

CS 5787 Assignment 3

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Q1

(1) Processing

Code for this problem is attached in the end.

(2) Implement your RNN module, train the model and report accuracy on the test set.

RNN:

```
: 1 class GRU(nn.Module):
2     def __init__(self, feature_num):
3         super(GRU, self).__init__()
4         self.embedding = nn.Embedding(feature_num, 128)
5         self.rnn = nn.GRU( input_size=128,
6                             hidden_size=64,
7                             num_layers=1,
8                             dropout=0.5,
9                             batch_first=True)
10        self.linear1 = nn.Linear(64, 32)
11        self.linear2 = nn.Linear(32, 1)
12        self.sigmoid = nn.Sigmoid()
13
14    def forward(self, x):
15        embedded = self.embedding(x)
16        out, _ = self.rnn(embedded)
17        out_last = out[:, -1, :] # get last value
18
19        x = self.linear1(out_last.view(-1, out_last.shape[-1]))
20        x = self.linear2(F.relu(x))
21        x = self.sigmoid(x)
22        return x
23
```

```

1 optimizer = None
2 criterion = None
3
4 def get_accuracy(predict, target):
5     temp1 = predict >= 0.5
6     temp2 = target >= 0.5
7     temp3 = (temp1.numpy().reshape(BATCH_SIZE) == temp2.numpy().reshape(BATCH_SIZE))
8     return np.sum(temp3)/BATCH_SIZE
9
10 def train(model, train_loader, test_loader):
11     for time in range(10):
12         print(time)
13         for i, data in enumerate(train_loader):
14             inputs, labels = data
15
16             optimizer.zero_grad()
17             outputs = model(inputs)
18             loss = criterion(outputs, labels)
19             loss.backward()
20             optimizer.step()
21
22     print('Finished Training')
23
24     accuracy_sum = 0.0
25
26     for i, data in enumerate(test_loader):
27         inputs, label = data
28
29         output = model(inputs)
30         loss = criterion(output, label)
31
32         accuracy = get_accuracy(output, label)
33         accuracy_sum = accuracy_sum + accuracy
34     print("accuracy is " + str(accuracy_sum*BATCH_SIZE/3000))
35

```

Accuracy:

```

23
24 model1 = GRU(SIZE+2)
25 criterion = nn.BCELoss()
26 optimizer = optim.Adam(model1.parameters(), lr=0.001, betas=(0.9, 0.999))
27 train(model1, train_loader, test_loader)

```

```

0
1
2
3
4
5
6
7
8
9
Finished Training
accuracy is 0.7470000000000001

```

Part 3 - Comparison with a MLP

```
1 class MLP(nn.Module):
2     def __init__(self):
3         super(MLP, self).__init__()
4         self.embedding = nn.Embedding(SIZE+2, 64)
5
6         self.linear1 = nn.Linear(400 * 64, 32)
7         self.linear2 = nn.Linear(32, 1)
8         self.sigmoid = nn.Sigmoid()
9
10    def forward(self, x):
11        x = self.embedding(x)
12        x = x.view(-1, 400*64)
13
14        x = self.linear1(x)
15        x = self.linear2(x)
16        x = self.sigmoid(x)
17        return x
18
19 model2 = MLP()
20 criterion = nn.BCELoss()
21 optimizer = optim.Adam(model2.parameters(), lr=0.0001, betas=(0.9, 0.999))
22 train(model2, train_loader, test_loader)
```

0

1

2

3

4

5

6

7

8

9

Finished Training

accuracy is 0.5706666666666664

RNN performs much better on the test data.

Q2

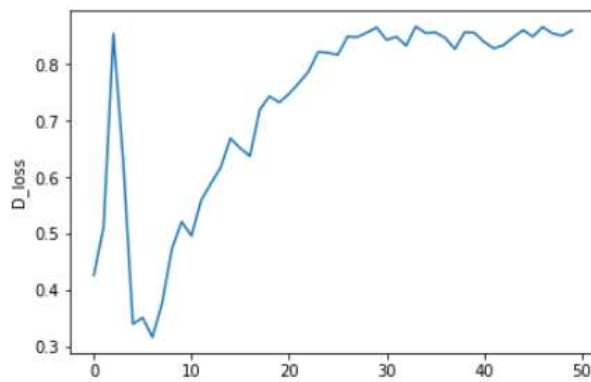
(1)

Train a basic GAN

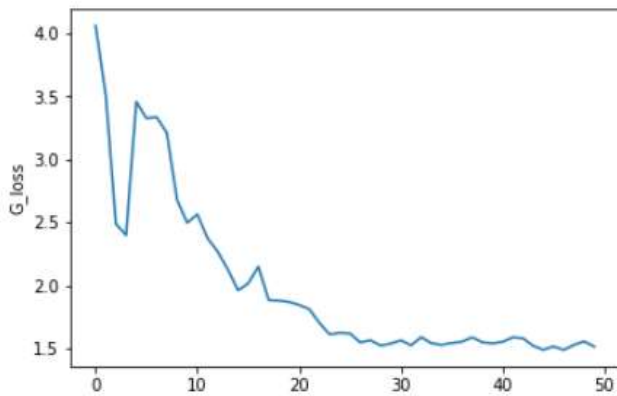
See code attached in the end.

Plot training loss curves for your G and D

```
1 plt.plot(D_loss)
2 plt.ylabel("D_loss")
3 plt.show()
```



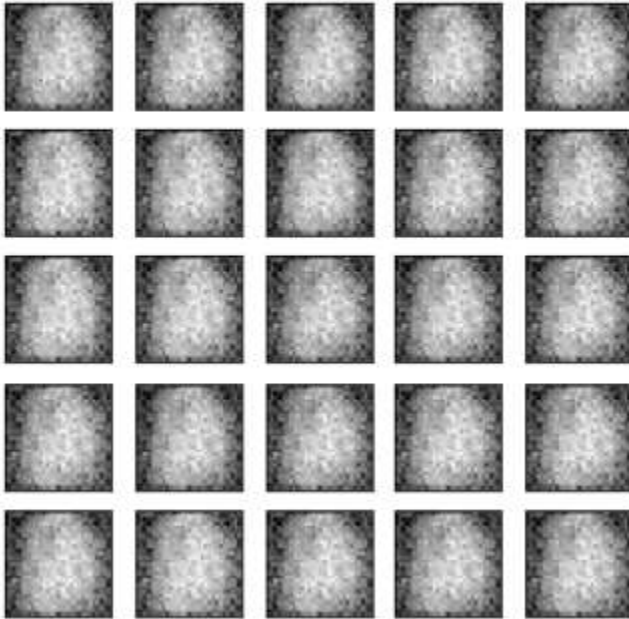
```
1 plt.plot(G_loss)
2 plt.ylabel("G_loss")
3 plt.show()
```



Show the generated samples from G in:

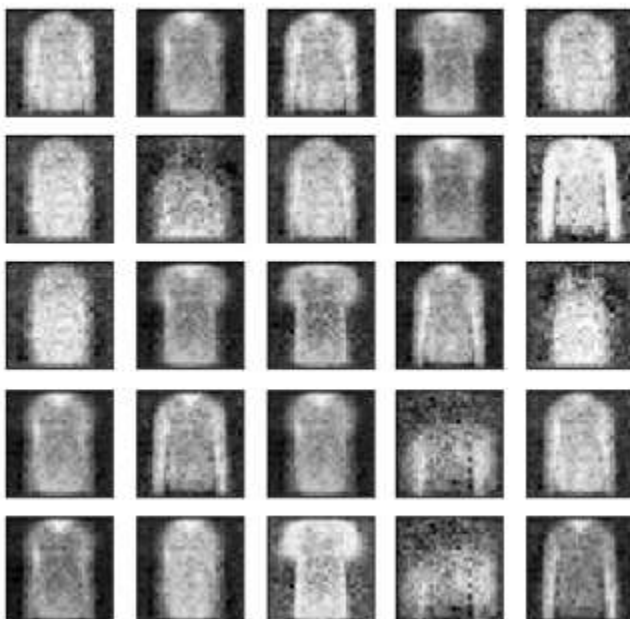
1) the beginning of the training;

epoch 2: loss_d: 0.855, loss_g: 2.487



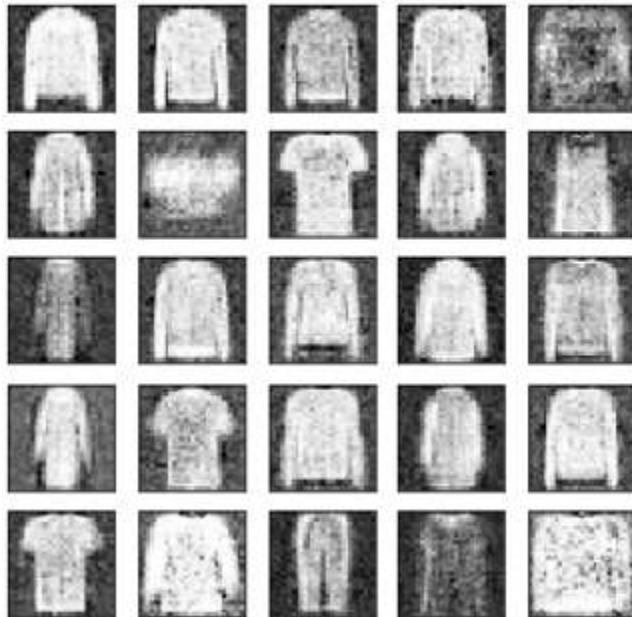
2) intermediate stage of the training;

epoch 10: loss_d: 0.496, loss_g: 2.563



3) after convergence.

