Machine Learning Project04

October 29, 2019

[1]:

```python
import torch
from torch.utils.data import Dataset, DataLoader
import torchvision.transforms as transforms
from torch.autograd import Variable
import torchvision
import os
import sys

from scipy.special import xlogy

import matplotlib.pyplot as plt
import numpy as np
import time


transform = transforms.Compose([#transforms.Resize((256,256)),
                                transforms.Grayscale(),                # the␣
 ↪code transforms.Graysclae() is for changing the size [3,100,100] to [1, 100,␣
 ↪100] (notice : [channel, height, width] )
                                transforms.ToTensor(),])


#train_data_path = 'relative path of training data set'
train_data_path = 'C:\\  ␣
 ↪  \\MachineLearningProject\\horse-or-human\\horse-or-human\\train'
trainset = torchvision.datasets.ImageFolder(root=train_data_path,␣
 ↪transform=transform)
# change the valuse of batch_size, num_workers for your program
# if shuffle=True, the data reshuffled at every epoch
trainloader = torch.utils.data.DataLoader(trainset, batch_size=1,␣
 ↪shuffle=False, num_workers=1)


validation_data_path = 'C:\\  ␣
 ↪  \\MachineLearningProject\\horse-or-human\\horse-or-human\\validation'
valset = torchvision.datasets.ImageFolder(root=validation_data_path,␣
 ↪transform=transform)
```

```
# change the valuse of batch_size, num_workers for your program
valloader = torch.utils.data.DataLoader(valset, batch_size=1, shuffle=False,␣
↪num_workers=1)
```

[2]:
```
train_labels=np.zeros(1027)
test_labels=np.zeros(256)

train_datas=np.zeros((1027,10000))
test_datas=np.zeros((256,10000))



for epoch in range(1):
    sum=0
    # load training images of the batch size for every iteration
    for i, data in enumerate(trainloader):

        inputs, labels = data
        train_labels[i]=int(labels)
        reinputs=inputs.reshape(10000)
        reinputs=np.array(reinputs)
        train_datas[i]=reinputs

    train_datas=train_datas.T

    for i, data in enumerate(valloader):
        sum+=1
        inputs, labels = data
        test_labels[i]=int(labels)
        reinputs=inputs.reshape(10000)
        reinputs=np.array(reinputs)
        test_datas[i]=reinputs

    test_datas=test_datas.T
```

[3]:
```
def accuracy_func(h_,label):
    label_result=np.zeros(len(h_))
    correct=0
    for i in range(len(label)):
        if(h_[i]<0.5):
            label_result[i]=0
        elif(h_[i]>=0.5):
            label_result[i]=1
```

```
        if(label_result[i]==label[i]):
            correct+=1
    total= correct/len(label)

    return total

np.set_printoptions(threshold=sys.maxsize)
```

1 sigmoid

[4]:
```
NUM_EPOCH=10000

total_loss=np.zeros(NUM_EPOCH)
total_loss_test=np.zeros(NUM_EPOCH)

accuracy=np.zeros(NUM_EPOCH)
accuracy_test=np.zeros(NUM_EPOCH)

known_data1=np.random.randn(10000,10)
known_data2=np.random.randn(10,3)
known_data3=np.random.randn(3,1)

b_1=np.random.randn(10,1)
b_2=np.random.randn(3,1)
b_3=np.random.randn(1,1)
```

