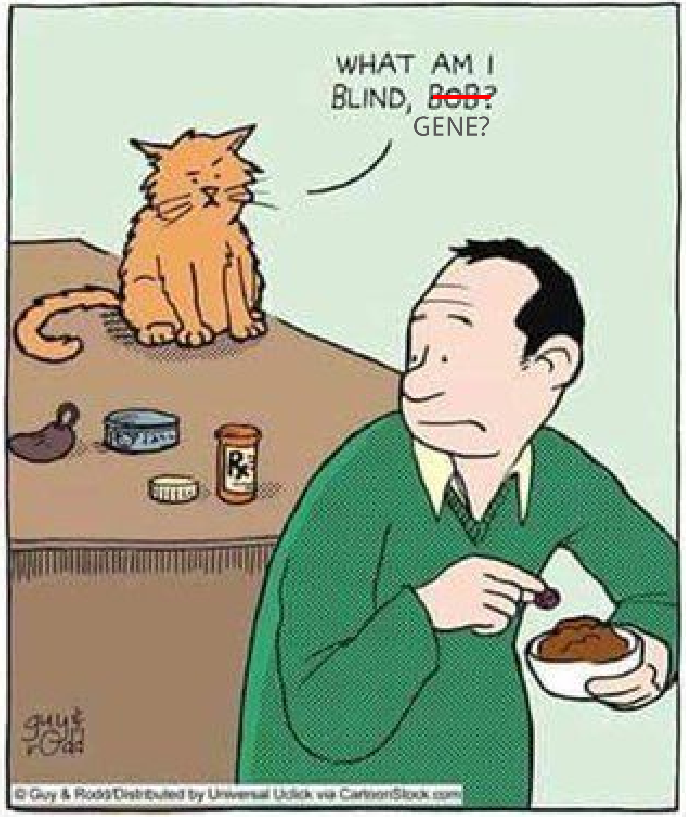




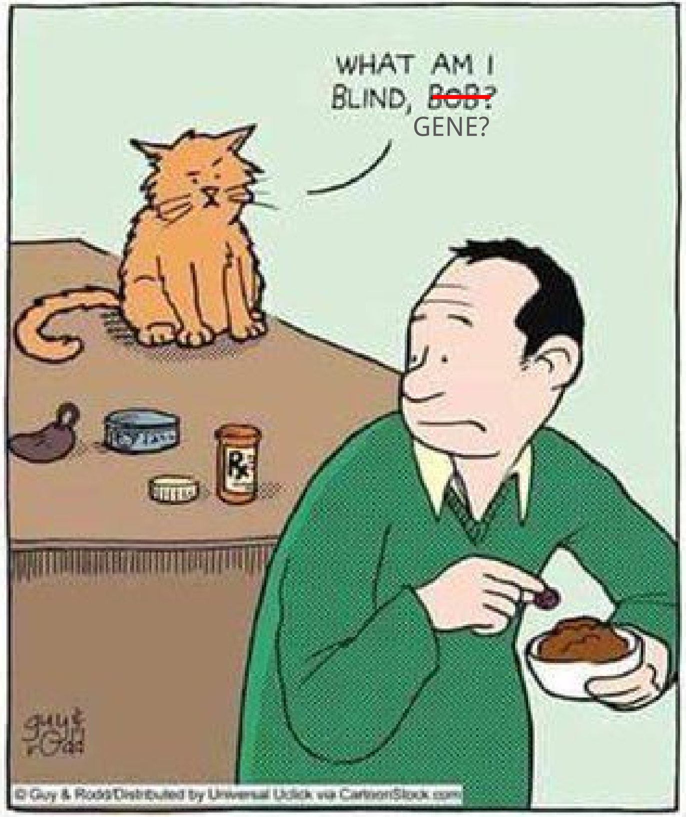
Any kind of medicine.

D

And D is pretty good at telling treats from medicine.

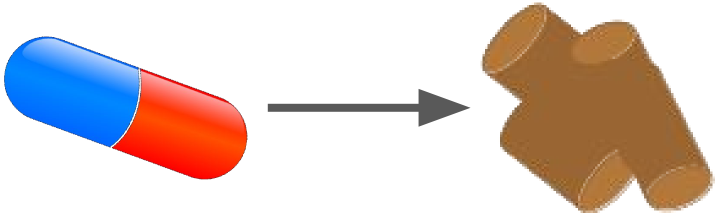

WHAT AM I BLIND, ~~BOB?~~ GENE?
© Guy & Rodd/Distributed by Universal Uclick via CartoonStock.com

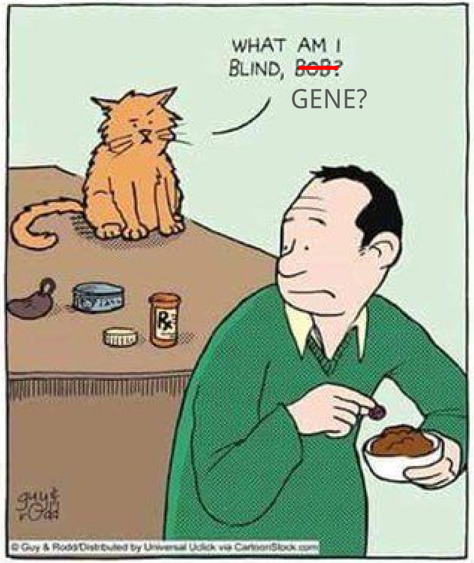
I’m Gene.



They call me G.
D is my dog.

D

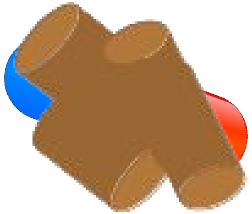


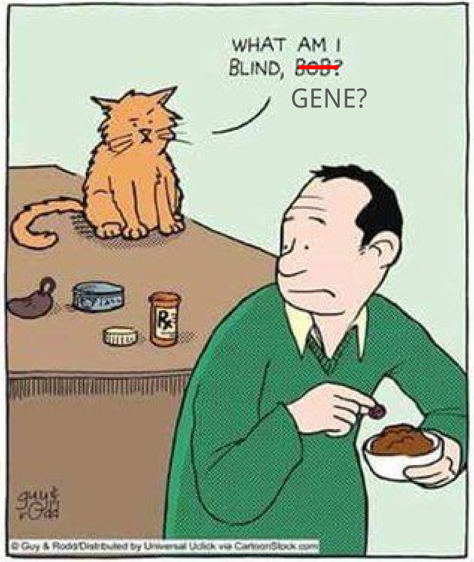


G = Gene

G wants to trick D into taking his medicine.

D





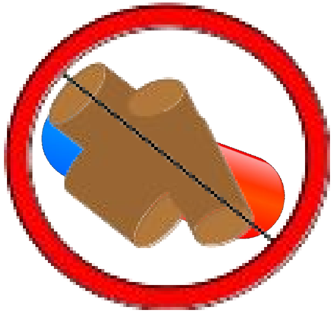
G = Gene

G tries to use something that looks like a yummy treat.

D

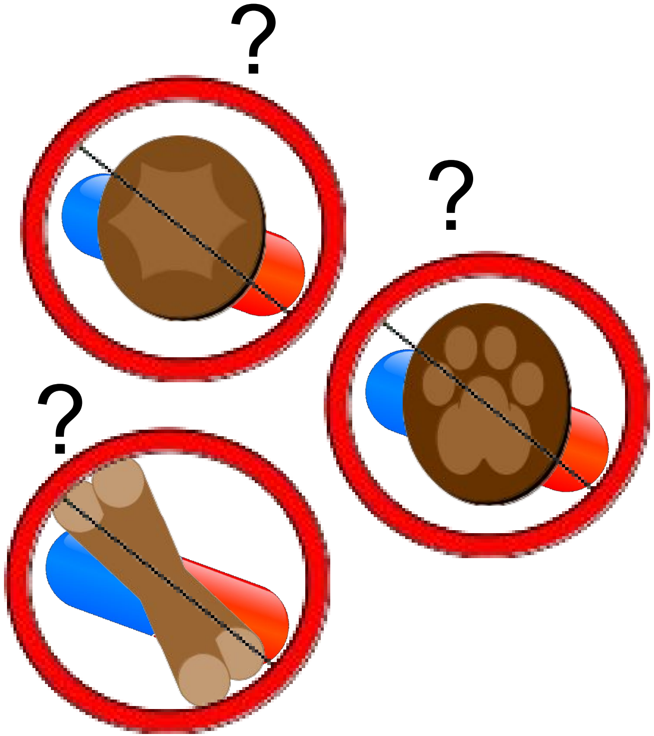
?

G



Medicine wrapped in tasty things still tastes like medicine.

