Implementing GAN on MNIST and SVHN

Shengjie Sun
ss5593
Department of Statistics
Columbia University
New York, NY 10027
ss5593@columbia.edu

Zeyu Yang
zy2327
Department of Statistics
Columbia University
New York, NY 10027
zy2327@columbia.edu

Abstract

We implement DCGAN on MNIST and SVHN dataset. The generated samples for both datasets are great although it takes quite some time to train the model. To help the model converge faster, we implement WGAN as well. The result **TBD**.

1 Introduction

Generative Adversarial Nets (GAN), first introduced by Ian Goodfellow in 2014[1], is a model that can be used to generate new images. It has been a hot topic since then.

The core idea of GAN is to create a two-player game. Build a generator that creates fake images while the discriminator tells whether the image is true or fake.

We train D to maximize the probability of assigning the correct label to both training examples and samples from G. We simultaneously train G to minimize $log(1 - D(G(z)))$.

The optimum case is that the generate can fully recover the distribution of the data and the discriminator cannot tell whether the image is fake or not i.e. the output of discriminator is $1/2$.

2 Implementation on MNIST

2.1 Architecture

We used Deep Convoltional GAN (DCGAN)[2] as our structure.

2.1.1 Generator

The input of the first dense layer the 100×1 random noise vector. We have $12,544$ neurons, apply batch normalization and activation function Leaky Relu, and reshape it to $7 \times 7 \times 256$.

The second Convoltional Transpose layer outputs $7 \times 7 \times 128$.

The third and fourth Convolutional layers have stride 2 and padding *same*, they alter the first two dimensions of the input and make the input from 7×7 to 14×14 to 28×28. The filter makes the third dimension from 128 to 64 to 1.

Thus the final output is a $28 \times 28 \times 1$ black and white image.

- First layer: Dense
  - Input: 100×1 vector
  - Units: $12,544$
  - Batch normalization

- Activation: leaky relu
  - Reshape $12,544$ to $7 \times 7 \times 256$
- Second layer: Conv2DTranspose
  - Input $7 \times 7 \times 256$
  - Filter: 128
  - Kernel size: 5
  - Stride: 1
  - Padding: same
  - Batch normalization
  - Activation: leaky relu
- Third layer: Conv2DTranspose
  - Input $7 \times 7 \times 128$
  - Filter: 64
  - Kernel size: 5
  - Stride: 2
  - Padding: same
  - Batch normalization
  - Activation: leaky relu
- Fourth layer: Conv2DTranspose
  - Input $14 \times 14 \times 64$
  - Filter: 1
  - Kernel size: 5
  - Stride: 2
  - Padding: same
  - Activation: tanh
  - Output $28 \times 28 \times 1$

2.1.2 Discriminator

The discriminator takes in a $28 \times 28 \times 1$ array. After three convolutional layers and one dense layer, the output will be a scalar. This scalar will be applied to a logistics function in future steps to be a probability that lies between 0 and 1. It is the probability of the input being a true image or a fake image.

- First layer: Conv2D
  - Input: $28 \times 28 \times 1$ array
  - Filter: 64
  - Kernel size: 5
  - Stride: 2
  - Padding: same
  - Activation: leaky relu
  - Dropout: 0.3
- Third layer: Conv2D
  - Filter: 128
  - Kernel size: 5
  - Stride: 2
  - Padding: same
  - Activation: leaky relu
  - Dropout: 0.3
- Fourth layer: Conv2D

    - Filter: 256
    - Kernel size: 5
    - Stride: 2
    - Padding: same
    - Activation: leaky relu
    - Dropout: 0.3
- Fifth layer: Flatten
- Sixth layer: Dense with output 1

2.1.3 Hyperparameters

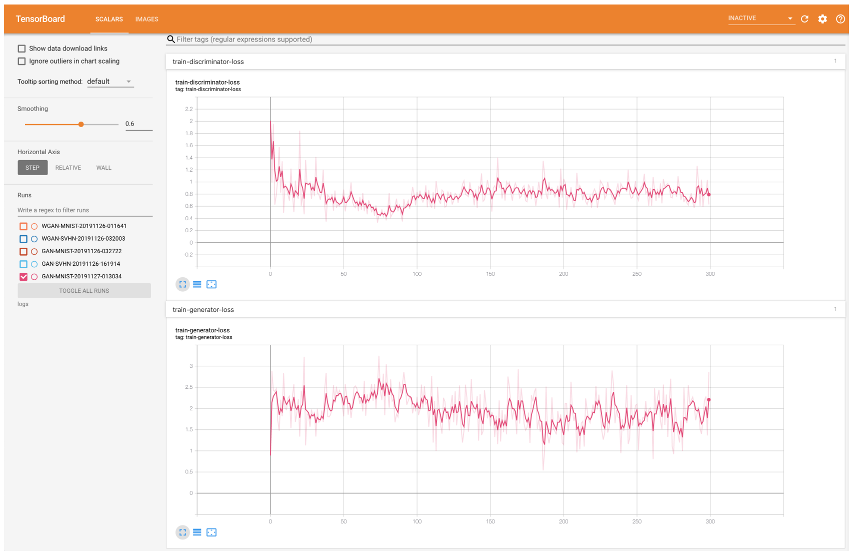
- Epoch: 100
- Batch: 256
- Learning rate
    - Generator: 1e-3
    - Discriminator: 1e-4

