

Generative Modeling: GANs

Akash Srivastava



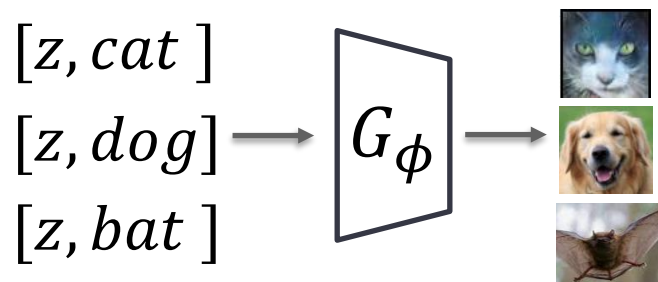
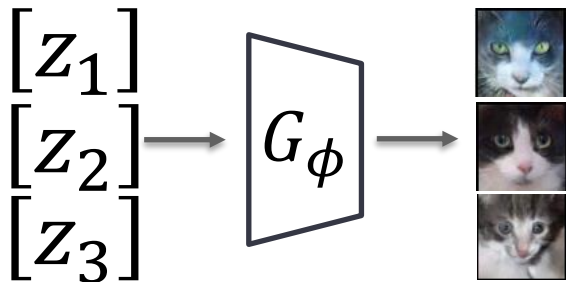
Conditional Generative Models

Lecture 8



Conditional Generative Model

- So far, we have seen that given a random sample Z , a trained GAN generates a random sample from the model distribution.
- This is great! But how do we control this generation process?
 - For Example,

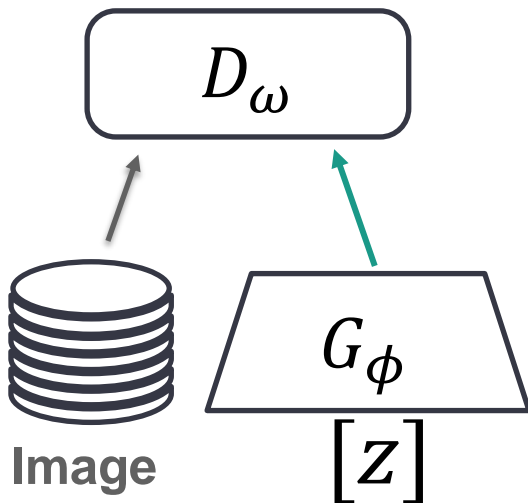


GAN vs Conditional GAN

(Mirza and Osindero, 2014)

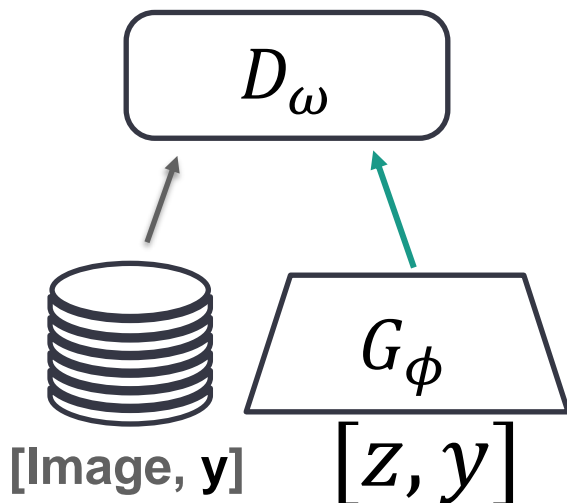
GAN

$$\min_{\phi} \max_{\omega} \mathbb{E}_{x \sim p_x} [\sigma(D_{\omega}(x))] + \mathbb{E}_{z \sim \mathcal{N}(0, I_K)} [1 - \sigma(D_{\omega}(G_{\phi}(z)))]$$



