PS2 - Breast Cancer

October 9, 2018

1 Classify the data for Breast Cancer

- Do this using the best practices discussed in class (i.e. one hot encoding, ReLU, CNNS when you should, etc.)
- Have reasonable hyperparameters

In [1]:
```
# Importing the libraries
import numpy as np
import keras
from matplotlib import pyplot as plt
import seaborn as sns
from keras.models import Sequential
from keras.layers import Dense, Dropout, Activation, Flatten, BatchNormalization
from keras.layers import Conv2D, MaxPooling2D
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
import pandas as pd
```

```
/home/anirudh/anaconda2/envs/py36/lib/python3.6/site-packages/h5py/__init__.py:36: FutureWarning
  from ._conv import register_converters as _register_converters
Using TensorFlow backend.
```

2 Loading the Data and Scaling the Features

In [2]:
```
# Loading the Training and Testing Data
X = pd.read_csv('./Breast Cancer/breastCancerData.csv')
Y = pd.read_csv('./Breast Cancer/breastCancerLabels.csv')

#Feature Scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X = sc.fit_transform(X)

Y= np.array(Y)
```

```
/home/anirudh/anaconda2/envs/py36/lib/python3.6/site-packages/sklearn/preprocessing/data.py:617:
  return self.partial_fit(X, y)
/home/anirudh/anaconda2/envs/py36/lib/python3.6/site-packages/sklearn/base.py:462: DataConversio
  return self.fit(X, **fit_params).transform(X)
```

3 Splitting the Data into Training, Validation and Test Data

```
In [3]: # Splitting the Data into Training and Test Data
        X_train, X_test,Y_train,Y_test = train_test_split(X,Y, test_size=0.15)

        # Splitting the Training Data into training and Validation Data
        X_train, X_val,Y_train,Y_val = train_test_split(X_train, Y_train, test_size=0.2)

        print("For this problem the number of training data is:" + str(X_train.shape[0]) +"\nThe
        " validation data is:" + str(X_val.shape[0]) + "\nand the number of test data is:" + str
```

```
For this problem the number of training data is:463
The number of validation data is:116
and the number of test data is:103
```

4 Showing the Training Data after Normalizing

```
In [4]: # Preview the training data
        print (pd.DataFrame(np.hstack((X_train[0:5],Y_train[0:5])),columns=
                            ['radius', 'texture','perimeter', 'area' , 'smoothness','compactness
                             'concave points', 'symmetry','Is it Malignant?']))
```

```
     radius   texture  perimeter      area  smoothness  compactness  \
0  1.974488  2.234474   2.270732  1.814105   -0.555361     1.778269
1  1.974488  0.929476   0.262989 -0.637916   -0.105532     0.127855
2  0.199843 -0.701771  -0.740883  0.062662   -0.555361    -0.697352
3  1.974488  2.234474   0.932237  0.062662   -0.105532     1.778269
4  0.199843  1.255725   1.266861 -0.637916    0.794126     1.228131

   concavity  concave points  symmetry  Is it Malignant?
0   0.226259       -0.612417 -0.348686               1.0
1  -0.181965       -0.284834  0.805702               1.0
2  -0.998412       -0.612417 -0.348686               0.0
3   0.226259        0.042749  0.228508               1.0
4  -0.181965        0.370332 -0.348686               0.0
```

5 Setting Hyper Paramters

In [5]:
```
# Hyper Parameters
batch_size = 32
num_classes = 2
epochs = 15
```

6 Creating Model

In [6]:
```
# create model
model = Sequential()
model.add(Dense(units = 64, kernel_initializer = 'uniform', activation = 'relu', input_d
model.add(Dropout( 0.2))
model.add(Dense(units = 32, kernel_initializer = 'uniform', activation = 'relu'))
model.add(Dropout(0.2))
model.add(Dense(units = 16, kernel_initializer = 'uniform', activation = 'relu'))
model.add(Dropout(0.2))
model.add(Dense(units = 1, kernel_initializer = 'uniform', activation = 'sigmoid'))

# Compile model
model.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])

# Get Model Summary
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 64)                640
_________________________________________________________________
dropout_1 (Dropout)          (None, 64)                0
_________________________________________________________________
dense_2 (Dense)              (None, 32)                2080
_________________________________________________________________
dropout_2 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_3 (Dense)              (None, 16)                528
_________________________________________________________________
dropout_3 (Dropout)          (None, 16)                0
_________________________________________________________________
dense_4 (Dense)              (None, 1)                 17
=================================================================
Total params: 3,265
Trainable params: 3,265
Non-trainable params: 0
_________________________________________________________________
```

