Generative Adversarial Nets (GAN)

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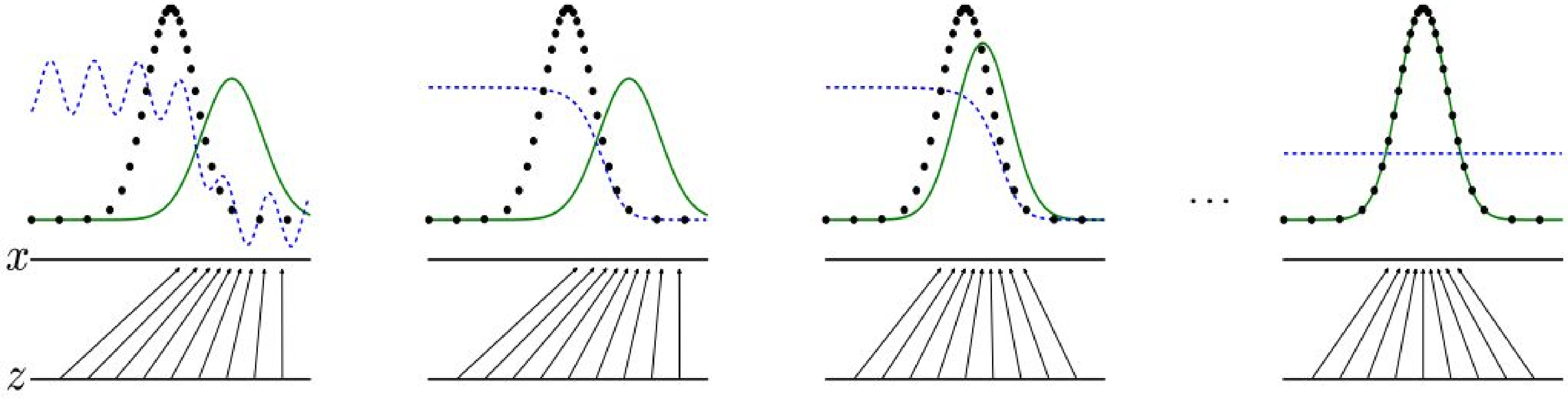
Generative/Discriminative Models

- Difference between generative and discriminative, P(x,y) **VS** P(y|x)
- Captures data distribution
  - Joint probability distribution (distribution of P(x,y)) ?
- Discriminative Models
  - **Examples:** Text classification
  - Learns **P(y|x)** i.e. probabilities on the target variables.
  - Does not need to model the data distribution
- Generative Models
  - **Example:** Language models, sequence completion
  - Learns **P(x, y)** ---> Convertible into P(y|x) for classification.
  - P(Sequence) - Captures data distribution so easy to compute
  - P(current word | previous sequence) - Bayes rule, models probs of all the variables

GAN Objective

- Learn a generative model approximating the data distribution
  - X → P(X)
- Train G to Maximize **D(G(x))**



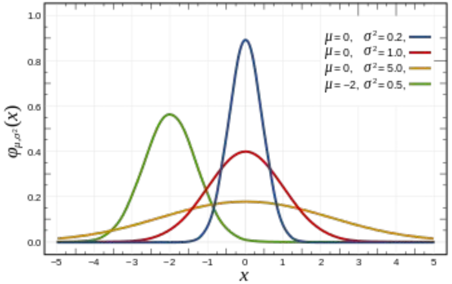
(a) (b) (c) (d)

GAN structure and Idea

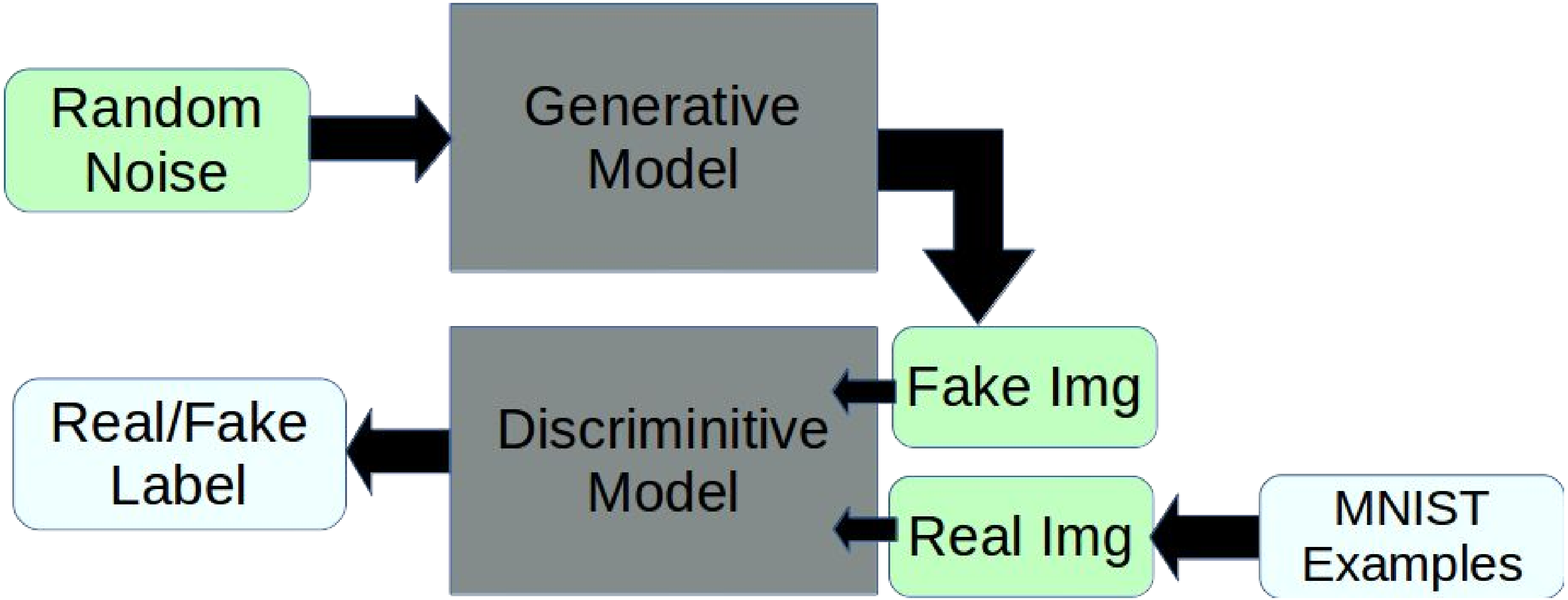
- Formulation of zero sum game
- Individual components and their role: G, D
  - G(z) - Generator for z. G(z) generates a samples which closely resembles the data.
  - D(x) - Discriminator for x. D(x) is the probability that x comes from data rather than $\mathbf{p_g}$ (the simulated data distribution by G)
- What to expect - Eventually the algo converges at a saddle point, where ‘G’ learns to “accurately approximate” the data distribution. The best that ‘D’ can do is to toss a coin (0.5)
- Analogy
  - Generator: Team of counterfeiters, printing fake currency
  - Discriminator - Police.

