IIT2016515_Q1

March 15, 2019

1 Newton's Method on Marks Data

1.0.1 Importing Libraries and Data

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.utils import shuffle
from sklearn.metrics import confusion_matrix
import seaborn as sns
```

In [2]:
```
df = pd.read_csv('marks.csv', index_col=0)
df = shuffle(df)
df.head()
```

Out[2]:

	marks1	marks2	selected
90	52.348004	60.769505	0
41	83.902394	56.308046	1
7	61.106665	96.511426	1
50	91.564975	88.696293	1
98	99.315009	68.775409	1

In [3]:
```
df.shape
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 100 entries, 90 to 87
Data columns (total 3 columns):
marks1      100 non-null float64
marks2      100 non-null float64
selected    100 non-null int64
dtypes: float64(2), int64(1)
memory usage: 3.1 KB
```

In [4]:
```
Y = df['selected']
X = df.drop(['selected'],axis=1)
```

```
In [5]: print(X.shape)
        print(Y.shape)
```

```
(100, 2)
(100,)
```

1.0.2 Data Preprocessing

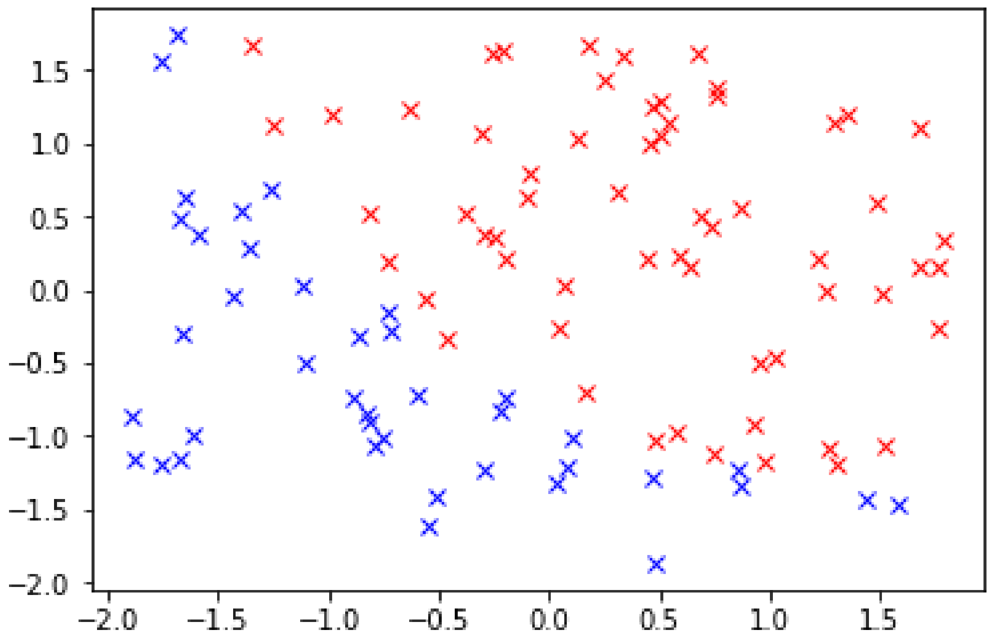
```
In [6]: Y = (np.array(Y)).reshape(Y.shape[0],1)
        print(Y.shape)
        X = np.array(X)

        #Normalising Inputs(2D input)
        def normalise(inp):
            return np.array((inp-inp.mean())/inp.std())
        X = normalise(X)

        X = np.hstack((np.ones((X.shape[0],1)),X))
        print(X.shape)
        print(X[:5])
```

```
(100, 1)
(100, 3)
[[ 1.         -0.71756088 -0.27274077]
 [ 1.          0.94912851 -0.50839314]
 [ 1.         -0.25493217  1.61513221]
 [ 1.          1.35386276  1.2023402 ]
 [ 1.          1.76321626  0.15012767]]
```

