Machine Learning Project05

October 31, 2019

1 Binary classification based on 3 layers neural network

- This is given by Professor

[4]:
```
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)
```

[5]:
```
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
```

[15]:
```
def relu_prime(A):
    dA= np.where(A>0,1,0)
    return dA
```

[14]:
```
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)
```

[521]:
```
NUM_EPOCH=6000

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

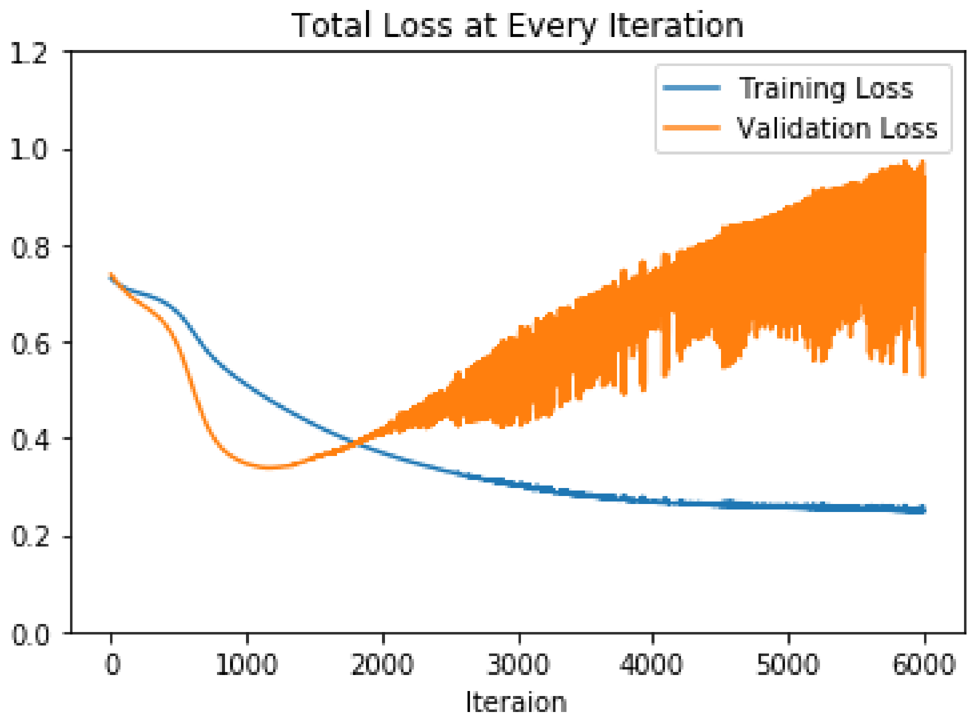
[522]:
```
#Learning rate
l_rate=0.0072
j=0
#Vertorizing Logistic Regression'c gradient Computation in 3 Layers
for i in range(NUM_EPOCH):

    #Forward propagation for train_set
    z1=np.dot(known_data1.T,train_datas)+b_1 #10x1027 =a
    A1=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

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)