epoch 48: loss_d: 0.851, loss_g: 1.556



(2) GAN Loss

MSE

Model:

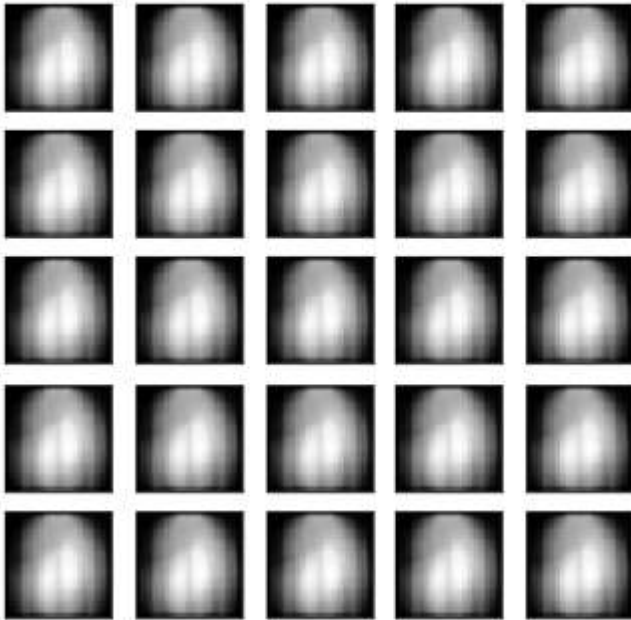
```
1  class generator(nn.Module):
2      def __init__(self):
3          super(generator, self).__init__()
4
5          self.layer0 = nn.Sequential(
6              nn.Linear(100, 256),
7              nn.ReLU(),
8          )
9
10         self.layer1 = nn.Sequential(
11             nn.Linear(256, 512),
12             nn.ReLU(),
13         )
14
15         self.layer2 = nn.Sequential(
16             nn.Linear(512, 1024),
17             nn.ReLU(),
18         )
19
20         self.layer3 = nn.Sequential(
21             nn.Linear(1024, 784),
22             nn.Tanh()
23         )
24
25     def forward(self, x):
26         x = self.layer0(x)
27         x = self.layer1(x)
28         x = self.layer2(x)
29         x = self.layer3(x)
30         return x
```


Train:

```
1 G_loss = []
2
3 # train
4 for epoch in range(epoch_number):
5     g_epoch_loss = []
6     for x, _ in data_loader:
7         x = x.view(-1, 28 * 28)
8         batch_size = x.size()[0]
9
10        # train generator G
11        noise = torch.randn((batch_size, 100))
12        y_target = torch.ones(batch_size)
13        noise, y_target = Variable(noise.cuda()), Variable(y_target.cuda())
14
15        G.zero_grad()
16        G_result = G(noise)
17        G_train_loss = criterion(G_result.to('cuda'), x.to('cuda'))
18        G_train_loss.backward()
19        G_optimizer.step()
20
21        g_epoch_loss.append(G_train_loss.cpu().data.item())
22
23    G_loss.append(sum(g_epoch_loss)/len(g_epoch_loss))
24
25    if (epoch == 0 or epoch == 1 or epoch == 2 or epoch == 10 or epoch == 20 or epoch == 30 or epoch == 48):
26        print('epoch %d: loss_g: %.3f' % (epoch, G_loss[epoch]))
27        show_result()
```

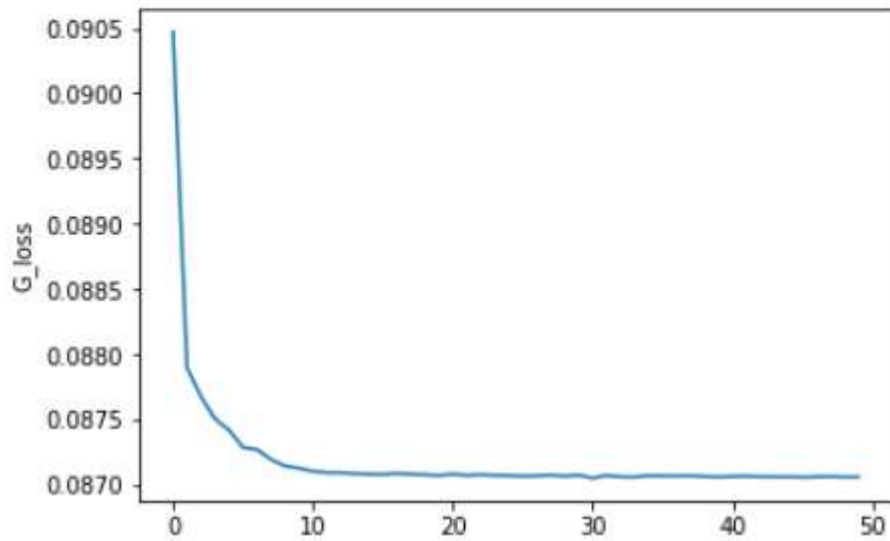
Generated graph:

epoch 48: loss_g: 0.087



Training loss:

```
]: 1 plt.plot(G_loss)
    2 plt.ylabel("G_loss")
    3 plt.show()
```



The MSE result is not very good because only the input image is used when training.

Wasserstein GAN (WGAN)

Model (c = 0.1):

```
1  class generator(nn.Module):
2      def __init__(self):
3          super(generator, self).__init__()
4
5          self.layer0 = nn.Sequential(
6              nn.Linear(100, 256),
7              nn.ReLU(),
8          )
9
10         self.layer1 = nn.Sequential(
11             nn.Linear(256, 512),
12             nn.ReLU(),
13         )
14
15         self.layer2 = nn.Sequential(
16             nn.Linear(512, 1024),
17             nn.ReLU(),
18         )
19
20         self.layer3 = nn.Sequential(
21             nn.Linear(1024, 784),
22             nn.Tanh()
23         )
24
25     def forward(self, x):
26         x = self.layer0(x)
27         x = self.layer1(x)
28         x = self.layer2(x)
29         x = self.layer3(x)
30         return x
```

```
1 class discriminator(nn.Module):
2     def __init__(self):
3         super(discriminator, self).__init__()
4
5         self.layer0 = nn.Sequential(
6             nn.Linear(784, 1024),
7             nn.ReLU(),
8             nn.Dropout(0.3)
9         )
10
11        self.layer1 = nn.Sequential(
12            nn.Linear(1024, 512),
13            nn.ReLU(),
14            nn.Dropout(0.3)
15        )
16
17        self.layer2 = nn.Sequential(
18            nn.Linear(512, 256),
19            nn.ReLU(),
20            nn.Dropout(0.3)
21        )
22
23        self.layer3 = nn.Sequential(
24            nn.Linear(256, 1),
25            # nn.Sigmoid()
26        )
27
28
29    def forward(self, x):
30        x = self.layer0(x)
31        x = self.layer1(x)
32        x = self.layer2(x)
33        x = self.layer3(x)
34        return x
```

Train:

```
1 # train
2 D_losses = []
3 G_losses = []
4 for epoch in range(epoch_number):
5     for x, _ in data_loader:
6         current_batch_size = x.size()[0]
7         x = autograd.Variable(x).detach().cuda()
8         x = x.view(x.shape[0], 28*28)
9
10        # Train discriminator
11        G_result = G(autograd.Variable(torch.randn(current_batch_size, 100), requires_grad=True).cuda())
12        D_optimizer.zero_grad()
13
14        D_result_real = D(x).mean()
15        D_result_fake = D(G_result).mean()
16        D_total_loss = ((-1)*D_result_real + D_result_fake)
17        D_total_loss.backward()
18        D_optimizer.step()
19
20        for p in D.parameters():
21            p.data.clamp_(-clamp, clamp)
22
23
24
25        # Train Generator
26        fake_image = G(autograd.Variable(torch.randn(current_batch_size, 100), requires_grad=True).cuda())
27        G_optimizer.zero_grad()
28
29        D_result = D(fake_image).mean()
30        G_train_loss = (-1) * D_result
31        G_train_loss.backward()
32        G_optimizer.step()
33
34        for p in G.parameters():
35            p.data.clamp_(-clamp, clamp)
36
37        G_losses.append(G_train_loss.item())
38        D_losses.append(D_total_loss.item())
39
40        if (epoch == 0 or epoch == 1 or epoch == 2 or epoch == 10 or epoch == 20 or epoch == 30 or epoch == 48):
41            # if (True):
42                print('epoch %d: loss_d: %f, loss_g: %f' % (epoch, D_losses[epoch], G_losses[epoch]))
43                show_result()
```

