Ambient Hidden Space of Generative Adversarial Networks

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Abstract

Generative adversarial models are powerful tools to model structure in complex distributions for a variety of tasks. Current techniques for learning generative models require an access to samples which have high quality, and advanced generative models are applied to generate samples from noisy training data through ambient modules. However, the modules are only practical for the output space of the generator, and their application in the hidden space is not well studied. In this paper, we extend the ambient module to the hidden space of the generator, and provide the uniqueness condition and the corresponding strategy for the ambient hidden generator in the adversarial training process. We report the practicality of the proposed method on the benchmark dataset.

1 Introduction

The structure in the large dataset could be represented by generative models, and this prospective is well studied these years. The generative models learn from the training dataset, and represent a mechanism that specify a stochastic procedure to produce samples from a probability distribution.

These has been much progress in the neural network based generative models within adversarial framework. The adversarial framework is first pioneered by the generative adversarial network (GAN) Goodfellow \textit{et al.} [2014]. In this framework, both a generator and a discriminator are trained through the adversarial training strategy where a two-player game is played in the training process. The generator learns to map a noise vector of a low-dimensional distribution (such as standard Gaussian or normal distribution) to points in a high-dimensional space. Simultaneously, a discriminator network is trained to distinguish between real and generated samples. This is achieved through setting up a min-max game between the generator and discriminator. The adversarial framework is shown to be successful in the generation of complex distributions.

However, this generative process requires an access to a large number of full-observed samples from the desired distribution. This large-scale dataset is hard to be obtained practically. In fact, the capture of the large-scale dataset is expensive. For example, a large number of sensing images of the brain is costly to be achieved. Besides, the sensing images are very noisy in the real world. Therefore, a training strategy for obtaining a generative model directly from noisy or incomplete samples are in great demand.

2 Related work

Two distinct approaches are applied to construct generative models: one is the auto-regressive generative model Kingma and Welling [2013] and the other is the adversarial generative model Goodfellow \textit{et al.} [2014]. The adversarial framework is then shown to be more powerful than the others in modeling complex data distributions Bertalmio \textit{et al.} [2001]. It is firstly represented to generate high-quality images from middle-scale datasets Goodfellow \textit{et al.} [2014]. Several advanced adversarial networks are proposed to generate high-quality images from the large-scale dataset Gulrajani \textit{et al.} [2017]. Furthermore, as the quality of generated images is low, spectral normalization is applied for generating high-quality image from the ImageNet dataset. Similarly, self-attention mechanism is applied to allow attention-driven, long-range dependency modeling for generating both a high variety and high quality images from ImageNet Zhang \textit{et al.} [2018]. These techniques are only practical when the image samples in the training dataset have
high quality. However, these techniques do not work for high quality images when the training samples are noisy. The methods for generation of a large-scale dataset from noisy examples is well studied. The ambientGAN strategy is applied on the generation of samples from noisy dataset. In particular, an ambient function is applied to the output end of the generator and a variety of lossy measurements are applied in order to evaluate the capability of generating samples effected by different types of noise [Bora et al.] [2018]. Besides, through applying both the local consistency and global consistency of images, the adversarial framework is applied to complete images of arbitrary resolutions by filling-in missing regions of any shape. Both the global and local context discriminators are trained to distinguish real images from completed images. In the adversarial framework, the image completion network is trained to fool the context discriminator networks [Iizuka et al.] [2017]. A different training procedure of learning a generative model is investigated, and the generative model is learned from the transition operator of a Markov chain. This chain could de-noise random noise sample and match the target distribution from the training noise. The information from the training target example is infused [Bordes et al.] [2017]. However, the de-noise module is applied to the output space of the generator network. The perspective of the application for the de-noise module in the hidden space of the generator network is not well studied. The study in this paper is meaningful as it is helpful to extend the practicability of the de-noise module for the adversarial generative model.

3 Methodology

In the adversarial framework [Goodfellow et al.] [2014], a generator’s distribution $p^y_g$ is learned over data $x$ from a prior on the input noise variables $p_x(z)$. The generator represents a mapping to data space as $G(x; \theta_g)$, where $G$ denotes a function represented by a neural network with parameters $\theta_g$. Another neural network $D(x; \theta_d)$ is built to output a single scalar. $D(x)$ is used to represent the probability that $x$ comes from the data rather than $p_g$. During the training process, $D$ is trained to maximize the probability of assigning the correct label to both the training samples and samples form $G$. Specifically, $D$ and $G$ could be seen as a two-player minimax game with the value function $V(G, D)$: $ \min_G \max_D V(G, D) = \mathbb{E}_{x \sim p_{\text{data}}(x)} \log D(x) + \mathbb{E}_{z \sim p_z} \log (1 - D(G(z)))$.