7 Weights and Biases for First Layer

In [7]:
```
# Before Training
weights = model.layers[0].get_weights()
w0 = np.array(weights[0])
b0 = np.array(weights[1])
print("The weights for first layer has dimensions of " + str(w0.shape))
print()
print("The Biases for first layer has dimensions of " + str(b0.shape)+" and the values a
print()
print("Just so we know that the weights have changed after training,\
 we will be comparing the sum of weights of the first layer before and after training.")
print()
print("The sum of weights of the first layer is :" + str(w0.sum()))
print("The sum of biases of the first layer is :" + str(b0.sum()))
```

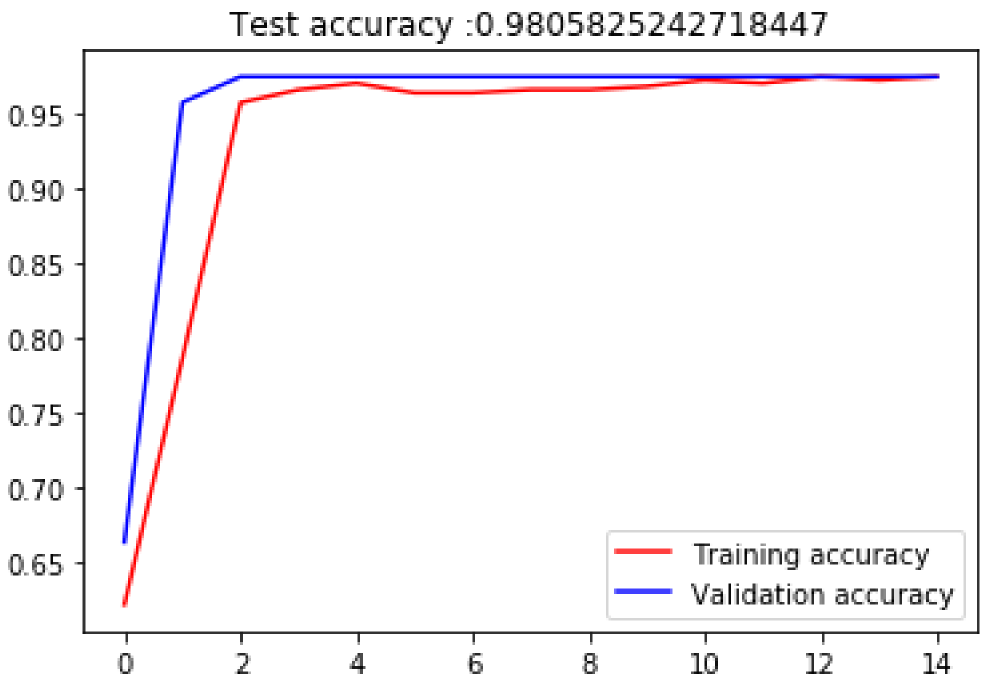
```
The weights for first layer has dimensions of (9, 64)

The Biases for first layer has dimensions of (64,) and the values are :
[0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]

Just so we know that the weights have changed after training, we will be comparing the sum of we

The sum of weights of the first layer is :-0.27367854
The sum of biases of the first layer is :0.0
```

