February 26, 2023

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

[2]:
```
df= pd.read_csv("Breast_cancer_data.csv")
```

[3]:
```
df
```

[3]:
```
     mean_radius  mean_texture  mean_perimeter  mean_area  mean_smoothness  \
0          17.99         10.38          122.80     1001.0          0.11840
1          20.57         17.77          132.90     1326.0          0.08474
2          19.69         21.25          130.00     1203.0          0.10960
3          11.42         20.38           77.58      386.1          0.14250
4          20.29         14.34          135.10     1297.0          0.10030
..           …            …              …          …               …
564        21.56         22.39          142.00     1479.0          0.11100
565        20.13         28.25          131.20     1261.0          0.09780
566        16.60         28.08          108.30      858.1          0.08455
567        20.60         29.33          140.10     1265.0          0.11780
568         7.76         24.54           47.92      181.0          0.05263

     diagnosis
0            0
1            0
2            0
3            0
4            0
..         …
564          0
565          0
566          0
567          0
568          1

[569 rows x 6 columns]
```

[5]:

```
data= df.to_numpy()
X= data[:, 0:5]
print(X.shape)
y= data[:, 5]
m= y.shape[0]
y= y.reshape(m, 1)
X= np.insert(X, 0, np.ones((1,m)), axis= 1)
print(X)
```

```
(569, 5)
[[1.000e+00 1.799e+01 1.038e+01 1.228e+02 1.001e+03 1.184e-01]
 [1.000e+00 2.057e+01 1.777e+01 1.329e+02 1.326e+03 8.474e-02]
 [1.000e+00 1.969e+01 2.125e+01 1.300e+02 1.203e+03 1.096e-01]
 …
 [1.000e+00 1.660e+01 2.808e+01 1.083e+02 8.581e+02 8.455e-02]
 [1.000e+00 2.060e+01 2.933e+01 1.401e+02 1.265e+03 1.178e-01]
 [1.000e+00 7.760e+00 2.454e+01 4.792e+01 1.810e+02 5.263e-02]]
```

[7]:

```
from sklearn.model_selection import train_test_split
```

[11]:

```
def hypothesis(X, theta):
    tmp = X@theta
    yest= 1/(1+(np.exp(-(tmp))))
    return yest

def cost(X, y, theta):
    m= X.shape[0]
    Yest= hypothesis(X, theta)
    lh1= np.log(Yest)
    lh2= np.log(1-Yest)
    cs= -((lh1.T@y)+lh2.T@(1-y))/m
    return cs

def gradient(X, y, theta):
    gr= np.zeros((6,1))
    Yest= hypothesis(X, theta)
    err= Yest- y
    m= X.shape[0]
    gr= X.T@err/m
    return gr

def normalize(X):
    cols= X.shape[1]
    Xmean= np.mean(X, axis= 0)
    Xmin= np.min(X, axis= 0)
    Xmax= np.max(X, axis= 0)
    X_norm = X.copy()
```

```
    for i in range(1, cols):
        X_norm[:, i]= (X_norm[:, i]- Xmean[i])/(Xmax[i]- Xmin[i])
    return X_norm

X_norm= normalize(X)
```

[12]:
```
X_norm
```

[12]:
```
array([[ 1.        ,  0.18281548, -0.30130702,  0.21305346,  0.14681268,
         0.1989683 ],
       [ 1.        ,  0.30492254, -0.05139156,  0.28284822,  0.28467058,
        -0.10490459],
       [ 1.        ,  0.26327362,  0.06629528,  0.26280814,  0.23249667,
         0.11952441],
       …,
       [ 1.        ,  0.11702912,  0.29727262,  0.11285306,  0.08619762,
        -0.10661985],
       [ 1.        ,  0.30634239,  0.3395452 ,  0.33260291,  0.25879571,
         0.19355167],
       [ 1.        , -0.3013532 ,  0.1775567 , -0.30439523, -0.20101341,
        -0.39478452]])
```

[13]:
```
X_train, X_test, Y_train, Y_test= train_test_split(X_norm, y, test_size=0.2,␣
 ↪random_state=0)
print("Number of training examples in train_set and test_set", X_train.
 ↪shape[0], Y_train.shape[0])
```

```
Number of training examples in train_set and test_set 455 455
```

[ ]:
```
N= 30000
alpha= 0.03
m= Y_train.shape[0]
theta= np.zeros((6, 1))
prev_cost= cost(X_train, Y_train, theta)
print("Cost before training:", prev_cost)
for i in range(N):
    print(i, prev_cost) # ------>   J_history
    theta= theta- alpha* gradient(X_train, Y_train, theta)
    current_cost= cost(X_train, Y_train, theta)
    if abs(prev_cost- current_cost)<1e-6:
        print(i)
        break
    prev_cost= current_cost
print("Final theta", theta)
print("\n")
print("Cost after Training:", prev_cost)
```

[22]:
```
def findMSE(X, y, theta):
    m= X.shape[0]
    Y_pred= hypothesis(X, theta)
    Y_pred= [1 if i>= 0.5 else 0 for i in Y_pred]
    Y_pred= np.array(Y_pred).reshape(m, 1)
    err= Y_pred- y
    mse= err.T@err/m
    return mse

print("Train_mse:", findMSE(X_train, Y_train, theta))
```

```
Train_mse: [[0.07692308]]
```

[23]:
```
print("Test_mse:", findMSE(X_test, Y_test, theta))
```

```
Test_mse: [[0.0877193]]
```