[ ]:
```
l_rate=0.085

delta = 1e-70
for i in range(NUM_EPOCH):
    #Vectorizing Logistic Regression for train_set
    z1=known_data1.T@train_datas+b_1 #10x1027 =a
    A1=1.0/(1+np.exp(-z1))
    z2=known_data2.T@A1 +b_2 #3x1027=b
    A2=1.0/(1+np.exp(-z2))
    z3=known_data3.T@A2+b_3 #1x1027=c
    A3=1.0/(1+np.exp(-z3))


    #Vectorizing Logistic Regression for validation_set
    z1_v=known_data1.T@test_datas+b_1 #10x256=a
    A1_v=1.0/(1+np.exp(-z1_v))
    z2_v=known_data2.T@A1_v+b_2 #3x256=b
    A2_v=1.0/(1+np.exp(-z2_v))
    z3_v=known_data3.T@A2_v+b_3 #1x256=c
```

```
    A3_v=1.0/(1+np.exp(-z3_v))

    j=-(xlogy(train_labels,A3)+xlogy(1-train_labels,1-A3)).sum()/1027
    j_v=-(xlogy(test_labels,A3_v)+xlogy(1-test_labels,1-A3_v)).sum()/256

    #backpropagation
    L_3=A3-train_labels #1027
    L_3=L_3.reshape(1027,1)
    L_2=known_data3@L_3.T*((1-A2)*A2)
    L_1=known_data2@L_2*((1-A1)*A1) #10x1027

    #backpropagation first-layer
    dL_3=(A2@L_3.T)/1027
    known_data3-=l_rate*dL_3
    b3=np.sum(L_3,axis=1,keepdims=True)/1027

    #backpropagation second-layer
    dL_2=(A1@L_2.T)/1027
    known_data2-=l_rate*dL_2
    b2=np.sum(L_2,axis=1,keepdims=True)/1027

    #backpropagation third-layer
    dL_1=(train_datas@L_1.T)/1027
    known_data1-=l_rate*dL_1
    b1=np.sum(L_1,axis=1,keepdims=True)/1027



    total_loss[i]=j
    A3=A3.reshape(1027)
    accuracy[i]=accuracy_func(A3,train_labels)

    A3_v=A3_v.reshape(256)
    total_loss_test[i]=j_v
    accuracy_test[i]=accuracy_func(A3_v,test_labels)
```

[ ]:
```
plt.plot(total_loss,label='Training Loss')
plt.plot(total_loss_test,label='Validation Loss')
plt.legend(loc='upper right')
plt.title("Total Loss at Every Iteration")
plt.xlabel("Iteraion")
```

[ ]:
```
plt.plot(accuracy,label='Training Accuracy')
plt.plot(accuracy_test,label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title("Total Accuracy")
```

```
plt.xlabel("Iteraion")
```

[ ]:
```
print("""
+-----------------------+-----------------------+---------------------+
|       Data set        |         Loss          |      Accuracy       |
+-----------------------+-----------------------+---------------------+
|       Training        |         %6.3f         |      %6.2f %%      |
+-----------------------+-----------------------+---------------------+
|      Validation       |         %6.3f         |      %6.2f %%      |
+-----------------------+-----------------------+---------------------+"""
%(total_loss[NUM_EPOCH-1],accuracy[NUM_EPOCH-1]*100,total_loss_test[NUM_EPOCH-1],accuracy_test
```

2 tanh

[109]:
```
NUM_EPOCH=4000

total_loss=np.zeros(NUM_EPOCH)
total_loss_test=np.zeros(NUM_EPOCH)

accuracy=np.zeros(NUM_EPOCH)
accuracy_test=np.zeros(NUM_EPOCH)

known_data1=np.random.randn(10000,10)
known_data2=np.random.randn(10,3)
known_data3=np.random.randn(3,1)

b_1=np.random.randn(10,1)
b_2=np.random.randn(3,1)
b_3=np.random.randn(1,1)
```

[110]:
```
l_rate=0.08

delta = 1e-70
for i in range(NUM_EPOCH):
    #Vectorizing Logistic Regression for train_set
    z1=known_data1.T@train_datas+b_1 #10x1027 =a
    A1=np.tanh(z1)
    z2=known_data2.T@A1 +b_2 #3x1027=b
    A2=np.tanh(z2)
    z3=known_data3.T@A2+b_3 #1x1027=c
    A3=1.0/(1+np.exp(-z3))


    #Vectorizing Logistic Regression for validation_set
    z1_v=known_data1.T@test_datas+b_1 #10x256=a
    A1_v=np.tanh(z1_v)
```