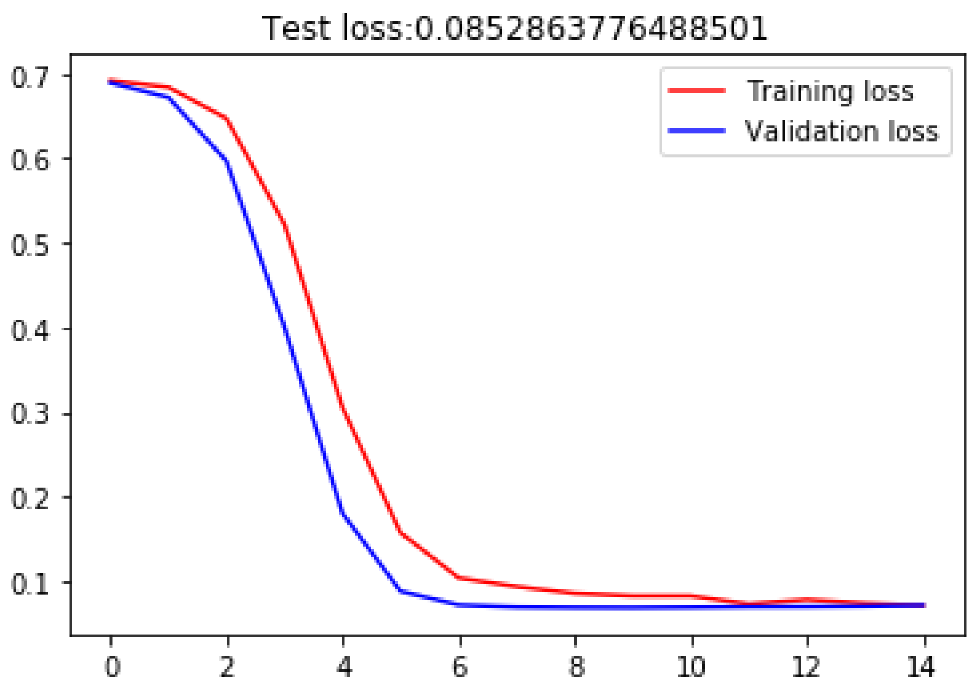
8 Training the Model

In [8]:
```
# Train
h = model.fit(X_train, Y_train,
          batch_size=batch_size,
          epochs=epochs,
          verbose=0,
validation_data=(X_val, Y_val))

# Evaluate Accuracy

score = model.evaluate(X_test, Y_test, verbose=0)

print('Training Loss:', h.history['loss'][-1])
print('Training Accuracy:', h.history['acc'][-1])
print()
print('Validation Loss:', h.history['val_loss'][-1])
print('Validation Accuracy:', h.history['val_acc'][-1])
print()
```

```python
        print('Test Loss:', score[0])
        print('Test Accuracy:', score[1])
        print()

        # Plot Graphs
        # print(h.history.keys())
        accuracy = h.history['acc']
        val_accuracy = h.history['val_acc']
        loss = h.history['loss']
        val_loss = h.history['val_loss']
        epochs = range(len(accuracy))
        plt.plot(epochs, accuracy, 'r', label='Training accuracy')
        plt.plot(epochs, val_accuracy, 'b', label='Validation accuracy')
        plt.title('Test accuracy :' + str(score[1]))
        plt.legend()
        plt.show()
        plt.figure()
        plt.plot(epochs, loss, 'r', label='Training loss')
        plt.plot(epochs, val_loss, 'b', label='Validation loss')
        plt.title('Test loss:'+str(score[0]))
        plt.legend()
        plt.show()
```

```
Training Loss: 0.0713097348479357
Training Accuracy: 0.9740820734341252

Validation Loss: 0.07167263894245543
Validation Accuracy: 0.9741379289791502

Test Loss: 0.0852863776488501
Test Accuracy: 0.9805825242718447
```


Test accuracy :0.9805825242718447
0.95
0.90
0.85
0.80
0.75
0.70
0.65
Training accuracy
Validation accuracy
0
2
4
6
8
10
12
14


Test loss:0.0852863776488501
0.7
0.6
0.5
0.4
0.3
0.2
0.1
Training loss
Validation loss
0
2
4
6
8
10
12
14

9 Inferences

- Here a simple fully connected model was bale to get a convergence in 15 epochs with a batch size of 32.
- As the test accuracy was also above 97 %, we can say that the parameters chosen are correct.
- A simple fully connected model worked here as the input is a relatively less complex matrix as compared to images in MNIST and fashion MNIST.
- ** Dense Layers: ** Four fully connect layers are used with dropouts in between. The hidden units are again taken in power of 2.
- ** Drop Out: ** This is very Essential as it helps prevent over fitting. The drop out rate was set to 0.1.
- Using other methods like BatchNormalization and Maxpolling is not required here because of the simplicity of the model or the less number of weights.
- As this is a binary classifier, the final layer consists of sigmoid function as activation and the loss function used is a binary_crossentropy loss.

