一、近期工作：

1.参加 CCFADL，《城市智能与计算》；
2.翻译工作；
3.对 DCGAN、f-GAN、WGAN 学习；
4.对心电图项目的思考；

二、下一步计划：

1.选择一个合适的 GAN 模型，应用在项目中；

论文	出版社	功能	训练数据	模型结构	损失函数
GAN	NIPS 2014	通过对抗训练生成真实图像		一个生成器 G、一个判别器 D	L_GAN(G,D)
CycleGAN	ICCV 2017	实现交叉图像领域之间的映射关系	Unpaired	F(G(X))=X 两个生成器、两个判别器	$L\_GAN(G;D_Y;X;Y) + L\_GAN(F;D_X;Y;X) + L\_cyc(G;F)$
DiscoGAN	ICML 2017	实现交叉图像领域之间的映射关系	Unpaired	F(G(X))=X 两个生成器、两个判别器	$L_G = L_{GA} + L_{GB} = L_{GANB} + L_{CONSTA} + L_{GANA} + L_{CONSTB}$ $L_D = L_{DA} + L_{DB}$
Image-to-Image with cGAN	ECCV 2016	用 cGAN 完成图像到图像的映射	paired	在生成器中，用 U-net 结构代替 encoder-decoder	G*= arg minGmaxD $L_{cGAN}(G;D)+\lambda L_{L1}(G)$
f-GAN	NIPS 2016	衡量两种分布之间的相似度			
WGAN	arXiv 2017	用‘推土机’衡量两种分布的距离			
DCGAN	ICLR 2016	将生成器和判别器的网络结构用深度卷积网络替换		用深度卷积网络替代生成器和判别器的网络模型	

2.完成实验，分析结果；
3.构思 paper；

三、DCGAN（ICLR 2016）

1.主要工作：
- 将生成器与判别器中的网络用深度卷积网络代替,并为了能够稳定训练 GAN，对网络做出了一些修改；
- 用训练好的判别器对 CIFAR 10 数据进行分类，取得了不错的效果；
- 对 GAN 的学习效果进行了可视化；
- 生成器具有有趣的向量运算性质，可以对生成样本的许多语义进行简单的操作；

2.稳定网络的训练
- 其中池化层用 strided convolutions（判别器）and fractional-strided

convolutions (生成器)替代;

- 在生成器和判别器中分别使用 批正则化处理（Batch Normalization）;
- 删除了最后全连接层的隐藏层;
- 生成器中除了输出层使用 Tanh 外,其他各层都使用 ReLU 激活函数;
- 判别器的所有层使用 LeakyReLU 激活函数;

3.结构模型

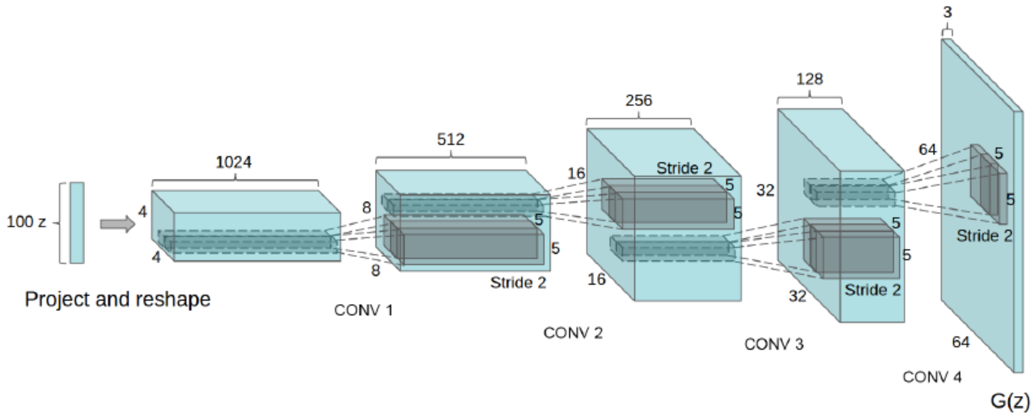


Figure 1: DCGAN generator used for LSUN scene modeling. A 100 dimensional uniform distribution Z is projected to a small spatial extent convolutional representation with many feature maps. A series of four fractionally-strided convolutions (in some recent papers, these are wrongly called deconvolutions) then convert this high level representation into a 64×64 pixel image. Notably, no fully connected or pooling layers are used.