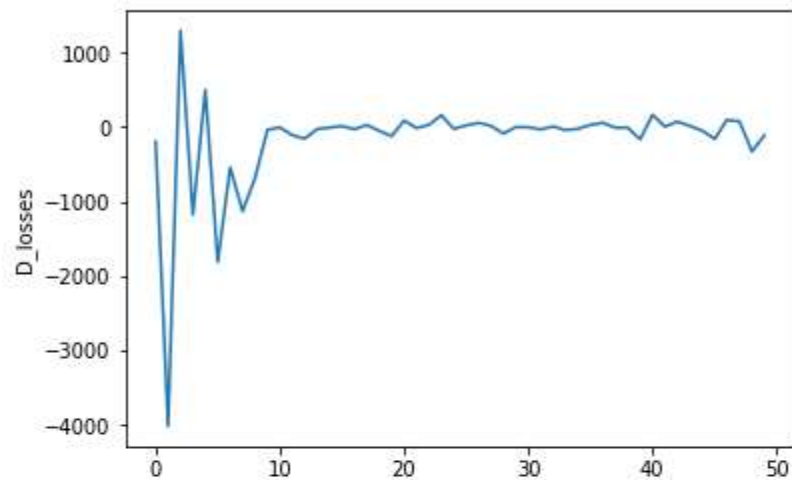
Graph generated:

epoch 48: loss_d: -327.651855, loss_g: -402.395721

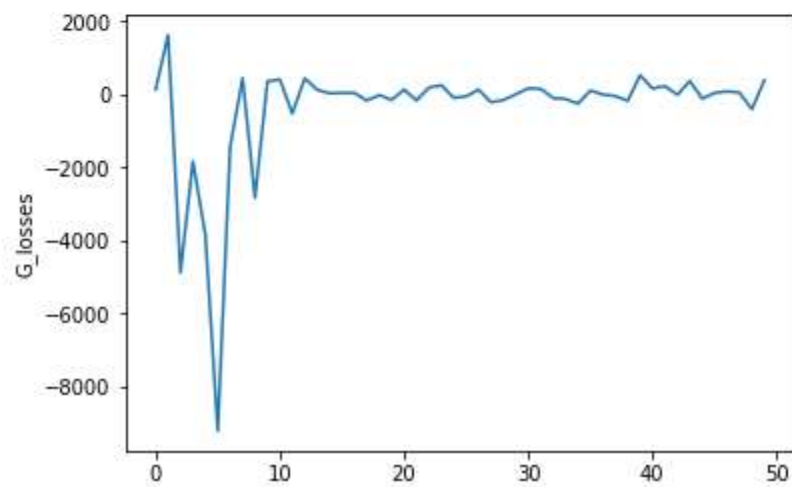


Training loss:

```
In [13]: 1 plt.plot(D_losses)
          2 plt.ylabel("D_losses")
          3 plt.show()
```



```
In [14]: 1 plt.plot(G_losses)
          2 plt.ylabel("G_losses")
          3 plt.show()
```



I also tried c with 0:01, 0:001 and 0:0001. The smaller C is, the harder for the model to coverage.

Least Square GAN

Model:

```
: 1 class generator(nn.Module):
2     def __init__(self):
3         super(generator, self).__init__()
4
5         self.layer0 = nn.Sequential(
6             nn.Linear(100, 256),
7             nn.ReLU(),
8         )
9
10        self.layer1 = nn.Sequential(
11            nn.Linear(256, 512),
12            nn.ReLU(),
13        )
14
15        self.layer2 = nn.Sequential(
16            nn.Linear(512, 1024),
17            nn.ReLU(),
18        )
19
20        self.layer3 = nn.Sequential(
21            nn.Linear(1024, 784),
22            nn.Tanh()
23        )
24
25    def forward(self, x):
26        x = self.layer0(x)
27        x = self.layer1(x)
28        x = self.layer2(x)
29        x = self.layer3(x)
30        return x
```



```
: 1 class discriminator(nn.Module):
2     def __init__(self):
3         super(discriminator, self).__init__()
4
5         self.layer0 = nn.Sequential(
6             nn.Linear(784, 1024),
7             nn.ReLU(),
8             nn.Dropout(0.3)
9         )
10
11        self.layer1 = nn.Sequential(
12            nn.Linear(1024, 512),
13            nn.ReLU(),
14            nn.Dropout(0.3)
15        )
16
17        self.layer2 = nn.Sequential(
18            nn.Linear(512, 256),
19            nn.ReLU(),
20            nn.Dropout(0.3)
21        )
22
23        self.layer3 = nn.Sequential(
24            nn.Linear(256, 1),
25            nn.Sigmoid()
26        )
27
28
29    def forward(self, x):
30        x = self.layer0(x)
31        x = self.layer1(x)
32        x = self.layer2(x)
33        x = self.layer3(x)
34        return x
```


Train:

```
: 1 G = generator()
2 D = discriminator()
3 G.cuda()
4 D.cuda()
5
6 criterion = nn.BCELoss()
7
8 G_optimizer = optim.RMSprop(G.parameters(), lr=lr)
9 D_optimizer = optim.RMSprop(D.parameters(), lr=lr)

: 1 # train
2 D_losses = []
3 G_losses = []
4 for epoch in range(epoch_number):
5     for x, _ in data_loader:
6         current_batch_size = x.size()[0]
7         x = autograd.Variable(x.detach()).cuda()
8         x = x.view(x.shape[0], 28*28)
9
10        # Train discriminator
11        G_result = G(autograd.Variable(torch.randn(current_batch_size, 100), requires_grad=True).cuda())
12        D_optimizer.zero_grad()
13
14        D_result_real = D(x)
15        D_result_fake = D(G_result)
16        D_total_loss = torch.mean((D_result_real-1)**2) + torch.mean(D_result_fake**2)
17        D_total_loss.backward()
18        D_optimizer.step()
19
20        # Train Generator
21        fake_image = G(autograd.Variable(torch.randn(current_batch_size, 100), requires_grad=True).cuda())
22        G_optimizer.zero_grad()
23
24        D_result = D(fake_image)
25        G_train_loss = torch.mean((D_result-1)**2)
26        G_train_loss.backward()
27        G_optimizer.step()
28
29        G_losses.append(G_train_loss.item())
30        D_losses.append(D_total_loss.item())
31
32        if (epoch == 0 or epoch == 1 or epoch == 2 or epoch == 10 or epoch == 20 or epoch == 30 or epoch == 48):
33            # if (True):
34                print('epoch %d: loss_d: %f, loss_g: %f' % (epoch, D_losses[epoch], G_losses[epoch]))
35                show_result()

epoch 0: loss_d: 0.655075 loss_g: 0.657075
```

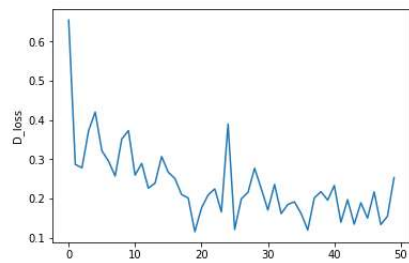
Graph generated:

epoch 48: loss_d: 0.154834, loss_g: 0.736266

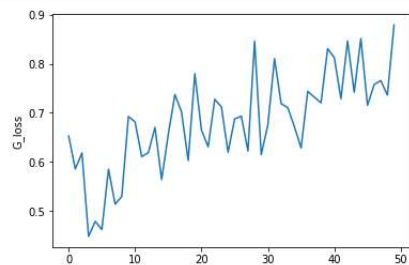


Training loss:

```
1 plt.plot(D_losses)
2 plt.ylabel("D_loss")
3 plt.show()
```



```
1 plt.plot(G_losses)
2 plt.ylabel("G_loss")
3 plt.show()
```



The MSE takes less time to train, but the result is hard to see. WGAN and Least Square Gan can produce high quantity image from random noise.

Part 3 - Mode Collapse in GANs

To output a classifier, I change the output dimension from 1 to 10 and then train the model using training data and test the result using test data.

```
1 class classifier(nn.Module):
2     def __init__(self):
3         super(classifier, self).__init__()
4
5         self.layer0 = nn.Sequential(
6             nn.Linear(784, 1024),
7             nn.ReLU(),
8             nn.Dropout(0.3)
9         )
10
11        self.layer1 = nn.Sequential(
12            nn.Linear(1024, 512),
13            nn.ReLU(),
14            nn.Dropout(0.3)
15        )
16
17        self.layer2 = nn.Sequential(
18            nn.Linear(512, 256),
19            nn.ReLU(),
20            nn.Dropout(0.3)
21        )
22
23        self.layer3 = nn.Sequential(
24            nn.Linear(256, 10),
25            nn.Softmax()
26        )
27
28
29    def forward(self, x):
30        x = self.layer0(x)
31        x = self.layer1(x)
32        x = self.layer2(x)
33        x = self.layer3(x)
34        return x
```

The accuracy is

```
1 #test
2 acc_list = []
3 for x, label in data_loader2:
4     current_batch_size = x.size()[0]
5
6     x = autograd.Variable(x).detach().cuda()
7     x = x.view(x.shape[0], 28*28)
8
9     y_real = Variable(label.cuda())
10    C_result_real = C(x).detach()
11    acc_list.append(get_accuracy(C_result_real, y_real))
12
13 acc_list = acc_list[:-1]
14 print(sum(acc_list)/len(acc_list))
15
```

0.8095953525641025

Then I training the GAN network and generate 3000 samples and draw their distributions.

```

1 count_map = {}
2
3 for i in range(10):
4     count_map[i] = 0
5
6 for i in range(3000):
7     value = generate_image()
8     count_map[value] = count_map[value] + 1
9
10 print(count_map)

```

{0: 603, 1: 131, 2: 1677, 3: 331, 4: 0, 5: 3, 6: 107, 7: 0, 8

```

1 plot_values = [0]*10
2 for i in range(10):
3     plot_values[i] = count_map[i]
4
5 plot_values

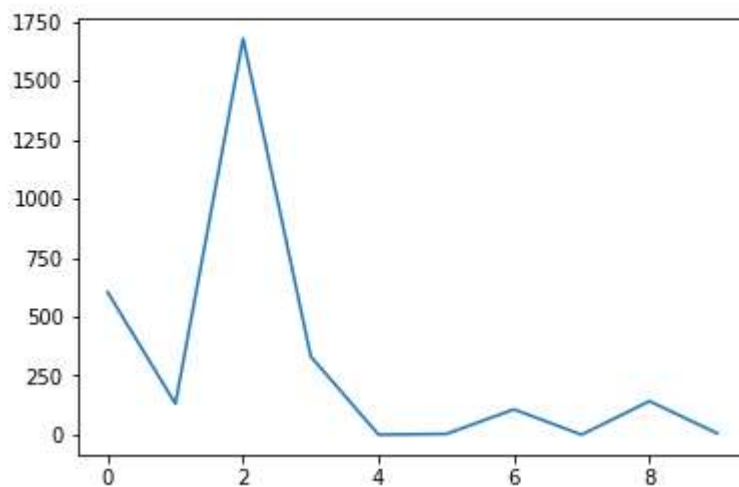
```

[603, 131, 1677, 331, 0, 3, 107, 0, 142, 6]

```

1 plt.plot(range(10), plot_values)
2 plt.show()

```



Q3

(1) Using Discrete States

```
1 import numpy as np
2 import random
3 from matplotlib import pyplot as plt
```

```
1 qtable = np.zeros((81, 4))
```

```
1 def load_prob(path, prob_map):
2     f = open(path)
3     lines = f.readlines()
4     f.close
5     for line in lines:
6         l = line.split()
7         key = int(l[0])
8         value = int(l[1])
9         prob = float(l[2])
10        if key in prob_map:
11            prob_map[key].append([value, prob])
12        else:
13            prob_map[key] = [[value, prob]]
14
15 def get_state_by_prob(state_prob_s):
16     acc = 0.0
17     r_prob = random.random()
18     for name in state_prob_s:
19         acc = acc + name[1]
20         if acc >= r_prob:
21             return name[0]
22     print("None!!!")
23     return None
24 #     return lofprob[-1][0]
25
26 def get_action_state(s, action):
27     if action == 0:
28         return get_state_by_prob(left_prob[s])
29     if action == 1:
30         return get_state_by_prob(up_prob[s])
31     if action == 2:
32         return get_state_by_prob(right_prob[s])
33     if action == 3:
34         return get_state_by_prob(down_prob[s])
35     return None
```



```
1 left_prob = {}
2 up_prob = {}
3 right_prob = {}
4 down_prob = {}
5
6 load_prob("rl-files/prob-a1.txt", left_prob)
7 load_prob("rl-files/prob-a2.txt", up_prob)
8 load_prob("rl-files/prob-a3.txt", right_prob)
9 load_prob("rl-files/prob-a4.txt", down_prob)
```

```
1 def get_state_reward(s):
2     if s == 47 or s == 49 or s == 51 or s == 65 or s == 67 or s == 69:
3         return -1
4     if s == 79:
5         return 1
6     return 0
7
8 def is_playing(s):
9     return get_state_reward(s) == 0
```

```
1 def processAction(current_s, action):
2     playing = is_playing(current_s)
3     new_state = get_action_state(current_s, action)
4     reward = get_state_reward(current_s)
5     return new_state, reward, playing
```

```
1 def get_max_action(s):
2     max_value = max(qtable[s][0], qtable[s][1], qtable[s][2], qtable[s][3])
3     if max_value == qtable[s][0]:
4         return 0
5     if max_value == qtable[s][1]:
6         return 1
7     if max_value == qtable[s][2]:
8         return 2
9     if max_value == qtable[s][3]:
10        return 3
11    print("None 2!!!!")
12    return None
13
```

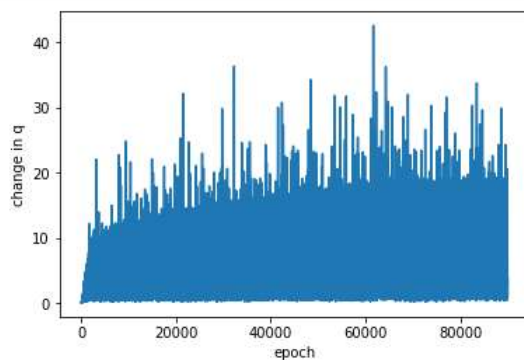
Train

```
: 1 eps = 0.8
2 alpha = 0.1
3 r = 0.99
4
5 delta_q = []
6
7 for i in range(90000):
8     if (i % 100 == 0):
9         eps = eps*0.8
10        eps = max(eps, 0.2)
11        playing = True
12        current_state = 3
13
14        qtable_before = np.copy(qtable)
15
16        while playing:
17            action = None
18            if random.random() <= eps:
19                action = random.randint(0,3)
20            else:
21                action = get_max_action(current_state)
22            new_state, reward, playing = processAction(current_state, action)
23            # print("current_state is " + str(current_state))
24            # print("new_state is " + str(new_state))
25            # print("action is " + str(action))
26            new_q_value = (1-alpha)*qtable[current_state][action] + alpha*(reward+r*np.max(qtable[new_state]))
27            qtable[current_state][action] = new_q_value
28            current_state = new_state
29
30        delta_q.append(np.linalg.norm(qtable-qtable_before))
```

```
: 1 qtable[70]
```

Plot Q:

```
1 plt.plot(range(len(delta_q)), delta_q)
2 plt.xlabel("epoch")
3 plt.ylabel("change in q")
4 plt.show()
```



Plot table:

```
1 dir = ['←', '↑', '→', '↓']
2 special = {47: 'x', 49: 'x', 65: 'x', 67: 'x', 51: 'x', 69: 'x', 79: 'o'}
3
4 for i in range(9):
5     for j in range(9):
6         cur = i + j * 9
7         if cur in special:
8             print(' ', special[cur], end='')
9         elif not np.sum(qtable[cur]) == 0:
10            print(' ', dir[np.argmax(qtable[cur])], end='')
11        else:
12            print(' ', '.', end='')
13    print('\n')
```

```
. . . . .
. . . . .
. → → ↓ . x ↓ x .
→ ↑ . ↓ ← ← ↓ ← .
. . ↓ ← . x ↓ x .
. . ↓ . . . ↓ . .
. ↓ ← . . x ↓ x .
. ↓ . → → → → → o
. → → ↑ . ↑ → ↑ .
```

I played around with the epsilon parameter. When it's small, it's hard for the agent to learn new states. When it's big, it's easier to explore new states but hard to coverage to a good policy. Given this information, I used a reducing epsilon corresponding to epoch number. It will learn fast in the beginning, and do a better job in coverage after exploring enough number of new states.

