Machine Learning Project04

October 30, 2019

1 Binary classification based on 3 layers neural network

- This is given by Professor

[1]:
```
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)
```

- This is given by Professor

[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
```

- Calculating Accuracy of labels

[3]:
```python
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)
```

1.1 sigmoid

- Initialization Train and Validation set.

[684]:
```python
NUM_EPOCH=15000

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_data is weight sets.
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)
```

- Optimization in 3 Layers
- Vertorizing Logistic Regression'c gradient Computation in 3 Layers
- Neural Network Representations
- known_data1 => 10000 x 10 , known_data2 => 10 x 3 ,known_data3 => 3 x 1

[685]:
```python
l_rate=0.085
j=0
#Vertorizing Logistic Regression'c gradient Computation in 3 Layers
while(True):
```

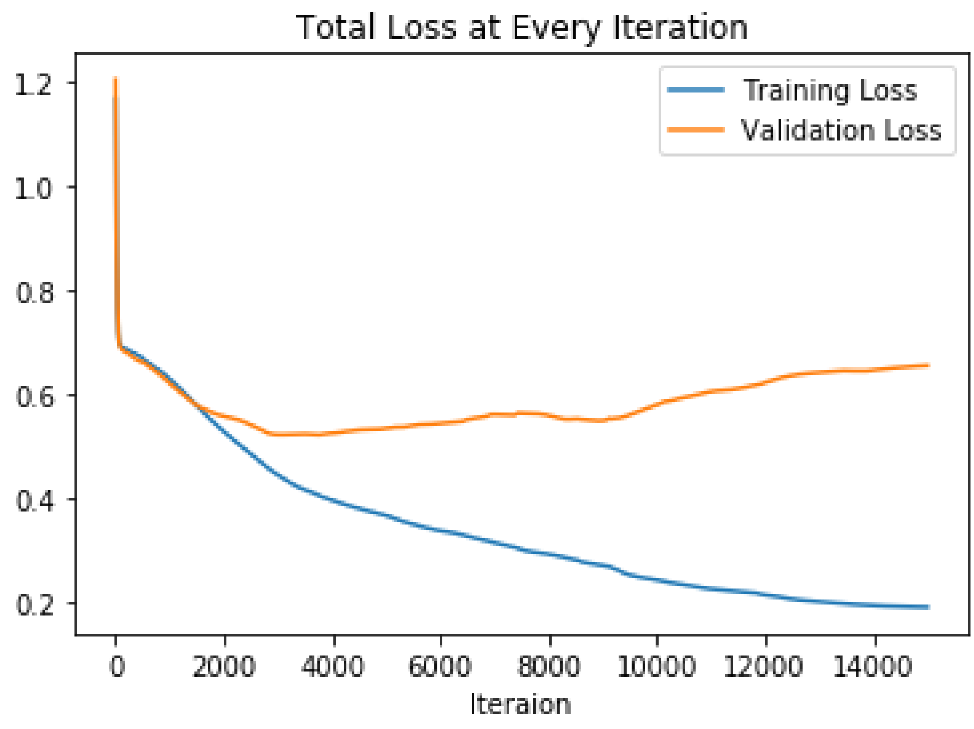
```
#Forward propagation for train_set
z1=np.dot(known_data1.T,train_datas)+b_1 #10x1027 =a
A1=1.0/(1+np.exp(-z1))
z2=np.dot(known_data2.T,A1)+b_2 #3x1027=b
A2=1.0/(1+np.exp(-z2))
z3=np.dot(known_data3.T,A2)+b_3 #1x1027=c
A3=1.0/(1+np.exp(-z3))


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

#Calculating total cost
pre_j==j
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

#Stop the iteration if train sets converge.
if(pre_j==j):
    NUM_EPOCH=i+1
    break

#Backpropagation
L_3=A3-train_labels #1027
L_3=L_3.reshape(1,1027)
L_2=np.dot(known_data3,L_3)*((1-A2)*A2)
L_1=np.dot(known_data2,L_2)*((1-A1)*A1) #10x1027

#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
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
known_data1-=l_rate*dL_1
b1=np.sum(L_1,axis=1,keepdims=True)/1027
```