cGAN

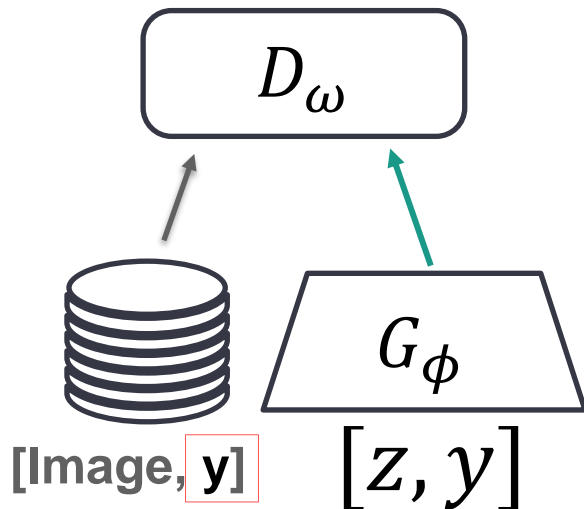
$$\min_{\phi} \max_{\omega} \mathbb{E}_{x \sim p_x} [\sigma(D_{\omega}(x|y))] + \mathbb{E}_{z \sim \mathcal{N}(0, I_K)} [1 - \sigma(D_{\omega}(G_{\phi}(z|y)))]$$



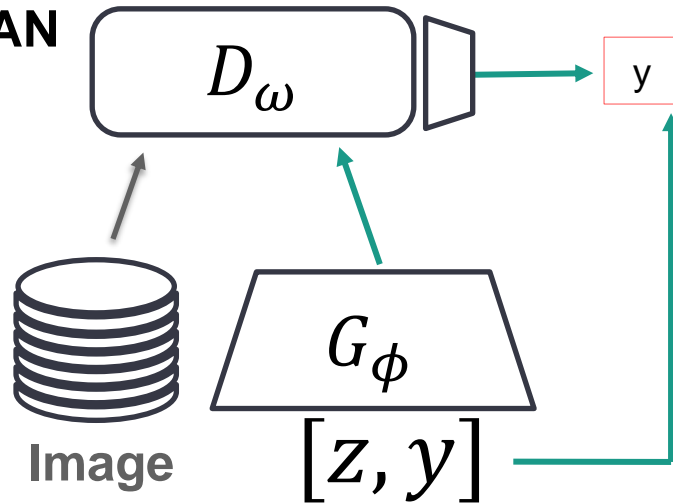
cGAN vs InfoGAN

cGAN allows conditioning on a label. In contrast, InfoGAN can be used to condition on a latent random variable using mutual information maximisation.

