General Sir John Kotelawala Defense University

Department of Electrical, Electronics & Telecommunication Engineering

Machine Learning

ET 4103

Assignment – 03

Unregularized Logistic Regression

Index No : D/ENG/22/0120/ET

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Q1. Utilize the given Jupyter notebook[1] for Unregularized Logistic Regression. Comment on the code and the output of the program, explaining utilized Machine Learning concepts where necessary

The following code is a python program that demonstrates Unregularized Logistic Regression. Logistic Regression is a type of statistical model used to classify data into binary outcomes. It is a supervised learning algorithm that used a sigmoid function to generate probability values for a set of linear inputs. This probability value is then used to classify the data into one of two classes.

```
# File Location: The file we want to access is currently placed in the current working directory of Python.

from google.colab import drive
drive.mount('/content/drive') # Grants Colab access to Google Drive in order to retrieve the data files
%cd "/content/drive/MyDrive/ML_files"
```

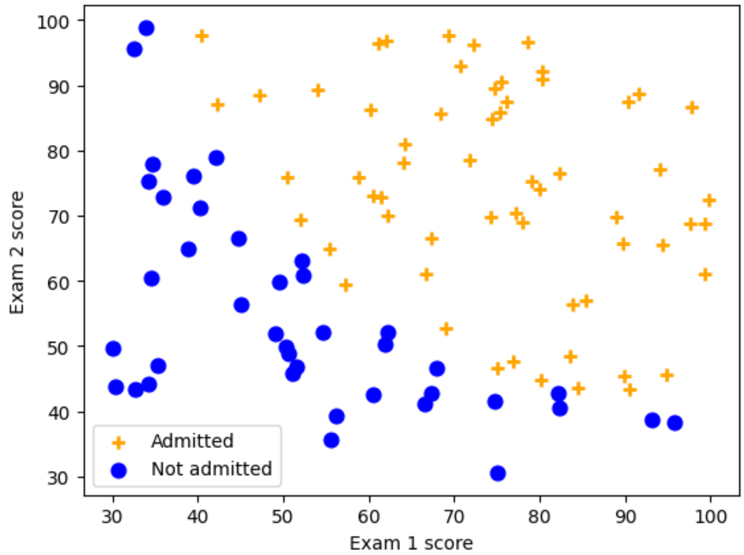
```
/content/drive/MyDrive/ML_files
```

```
# Importing Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

# Reading the data file
data_path = 'ex2data1.txt'
data = pd.read_csv(data_path, header=None, names = ["x1","x2","y"])
data.head()
```

	x1	x2	y
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

```
# Plots the data on a scatter plot
neg = data['y'] == 0
pos = data['y'] == 1
# Marks positive data with a yellow cross
plt.scatter(data[pos]['x1'],data[pos]['x2'], marker='+', c='orange', s=60, linewidth=2, label = "Admitted")
# Marks negative data with a blue dot
```

```
plt.scatter(data[neg]['x1'], data[neg]['x2'], c='blue', s=60, label =
"Not admitted" )
plt.xlabel('Exam 1 score')
plt.ylabel('Exam 2 score')
plt.legend(loc='best')
plt.show()
```




```
# Converts data
n = data.shape[1]-1
x = data[data.columns[0:n]]

y = data[data.columns[n:n+1]]
# convert to np.array
X = x.values
# insert 1's (x_0)
X = np.insert(X, 0, 1, axis=1)
y = y.values

### Sigmoid function

def sigmoid(z):
    return(1 / (1 + np.exp(-z)))

### Hypothesis and cost function

m = X.shape[0]
def Cost(theta, X, y):
    h = sigmoid(X.dot(theta))
    J = -1*(1/m)*(np.log(h).T.dot(y)+np.log(1-h).T.dot(1-y))

    if np.isnan(J.item()):
        return(np.inf)
```

```
    return(J.item())

# Calculation of the cost function for an initial (zero) value of theta
theta_initial = np.zeros(X.shape[1]).reshape(-1,1)
Cost(theta_initial,X,y)
```

```
0.6931471805599453
```