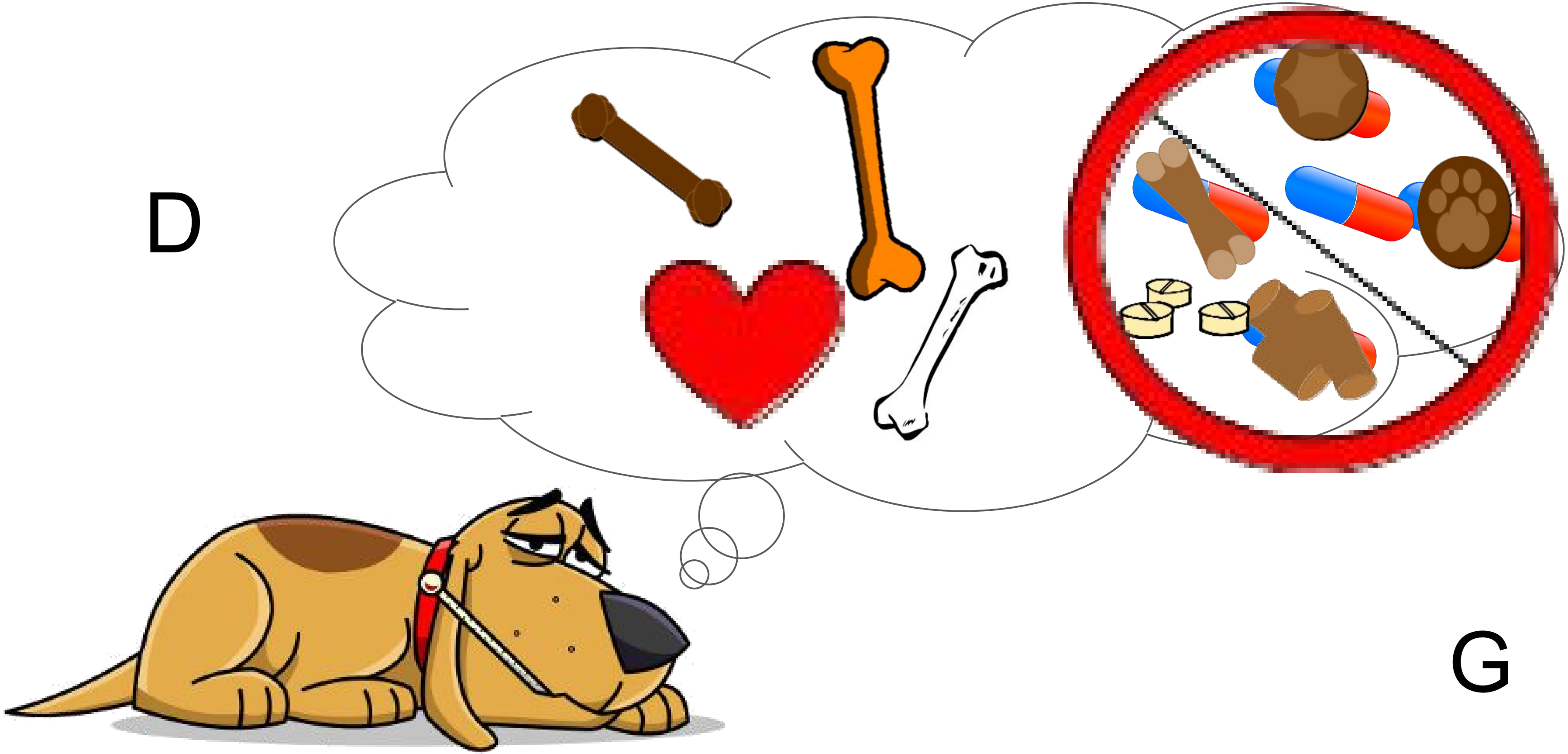
D



G

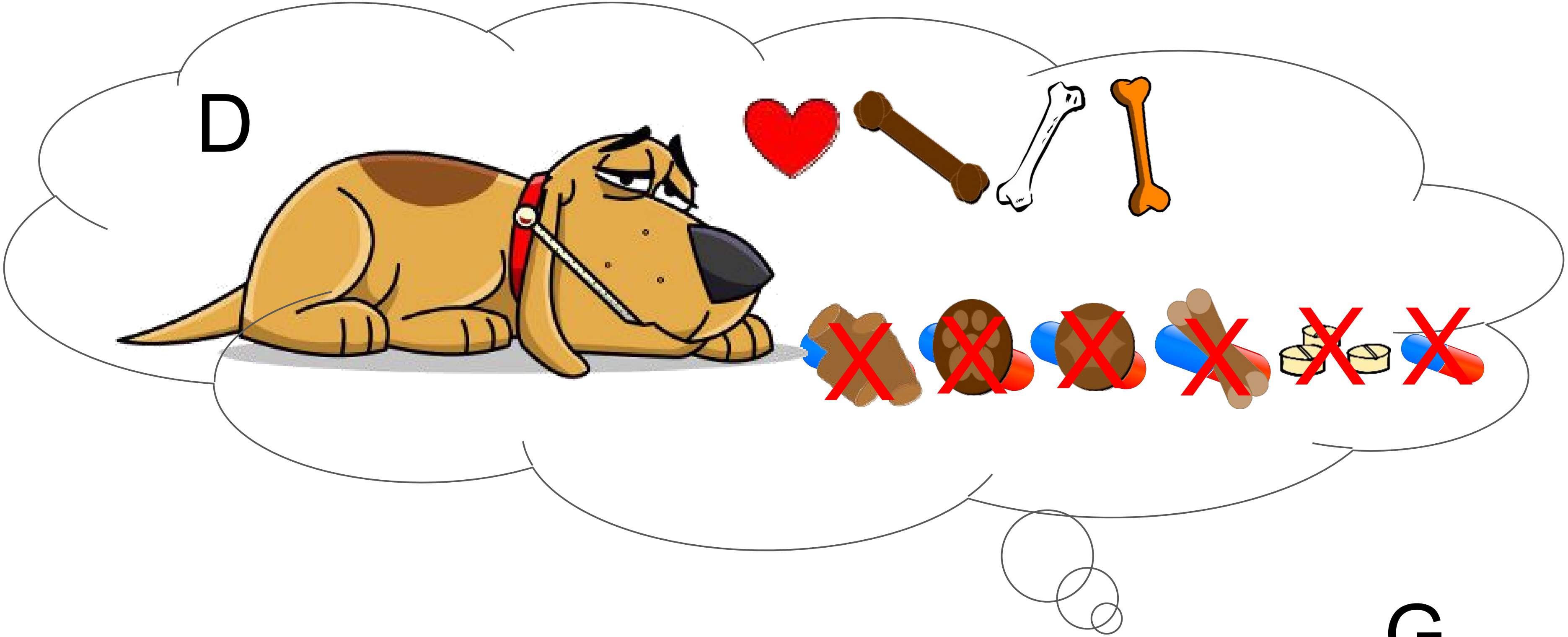
G tried all manner of things to trick D.

D



G

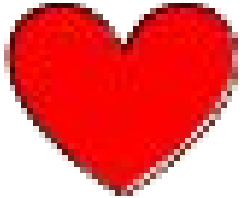
And D kept learning….



G

But so did G.

D



G

Until eventually,
G could fool D.

What is a GAN?

- Two deep learning networks
  - one discriminative
  - one generative
- Uses two player minimax game

D

G

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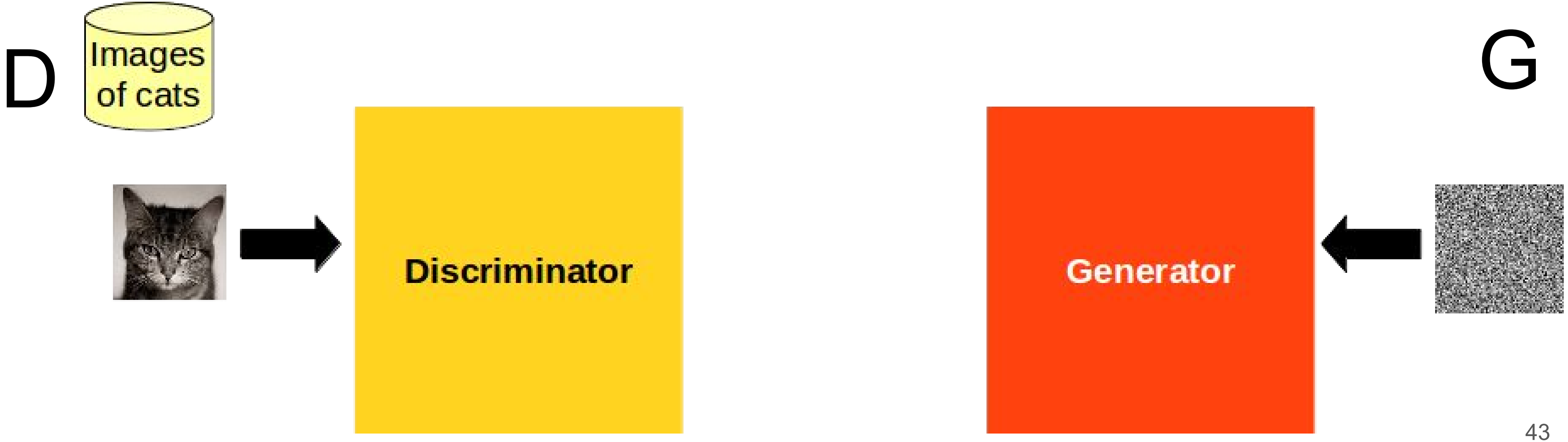
What is a GAN?

