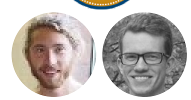
Zurich University
of Applied Sciences

Artificial Intelligence
V11: Generative Adversarial Learning for Image Synthesis

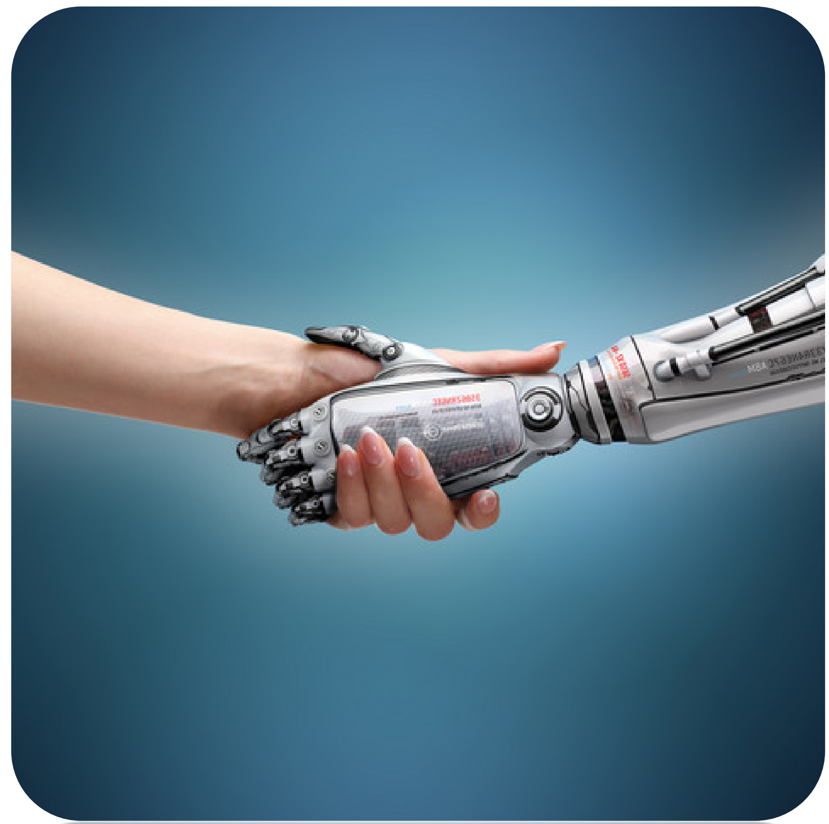
Generative Adversarial Nets
Use case: image inpainting

Mentimeter quizzes: https://www.menti.com/9kfo33dbw3

With material from
- Stuart Russell, UC Berkeley
- Arthur Juliani’s and Brandon Amos’ blog post
- Ian Goodfellow, UC Berkeley COMPSCI 294 guest lecture



OpenAI



Zurich University of Applied Sciences and Arts
CAI Centre for Artificial Intelligence (stdm)

Educational objectives

- **Know** the **general idea** behind Generative Adversarial Nets (**GAN**s)
- **Understand** the **training** process (and inherent difficulties) **for GANs**
- **Be able** to start **working on open-source GAN** code

➔ Reading: AIMA, ch. 22.1, 22.3, 22.7 (partially)

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1. GENERATIVE ADVERSARIAL NETS