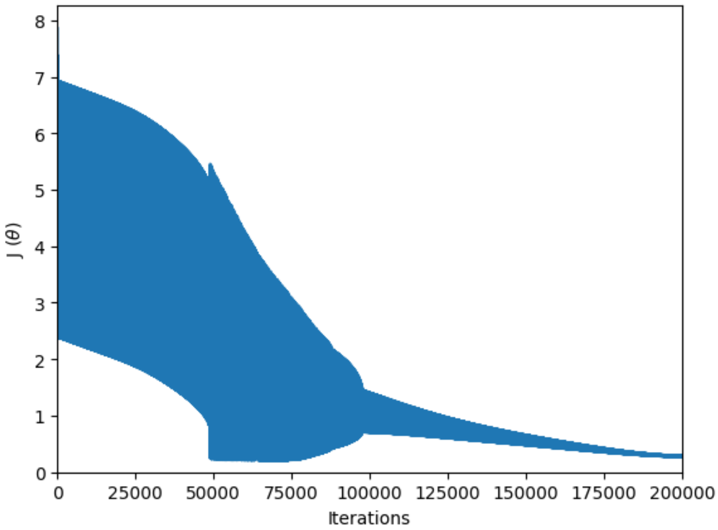
```
# Gradient function for regression
def gradient(theta, X, y):
    h = sigmoid(X.dot(theta))

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

    return grad

# Calculating cost and gradient for theta_initial
theta_initial = np.zeros(X.shape[1]).reshape(-1,1)
cost = Cost(theta_initial, X, y)
grad = gradient(theta_initial, X, y)
print('Cost: \n', cost)
print('Grad: \n', grad)
```

```
Cost:
 0.6931471805599453
Grad:
 [[ -0.1        ]
 [-12.00921659]
 [-11.26284221]]
```

```
# Gradient descent function
def gradientDescent(X, y, theta, alpha, num_iters):
    J_history = np.zeros(num_iters)

    for iter in np.arange(num_iters):

        theta = theta - alpha*gradient(theta,X,y)
        J_history[iter] = Cost(theta,X,y)
    return(theta, J_history)
theta_initial = np.zeros(X.shape[1]).reshape(-1,1)
alpha = 0.005 # Learning Rate
iterations = 200000 # Number of gradient descent steps
theta, cost_history =
gradientDescent(X,y,theta_initial,alpha,iterations)
theta
```

```
array([[-29.86812752],
       [  0.26028092],
       [  0.25275129]])
```

```
# Plot of cost history vs Iterations
plt.plot(cost_history)
plt.ylabel('J' + ' (' + r'$\theta$' +')')
# or plt.ylabel('J' + ' (\u0398)' )
plt.xlabel('Iterations')
plt.ylim(ymin = 0)
plt.xlim(0,iterations)
```




```
## Optimization (using Scipy)
import scipy.optimize as sp
theta_opt = sp.fmin( Cost, x0=theta_initial, args=(X, y), maxiter=500,
full_output=True)
```

```
Optimization terminated successfully.
         Current function value: 0.203498
         Iterations: 157
         Function evaluations: 287
```

```
# Prediction function for binary classification
def predict(theta, X, threshold=0.5):
    p = sigmoid(X.dot(theta.T)) >= threshold
    return(p.astype('int'))
theta_opt = theta_opt[0]
theta_opt
```

```
array([-25.16130062,   0.20623142,   0.20147143])
```

```
# Calculating probability for values of scikit fmin theta
sigmoid(np.array([1, 45, 85]).dot(theta_opt.T))
```

```
np.float64(0.7762915904112411)
```

```
# Calculates the accuracy of fmin model
p = predict(theta_opt, X)
print('Train accuracy {}%'.format(100*sum(p == y.ravel())/p.size))
```

```
Train accuracy 89.0%
```

```python
###### Using theta obtained from gradient descent
def predict1(theta1, X, threshold=0.5):
    p1 = sigmoid(X.dot(theta1)) >= threshold
    return(p1.astype('int'))

# Calculates accuracy of manually derived model
p1 = predict1(theta,X)
print('Train accuracy {}%'.format(100*sum(p1.ravel() ==
y.ravel())/p1.size))
```

