Introduction to Deep Learning (CS474)

Lecture 26

Outline

Module 4

- Introduction to Generative Adversarial Networks (GANs)

Recap

- We have talked about how to make **predictions**.
- We used deep neural networks learned **mappings** from data examples to labels.
- This kind of learning is called ***discriminative learning***, as in, we'd like to be able to discriminate between photos cats and photos of dogs.
- Classification accuracies on high-resolution images has gone from useless to human-level (with some caveats) in just 5-6 years.

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Motivation

- But there is **more** to machine learning than just solving discriminative tasks.

- For example, given a large dataset, without any labels, we might want to learn a model that concisely captures the *characteristics* of this data.

- Given such a model, we could sample **synthetic** data examples that resemble the distribution of the training data.

- For example, given a large corpus of photographs of faces, we might want to be able to **generate** a new **photorealistic image** that looks like it might plausibly have come from the same dataset.

- This kind of learning is called **generative modeling.**

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Generative Modeling

- In 2014, a breakthrough paper introduced Generative adversarial networks (GANs), a clever new way to leverage the power of discriminative models to get good generative models.

Input samples

Generated samples

  - How can we learn $P_{model}(x)$ similar to $P_{data}(x)$?

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Generative Modeling

- At their heart, GANs rely on the idea that a data generator is good if we cannot tell fake data apart from real data.

- In statistics, this is called a two-sample test - a test to answer the question whether datasets $X = \{x_1 , . . . , x_n \}$ and $X ′ = \{x ′_1 , . . . , x ′_n\}$ were drawn from the same distribution.

- No explicit model but allows one to sample the model distribution

- Sampling is done using a deep neural network

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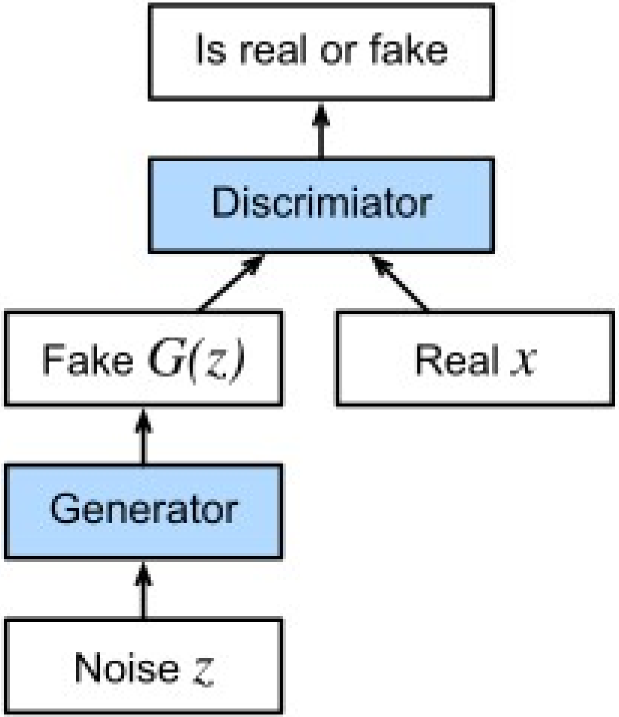
Slide credit 2: Dr. G. Krishnamurthy

GAN Architecture



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GAN Architecture

- As you can see, there are two pieces in GAN architecture -

- first off, we need a device (say, a deep network but it really could be anything, such as a game rendering engine) that might potentially be able to generate data that looks just like the real thing.

- If we are dealing with images, this needs to generate images. If we are dealing with speech, it needs to generate audio sequences, and so on.

- We call this the generator network.

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GAN Architecture

- The second component is the discriminator network.

- It attempts to distinguish fake and real data from each other. Both networks are in competition with each other.

- The generator network attempts to fool the discriminator network. At that point, the discriminator network adapts to the new fake data.

- This information, in turn is used to improve the generator network, and so on.

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MiniMax Game

- Discriminator (D) and Generator (G) are playing a “minimax” game.

- $$\min_D \{-y \log D(\mathbf{x}) - (1-y) \log(1 - D(\mathbf{x}))\}$$

- $$\max_G \{-(1-y) \log(1 - D(G(\mathbf{z})))\} = \max_G \{-\log(1 - D(G(\mathbf{z})))\}$$

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References

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