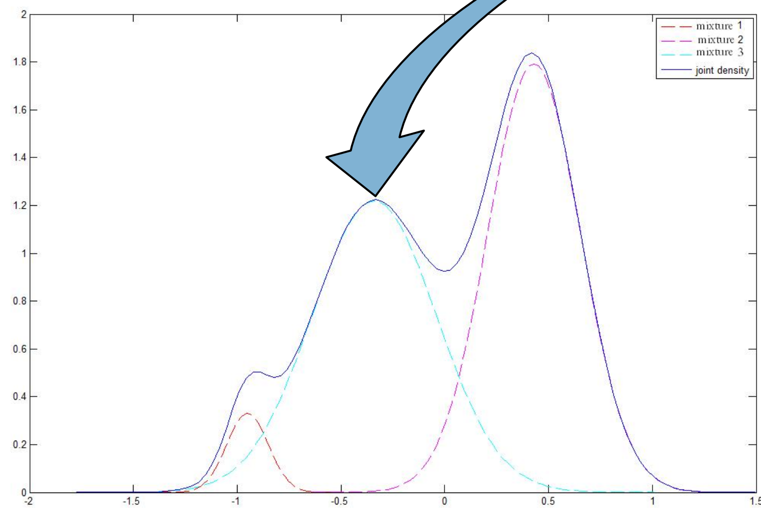
Probability distributions as generative models

Terminology: its probability density function (pdf) is one way to describe a distribution.

What does a pdf tell about a set of data?

➔ For data coming from some stochastic processes, the pdf tells **everything there is to know** about the data *without seeing it*

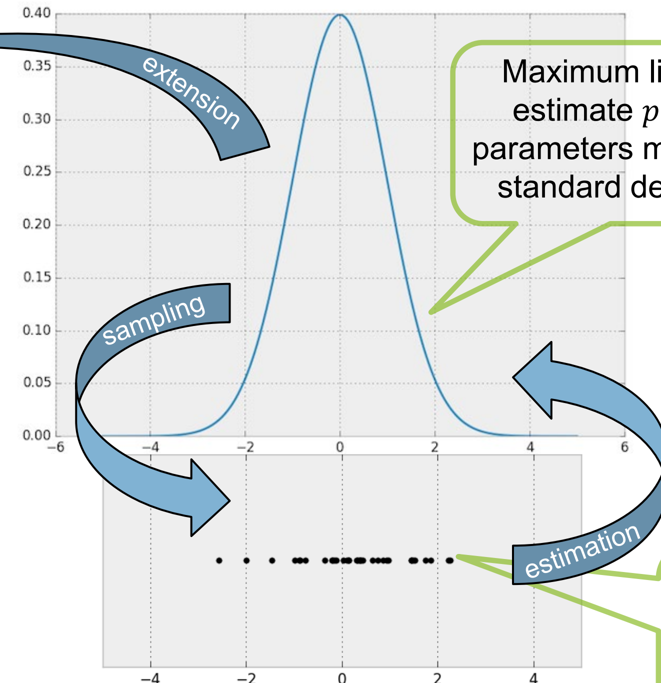
➔ **Allows for sampling** data from the underlying distribution



Example of a multimodal (but univariate) distribution, approximated by a Gaussian Mixture Model (GMM) with 3 mixtures.

A Gaussian as base generative model

- Recovering a known, parametric pdf: The univariate Gaussian



Maximum likelihood estimate $p(x)$ with parameters mean μ and standard deviation σ

Given data points x_i; Assumption: $x_i \sim p(x;\theta) = N(x;\mu,\sigma)$

Source: Brandon Amos, «*Image Completion with Deep Learning in TensorFlow*», 2016, https://bamos.github.io/2016/08/09/deep-completion/

Pros and cons of generative models

Flavors of generative models
- **Statistical** models that directly model the pdf (e.g., GMM, hidden Markov model HMM)
- **Graphical** (i.e., graph-based) models with latent variables (e.g., Boltzmann machines RBM/DBM, deep belief networks DBN)
- **Autoencoders** (e.g., Kingma & Welling, *"Autoencoding Variational Bayes"*, 2013)