cGAN

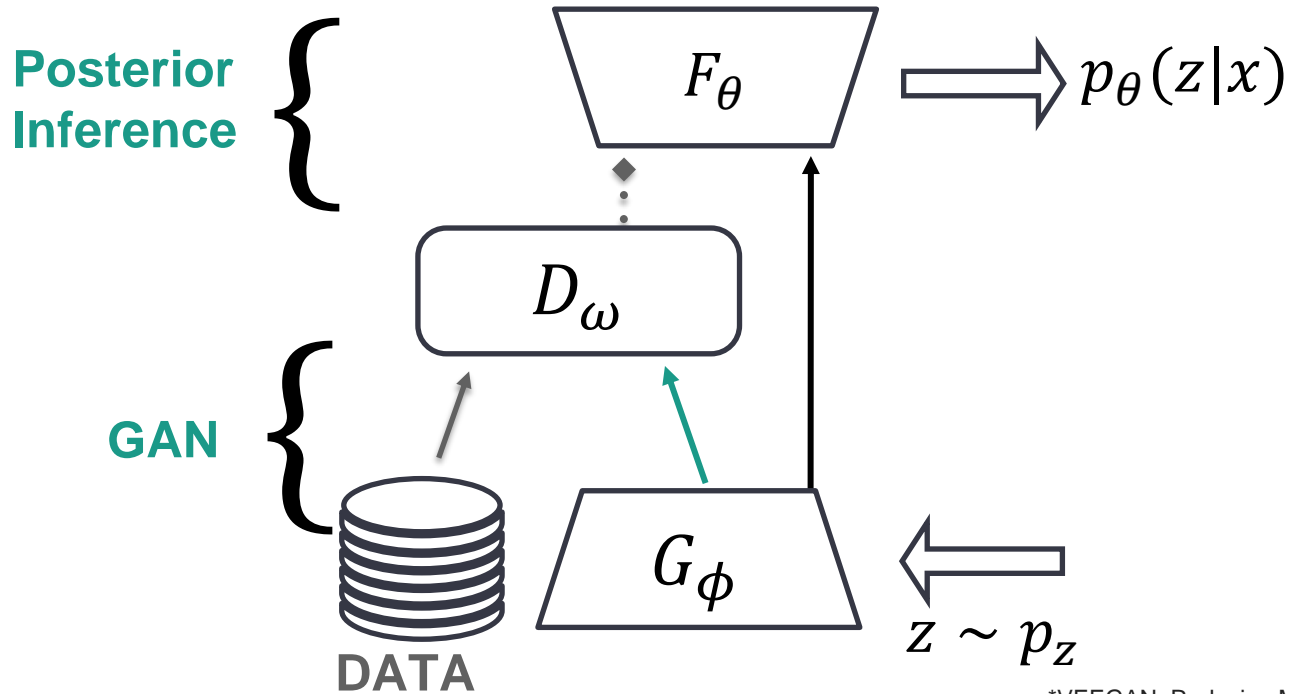


InfoGAN



*InfoGAN: Interpretable Representation Learning by Information Maximizing Generative Adversarial Nets

GANs as upside-down VAEs

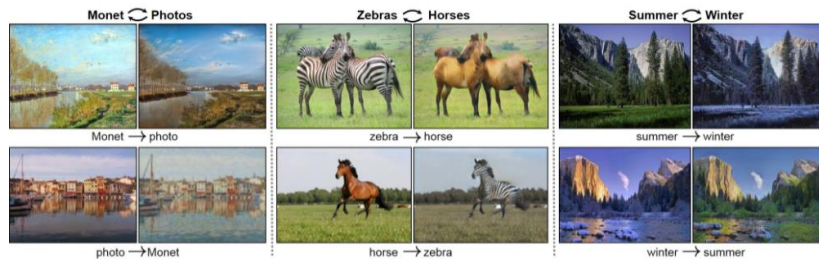


- Using conditioning in a specific way, allows us to write down GANs as upside-down VAEs that can do posterior inference!

*VEEGAN: Reducing Mode Collapse in GANs using Implicit Variational Learning.

Conditional Generative Model

- Conditioning in GANs comes in many different flavours.
 - AAE, ALI, BiGAN, BigGAN, BigBiGAN, ... this is an endless list of methods
- Even methods such as Disco GAN and Cycle GAN (and all the newer avatars) use conditioning to achieve style transfer.



*Source: <https://junyanz.github.io/CycleGAN/>



Ethical Issues

Lecture 9



Ethical Issues

- Deepfakes.
- Energy consumption.



Deep Fakes

CBS News

Doctored Nancy Pelosi video highlights threat of "deepfake" tech

Doctored Nancy Pelosi video highlights threat of "deepfake" tech ... A doctored video of House Speaker Nancy Pelosi, in which she appears to be ...
May 26, 2019



CNN

No, Tom Cruise isn't on TikTok. It's a deepfake

A series of deepfake videos of Tom Cruise is confusing millions of TikTok users. See the convincing videos and learn how this technology could ...
Mar 2, 2021



WION

Tom Cruise, Obama, Elon Musk, Mark Zuckerberg and more: Deepfake videos raise alarm

Deepfake is the new age photoshop that gives a person the power to make anyone do anything on camera. These videos look and sound too real ...
Mar 2, 2021



The Wash

Another fake video of Pelosi goes viral on Facebook

A manipulated and widely shared video that depicts House Speaker Nancy Pelosi (D-Calif.) slurring her speech and appearing intoxicated was ...
Aug 3, 2020



[https://www.youtube.com > watch](https://www.youtube.com/watch)

TRUMP vs BIDEN [DeepFake] - YouTube



TRUMP vs BIDEN [DeepFake]. 165,050 views165K ... The Story of the Best Meme EVER: "Never Gonna Give ...
Oct 31, 2020 · Uploaded by Ctrl Shift Face



Generative Models Power Deep Fakes

The drastic improvement in high resolution image generation has unfortunately allowed some bad actors to use this technology for malicious intent.