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  #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
```

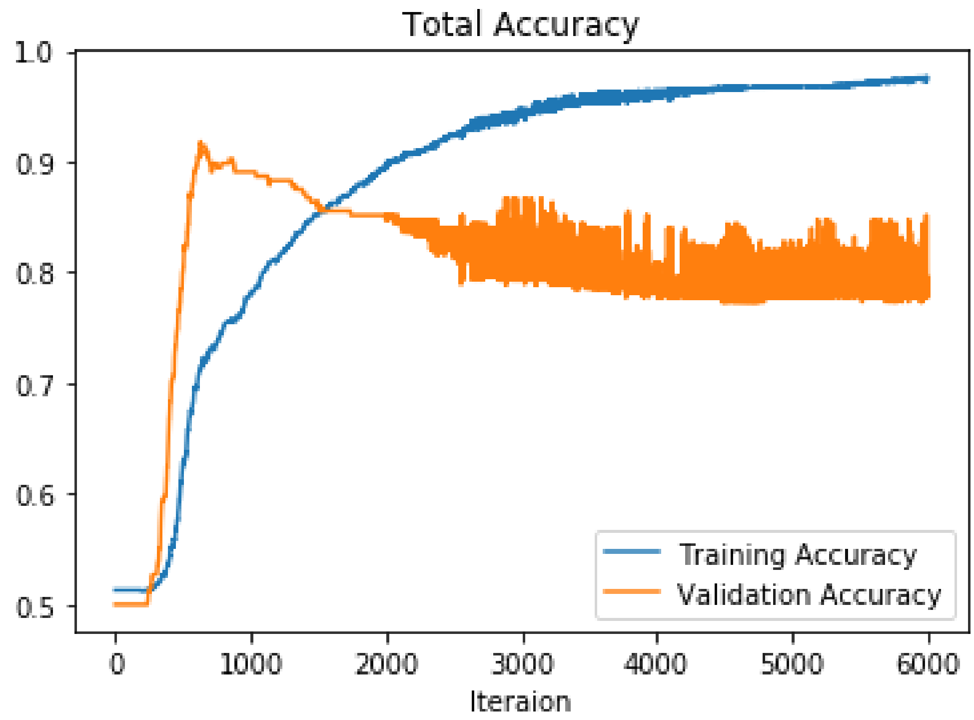
[526]:
```
plt.plot(total_loss,label='Training Loss')
plt.plot(total_loss_test,label='Validation Loss')
plt.ylim([0,1.2])
plt.legend(loc='upper right')
plt.title("Total Loss at Every Iteration")
plt.xlabel("Iteraion")
```

[526]:
```
Text(0.5, 0, 'Iteraion')
```



[524]:
```
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")
```

[524]:
```
Text(0.5, 0, 'Iteraion')
```




```
[525]: 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        |          Loss         |      Best   Accuracy    |
+------------------------+-----------------------+-------------------------+
|      Validation        |         %6.3f        |          %6.2f %%       |
+------------------------+-----------------------+-------------------------+"""
%(total_loss[NUM_EPOCH-3],accuracy[NUM_EPOCH-1]*100,total_loss_test[NUM_EPOCH-1],accuracy_test
 ↪max(accuracy_test)*100))
```

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

```
+-----------------------------+-----------------------+---------------------+
|       Training              |          0.249        |       97.57 %       |
+-----------------------------+-----------------------+---------------------+
|      Validation             |          0.901        |       81.64 %       |
+-----------------------------+-----------------------+---------------------+

                 <When the best validation accuracy>
+-----------------------+-----------------------+------------------------+
|       Data set        |          Loss         |      Best  Accuracy    |
+-----------------------+-----------------------+------------------------+
|     Validation        |         0.484         |        91.80 %         |
+-----------------------+-----------------------+------------------------+
```

[555]:
```python
NUM_EPOCH=6600

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

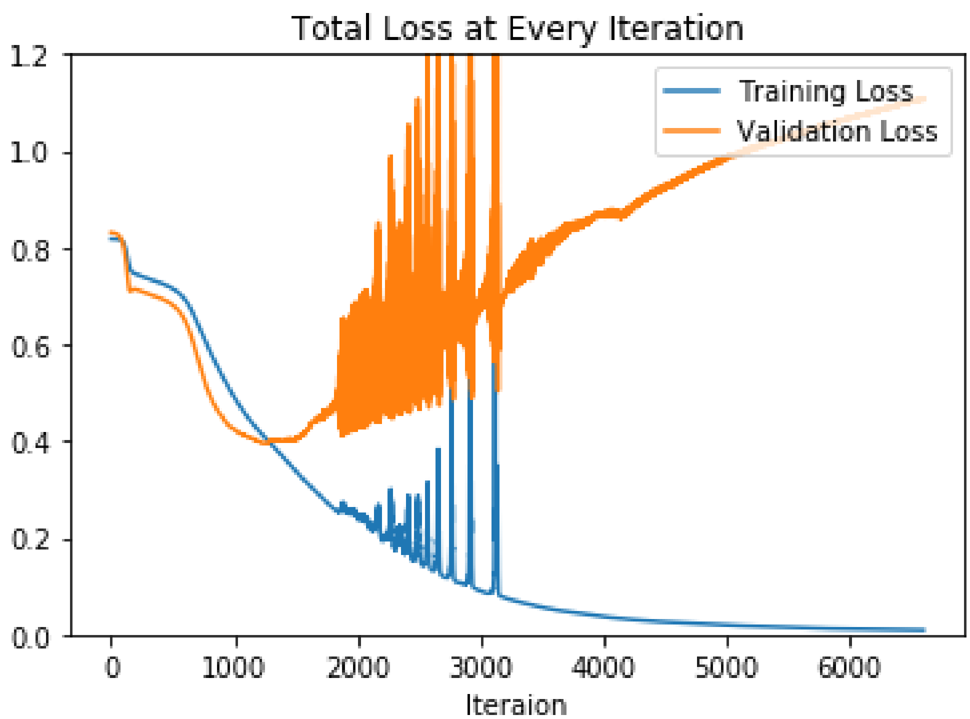
[556]:
```python
#Learning rate
l_rate=0.00725
j=0
#Vertorizing Logistic Regression'c gradient Computation in 3 Layers
for i in range(NUM_EPOCH):

    #Forward propagation for train_set
    z1=np.dot(known_data1.T,train_datas)+b_1 #10x1027 =a
    A1=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

    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)

    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  #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
```