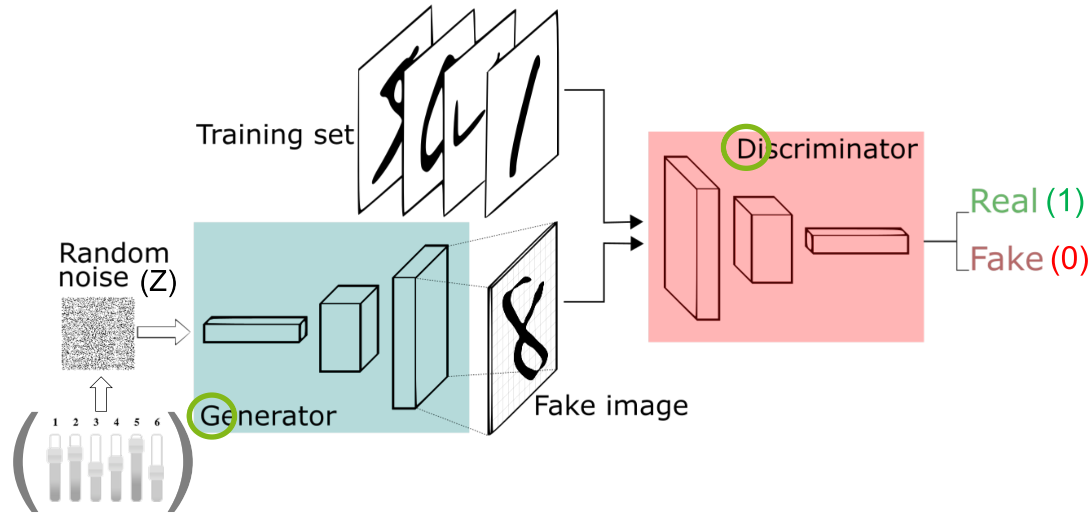
Promises
- Help **learning about** high-dimensional, complicated probability **distributions** *(even if pdf is not represented explicitly)*
- **Simulate** possible futures for planning or simulated reinforcement learning
- Handle **missing data** (in particular, semi-supervised learning)
- Some applications actually require **generation** (e.g., sound synthesis, identikit pictures, content reconstruction)

Common drawbacks
- Statistical models suffer severely from the **curse of dimensionality**
- Approximations needed for **intractable probabilistic computations** during ML estimation
- **Unbacked assumptions** (e.g., Gaussianity) and averaging e.g., in VAEs

Maximum Likelihood

Adversarial nets
Bootstrapping implicit generative representations

Train 2 models simultaneously [1]
- G: Generator
  → learns to generate data points x
- D: Discriminator
  → learns $p(x\ not\ being\ generated)$



Sources: https://deeplearning4j.org/generative-adversarial-network; http://www.dpkingma.com/sgvb_mnist_demo/demo.html

➔ Both differentiable functions D&G learn while competing
➔ The latent space Z serves as a source of variation to generate different data points
➔ Only D has access to real data

[1] Schmidhuber, «Learning Factorial Codes by Predictability Minimization», 1992

Mentimeter

No weenies allowed! How SpongeBob helps..

…to understand bootstrapping untrained (G)enerator & (D)iscriminator

Bouncer newbie (D) decides on entry: for tough guys only

SpongeBob (G) wants to appear tough to be admitted (i.e., synthesizes behavior)

In the beginning, D focuses on obvious things to discriminate: e.g., physical strength