```
#Calculating Accuracy
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)
```

- Plot the loss of Train and Validation at every iteration

[686]:
```
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")
```

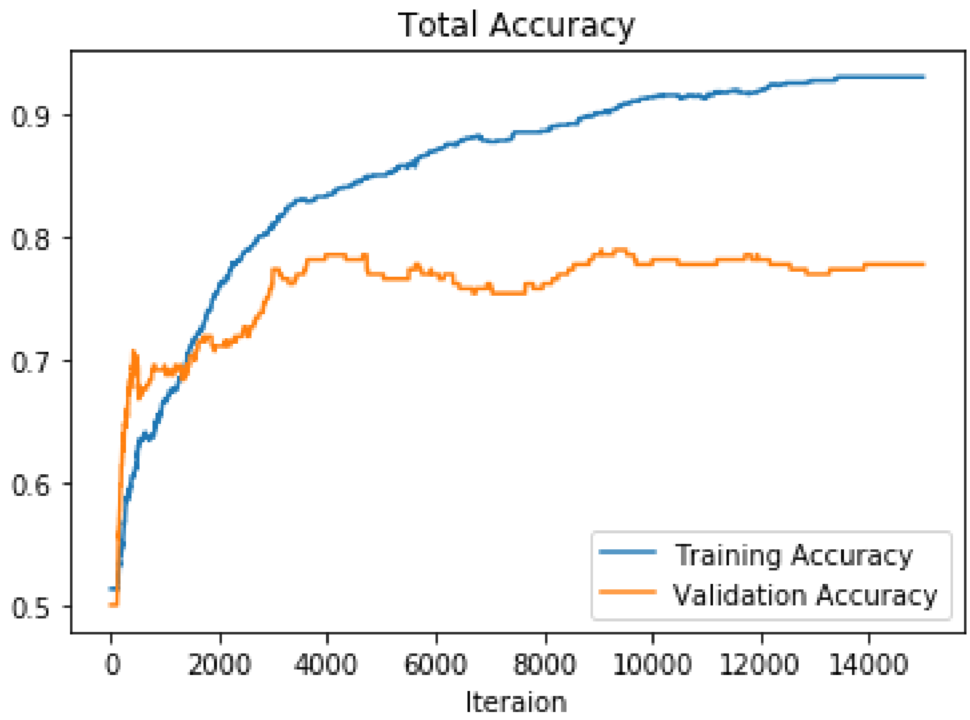
[686]:
```
Text(0.5, 0, 'Iteraion')
```



- Plot the Accuracy of Train and Validation

[687]:
```
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")
```

[687]:
```
Text(0.5, 0, 'Iteraion')
```



- Present the table for the final accuracy and loss with training and validation datasets
- Accuracy multiply 100 to present as a persent(%)

[688]:
```
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        |         0.189         |      92.99 %       |
+-----------------------+-----------------------+--------------------+
|      Validation       |         0.654         |      77.73 %       |
+-----------------------+-----------------------+--------------------+
```

2 tanh

- Initialization Train and Validation set.

[969]:
```
NUM_EPOCH=15000

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)
```

- Optimization in 3 Layers
- Vertorizing Logistic Regression'c gradient Computation in 3 Layers
- Neural Network Representations
- known_data1 => 10000 x 10 , known_data2 => 10 x 3 ,known_data3 => 3 x 1

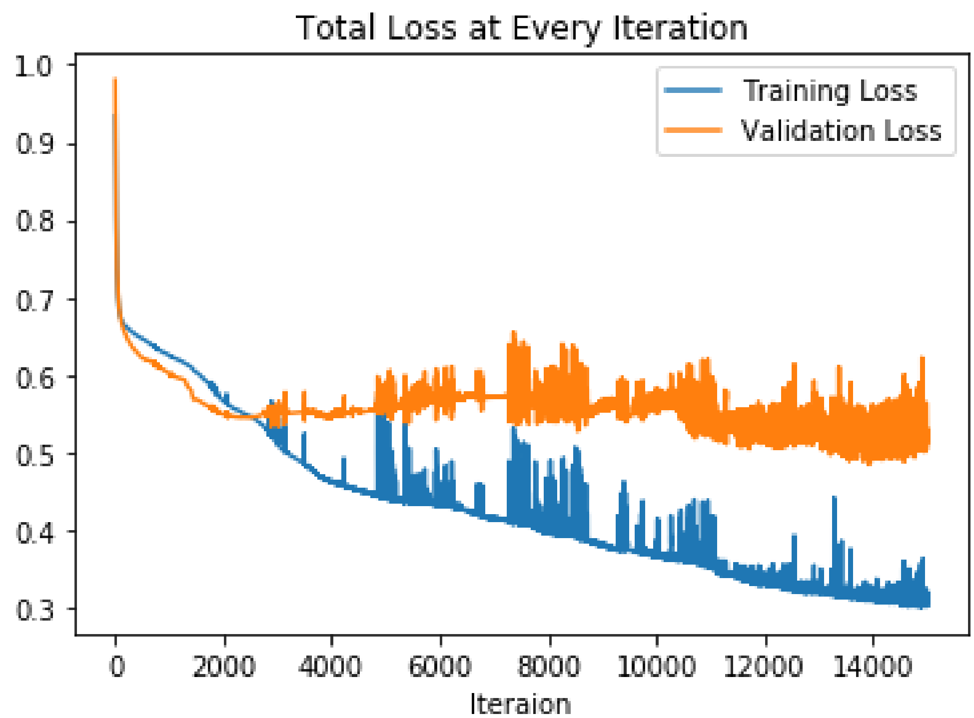
[970]:
```
#Learning rate
l_rate=0.09