10 Weights and Biases for First Layer After Training

```
In [9]: # After Training
        weights = model.layers[0].get_weights()
        w0 = np.array(weights[0])
        b0 = np.array(weights[1])
        print("The weights for first layer has dimensions of " + str(w0.shape))
        print()
        print("The Biases for first layer has dimensions of " + str(b0.shape)+" and the values a
        print()
        print("The sum of weights of the first layer is :" + str(w0.sum()))
        print("The sum of biases of the first layer is :" + str(b0.sum()))
        print("As we can see the sum has changed, indicating that the weights are now tuned.")
```

```
The weights for first layer has dimensions of (9, 64)

The Biases for first layer has dimensions of (64,) and the values are :
[0.00565082 0.11447307 0.11100366 0.12224284 0.11190101 0.11120802
 0.09813787 0.0932091  0.10682337 0.10079738 0.10276962 0.10654137
 0.11700526 0.11261878 0.11765338 0.1042446  0.12294795 0.12512106
 0.11745223 0.10702112 0.13799985 0.09850707 0.11602484 0.1184485
 0.11815976 0.122028   0.0988709  0.13012977 0.10767307 0.12677155
 0.09933781 0.12721375 0.09612524 0.08008504 0.09697195 0.1109754
 0.0802253  0.11672504 0.12173473 0.11094635 0.10507268 0.11560145
 0.11227549 0.04680694 0.1264726  0.11976074 0.07090484 0.10593776
 0.10071041 0.12147024 0.11003634 0.09747186 0.09982739 0.10775392
 0.12674405 0.11154057 0.11493925 0.14127669 0.11108415 0.13439618
 0.1074697  0.12055368 0.0631986  0.1232283 ]

The sum of weights of the first layer is :-15.355629
The sum of biases of the first layer is :6.9183106
```

As we can see the sum has changed, indicating that the weights are now tuned.

11 Calculate Confusion Matrix

In [10]:
```
# Predict the values from the validation dataset
Y_pred1 = model.predict(X_test)
Y_pred= (Y_pred1>0.5)*1
# compute the confusion matrix
confusion_mtx = confusion_matrix(Y_test, Y_pred)
print("Confusion Matrix is :\n"+str(confusion_mtx))
```

```
Confusion Matrix is :
[[62  1]
 [ 1 39]]
```

12 Incorrect Predictions

In [11]:
```
# Errors are difference between predicted labels and true labels
errors = (Y_pred - Y_test != 0)
incorrect = (errors*1).sum()
print ("Number of Incorrect Predicitons are: " + str(incorrect)+ " out of "+ str (error
Y_pred_errors = Y_pred1[errors]
Y_true_errors = Y_test[errors]
errordata = np.zeros(shape=(incorrect,11))
pos = np.where(errors == True)
for i in range(0,pos[0].size):
    errordata1 = np.hstack((X_test[pos[0][i]],Y_test[pos[0][i]]))
    errordata1 = np.reshape(np.hstack((errordata1,Y_pred[pos[0][i]])),(1,11))
    errordata[i] = errordata1

print()
print("Displaying the errors")
# Preview the training data
print (pd.DataFrame(errordata,columns=
                    ['radius', 'texture','perimeter', 'area' , 'smoothness','compactnes
                     'concave points', 'symmetry','Actual Value','Predictd Value']))
```

```
Number of Incorrect Predicitons are: 2 out of 103 inputs

Displaying the errors
     radius   texture  perimeter      area  smoothness  compactness  \
0  0.199843 -0.701771  -0.406259  2.514682    0.344297     0.402924
1 -0.155086 -0.701771  -0.740883  0.062662   -1.005190     0.402924

   concavity  concave points  symmetry  Actual Value  Predictd Value
```

0	-0.590189	-0.612417	-0.348686	0.0	1.0
1	-0.590189	-0.612417	-0.348686	1.0	0.0