So G tries to imitate that, but fails

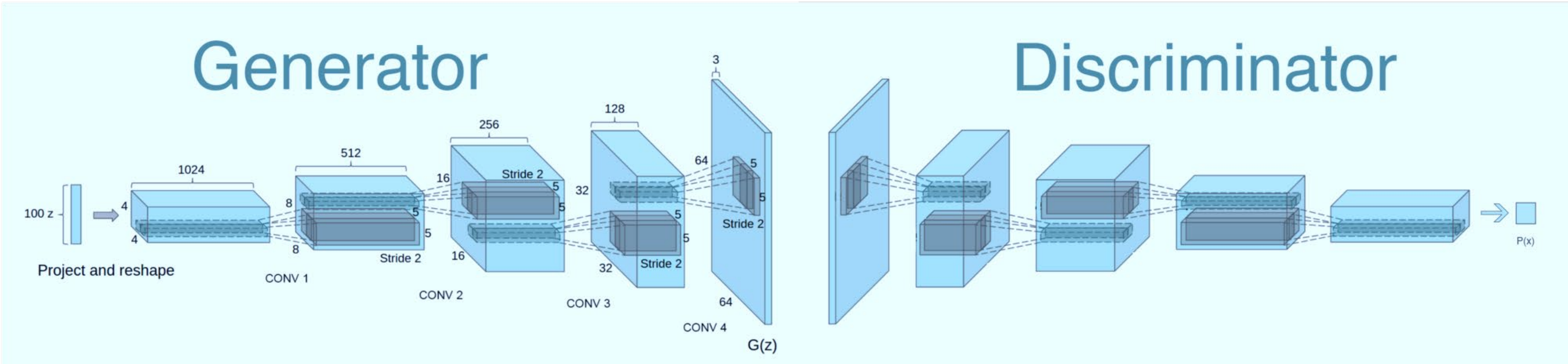
By observation, G discovers more detailed features of tough guys: e.g., fighting

So G learns to imitate that as well

…and eventually tricks D.

Source: Arthur Juliani, «*Generative Adversarial Networks Explained with a Classic Spongebob Squarepants Episode*», 2016, https://medium.com/@awjuliani/generative-adversarial-networks-explained-with-a-classic-spongebob-squarepants-episode-54deab2fce39#.gcoxuaruk

GAN model formulation (improved)
Deep convolutional generative adversarial nets [2]



Implement both G and D as deep convnets (DCGAN)

- **No pooling**, only fractionally-strided convolutions (G) and strided convolutions (D)
- **No fully connected** hidden **layers** for deeper architectures
- Apply **batchnorm** in both
- **ReLU** activation **in G** (output layer: tanh)
- **LeakyReLU** activation in **D** (all layers)

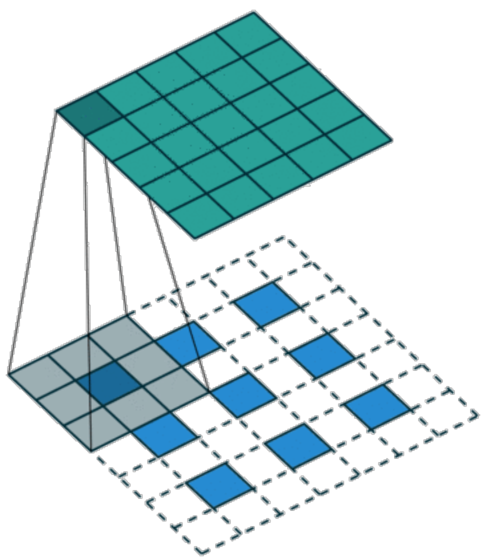
[2] Radford, Metz, Chintala, «Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks», 2016

Strided what? Convolutional arithmetic [3]

NN wiring to save weights while exploiting local structure

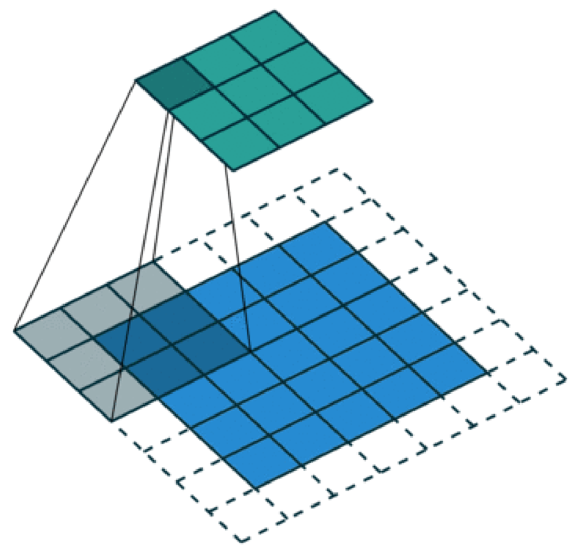
Fractionally-strided conv. in G

- Performing transposed convolution
- Used to «**up-sample**» from input (blue) to output (green)