- The discriminator is given actual real data samples
- The generator is not, instead it is initialized with random noise sample



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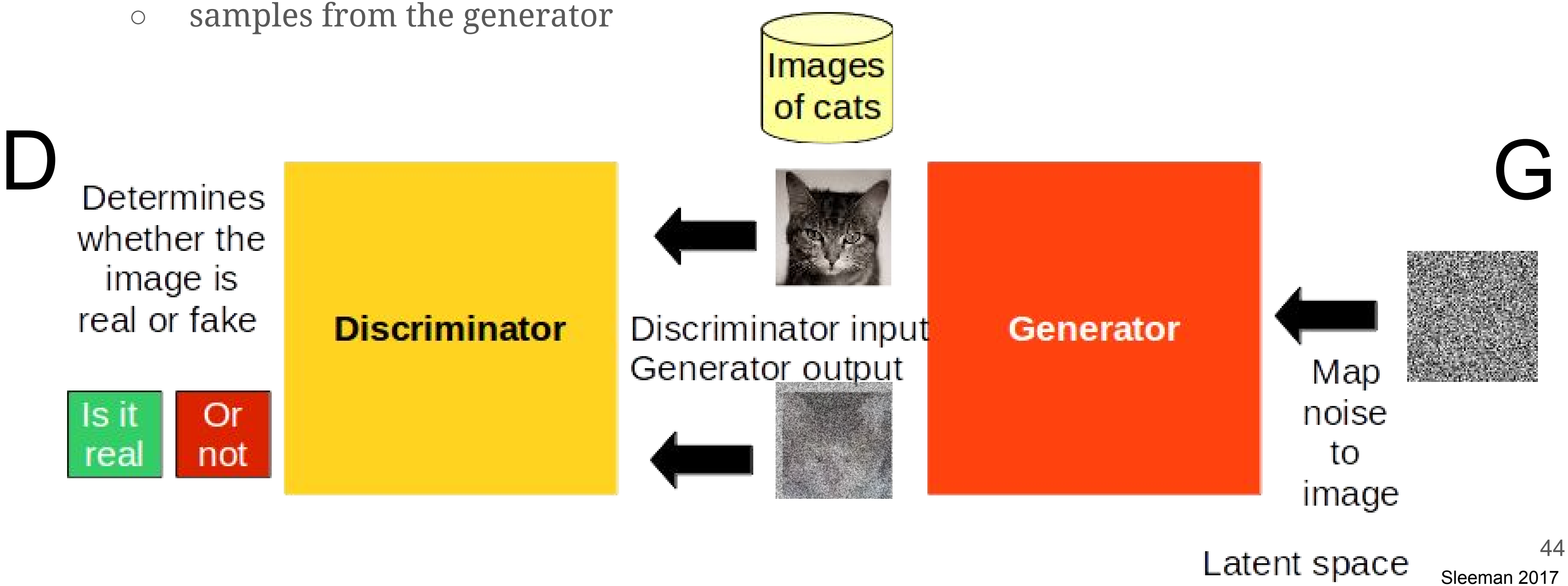
What is a GAN?

- The discriminator receives as input
  - samples from the real data
  - samples from the generator



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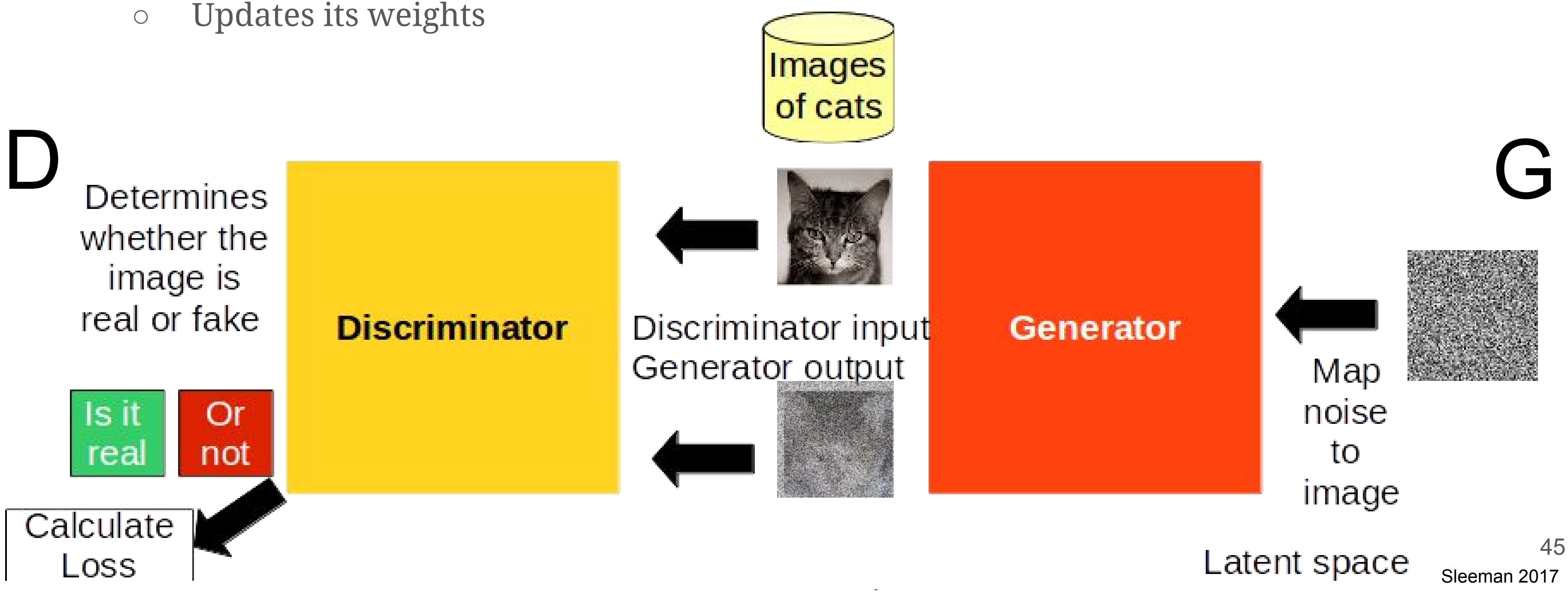
What is a GAN?

- The discriminator calculates loss
  - Backpropagates error
  - Updates its weights



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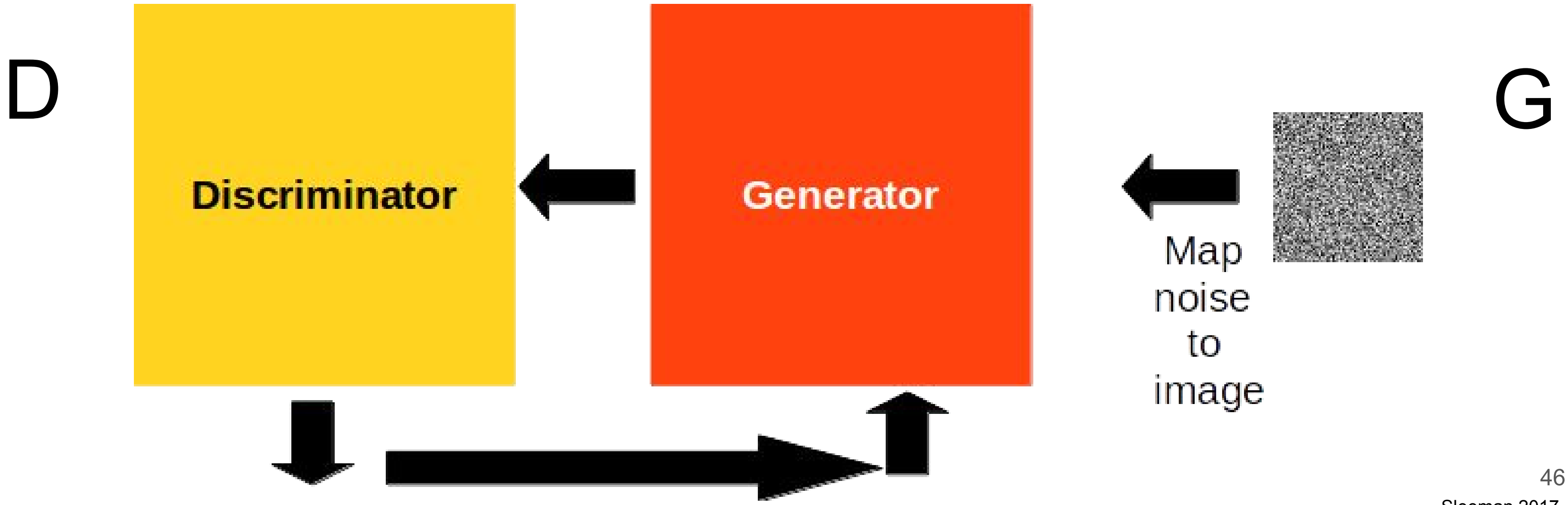
What is a GAN?

- The adversarial part
  - Negation of loss from discriminator used to train generator



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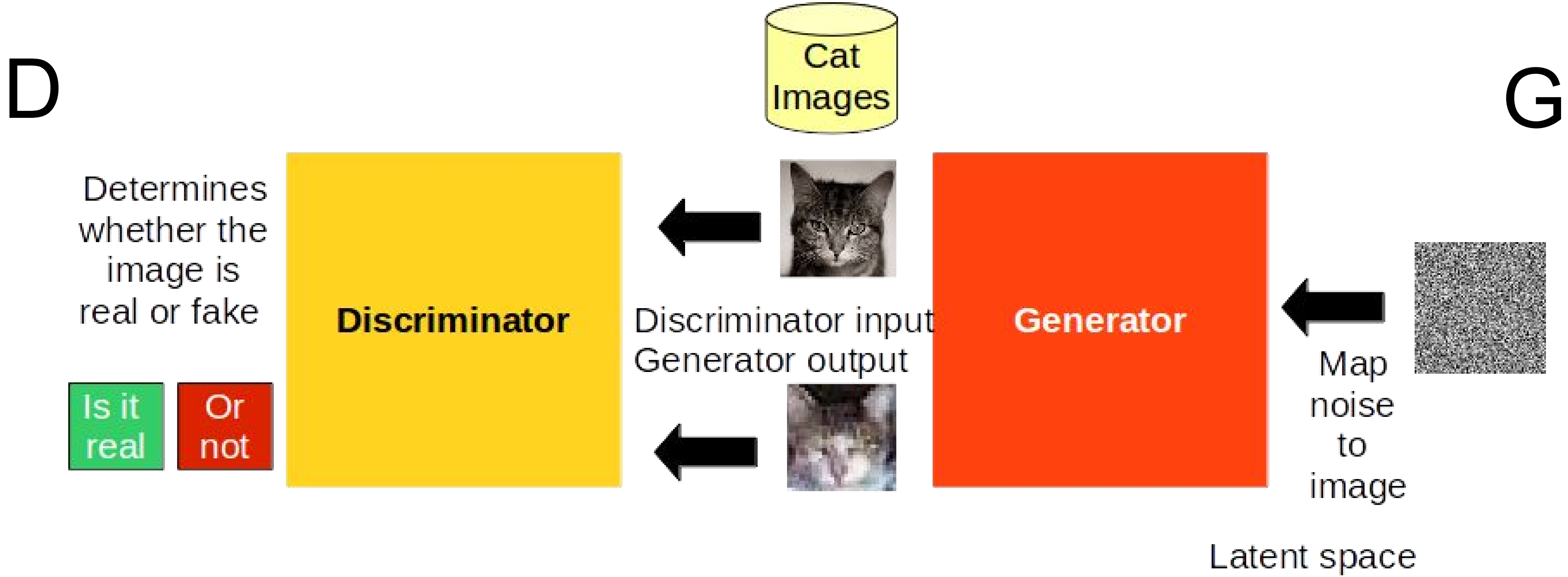
What is a GAN?



