ABSTRACT

In this paper, we address the image generation task using an autoencoder, a representative latent model. Unlike many studies regularizing the latent variable’s distribution by assuming a manually specified prior, we approach the image generation task using an autoencoder by directly estimating the latent distribution. To achieve this, we introduce ‘latent density estimator’ which captures latent distribution explicitly and propose its structure. Through experiments, we show that our generative model generates images with the improved visual quality compared to previous autoencoder-based generative models.

Index Terms— Autoencoder, Image Generation, Generative Model, Density Estimation, Mixture Model

1. INTRODUCTION

Data generation using an autoencoder is performed by sampling from the latent distribution which is the distribution of the latent variables. Therefore, how to express the latent distribution and how to sample a latent variable is a core problem in the task of extending an autoencoder to a generative model.

Most existing studies, such as variational autoencoder (VAE) [1], address this problem by assuming a prior as a manually specified distribution (e.g. fully factorized Gaussian). However, manually specified prior may differ from the actual latent nature of the data. This difference makes a trade-off between reconstruction and prioritized regularization. In the Figure 2, we can see that the reconstructed digits are blurry as the weight $\beta$ of the regularization term increases. As a result, it adversely affects the reconstruction and makes a difference between the real latent distribution and the prior, which leads to degradation of the generation quality.

As another approach, we can think of extending autoencoders to generative models by estimating the empirical distribution of latent variables obtained from a given dataset using an additional network named as the Latent Density Estimator (LDE). The proposed LDE learns complex distributions flexibly using an auto-regressive approach. Also, in order to preferentially learn the important representation of the given data through the latent variables, we exploit a training strategy that incrementally increases the effective size of the latent vector. As shown in Figure 1, our method generates clear and diverse images that reflect the characteristics of data well.

2. RELATED WORKS

A typical study, variational autoencoder (VAE) [1], performs regularization to minimize the KL divergence between the distribution of latent variables and the assumed prior by maximizing the evidence lower bound (ELBO). Another study, adversarial autoencoder (AAE) [2], uses adversarial training. The encoder is considered as a generator of the latent variables and it is learned to imitate the prior distribution, which acts as a regularization for the latent distribution.

These studies have a drawback in that they must assume...
3. LATENT DENSITY ESTIMATION

3.1. Problem formulation

An autoencoder consists of an encoder and a decoder, which encodes a data point \( x \) into a latent vector \( z (z = f_{\theta}(x)) \) and reconstructs \( x \) from \( z (x = g_{\psi}(z)) \), respectively. Ideally, if a latent vector \( z \) can be sampled from a true distribution of \( z \), it is possible to generate data using the decoder.

Our goal is to directly estimate the latent distribution which represents the dataset well. We deal with this problem by estimating the probability density function of \( p(z) \) from dataset using a additional density estimator parameterized by \( \lambda \). The density estimator is trained to find \( \lambda \) that maximizes the likelihood of \( z \) for \( \lambda \) as follows.

\[
\lambda = \underset{\lambda}{\text{argmax}} \mathbb{E}_{z \sim p_{\text{data}}(z)}(\log p_{\lambda}(z)).
\]

(1)

Here, the \( p_{\text{data}}(z) \) is the empirical latent distribution obtained from \( p_{\text{data}}(x) \) and the encoder \( f_{\theta}(x) \) and the LDE estimates \( p_{\text{data}}(z) \) by \( p_{\lambda}(z) \).

3.2. Overview of the proposed method

Figure 3 shows the overall structure of the proposed method for extending autoencoder into generative models. As can be seen in the figure, the architecture of the proposed generative framework consists of an encoder, a decoder and a latent density estimator (LDE).

The encoder and the decoder are used in the form of the deterministic function. The LDE expresses the probability density function of \( p_{\lambda}(z) \) explicitly. In the generation process, a latent vector \( z' \) is randomly sampled from \( p_{\lambda}(z) \) and generates new data \( x' \) through the decoder.

In this framework, the autoencoder and the LDE are trained according to the following training procedure. First, we train the autoencoder \( \hat{x} = g_{\psi}(f_{\theta}(x)) \) to reconstruct \( x \). Second, after the completion of training the autoencoder, we obtain \( p_{\text{data}}(z) \) from \( p_{\text{data}}(x) \) using the encoder \( f_{\theta}(x) \). Finally, we train the latent density estimator to estimate \( p_{\text{data}}(z) \) using \( p_{\lambda}(z) \).