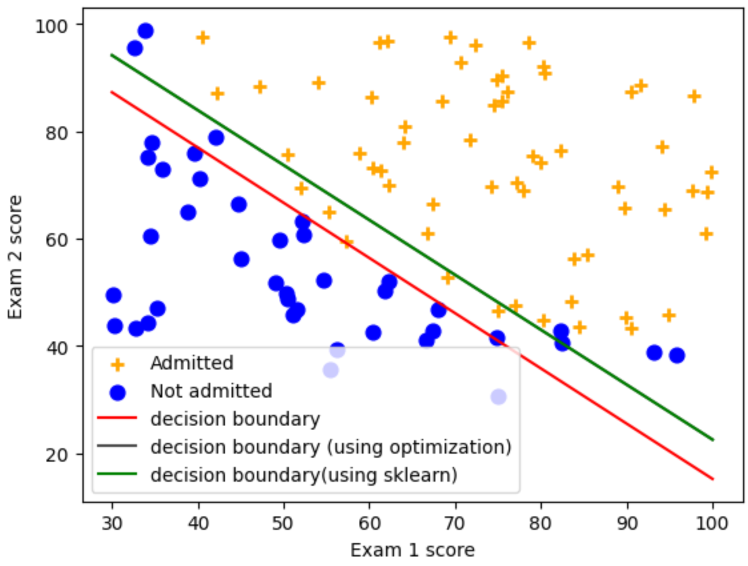
```
Train accuracy 92.0%
```

```python
#### sklearn
from sklearn import linear_model
reg = linear_model.LogisticRegression()
reg.fit (X[:,[1,2]],y.ravel());

from sklearn.metrics import accuracy_score
y_pred = reg.predict(X[:,[1,2]])
print('Train accuracy: ' + str(100*accuracy_score(y_pred,y))+'%')
```

```
Train accuracy: 89.0%
```