Eventually, the generator distribution looks similar to the true data distribution.

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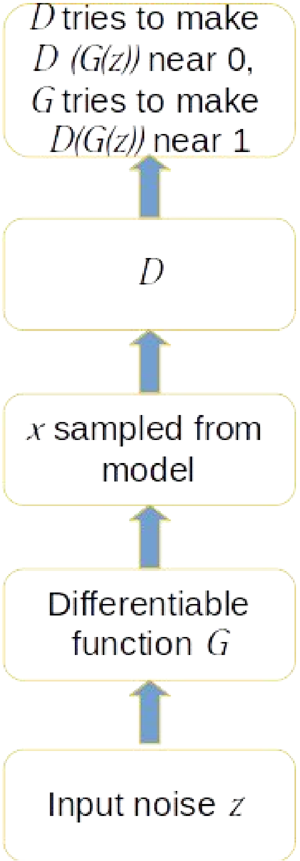
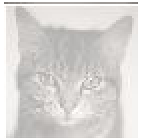
Another View of the Two Networks

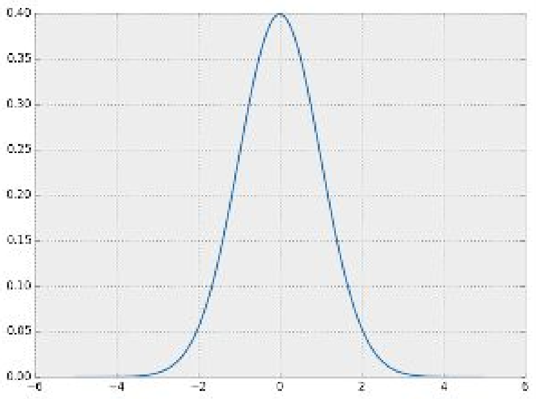
- x = training samples from training set
- z = inputs to generator randomly sampled
- Discriminator receives input (fake) $G(z)$
- Discriminator makes $D(x)$ approach 1
- Discriminator makes $D(G(z))$ approach 0
- Generator makes $D(G(z))$ approach 1



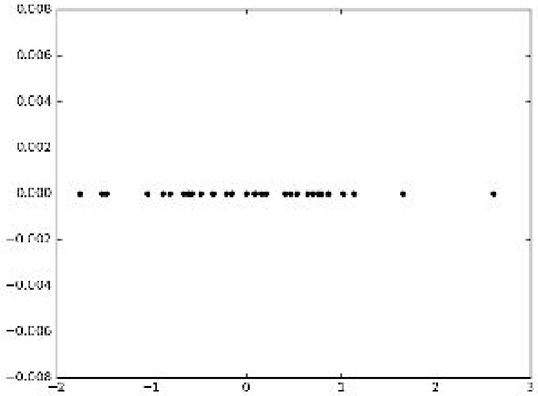


Based on: Ian Goodfellow, 2016 Talk at NIPS 2016

Simulating GAN training



1-D sample from normal distribution



This simulation was created with the following python code from: https://bamos.github.io/2016/08/09/deep-completion

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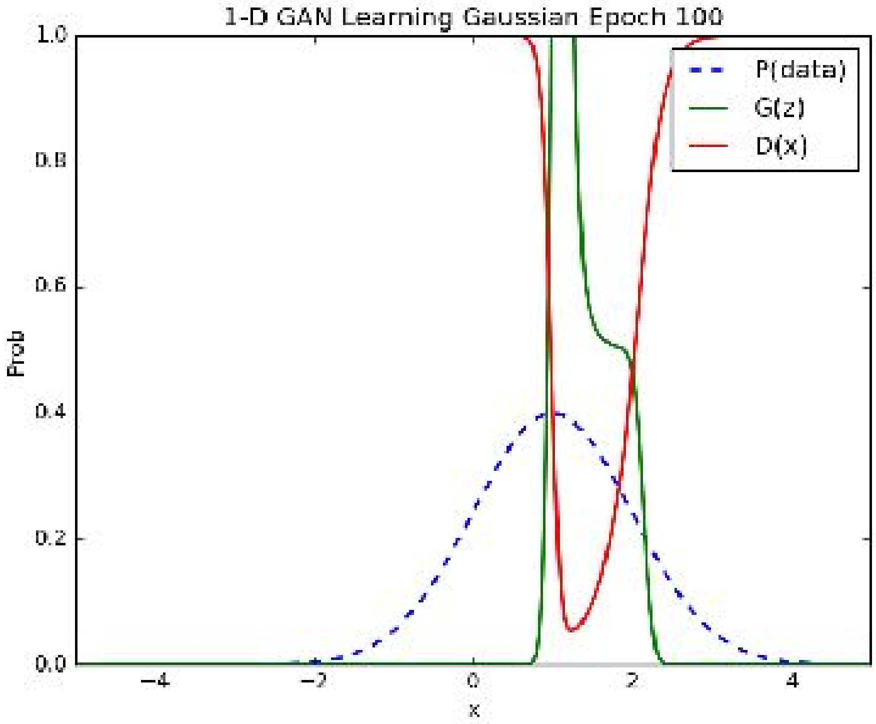
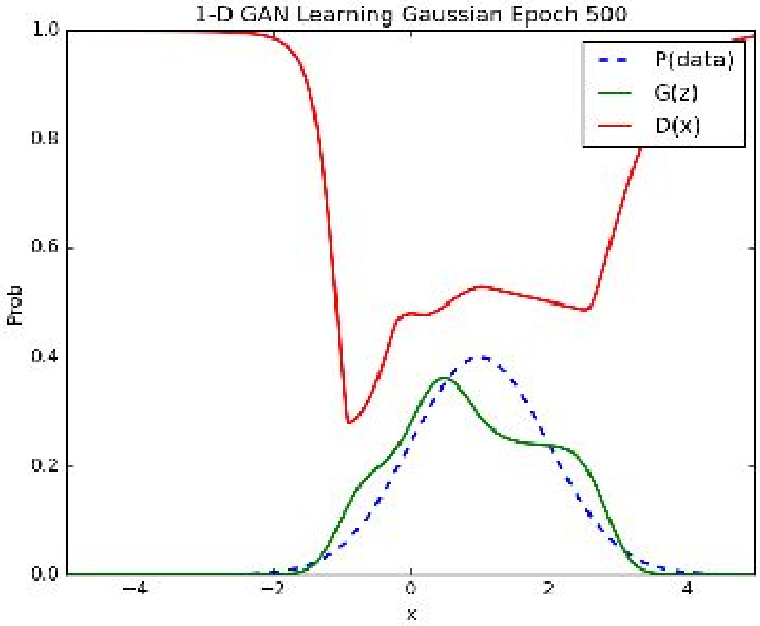
Simulating GAN training

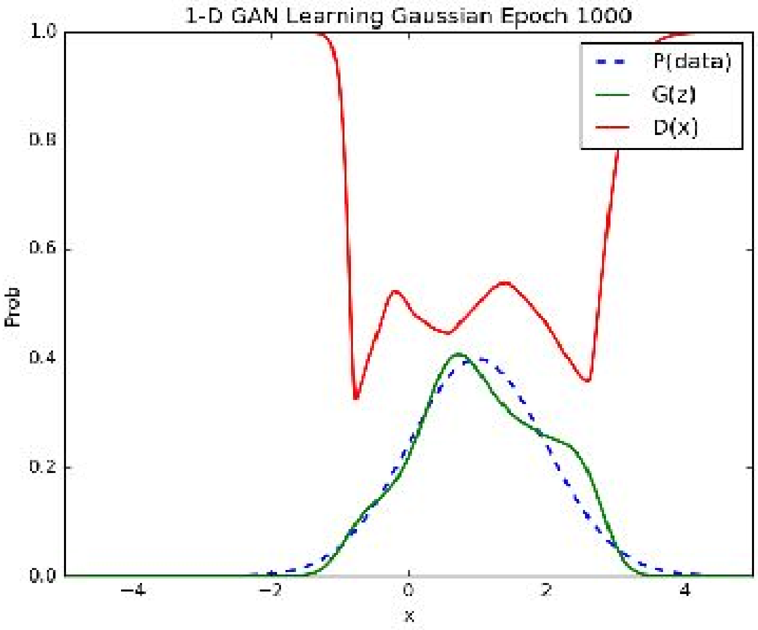
Simulation of interaction between discriminator and generator



The code for this simulation is based on: :https://gist.github.com/Newmu/4ee0a712454480df5ee3

