Machine Learning Project06

November 7, 2019

1 Binary classification based on 3 layers neural network

- This is given by Professor

[2]:
```
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:\\Users\\newmi\\OneDrive\\ ␣
 ↪ \\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:\\Users\\newmi\\OneDrive\\ ␣
↪ \\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

[3]:
```
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

[978]:
```python
def accuracy_func(h_,label):
    correct=0
    for i in range(len(label)):
        if(h_[i]<0.5 and label[i]==0):
            correct+=1
        elif(h_[i]>=0.5 and label[i]==1):
            correct+=1
    total= correct/len(label)

    return total

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

1.1 Bias: When Lamda is too big (Underfitting)

[1159]:
```python
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_data is weight sets.
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
```

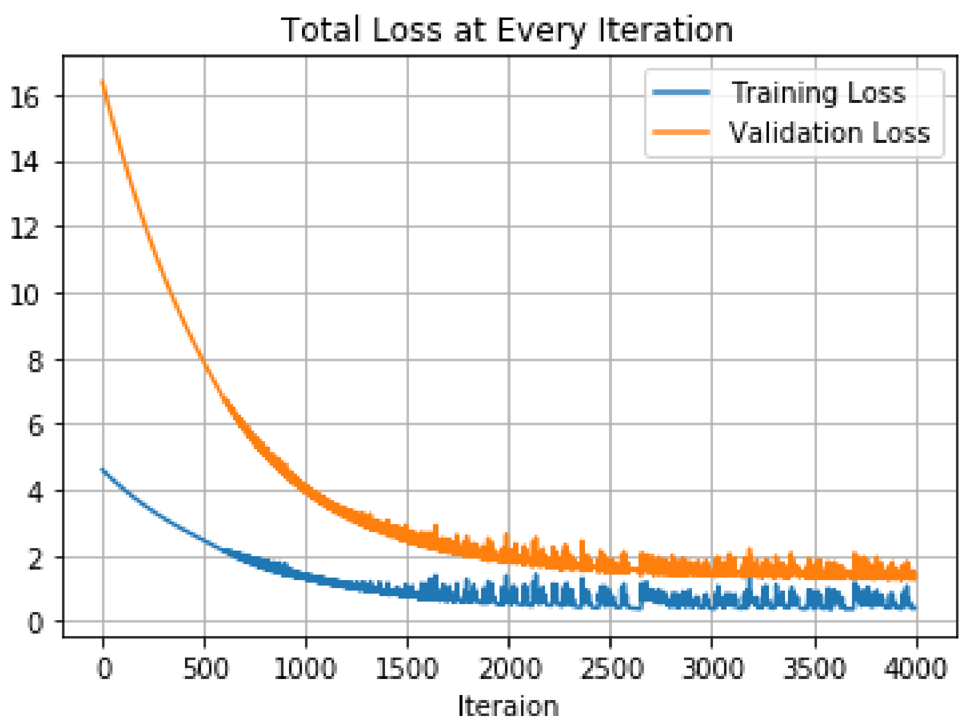
[1160]:
```python
l_rate=0.2
j=0

lamd=4.0

#Vertorizing Logistic Regression'c gradient Computation in 3 Layers
for i in range(NUM_EPOCH):

    #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 + ((lamd/
↪2)*((known_data1*known_data1).sum()+
                      (known_data2*known_data2).sum()+(known_data1*known_data1).
↪sum()))/1027
    j_v=-(xlogy(test_labels,A3_v)+xlogy(1-test_labels,1-A3_v)).sum()/256 +␣
↪((lamd/2)*((known_data1*known_data1).sum()+
                      (known_data2*known_data2).sum()+(known_data1*known_data1).
↪sum()))/256

    #Calculating Accuracy
    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)

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

    A3=A3.reshape(1,1027)
    A3_v=A3_v.reshape(1,256)