3.3. Latent Density Estimator (LDE)

The proposed approach of LDE is based on the method in RNADE [8]. If \( z \) is a \( D \)-dimensional real-valued vector whose \( i \)-th element is denoted by \( z_i \), we factorize \( p_{\lambda}(z) \) using the chain rule:

\[
p_{\lambda}(z) = \prod_{i}^{D} p_{\lambda}(z_i | z_{<i}).
\]

(2)

Here, \( z_{<i} \) is \( z_1, \ldots, z_{i-1} \). The estimated probability density of the \( i \)-th variable of \( z \) is conditionally calculated by the values of the variables with lower indices as \( p_{\lambda}(z_i | z_{<i}) \). It is calculated as follows by the mixture of \( K \) univariate Gaussian with its parameters being the mixing coefficient \( \pi_i = \{\pi_{i,1}, \ldots, \pi_{i,K}\} \), the mean \( \mu_i = \{\mu_{i,1}, \ldots, \mu_{i,K}\} \) and the standard deviation \( \sigma_i = \{\sigma_{i,1}, \ldots, \sigma_{i,K}\} \):

\[
p_{\lambda}(z_i | z_{<i}) = \sum_{k}^{K} \pi_{i,k} \mathcal{N}(z_i; \mu_{i,k}, \sigma_{i,k}^2).
\]

(3)
Here, the parameters $\pi_i, \mu_i$ and $\sigma_i$ are estimated by the LDE. The LDE is learned to find $\pi_i, \mu_i$ and $\sigma_i$ by minimizing the loss function which is calculated as the average of all the negative log of (3), $i = 1, \cdots, D$:

$$L_z = -\frac{1}{D} \sum_{i} \log p_{\lambda}(z_i | z_{<i}). \tag{4}$$

As shown in Figure 4, the LDE network consists of two parts: dilated causal convolution [9] and Mixture Density Network [10]. The dilated causal convolution outputs a series of causal features $h = \{h_1, \ldots, h_D\}$ using $z$. Each $h_i$ observes $z_{<i}$. The zero vector $p$ is used to match the dimension of the input to the first output $h$ to $D$, and $m$ is used to distinguish $z$ from $p$ by setting the masking value as 1 and 0, respectively. The Mixture Density Network estimates the parameters of the $K$ mixture of Gaussians, $\pi_i, \mu_i$ and $\sigma_i$, from $h_i$ using an $1 \times 1$ convolution layer. Here, $\mu_i$ and $\sigma_i$ are obtained by the linear and the exponential activations, respectively, and $\pi_i$ is the softmax output for the $K$ Gaussians.

3.4. Incremental learning of latent vector

Instead of adding an regularization term to the objective function, we use the structural characteristics of an autoencoder to make an autoencoder learn salient factors of data. In the training process, initially only a small part of the latent vector is used to learn the autoencoder. Then, as the iteration goes on, the effective size of the latent vector is increased gradually. Here, the unused part of the latent vector is masked to zero. This incremental learning strategy of the latent variables induces the autoencoder to learn the most important representation of data first.

3.5. Objective Function

For the training of the autoencoder, we use the distance in the pixel space and the perceptual loss [11] as follows:

$$L_z = L_{MSE}(x, \hat{x}) + \beta L_{perc}(x, \hat{x}), \tag{5}$$

where $L_{MSE}(x, \hat{x})$ is the mean squared error in the pixel space, $L_{perc}(x, \hat{x})$ is perceptual loss as in [11] and $\beta$ is the weight parameter for the perceptual loss.

4. EXPERIMENTS

We will call the autoencoder whose latent vector is trained by applying the incremental learning as IAE. And, AE will denote an autoencoder trained without the incremental learning. For fair comparison, the autoencoders of AAE and ours use the same structure. We use (5) as the reconstruction loss of AAE and ours with the $\beta$ of 0.1. The perceptual loss was calculated using the feature maps at relu11, relu21, and relu31 of Imagenet [12] pretrained VGG19 [13].