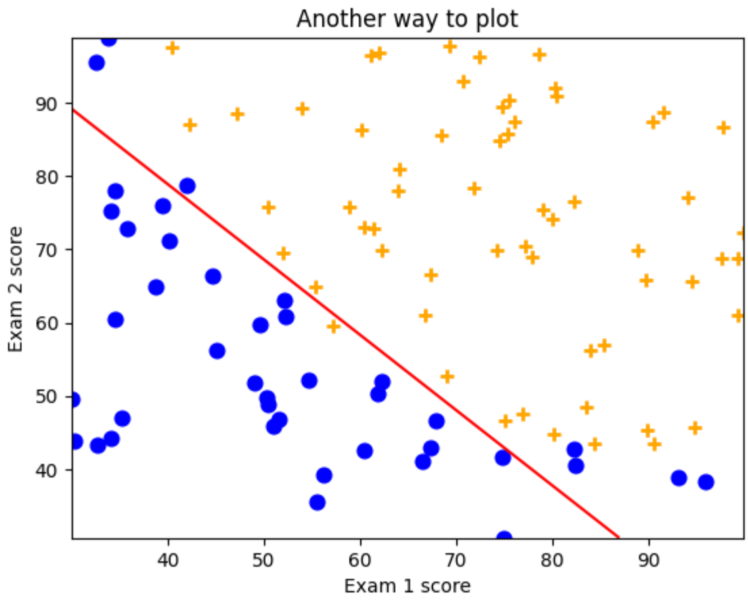
```python
# Plots the decision boundaries along with the scatter plot of data
## Decision boundary
neg = data['y'] == 0
pos = data['y'] == 1
plt.scatter(data[pos]['x1'],data[pos]['x2'], marker='+', c='orange',
s=60, linewidth=2, label = "Admitted")
plt.scatter(data[neg]['x1'], data[neg]['x2'], c='blue', s=60, label =
"Not admitted" )

xx = np.linspace(30,100,100)
yy = (-1./theta[2])*(theta[0] + theta[1]*xx)
plt.plot(xx,yy,color='r',label='decision boundary')


yy_opt = (-1./theta_opt[2])*(theta_opt[0] + theta_opt[1]*xx)
plt.plot(xx,yy_opt,color='k',label='decision boundary (using
optimization)',alpha=0.7)

coef = reg.coef_
intercept = reg.intercept_
ex2 = -(coef[:, 0] * xx + intercept.item()) / coef[:,1]
plt.plot(xx,ex2,color='g',label='decision boundary(using sklearn)')

plt.xlabel('Exam 1 score')
```

```
plt.ylabel('Exam 2 score')
plt.legend(loc='best')
plt.show()
```




```
### Alternate way to plot decision boundary (using contour)
x1_min, x1_max = data['x1'].min(), data['x1'].max(),
x2_min, x2_max = data['x2'].min(), data['x2'].max(),
xx1, xx2 = np.meshgrid(np.linspace(x1_min, x1_max), np.linspace(x2_min,
x2_max))

B0 = np.linspace(x1_min,x1_max)
B1 = np.linspace(x2_min,x2_max)
#xx, yy = np.meshgrid(B0, B1, indexing='xy')
Z = np.zeros((B0.size,B1.size))

def h(x1,x2):
    stacked = np.hstack((x1,x2))
    a = np.insert(stacked,0,1)
    return a.dot(theta)

for i in range (B0.size):
    for j in range(B1.size):
        Z[i,j] = h(xx1[i,j],xx2[i,j])

plt.contour(xx1,xx2,Z,[0.5],colors='r')

neg = data['y'] == 0
pos = data['y'] == 1
plt.scatter(data[pos]['x1'],data[pos]['x2'], marker='+', c='orange',
s=60, linewidth=2, label = "Admitted")
```

```
plt.scatter(data[neg]['x1'], data[neg]['x2'], c='blue', s=60, label =
"Not admitted" )

plt.xlabel('Exam 1 score')
plt.ylabel('Exam 2 score')
plt.title('Another way to plot')
plt.show()
```



The above code demonstrates Unregularized Logistic Regression being performed on a common dataset of student scores on two exams that aims to classify the scores into two categories: admitted and not admitted.

The dataset is loaded from a text file, visualized using a scatter plot, and then converted into NumPy arrays for mathematical operations.

First, a custom Sigmoid function, cost function, and gradient function are designed based on the mathematical theory behind them. This allows us to understand the actual mathematical calculations performed during logistic regression. Two different methods are used in this program, in order to find the best parameters (theta): First, a custom Gradient Descent function is run over 20,000 iterations in order to calculate the value of theta that gives the minimal cost function. The other method uses the built-in `scipy.optimize.fmin` function to achieve the same goal, albeit through different means.

After training these models, the program compares the accuracy of each, with the manually derived model giving an accuracy of 92.0%, while the scipy fmin model gives us an accuracy of 89.0%. This allows us to compare how manual and library-based optimizations work side by side. Additionally, the program uses sklearn's built in Logistic Regression tool as a third model to compare on the data. This too, gives us an accuracy of 89.0%

Finally, the decision boundaries of all three models are plotted over the scatter plot of the data in order to visualize how well each method separates the two classes. This gives us a clear picture of how logistic regression draws a line (or plane) to divide different outcomes, and how changing the optimization approach can affect the final boundary.

An additional section provides an alternate method of plotting the final results, using contours to plot the decision boundary.

Overall, this program ties together data handling, math, and visualization to demonstrate the inner workings of logistic regression in a very hands-on way.

Code Source:

[1]
https://colab.research.google.com/drive/1UkjHqm0FZ_HiRjA1zWlLIUiSrf2bmJIh