    #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+(lamd/1027)*known_data3)
    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+(lamd/1027)*known_data2)
    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+(lamd/1027)*known_data1)
    b1=np.sum(L_1,axis=1,keepdims=True)/1027
```

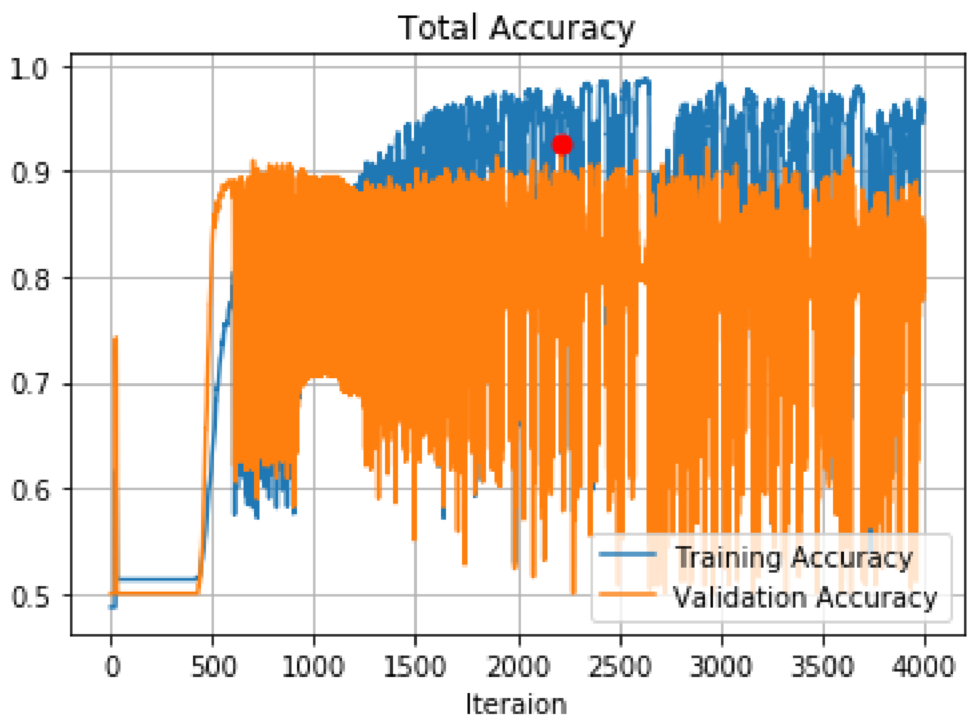
[1064]:
```
plt.plot(total_loss,label='Training Loss')
plt.plot(total_loss_test,label='Validation Loss')
#plt.ylim([0,1.2])
plt.grid()
plt.legend(loc='upper right')
plt.title("Total Loss at Every Iteration")
plt.xlabel("Iteraion")
```

[1064]:
```
Text(0.5, 0, 'Iteraion')
```



[1065]:
```python
max_index=np.argmax(accuracy_test)
plt.plot(accuracy,label='Training Accuracy')
plt.plot(accuracy_test,label='Validation Accuracy')
plt.legend(loc='lower right')
plt.grid()
plt.scatter(max_index,accuracy_test[max_index],c='r',s=50,label='Best␣
 ↪accuracy',zorder=10)
plt.title("Total Accuracy")
plt.xlabel("Iteraion")
```

[1065]: Text(0.5, 0, 'Iteraion')



[1066]:
```python
max_index=np.argmax(accuracy_test)
print("""
                            <At convergence>
+------------------------------+------------------------+---------------------+
|        At convergence        |          Loss          |       Accuracy      |
+------------------------------+------------------------+---------------------+
|        Training              |         %6.3f         |       %6.2f %%       |
+------------------------------+------------------------+---------------------+
|       Validation             |         %6.3f         |       %6.2f %%       |
+------------------------------+------------------------+---------------------+

```

```
                  <When the best validation accuracy>
+-----------------------+-----------------------+
|       Data set        |      Best  Accuracy    |
+-----------------------+-----------------------+
|     Validation        |         %6.2f %%       |
+-----------------------+-----------------------+"""
%(total_loss[NUM_EPOCH-1],accuracy[NUM_EPOCH-1]*100,total_loss_test[NUM_EPOCH-1],accuracy_test
 ↪max(accuracy_test)*100))
```

