Generative Adversarial Networks

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Outline

1. Motivation
   - Why should we study generative models?
   - Some results from recent GAN works
2. How does GAN work?
   - GAN Architecture
   - Formutalation of GAN
   - Training procedure of GANs
3. Applications of GANs
   - Computer Vision
   - Reinforcement Learning

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- If we want our computers to understand, we have to teach them to create. (I do not understand what I cannot create. – Richard Feynman)

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Recent works

- Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network [Ledig et al., 2016]

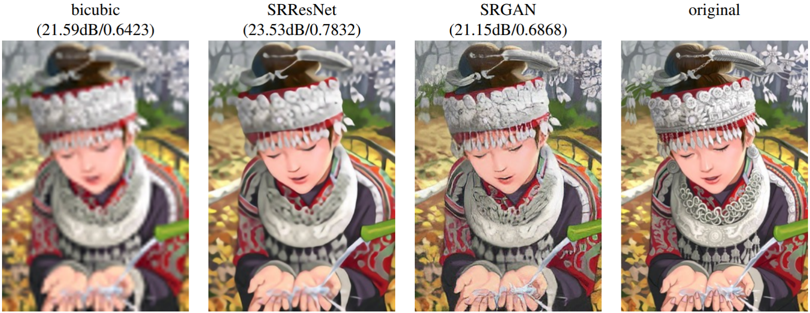

Figure: Work by Ledig et al., 2016

Recent works

- Plug & Play Generative Networks: Conditional Iterative Generation of Images in Latent Space [Nguyen et al., 2017]

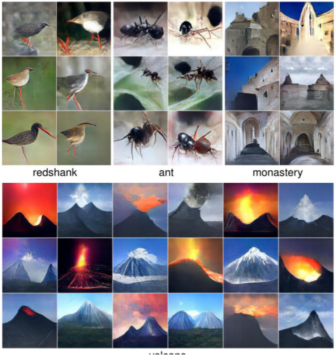

Figure: Synthetic images generated from ImageNet classes.

Outline

Discriminator and Generator Networks

- What is a generative model?

Discriminator and Generator Networks

- What is a generative model?
- Discriminator's role in GAN is to predict whether the input is generated or sampled from training data.
- The aim of generator is to capture the distribution of the training data.
- According to Goodfellow et al., it is a minimax game between generator and discriminator where generator tries to fool discriminator.(There are some debates about it.)

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- The description of GANs leads us to formulation for loss:

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

- Where both networks rely on gradients flowing through discriminator.

Outline

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.

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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

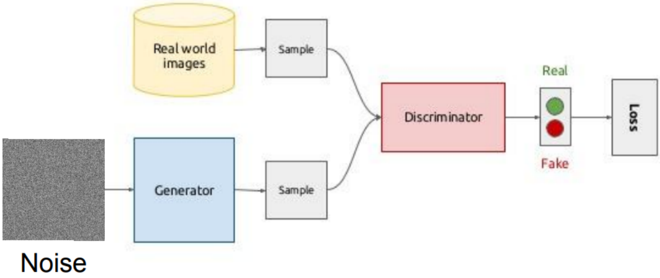
- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Update the generator by descending its stochastic gradient:

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

end for

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

GAN Framework



From now and on, we have a basic grasp of GAN, therefore we can code our own GAN! The starter code can be found in my GitHub Repository: github.com/norveclibalikci/InzvaGanStarter

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Computer Vision Applications

- Image generation(Plug and Play GAN)
- Style transfer(CycleGAN)
- Image inpainting, super-resolution(SRGAN)
- Image to text (Image captioning - Generative Adversarial Text to Image Synthesis)

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- Image generation(Plug and Play GAN)
- Style transfer(CycleGAN)
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- Image to text (Image captioning - Generative Adversarial Text to Image Synthesis)
- There are many applications which are not covered above.

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Applications to real life

- Discriminator can be rewarded for labeling correctly and a new loss can be defined by that way. (Still on research)
- Generating environment and test for reinforcement learning applications.
- Simulating particle experiments like they do in CERN.

Many things can be done with GANs however, GANs have limitations as well.

- There is no training procedure that has been proven to be successful.

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- After from some point, generator keeps generating similar examples.
- Losses of models are not meaningful as classifier's. It just keep oscillating back and forth.

Loss graphic of a GAN

Figure: Taken from http://www.rricard.me

Summary

- GANs are very powerful tools for generating new samples from data yet it has serious issues.
- GAN uses semi-supervised approach therefore, there is no need for data-labeling.
- Unsupervised learning is the cake of true AI. (Yann LeCun, Head of Facebook Research)

For Further Reading I

Chintala et al.
GAN Hacks
github.com/soumith/ganhacks

Goodfellow et al.
Generative Adversarial Networks
arXiv: 1406.2661, 2014.