We have experimented on different bacthes and epoches and we believe a batch of 256 samples and 100 epoches already produced satisfying result. In fact, the quality of the image does not seem to have significant improve after 50 epoches.

The reason why we choose the learning rate for the discriminator 10 times smaller than the learning rate for generator is because we noticed the loss of discriminator is much smaller than the loss of generator. To avoid the gradient jumping back and forth around the optimum spot, we lower the learning rate for discriminator. The training result shows that the loss for both of them are at the same magnitude after the modification.

2.2 Result

2.2.1 Tensorboard


TensorBoard
SCALARS
IMAGES
INACTIVE
Filter tags (regular expressions supported)
Show data download links
Ignore outliers in chart scaling
Tooltip sorting method: default
Smoothing
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Horizontal Axis
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Runs
Write a regex to filter runs
WGAN-MNIST-20191126-011641
WGAN-SVHN-20191126-032003
GAN-MNIST-20191126-032722
GAN-SVHN-20191126-161914
GAN-MNIST-20191127-013034
TOGGLE ALL RUNS
logs
train-discriminator-loss
tag: train-discriminator-loss
train-generator-loss
tag: train-generator-loss

Figure 1: Tensorboard GAN MNSIT

2.2.2 Generated samples

From Figure 2, we can see the generated samples has a good approximation after 30 epoches.

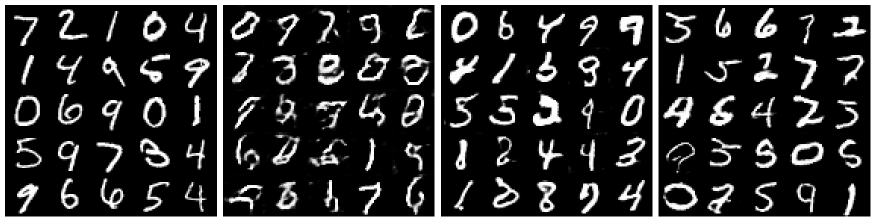

(a) MNIST data (b) Epoch 10/100 (c) Epoch 30/100 (d) Epoch 100/100

Figure 2: Comparison of MNIST data and generated samples from DCGAN

The samples from the 10th are quite blury and they cannot have a good representation of number 2, 5, 8, etc.

The latter samples are clearer and the edges of the numbers are smoother. Number 0, 1, 3, 5, 7, 9 are quite ideal.

Although not all samples are of high quality, there are a proportion of the images that have the quality of the samples presented in paper[1] 2(a).

3 Implementation on SVHN

3.1 Architecture

3.1.1 Generator

The generator is slightly modifed from the generator for MNIST. The output of the first dense layer is changed to $8 \times 8 \times 256$ and the filter of the fourth layer (Conv2DTranspose) has changed from 1 to 3 so that the output of the whole generator would be a $32 \times 32 \times 3$ image.

3.1.2 Discriminator

Discriminator is exactly the same as the previous one.

3.1.3 Hyperparameters

- Epoch: 200
- Batch: 256
- Learning rate
  - Generator: 1e-3
  - Discriminator: 1e-4

Since the SVHN dataset is more complicated, we train the model with 200 epoches.