Strided convolutions in D

- Stride (stepsize) = 2
- Used instead of (max) **pooling** [4]



[3] Dumoulin, Visin, «A guide to convolution arithmetic for deep learning », 2016
[4] Springenberg, Dosovitsiy, Brox, Riedmiller, «Striving for simplicity: The all convolutional net», 2014

Model training [5]

for number of training iterations **do**

Usually, $k = 1$ (or ½)

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 $\boxed{\text{discriminator}}$ by $\boxed{\text{ascending}}$ its stochastic gradient:

change θ_D to **maximize**

$$\nabla_{\theta_d} \underbrace{\frac{1}{m} \sum_{i=1}^{m}}_{\text{average}} \left[\underbrace{\log D\left(\boldsymbol{x}^{(i)}\right)}_{\text{log likelihood of } x \text{ being real} \rightarrow 0} + \underbrace{\log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right)}_{\text{log likelihood } G(z) \textbf{ not} \text{ being real} \rightarrow 0} \right].$$

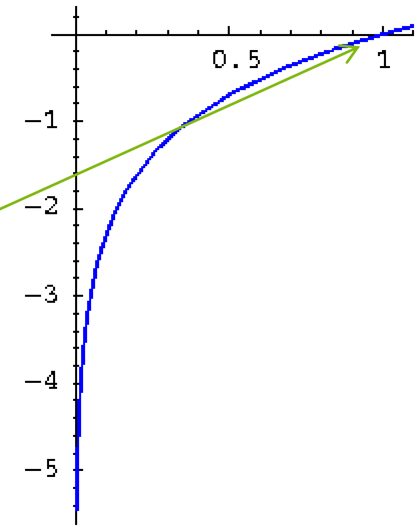
end for

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

change θ_G to **minimize**

$$\nabla_{\theta_g} \underbrace{\frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right)}_{\text{G just get's gradients on how well it can fool D (no direct training labels)}}.$$

end for



[5] Goodfellow, Pouget-Abadie, Mirza, Xu, Warde-Farley, Ozair, Courville, Bengio, «**Generative Adversarial Nets**», 2014

Visualizing the training process

Observations

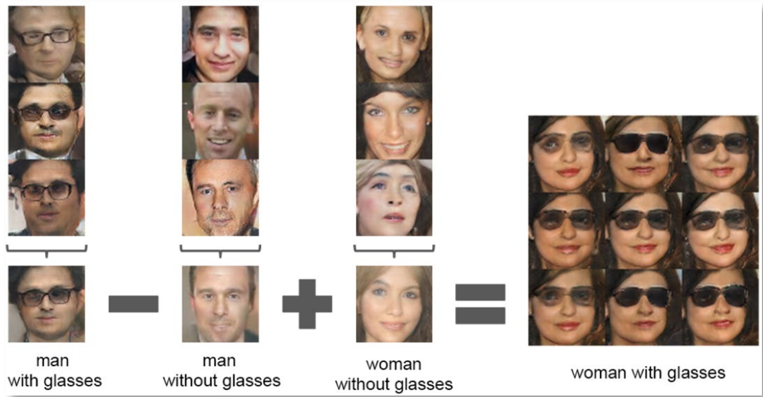
- G starts with producing **random noise**
- Quickly arrives at what seems to be **pencil strokes**
- It takes a while for the network to produce **different images** for different z
- It takes nearly to the end before the synthesized **images per z stabilize** at certain digits

6x6 samples $G(z)$ from fixed z's every 2 mini batches (for 50k iterations). See https://stdm.github.io/Experimenting-with-generative-adversarial-nets/.

