LatentGAN Autoencoder: Learning Disentangled Latent Distribution

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Abstract

In autoencoder, the encoder generally approximates the latent distribution over the dataset, and the decoder generates samples using this learned latent distribution. There is very little control over the latent vector as using the random latent vector for generation will lead to trivial outputs. This work tries to address this issue by using the LatentGAN generator to directly learn to approximate the latent distribution of the autoencoder and show meaningful results on MNIST, 3D Chair, and CelebA datasets, an additional information-theoretic constraint is used which successfully learns to control autoencoder latent distribution. With this, our model also achieves an error rate of 2.38 on MNIST unsupervised image classification, which is better as compared to InfoGAN and AAE.

Introduction

Generative models like GAN(Goodfellow et al. 2014) and VAE(Kingma and Welling 2014) have shown remarkable progress in recent years. Generative adversarial networks have shown state-of-the-art performance in a variety of tasks like Image-To-Image translation(Isola et al. 2018), video prediction(Liang et al. 2017), Text-to-Image translation(Zhang et al. 2017), drug discovery(Hong et al. 2019), and privacy-preserving(Shi et al. 2018). VAE has shown state-of-the-art performance in a variety of tasks like image generation(Gregor et al. 2015), semi-supervised learning(Maaløe et al. 2016), and interpolating between sentences(Bowman et al. 2016). VAE approximates its latent distribution by ELBO method and uses Gaussian or uniform distribution as a marginal latent distribution which leads to huge reconstruction error. Adversarial autoencoder(AAE)(Makhzani et al. 2016) uses adversarial training to train VAE, and LatentGAN is directly inspired by the AAE strategy of training VAE. $\beta$-VAE(Burgess et al. 2018) can be used for learning disentangled representation, but it needs $\beta$ hyperparameter search and also huge $\beta$ would lead to huge reconstruction error. InfoGAN(Chen et al. 2016) have shown to learn disentangled representation in GAN. It learns to disentangle representation by maximizing the mutual information between a subset of generated sample and the output of the recognition network. Learning disentangled representation and understanding generative factors might help in a variety of tasks and domains(Bengio, Courville, and Vincent 2013; Burgess et al. 2018). Disentangled representation can be defined as one where single latent units are sensitive to changes in single generative factors, while being relatively invariant to changes in other factors. Disentangled representations could boost the performance of state-of-the-art AI approaches in situations where they still struggle but where humans excel(Lake et al. 2016). In this paper, we have addressed the issue of learning disentangled control by learning the latent distribution of autoencoder directly using LatentGAN generator, and LatentGAN discriminator which tries to discriminate whether the sample belongs to real or fake latent distribution. Additionally, we also use mutual information inspired directly from InfoGAN to learn disentangled representation.

Related Work

In this work, we present a new way to learn control over autoencoder latent distribution with the help of AAE(Makhzani et al. 2016) which approximates posterior of the latent distribution of autoencoder using any arbitrary prior distribution and using(Chen et al. 2016) for learning disentangled representation. The previous work by(Wang, Peng, and Ko 2019) had used a similar method of learning the latent prior using AAE along with a perceptual loss and Information maximization regularizer to train the decoder with the help of an extra discriminator.

Contribution

In this work, we are trying to learn control over autoencoder and in doing so following are our contribution:

• We have shown that it is possible to approximate autoencoder latent distribution directly using LatentGAN generator $G$ without using extra discriminator as in (Wang, Peng, and Ko 2019).

• We are also able to learn disentangled control over autoencoder latent distribution by using same LatentGAN Discriminator $D$ and have shown some results in the experiment section.

And in doing so we are also able to get 2.38 error rate on MNIST unsupervised classification which is far less than InfoGAN and Adversarial autoencoder.
Method
We train autoencoder i.e. $\text{Dec}(\text{Enc}(X)) \sim f_{\text{autoencoder}}(X)$ and LatentGAN generator $G$ and discriminator $D$ simultaneously; this helps generator to compete with discriminator. Autoencoder training objective is as follows:

$$L_{\text{autoencoder}} = ||X - f_{\text{autoencoder}}(X)||^2$$  \(1\)

LatentGAN tries to model data distribution $x \sim p_{data}(z)$ where $z$ is the latent embedding of the autoencoder, and $lc$ denotes latent code which generated by concatenating Gaussian $P$ and code $c$, as show in the Figure 1 LatentGAN training objective is as follows:

$$\min_{G} \max_{D} V(D, G) = E_{x \sim p_{data}(z)}[\log D(x)] + E_{l_c \sim \text{concat}(p, c)}[\log 1 - D(G(l_c))]$$  \(2\)

For learning the control over latent distribution additional mutual information based objective inspired by (Chen et al. 2016) is used,

$$L_{\text{latentGAN}} = V(D, G) - \lambda I(c; G(p, c))$$  \(3\)

by defining variational lower bound over second term of the equation $3$ $L_{\text{latentGAN}}$ can be further written as:

$$L_{\text{latentGAN}} = V(D, G) - \lambda L_1(G, Q)$$  \(3\)

$\lambda$ term insures that GAN loss and differential entropy loss are on same scale.