```
In [7]: for i in range(X.shape[0]):
            if Y[i]==1:
                plt.plot(X[i,1],X[i,2],'rx')
            else:
                plt.plot(X[i,1],X[i,2],'bx')
        plt.show()
```




```
In [8]: # Splitting data in train and test sets
        X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3)
        print(X_train.shape, y_train.shape)
        print(X_test.shape, y_test.shape)
```

```
(70, 3) (70, 1)
(30, 3) (30, 1)
```

1.0.3 Defining functions

```
In [9]: def sigmoid(x) :
            return 1.0 / (1.0 + np.exp(-x))
```

```
In [10]: # Cost Function with Regularization
         def cost(X, Y, theta, _lambda=0.1):
             m = len(Y)
             h = sigmoid(X.dot(theta))
             reg = (_lambda/(2 * m)) * np.sum(theta**2)
             return (1 / m) * (-Y.T.dot(np.log(h)) - (1 - Y).T.dot(np.log(1 - h))) + reg
```

```
In [11]: # Regularized gradient function
         def gradient(X, Y, theta, _lambda = 0.1):
             m, n = X.shape
             h = sigmoid(X.dot(theta))
             reg = _lambda * theta /m
             return ((1 / m) * X.T.dot(h - Y)) + reg
```

In [12]:
```python
# Regularised Hessian function
# Hessian = (X.T)DX
def hessian(X, Y, theta, _lambda=0.1):
    D = np.zeros((X.shape[0],X.shape[0]))
    for i in range(X.shape[0]):
        D[i][i] = sigmoid(X[i].dot(theta)) * (1 - sigmoid(X[i].dot(theta)))
    h1 = np.dot(np.dot(np.transpose(X), D), X)

    h2 = np.zeros((X.shape[1],X.shape[1]))
    for i in range(1, X.shape[1]) :
        h2[i][i] = _lambda
    return h1 + h2
```

In [13]:
```python
# Training using newton's method
def train(X, Y, iterations = 100, _lambda=0.1):
    costs = np.empty([iterations])
    i = 0
    m = X.shape[0]
    theta = np.random.randn(X.shape[1],1)

    while i < iterations:
        costs[i] = cost(X, Y, theta, _lambda)

        g = gradient(X,Y,theta,_lambda)
        hess = hessian(X,Y,theta,_lambda)
        h_inv = np.linalg.inv(hess)

        theta = theta - np.dot(h_inv,g)
        i = i + 1
    return theta, costs
```

In [14]:
```python
def test(X, Y, theta):
    pred = sigmoid(X.dot(theta))
    counts = 0
    a, b = X.shape
    Y_pred = np.empty([Y.shape[0]])
    for i in range(a):
        if pred[i] > 0.5:
            Y_pred[i] = 1
            if int(Y[i]) == 1:
                counts = counts + 1
        else:
            Y_pred[i] = 0
            if int(Y[i]) == 0 :
                counts = counts + 1

    print('Accuracy:',counts/a * 100)
```

```
        Y_pred = Y_pred.reshape(Y.shape[0],1)
        return Y_pred
```

1.0.4 Training with Regularization (lambda = 0.1)