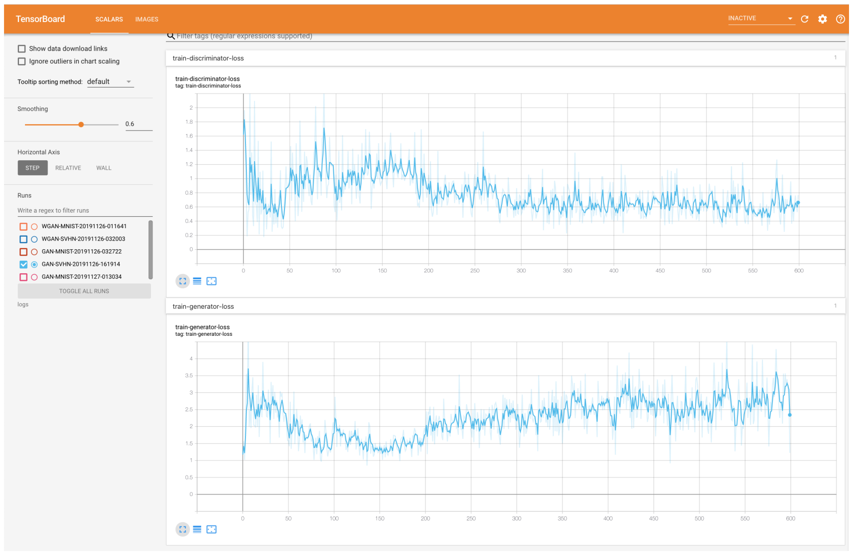
3.2 Result

3.2.1 Tensorboard

3.2.2 Generated samples

The quality of the generated samples are not as good as the MNIST samples since the SVHN dataset is more complicated. This complexity makes the model harder to converge i.e. uses more epoches to get good generated samples.

Although complicated as the dataset is, the generated samples demonstrate some qualities such as the variety of the samples. There are different combinations of gree, white, and red background with white, blue, and red fonts.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tag: train-discriminator-loss
train-generator-loss
tag: train-generator-loss
logs

☐ Show data download links
☐ Ignore outliers in chart scaling

Tooltip sorting method: default

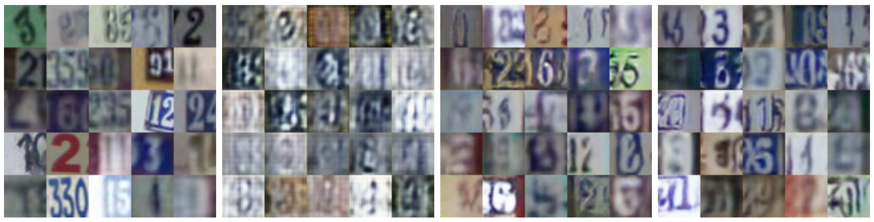
Smoothing: 0.6

Horizontal Axis: [✓ STEP] RELATIVE WALL

Runs

☐ WGAN-MNIST-20191126-011641
☐ WGAN-SVHN-20191126-032003
☐ GAN-MNIST-20191126-032722
☑ GAN-SVHN-20191126-161914
☐ GAN-MNIST-20191127-013034

Figure 3: Tensorboard GAN SVHN



(a) SVHN data (b) Epoch 30/200 (c) Epoch 150/200 (d) Epoch 200/200

Figure 4: Comparison of SVHN data and generated samples from DCGAN

4 WGAN

Wasserstein GAN is a modified GAN introduced by Arjovsky, Martin, et al.(2017)[3]. It proposed Wasserstein that has a better property than Jensen-Shannon divergence.

Down to the implementation, the main difference is the loss function. We modified the loss function from *BinaryCrossentropy* to a customized loss function.

The generator and discriminator are exactly the same as the GAN.

The hyperparameters are the same except this time we only train 50 epoches for each model.

4.1 WGAN on MNIST

4.2 WGAN on SVHN

5 Summary

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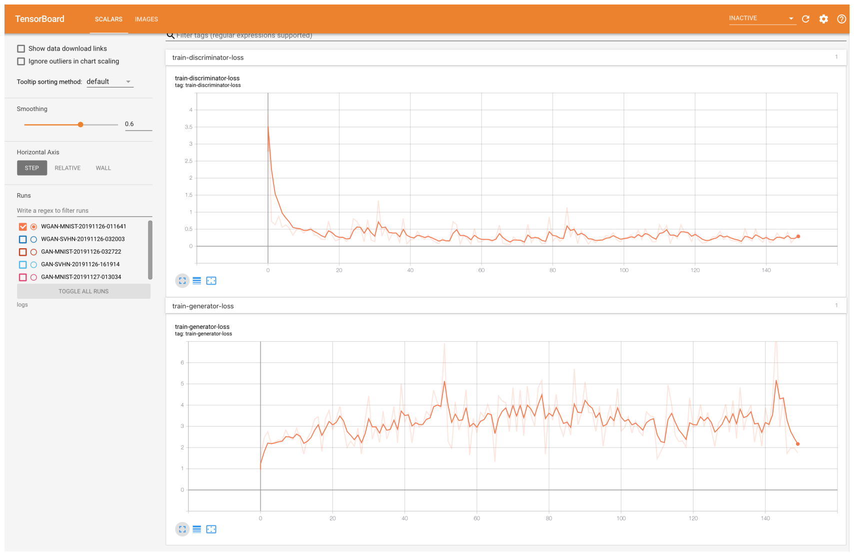
5.1 Future steps

