

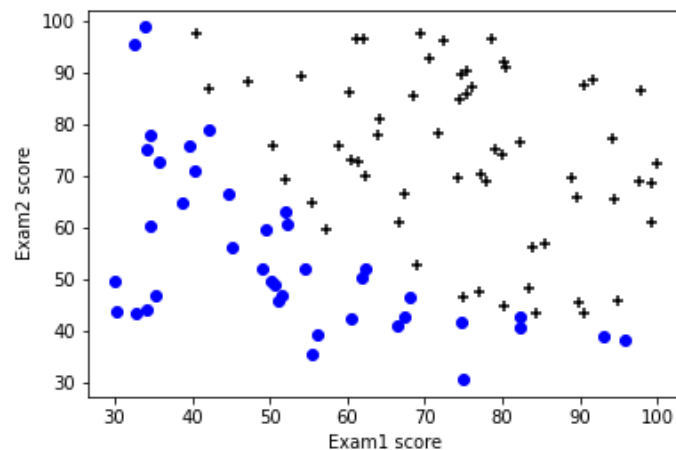
ECE 1395 – Homework 3 report

- 1) a) The size of matrix X and Y are shown below. X has 100 rows and 3 columns (Exam1 scores, Exam2 scores and x_0), and Y has 100 rows (for each training sample) and 1 column (decision)

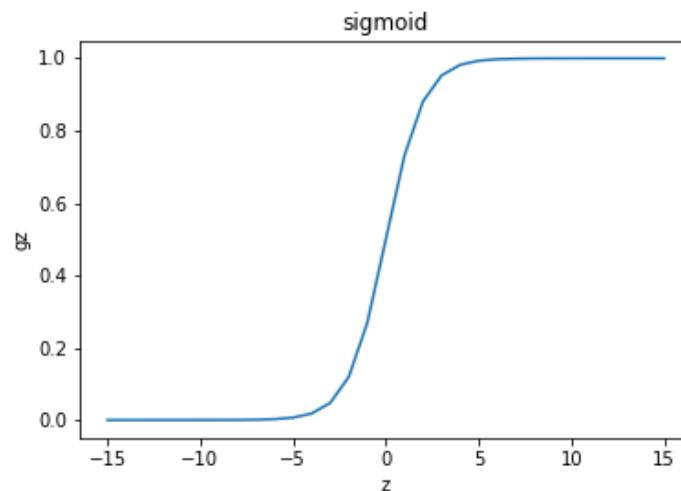
```
In [3]: runfile('C:/Users/RAYAN/OneDrive/Desktop/
ps3.py', wdir='C:/Users/RAYAN/OneDrive/Desktop')
Reloaded modules: sigmoid, costFunction, gradFunction,
normalEqn
Size of matrix X is: (100, 3)
Size of matrix Y is: (100, 1)

In [4]:
```

- b) This is the scatter plot of training data (saved as ps3-1-b.png)



- c) Data divided randomly into training set and test set using `test_train_split` (view code)
- d) The following shows the g_z versus z plot for the sigmoid function (ps3-1-c.png)



e) Here is the cost value obtained from function costFunction for the toy set

```
Cost J for the toy set when theta=[0,0,0] is: 0.6931471805599453
```

```
In [13]:
```

And this is the gradient of the cost obtained using gradFunction

```
Gradient of the cost of the toy set is: [[ 0. ]  
[ 0. ]  
[-0.75]]
```

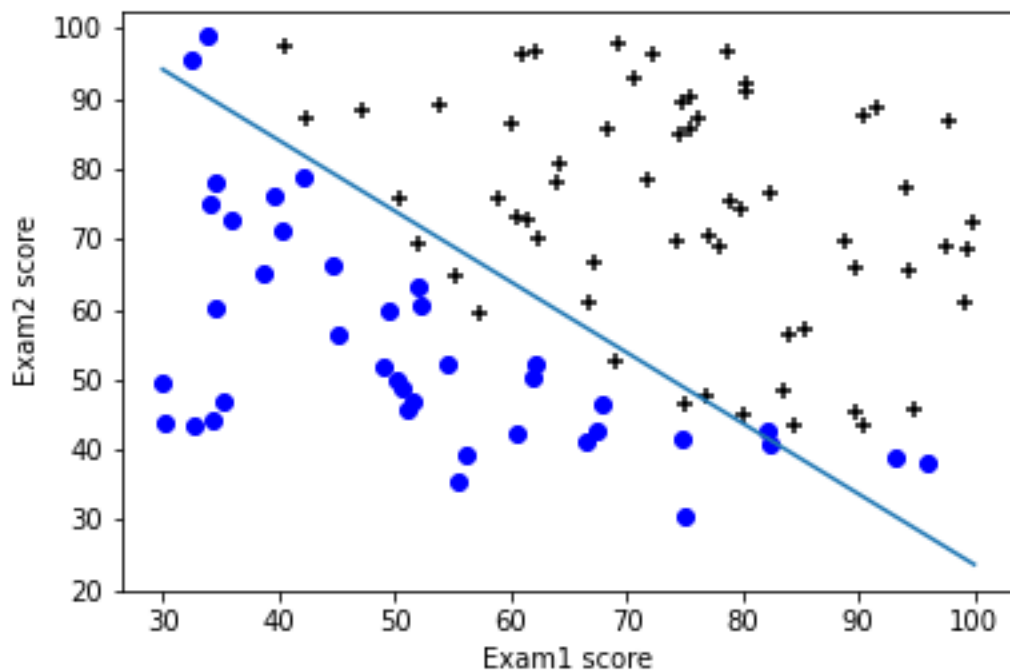
f) The following screenshot shows output of the min_bfgs function as long as the optimal parameter theta.

```
Optimization terminated successfully.  
Current function value: 0.216343  
Iterations: 21  
Function evaluations: 29  
Gradient evaluations: 29  
The optimal parameter theta is: [-23.87964054  0.19345199  0.19185897]
```