![Figure 1: LatentGAN Autoencoder model](image)

**Implementation Details**
We train autoencoder which consist of encoder $\text{Enc}$ which models $p(z|X)$, where $z$ is latent distribution and $X$ is the input image and decoder $\text{Dec}$ which models $p(X|z)$ using equation 1. LatentGAN generator $G$ and discriminator $D$ as shown in Figure 1 can be implemented using linear layer with relu non-linearity. The $Q$ network also has linear layer and shares parameters with $D$. Then $G, D$ and $Q$ are trained using follow process:

1. Random Gaussian noise $P$ is sampled from $N(0, I)$ along with latent code, which can be uniformly continuous $U$ or categorically discrete $\text{Cat}(K)$ where $K$ is the number of categories.
2. Latent code and Gaussian noise $P$ are passed through $G$, which generates $G(P, c)$ where $c$ can be $U$ or $\text{Cat}(K)$ code.
3. $D$ gets input from $Enc(X) \sim p_{data}(z)$ and $G(P, c)$, which outputs whether the sample belongs to $p_{data}(z)$ or not.
4. $Q$ receives input from $D$, and outputs code $c$, which will be used for optimizing equation 3.

It has been observed that using layer initializations from DCGAN (Radford, Metz, and Chintala 2016) hurts LatentGAN training process but the suggestion of using noisy labels for training $D$ helps during training.

Experiments

**MNIST Dataset**

| Method | $K$ | Test error (\%) |
|--------|-----|-----------------|
| InfoGAN | 10  | 5 \(\pm\) 0.01 |
| AAE    | 32  | 4.10 \(\pm\) 1.13 |
| ours   | 10  | 2.38 \(\pm\) 0.38 |

Table 1: MNIST Unsupervised Classification test error.

![Figure 2: Varying $\text{Cat}(K)$ changes the digit category. Every row coresponds to different $K$, and every column have same $K$ but different Gaussian noise $P$.](image)

In MNIST (LeCun and Cortes 2010) dataset, we use one categorical discrete variable $\text{Cat}(K)$ with $K = 10$, and two continuous uniform variable $U_1(-1, 1)$ and $U_2(-1, 1)$ as an input latent code to $G$. After training, random samples are generated by choosing $\text{Cat}(k)$, $P$, $U_1$ and $U_2$ and output is shown in the Figure 2. This shows that LatentGAN generator $G$ is able to approximate latent distribution of autoencoder directly. We have also shown learned disentangled rotation control as shown in the Figure 3 and disentangled thickness control in the Figure 4. This shows that we can directly
Figure 3: Varying \( U_1 (-1.5, 1.5) \) changes the thickness of the digit. Every row has different \( K \) and Gaussian noise \( P \), and every column has different \( U_1 \) but same Gaussian noise \( P \) and \( K \).

Figure 4: Varying \( U_2 (-1.5, 1.5) \) rotates the digit. Every row has different \( K \) and Gaussian noise \( P \), and every column has different \( U_2 \) but same Gaussian noise \( P \) and \( K \).

learn control on latent distribution of autoencoder. Also, we can use discriminator \( D \) for unsupervised classification, and Table 1 shows that our method has better test error than InfoGAN and AAE, and \( \downarrow \) denotes lower the score better the performance. For training LatentGAN Autoencoder on MNIST dataset, we have used architecture as mentioned in the Table 2 with \( \lambda_{cont} \) and \( \lambda_{disc} \) is set to 1 and 0.1 respectively.

### 3D Chair Dataset

In 3D Chair (Aubry et al. 2014) dataset, we use 3 discrete categorical variables \( Cat(K) \) where \( K = 20 \) and 1 continuous uniform variable \( U_1 (-1, 1) \) as an input to \( G \). We are able to generate meaningful sample as shown in the Figure 5 that means \( G \) is able to approximate autoencoder latent distribution. We are also able to learn disentangled rotational control on the chair dataset as shown in the Figure 6. Hyperparameter setting for 3D Chair dataset is same as MNIST Dataset except \( \lambda_{cont} \) and \( \lambda_{disc} \) is set to 1 and 10 respectively.