```
In [15]: theta, costs = train(X_train, y_train, _lambda=0.1)
         print(theta)
```

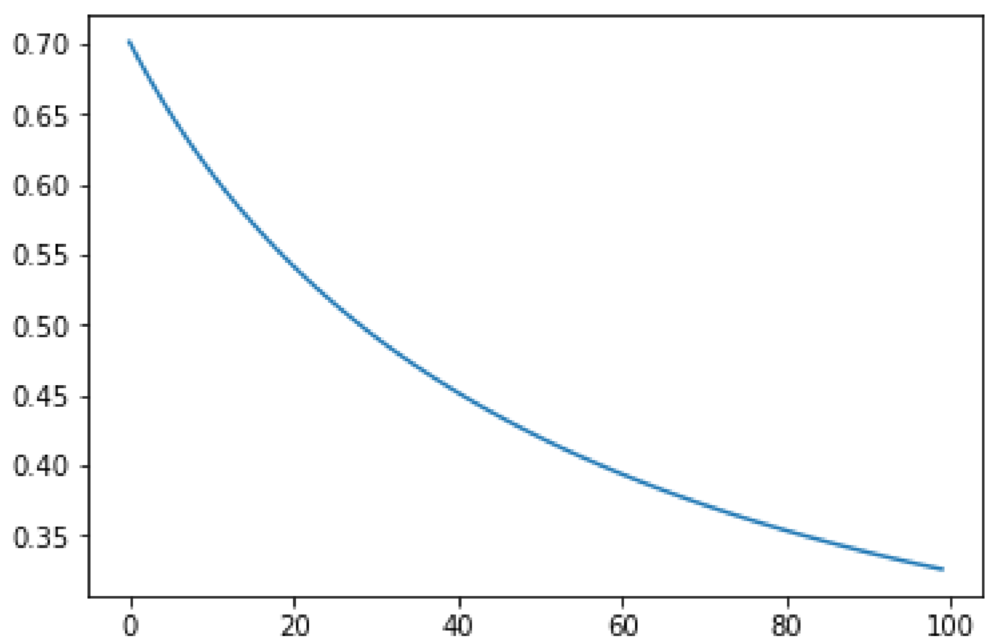
```
[[0.63292359]
 [1.71286238]
 [1.14186915]]
```

```
In [16]: y_pred_test = test(X_test,y_test,theta)
```

```
Accuracy: 96.66666666666667
```

```
In [17]: plt.plot(range(len(costs)),costs)
```

```
Out[17]: [<matplotlib.lines.Line2D at 0x7fd32fed4ac8>]
```




```
In [18]: y_pred_train = test(X_train,y_train,theta)
```

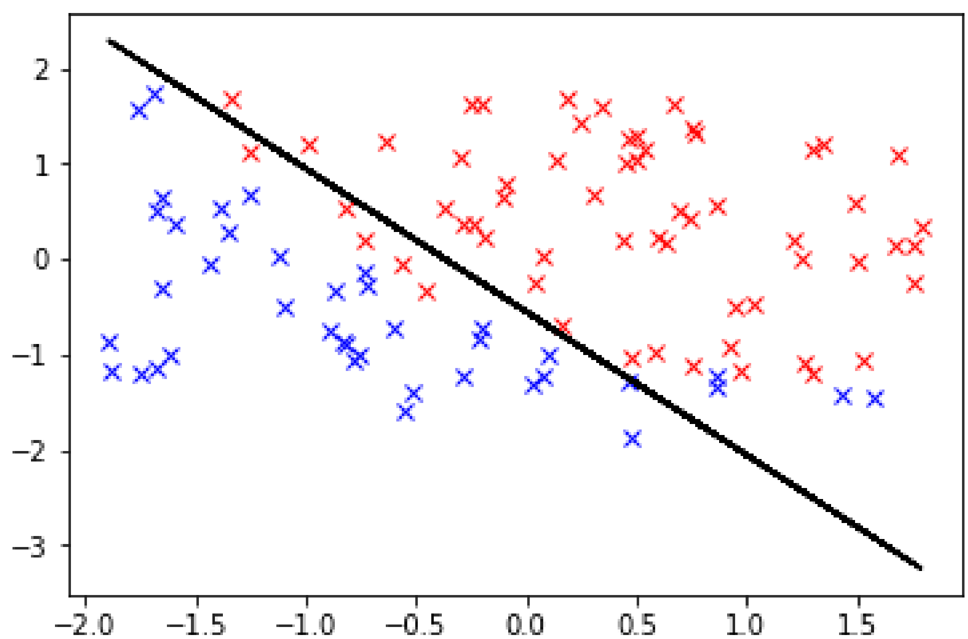
```
Accuracy: 88.57142857142857
```

In [19]:
```
# plotting decision boundary

for i in range(X.shape[0]):
    if Y[i]==1:
        plt.plot(X[i,1],X[i,2],'rx')
    else:
        plt.plot(X[i,1],X[i,2],'bx')