Simulating GAN training

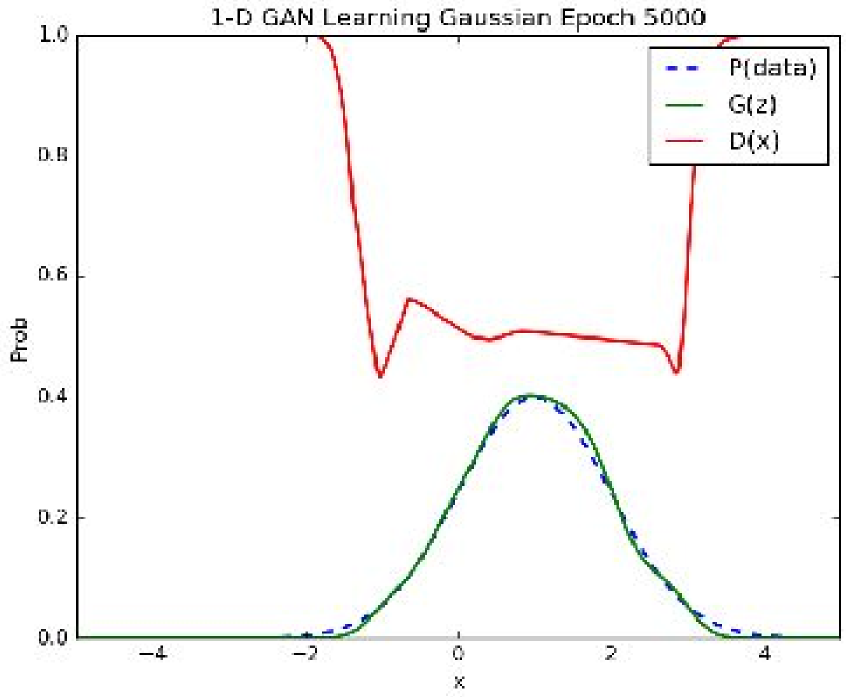




The code for this simulation is based on: :https://gist.github.com/Newmu/4ee0a712454480df5ee3

Simulating GAN training

Over time, curve for generator gets closer to true distribution



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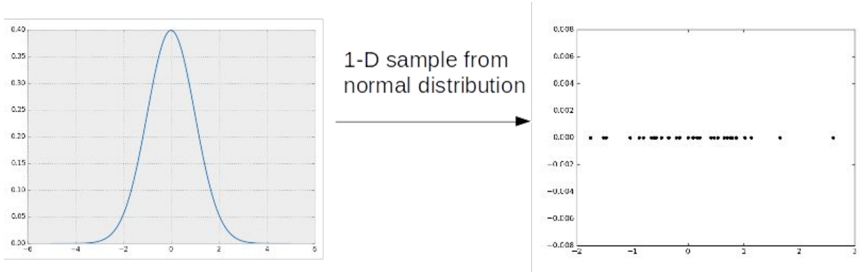
Generator and Discriminator Networks

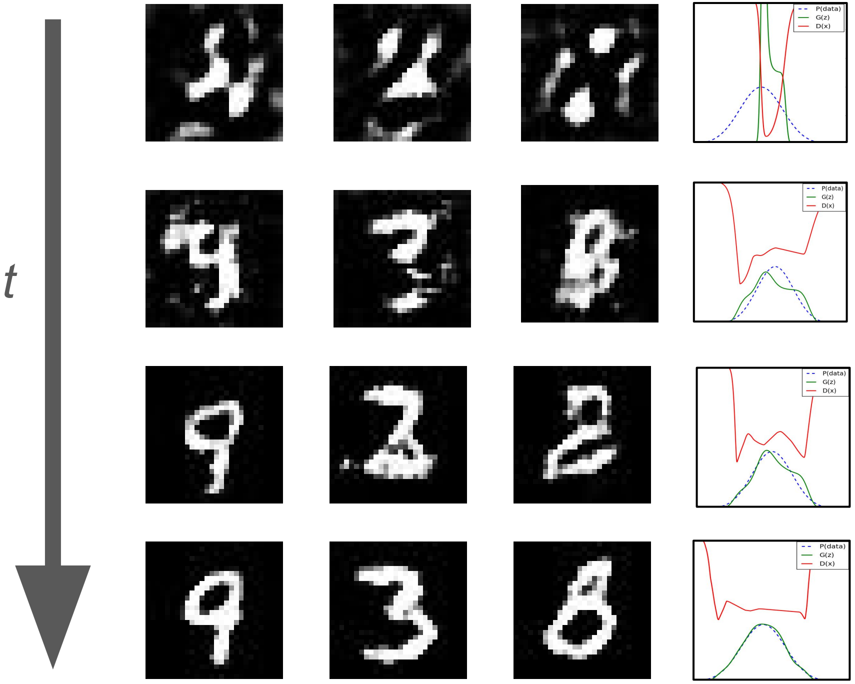


Key intuition:

View images as samples from complex probability distribution with many dimensions

Image Credit: Cat vs Dog Kaggle Data set https://www.kaggle.com/c/dogs-vs-cats
This simulation and intuition was obtained by reading and using the code from: https://bamos.github.io/2016/08/09/deep-completion

Generator and Discriminator Networks



Generator distribution slowly over time looks more and more similar to the true data distribution

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Advancements in Generative Adversarial Networks

LAPGAN

- Train a Laplacian pyramid of networks
  - Each network gets a coarse version of image
  - Sequence of convolutional networks
  - Generates refinement to reconstruct

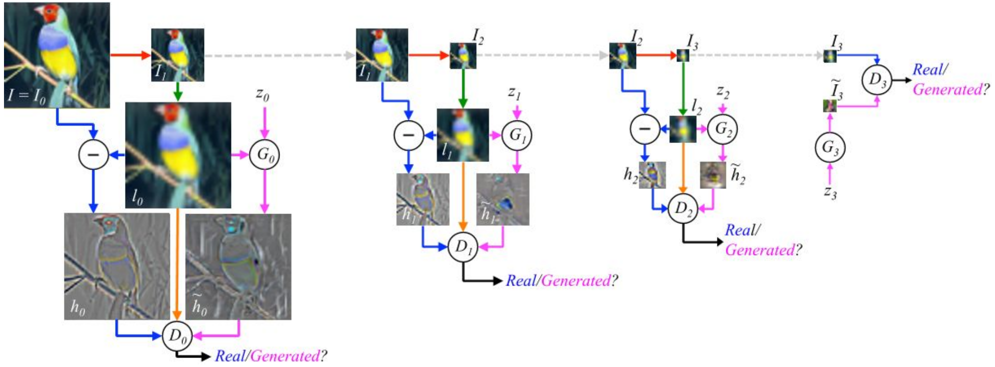


Image source:https://github.com/facebook/eyescream

Emily Denton
http://www.cs.nyu.edu/~denton/

Soumith Chintala
Facebook AI Research

Deep generative image models using a Laplacian pyramid of adversarial networks.
E Denton, S Chintala, A Szlam, R Fergus
NIPS, 2015

LAPGAN

- Major advancement for GANs
- https://github.com/facebook/eyescream
- High quality generated images
- Based on human assessment
  - Mistaken for real images ~40% of the time
- Best for images at 32 x 32 and 64 x 64 resolution

Deep generative image models using a Laplacian pyramid of adversarial networks.
E Denton, S Chintala, A Szlam, R Fergus
NIPS, 2015

Image source:https://github.com/facebook/eyescream

DCGAN

- A number of improvements to stabilized GANs
  - Strided convolutions in discriminator
    Fractional-strided convolutions in the generator
  - no pooling
  - batchnorm in both nets
  - No more fully connected hidden layers
  - Generator ReLU activation all layers except output
  - Discriminator LeakyReLU activation all layers

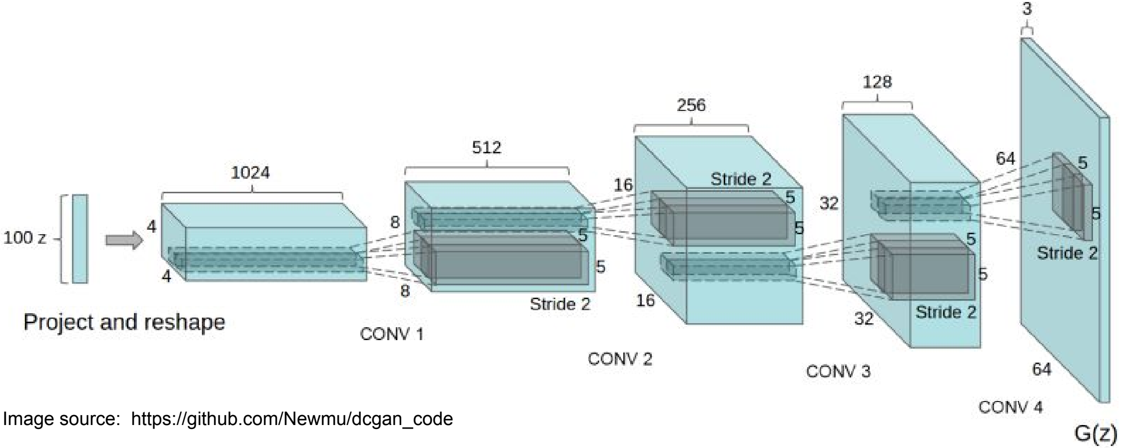
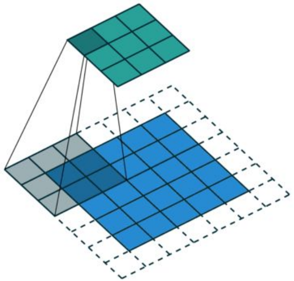
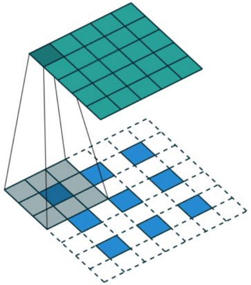


Image source: https://github.com/Newmu/dcgan_code



from convolutions



to fractionally-strided convolutions to upsample images

Images source: https://github.com/vdumoulin/conv_arithmetic
Discussion related to fractionally-strided convolutions: https://bamos.github.io/2016/08/09/deep-completion/