1 Confusion Matrix Evaluation

[24]:
```
true_positive, true_negative, false_positive, false_negative= 0,0, 0, 0
m= X_test.shape[0]
Y_pred= hypothesis(X_test, theta)
Y_pred= [1 if i>= 0.5 else 0 for i in Y_pred]
Y_pred= np.array(Y_pred).reshape(m, 1)
for i in range(m):
    if Y_pred[i]== 0 and Y_test[i]==0:
        true_negative+=1
    elif Y_pred[i]==1 and Y_test[i]==0:
        false_positive+=1
    elif Y_pred[i]==1 and Y_test[i]==1:
        true_positive+=1
    elif Y_pred[i]==0 and Y_test[i]==1:
        false_negative+=1
print(true_positive, true_negative, false_positive, false_negative)
P = true_positive/(true_positive+false_positive)
R = true_positive/(true_positive+false_negative)
F1 = 2*P*R/(P+R)
print("Accuracy:",(true_positive+true_negative)/m)
print("P R F1",P,R,F1)
```

```
63 41 6 4
Accuracy: 0.9122807017543859
P R F1 0.9130434782608695 0.9402985074626866 0.9264705882352942
```

2 Logistic Regression on mnist dataset

[3]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

[4]:
```
traindata= pd.read_csv("mnist_train.csv")
testdata= pd.read_csv("mnist_test.csv")
traindataset= traindata.to_numpy()
testdataset= testdata.to_numpy()
print(traindataset.shape, testdataset.shape)
train_labels= traindataset[:, 0].reshape(60000, 1)     # 60000 training samples␣
↪are present in traindataset
test_labels= testdataset[:, 0].reshape(10000, 1)          # 10000 testing␣
↪samples are present in testdataset
train_features= traindataset[:, 1:]
test_features= testdataset[:, 1:]
```

```
(60000, 785) (10000, 785)
```

3 sample Representation

[7]:
```
i= 5   # ith sample in the data
np.printoptions(linewidth= 600)
print(train_features[i, :].reshape((28, 28)))         #the each samples have 784␣
↪values which can be reshaped into 28*28 matrix form
plt.imshow(train_features[i, :].reshape((28, 28)))    # imshow shows the pixels␣
↪by taking the values as the value of intensity
plt.show()
print("This is:", train_labels[i, 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   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   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  13  25 100
  122   7   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0  33 151 208 252 252
  252 146   0   0   0   0   0   0   0   0]
```

```
[  0   0   0   0   0   0   0   0   0   0   0  40 152 244 252 253 224 211
 252 232  40   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   0  15 152 239 252 252 252 216  31  37
 252 252  60   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   0  96 252 252 252 252 217  29   0  37
 252 252  60   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   0 181 252 252 220 167  30   0   0  77
 252 252  60   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   0  26 128  58  22   0   0   0   0 100
 252 252  60   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0 157
 252 252  60   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   0   0   0   0   0 110 121 122 121 202
 252 194   3   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   0   0  10  53 179 253 253 255 253 253
 228  35   0   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   5  54 227 252 243 228 170 242 252 252
 231 117   6   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   6  78 252 252 125  59   0  18 208 252 252
 252 252  87   7   0   0   0   0   0   0]
[  0   0   0   0   0   0   5 135 252 252 180  16   0  21 203 253 247 129
 173 252 252 184  66  49  49   0   0   0]
[  0   0   0   0   0   3 136 252 241 106  17   0  53 200 252 216  65   0
  14  72 163 241 252 252 223   0   0   0]
[  0   0   0   0   0 105 252 242  88  18  73 170 244 252 126  29   0   0
   0   0   0  89 180 180  37   0   0   0]
[  0   0   0   0   0 231 252 245 205 216 252 252 252 124   3   0   0   0
   0   0   0   0   0   0   0   0   0   0]
[  0   0   0   0   0 207 252 252 252 252 178 116  36   4   0   0   0   0
   0   0   0   0   0   0   0   0   0   0]
[  0   0   0   0   0  13  93 143 121  23   6   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   0   0   0   0   0   0   0   0   0]
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   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]]
```

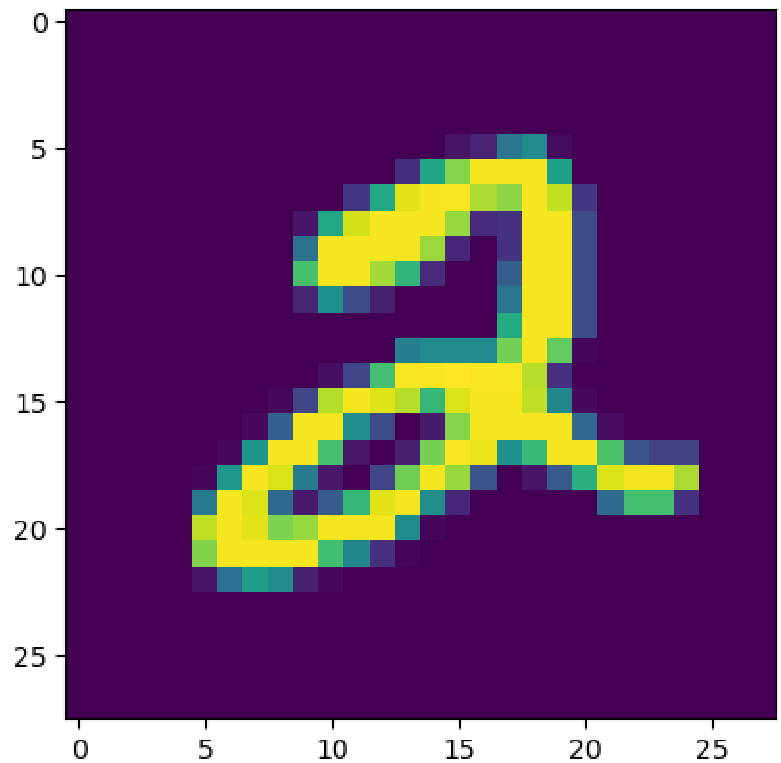

This is: 2

4 Normalize features

[8]:
```
# Here normalizeation is done by diving the dataset with max value in the data␣
↪i.e in MNIST the max value is approx 255.
train_features= train_features/255
test_features= test_features/255
```

