GENERATIVE ADVERSARIAL NETWORKS

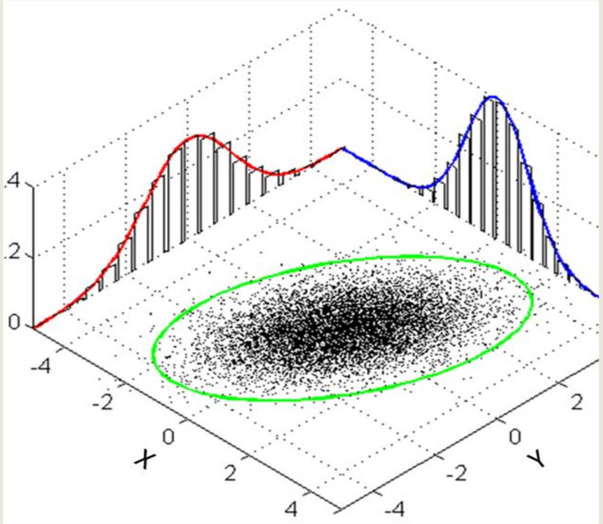
KAIM 2018

Anand Krish

Agenda

- Introduction to Generative Models
- GANs
- Objectives

Generative Modelling



- Going beyond traditional classification and Prediction –
  - *Learn to simulate the data generator*
  - *Probabilistically – learn the data generating distribution*
  - *Generate new samples of data*
  - *Unsupervised learning*
- Inference based on data generation
  - *Learn latent representations and features*
- Myriad of Applications –
  - *Super-resolution, Text-to-speech*
  - *Fake image generation, style transfer*
  - *Face modification, speech generation*
  - *Drug discovery : new candidate molecules*

Problems with Generative models

Problem	Solution
Sampling from Complex distribution	Use simple transformations to form samples of complex distribution
Intractable probability distributions	Implicit density generation
Adversarial Attacks	Use a generalized critic model – Game Theoretic approach

Advantages –

- *No need for variational methods/Monte Carlo methods*
- *No need of latent variable models*
- *Simple architectures and straight-forward training*

GAN

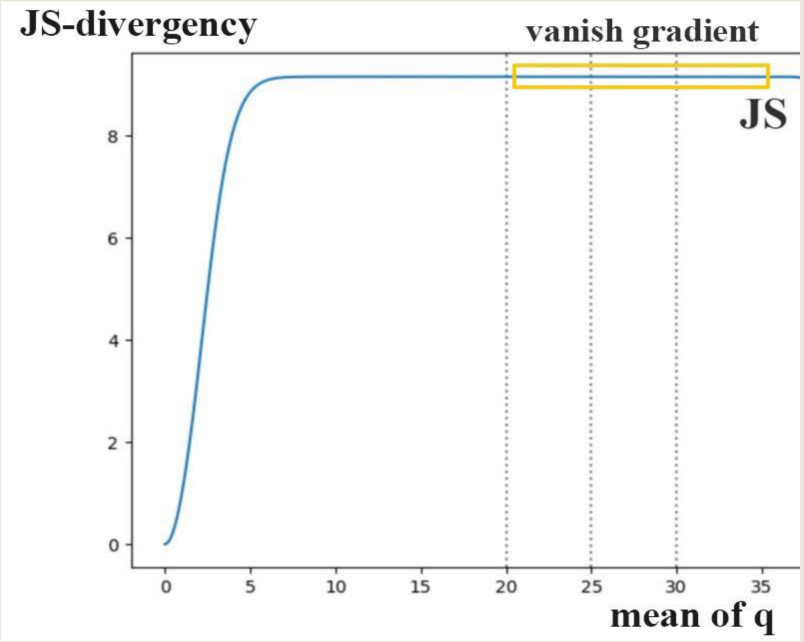
- Two parts – **Generator** and **Discriminator.**
  - *Generator (G) learns the data distribution from samples implicitly*
  - *Discriminator (D) learns to differentiate the original data from the samples from the Generator (Adversary)*
- Formal description of GANs – *Divergence Minimization.* Minimize the *distance* between probability distributions.

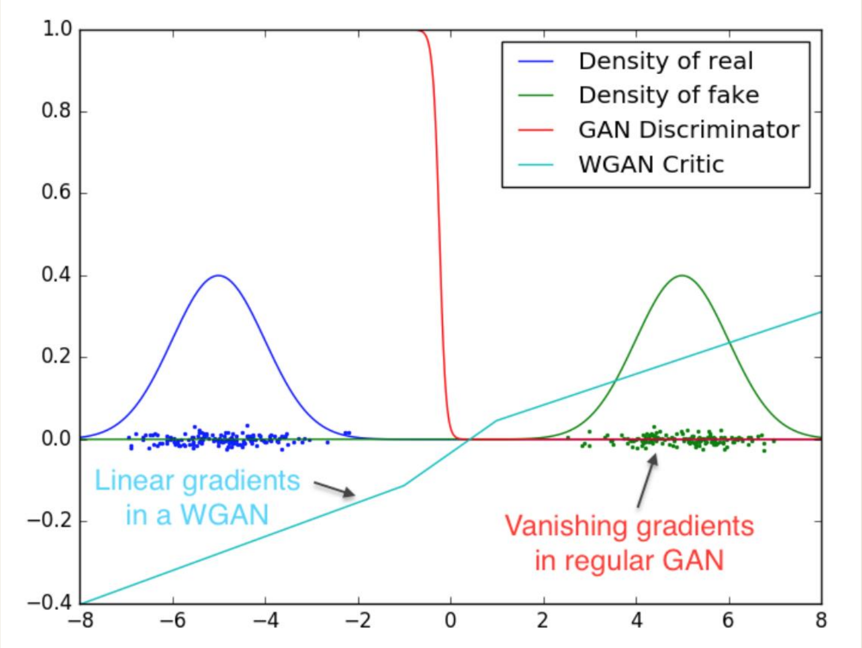
$$\boxed{\min_G \max_D \mathbb{E}_{x \backsim p_0}[\log D(x)] + \mathbb{E}_{z \backsim q_\theta}[\log(1 - D(G(z)))]}$$

Where p_0 is the original data distribution and q_θ is the distribution learned by the network. The above objective represents the Jenson-Shannon (JS) divergence. Train by alternatively training the D and G networks.

GAN Objectives

- Core problem with the native objective – modal collapse
  - *Learning just few correct samples to fool the discriminator*
  - *Reason – The divergence function (JS divergence) saturates at larger deviations.*
  - *Solution – Use Different Metric – Wasserstein Metric (linear gradients)*





Pic Courtesy – Jonathan Hui - https://medium.com/@jonathan_hui/gan-wasserstein-gan-wgan-gp-6a1a2aa1b490

GAN Objectives

- Further Problems –
  - *Wasserstein Metric is **intractable***

$$W(p_0, q_\theta) = \inf_{\gamma \in \Gamma} \mathbb{E}_{(x,y) \backsim \gamma}[||x - y||]$$

English Translation: Take the largest value of the expectation of the set of all joint distributions whose marginals are p_0 and q_θ. (Kinda made is worse!!)

  - *Solution – Use simple approximation*

$$\mathbb{E}_{x \backsim p_0}[D(x)] - \mathbb{E}_{x \backsim q_\theta}[D(x)]$$

  - *Major Problem – Approximation works only for $1-$Lipschitz discriminator functions D*
  - *Solution – Way too many!!!*
    - Gradient Clipping
    - Gradient Penalty
    - Spectral Normalization

$\left.\begin{array}{l} \\ \\ \\ \end{array}\right\}$ Most Promising Solutions

THANK YOU