Features of (DC)GANs

Learn semantically meaningful latent space

- Examples of z**-space vector arithmetic** from DCGAN paper [2]:



The z vectors in the left 3 columns have been averaged, then arithmetic has been performed. The middle image on the right is the output of $G(resulting\ z\ vector)$. The other 8 pictures are the result of adding noise to the resulting z vector (showing that smooth transitions in input space result in smooth transitions in output space).

Training is not guaranteed to converge

- D and G play a **game-theoretic game** against each other (in terms of slide 10: minimax)
- **Gradient descent isn't meant to find** the corresponding Nash Equilibria (saddle point of joint loss function, corresponding to minima of both player's costs) [6]
- How to **sync D's and G's training** is experimental (if G is trained too much, it may collapse all of z's variety to a single convincing output)
- The improvements of [2] and [7] make them **stable enough for first** practical **applications**
- **Research** on adversarial training of neural networks is still **ongoing** (as of 2021)

[6] Goodfellow, Courville, Bengio, «Deep Learning», ch. 20.10.4, 2016
[7] Salimans, Goodfellow, Zaremba, Cheung, «Improved Techniques for Training GANs», 2016

2. USE CASE: IMAGE INPAINTING

Based on material from Brandon Amos,
«Image Completion with Deep Learning in TensorFlow», 2016

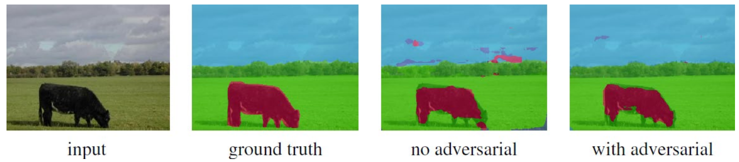
https://bamos.github.io/2016/08/09/deep-completion/

GAN use cases

Research has **gained** a lot of **momentum very quickly**; see appendix for more!

- Generate images from text
  Reed et al., *«Generative Adversarial Text to Image Synthesis»*, 2016

- Segment images into semantically meaningful parts
  Luc et al., *«Semantic Segmentation using Adversarial Networks»*, 2016



- Complete missing parts in images
  Yeh et al., *«Semantic Image Inpainting with Perceptual and Contextual Losses»*, 2016
  ➔ see next slides

Image inpainting as a sampling problem
…approached by machine learning

Yeh et al., *«Semantic Image Inpainting with Perceptual and Contextual Losses»*, 2016

Training: Regard **images as samples of** some underlying probability distribution $\boldsymbol{p_G}$

1. Learn to represent this distribution using a GAN setup (G and D)

--

Testing/Application: Draw a ***suitable*** **sample** from p_G by…

1. **Fixing parameters** $\boldsymbol{\Theta_G}$ and Θ_D of G and D, respectively
2. ***Finding*** *input* $\hat{\boldsymbol{z}}$ to G such that $\mathrm{G}(\hat{z})$ fits **two constraints**:
   a) **Contextual**: Output must **match** the **known parts of** the **image** that needs inpainting
   b) **Perceptual**: Output must **look generally «real»** according to D's judgment
3. …**by** using gradient-based **optimization on** $\hat{\boldsymbol{z}}$

Powerful idea: application of trained ML model may again involve optimization!

Reconstruction formulation

Given

- Uncomplete/corrupted image $x_{corrputed}$
- Binary mask M (same size as $x_{corrputed}$, 1 for given pixels, 0 for missing/corrupted pixels)
- Trained generator network $G()$, discriminator network $D()$

Problem

- Find $\hat{z}$ such that $x_{reconstructed} = M \odot x_{corrputed} + (1 - M) \odot G(\hat{z})$
  ($\odot$ here is the element-wise product of two matrices)

$$\underset{\text{Input}}{\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}} \odot \underset{\text{Binary Mask}}{\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}} = \underset{\text{Output}}{\begin{bmatrix} 1 & 0 \\ 0 & 4 \end{bmatrix}}$$