[9]:
```
m_train = train_features.shape[0]
m_test= test_features.shape[0]
train_features= np.insert(train_features, 0, np.ones((1, m_train)), axis= 1)
test_features= np.insert(test_features, 0, np.ones((1, m_test )), axis= 1)
```

[14]:
```
def hypothesis(X, theta):
    tmp = X@theta
    Yest= 1/(1+(np.exp(-tmp)))
    return Yest

def cost(X, y, theta):
    m= X.shape[0]
```

```
    lh1= np.log(hypothesis(X, theta))
    lh2= np.log(1- (hypothesis(X, theta)))
    cs= -(lh1.T@y+lh2.T@(1-y))/m
    return cs
def gradient(X, y, theta):
    m= y.shape[0]
    Yest= hypothesis(X, theta)
    err= Yest- y
    gr= (X.T@err)/m
    return gr

train_labels0= np.array([1 if i==0 else 0 for i in train_labels]).
 ↪reshape(m_train, 1)
train_labels1= np.array([1 if i==1 else 0 for i in train_labels]).
 ↪reshape(m_train, 1)
train_labels2= np.array([1 if i==2 else 0 for i in train_labels]).
 ↪reshape(m_train, 1)
train_labels3= np.array([1 if i==3 else 0 for i in train_labels]).
 ↪reshape(m_train, 1)
train_labels4= np.array([1 if i==4 else 0 for i in train_labels]).
 ↪reshape(m_train, 1)
train_labels5= np.array([1 if i==5 else 0 for i in train_labels]).
 ↪reshape(m_train, 1)
train_labels6= np.array([1 if i==6 else 0 for i in train_labels]).
 ↪reshape(m_train, 1)
train_labels7= np.array([1 if i==7 else 0 for i in train_labels]).
 ↪reshape(m_train, 1)
train_labels8= np.array([1 if i==8 else 0 for i in train_labels]).
 ↪reshape(m_train, 1)
train_labels9= np.array([1 if i==9 else 0 for i in train_labels]).
 ↪reshape(m_train, 1)
```

[15]:

```
def gradient_descent(X, y, theta_initial, alpha, tol, N):
    theta= theta_initial
    prev_cost= cost(X, y, theta)
    print("Cost before training:", prev_cost)
    for i in range(N):
        print("-", end= "")
        theta= theta- alpha*gradient(X, y, theta)
        cs= cost(X, y, theta)
        if abs(prev_cost- cs)<tol:
            print(i)
            break
        prev_cost= cs
    print("the cost after training:", prev_cost)
    return theta
```

[16]:

```python
theta_inital= np.zeros((785, 1))
theta0= gradient_descent(train_features, train_labels0, theta_inital, 0.03, 1e-6, 3000 )
theta1= gradient_descent(train_features, train_labels1, theta_inital, 0.03, 1e-6, 3000 )
theta2= gradient_descent(train_features, train_labels2, theta_inital, 0.03, 1e-6, 3000 )
theta3= gradient_descent(train_features, train_labels3, theta_inital, 0.03, 1e-6, 3000 )
theta4= gradient_descent(train_features, train_labels4, theta_inital, 0.03, 1e-6, 3000 )
theta5= gradient_descent(train_features, train_labels5, theta_inital, 0.03, 1e-6, 3000 )
theta6= gradient_descent(train_features, train_labels6, theta_inital, 0.03, 1e-6, 3000 )
theta7= gradient_descent(train_features, train_labels7, theta_inital, 0.03, 1e-6, 3000 )
theta8= gradient_descent(train_features, train_labels8, theta_inital, 0.03, 1e-6, 3000 )
theta9= gradient_descent(train_features, train_labels9, theta_inital, 0.03, 1e-6, 3000 )
```

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Cost before training: [[0.69314718]]
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Cost before training: [[0.69314718]]
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Cost before training: [[0.69314718]]
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----------------------------------------the cost after training: [[0.12399921]]
```

[18]:
```
theta= np.concatenate((theta0, theta1, theta2, theta3, theta4, theta5, theta6,
    theta7, theta8, theta9), axis= 1)
```

[20]:
```
theta.shape
```

[20]:
```
(785, 10)
```

[21]:
```
theta
```

[21]:
```
array([[-0.67947939, -0.12596979, -0.76482933, …, -0.3033674 ,
        -1.68213952, -0.9087435 ],
       [ 0.        ,  0.        ,  0.        , …,  0.        ,
         0.        ,  0.        ],
       [ 0.        ,  0.        ,  0.        , …,  0.        ,
         0.        ,  0.        ],
       …,
       [ 0.        ,  0.        ,  0.        , …,  0.        ,
```

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          0.        ,  0.        ],
        [ 0.        ,  0.        ,  0.        , …,  0.        ,
          0.        ,  0.        ],
        [ 0.        ,  0.        ,  0.        , …,  0.        ,
          0.        ,  0.        ]])
```