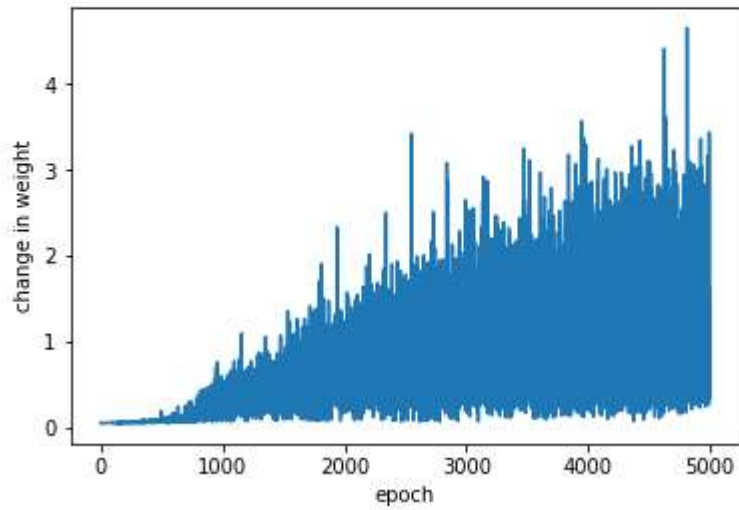
Part 2 - Using One-Hot Vectors

Model (gradient descent update rule and implementation):

```
1 w = np.zeros((4, 82))
2 losses = []
3 delta_w = []
4
5 eps = 0.8
6 r = 0.99
7 alpha = 0.05
8
9 for i in range(5000):
10     if (i % 100 == 0):
11         print(i)
12         eps = eps*0.8
13         eps = max(eps, 0.2)
14     playing = True
15     current_state = 3
16     current_state_vector = encode(current_state)
17     w_before = np.copy(w)
18
19     while playing:
20         action = get_next_move(current_state, w, eps)
21         next_state, reward, playing = processAction(current_state, action)
22
23         next_state_vector = encode(next_state)
24         max_q = max([w[i].dot(next_state_vector) for i in range(4)])
25         qplus = reward + r * max_q
26
27         losses.append(0.5*((np.dot(w[action], current_state_vector) - qplus) ** 2))
28         gradient = np.dot(np.dot(w[action], current_state_vector) - qplus, current_state_vector)
29         w[action] = w[action] - alpha * gradient
30
31         current_state = next_state
32         current_state_vector = next_state_vector
33
34     delta_w.append(np.linalg.norm(w-w_before))
```

Weight change:

```
1 plt.plot(range(len(delta_w)), delta_w)
2 plt.xlabel("epoch")
3 plt.ylabel("change in weight")
4 plt.show()
```



Plot table:

:

1 plot_table(q)

.
.	→	→	↓	.	x	↓	x	.
→	↑	.	→	→	→	↓	←	.
.	.	→	↑	.	x	↓	x	.
.	.	↑	.	.	.	↓	.	.
.	↑	↑	.	.	x	↓	x	.
.	↑	.	→	→	→	→	→	0
.	↑	↑	↑	.	↑	↑	←	.
.

In the red circle, the result is different from part 1. In part 1, it actually wants to run away from the path close to many dragons, but in part 2 it takes the path that is close to many dragons.

p1

April 26, 2019

```
In [1]: # P1
```

```
In [ ]: import re
import numpy as np

import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import TensorDataset, DataLoader
```

```
In [2]: import torch.optim as optim
```

```
In [3]: f_train_pos = open("sentiment_data/train_pos_merged.txt", encoding="utf8")
f_train_neg = open("sentiment_data/train_neg_merged.txt", encoding="utf8")
f_test_pos = open("sentiment_data/test_pos_merged.txt", encoding="utf8")
f_test_neg = open("sentiment_data/test_neg_merged.txt", encoding="utf8")
```

```
In [4]: lines_train_pos = f_train_pos.readlines()
lines_train_neg = f_train_neg.readlines()
lines_test_pos = f_test_pos.readlines()
lines_test_neg = f_test_neg.readlines()
```

```
f_train_pos.close()
f_train_neg.close()
f_test_pos.close()
f_test_neg.close()
```

```
In [5]: skip_words = set(['br', 'as', 'an', 'and', 'are', 'at', 'by', 'for', 'has', 'in',
                        'it', 'of', 'on', 'that', 'the', 'there', 'to', 'with', 'they',
                        'this', 'is', 's', 'a', 'be', 'their', 'have', 'was', 'were', 'd',
                        'll', 'he', 'she', 'his', 'her', 'i', 'your', 'or', 'them'])
```

```
In [6]: def clean_data(lines):
    ret = [None]*len(lines)
    for index in range(len(lines)):
        line = lines[index].lower()
        temp = re.sub('[^0-9a-zA-Z]+', ' ', line)
        join_string_list = []
```

```

        words = temp.split()
        for word in words:
            if not word in skip_words:
                join_string_list.append(word)
        ret[index] = ' '.join(join_string_list)
    return ret

In [7]: lines_train_pos = clean_data(lines_train_pos)
        lines_train_neg = clean_data(lines_train_neg)
        lines_test_pos = clean_data(lines_test_pos)
        lines_test_neg = clean_data(lines_test_neg)

In [8]: def load_set(lines, word_num_set):
        for line in lines:
            words = line.split()
            for word in words:
                if word in skip_words:
                    continue
                word_num_set.add(word)

In [9]: word_num_map = {}
        index_acc = 2 # 0 means padding, 1 means unknown

        train_word_set = set()
        load_set(lines_train_pos, train_word_set)
        load_set(lines_train_neg, train_word_set)

        test_word_set = set()
        load_set(lines_test_pos, test_word_set)
        load_set(lines_test_neg, test_word_set)

        all_word_set = set()
        for word in train_word_set:
            if word in test_word_set:
                all_word_set.add(word)

        for word in test_word_set:
            if word in train_word_set:
                all_word_set.add(word)

        for word in all_word_set:
            word_num_map[word] = index_acc
            index_acc = index_acc + 1

In [10]: def get_word_number(word):
        if not word in word_num_map:
            return 1
        return word_num_map[word]

```

```

In [11]: def line_to_num_list(line):
    ret = [0]*400
    words = line.split()
    if len(words) >= 400:
        for i in range(400):
            word = words[i]
            ret[i] = get_word_number(word)
    else:
        index_padding = 400-len(words)
        for i in range(len(words)):
            word = words[i]
            ret[i+index_padding] = get_word_number(word)
    return ret

def word_to_num(lines):
    ret = np.zeros((len(lines), 400), dtype=np.int32)
    for index in range(len(lines)):
        ret[index] = line_to_num_list(lines[index])
    return ret

```

```

In [12]: array_train_pos = word_to_num(lines_train_pos)
array_train_neg = word_to_num(lines_train_neg)
array_test_pos = word_to_num(lines_test_pos)
array_test_neg = word_to_num(lines_test_neg)

```

```

In [13]: SIZE = len(word_num_map)
BATCH_SIZE = 50
SIZE

```

Out[13]: 17752

```

In [15]: train_x = np.concatenate((array_train_pos, array_train_neg), axis=0)
print(train_x.shape)
train_y = np.concatenate((np.ones(array_train_pos.shape[0]), np.zeros(array_train_neg
print(train_y.shape)

```

```

(3000, 400)
(3000,)

```

```

In [16]: test_x = np.concatenate((array_test_pos, array_test_neg), axis=0)
print(test_x.shape)
test_y = np.concatenate((np.ones(array_test_pos.shape[0]), np.zeros(array_test_neg.sh
print(test_y.shape)

```

```

(3000, 400)
(3000,)

```

```

In [17]: train_data = TensorDataset(torch.from_numpy(train_x).type(torch.LongTensor), torch.from_numpy(train_y).type(torch.LongTensor))
train_loader = DataLoader(train_data, shuffle=True, batch_size=BATCH_SIZE)
test_data = TensorDataset(torch.from_numpy(test_x).type(torch.LongTensor), torch.from_numpy(test_y).type(torch.LongTensor))
test_loader = DataLoader(test_data, shuffle=True, batch_size=BATCH_SIZE)

In [18]: optimizer = None
criterion = None

def get_accuracy(predict, target):
    temp1 = predict >= 0.5
    temp2 = target >= 0.5
    temp3 = (temp1.numpy().reshape(BATCH_SIZE) == temp2.numpy().reshape(BATCH_SIZE))
    return np.sum(temp3)/BATCH_SIZE

def train(model, train_loader, test_loader):
    for time in range(10):
        print(time)
        for i, data in enumerate(train_loader):
            inputs, labels = data

            optimizer.zero_grad()
            outputs = model(inputs)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

        print('Finished Training')

    accuracy_sum = 0.0

    for i, data in enumerate(test_loader):
        inputs, label = data

        output = model(inputs)
        loss = criterion(output, label)

        accuracy = get_accuracy(output, label)
        accuracy_sum = accuracy_sum + accuracy
    print("accuracy is " + str(accuracy_sum*BATCH_SIZE/3000))

In [19]: class GRU(nn.Module):
    def __init__(self, feature_num):
        super(GRU, self).__init__()
        self.embedding = nn.Embedding(feature_num, 128)
        self.rnn = nn.GRU( input_size=128,
                           hidden_size=64,
                           num_layers=1,
                           dropout=0.5,