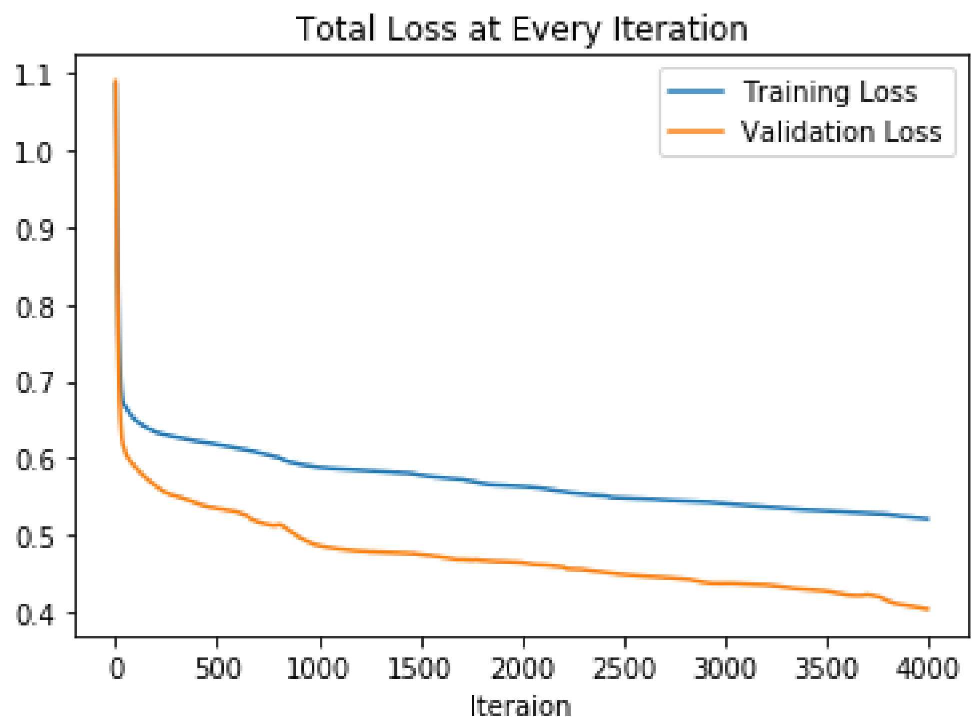
```
    z2_v=known_data2.T@A1_v+b_2 #3x256=b
    A2_v=np.tanh(z2_v)
    z3_v=known_data3.T@A2_v+b_3 #1x256=c
    A3_v=1.0/(1+np.exp(-z3_v))

    j=-(xlogy(train_labels,A3)+xlogy(1-train_labels,1-A3)).sum()/1027
    j_v=-(xlogy(test_labels,A3_v)+xlogy(1-test_labels,1-A3_v)).sum()/256

    #backpropagation
    L_3=A3-train_labels  #1027
    L_3=L_3.reshape(1,1027) #3x1
    L_2=known_data3@L_3*(1-A2*A2)     #1x1027
    L_1=known_data2@L_2*(1-A1*A1)

    #backpropagation first-layer
    dL_3=(A2@L_3.T)/1027 #3x1
    known_data3-=l_rate*dL_3
    b3=np.sum(L_3,axis=1,keepdims=True)/1027

    #backpropagation second-layer
    dL_2=(A1@L_2.T)/1027
    known_data2-=l_rate*dL_2
    b2=np.sum(L_2,axis=1,keepdims=True)/1027

    #backpropagation third-layer
    dL_1=(train_datas@L_1.T)/1027
    known_data1-=l_rate*dL_1
    b1=np.sum(L_1,axis=1,keepdims=True)/1027



    total_loss[i]=j
    A3=A3.reshape(1027)
    accuracy[i]=accuracy_func(A3,train_labels)

    A3_v=A3_v.reshape(256)
    total_loss_test[i]=j_v
    accuracy_test[i]=accuracy_func(A3_v,test_labels)
```

```
     ␣
↪---------------------------------------------------------------------------

    KeyboardInterrupt                         Traceback (most recent call␣
↪last)

    <ipython-input-110-d8d7edb2d12a> in <module>
```

```
     38     #backpropagation third-layer
     39     L_1=known_data2@L_2*(1-A1*A1) #10x1027
---> 40     dL_1=(train_datas@L_1.T)/1027
     41     known_data1-=l_rate*dL_1
     42     b1=np.sum(L_1,axis=1,keepdims=True)/1027


KeyboardInterrupt:
```

[26]:
```python
plt.plot(total_loss,label='Training Loss')
plt.plot(total_loss_test,label='Validation Loss')
plt.legend(loc='upper right')
plt.title("Total Loss at Every Iteration")
plt.xlabel("Iteraion")
```

[26]:
```
Text(0.5, 0, 'Iteraion')
```



[ ]:
```python
plt.plot(accuracy,label='Training Accuracy')
plt.plot(accuracy_test,label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title("Total Accuracy")
plt.xlabel("Iteraion")
```