j=0
#Vertorizing Logistic Regression'c gradient Computation in 3 Layers
while(True):

    #Forward propagation for train_set
    z1=np.dot(known_data1.T,train_datas)+b_1 #10x1027 =a
    A1=np.tanh(z1)
    z2=np.dot(known_data2.T,A1)+b_2 #3x1027=b
    A2=np.tanh(z2)
    z3=np.dot(known_data3.T,A2)+b_3 #1x1027=c
    A3=1.0/(1+np.exp(-z3))


    #Forward propagation for validation_set
```

```
z1_v=np.dot(known_data1.T,test_datas)+b_1 #10x256=a
A1_v=np.tanh(z1_v)
z2_v=np.dot(known_data2.T,A1_v)+b_2 #3x256=b
A2_v=np.tanh(z2_v)
z3_v=np.dot(known_data3.T,A2_v)+b_3 #1x256=c
A3_v=1.0/(1+np.exp(-z3_v))

#Calculating total cost
pre_j==j
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

#Stop the iteration if train sets converge.
if(pre_j==j):
    NUM_EPOCH=i+1
    break

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

#backpropagation first-layer
dL_3=np.dot(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=np.dot(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=np.dot(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)
```

- Plot the loss of Train and Validation at every iteration

[971]:
```
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")
```

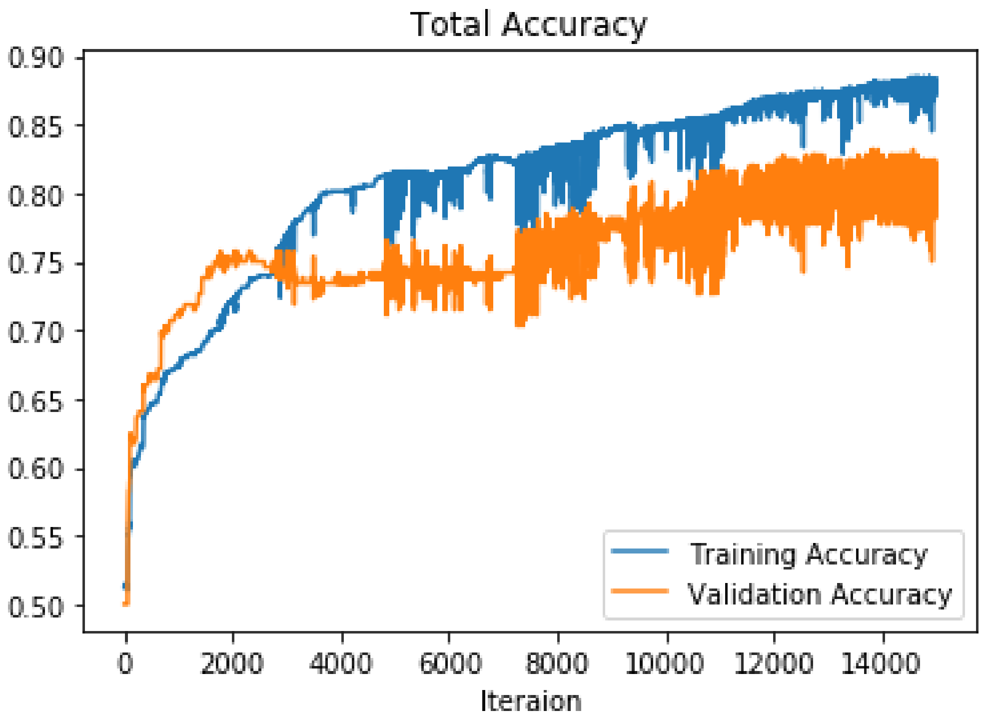
[971]:
```
Text(0.5, 0, 'Iteraion')
```



- Plot the Accuracy of Train and Validation

[972]:
```
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")
```

[972]:
```
Text(0.5, 0, 'Iteraion')
```



- Present the table for the final accuracy and loss with training and validation datasets
- Accuracy multiply 100 to present as a persent(%)

[973]:
```
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        |          0.303         |       88.41 %      |
+-----------------------+-----------------------+---------------------+
|      Validation       |          0.506         |       82.03 %      |
+-----------------------+-----------------------+---------------------+
```

3 ReLu

- Function for calculating gradient ReLu

[757]:
```
def relu_prime(A):
    dA= np.where(A>0,1,0)
    return dA
```

- Initialization Train and Validation set.

[893]:
```
NUM_EPOCH=5000