```
                           <At convergence>
+-----------------------------+-----------------------+---------------------+
|       At convergence        |          Loss         |       Accuracy      |
+-----------------------------+-----------------------+---------------------+
|       Training              |          0.411        |        94.64 %      |
+-----------------------------+-----------------------+---------------------+
|      Validation             |          1.282        |        85.55 %      |
+-----------------------------+-----------------------+---------------------+

                  <When the best validation accuracy>
+-----------------------+-----------------------+
|       Data set        |      Best  Accuracy    |
+-----------------------+-----------------------+
|     Validation        |         92.58 %        |
+-----------------------+-----------------------+
```

1.2 Variance: When Lamda is too small (Overfitting)

- Initialization Train and Validation set.

[962]:
```
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_data is weight sets.
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
```

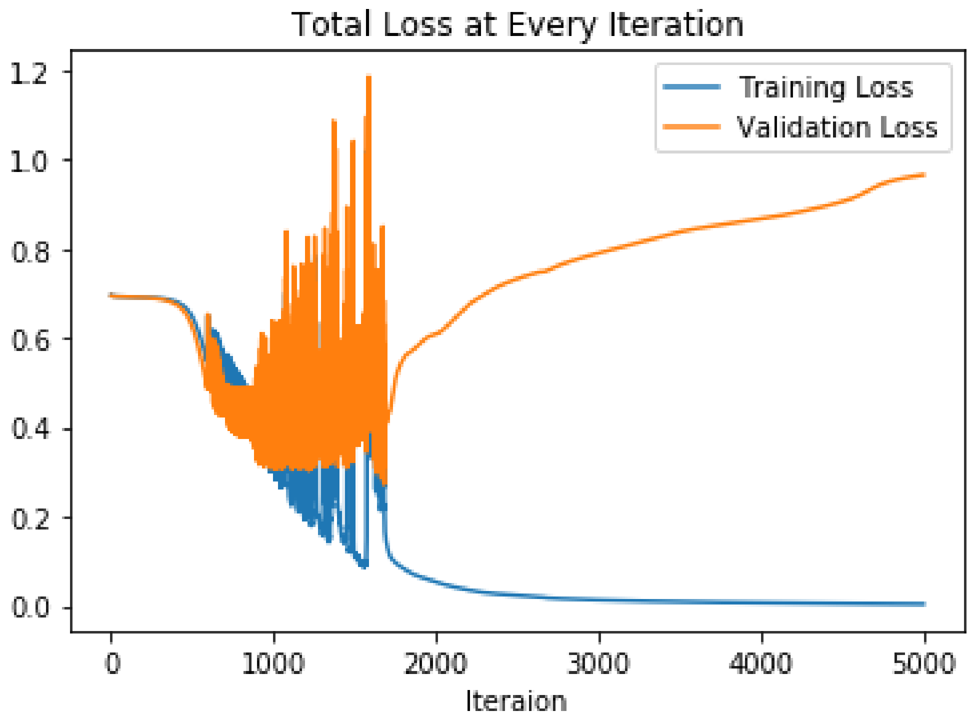
[963]:
```python
l_rate=0.2
j=0

lamd=0.0000000001

#Vertorizing Logistic Regression'c gradient Computation in 3 Layers
for i in range(NUM_EPOCH):