[27]:
```
print("""
+-----------------------+-----------------------+---------------------+
|       Data set        |          Loss         |      Accuracy       |
+-----------------------+-----------------------+---------------------+
|       Training        |         %6.3f         |      %6.2f %%       |
+-----------------------+-----------------------+---------------------+
|      Validation       |         %6.3f         |      %6.2f %%       |
+-----------------------+-----------------------+---------------------+"""
%(total_loss[NUM_EPOCH-1],accuracy[NUM_EPOCH-1]*100,total_loss_test[NUM_EPOCH-1],accuracy_test
```

```
+-----------------------+-----------------------+---------------------+
|       Data set        |          Loss         |      Accuracy       |
+-----------------------+-----------------------+---------------------+
|       Training        |          0.521        |       74.88 %       |
+-----------------------+-----------------------+---------------------+
|      Validation       |          0.404        |       84.38 %       |
+-----------------------+-----------------------+---------------------+
```

3 ReLu

[342]:
```
def relu_prime(A):
    dA= np.where(A>0,1,0)
    return dA
```

[347]:
```
NUM_EPOCH=4000

total_loss=np.zeros(NUM_EPOCH)
total_loss_test=np.zeros(NUM_EPOCH)

accuracy=np.zeros(NUM_EPOCH)
accuracy_test=np.zeros(NUM_EPOCH)

known_data1=np.random.randn(10000,10)*0.1
known_data2=np.random.randn(10,3)*0.1
known_data3=np.random.randn(3,1)*0.1

b_1=np.random.randn(10,1)*0.1
b_2=np.random.randn(3,1)*0.1
b_3=np.random.randn(1,1)*0.1
```

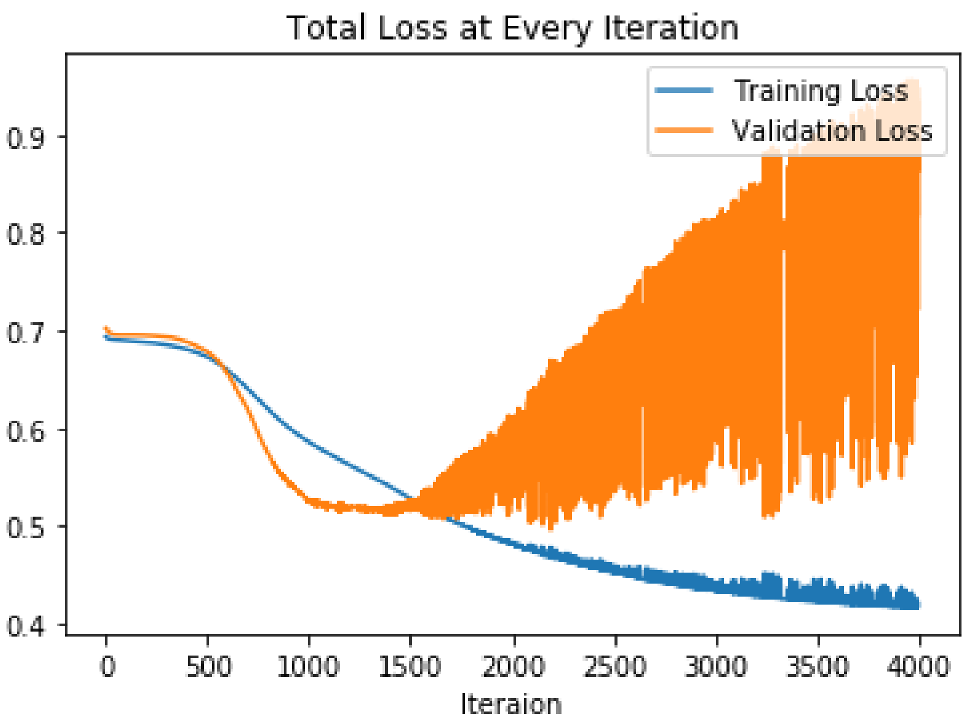
[348]:
```
l_rate=0.0087

delta = 1e-70
for i in range(NUM_EPOCH):
    #Vectorizing Logistic Regression for train_set
    z1=np.dot(known_data1.T,train_datas)+b_1 #10x1027 =a
```

```
    A1=np.maximum(0,z1)
    z2=np.dot(known_data2.T,A1) +b_2 #3x1027=b
    A2=np.maximum(0,z2)
    z3=np.dot(known_data3.T,A2)+b_3 #1x1027=c
    A3=1.0/(1+np.exp(-z3))

    #Vectorizing Logistic Regression for validation_set
    z1_v=np.dot(known_data1.T,test_datas)+b_1 #10x256=a
    A1_v=np.maximum(0,z1_v)
    z2_v=np.dot(known_data2.T,A1_v)+b_2 #3x256=b
    A2_v=np.maximum(0,z2_v)
    z3_v=np.dot(known_data3.T,A2_v)+b_3 #1x256=c
    A3_v=1.0/(1+np.exp(-z3_v))

    j=-(xlogy(train_labels,A3)+xlogy(1-train_labels,1-A3)).sum()/1027
    j_v=-(xlogy(test_labels,A3_v)+xlogy(1-test_labels,1-A3_v)).sum()/256


    #backpropagation
    L_3=A3-train_labels  #L_3=1x1027
    L_3=L_3.reshape(1,1027)
    L_2=np.multiply(np.dot(known_data3,L_3),relu_prime(A2)) #L_2= 3x1027
    L_1=np.multiply(np.dot(known_data2,L_2),relu_prime(A1)) #L_1= 10x1027

#    print(j)
    #backpropagation first-layer
    dL_3=np.dot(A2,L_3.T)/1027
    known_data3-=l_rate*dL_3
    b3=np.sum(L_3,axis=1,keepdims=True)/1027

    #backpropagation second-layer
    dL_2=np.dot(A1,L_2.T)/1027 #10x3
    known_data2-=l_rate*dL_2
    b2=np.sum(L_2,axis=1,keepdims=True)/1027

    #backpropagation third-layer
    dL_1=np.dot(train_datas,L_1.T)/1027 #10000x10
    known_data1-=l_rate*dL_1
    b1=np.sum(L_1,axis=1,keepdims=True)/1027


    total_loss[i]=j
    A3=A3.reshape(1027)
    accuracy[i]=accuracy_func(A3,train_labels)

    A3_v=A3_v.reshape(256)
    total_loss_test[i]=j_v
```

```
    accuracy_test[i]=accuracy_func(A3_v,test_labels)
```

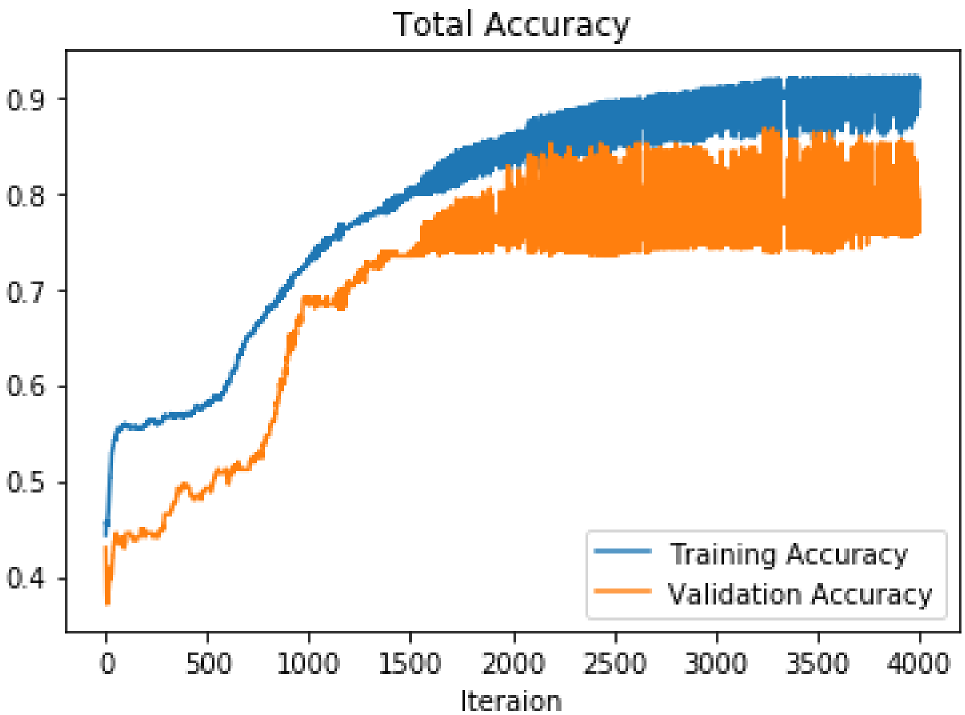
[349]:
```
plt.plot(total_loss,label='Training Loss')
plt.plot(total_loss_test,label='Validation Loss')
plt.legend(loc='upper right')
plt.title("Total Loss at Every Iteration")
plt.xlabel("Iteraion")
```