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DCGAN

- Pushed GAN research forward
- Able to show realistic generated images

Unsupervised representation learning with deep convolutional generative adversarial networks.
Radford et al.
2015

Images source: https://github.com/Newmu/dcgan_code

DCGAN

Unsupervised representation learning with deep convolutional generative adversarial networks.
Radford et al.
2015

Images source: https://github.com/Newmu/dcgan_code

DCGAN

Unsupervised representation learning with deep convolutional generative adversarial networks.
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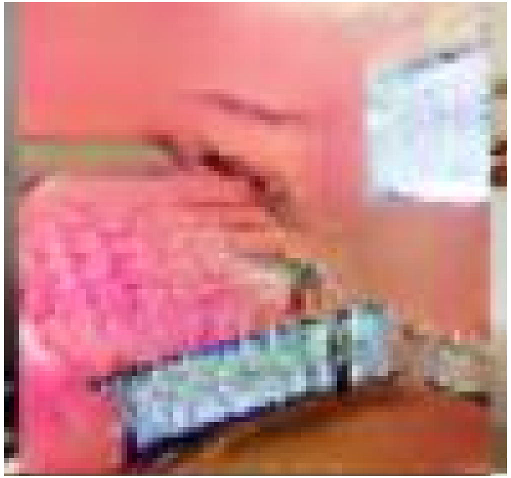
DCGAN

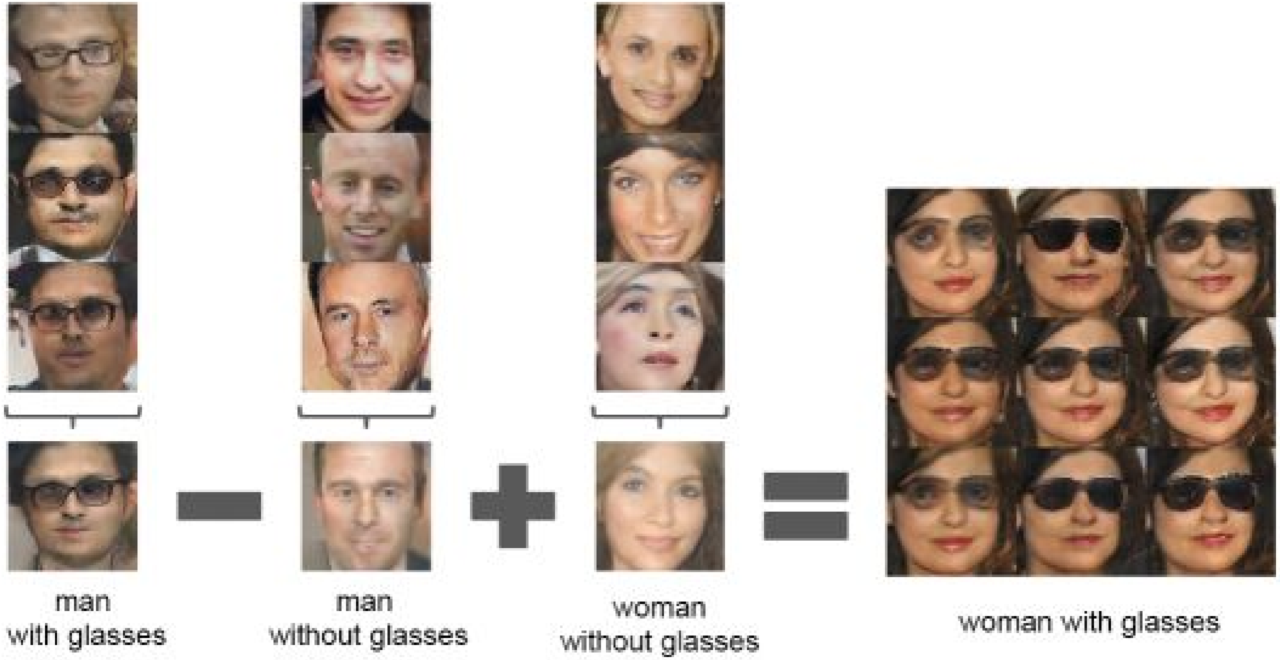


Unsupervised representation learning with deep convolutional generative adversarial networks.
Radford et al.
2015

Images source: https://github.com/Newmu/dcgan_code

DCGAN

- Able to show how to apply vector arithmetic to images to generate more images



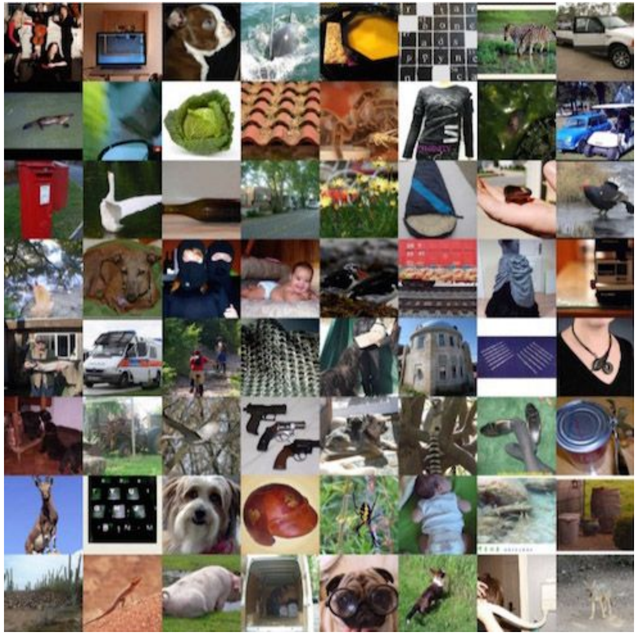
Unsupervised representation learning with deep convolutional generative adversarial networks.
Radford et al.
2015

Images source: https://github.com/Newmu/dcgan_code

Most Recent Advancements

Improving GANs

- Scale up GANs to 128 x 128
- Feature matching
- Minibatch discrimination
- Convergence of GANs
- Semi-supervised learning



Real Images

Generated Images

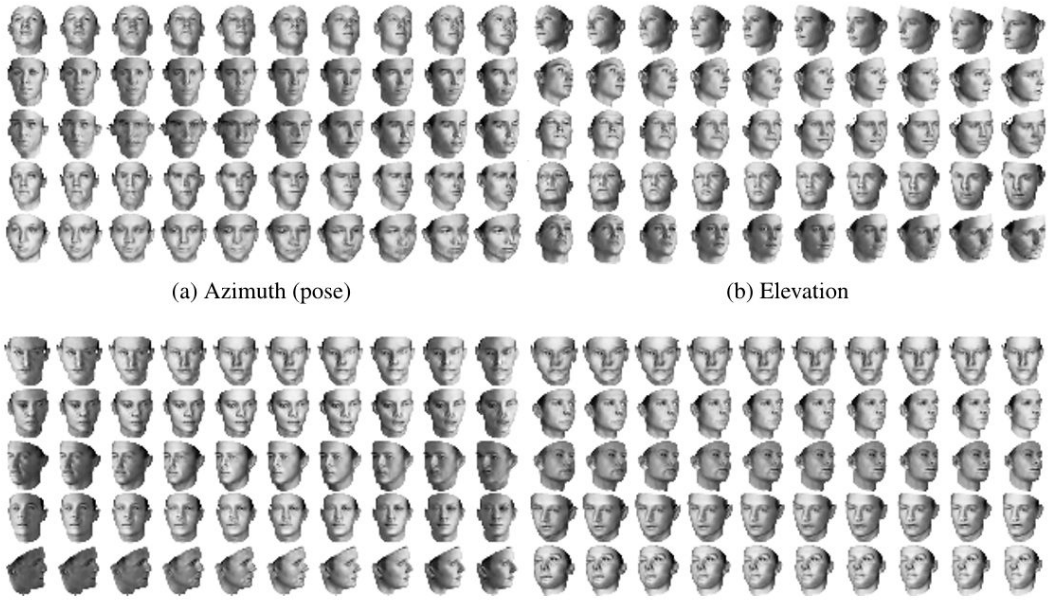
Improved Techniques for Training GANs.
Tim Salimans et al.
2016

Images source: https://openai.com/blog/generative-models/

InfoGAN

- Learn disentangled representations
  - Writing style from shapes
  - Pose from lighting of 3D rendered images
- Variation of Wake-Sleep algorithm

InfoGAN: Interpretable Representation Learning by Information Maximizing Generative Adversarial Nets.
Xi Chen et al.
2016



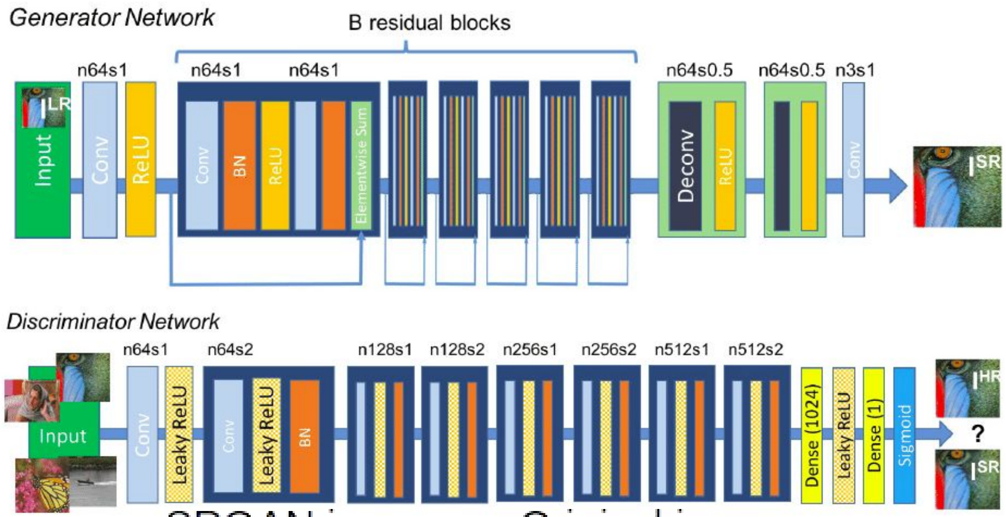
(a) Azimuth (pose) (b) Elevation

(c) Lighting (d) Wide or Narrow

Images source: https://arxiv.org/pdf/1606.03657v1.pdf

Photo-Realistic Single Image Super-Resolution Using a GAN

- State of the art resolution of single image generation
- 4x upscaling factor
- Benchmark:
  - https://github.com/huangzehao/Super-Resolution.Benckmark