[557]:
```
plt.plot(total_loss,label='Training Loss')
plt.plot(total_loss_test,label='Validation Loss')
```

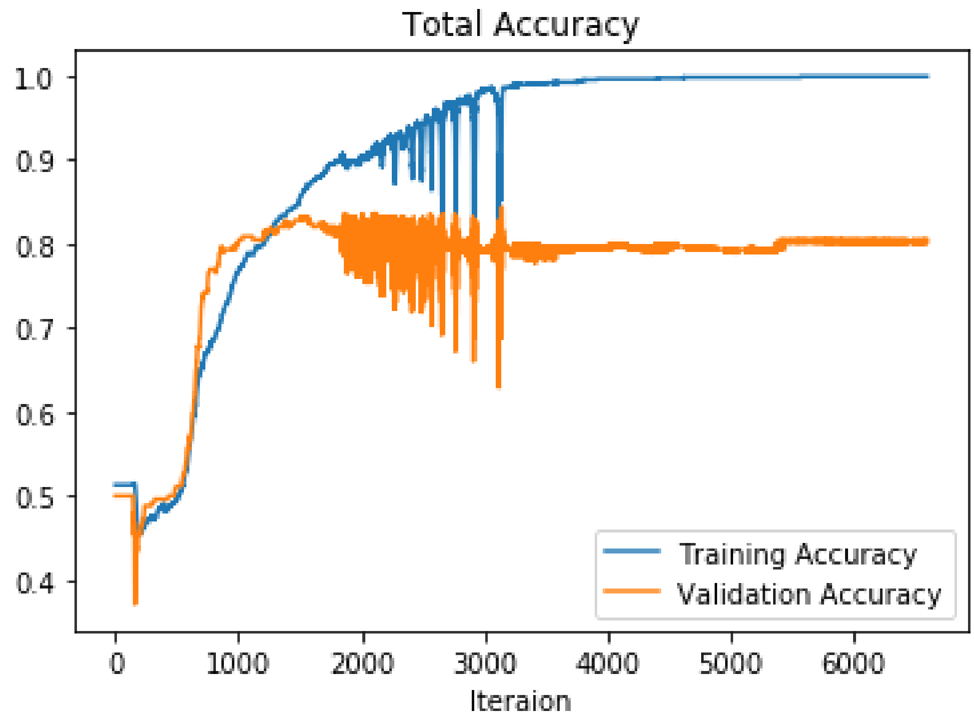
```
plt.ylim([0,1.2])
plt.legend(loc='upper right')
plt.title("Total Loss at Every Iteration")
plt.xlabel("Iteraion")
```

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



[558]:
```
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")
```

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



[559]:
```
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        |          Loss          |      Best  Accuracy     |
+------------------------+------------------------+-------------------------+
|      Validation        |          %6.3f       |          %6.2f %%      |
+------------------------+------------------------+-------------------------+"""
%(total_loss[NUM_EPOCH-3],accuracy[NUM_EPOCH-1]*100,total_loss_test[NUM_EPOCH-1],accuracy_test
 ↪max(accuracy_test)*100))
```

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

Training	0.009	99.90 %
Validation	1.106	78.91 %

<When the best validation accuracy>

Data set	Loss	Best Accuracy
Validation	0.504	84.38 %

[ ]: