Generative Adversarial Nets

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Overview

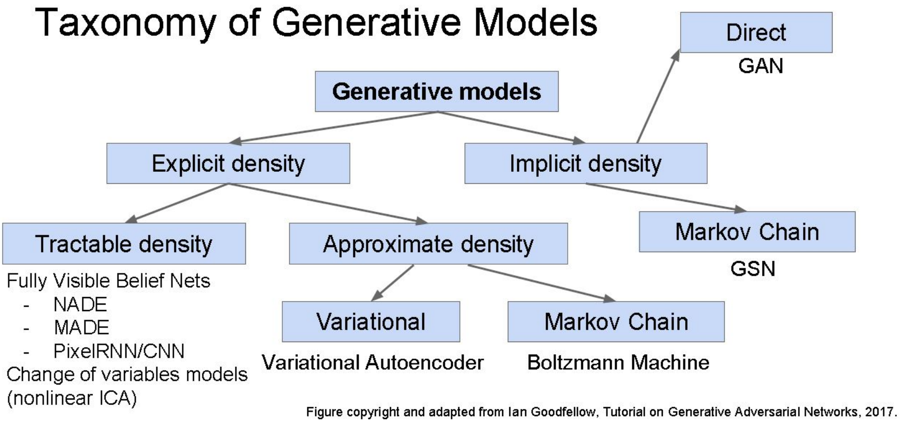
Generative models

Here we focus on using generative model to solve the unsupervised problem:
given training data(without labels), generate new samples from same distribution.

Training data ~ $p_{data}(x)$

Generated samples ~ $p_{model}(x)$

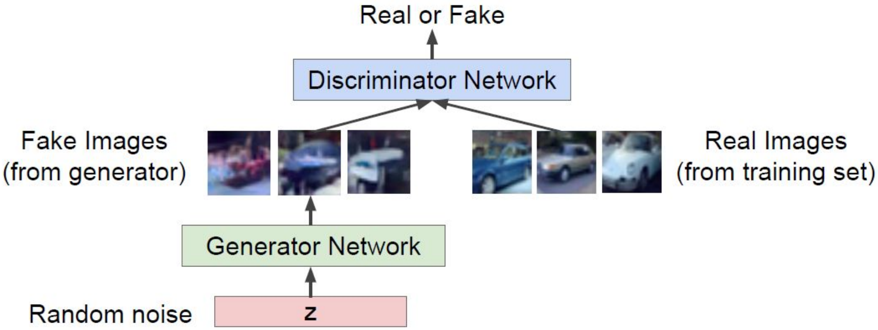
Question: why generative models?



GANs: don't work with explicit density function.

Basic idea: two-player game

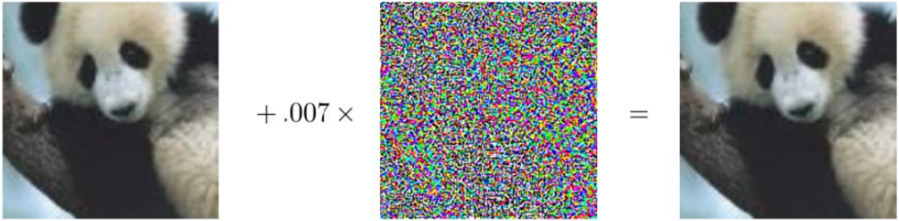
Generator network: try to fool the discriminator by generating real-looking images.
Discriminator network: try to distinguish between real and fake images.



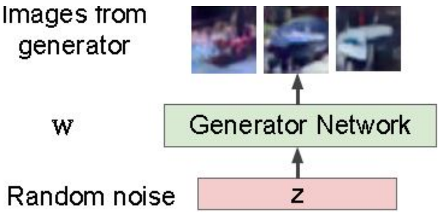
First perspective on the motivation: adversarial example

Adversarial example

Panda or gibbon?



Second perspective: what is maximum likelihood?



In this case likelihood is intractable, because we cannot go back from images to latent variable. Therefore, we change the direction.

Vanilla GAN

Objective function:

$$\min_G \max_D [E_{x \sim p_{data}} \log D(x) + E_{z \sim noise} \log(1 - D(G(z)))]$$

Here, discriminator outputs likelihood in $(0, 1)$ of input images.
Alternating optimization leads to the minimization problem unbounded.
Therefore, usually we alternate between:

$$\max_D [E_{x \sim p_{data}} \log D(x) + E_{z \sim noise} \log(1 - D(G(z)))]$$

$$\max_G E_{z \sim noise} \log(D(G(z)))$$

The algorithm

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

Demonstrations

Demo on MNIST example (compare with VAE): ▸ MNIST

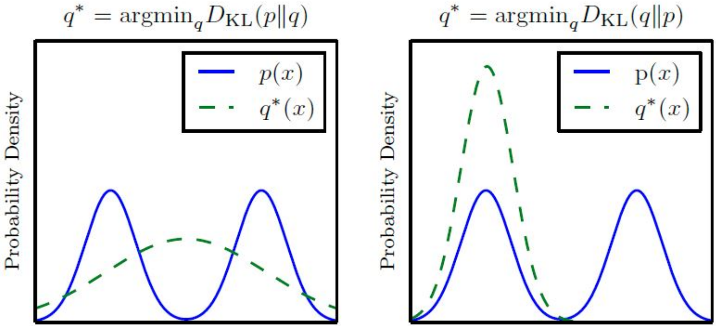
Demo on 1D example: ▸ 1D

Why it works?

Does the choice of divergence matter?
Loosely speaking, GAN would find a p_{model} such that the following Jensen-Shannon divergence is minimized:

$$JSD(p_{data}||p_{model}) = \frac{KL(p_{data}||\frac{p_{data}+p_{model}}{2}) + KL(p_{model}||\frac{p_{data}+p_{model}}{2})}{2}.$$

In contrast, VAE minimizes KL divergence.



Unfortunately...

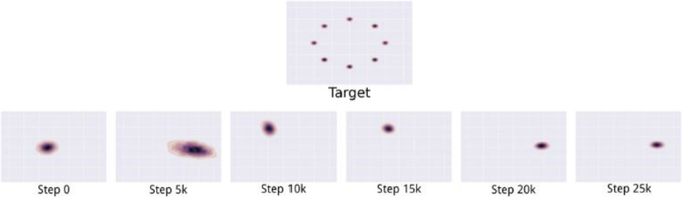
But that is not the answer!
We can minimize KL divergence in GAN framework by minimizing

$$J^G = \frac{1}{2} E_{z \sim p_{model}} \exp(\sigma^{-1}(D(G(z)))).$$

And it still works.

Why it does not work?

The problem of mode collapse: GANs often choose to generate from very few modes; fewer than the limitation imposed by the model capacity.



One explanation: it is problematic to use alternating minimization as minimax is not equivalent to maxmin in this case.

Variations of GANs

GAN	Discriminator Loss	Generator Loss
MM GAN	$\mathcal{L}_{\mathrm{D}}^{\mathrm{GAN}} = -\mathbb{E}_{x\sim p_d}[\log(D(x))] + \mathbb{E}_{\hat{x}\sim p_g}[\log(1 - D(\hat{x}))]$	$\mathcal{L}_{\mathrm{G}}^{\mathrm{GAN}} = -\mathcal{L}_{\mathrm{D}}^{\mathrm{GAN}}$
NS GAN	$\mathcal{L}_{\mathrm{D}}^{\mathrm{NSGAN}} = \mathcal{L}_{\mathrm{D}}^{\mathrm{GAN}}$	$\mathcal{L}_{\mathrm{G}}^{\mathrm{NSGAN}} = \mathbb{E}_{\hat{x}\sim p_g}[\log(D(\hat{x}))]$
WGAN	$\mathcal{L}_{\mathrm{D}}^{\mathrm{WGAN}} = -\mathbb{E}_{x\sim p_d}[D(x)] + \mathbb{E}_{\hat{x}\sim p_g}[D(\hat{x})]$	$\mathcal{L}_{\mathrm{G}}^{\mathrm{WGAN}} - = \mathcal{L}_{\mathrm{D}}^{\mathrm{WGAN}}$
WGAN GP	$\mathcal{L}_{\mathrm{D}}^{\mathrm{WGAN}} = \mathcal{L}_{\mathrm{D}}^{\mathrm{WGAN}} + \lambda\mathbb{E}_{\hat{x}\sim p_g}[(\lvert\lvert\nabla D(\alpha x + (1 - \alpha\hat{x})\rvert\rvert_2 - 1)^2]$	$\mathcal{L}_{\mathrm{G}}^{\mathrm{WGAN}} = -\mathbb{E}_{\hat{x}\sim p_g}[D(\hat{x})]$
LS GAN	$\mathcal{L}_{\mathrm{D}}^{\mathrm{LSGAN}} = -\mathbb{E}_{x\sim p_d}[(D(x) - 1)^2] + \mathbb{E}_{\hat{x}\sim p_g}[D(\hat{x})^2]$	$\mathcal{L}_{\mathrm{G}}^{\mathrm{LSGAN}} = -\mathbb{E}_{\hat{x}\sim p_g}[(D(\hat{x} - 1)^2]$
DRAGAN	$\mathcal{L}_{\mathrm{D}}^{\mathrm{DRAGAN}} = \mathcal{L}_{\mathrm{D}}^{\mathrm{GAN}} + \lambda\mathbb{E}_{\hat{x}\sim p_d + \mathcal{N}(0,c)}[(\lvert\lvert\nabla D(\hat{x})\rvert\rvert_2 - 1)^2]$	$\mathcal{L}_{\mathrm{G}}^{\mathrm{DRAGAN}} = -\mathcal{L}_{\mathrm{D}}^{\mathrm{NS\ GAN}}$
BEGAN	$\mathcal{L}_{\mathrm{D}}^{\mathrm{BEGAN}} = \mathbb{E}_{x\sim p_d}[\lvert\lvert x - \mathrm{AE}(x)\rvert\rvert_1] - k_t\mathbb{E}_{\hat{x}\sim p_g}[\lvert\lvert\hat{x} - \mathrm{AE}(\hat{x})\rvert\rvert_1]$	$\mathcal{L}_{\mathrm{G}}^{\mathrm{BEGAN}} = \mathbb{E}_{\hat{x}\sim p_g}[\lvert\lvert\hat{x} - \mathrm{AE}(\hat{x})\rvert\rvert_1]$

What? They are equal? ▸ Are GANs Created Equal? A Large-Scale Study

Tricks and tips

- Tanh as the last layer of the generator output
- Dropout
- Conditional on labels (reduce the number of modes)
- Batch normalization
- Deeper discriminator
- Label smoothing for discriminator

Improved techniques for training GANs. Tips and tricks to make GANs work

Fun stuff and references

Cycle GAN: ▸ Cycle GAN ▸ Face change with Cycle GAN

Adversarial examples: ▸ Adversarial examples and adversarial training

Tutorial: ▸ Tutorial on GAN

Stanford course video: ▸ Generative models

The End