Tools	Links	Key Features
Faceswap	https://github.com/deepfakes/faceswap	<ul style="list-style-type: none">- Using two encoder-decoder pairs.- Parameters of the encoder are shared.
Faceswap-GAN	https://github.com/shaoanlu/faceswap-GAN	Adversarial loss and perceptual loss (VGGface) are added to an auto-encoder architecture.
Few-Shot Face Translation	https://github.com/shaoanlu/fewshot-face-translation-GAN	<ul style="list-style-type: none">- Use a pre-trained face recognition model to extract latent embeddings for GAN processing.- Incorporate semantic priors obtained by modules from FUNIT [42] and SPADE [43].
DeepFaceLab	https://github.com/iperov/DeepFaceLab	<ul style="list-style-type: none">- Expand from the Faceswap method with new models, e.g. H64, H128, LIAEF128, SAE [44].- Support multiple face extraction modes, e.g. S3FD, MTCNN, dlib, or manual [44].
DFaker	https://github.com/dfaker/df	<ul style="list-style-type: none">- DSSIM loss function [45] is used to reconstruct face.- Implemented based on Keras library.
DeepFake_tf	https://github.com/StromWine/DeepFake_tf	Similar to DFaker but implemented based on tensorflow.
AvatarMe	https://github.com/lattas/AvatarMe	<ul style="list-style-type: none">- Reconstruct 3D faces from arbitrary “in-the-wild” images.- Can reconstruct authentic 4K by 6K-resolution 3D faces from a single low-resolution image [46].
MarioNETte	https://hyperconnect.github.io/MarioNETte	<ul style="list-style-type: none">- A few-shot face reenactment framework that preserves the target identity.- No additional fine-tuning phase is needed for identity adaptation [47].
DiscoFaceGAN	https://github.com/microsoft/DiscoFaceGAN	<ul style="list-style-type: none">- Generate face images of virtual people with independent latent variables of identity, expression, pose, and illumination.- Embed 3D priors into adversarial learning [48].
StyleRig	https://gvv.mpi-inf.mpg.de/projects/StyleRig	<ul style="list-style-type: none">- Create portrait images of faces with a rig-like control over a pretrained and fixed StyleGAN via 3D morphable face models.- Self-supervised without manual annotations [49].

*Deep Learning for Deepfakes Creation and Detection: A Survey



Energy Consumption

- Training deep generative models require sophisticated hardware such as GPUs and TPUs.
- Do you know, roughly how much energy these specialized processors consume?

The short answer is a lot! We will explore this further in the tutorial session.

There is a significant emphasis on reducing **inference time power consumption** for all sorts of deep learning methods as that allows us to run ML on small **edge devices**. But there is significantly less awareness about the **environmental impact that training large models** create.



Recap and Advanced Topics

Lecture 10



Generative Modelling

Given: $X = \{x_i | \forall j, x_j \in \mathbb{R}^D\}_{i=1}^N$ where $x \sim p_x$ is the unknown true data distribution.

Goal: Estimate p_x using only the samples in X .

Lets define a class of probability or statistical models: p_θ

and cast our estimation problem as an optimisation task of finding θ^* such that,

$$\theta^* = \operatorname{argmin}_{\theta} D[p_x \parallel p_\theta]$$

some measure of distance D between p_x and p_θ .