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
```

- Optimization in 3 Layers
- Vertorizing Logistic Regression'c gradient Computation in 3 Layers
- Neural Network Representations
- known_data1 => 10000 x 10 , known_data2 => 10 x 3 ,known_data3 => 3 x 1

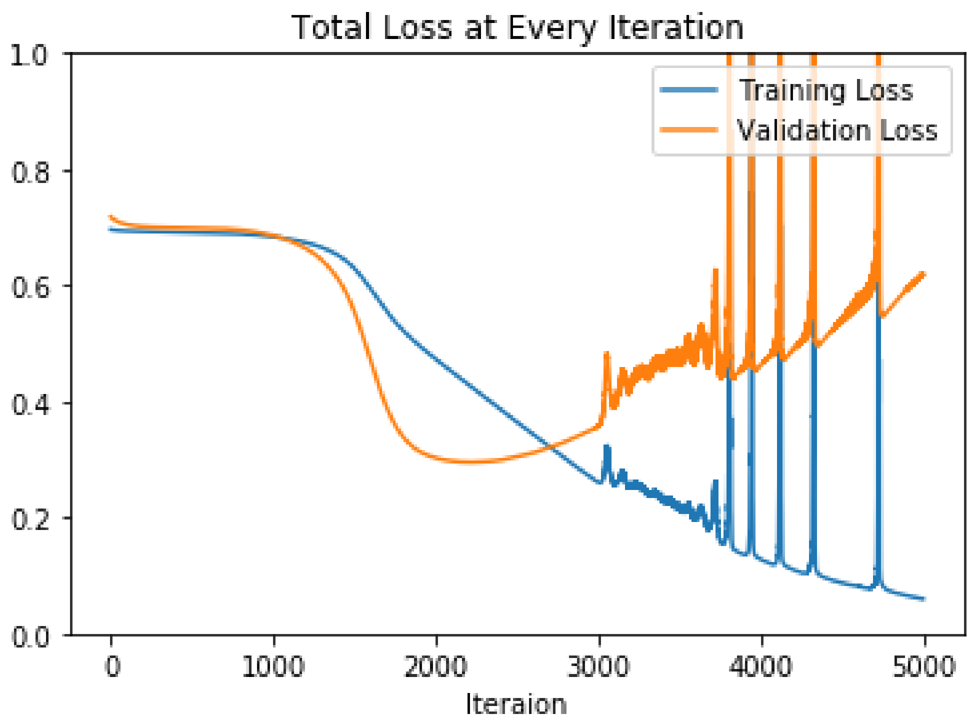
[894]:
```
#Learning rate
l_rate=0.007
j=10

#Vertorizing Logistic Regression'c gradient Computation in 3 Layers
while(True):

    #Forward propagation 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))

    #Forward propagation 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))

#Calculating total cost
pre_j==j
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
total_loss[i]=j
total_loss_test[i]=j_v

#Stop the iteration if train sets converge.
if(pre_j==j):
    NUM_EPOCH=i+1
    break

#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

#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

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

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

- Plot the loss of Train and Validation at every iteration

```
[898]: plt.plot(total_loss,label='Training Loss')
       plt.plot(total_loss_test,label='Validation Loss')
       plt.ylim([0,1])
       plt.legend(loc='upper right')
       plt.title("Total Loss at Every Iteration")
       plt.xlabel("Iteraion")
```