    #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+ ((lamd/
↪2)*((known_data1*known_data1).sum()+
                          (known_data2*known_data2).sum()+(known_data1*known_data1).
↪sum()))/1027
    j_v=-(xlogy(test_labels,A3_v)+xlogy(1-test_labels,1-A3_v)).sum()/256+␣
↪((lamd/2)*((known_data1*known_data1).sum()+
                          (known_data2*known_data2).sum()+(known_data1*known_data1).
↪sum()))/256


    total_loss[i]=j
    total_loss_test[i]=j_v

    #Calculating Accuracy
    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)
```

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

    A3=A3.reshape(1,1027)
    A3_v=A3_v.reshape(1,256)

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

- Plot the loss of Train and Validation at every iteration

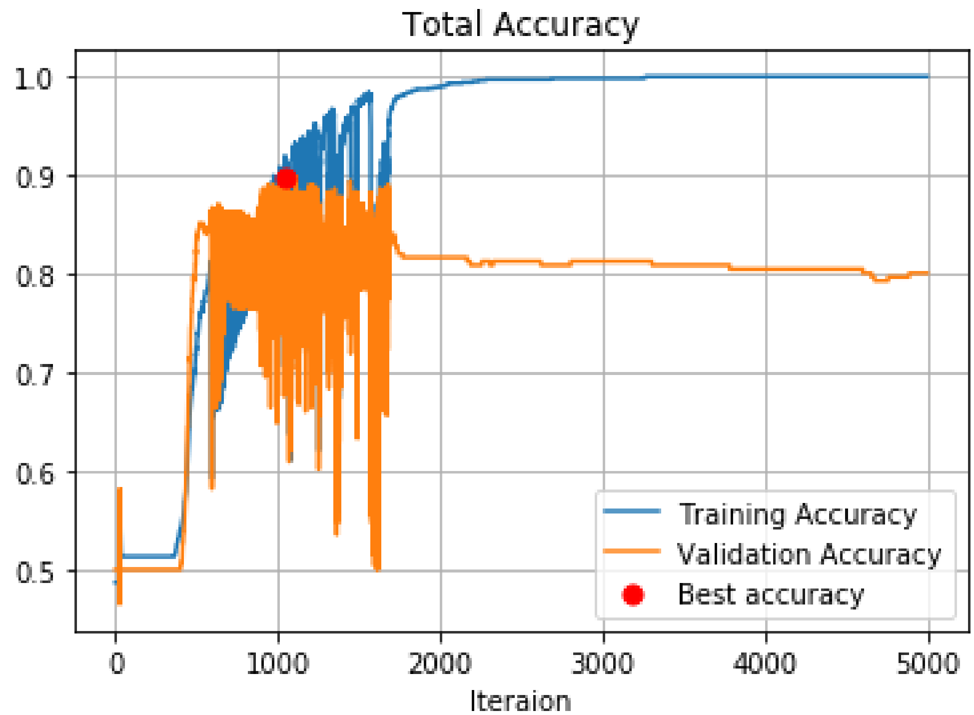
[964]:
```
plt.plot(total_loss,label='Training Loss')
plt.plot(total_loss_test,label='Validation Loss')
plt.legend(loc='upper right')
plt.title("Total Loss at Every Iteration")
plt.xlabel("Iteraion")
```

[964]:
```
Text(0.5, 0, 'Iteraion')
```



[970]:
```
max_index=np.argmax(accuracy_test)
plt.plot(accuracy,label='Training Accuracy')
plt.plot(accuracy_test,label='Validation Accuracy')
plt.scatter(max_index,accuracy_test[max_index],c='r',s=50,zorder=10,label='Best␣
↪accuracy')
plt.legend(loc='lower right')
plt.grid()
plt.title("Total Accuracy")
plt.xlabel("Iteraion")
```

[970]:
```
Text(0.5, 0, 'Iteraion')
```



[966]:
```
max_index=np.argmax(accuracy_test)
print("""
                            <At convergence>
+------------------------------+------------------------+---------------------+
|        At convergence        |          Loss          |       Accuracy      |
+------------------------------+------------------------+---------------------+
|        Training              |         %6.3f         |       %6.2f %%       |
+------------------------------+------------------------+---------------------+
|       Validation             |         %6.3f         |       %6.2f %%       |
+------------------------------+------------------------+---------------------+