For training LatentGAN Autoencoder on 3D Chair

Table 2: MNIST Network Architecture

| Encoder \( Enc \) | Decoder \( Dec \) | Discriminator \( D/Q \) | Generator \( G \) |
|------------------|------------------|---------------------|------------------|
| Input \( 32X32 \) | Input \( 64 \)   | Input \( 1000 \)     | Input \( 64 \)   |
| \( c64 \-c32-s2-r \) | \( u2-c3-o64-p1-n\) | \( fc-o1000 \-fc-o64 \) |                  |
| \( c32 \-c16-s2-r \) | \( u2-c3-o32-p1-tanh \) | \( fc-o512 \) |                  |
| \( c16 \-c8-s2-r \) |                   | \( fc-o1000 \) |                  |
| \( c8 \-c4-s2-r \) |                   | \( fc-o1000 \) |                  |
| \( c4 \-c2-s2-r \) |                   | \( fc-o1000 \) |                  |

Conventions used, \( c \) is convolution, \( o \) is output channels, \( s \) is stride, \( u \) is bilinear upsampling, \( p \) is padding, \( r \) is relu, \( sig \) is sigmoid and \( bn \) is batchnorm. In column 3 of the table final output have 3 sections, 1st section belongs to discriminator \( D \) and other sections belong to \( Q \) network.

In 3D Chair (Aubry et al. 2014) dataset, we use 3 discrete categorical variable \( Cat(K) \) where \( K = 20 \) and 1 continuous uniform variable \( U_1 (-1, 1) \) as an input to \( G \). We are able to generate meaningful sample as shown in the Figure 5 that means \( G \) is able to approximate autoencoder latent distribution. We are also able to learn disentangled rotational control on the chair dataset as shown in the Figure 6. Hyperparameter setting for 3D Chair dataset is same as MNIST Dataset except \( \lambda_{cont} \) and \( \lambda_{disc} \) is set to 1 and 10 respectively.

For training LatentGAN Autoencoder on 3D Chair
Figure 6: Varying $U_1(-1,1)$ will rotate the chair.

Table 3: 3D Chair Network Architecture

| Encoder $Enc$ | Decoder $Dec$ | Discriminator $D/Q$ | Generator $G$ |
|---------------|---------------|---------------------|--------------|
|               | Input $\in \mathbb{R}^{128}$ | Input $\in \mathbb{R}^{190}$ | Input $\in \mathbb{R}$ |
| $c4$-$o64$-$s2$-$r$ | $r$-$u4$-$c3$-$o512$-$p1$-$bn128$-$r$ | $fc$-$o3000$-$r$ | $fc$-$o128$ |
| $c4$-$o128$-$s2$-$r$ | $u2$-$c3$-$o256$-$p1$-$bn64$-$r$ | $fc$-$o3000$-$r$ | $fc$-$o128$ |
| $c4$-$o256$-$s2$-$r$ | $c4$-$o512$-$s2$-$r$ | $fc$-$o128$-$r$ | $fc$-$o128$ |
| $c4$-$o512$-$s2$-$r$ | $c4$-$o1024$-$s2$-$r$ | $fc$-$o128$-$r$ | $fc$-$o128$ |
| $c4$-$o1024$-$s2$-$r$ | $c4$-$o128$-$s2$-$r$ | $fc$-$o128$-$r$ | $fc$-$o128$ |

Figure 7: CelebA Generated samples

Table 4: CelebA Network Architecture

| Encoder $Enc$ | Decoder $Dec$ | Discriminator $D/Q$ | Generator $G$ |
|---------------|---------------|---------------------|--------------|
|               | Input $\in \mathbb{R}^{128}$ | Input $\in \mathbb{R}^{128}$ | Input $\in \mathbb{R}$ |
| $c4$-$o64$-$s2$-$r$ | $c4$-$o128$-$s2$-$r$ | $c4$-$o128$-$s2$-$r$ | $c4$-$o128$-$s2$-$r$ |
| $c4$-$o128$-$s2$-$r$ | $fc$-$o128$-$r$ | $fc$-$o128$-$r$ | $fc$-$o128$-$r$ |

perparameter setting for CelebA dataset is same as MNIST Dataset except $\lambda_{disc}$ is set to 1.

Conclusion

We proposed LatentGAN autoencoder which can learn to control directly over autoencoder latent distribution and in doing so it is able to generate meaningful samples. Experimentally, we are able to verify that LatentGAN autoencoder can be used to learn meaningful disentangled representation over latent distribution and in unsupervised MNIST classification task performs better then InfoGAN and AAE. This further suggests that rather than making generator learn image distribution which may be challenging, we can approximate latent distribution which is less challenging and easy for generator to learn.

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