We can see that the optimal parameters theta = [-23.8796, 0.1934, 0.1918]

And the value of the cost function at convergence is 0.216343

g) The decision boundary can be seen next (saved as ps3-1-f.png)



Rayan Hassan
4511021

h) This is the code to calculate the accuracy, as well as the resulting output

```
#-----Accuracy of logistic regression-----#
theta = np.array([[op1[0]], [op1[1]], [op1[2]]])

h_test= np.dot(X_test,theta)

h_test = h_test>0 #if True (1) -> admitted, else not admitted

correctly_classified = 0
for i in range(len(h_test)):
    if int(h_test[i][0]) == Y_test[i][0]:
        correctly_classified += 1

accuracy = correctly_classified/len(Y_test)
print("Accuracy of logistic regression is: ",accuracy)
```

```
Accuracy of logistic regression is: 1.0
```

i) The admission probability for student who got 80 on test1 and 50 on test 2 is shown below

```
Admission probability is: 76.66457328124595 %
```

The decision should be "admitted"

j) BONUS. Please see the pictures below

$$J(\theta) = -\frac{1}{m} \sum_{i=1}^m \left[y \log(h_0(x)) + (1-y) \log(1-h_0(x)) \right]$$

Applying the chain rule:

$$\frac{\partial J(\theta)}{\partial \theta_j} = -\frac{1}{m} \sum_{i=1}^m \left[y \frac{1}{h_0(x)} \frac{\partial h_0(x)}{\partial \theta_j} + (1-y) \frac{1}{1-h_0(x)} \frac{\partial (1-h_0(x))}{\partial \theta_j} \right]$$

* Now let's find $\frac{\partial h_0(x)}{\partial \theta_j}$

We know $h_0(x) = \frac{1}{1+e^{-x}}$

Let's find the derivative of $\sigma(x) = \frac{1}{1+e^{-x}}$

$$\begin{aligned} \frac{d\sigma(x)}{dx} &= \frac{d}{dx} (1+e^{-x})^{-1} \\ &= -1 (1+e^{-x})^{-2} (-e^{-x}) \\ &= \frac{-e^{-x}}{-(1+e^{-x})^2} = \frac{e^{-x}}{(1+e^{-x})^2} \\ &= \frac{1}{1+e^{-x}} \cdot \frac{e^{-x}}{1+e^{-x}} = \frac{1}{1+e^{-x}} \cdot \frac{(1+e^{-x})-1}{1+e^{-x}} \\ &= \frac{1}{1+e^{-x}} \cdot \left[\frac{1+e^{-x}}{1+e^{-x}} - \frac{1}{1+e^{-x}} \right] \\ &= \frac{1}{1+e^{-x}} \left[1 - \frac{1}{1+e^{-x}} \right] = \boxed{\sigma(x)(1-\sigma(x))} \end{aligned}$$

So now $\frac{\partial h_0(x)}{\partial \theta_j} = h_0(x)(1-h_0(x)) \frac{\partial \theta^T x}{\partial \theta_j}$

following the pattern of the derivative of Sigmoid function.

Similarly $\frac{\partial (1-h_0(x))}{\partial \theta_j} = -h_0(x)(1-h_0(x)) \frac{\partial \theta^T x}{\partial \theta_j}$

and we know $\frac{\partial \theta^T x}{\partial \theta_j} = x_j$

So we can write:

$$\begin{aligned}
 \frac{\partial J(\theta)}{\partial \theta_j} &= \frac{1}{n} \sum_{i=1}^n \left[y \frac{1}{h_\theta(x)} h_\theta(x)(1-h_\theta(x)) x_j^i \right. \\
 &\quad \left. + (1-y) \frac{1}{1-h_\theta(x)} (-h_\theta(x))(1-h_\theta(x)) x_j^i \right] \\
 &= \frac{1}{n} \sum_{i=1}^n \left[y (1-h_\theta(x)) x_j^i + (1-y) (-h_\theta(x)) x_j^i \right] \\
 &= \frac{1}{n} \sum_{i=1}^n \left[y (1-h_\theta(x)) - (1-y) h_\theta(x) \right] x_j^i \\
 &= \frac{1}{n} \sum_{i=1}^n \left[y - y h_\theta(x) - h_\theta(x) + y h_\theta(x) \right] x_j^i \\
 &= \frac{1}{n} \sum_{i=1}^n \left[y - h_\theta(x) \right] x_j^i \\
 &= \boxed{\frac{1}{n} \sum_{i=1}^n (h_\theta(x) - y) x_j^i} \quad \text{final answer}
 \end{aligned}$$

2) a) The learned model parameter is shown below:

```

The learned model parameter is: [[ 2.19256629e+05]
 [-7.75886157e+02]
 [ 1.06170508e+01]]

```

b) The data and the model are plotted on the following figure (saved as ps3-2-b.png)

Rayan Hassan
4511021