4.实验效果

基于三种数据集：Large-scale Scene Understanding (LSUN)、 Imagenet-1k、a newly assembled Faces dataset

1 次 epoch 结果

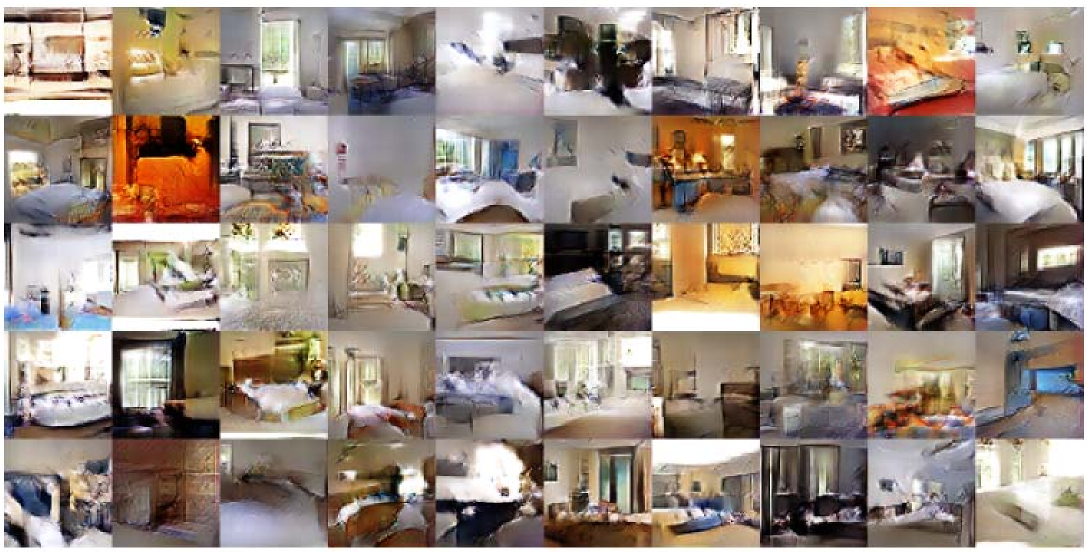


Figure 2: Generated bedrooms after one training pass through the dataset. Theoretically, the model could learn to memorize training examples, but this is experimentally unlikely as we train with a small learning rate and minibatch SGD. We are aware of no prior empirical evidence demonstrating memorization with SGD and a small learning rate.

5 次 epochs 结果

Figure 3: Generated bedrooms after five epochs of training. There appears to be evidence of visual under-fitting via repeated noise textures across multiple samples such as the base boards of some of the beds.

使用 DCGAN 的训练网络分类 CIFAR-10 和 SVHN 数据的结果

Table 1: CIFAR-10 classification results using our pre-trained model. Our DCGAN is not pre-trained on CIFAR-10, but on Imagenet-1k, and the features are used to classify CIFAR-10 images.

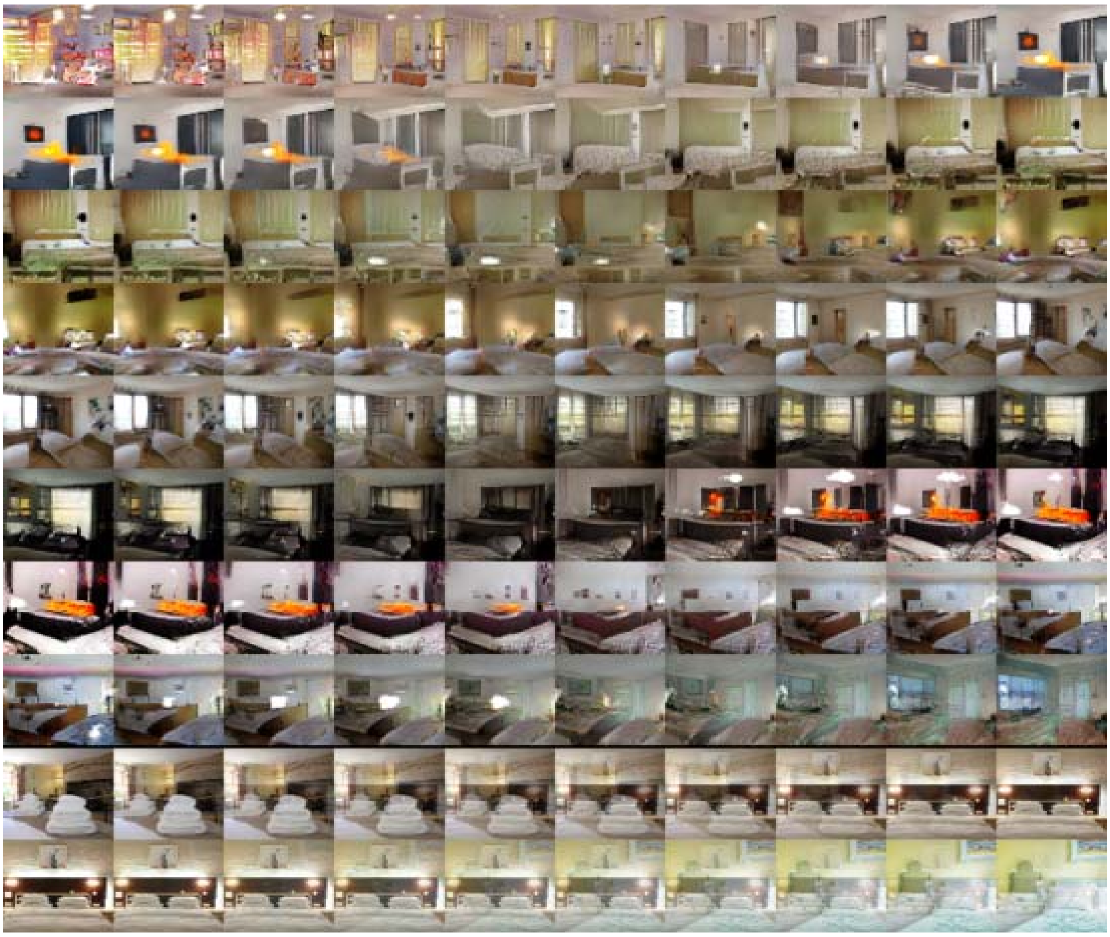
Model	Accuracy	Accuracy (400 per class)	max # of features units
1 Layer K-means	80.6%	63.7% (±0.7%)	4800
3 Layer K-means Learned RF	82.0%	70.7% (±0.7%)	3200
View Invariant K-means	81.9%	72.6% (±0.7%)	6400
Exemplar CNN	84.3%	77.4% (±0.2%)	1024
DCGAN (ours) + L2-SVM	82.8%	73.8% (±0.4%)	512