[349]: Text(0.5, 0, 'Iteraion')



[350]:
```
plt.plot(accuracy,label='Training Accuracy')
plt.plot(accuracy_test,label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title("Total Accuracy")
plt.xlabel("Iteraion")
```

[350]: Text(0.5, 0, 'Iteraion')



4 Leaky ReLu

[311]:
```
def leakyrelu_prime(A):
    dA=np.where(A<0,0.01,1.0)
    return dA
```

[ ]:
```
NUM_EPOCH=10000

total_loss=np.zeros(NUM_EPOCH)
total_loss_test=np.zeros(NUM_EPOCH)

accuracy=np.zeros(NUM_EPOCH)
accuracy_test=np.zeros(NUM_EPOCH)

known_data1=np.random.randn(10000,25)
known_data2=np.random.randn(25,3)
known_data3=np.random.randn(3,1)

b_1=np.random.randn(25,1)
b_2=np.random.randn(3,1)
b_3=np.random.randn(1,1)
```

```
[ ]: l_rate=0.065

     delta = 1e-70
     for i in range(NUM_EPOCH):
         #Vectorizing Logistic Regression for train_set
         z1=np.dot(known_data1.T,train_datas)+b_1 #10x1027 =a
         A1=np.maximum(0.01*z1,z1)
         z2=np.dot(known_data2.T,A1) +b_2 #3x1027=b
         A2=np.maximum(0.01*z2,z2)
         z3=np.dot(known_data3.T,A2)+b_3 #1x1027=c
         A3=1.0/(1+np.exp(-z3))

         #Vectorizing Logistic Regression for validation_set
         z1_v=np.dot(known_data1.T,test_datas)+b_1 #10x256=a
         A1_v=np.maximum(0.01*z1_v,z1_v)
         z2_v=np.dot(known_data2.T,A1_v)+b_2 #3x256=b
         A2_v=np.maximum(0.01*z2_v,z2_v)
         z3_v=np.dot(known_data3.T,A2_v)+b_3 #1x256=c
         A3_v=1.0/(1+np.exp(-z3_v))

         j=-(xlogy(train_labels,A3)+xlogy(1-train_labels,1-A3)).sum()/1027
         j_v=-(xlogy(test_labels,A3_v)+xlogy(1-test_labels,1-A3_v)).sum()/256


         #backpropagation
         L_3=A3-train_labels  #L_3=1x1027
         L_3=L_3.reshape(1,1027)
         L_2=np.multiply(np.dot(known_data3,L_3),leakyrelu_prime(A2)) #L_2= 3x1027
         L_1=np.multiply(np.dot(known_data2,L_2),leakyrelu_prime(A1)) #L_1= 10x1027

     #    print(j)
         #backpropagation first-layer
         dL_3=np.dot(A2,L_3.T)/1027
         known_data3-=l_rate*dL_3
         b3=np.sum(L_3,axis=1,keepdims=True)/1027

         #backpropagation second-layer
         dL_2=np.dot(A1,L_2.T)/1027 #10x3
         known_data2-=l_rate*dL_2
         b2=np.sum(L_2,axis=1,keepdims=True)/1027

         #backpropagation third-layer
         dL_1=np.dot(train_datas,L_1.T)/1027 #10000x10
         known_data1-=l_rate*dL_1
         b1=np.sum(L_1,axis=1,keepdims=True)/1027
```

```python
    total_loss[i]=j
    A3=A3.reshape(1027)
    accuracy[i]=accuracy_func(A3,train_labels)

    A3_v=A3_v.reshape(256)
    total_loss_test[i]=j_v
    accuracy_test[i]=accuracy_func(A3_v,test_labels)
```

[ ]:
```python
plt.plot(total_loss,label='Training Loss')
plt.plot(total_loss_test,label='Validation Loss')
plt.legend(loc='upper right')
plt.title("Total Loss at Every Iteration")
plt.xlabel("Iteraion")
```

[ ]:
```python
plt.plot(accuracy,label='Training Accuracy')
plt.plot(accuracy_test,label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title("Total Accuracy")
plt.xlabel("Iteraion")
```