Since plenty new models have been published other than WGAN, we can try other models such as triple-GAN, Self-attention neural network, etc..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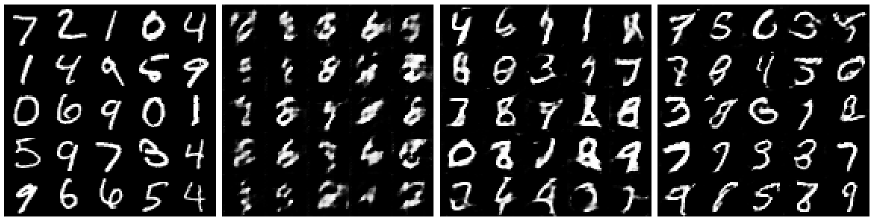
train-generator-loss
tag: train-generator-loss

Tooltip sorting method: default

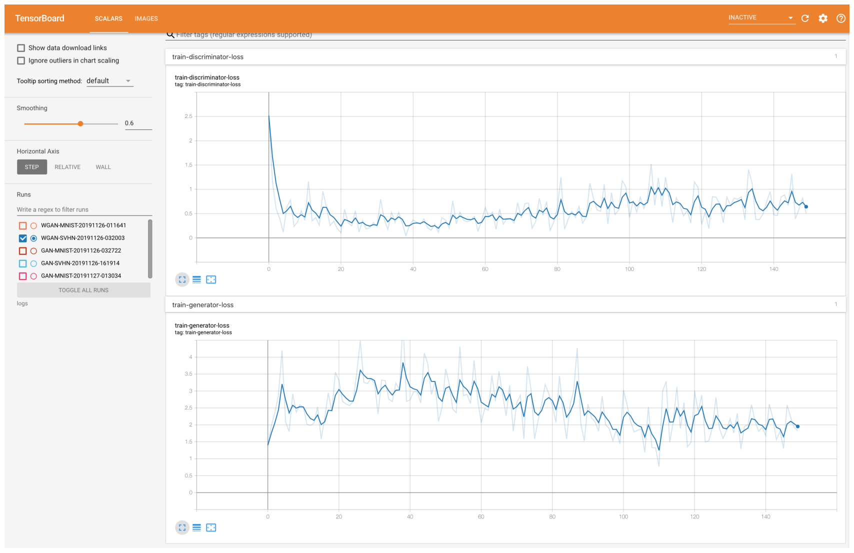
Smoothing 0.6

Figure 5: Tensorboard WGAN MNSIT



(a) MNIST data (b) Epoch 10/50 (c) Epoch 30/50 (d) Epoch 50/50

Figure 6: Comparison of MNIST data and generated samples from WGAN


TensorBoard
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tag: train-discriminator-loss
train-generator-loss
tag: train-generator-loss

Tooltip sorting method: default

Smoothing 0.6

Figure 7: Tensorboard WGAN SVHN

References

[1] Goodfellow, Ian, et al. "Generative adversarial nets." Advances in neural information processing systems. 2014.

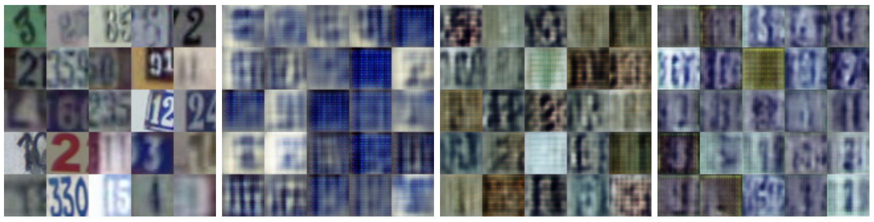
(a) SVHN data (b) Epoch 10/50 (c) Epoch 30/50 (d) Epoch 50/50

Figure 8: Comparison of SVHN data and generated samples from WGAN

[2] Radford, Alec, Luke Metz, and Soumith Chintala. "Unsupervised representation learning with deep convolutional generative adversarial networks." arXiv preprint arXiv:1511.06434 (2015).

[3] Arjovsky, Martin, Soumith Chintala, and Léon Bottou. "Wasserstein gan." arXiv preprint arXiv:1701.07875 (2017).