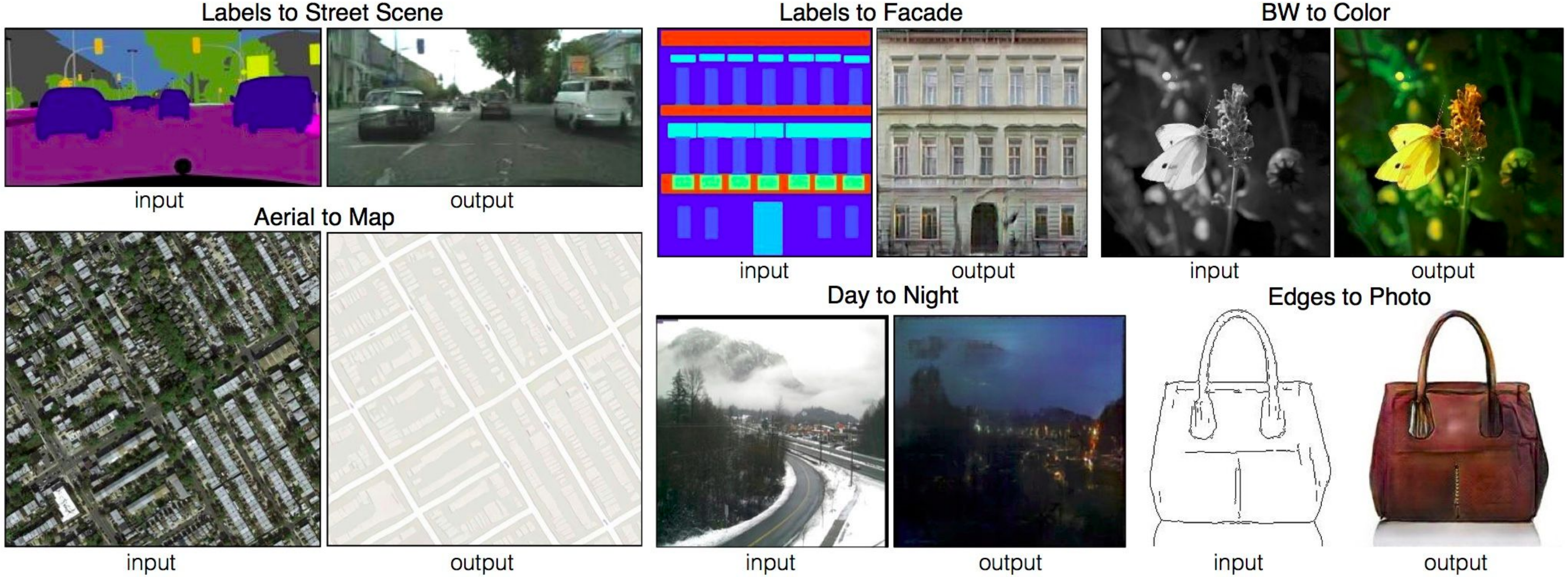
SRGAN image

Original image

Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network.
Christian Ledig et al.
2016

Image source: https://arxiv.org/pdf/1609.04802v3.pdf

Image to Image Translation (pix2pix)



- Conditional adversarial networks
- Learns mapping from input to output image
- Learns the loss function to perform mapping

Image-to-Image Translation with Conditional Adversarial Nets.
Phillip Isola et al.
2016
Source code: https://phillipi.github.io/pix2pix/

Image Source: https://phillipi.github.io/pix2pix/
Paper: https://arxiv.org/pdf/1611.07004v1.pdf

Your first GAN in less than 15 minutes

How to create your first GAN

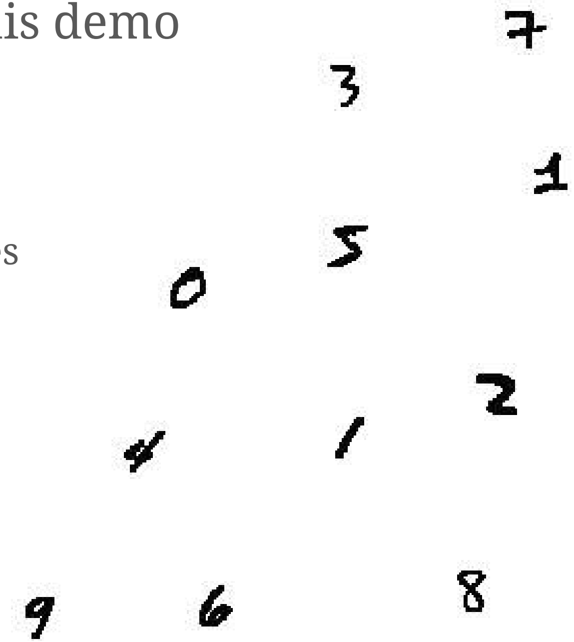
In this example, I used Keras

- Keras is a well supported deep learning library
  - https://keras.io/
  - Written in Python
  - Can run on top of TensorFlow or Theano
  - Supports fast experimentation
- Other libraries I often use:
  - Torch
  - Tensorflow

Sleeman 2017

Your First Gan

- We are going to use the MNIST digits for this demo (http://yann.lecun.com/exdb/mnist/)
  - Handwritten
  - Sized at 28 x 28
  - 60,000 training examples and 10,000 test examples
  - Black and white images
- We are running on AWS
  - Using ipython notebook
  - Keras running on top of Theano



What Are GANs Doing?

- MNIST digits
- Using t-sne embedding

Sleeman 2017

Image source: https://indico.io/blog/visualizing-with-t-sne/

Applications of Generative Adversarial Networks

Uses - Image Generation

Image source: https://github.com/mattya/chainer-DCGAN

Image source: https://github.com/aleju/cat-generator

Image Source: https://github.com/hardmaru/cppn-gan-vae-tensorflow

Uses - Image Generation

Image Source: https://openai.com/blog/generative-models/

Image Source: http://torch.ch/blog/2015/11/13/gan.html

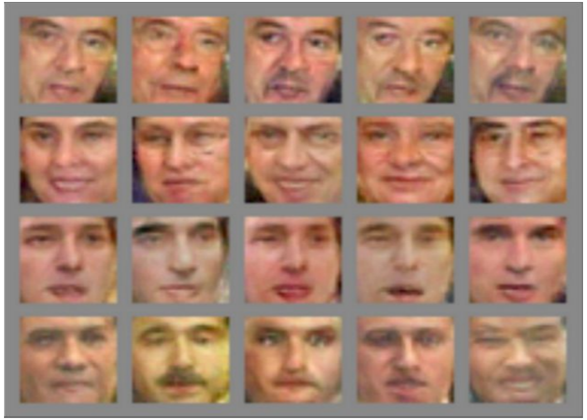
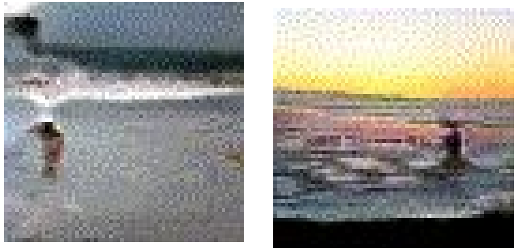


Image Source: http://www.foldl.me/2015/conditional-gans-face-generation

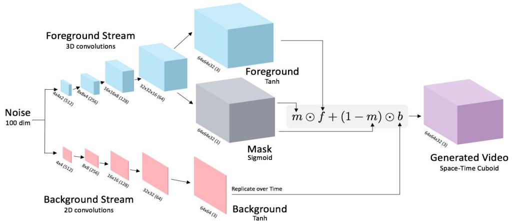
comic | input | SRResNet MSE | SRResNet MSE VGG22 | SRResNet MSE VGG54

Image Source: https://github.com/huangzehao/torch-srgan

Uses - Video Generation



Input Output



- Video Generation
- Conditional video generation
- Add animation to static image

Generating Videos with Scene Dynamics.
Vondrick et al.,
2016

- Next frame prediction
- Internally model frame prediction
- Given sequence of frames discriminative model predicts probability that last frames in sequence generated by generative model

Image Sources: http://cs.nyu.edu/~mathieu/iclr2016extra.html

Deep multi-scale video prediction beyond mean square error.
Mathieu et al.
2015

Image Sources: http://web.mit.edu/vondrick/tinyvideo/

Uses – Interactive Image Generation

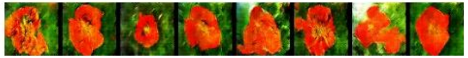
- As user draws
- iGAN uses GAN to generate image most similar