Solution

- Define contextual and perceptual loss as follows:
  $L_{contextual}(z) = \left\|M \odot G(z) - M \odot x_{corrupted}\right\|_1$ (distance between known parts of image and reconstruction)
  $L_{perceptual}(z) = \log\left(1 - D\left(G(z)\right)\right)$ (as before: log-likelihood of $G(z)$ **not** being real according to D)
  $L(z) = L_{contextual}(z) + \lambda \cdot L_{perceptual(z)}$ (combined loss)

➔ Optimize $\hat{z} = \arg\min_{z} L(z)$

Results

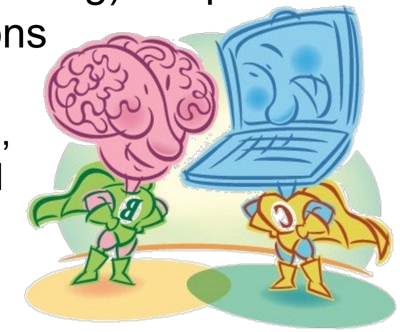
See it move: https://github.com/bamos/dcgan-completion.tensorflow

Where's the intelligence?
Man vs. machine

- **Learning** smooth approximations of complex probability **density** functions (PDF) enables us to **sample previously unseen examples**
  - That is, we can ***create*** new images, new music, …

Source: https://nerdist.com/nvidia-ai-headshots-fake-celebrities/.

- But isn't **creativity** more **the power to surprise**, i.e., (technically speaking) the power to **come up with new yet reasonable PDFs** instead of new instantiations from a given PDF?
  - That would mean that to create does not mean to know the PDF of *«things»*, but the PDF of the *«reasonableness of things»*. As this is unknown for novel things, it needs to be **continually explored**.



Review

- **Neural networks** with at least one hidden layer **are general function approximators**, trained by gradient descent

- **GANs** have been shown to **produce realistic output** on a wide range of (still smallish) image, audio and text generation tasks
- **Finding Nash equilibria** in high-dimensional, continuous, non-convex games **is an** important **open** research **problem**

- **Image inpainting works by optimizing the output** of a fully trained generator to fit the given context & realism criteria, **using** again **gradient descent**
  ➔ Applying machine learned models might involve optimization (~training) steps again
  ➔ **This is in line with human learning**: Once trained to draw, hand-copying a painting involves "optimization" on the part of the painter

Further reading: Goodfellow, *«NIPS 2016 Tutorial: Generative Adversarial Networks»*, 2016

APPENDIX

Recap: Basic idea of deep learning

Add depth (layers ➔ capability) to learn features automatically

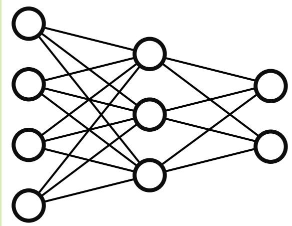
Classic computer vision

**Feature extraction
(SIFT, SURF, LBP, HOG, etc.)**

(0.2, 0.4, …)

(0.4, 0.3, …)

**Classification
(SVM, neuronal net, etc.)**



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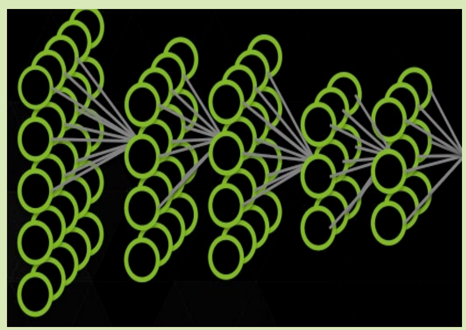
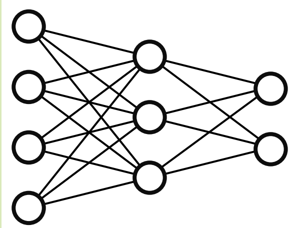
Convolutional neural networks (CNNs)

Takes raw pixels as input, learns good features automatically!