4.1. Log-likelihood of the Latent Density Estimator

To quantitatively compare the density estimation performance of the LDE, we measured the log-likelihood in natural images according to the experimental setup of [8, 14]. We perform the same preprocessing of [8, 14] in the BSDS300[16] dataset. Table 1 shows the log-likelihoods of various density estimators. In this experiment, when $K$ is 10 and 30, the results of our method, LDE, not only outperformed mixture of Gaussian

| Method                        | Log Likelihood |
|-------------------------------|----------------|
| Deep RNADE (K=10) [14]        | 155.2          |
| MADE MoG (K=10) [15]          | 153.71 ± 0.28  |
| Real NVP [7]                  | 153.28 ± 1.78  |
| MAF MoG (K=10) [5]            | 156.36 ± 0.28  |
| MAF-DDSF [6]                  | 157.73 ± 0.04  |
| LDE (K=1)                     | 152.68 ± 0.52  |
| LDE (K=10)                    | 157.75 ± 0.06  |
| LDE (K=30)                    | **158.02 ± 0.06** |
| LDE (K=100)                   | 157.03 ± 0.30  |

Table 1: Log-likelihood and 2 standard deviations (5 trials) of various density estimation methods on $8 \times 8$ patches of BSDS300 test set. Error bars of 2 standard deviations.
4.2. Latent Space Walking on Two Domains

In order to understand the representation and structure of the latent space, we perform linearly interpolating two latent vectors. We trained the AAE with a Gaussian prior \( \mathcal{N}(0, I) \), the AAE with a mixture of two Gaussian prior \( \mathcal{N}(-3, I) \) and \( \mathcal{N}(3, I) \), AE and IAE that use an 100-dimensional latent vector using the Shoes[17] and CelebA[18] datasets with a size of 64 × 64. Figure 5 shows the results obtained by linearly interpolating two test samples in the latent space for three cases. Figure 5 (a) shows the interpolation on the CelebA and (b) shows the results on the Shoes datasets, both of which are the interpolation in the same domain. Every results of (a) are generally plausible, it shows that the face attributes such as visual age change smoothly. However, in (b), only the results of IAE change the shape continuously. Figure 5 (c) shows the interpolation between different data domains. AAE produces an image in which a person’s face and shoes are overlapped during interpolation. In contrast to AAE, our IAE produces images that can not be seen as shoes or human faces in the middle. In fact, the images of a person’s face and those of shoes belong to the semantically different data domain from each other, so this gap can be meaningful for the latent representation of an autoencoder.

4.3. Image Generation

For qualitative comparison of generation results, We performed image generation on CelebA. The LDE with 30 mixture of Gaussian was applied to AE and IAE. Figure 6 shows 6 random generation results for AAE, AE with LDE, and IAE with LDE. For a fair comparison, we present successively generated samples, not cherry picking the samples. As with the image quality, the generation results of AAE are generally unclear. AE with LDE produces the more sharp and detailed image compared to AAE, but failure cases are often generated. The results of IAE with LDE show the most stable and best image quality among the compared methods.

| Method         | MNIST(10K) | TFD(10K) |
|----------------|------------|----------|
| Deep GSN [19]  | 214±1      | 1890±29  |
| GAN [20]       | 225±2      | 2057±26  |
| GMMN + AE [21] | 282±2      | 2204±20  |
| AAE [2]        | 340±2      | 2252±16  |
| VAE + IAF [4]  | 272±2      | -        |
| eVAE [22]      | 337±2      | 2371±20  |
| AE + LDE       | 326±2      | 2476±32  |
| IAE + LDE      | 326±2      | 2507±32  |

Table 2: Test log-likelihood and the standard error of various generative models on MNIST and TFD dataset. Obtained through Parzen window based density estimation.

4.4. Log-likelihood of Generative Models

When the log-likelihood can not be computed directly, the Parzen window based density estimation is a commonly used method for evaluation of generative models. We used this evaluation method as specified in [19, 21, 2]. We trained our generative models without perceptual loss. The dimensional-ity of the latent vector used was 8 for MNIST[23] and 15 for TFD[24]. \( K \) of LDE is 30 and the scale parameters of the Gaussian kernel are found through the grid search on the validation set. As can be seen in the table 2, our results show the lower likelihood compared to AAE and eVAE on MNIST, but we achieved the highest log-likelihood far beyond the previous methods on TFDs, relatively a more complex dataset than MNIST.

5. CONCLUSION

In this paper, we tackle the autoencoder-based image generation task without using regularization by a specified prior. We introduced the latent density estimator to estimate the latent distribution. In addition, we proposed an incremental learning strategy of latent vector so that the autoencoder can learn a meaningful representation. The proposed LDE showed better performance than the previous studies in density estimation. As a result, the autoencoder applying the latent density estimator improves the generation quality of the autoencoder based generative models.
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