```



```

        batch_first=True)
    self.linear1 = nn.Linear(64, 32)
    self.linear2 = nn.Linear(32, 1)
    self.sigmoid = nn.Sigmoid()

    def forward(self, x):
        embedded = self.embedding(x)
        out, _ = self.rnn(embedded)
        out_last = out[:, -1, :] # get last value

        x = self.linear1(out_last.view(-1, out_last.shape[-1]))
        x = self.linear2(F.relu(x))
        x = self.sigmoid(x)
        return x

model1 = GRU(SIZE+2)
criterion = nn.BCELoss()
optimizer = optim.Adam(model1.parameters(), lr=0.001, betas=(0.9, 0.999))
train(model1, train_loader, test_loader)

```

0

```

C:\Users\rj369\AppData\Local\Continuum\anaconda3\lib\site-packages\torch\nn\modules\rnn.py:46:
  "num_layers={}".format(dropout, num_layers))
C:\Users\rj369\AppData\Local\Continuum\anaconda3\lib\site-packages\torch\nn\functional.py:2016:
  "Please ensure they have the same size.".format(target.size(), input.size()))

```

1
2
3
4
5
6
7
8
9

Finished Training
accuracy is 0.7470000000000001

```

In [23]: class MLP(nn.Module):
        def __init__(self):
            super(MLP, self).__init__()
            self.embedding = nn.Embedding(SIZE+2, 64)

            self.linear1 = nn.Linear(400 * 64, 32)
            self.linear2 = nn.Linear(32, 1)

```

```

        self.sigmoid = nn.Sigmoid()

    def forward(self, x):
        x = self.embedding(x)
        x = x.view(-1, 400*64)

        x = self.linear1(x)
        x = self.linear2(x)
        x = self.sigmoid(x)
        return x

model2 = MLP()
criterion = nn.BCELoss()
optimizer = optim.Adam(model2.parameters(), lr=0.0001, betas=(0.9, 0.999))
train(model2, train_loader, test_loader)

0
1
2
3
4
5
6
7
8
9
Finished Training
accuracy is 0.5706666666666664

```

p2_1

April 26, 2019

```
In [1]: import os
import matplotlib.pyplot as plt
import itertools
import pickle
import imageio
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torchvision import datasets, transforms
from torch.autograd import Variable
import torchvision

In [3]: transform = transforms.Compose([transforms.ToTensor()])

In [4]: BATCH_SIZE = 128

In [5]: fmnist = torchvision.datasets.FashionMNIST(root=".", train=True, transform=transform,
data_loader = torch.utils.data.DataLoader(dataset=fmnist, batch_size=BATCH_SIZE, shuffle=True))

In [6]: torch.cuda.is_available()

Out[6]: True

In [7]: class generator(nn.Module):
    def __init__(self):
        super(generator, self).__init__()

        self.layer0 = nn.Sequential(
            nn.Linear(100, 256),
            nn.ReLU(),
        )

        self.layer1 = nn.Sequential(
            nn.Linear(256, 512),
            nn.ReLU(),
        )
```

```

self.layer2 = nn.Sequential(
    nn.Linear(512, 1024),
    nn.ReLU(),
)

self.layer3 = nn.Sequential(
    nn.Linear(1024, 784),
    nn.Tanh()
)

def forward(self, x):
    x = self.layer0(x)
    x = self.layer1(x)
    x = self.layer2(x)
    x = self.layer3(x)
    return x

```

```

In [8]: class discriminator(nn.Module):
    def __init__(self):
        super(discriminator, self).__init__()

        self.layer0 = nn.Sequential(
            nn.Linear(784, 1024),
            nn.ReLU(),
            nn.Dropout(0.3)
        )

        self.layer1 = nn.Sequential(
            nn.Linear(1024, 512),
            nn.ReLU(),
            nn.Dropout(0.3)
        )

        self.layer2 = nn.Sequential(
            nn.Linear(512, 256),
            nn.ReLU(),
            nn.Dropout(0.3)
        )

        self.layer3 = nn.Sequential(
            nn.Linear(256, 1),
            nn.Sigmoid()
        )

    def forward(self, x):
        x = self.layer0(x)
        x = self.layer1(x)

```

```

        x = self.layer2(x)
        x = self.layer3(x)
        return x

```

```

In [9]: def show_result():
        noise = Variable(torch.randn((5*5, 100)).cuda())

        G.eval()
        test_images = G(noise)
        G.train()

        size_figure_grid = 5
        fig, ax = plt.subplots(size_figure_grid, size_figure_grid, figsize=(5, 5))
        for i, j in itertools.product(range(size_figure_grid), range(size_figure_grid)):
            ax[i, j].get_xaxis().set_visible(False)
            ax[i, j].get_yaxis().set_visible(False)

        for k in range(5*5):
            i = k // 5
            j = k % 5
            ax[i, j].cla()
            ax[i, j].imshow(test_images[k, :].cpu().data.view(28, 28).numpy(), cmap='gray')

        label = ""
        fig.text(0.5, 0.04, label, ha='center')
        plt.show()

```

```

In [10]: batch_size = 128
        lr = 0.0002
        epoch_number = 50

```

```

In [11]: G = generator()
        D = discriminator()
        G.cuda()
        D.cuda()

        criterion = nn.BCELoss()

        G_optimizer = optim.Adam(G.parameters(), lr=lr)
        D_optimizer = optim.Adam(D.parameters(), lr=lr)

```

```

In [12]: temp_index = 0

        D_loss = []
        G_loss = []

        # train
        for epoch in range(epoch_number):
            d_epoch_loss = []

```

```

g_epoch_loss = []
for x, _ in data_loader:
    #     print(temp_index)
    #     temp_index = temp_index + 1
    #     if (temp_index >= 5000):
    #         break

    x = x.view(-1, 28 * 28)
    batch_size = x.size()[0]
    # train D
    y_real = torch.ones(batch_size)
    y_fake = torch.zeros(batch_size)
    x, y_real, y_fake = Variable(x.cuda()), Variable(y_real.cuda()), Variable(y_fake.cuda())

    # get real image
    D.zero_grad()
    D_result_real = D(x)
    D_real_loss = criterion(D_result_real, y_real)

    # get fake image
    noise = Variable(torch.randn((batch_size, 100)).cuda())
    G_result = G(noise)
    D_result_fake = D(G_result)
    D_fake_loss = criterion(D_result_fake, y_fake)

    D_total_loss = D_real_loss + D_fake_loss

    D_total_loss.backward()
    D_optimizer.step()

    d_epoch_loss.append(D_total_loss.cpu().data.item())

    # train generator G
    noise = torch.randn((batch_size, 100))
    y_target = torch.ones(batch_size)
    noise, y_target = Variable(noise.cuda()), Variable(y_target.cuda())

    G.zero_grad()
    G_result = G(noise)
    D_result = D(G_result)

    G_train_loss = criterion(D_result, y_target)
    G_train_loss.backward()
    G_optimizer.step()

    g_epoch_loss.append(G_train_loss.cpu().data.item())