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…

The GAN zoo

Avinash Hindupur's list at https://github.com/hindupuravinash (as of Apr 2017; last update Sep 2018: #502 GANs)

GAN - Generative Adversarial Networks
3D-GAN - Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling
AC-GAN - Conditional Image Synthesis With Auxiliary Classifier GANs
AdaGAN - AdaGAN: Boosting Generative Models
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
AMGAN - 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
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
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
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
LAPGAN - Deep Generative Image Models using a Laplacian Pyramid of Adversarial Networks
LR-GAN - LR-GAN: Layered Recursive Generative Adversarial Networks for Image Generation
LSGAN - Least Squares Generative Adversarial Networks
LS-GAN - Loss-Sensitive Generative Adversarial Networks on Lipschitz Densities
MGAN - Precomputed Real-Time Texture Synthesis with Markovian Generative Adversarial Networks
MAGAN - MAGAN: Margin Adaptation for Generative Adversarial Networks
MAD-GAN - Multi-Agent Diverse Generative Adversarial Networks
MalGAN - Generating Adversarial Malware Examples for Black-Box Attacks Based on GAN
MARTA-GAN - Deep Unsupervised Representation Learning for Remote Sensing Images
McGAN - McGan: Mean and Covariance Feature Matching GAN
MedGAN - Generating Multi-label Discrete Electronic Health Records using Generative Adversarial Networks
MIX+GAN - Generalization and Equilibrium in Generative Adversarial Nets (GANs)
MPM-GAN - Message Passing Multi-Agent GANs
MV-BiGAN - Multi-view Generative Adversarial Networks
pix2pix - Image-to-Image Translation with Conditional Adversarial Networks
PPGN - Plug & Play Generative Networks: Conditional Iterative Generation of Images in Latent Space
PrGAN - 3D Shape Induction from 2D Views of Multiple Objects
RenderGAN - RenderGAN: Generating Realistic Labeled Data
RTT-GAN - Recurrent Topic-Transition GAN for Visual Paragraph Generation
SGAN - Stacked Generative Adversarial Networks
SGAN - Texture Synthesis with Spatial Generative Adversarial Networks
SAD-GAN - SAD-GAN: Synthetic Autonomous Driving using Generative Adversarial Networks
SalGAN - SalGAN: Visual Saliency Prediction with Generative Adversarial Networks
SEGAN - SEGAN: Speech Enhancement Generative Adversarial Network
SeGAN - SeGAN: Segmenting and Generating the Invisible
SeqGAN - SeqGAN: Sequence Generative Adversarial Nets with Policy Gradient
SketchGAN - Adversarial Training For Sketch Retrieval
SL-GAN - Semi-Latent GAN: Learning to generate and modify facial images from attributes
Softmax-GAN - Softmax GAN
SRGAN - Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network
S^2GAN - Generative Image Modeling using Style and Structure Adversarial Networks
SSL-GAN - Semi-Supervised Learning with Context-Conditional Generative Adversarial Networks
StackGAN - StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks
TGAN - Temporal Generative Adversarial Nets
TAC-GAN - TAC-GAN - Text Conditioned Auxiliary Classifier Generative Adversarial Network
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
VGAN - Generating Videos with Scene Dynamics
VGAN - Generative Adversarial Networks as Variational Training of Energy Based Models
VAE-GAN - Autoencoding beyond pixels using a learned similarity metric
VariGAN - Multi-View Image Generation from a Single-View
ViGAN - Image Generation and Editing with Variational Info Generative Adversarial Networks
WGAN - Wasserstein GAN
WGAN-GP - Improved Training of Wasserstein GANs
WaterGAN - WaterGAN: Unsupervised Generative Network to Enable Real-time Color Correction of Monocular Underwater Images