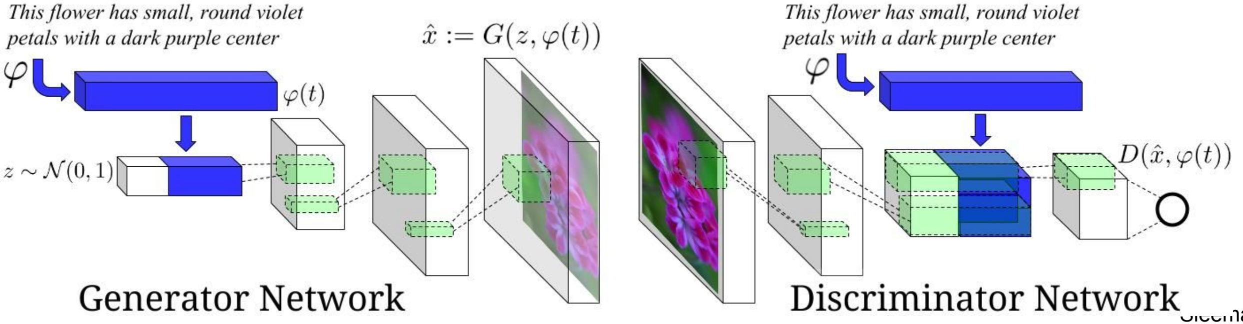
Generative Visual Manipulation on the Natural Image Manifold.
Jun-Yan Zhu, Philipp Krähenbühl, Eli Shechtman, Alexei A. Efros
2016

Image Source: http://people.eecs.berkeley.edu/~junyanz/projects/gvm/
Paper: https://arxiv.org/pdf/1609.03552v2.pdf

Uses - Text to Image Synthesis

- Image generation from caption
- Uses skip thought vectors
- Uses GAN and deep convolutional and recurrent text encoders

Caption	Generated Images
the flower shown has yellow anther red pistil and bright red petals	
this flower has petals that are yellow, white and purple and has dark lines	
the petals on this flower are white with a yellow center	
this flower has a lot of small round pink petals.	
this flower is orange in color, and has petals that are ruffled and rounded.	
the flower has yellow petals and the center of it is brown	

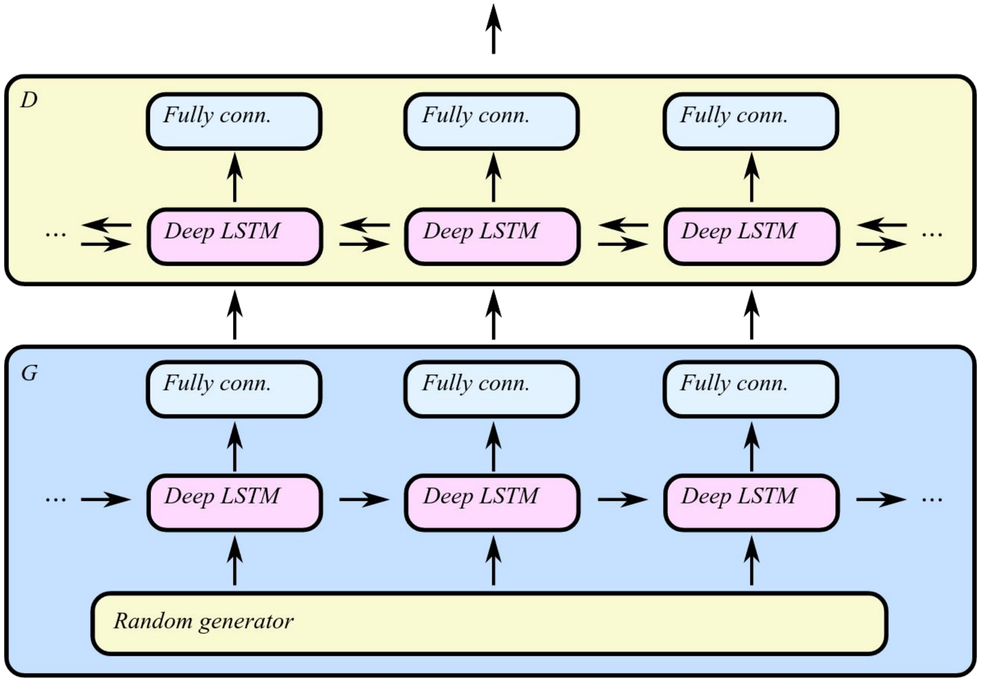


Generative Adversarial Text to Image Synthesis.
Scott Reed et al.
2016

Image Sources: https://github.com/paarthneekhara/text-to-image

Uses – Text, Music, etc.

- Typically RNNs used for text and audio
- New work looks to combine GANs and RNN
  - generative adversarial model for continuous sequential data
  - Trained on classical music
  - http://mogren.one/publications/2016/c-rnn-gan/



http://mogren.one/files/c-rnn-gan-sample11.mp3

Image and mp3 source: http://mogren.one/publications/2016/c-rnn-gan/

When GANs Go Rogue

When GANs Go Rogue

- With the latest research, GANs are producing images as large as 128 x 128
- Goodfellow et al. 2016 classified typical problems encountered as:
  - Counting
  - Perspective
  - Global Structure

Why are there dog faces everywhere?

Sleeman 2017

Concepts Source: Goodfellow, 2016, https://arxiv.org/pdf/1701.00160v2.pdf

When GANs Go Rogue

Examples of counting issues

Image Source: Goodfellow, 2016, https://arxiv.org/pdf/1701.00160v2.pdf

When GANs Go Rogue

Examples 3-dimensional perspective issues



Image Source: Goodfellow, 2016, https://arxiv.org/pdf/1701.00160v2.pdf

When GANs Go Rogue

Examples of global structure issues

Image Source: Goodfellow, 2016, https://arxiv.org/pdf/1701.00160v2.pdf

Tips and Tricks

- DCGAN introduced a lot of stabilizing techniques
  - Adding Instance Noise To Improve Convergence
  - Basic Idea:
    - Add noise to real and synthetic data during training
    - Make the job of the discriminator harder
  - http://www.inference.vc/instance-noise-a-trick-for-stabilising-gan-training/
  - https://arxiv.org/abs/1610.04490
- Soumith et al. are formalizing standards for GANs
  - https://github.com/soumith/ganhacks/blob/master/README.md

Conclusions

Conclusions

- GANs are a type of generative model
- They involve 2 networks that play a minimax zero-sum game
- GANs are dominating Neural Network conferences
- Can be used for a number of tasks:
  - Supplement training data for sparse classes
  - Interactive tools
  - Simulations

Where to go from here?

Recommendations

- If you want to jump right in, I would read the NIPS 2016 Tutorial on Generative Adversarial Networks paper (video to be released):
  - https://arxiv.org/pdf/1701.00160v2.pdf
- Join the Facebook Adversarial Training group:
  - https://www.facebook.com/groups/675606912596390
- There is also a Generative Adversarial Network course
  - http://wiki.ubc.ca/Course:CPSC522/Generative_Adversarial_Networks
- If you need a stronger foundation in deep learning, the following book is free:
  - http://www.deeplearningbook.org/
  - Thanks Ian Goodfellow, et.al.

Notable Papers

- GAN
  - http://papers.nips.cc/paper/5423-generative-adversarial-nets.pdf
  - https://arxiv.org/abs/1412.6572
- LAPGAN
  - https://arxiv.org/abs/1506.05751
  - http://papers.nips.cc/paper/5773-deep-generative-image-models-using-a-laplacian-pyramid-of-adversarial-networks.pdf
- DCGAN
  - https://arxiv.org/pdf/1511.06434v2.pdf
- SRGAN
  - https://arxiv.org/pdf/1609.04802.pdf
- 3D-GAN
  - https://arxiv.org/pdf/1610.07584v2.pdf
- Stack GAN
  - https://arxiv.org/pdf/1612.03242v1.pdf
- Energy Based GANs
  - https://arxiv.org/pdf/1609.03126.pdf
- Image-to-Image Conditional Adversarial Nets
  - https://arxiv.org/pdf/1611.07004v1.pdf

Tutorials

- Generative Models
  - https://openai.com/blog/generative-models/
- NIPS 2016 Tutorial: Generative Adversarial Networks
  - https://arxiv.org/abs/1701.00160
- Conceptual using TensorFlow
  - https://github.com/ericjang/genadv_tutorial/blob/master/genadv1.ipynb
  - http://blog.aylien.com/introduction-generative-adversarial-networks-code-tensorflow/
- EyeScream Project
  - http://soumith.ch/eyescream/
- Generating Faces With Torch
  - http://torch.ch/blog/2015/11/13/gan.html

Tutorials

- Step-by-Step with code examples and Keras
  - http://www.kdnuggets.com/2016/07/mnist-generative-adversarial-model-keras.html
- Deep Learning Research Review
  - https://adeshpande3.github.io/adeshpande3.github.io/Deep-Learning-Research-Review-Week-1-Generative-Adversarial-Nets
- Generative Adversarial Networks using SpongeBob
  - https://medium.com/@awjuliani/generative-adversarial-networks-explained-with-a-classic-spongebob-squarepants-episode-54deab2fce39#.v4dk9tevd
- A Course on GANs
  - http://wiki.ubc.ca/Course:CPSC522/Generative_Adversarial_Networks

Deep Learning Frameworks

- Torch
  - LAPGAN https://github.com/skaae/torch-gan
  - DCGAN https://github.com/soumith/dcgan.torch
  - Conditional Adversarial Nets https://github.com/phillipi/pix2pix
- Keras
  - GANs https://github.com/osh/KerasGAN
  - DCGAN https://github.com/jacobgil/keras-dcgan
  - SRGAN https://github.com/titu1994/Super-Resolution-using-Generative-Adversarial-Networks
- TensorFlow
  - VAE, GANs and DRAW https://github.com/ikostrikov/TensorFlow-VAE-GAN-DRAW
  - DCGAN https://github.com/carpedm20/DCGAN-tensorflow
- Theano
  - GANs https://github.com/goodfeli/adversarial
  - DCGAN https://github.com/Newmu/dcgan_code
  - Improved-GAN https://github.com/openai/improved-gan
- Chainer
  - DCGAN https://github.com/mattya/chainer-DCGAN

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Thank you for attending my talk.
I hope you found the content interesting and useful...and possibly exciting?

Questions