Generative Adversarial Networks

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1 Summary

0. A new framework for estimating generative models via an adversarial process is proposed. This is done by simultaneously training two networks, one generative G and the other discriminative D which estimates probability that a sample came from data rather than G. The generative network's objective is to maximize D's probability of making mistake. After showing theoretical results, experiments using multilayer perceptrons demonstrate promising results.

1. The paper is motivated that recent developments in discriminative networks were effective but not generative networks due to non-trivial piecewise linear adaptation to this setting. Existing literature in generative models are either intractable or do not leverage the power of recenyl developed piecewise linear networks. The proposed network can generate diverse densities with minimal modeling restrictions.

2. **Adversarial Nets.** The generator distributor p_g over data $\mathbf{x}$ learnt using input distribution $p_z(\mathbf{z})$. The generator is represented by $G(\mathbf{z}; \theta_g)$ where θ_g captures the parameters of the perceptron. The second perceptron $D(\mathbf{x}; \theta_d)$ predicts the probability $D(\mathbf{x})$ that the sample from the data and not the generator while G tries to minimize $\log(1 - D(G(z)))$. The discriminator tries to correctly predict when sample is from data and not. This is a two-player minimax game given by

$$\min_G \max_D V(D, G) = \mathcal{E}_{\mathbf{x} \sim p_{data}(\mathbf{x})} \left[\log D(x) \right] + \mathcal{E}_{\mathbf{z} \sim p_{\mathbf{z}}(\mathbf{z})} \left[\log(1 - D(G(z))) \right]$$

3. **Theoretical Results.** The theoretical results are presented assuming infinite capacity non-parametric setting. The main result is that the game model proposed achieves an equilibrium of $p_g = p_{\text{data}}$.

4. Experiments are conducted by training the competing networks alternatively with a specific frequency and other carefully designed details. Although it is not shown that the results are better than existing models, the paper argues that the approach is promising.

2 Analysis

This is a different approach to generative tasks and since publishing this paper has become a seminal work in image generation. It is able to produce rich data by leveraging the power of recent developments in multilayer perceptrons and other minimal modeling restrictions.