[25]:

```
testPrediction = 1/(1+np.exp(-test_features@theta))
i = 1003
print(testPrediction[i,:])
print(np.argmax(testPrediction[i,:]))
print(test_labels[i])
```

```
[3.61221678e-04 3.14821596e-07 5.16941061e-04 4.00406839e-01
 1.89973454e-06 5.53674883e-01 3.82089047e-07 2.16860535e-06
 9.53381239e-02 2.06206713e-05]
5
[5]
```

[26]:

```
testPred = np.argmax(testPrediction,axis=1).reshape(10000,1)
print(testPred)
```

```
[[7]
 [2]
 [1]
 …
 [4]
 [8]
 [6]]
```

[27]:

```
correct = [1 if testPred[i]==test_labels[i] else 0 for i in range(0,10000)]
accuracy = np.sum(correct)/10000
print(accuracy*100)
```

```
89.92
```

5 Logistic_regression on university admission dataset

[1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

[2]:

```
df = pd.read_csv('E:\VS␣
↪CODE\machine-learning-andrew-ng-master\machine-learning-andrew-ng-master\data\ex2data1.
↪txt', sep=',', header=None)
df.columns = ['exam_score_1', 'exam_score_2', 'label']
```

[3]:
```
df
```

[3]:

	exam_score_1	exam_score_2	label
0	34.623660	78.024693	0
1	30.286711	43.894998	0
2	35.847409	72.902198	0
3	60.182599	86.308552	1
4	79.032736	75.344376	1
..	…	…	…
95	83.489163	48.380286	1
96	42.261701	87.103851	1
97	99.315009	68.775409	1
98	55.340018	64.931938	1
99	74.775893	89.529813	1

[100 rows x 3 columns]

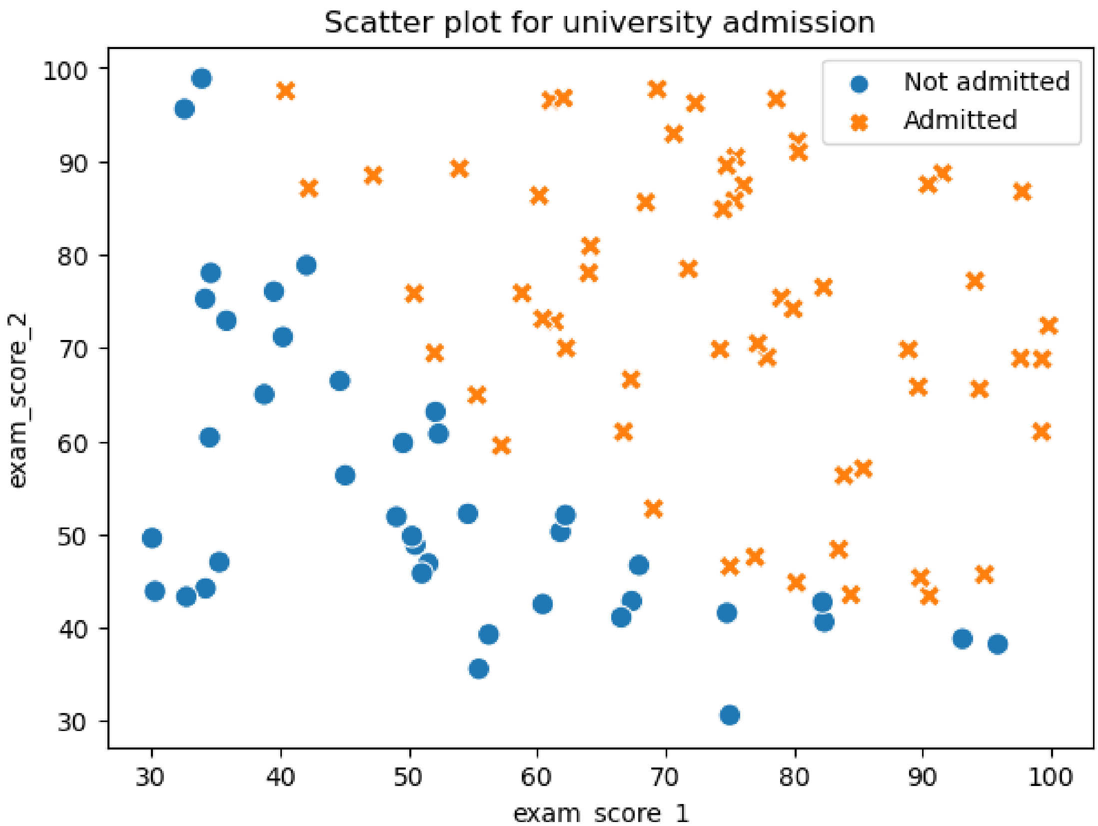
[4]:
```
df.describe().T
```

[4]:

	count	mean	std	min	25%	50%	\
exam_score_1	100.0	65.644274	19.458222	30.058822	50.919511	67.032988	
exam_score_2	100.0	66.221998	18.582783	30.603263	48.179205	67.682381	
label	100.0	0.600000	0.492366	0.000000	0.000000	1.000000	

	75%	max
exam_score_1	80.212529	99.827858
exam_score_2	79.360605	98.869436
label	1.000000	1.000000

