Paper Review :

Generative Adversarial Nets

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INDEX :

OVERVIEW

Generative Adversarial Nets

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Abstract

We propose a new framework for estimating generative models via an adversarial process, in which we simultaneously train two models: a generative model G that captures the data distribution, and a discriminative model D that estimates the probability that a sample came from the training data rather than G. The training procedure for G is to maximize the probability of D making a mistake. This framework corresponds to a minimax two-player game. In the space of arbitrary functions G and D, a unique solution exists, with G recovering the training data distribution and D equal to $\frac{1}{2}$ everywhere. In the case where G and D are defined by multilayer perceptrons, the entire system can be trained with backpropagation. There is no need for any Markov chains or unrolled approximate inference networks during either training or generation of samples. Experiments demonstrate the potential of the framework through qualitative and quantitative evaluation of the generated samples.

❖ adversarial process(경쟁하는 과정)를 통해
generative model(생성자)을 추정하는 새로운 프레임워크

❖ 동시에 두 가지 모델을 학습
1) 학습데이터의 분포를 모사하는 generative model(생성모델) G

2) 입력된 G모델에서 나온 데이터가 아닌, 실제 학습데이터에서 나온 데이터일 것이라고 확률을 추정하는 discriminative model(판별자) D

❖ minimax two-player game(미니맥스게임)
한쪽은 함수를 최대화, 다른 한쪽은 최소화

INTRODUCTION

1 Introduction

The promise of deep learning is to discover rich, hierarchical models [2] that represent probability distributions over the kinds of data encountered in artificial intelligence applications, such as natural images, audio waveforms containing speech, and symbols in natural language corpora. So far, the most striking successes in deep learning have involved discriminative models, usually those that map a high-dimensional, rich sensory input to a class label [14, 22]. These striking successes have primarily been based on the backpropagation and dropout algorithms, using piecewise linear units [19, 9, 10] which have a particularly well-behaved gradient . Deep *generative* models have had less of an impact, due to the difficulty of approximating many intractable probabilistic computations that arise in maximum likelihood estimation and related strategies, and due to difficulty of leveraging the benefits of piecewise linear units in the generative context. We propose a new generative model estimation procedure that sidesteps these difficulties. [1]

In the proposed *adversarial nets* framework, the generative model is pitted against an adversary: a discriminative model that learns to determine whether a sample is from the model distribution or the data distribution. The generative model can be thought of as analogous to a team of counterfeiters, trying to produce fake currency and use it without detection, while the discriminative model is analogous to the police, trying to detect the counterfeit currency. Competition in this game drives both teams to improve their methods until the counterfeits are indistiguishable from the genuine articles.

This framework can yield specific training algorithms for many kinds of model and optimization algorithm. In this article, we explore the special case when the generative model generates samples by passing random noise through a multilayer perceptron, and the discriminative model is also a multilayer perceptron. We refer to this special case as *adversarial nets*. In this case, we can train both models using only the highly successful backpropagation and dropout algorithms [17] and sample from the generative model using only forward propagation. No approximate inference or Markov chains are necessary.

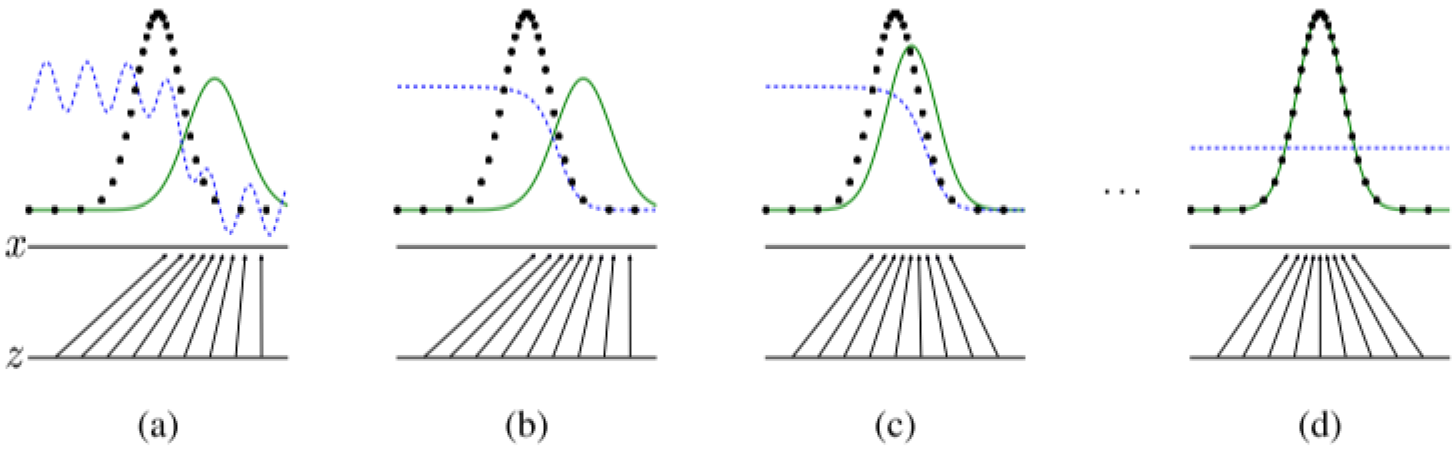
❖ 다른 Deep generative model들의 어려움
  – 최대 우도 추정 시 확률 연산들을 근사화하는 것이 어려움
  – generative context 에서 linear unit들의 이점을 가져오는 것이 어려움