What is the next best to GAN's (Literature Survey)

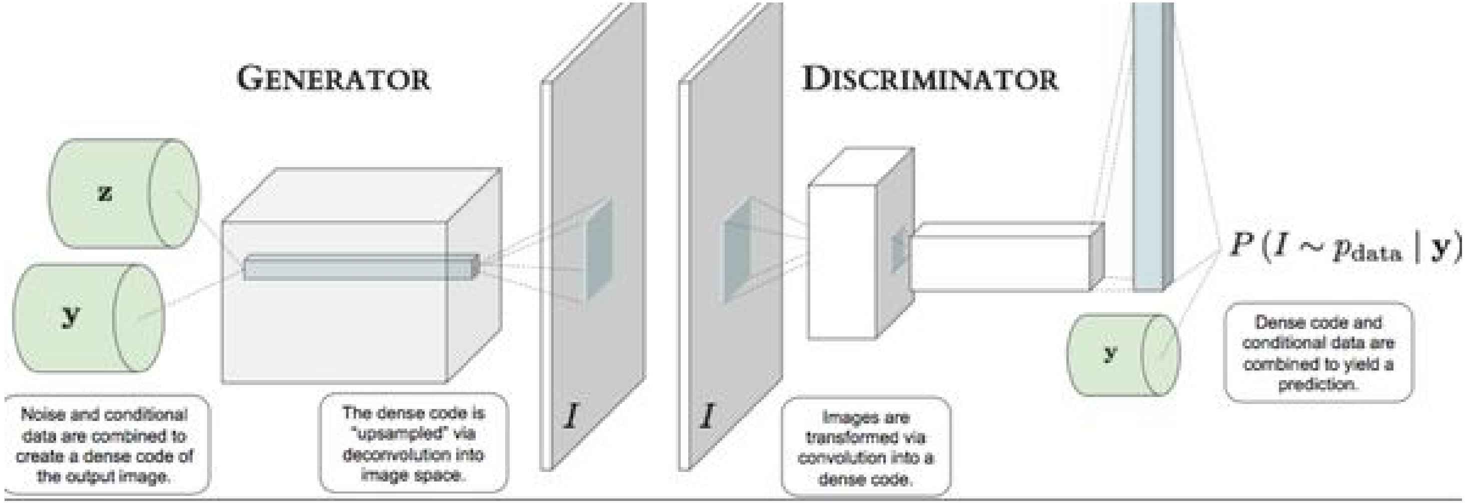
- Deep Generative model.
    - Best example: Deep Boltzmann Machines
    - These models provide parametric specification of a *pdf*
    - Maximize log-likelihood.
    - Problem - Intractable Likelihood function.
    - Numerous approximations are needed.
- Generative stochastic networks (GSMs)
    - Do not explicitly represent the likelihood [Thereby avoiding intractability, approximations]
    - Can be trained with simple backprop
    - Current work extends generative stochastic networks [NIPS 2010, Bengio]
- Noise Contrastive Estimation



Simplified GAN Structure - Image example



GAN Structure



- Normally, Both G, D are multilayer perceptrons.
- Generic GAN architecture, with an optional input variable - Z. For ex. It can be a class variable of input image.

Training The Network

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

Can we generate text using GAN?

- NO !!
- It cannot be applied since the output produced by the generator should be a continuous vector and small delta change in it should result in a meaningful entity

Cont.

- Images exist in continuous domains
- Text consists of discrete entities, words
- Even with recent continuous representations of text - word embeddings, existing framework would still fail.
- For e.g. Consider a GAN trying to generate one word at a time
- W is a continuous representation generated by generator, now W + epsilon (epsilon is a std. Gaussian noise) may not be a valid word vector
- Word vectors exists as discrete points in the real space.

Future

- Adapting GANs in text scenario.
- SeqGAN recent example
- Some works in NIPS addressing this problem.
- Adversarial learning workshop - NIPS
- Video lecture of GAN by IAN Goodfellow - NIPS Tutorial
  - https://channel9.msdn.com/Events/Neural-Information-Processing-Systems-Conference/Neural-Information-Processing-Systems-Conference-NIPS-2016/Generative-Adversarial-Networks

Thank You.