```

```

D_loss.append(sum(d_epoch_loss)/len(d_epoch_loss))
G_loss.append(sum(g_epoch_loss)/len(g_epoch_loss))

if (epoch == 0 or epoch == 1 or epoch == 2 or epoch == 10 or epoch == 20 or epoch
    print('epoch %d: loss_d: %.3f, loss_g: %.3f' % (
        epoch, D_loss[epoch], G_loss[epoch]))
    show_result()

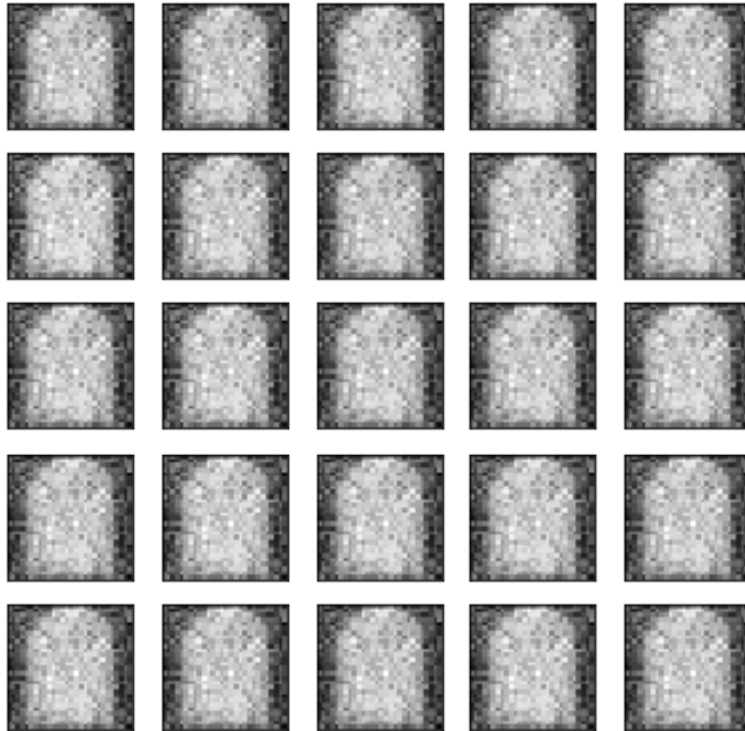
```

```

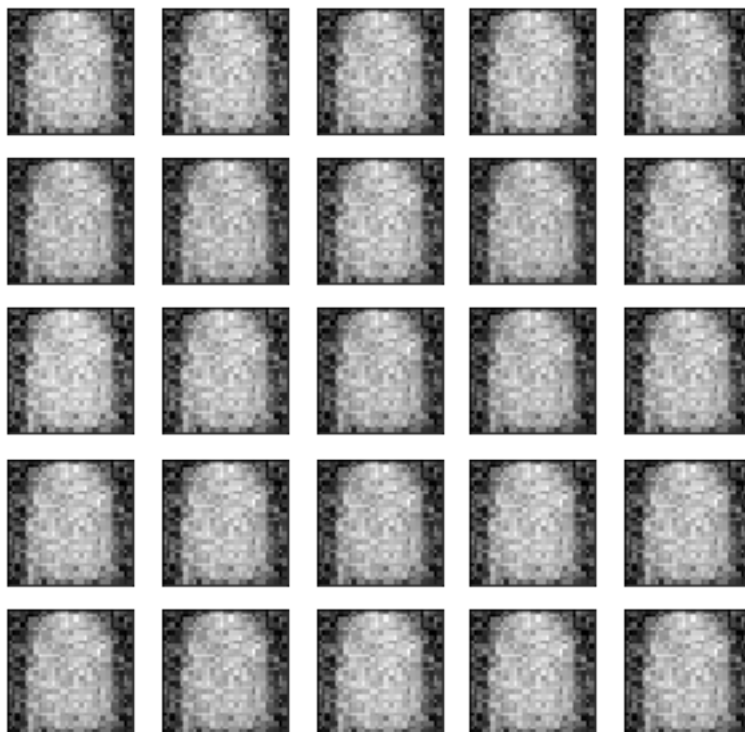
C:\Users\rj369\AppData\Local\Continuum\anaconda3\lib\site-packages\torch\nn\functional.py:2016
    "Please ensure they have the same size.".format(target.size(), input.size()))
C:\Users\rj369\AppData\Local\Continuum\anaconda3\lib\site-packages\torch\nn\functional.py:2016
    "Please ensure they have the same size.".format(target.size(), input.size()))