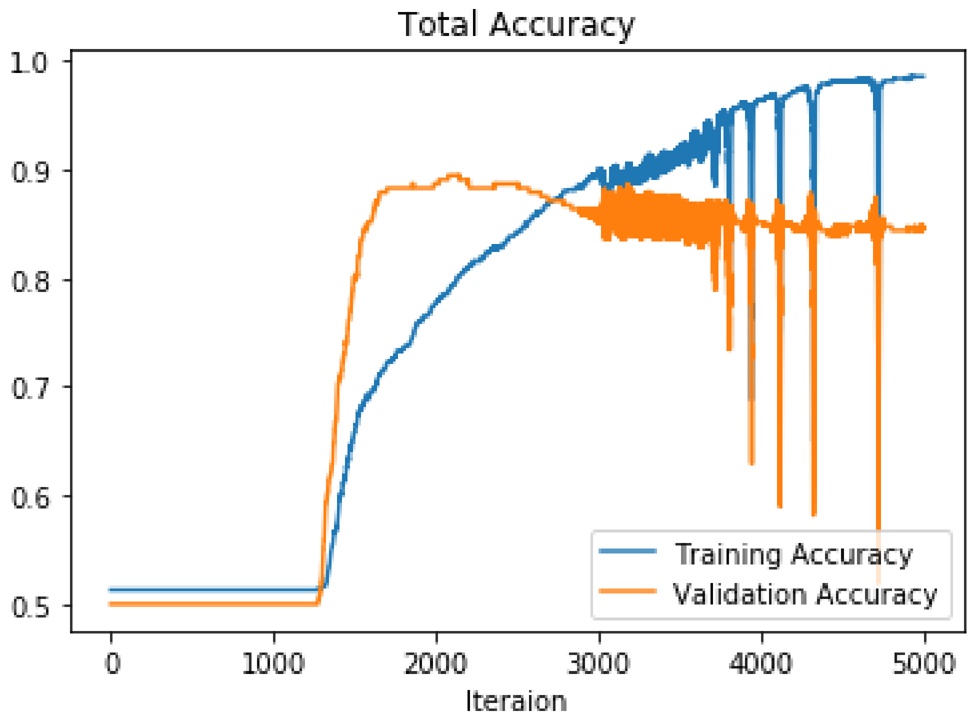
```
[898]: Text(0.5, 0, 'Iteraion')
```



- Plot the Accuracy of Train and Validation

```
[896]: 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")
```

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



- Present the table for the final accuracy and loss with training and validation datasets
- Accuracy multiply 100 to present as a persent(%)

[897]:
```
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        |          0.060        |       98.54 %      |
+-----------------------+-----------------------+--------------------+
|      Validation       |          0.619        |       84.77 %      |
+-----------------------+-----------------------+--------------------+
```

4 Leaky ReLu

- Function for calculating gradient Leaky ReLu

[647]:
```
def leakyrelu_prime(A):
    dA=np.where(A<0,0.01,1.0)
    return dA
```

- Initialization Train and Validation set.

[928]:
```
NUM_EPOCH=8500

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)*0.8
known_data2=np.random.randn(10,3)*0.8
known_data3=np.random.randn(3,1)*0.8

b_1=np.random.randn(10,1)*0.8
b_2=np.random.randn(3,1)*0.8
b_3=np.random.randn(1,1)*0.8
```

- Optimization in 3 Layers
- Vertorizing Logistic Regression'c gradient Computation in 3 Layers
- Neural Network Representations
- known_data1 => 10000 x 10 , known_data2 => 10 x 3 ,known_data3 => 3 x 1