                   <When the best validation accuracy>
+------------------------+------------------------+
|        Data set        |      Best  Accuracy    |
+------------------------+------------------------+
|      Validation        |       %6.2f %%         |
+------------------------+------------------------+"""
%(total_loss[NUM_EPOCH-1],accuracy[NUM_EPOCH-1]*100,total_loss_test[NUM_EPOCH-1],accuracy_test
 ↪max(accuracy_test)*100))
```

```
                            <At convergence>
+------------------------------+------------------------+---------------------+
|        At convergence        |          Loss          |       Accuracy      |
```

```
+------------------------------+-----------------------+---------------------+
|       Training               |          0.004        |       100.00 %      |
+------------------------------+-----------------------+---------------------+
|      Validation              |          0.965        |        80.08 %      |
+------------------------------+-----------------------+---------------------+

                  <When the best validation accuracy>
+------------------------+------------------------+
|       Data set         |      Best  Accuracy    |
+------------------------+------------------------+
|     Validation         |          89.84 %       |
+------------------------+------------------------+
```

1.3 Best Generalization: When Lamda is appropriate

- Initialization Train and Validation set.

[1167]:

```python
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_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

[1168]:

```python
l_rate=0.085
j=0

lamd=10

#Vertorizing Logistic Regression'c gradient Computation in 3 Layers
for i in range(NUM_EPOCH):

    #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+((lamd/
↪2)*((known_data1*known_data1).sum()+
                      (known_data2*known_data2).sum()+(known_data1*known_data1).
↪sum()))/1027
    j_v= -(xlogy(test_labels,A3_v)+xlogy(1-test_labels,1-A3_v)).sum()/
↪256+((lamd/2)*((known_data1*known_data1).sum()+
                      (known_data2*known_data2).sum()+(known_data1*known_data1).
↪sum()))/256


    total_loss[i]=j/1000
    total_loss_test[i]=j_v/1000

    #Calculating Accuracy
    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)


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

    A3=A3.reshape(1,1027)
    A3_v=A3_v.reshape(1,256)

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

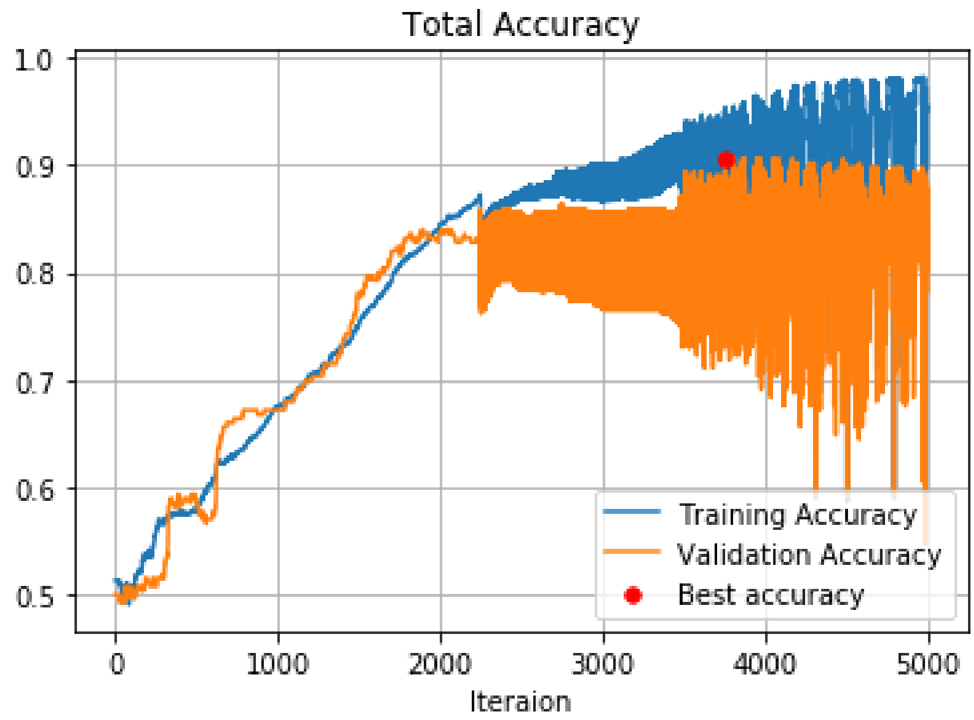
- Plot the loss of Train and Validation at every iteration

[1169]:
```
plt.plot(total_loss,label='Training Loss')
plt.plot(total_loss_test,label='Validation Loss')
plt.grid()
plt.legend(loc='upper right')
plt.title("Total Loss at Every Iteration")
plt.xlabel("Iteraion")
```

[1169]:
```
Text(0.5, 0, 'Iteraion')
```

[1183]:
```
max_index=np.argmax(accuracy_test)
plt.scatter(max_index,accuracy_test[max_index],c='r',s=30,zorder=3,label='Best␣
↪accuracy')
plt.plot(accuracy,label='Training Accuracy')
plt.plot(accuracy_test,label='Validation Accuracy')
plt.grid()
plt.legend(loc='lower right')
plt.title("Total Accuracy")
plt.xlabel("Iteraion")
```

[1183]:
```
Text(0.5, 0, 'Iteraion')
```



[1189]:
```
max_index=np.argmax(accuracy_test)
print("""
                              <At convergence>
+------------------------------+------------------------+---------------------+
|        At convergence        |          Loss          |      Accuracy       |
+------------------------------+------------------------+---------------------+
|        Training              |         %6.3f          |     %6.2f %%        |
+------------------------------+------------------------+---------------------+
|       Validation             |         %6.3f          |     %6.2f %%        |
+------------------------------+------------------------+---------------------+