Table 2: SVHN classification with 1000 labels

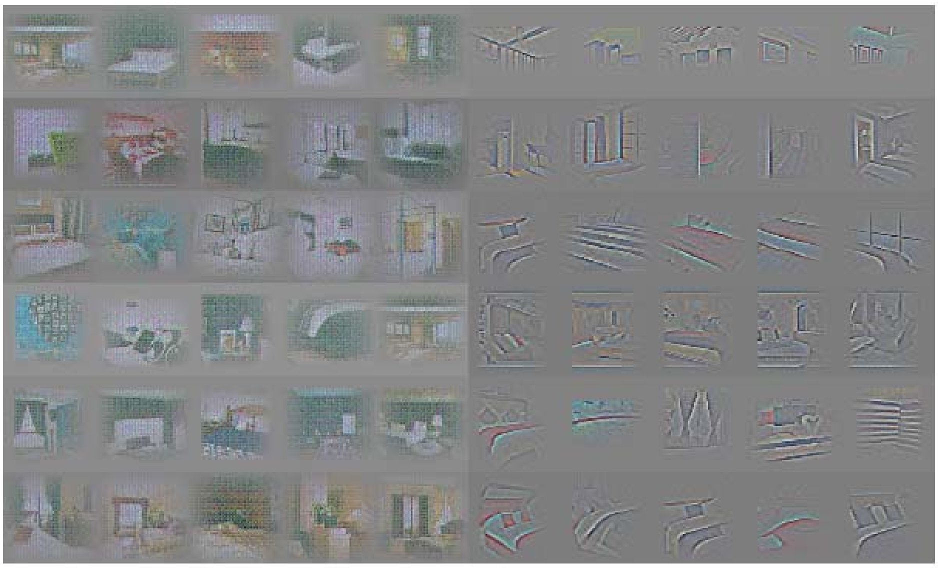
Model	error rate
KNN	77.93%
TSVM	66.55%
M1+KNN	65.63%
M1+TSVM	54.33%
M1+M2	36.02%
SWWAE without dropout	27.83%
SWWAE with dropout	23.56%
DCGAN (ours) + L2-SVM	22.48%
Supervised CNN with the same architecture	28.87% (validation)

5. 网络内部结构的可视化

- 为了了解网络是否真正的学习到图片的特征，作者对隐藏空间进行了可视化；下图为随机改变 Z 中的 9 个点，图片发生的变化效果。



- 判别器的可视化，检验 DCGAN 是否也可以学习到感兴趣的特征



Random filters **Trained filters**

Figure 5: On the right, guided backpropagation visualizations of maximal axis-aligned responses for the first 6 learned convolutional features from the last convolution layer in the discriminator. Notice a significant minority of features respond to beds - the central object in the LSUN bedrooms dataset. On the left is a random filter baseline. Comparing to the previous responses there is little to no discrimination and random structure.

● 生成器的可视化：“忘记”一些目标、对人脸图片样本的矢量运算