[8]:
```
plt.figure(figsize=(7,5))
plot= sns.scatterplot(x= "exam_score_1", y= "exam_score_2", data= df, hue=␣
 ↪"label", style= "label", s= 80)
#hue---> here hue means how color to be differentiated, so here labe column is␣
 ↪used to differentiate the color
#style---> Here style means how to differentiate the markers to be used, so␣
 ↪here the lanel column is used to differentiate the style
# s--> size of marker
handles, labels= plot.get_legend_handles_labels()
plot.legend(handles[0:], ["Not admitted", "Admitted"])
plt.title("Scatter plot for university admission")
plt.show()
```



[92]:
```
def sigmoid(z):
    z= np.array(z)
    return 1/(1+np.exp(-z))
```

[123]:
```
def cost_function(theta, X, y):
    m = y.shape[0]
    theta = theta[:, np.newaxis] #trick to make numpy minimize work
    h = sigmoid(X.dot(theta))
    J = (1/m) * (-y.T.dot(np.log(h)) - (1-y).T.dot(np.log(1-h)))

    diff_hy = h - y
    grad = (1/m) * diff_hy.T.dot(X)

    return J, grad
```

[124]:
```
m = df.shape[0]
X = np.hstack((np.ones((m,1)),df[['exam_score_1', 'exam_score_2']].values))
y = np.array(df.label.values).reshape(-1,1)
initial_theta = np.zeros(shape=(X.shape[1]))
```

[125]:
```
cost, grad = cost_function(initial_theta, X, y)
print('Cost at initial theta (zeros):', cost)
print('Expected cost (approx): 0.693')
print('Gradient at initial theta (zeros):')
print(grad.T)
print('Expected gradients (approx):\n -0.1000\n -12.0092\n -11.2628')
```

```
Cost at initial theta (zeros): [[0.69314718]]
Expected cost (approx): 0.693
Gradient at initial theta (zeros):
[[ -0.1       ]
 [-12.00921659]
 [-11.26284221]]
Expected gradients (approx):
 -0.1000
 -12.0092
 -11.2628
```

[126]:
```
import scipy.optimize as opt
def optimize_theta(X, y, initial_theta):
    opt_results = opt.minimize(cost_function, initial_theta, args=(X, y),␣
 ↪method='TNC',
                               jac=True, options={'maxiter':400})
    return opt_results['x'], opt_results['fun']
```

[127]:
```
opt_theta, cost = optimize_theta(X, y, initial_theta)
```

```
C:\Users\JAGADISH\AppData\Local\Temp\ipykernel_10980\1274892550.py:3:
DeprecationWarning: 'maxiter' has been deprecated in favor of 'maxfun' and will
be removed in SciPy 1.11.0.
  opt_results = opt.minimize(cost_function, initial_theta, args=(X, y),
method='TNC',
```