```

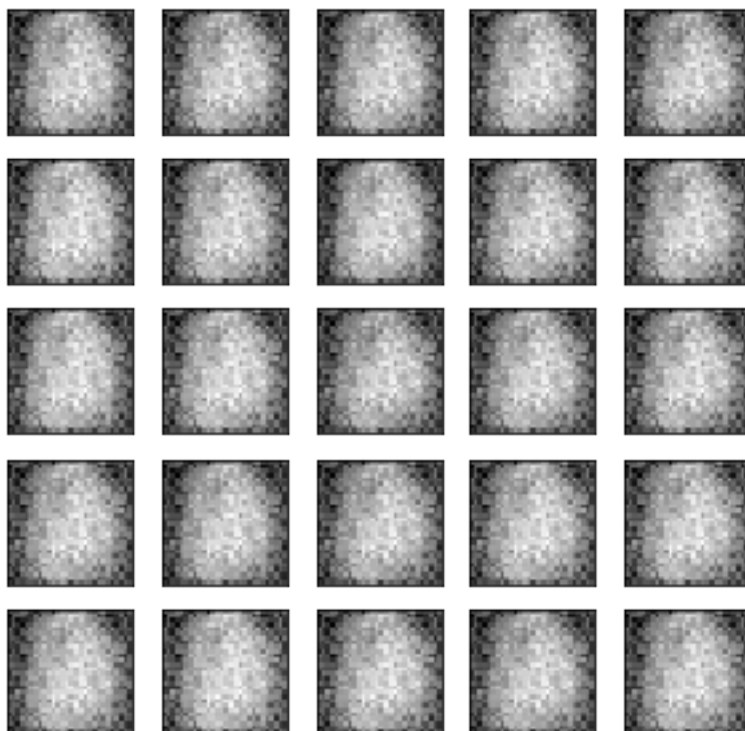
epoch 0: loss_d: 0.427, loss_g: 4.058



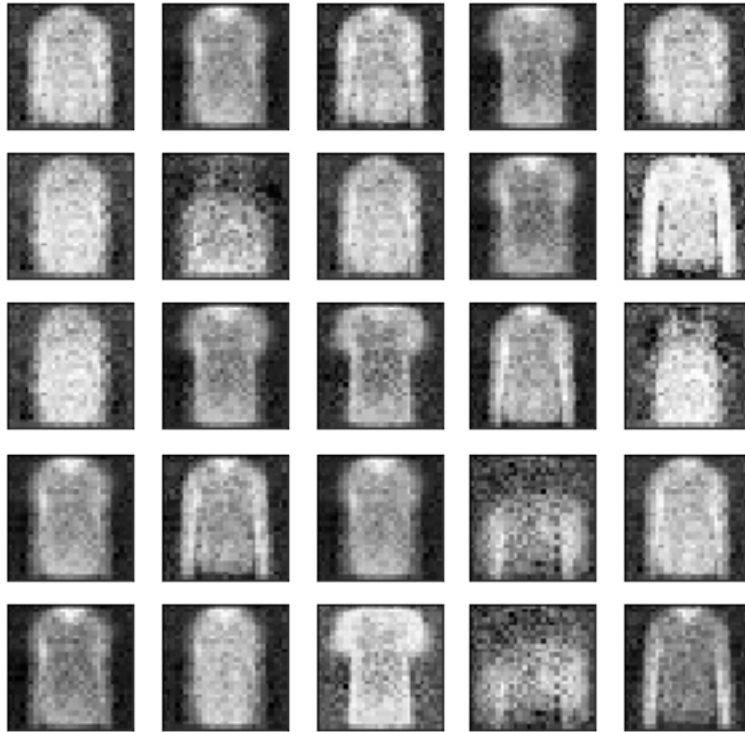
epoch 1: loss_d: 0.512, loss_g: 3.512



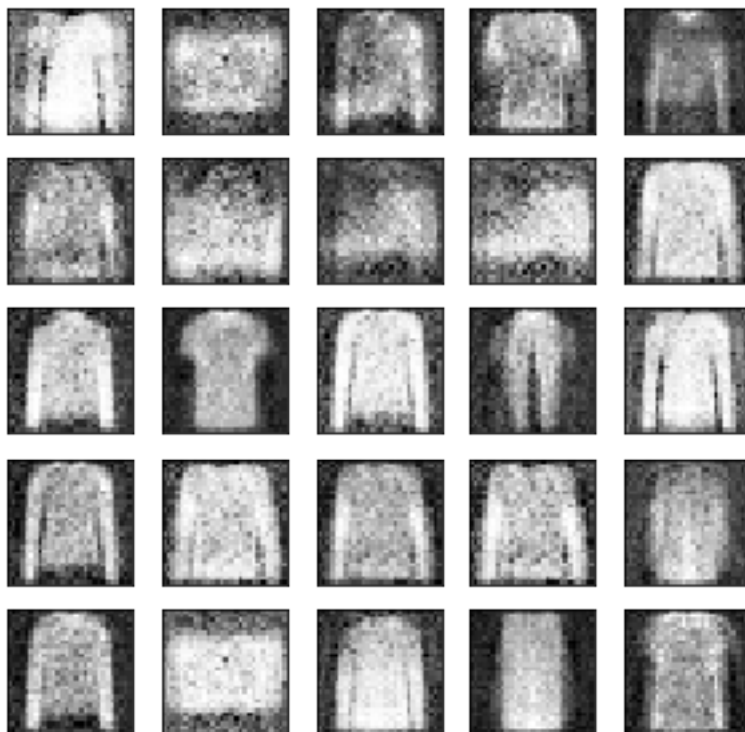
epoch 2: loss_d: 0.855, loss_g: 2.487



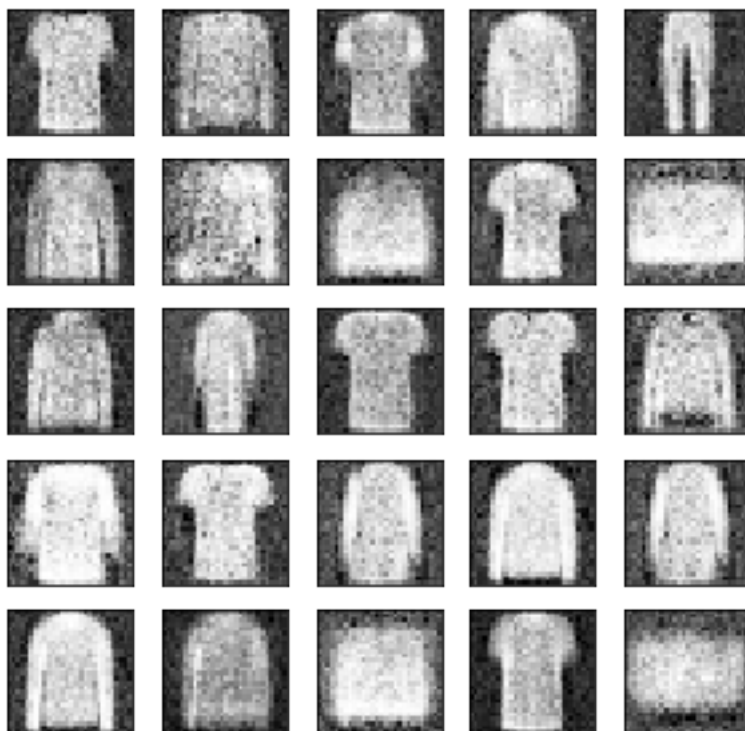
epoch 10: loss_d: 0.496, loss_g: 2.563



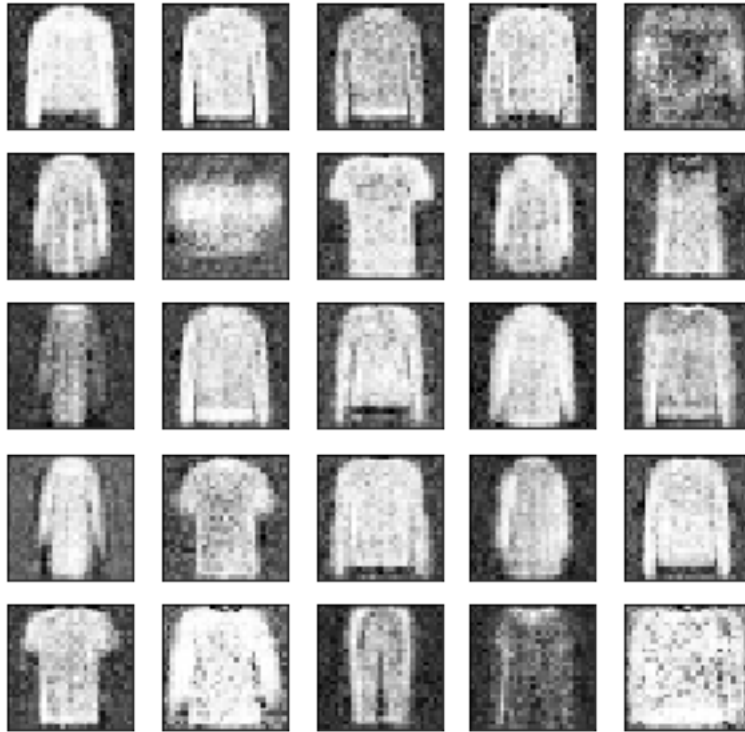
epoch 20: loss_d: 0.748, loss_g: 1.845



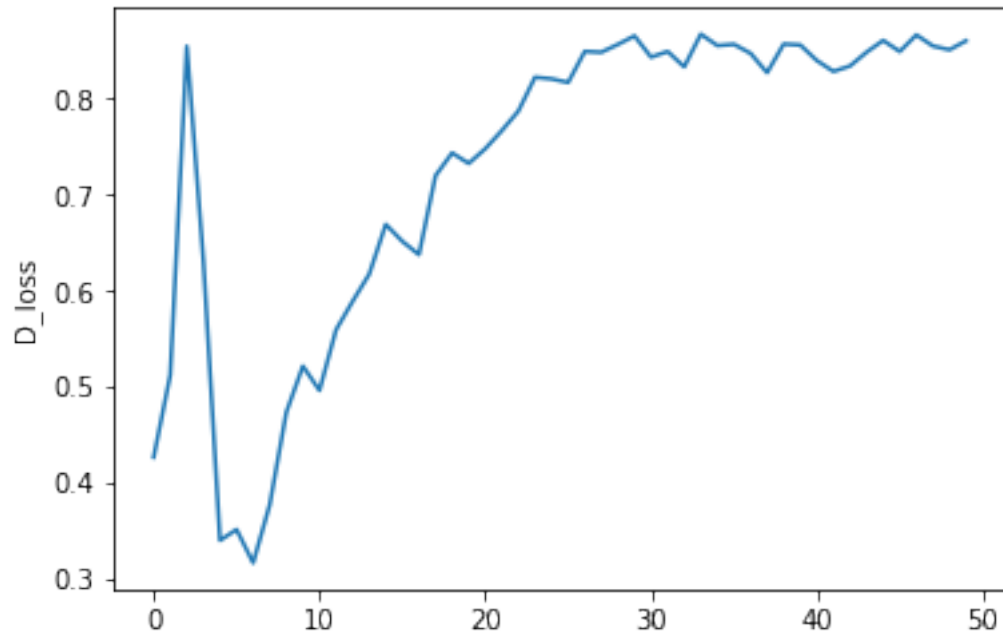
epoch 30: loss_d: 0.843, loss_g: 1.565



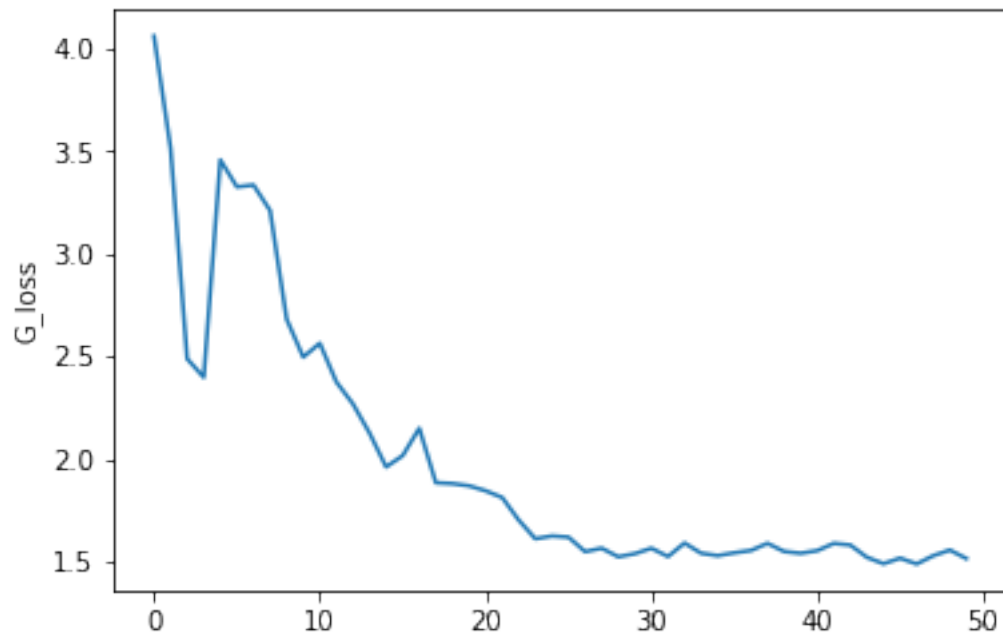
epoch 48: loss_d: 0.851, loss_g: 1.556



```
In [16]: plt.plot(D_loss)
         plt.ylabel("D_loss")
         plt.show()
```



```
In [17]: plt.plot(G_loss)
plt.ylabel("G_loss")
plt.show()
```



In [13]: D_loss

Out[13]: [0.42667620823279756,
0.5123352119282111,
0.8547294700164785,
0.6313243359327316,
0.34006550007346853,
0.35136317059810734,
0.31668396443446306,
0.37721978458387256,
0.47344570131952574,
0.521587454179711,
0.4962965416183858,
0.5593825981243333,
0.5891309815810434,
0.617374784466046,
0.6692556641630526,
0.6515478943583808,
0.6376994784071501,
0.7199377847759962,
0.7436438177440212,
0.7327160112766314,
0.748040123153597,
0.7669215342129218,
0.7873478012044293,
0.8224746010450921,
0.8207837517327591,
0.8170455678312509,
0.8493734579096471,
0.8485193214436838,
0.856657028325331,
0.8655583880095086,
0.8434241771189643,
0.8493106560920601,
0.8333091458786271,
0.8673819196757986,
0.8554345772210469,
0.8567973292712718,
0.8473844689601011,
0.8272574177937213,
0.8570642065900221,
0.8560907423877513,
0.8398703744670729,
0.8285451404321422,
0.8341935348154893,
0.8485930802217171,
0.8608230607850211,
0.8492864325864992,

```
0.8666080279645126,  
0.8549946855380337,  
0.8510942226533951,  
0.8604613430718623]
```

```
In [14]: G_loss
```

```
Out[14]: [4.057948192680822,  
3.511917046106446,  
2.4871945935509987,  
2.3969935481228046,  
3.455103845738653,  
3.3239485223664405,  
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