decision_x_vals = X[: , 1]
decision_y_vals = -1.0 * ((theta[0] + theta[1] * decision_x_vals) / (theta[2]))

plt.plot(decision_x_vals, decision_y_vals, 'k')
plt.show()
```

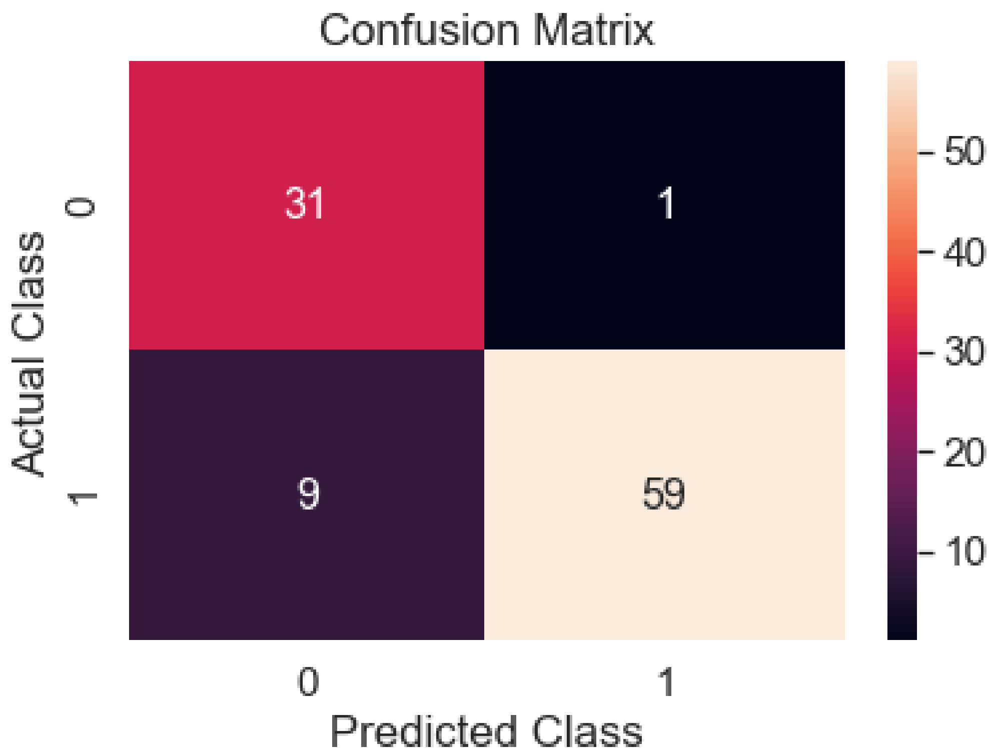


In [23]:
```
# Function to plot Confusion Matrix
def plot_confusion_matrix(Y_pred,Y):
    cm = confusion_matrix(Y_pred, Y, labels=None, sample_weight=None)

    df_cm = pd.DataFrame(cm, range(2), range(2))
    sns.set(font_scale = 1.4) #for label size
    ax = sns.heatmap(df_cm, annot = True, annot_kws = {"size": 16})
    ax.set_title("Confusion Matrix")
    ax.set(xlabel = 'Predicted Class', ylabel = 'Actual Class')
    plt.show()
    return cm
```

In [24]:
```
# Confusion matrix on complete data
cm = plot_confusion_matrix(test(X,Y,theta),Y)
```

Accuracy: 90.0



In [25]:
```
# Calcuating precision, recall and F1 score
TN = cm[0][0]
FP = cm[0][1]
FN = cm[1][0]
TP = cm[1][1]

precision = TP / (TP + FP)
recall = TP / (TP + FN)
print("Precision:", precision * 100)
print("Recall:", recall * 100)

F1_score = (2 * precision * recall) / (precision + recall)
print("F1 score:", F1_score)
```

```
Precision: 98.33333333333333
Recall: 86.76470588235294
F1 score: 0.9218749999999999
```