goo.gl/fLLMDn

Generative Adversarial Networks

EE4-66 Topics in Large Dimensional Data Processing

Angelos Filos

December 12, 2017

Department of Electrical Engineering, Imperial College London

Problem Definition

Objective

Layman's Terms

$\mathcal{Q}$: Want to sample from complex, high-dimensional training distribution.
$\mathcal{A}$: Sample from a simple distribution, e.g. random noise. Learn transformation to training distribution.
$\mathcal{Q}$: How to represent this complex transformation?
$\mathcal{A}$: Use a Neural Network.

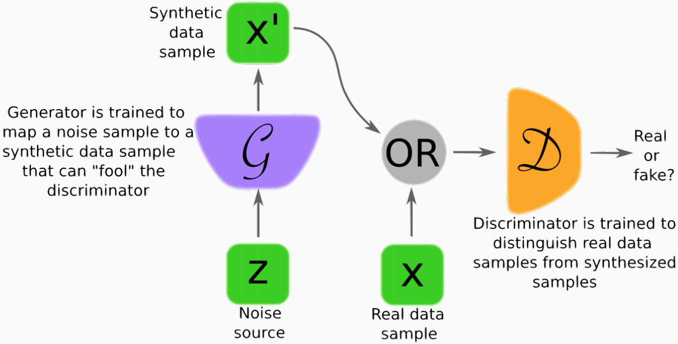
Formulation

Let a distribution p_{data} and available samples $\mathbf{x}_i$, drawn from p_{data}. If $p_{\mathbf{z}}$ is a simple distribution (assume uniform $\mathcal{U}$), we want to find a transformation $\mathcal{G}$ such that:

$$\mathcal{G} : \mathbf{z} \rightarrow \mathbf{x}$$

Adversarial Networks

Architecture



Training

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.

Experiments

$p_{data} \sim \mathcal{N}(\mu, \sigma)$

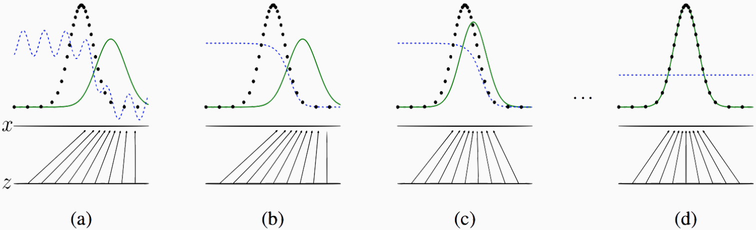


Figure 1: Generative adversarial nets are trained by simultaneously updating the **d**iscriminative distribution (D, blue, dashed line) so that it discriminates between samples from the data generating distribution (black, dotted line) $p_{\boldsymbol{x}}$ from those of the **g**enerative distribution p_g (G) (green, solid line). The lower horizontal line is the domain from which $\boldsymbol{z}$ is sampled, in this case uniformly. The horizontal line above is part of the domain of $\boldsymbol{x}$. The upward arrows show how the mapping $\boldsymbol{x} = G(\boldsymbol{z})$ imposes the non-uniform distribution p_g on transformed samples. G contracts in regions of high density and expands in regions of low density of p_g. (a) Consider an adversarial pair near convergence: p_g is similar to p_{data} and D is a partially accurate classifier. (b) In the inner loop of the algorithm D is trained to discriminate samples from data, converging to $D^*(\boldsymbol{x}) = \frac{p_{\text{data}}(\boldsymbol{x})}{p_{\text{data}}(\boldsymbol{x})+p_g(\boldsymbol{x})}$. (c) After an update to G, gradient of D has guided $G(\boldsymbol{z})$ to flow to regions that are more likely to be classified as data. (d) After several steps of training, if G and D have enough capacity, they will reach a point at which both cannot improve because $p_g = p_{\text{data}}$. The discriminator is unable to differentiate between the two distributions, i.e. $D(\boldsymbol{x}) = \frac{1}{2}$.

Computer Vision

Questions?

References

Antonia Creswell.
Generative Adversarial Networks: An Overview, 2017.
[Online]. Available: https://arxiv.org/pdf/1710.07035.pdf. [Accessed: 27- Nov- 2017].

Ian J. Goodfellow.
Generative Adversarial Nets, 2014.
[Online]. Available: https://arxiv.org/pdf/1406.2661.pdf. [Accessed: 27- Nov- 2017].

Wikipedia.
Imperial College London, 2017.
[Online]. Available: https://upload.wikimedia.org/wikipedia/commons/thumb/a/ad/Imperial_College_London_crest.svg/1200px-Imperial_College_London_crest.svg.png. [Accessed: 07- Nov- 2017].