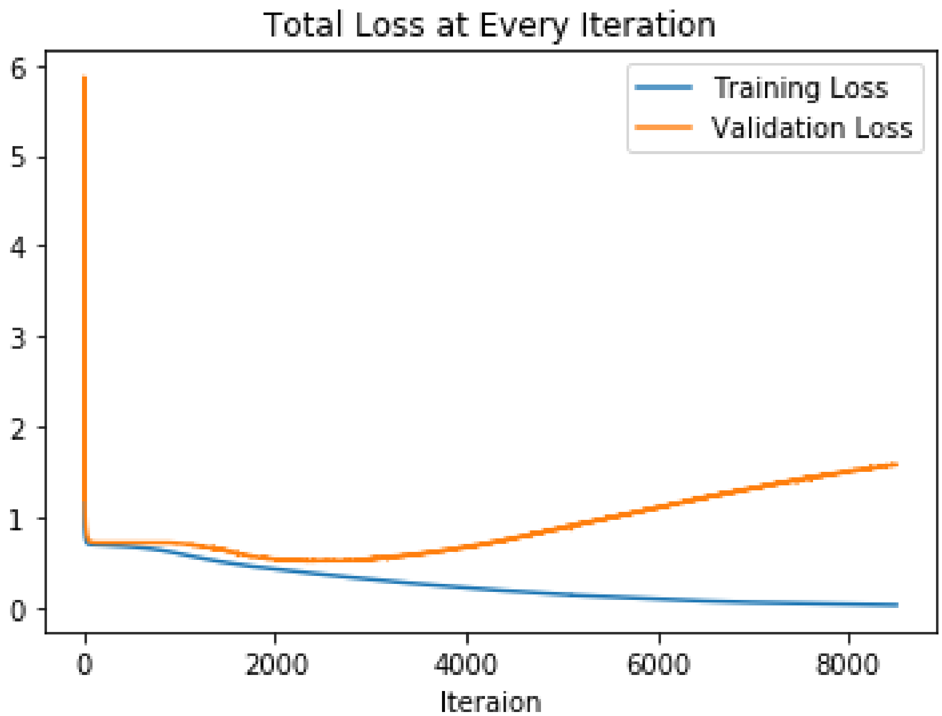
[929]:
```
l_rate=0.09
j=0

#Vertorizing Logistic Regression'c gradient Computation in 3 Layers
while(True):

    #Forward propagation 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))

    #Forward propagation 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))

#Calculating total cost
pre_j==j
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
total_loss[i]=j
total_loss_test[i]=j_v

#Stop the iteration if train sets converge.
if(pre_j==j):
    NUM_EPOCH=i+1
    break

#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

#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


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

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

- Plot the loss of Train and Validation at every iteration

[930]:
```
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")
```

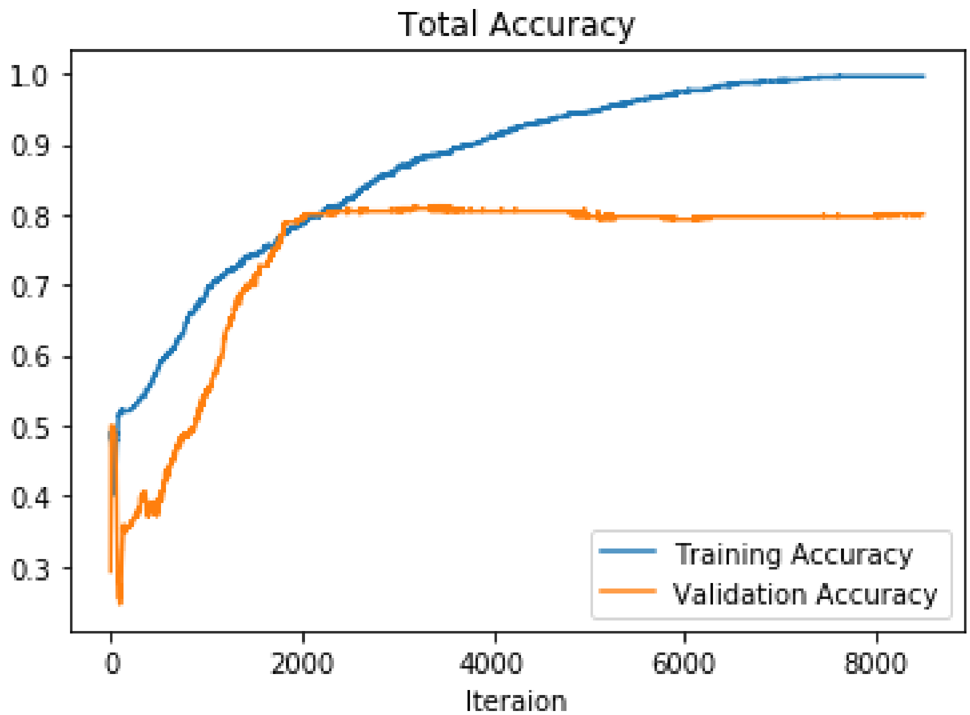
[930]: Text(0.5, 0, 'Iteraion')



- Plot the Accuracy of Train and Validation

[931]:
```
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")
```

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



- Present the table for the final accuracy and loss with training and validation datasets
- Accuracy multiply 100 to present as a persent(%)

[932]:
```
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        |         0.027         |      99.61 %       |
+-----------------------+-----------------------+--------------------+
|      Validation       |         1.581         |      80.08 %       |
+-----------------------+-----------------------+--------------------+
```