3.1 Ambient generative models

Let $r$ denote real or true distribution, $g$ denote the generated distribution, $x$ denote the underlying space and $y$ denote the measurements. $p^y_r$ is a real underlying distribution over $\mathbb{R}^n$. Lossy measurements could be observed on samples from $p^y_r$. Let $m$ be the size of each observed measurement. Parameterized by $\theta$, the lossy function is $f_\theta : \mathbb{R}^n \rightarrow \mathbb{R}^m$. Therefore, for a given $x$ and $\theta$, the measurements are given by $y = f_\theta(x)$, and the distribution over the measurements $y$ is naturally induced as $p^y_r$. That is, $Y = f_\theta(X) \sim p^y_r$ if $X \sim p^y_r$ and $\Theta \sim p_\theta$.

In order to create an implicit generative model of $p^y_r$ given an unknown distribution $p^y_r$ and a known distribution $p_g$, the IID realizations $\{y_1, y_2, \ldots, y_s\}$ from the distribution $p^y_r$ could be applied. However, unlike the standard GAN setting, the desired objects $X \sim p^y_r$ is not obtained. Instead, a dataset of measurements $Y \sim p^y_r$ is achieved. That is, the goal is to generate clean samples $X \sim p^y_r$ with only noisy available samples $Y \sim p^y_r$. The adversarial framework is then updated by $\min_G \max_D V(G, D) = \mathbb{E}_{Y \sim p^y_r} \log D(y) + \mathbb{E}_{z \sim p_z} \log (1 - D(f_\theta(G(z))))$.

If there is a unique distribution $p^y_r$ that can induce the measurement distribution $p^y_r$, the minimax game can exist. If the discriminator $D$ is optimal such that $D(.) = \frac{p^y_r(\cdot)}{p^y_r(Y) + p^g(\cdot)}$, a generator $G$ is optimal if and only if $p^y_r = p^y_r$.

3.2 Ambient hidden space

The ambient mapping function $f_\theta$ works in the domain of $X \sim p^y_r$ or the domain of output of the generator $G$. Both domains are in the same rgb image space. However, it is not clear whether the ambient mapping function $f_\theta$ works in the hidden space of the generator $G$. We investigate the updated formulation: $\min_G \max_D V(G, D) = \mathbb{E}_{Y \sim p^y_r} \log D(y) + \mathbb{E}_{z \sim p_z} \log (1 - D(G(f_\theta(G(z))))$. That is, one $f_\theta$ function mapping from $\mathbb{R}^n$ to $\mathbb{R}^m$ works in the rgb image space, and the other $f_\theta$ function works in the hidden space of generator networks. In the following, we study the minimax two-player game for this setting as illustrated in Figure.

3.2.1 Uniqueness

For the $f_\theta$ function at the output end of the generator $G$ and in the hidden space of $G$, we denote $l_1 = f_\theta(l_2)$ as the mapping process. Particularly,

$$\begin{cases} l_1 = l_2 & \text{w.p. } p, \\ l_1 \neq l_2 & \text{w.p. } 1 - p. \end{cases}$$

We call this condition as the uniqueness condition for the ambient function when $p = 0$. Specifically, if $l_2$ is represented as $X \sim p^y_r$, then $l_1$ is represented as $Y \sim p^y_r$.
3.2.2 Global optimality

The global optimality could be achieved when the condition of the above independence is satisfied. For any given generator $G$, we first discuss the optimal discriminator $D$ as following.

The training criterion for the discriminator $D$, given any generator $G$, is to maximize the quantity

$$V(G, D) = \int_y p_y(y) \log(D(y))dy + \int_z p_z(z)\log(1 - D(G_1(f_\Theta(G_2(z)))))dz.$$

As $y = f_\Theta(x)$,

$$\begin{cases} y = x & \text{w.p. } p_1, \\ y \neq x & \text{w.p. } 1 - p_1, \end{cases}$$

and $y_h = f_\Theta(x_h)$, the generator is updated as $G_1(y_h)$ when $G_2(z)$ is denoted as $x_h$. Similarly as above, $y_h = x_h$ with probability $p_2$ and $y \neq x$ with probability $1 - p_2$.

That is, $G_1(f_\Theta(G_2(z))) = G_1(G_2(z))$ with probability $p_2$, $G_1(f_\Theta(G_2(z))) \neq G_1(G_2(z))$ with probability $1 - p_2$. 