Quantifying Discrepancy Between Probability Distributions

Using the ratio of the two densities:

$$D_f[P_x \parallel P_\theta] = \mathbb{E}_{x \sim p_\theta} \left[f\left(\frac{p_x}{p_\theta}\right) \right]$$

Using the sup of the difference of expectations under the two distributions:

$$IPM_{\mathcal{F}}[P_x \parallel P_\theta] = \sup_{f \in \mathcal{F}} \mathbb{E}_{x \sim p_x} [f(x)] - \mathbb{E}_{x \sim p_\theta} [f(x)]$$



GAN Recipe

f-GAN

Estimate Density Ratio

Stable

Plug the estimator in an f-divergence and train the generator.

Un-Stable

Examples:

1. GAN
2. f-GAN
3. cGAN
4. VEEGAN

IPM-GAN

Maximise/Estimate IPM

Un-Stable

Minimize the IPM to train the generator.

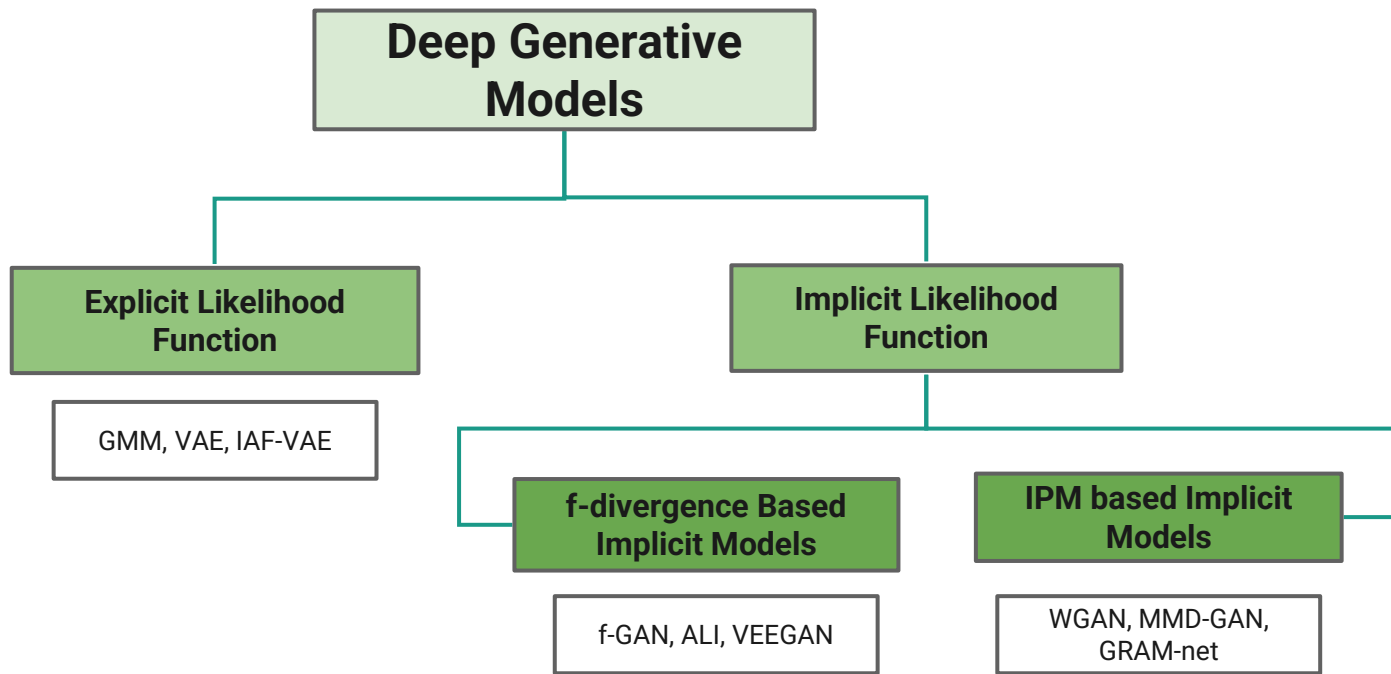
Stable

Examples:

1. MMD-GAN
2. WGAN
3. WGAN-GP
4. GRAM-net



Landscape of DGMs we covered!