                    <When the best validation accuracy>
+------------------------+-------------------------+
|        Data set        |      Best  Accuracy     |
+------------------------+-------------------------+
|      Validation        |        %6.2f %%         |
+------------------------+-------------------------+"""
%(total_loss[NUM_EPOCH-1],accuracy[NUM_EPOCH-2]*100,total_loss_test[NUM_EPOCH-1],accuracy_test
 ↪max(accuracy_test)*100))
```

```
                              <At convergence>
+------------------------------+------------------------+---------------------+
|        At convergence        |          Loss          |      Accuracy       |
```

```
+-----------------------------+-----------------------+--------------------+
|       Training              |          0.011        |       98.62 %      |
+-----------------------------+-----------------------+--------------------+
|      Validation             |          0.019        |       90.77 %      |
+-----------------------------+-----------------------+--------------------+

                  <When the best validation accuracy>
+-----------------------+------------------------+
|       Data set        |      Best  Accuracy    |
+-----------------------+------------------------+
|     Validation        |         92.62 %        |
+-----------------------+------------------------+
```

2 Summary:

- Bias Training converge loss is bigger than others.
- Accuracy is not decreasing in Best Lamda iterations.
- Accuracy is the best when Lamda is appropriate.

[1190]:
```
print("""

<At convergence>
+-----------------------------+-----------------------+--------------------+-------------------
|       At convergence        |          Bias         |      Variance      |  ␣
↪ Best Lamda     |
+-----------------------------+-----------------------+--------------------+-------------------
|       Training Loss         |          0.411        |         0.004      |  ␣
↪  0.011         |
+-----------------------------+-----------------------+--------------------+-------------------
|       Test Accuracy         |          85.55%       |        80.08%      |  ␣
↪  90.77%        |
+-----------------------------+-----------------------+--------------------+-------------------

""")
```

```
<At convergence>
+-----------------------------+-----------------------+--------------------+----
----------------+
|       At convergence        |          Bias         |      Variance      |
Best Lamda     |
+-----------------------------+-----------------------+--------------------+----
----------------+
|       Training Loss         |          0.411        |         0.004      |
0.011          |
+-----------------------------+-----------------------+--------------------+----
```

```
---------------+
|       Test Accuracy          |          85.55%        |         80.08%      |
90.77%       |
+-----------------------------+-----------------------+--------------------+----
---------------+
```