[128]:
```
opt_theta
```

[128]:
```
array([-25.16131862,   0.20623159,   0.20147149])
```

[129]:
```
cost
```

[129]:
```
0.20349770158947464
```

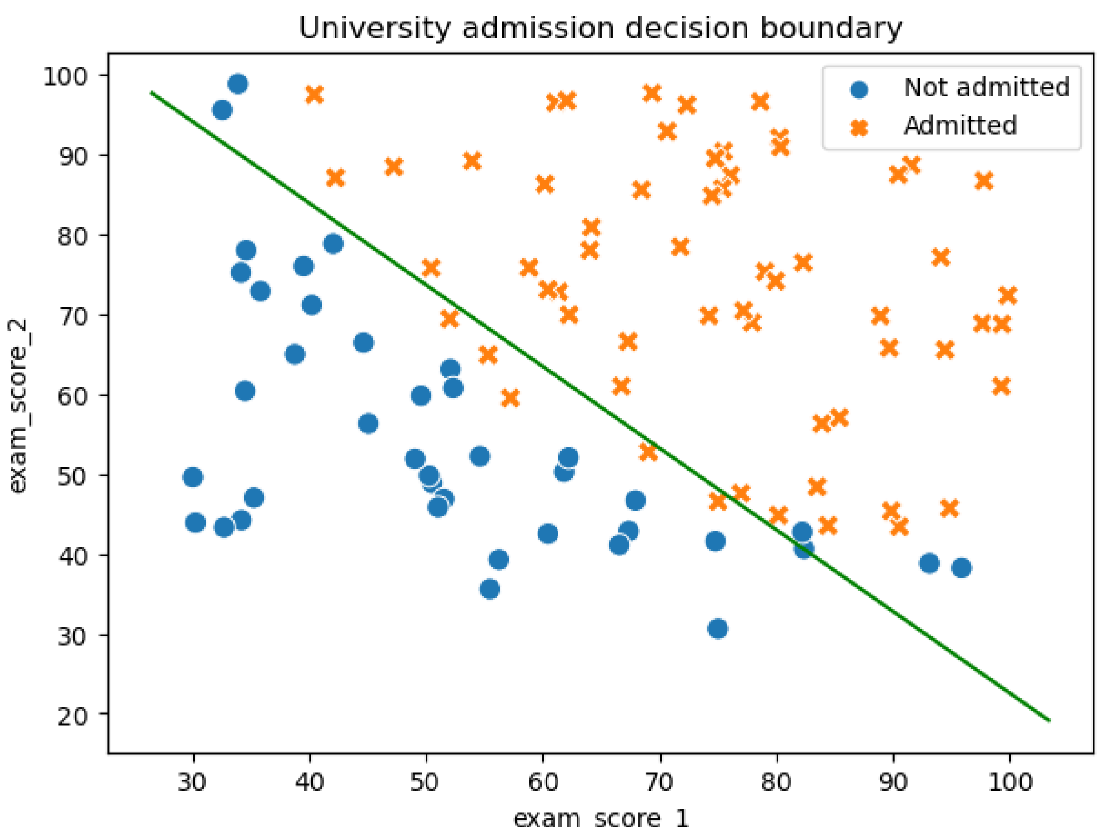
6 Decision Boundary

[156]:
```
plt.figure(figsize= (7, 5))
plot= sns.scatterplot(x= "exam_score_1", y= "exam_score_2", data= df, hue=␣
 ↪"label", style= "label", s= 80)
```

```python
handles, labels= plot.get_legend_handles_labels()
plot.legend(handles[0:], ["Not admitted", "Admitted"])
plt.title("University admission decision boundary")

plot_x= np.array(plot.get_xlim())
print(plot_x)
plot_y = (-opt_theta[1]/opt_theta[2]) * plot_x - opt_theta[0]/opt_theta[2]
plt.plot(plot_x, plot_y, "-", c= "green")
plt.show(plot)
```

```
[ 26.57037068 103.31630956]
```



7 Evaluating Logistic Regression

[157]:
```python
prob= sigmoid(np.array([1, 45, 85]).dot(opt_theta))
print("The prob of getting admission of student with 45 and 85 marks is:", prob)
```

```
The prob of getting admission of student with 45 and 85 marks is:
0.7762906236225744
```

8 Accuracy on training set

[160]:
```
def predict(X, theta):
    y_pred= [1 if sigmoid(X[i, :].dot(theta))>= 0.5 else 0 for i in range(0, X.
 ↪shape[0])]
    return y_pred
```

[161]:
```
y_pred_prob = predict(X, opt_theta)
```

[162]:
```
y_pred_prob
```

[162]:
```
[0,
 0,
 0,
 1,
 1,
 0,
 1,
 0,
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```

```
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 1,
 0,
 1]
```

[165]:
```
y_pred_prob== df.label.values
```

[165]:
```
array([ True,  True,  True,  True,  True,  True,  True, False,  True,
        True, False,  True,  True,  True,  True,  True, False,  True,
        True,  True,  True,  True,  True,  True,  True,  True,  True,
       False,  True,  True,  True,  True,  True, False,  True,  True,
       False,  True,  True,  True,  True,  True,  True, False,  True,
        True,  True,  True,  True,  True,  True,  True,  True,  True,
        True,  True,  True, False,  True,  True,  True,  True,  True,
        True,  True,  True,  True,  True,  True,  True,  True,  True,
        True,  True,  True,  True,  True,  True,  True, False,  True,
        True,  True, False,  True,  True,  True,  True,  True,  True,
        True,  True,  True,  True,  True,  True,  True,  True, False,
        True])
```

[163]:
```
f'Train Accuracy: {np.mean(y_pred_prob== df.label.values)*100}'
```

[163]:
```
'Train Accuracy: 89.0'
```

9 Equivalent with Sklearn

[167]:
```
from sklearn.linear_model import LogisticRegression
log_reg= LogisticRegression(solver= "newton-cg", max_iter= 400)
log_reg.fit(df[['exam_score_1', "exam_score_2"]].values, df.label.values)
```

[167]:
```
LogisticRegression(max_iter=400, solver='newton-cg')
```

[168]:
```
log_reg.intercept_, log_reg.coef_
```

[168]: (array([-25.05200378]), array([[0.2053533 , 0.20058239]]))

#Accuracy with sklearn

[170]:
```
log_reg.score(df[['exam_score_1', 'exam_score_2']].values,df.label.values)
```

[170]: 0.89

10 Regularized Logistic Regression

Visualization of the data

[181]:
```
df2= pd.read_csv("E:\VS␣
↪CODE\machine-learning-andrew-ng-master\machine-learning-andrew-ng-master\data\ex2data2.
↪txt", sep =",", header= None)
df2.columns= ['test_1', 'test_2', 'label']
```

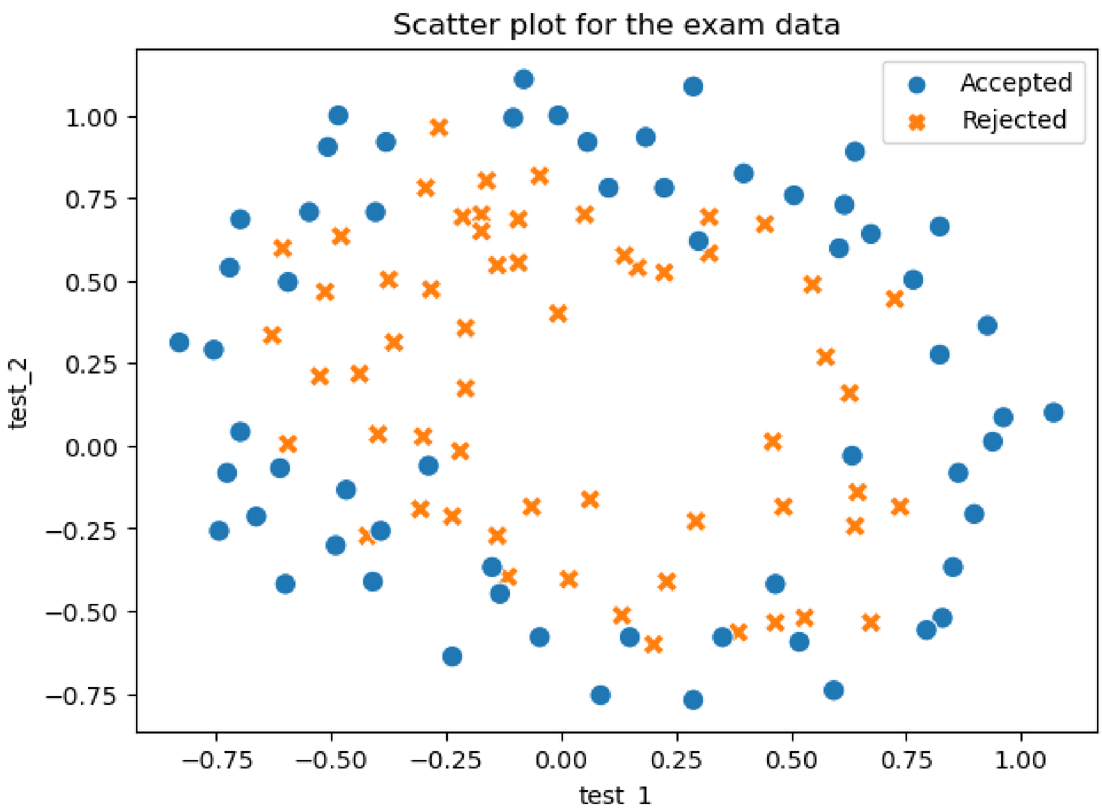
[182]:
```
df2
```

[182]:
```
       test_1    test_2  label
0    0.051267  0.699560      1
1   -0.092742  0.684940      1
2   -0.213710  0.692250      1
3   -0.375000  0.502190      1
4   -0.513250  0.465640      1
..        ...       ...    ...
113 -0.720620  0.538740      0
114 -0.593890  0.494880      0
115 -0.484450  0.999270      0
116 -0.006336  0.999270      0
117  0.632650 -0.030612      0