(Too Many) Methods for Unsupervised Representation Learning

Variational Autoencoders

Auto-encoding variational bayes

DP Kingma, M Welling - arXiv preprint arXiv:1312.6114, 2013 - arxiv.org

How can we perform efficient inference and learning in directed probabilistic models, in the presence of continuous latent variables with intractable posterior distributions, and large datasets? We introduce a stochastic variational inference and learning algorithm that scales ...

★ 99 Cited by 13162 Related articles All 28 versions »

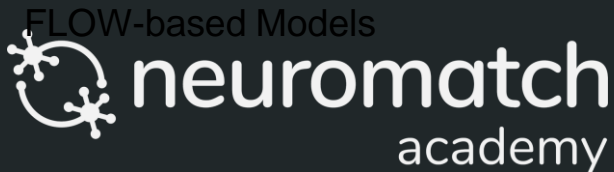
Generative Adversarial Networks

Generative adversarial networks

IJ Goodfellow, J Pouget-Abadie, M Mirza, B Xu... - arXiv preprint arXiv ..., 2014 - arxiv.org

We propose a new framework for estimating generative models via an adversarial process, in which we simultaneously train two models: a generative model G that captures the data distribution, and a discriminative model D that estimates the probability that a sample came ...

★ 99 Cited by 28510 Related articles All 55 versions »



Contrastive Learning

Variational inference with normalizing flows

D Rezende, S Mohamed - International Conference on ..., 2015 - proceedings.mlr.press

The choice of the approximate posterior distribution is one of the most important aspects of variational inference. Most applications of variational inference require the use of approximate posteriors in order to allow for efficient inference.

★ 99 Cited by 1380 Related articles All 6 versions »

Improving variational inference with inverse autoregressive

DP Kingma, T Salimans, R Jozefowicz, X Chen... - arXiv preprint arXiv ..., 2016 - arxiv.org

The framework of normalizing flows provides a general strategy for flexible inference of posteriors over latent variables. We propose a new type of normalizing flow, the inverse autoregressive flow (IAF), that, in contrast to other published methods, scales well to ...

★ 99 Cited by 876 Related articles All 11 versions »

Glow: Generative flow with invertible 1x1 convolutions

D Kingma, P Dhariwal - arXiv preprint arXiv:1807.03039, 2018 - arxiv.org

... a generative flow coined Glow, with various new elements as described in Section 3. In Section 5, we compare our model quantitatively with previous flows, and in Section 6, we study the qualitative aspects of our model on high ... 2 Background: Flow-based Generative Models ...

★ 99 Cited by 886 Related articles All 6 versions »

A simple framework for contrastive learning of visual representations

T Chen, S Kornblith, M Norouzi... - on machine learning, 2020 - proceedings.mlr.press

This paper presents a simple framework for contrastive learning of visual representations. We simplify recent approaches to contrastive learning by removing the need for complex loss functions or complicated data augmentations. Our framework achieves state-of-the-art performance on a wide range of tasks without requiring any hyperparameter tuning or complex data augmentations. In this paper, we propose a simple framework for contrastive learning of visual representations that consistently outperforms cross-entropy as a supervised learning task across different ...

★ 99 Cited by 12 Related articles All 9 versions »

Exploring Simple Siamese Representation Learning

X Chen, K He, arXiv preprint arXiv:1711.10507, 2017 - arxiv.org

Siamese networks have become a common structure in various recent models for unsupervised visual representation learning. These models maximize the similarity between two augmentations of one image, subject to certain conditions for avoiding collapsing solutions. In this paper, we present empirical results that simple Siamese networks

... a simple framework for contrastive learning of visual representations. We simplify recent approaches to contrastive learning by removing the need for complex loss functions or complicated data augmentations. Our framework achieves state-of-the-art performance on a wide range of tasks without requiring any hyperparameter tuning or complex data augmentations. In this paper, we propose a simple framework for contrastive learning of visual representations that consistently outperforms cross-entropy as a supervised learning task across different ...

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Clue:
They all involve
Density Ratios!