Generative Adversarial Network

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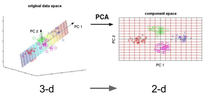
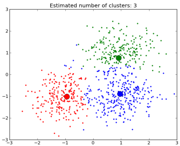
Why are we here?

The common task in unsupervised learning is to understand the **hidden structure of our data.**



Dimensionality Reduction

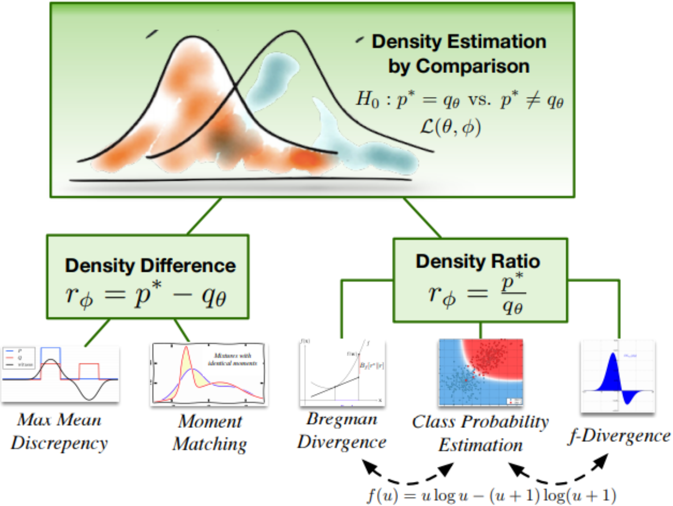


Clustering

Other examples include:

- Feature Learning: Auto-encoder
- Density estimation.

Generative Models



Source: Learning in Implicit Generative Model

Generative Models

Various generative models exist:

- PixelRNN/CNN
- Variational Auto Encoder
- **Generative Adversarial Nework**

Outline

1. Setting the Scene
2. Architecture of Generative Adversarial Network
3. Potential Applications of GAN
4. Algorithm of GAN
5. Properties of Generative Adversarial Network
    - Assumptions
    - Limitations
    - Strength and Weakness
6. Demo *
7. Flavors of GAN

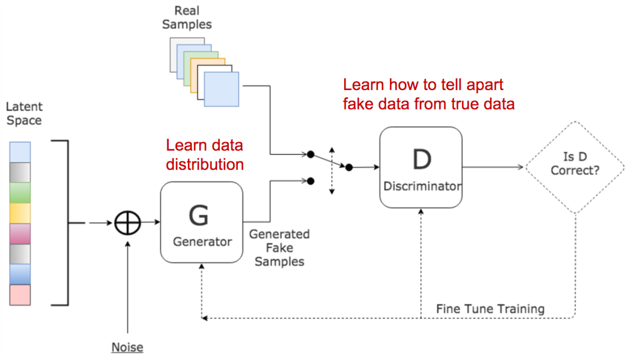
Setting the Scene

Is this money fake or not?

Generate fake currency to fool the teller

AIM: to achieve a zero-sum game.

Architecture of Generative Adversarial Network



Source: Lil'Log

There are 2 competing networks:

- Discriminator Network
- Generator Network

Potential Applications of GAN

Figure 7: Generated samples

For Generating Anime Character

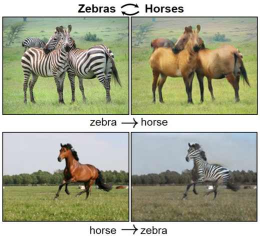
Figure 5: 1024 × 1024 images generated using the CELEBA-HQ dataset. See Appendix F for a larger set of results, and the accompanying video for latent space interpolations.

Realistic Images

Potential Applications of GAN

(b) Handbag images (input) & **Generated** shoe images (output)

Transfer Style (DiscoGAN)



Cross-Domain Transfer between pair of images(CycleGAN)

Potential Applications of GAN

LOT 363

Edmond de Belamy, from La Famille de Belamy

Price realised

USD 432,500

Estimate

USD 7,000 - USD 10,000

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Source: christies.com

”GAN print, on canvas, 2018, signed with loss function in ink by the publisher, from a series of eleven unique images, published by Obvious Art, Paris, with original gilded wood frame”

Algorithm of GAN

Algorithm 1 Minibatch stochastic gradient descent training of generative adversarial nets. The number of steps to apply to the discriminator, k, is a hyperparameter. We used $k = 1$, the least expensive option, in our experiments.

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:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right)\right].$$

  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 descending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right).$$

end for

The gradient-based updates can use any standard gradient-based learning rule. We used momentum in our experiments.

Algorithm of GAN (Cont'd)

Objective Function

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z)))]$$

Properties of Generative Adversarial Network

Assumptions

The Generator G is a differentiable function and the models are multi-layer perceptron

Limitations

Updating the gradients of both Discriminator and Generator concurrently cannot guarantee a convergence

Strength

The use of Backdrop instead of Markov Chain in obtaining the gradients makes the representations sharp instead of blurry (wGAN and InfoGAN)

Demo

I would review the result of a short demo using real datasets. The demo jupyter notebook would be shared to the drive and you can play around with it (using google colab).

References

1. Paper: Generative Adversarial Nets
2. Paper: Progressive GAN
3. Blog: From-GAN-to-WGAN
4. Paper: Learning in Implicit Generative Models
5. Google

Conclusion

Richard Feynman

”What I cannot create, I do not understand”

- GAN is an interesting aspect of research especially in the aspect of ”semi-supervised learning” where you have the potential of generating data whose distribution is closer to that of the real data.
- It’s useful in simulating real world scenarios.