[118 rows x 3 columns]
```

[183]:
```
df2.describe().T
```

[183]:
```
        count      mean       std      min       25%       50%       75%  \
test_1  118.0  0.054779  0.496654 -0.83007 -0.372120 -0.006336  0.478970
test_2  118.0  0.183102  0.519743 -0.76974 -0.254385  0.213455  0.646563
label   118.0  0.491525  0.502060  0.00000  0.000000  0.000000  1.000000

           max
test_1  1.0709
test_2  1.1089
label   1.0000
```

[184]:
```python
plt.figure(figsize=(7,5))
plot= sns.scatterplot(x= "test_1", y= "test_2", data= df2, hue= "label", style=␣
↪"label", s= 80)
handles, labels= plot.get_legend_handles_labels()
plt.legend(handles[0:], ["Accepted", "Rejected"])
plt.title("Scatter plot for the exam data")
plt.show()
```



[187]:
```python
def map_feature(X1, X2, degree):
    X1 = np.array(X1).reshape(-1,1)
    X2 = np.array(X2).reshape(-1,1)

    out = np.ones((X1.shape[0], 1))
    for i in range(1, degree+1):
        for j in range(0, i+1):
            p = (X1**(i-j)) * (X2**j)
            out = np.append(out, p, axis=1)
    return out
```

[188]:
```python
X_p = map_feature(df2.test_1.values, df2.test_2.values, 6)
X_p.shape
```

[188]: (118, 28)

[189]:
```
def cost_function_reg(theta, X, y, lambda_reg):
    m = y.shape[0]
    theta = theta[:, np.newaxis]
    h = sigmoid(X.dot(theta))
    J = (1/m) * (-y.T.dot(np.log(h)) - (1-y).T.dot(np.log(1-h))) + (lambda_reg/
 ↪(2*m)) * np.sum(theta[1:]**2)

    diff_hy = h - y
    grad = (1/m) * diff_hy.T.dot(X) + ((lambda_reg/m) * theta.T)
    grad[0, 0] = (1/m) * diff_hy.T.dot(X[:, 0])

    return J, grad
```

[190]:
```
import scipy.optimize as opt
def optimize_theta_reg(X, y, initial_theta, lambda_reg):
    opt_results = opt.minimize(cost_function_reg, initial_theta, args=(X, y,␣
 ↪lambda_reg), method='TNC', jac=True, options={'maxiter':400})
    return opt_results['x'], opt_results['fun']
```

[191]:
```
m = df.shape[0]
X = X_p
y = np.array(df2.label.values).reshape(-1,1)
initial_theta = np.zeros(shape=(X.shape[1]))
```

[192]:
```
lambda_reg = 1
cost, grad = cost_function_reg(initial_theta, X, y, lambda_reg)
```

[193]:
```
print(grad.T[:5])
```

```
[[8.47457627e-03]
 [1.87880932e-02]
 [7.77711864e-05]
 [5.03446395e-02]
 [1.15013308e-02]]
```

[194]:
```
lambda_reg = 10
initial_theta = np.ones(shape=(X.shape[1]))
cost, grad = cost_function_reg(initial_theta, X, y, lambda_reg)
```

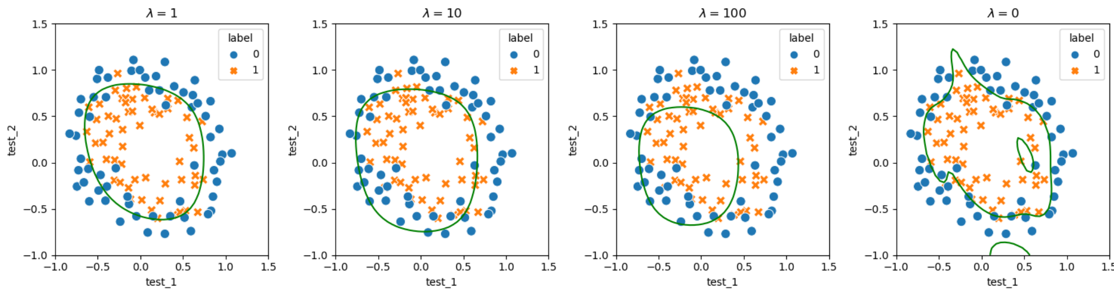
[195]:
```
print(grad.T[:5])
```