▶ 새로운 generative model estimation procedure를 제안
(예)위조지폐를 만들어 내는 G와 그것을 판별해 내는 D

❖ generative model이 multilayer perceptron을 통해서 임의의 noise가 첨가된 sample data를 생성하고, discriminative model도 multilayer perceptron으로 구성되어 해당 데이터를 구분해내는 사례를 소개

METHOD

생성된 이미지
instance z ▶



검은 점 : 원본학습 데이터 분포
초록색 선 : 생성모델(generative) 분포
파란색 점선 : 판별모델(discriminative) 분포

(a) 생성자의 분포가 원본데이터 분포를 잘 학습하지 못함
▶ 시간의 흐름에 따라 z를 샘플링해서 생성자에 매핑.
생성자의 분포가 원본 학습데이터의 분포를 잘 따를 수 있도록 학습 (d)

METHOD

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**

Discriminator▶

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:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right)\right].$$

Generator▶

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.

EXPERIMENT

Model	MNIST	TFD
DBN [3]	138 ± 2	1909 ± 66
Stacked CAE [3]	121 ± 1.6	$\mathbf{2110 \pm 50}$
Deep GSN [6]	214 ± 1.1	1890 ± 29
Adversarial nets	$\mathbf{225 \pm 2}$	$\mathbf{2057 \pm 26}$

Table 1: Parzen window-based log-likelihood estimates. The reported numbers on MNIST are the mean log-likelihood of samples on test set, with the standard error of the mean computed across examples. On TFD, we computed the standard error across folds of the dataset, with a different σ chosen using the validation set of each fold. On TFD, σ was cross validated on each fold and mean log-likelihood on each fold were computed. For MNIST we compare against other models of the real-valued (rather than binary) version of dataset.

Dataset : MNIST / Toronto Face Database(TFD) / CIFAR-10 등

EXPERIMENT

a). MNIST, b). TFD, c). CIFAR-10 (fully connected model) d). CIFAR-10(convolutional discriminator and deconvolutional generator)

❖ 학습 후 generator net에서 추출한 샘플

1) 노란색 박스 : 실제 학습데이터에 존재하는 이미지
2) 그 외 : GAN을 통해 만들어낸 이미지

CONCLUSION

7 Conclusions and future work

This framework admits many straightforward extensions:

1. A *conditional generative* model $p(\boldsymbol{x} \mid \boldsymbol{c})$ can be obtained by adding $\boldsymbol{c}$ as input to both G and D.
2. *Learned approximate inference* can be performed by training an auxiliary network to predict $\boldsymbol{z}$ given $\boldsymbol{x}$. This is similar to the inference net trained by the wake-sleep algorithm [15] but with the advantage that the inference net may be trained for a fixed generator net after the generator net has finished training.
3. One can approximately model all conditionals $p(\boldsymbol{x}_S \mid \boldsymbol{x}_{\not S})$ where S is a subset of the indices of $\boldsymbol{x}$ by training a family of conditional models that share parameters. Essentially, one can use adversarial nets to implement a stochastic extension of the deterministic MP-DBM [11].
4. *Semi-supervised learning*: features from the discriminator or inference net could improve performance of classifiers when limited labeled data is available.
5. *Efficiency improvements:* training could be accelerated greatly by divising better methods for coordinating G and D or determining better distributions to sample $\mathbf{z}$ from during training.

EOD.