$\text{Dataset}$

Figure 1: Hidden AmbientGAN training.

Figure 2: Block-Pixel & Block-Patch.
If \( p_1 = 0 \) and \( p_2 = 0 \), due to the Lemma 5.1 in the original ambient adversarial networks \cite{Bora2018}, both the generator \( G \) and the discriminator \( D \) could achieve optimal points. We denote these two points as \( D_1(\cdot) = \frac{p_r(\cdot)}{p_r(\cdot) + p_g(\cdot)} \) and \( G_1(\cdot) \) is attained if and only if \( p_x = p_x^r \). Here \( G_1(f_\Theta(G_2(z))) \sim p_g^0 \)

If \( p_1 = 0 \) and \( p_2 \neq 0 \), both the generator and the discriminator could achieve \( D_1(\cdot) \) and \( G_1(\cdot) \) when \( G_1(f_\Theta(G_2(z))) \neq G_1(G_2(z)) \) with probability \( 1 - p_2 \). However, when \( G_1(f_\Theta(G_2(z))) = G_1(G_2(z)) \) with probability \( p_2 \), the optimal points for \( G \) and \( D \) are different. Following the adversarial generative network framework \cite{Goodfellow2014}, \( D_2(\cdot) = \frac{p_r(\cdot)}{p_r(\cdot) + p_x(\cdot)} \) and \( G_2(\cdot) \) is achieved if and only if \( p_x = p_x^r = p_x^g \).

If \( p_2 \neq 0 \), both the generator and discriminator have the probability of achieving different stable points during training. It is hard for the generator and discriminator to achieve optimal points during the two-player training. In the following, we shall use the uniqueness condition \( p_1 = 0 \) and \( p_2 = 0 \).

## 4 Numerical experiments

The baseline is to ignore any measurement. Samples generated by the baseline and the hidden ambient models are displayed. For each experiment, samples from the dataset of measurements \( y^* \) available for training, samples both generated by the baselines and the hidden ambient models are presented. In addition, samples generated from the hidden space of the ambient function are provided.

### 4.1 Models

We propose several measurement models which satisfy the uniqueness condition. There are listed as following:

- **Block-Pixel**: each pixel is independently set to zero with probability \( p \).
- **Block-Patch**: a randomly chosen \( k \times k \) patch is set to zero.
- **Keep-Patch**: all pixels outside a randomly chosen \( k \times k \) patch are set to zero.
- **Extract-Patch**: a random \( k \times k \) patch is extracted. Unlike the measurement applied in the original AmbientGAN \cite{Bora2018}, the generated samples from the measurements of **Gaussian-Projection**, **Convolve+Noise** are messy, as these two measurements do not satisfy the uniqueness condition.

### 4.2 Results

#### 4.2.1 Block-Pixel

As shown in Figure 2(1), samples of lossy measurement are at the upper left. Randomly chosen patch in each image is blocked. Samples of ambient hidden space are at the upper right. Randomly chosen patch in each feature map is blocked. Samples generated by the baselines are at the lower left. Samples generated by the proposed hidden ambient model are at the lower right.
4.2.2 Block-Patch

As shown in Figure 2, samples of lossy measurement are at the upper left. Each pixel is blocked independently with probability \( p = 0.95 \). Samples of ambient hidden space are at the upper right. Each channel is blocked independently with probability \( p = 0.95 \). Samples generated by the baselines are at the lower left. Samples generated by the proposed hidden ambient model are at the lower right.

4.2.3 Keep-Patch

As shown in Figure 3, samples of lossy measurement are at the upper left. All pixels outside a randomly chosen patch are set to zero. Samples of ambient hidden space are at the upper right. All pixels outside a randomly chosen patch in each feature map is blocked. Samples generated by the baselines are at the lower left. Samples generated by the proposed hidden ambient model are at the lower right.

4.2.4 Extract-Patch

As shown in Figure 3, samples of lossy measurement are at the upper left. A random patch is extracted. Samples of ambient hidden space are at the upper right. A random patch in each feature map is extracted. Samples generated by the baselines are at the lower left. Samples generated by the proposed hidden ambient model are at the lower right.

5 Discussions

In this paper, we implement the ambient hidden module in the generative network during the adversarial training process, and we achieve good quality images generated from the noisy training samples under the uniqueness condition. This work is an extension of the ambient generative networks which the ambient module is only applied in the output space of the generative networks.

In this work, we consider several ambient functions in the hidden space of the adversarial network. In order to enlarge the practicality of hidden ambient modules in the adversarial networks, it is worthwhile to study generative methods that make use of noisy training data without knowing the noise distribution.

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