```
[[0.34604507]
 [0.16135192]
 [0.19479576]
 [0.22686278]
```

[0.09218568]]

[196]:
```
lambda_reg = [1, 10, 100, 0]
fig, axs = plt.subplots(nrows=1, ncols=4, figsize=(15,4))
u = np.linspace(-1, 1.5, 50)
v = np.linspace(-1, 1.5, 50)

for il, l in enumerate(lambda_reg):
    theta_opt, cost = optimize_theta_reg(X, y, initial_theta, l)
    z = np.zeros((u.shape[0], v.shape[0]))
    for i in range(len(u)):
        for j in range(len(v)):
            z[i,j] = map_feature(u[i], v[j], 6).dot(theta_opt)

    sns.scatterplot(x='test_1', y='test_2', hue='label', data=df2,␣
 ↪style='label', s=80, ax=axs[il])

    axs[il].contour(u, v, z.T, levels=[0], colors='green')
    axs[il].set_title('$\lambda={}$'.format(l))
fig.tight_layout()
plt.show()
```

```
C:\Users\JAGADISH\AppData\Local\Temp\ipykernel_10980\968707659.py:3:
DeprecationWarning: 'maxiter' has been deprecated in favor of 'maxfun' and will
be removed in SciPy 1.11.0.
  opt_results = opt.minimize(cost_function_reg, initial_theta, args=(X, y,
lambda_reg), method='TNC', jac=True, options={'maxiter':400})
C:\Users\JAGADISH\AppData\Local\Temp\ipykernel_10980\968707659.py:3:
DeprecationWarning: 'maxiter' has been deprecated in favor of 'maxfun' and will
be removed in SciPy 1.11.0.
  opt_results = opt.minimize(cost_function_reg, initial_theta, args=(X, y,
lambda_reg), method='TNC', jac=True, options={'maxiter':400})
C:\Users\JAGADISH\AppData\Local\Temp\ipykernel_10980\968707659.py:3:
DeprecationWarning: 'maxiter' has been deprecated in favor of 'maxfun' and will
be removed in SciPy 1.11.0.
  opt_results = opt.minimize(cost_function_reg, initial_theta, args=(X, y,
lambda_reg), method='TNC', jac=True, options={'maxiter':400})
C:\Users\JAGADISH\AppData\Local\Temp\ipykernel_10980\968707659.py:3:
DeprecationWarning: 'maxiter' has been deprecated in favor of 'maxfun' and will
be removed in SciPy 1.11.0.
  opt_results = opt.minimize(cost_function_reg, initial_theta, args=(X, y,
lambda_reg), method='TNC', jac=True, options={'maxiter':400})
```



[197]:
```python
lambda_reg = 1
theta, cost = optimize_theta_reg(X, y, initial_theta, lambda_reg)
theta
```

```
C:\Users\JAGADISH\AppData\Local\Temp\ipykernel_10980\968707659.py:3:
DeprecationWarning: 'maxiter' has been deprecated in favor of 'maxfun' and will
be removed in SciPy 1.11.0.
  opt_results = opt.minimize(cost_function_reg, initial_theta, args=(X, y,
lambda_reg), method='TNC', jac=True, options={'maxiter':400})
```

[197]:
```
array([ 1.27273509,  0.62525435,  1.18108521, -2.01994882, -0.91742556,
       -1.43167368,  0.12399628, -0.36552234, -0.35723208, -0.17514253,
       -1.4581339 , -0.05098852, -0.61553085, -0.27470069, -1.19280263,
       -0.24220871, -0.20601057, -0.04472767, -0.2777735 , -0.29536755,
       -0.45637086, -1.04318579,  0.02776829, -0.29241701,  0.01556523,
       -0.32737793, -0.14388044, -0.92463148])
```

[198]:
```python
y_pred_prob = predict(X, theta)
f'Train accuracy: {np.mean(y_pred_prob == df2.label.values) * 100}'
```

[198]:
```
'Train accuracy: 83.05084745762711'
```

[199]:
```python
from sklearn.linear_model import LogisticRegression
log_reg = LogisticRegression(solver='newton-cg', max_iter=400)
log_reg.fit(X[:,1:], df2.label.values)
```

[199]:
```
LogisticRegression(max_iter=400, solver='newton-cg')
```

[200]:
```python
log_reg.intercept_, log_reg.coef_
```

[200]:
```
(array([1.27273852]),
 array([[ 0.62527427,  1.18107953, -2.01995701, -0.91743361, -1.43166228,
          0.12400943, -0.36552879, -0.35723375, -0.1751281 , -1.45816817,
         -0.05099315, -0.61556795, -0.27470949, -1.19281161, -0.24218951,
         -0.20599958, -0.04473522, -0.27778736, -0.29537501, -0.45635027,
         -1.04321271,  0.02777197, -0.29243756,  0.0155633 , -0.32738395,
```

```
         -0.14388956, -0.92464266]]))
```

[201]:
```
log_reg.score(X[:,1:], df2.label.values)
```

[201]: 0.8305084745762712

[ ]:
```

```