Logistic Regression Model

This is a implementation of Logistic Regression model which is a machine learning algorithm based on supervised learning to predict whether a applicant's gets admitted into a university.

Problem Statement

Suppose that I am the administrator of a university department and I want to determine each applicant's chance of admission based on their results on two exams.

- I have historical data from previous applicant's that I can use as a training set for logistic regression.
- For each training example, I have the applicant's scores on two exams and the admissions decision.
- Goal is to build a classification model that estimates an applicant's probability of admission based on the scores from those two exams.

> The source of the dataset comes from [Supervised Machine Learning by Andrew Ng, Coursera]

Prepare Tools and Materials

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import math

df = pd.read_csv('/exam_Score.txt')

x_train = np.array(df[['exam 1','exam 2']])
y_train = np.array(df['pass'])
df.head()
```

	exam 1	exam 2	pass
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

`x_train` contains exam scores on two exams for a applicant's

- `y_train` is the admission decision
  - `y_train = 1` if the applicant was admitted
  - `y_train = 0` if the applicant was not admitted
- Both `X_train` and `y_train` are numpy arrays.

```
print('First 5 row of x_train:\n',x_train[:5])
print();
print('First 5 row of y_train:\n',y_train[:5])
```

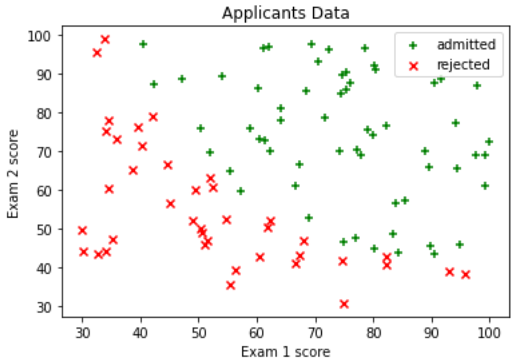
```
First 5 row of x_train:
 [[34.62365962 78.02469282]
 [30.28671077 43.89499752]
 [35.84740877 72.90219803]
 [60.18259939 86.3085521 ]
 [79.03273605 75.34437644]]

First 5 row of y_train:
 [0 0 0 1 1]
```

Visualize dataset

- `admitted` contain all exam score of admitted applicant's and it's shown as **green** in the graph
- `rejected` contain all exam score of rejected applicant's and it's shown as **red** in the graph

```
admitted = df[df['pass'] == 1]
rejected = df[df['pass'] == 0]
```

```
plt.scatter(admitted['exam 1'],admitted['exam 2'],c = 'g', label = 'admitted' , marker = '+')
plt.scatter(rejected['exam 1'],rejected['exam 2'],c = 'r', label = 'rejected' , marker = 'x')
plt.xlabel('Exam 1 score')
plt.ylabel('Exam 2 score')
plt.title('Applicants Data')
plt.legend()
plt.show()
```




```
print(f'Shape x train : {x_train.shape}')
print(f'Shape y train : {y_train.shape}')
print(f'We have {len(y_train)} training data from dataset')
```

```
Shape x train : (100, 2)
Shape y train : (100,)
We have 100 training data from dataset
```

```
# Set data length
m, n = x_train.shape
```

Build the model

Logistic Regression

For logistic regression, the model is represented as

$$f_{\mathbf{w},b}(x) = g(\mathbf{w} \cdot \mathbf{x} + b) \tag{1}$$

where function g is the sigmoid function. The sigmoid function is defined as:

$$g(z) = \frac{1}{1+e^{-z}} \tag{2}$$

The `sigmoid` function to calculate sigmoid equation(2)

```
def sigmoid(z):
    g = 1 / (1 + (math.e)**(-1*z))
    return g
```

Cost function for logistic regression

For logistic regression, the cost function is represented as

$$J(\mathbf{w},b) = \frac{1}{m} \sum_{i=0}^{m-1} \left[loss(f_{\mathbf{w},b}(\mathbf{x}^{(i)}), y^{(i)}) \right] \tag{3}$$

where:

- m is the number of training examples in the dataset
- $loss(f_{\mathbf{w},b}(\mathbf{x}^{(i)}), y^{(i)})$ is the cost for a single data point, where:

$$loss(f_{\mathbf{w},b}(\mathbf{x}^{(i)}), y^{(i)}) = (-y^{(i)} \log\left(f_{\mathbf{w},b}\left(\mathbf{x}^{(i)}\right)\right) - \left(1 - y^{(i)}\right) \log\left(1 - f_{\mathbf{w},b}\left(\mathbf{x}^{(i)}\right)\right) \tag{4}$$

- $f_{\mathbf{w},b}(\mathbf{x}^{(i)})$ is the model's prediction, while $y^{(i)}$, which is the actual label
- $f_{\mathbf{w},b}(\mathbf{x}^{(i)}) = g(\mathbf{w} \cdot \mathbf{x^{(i)}} + b)$ where function g is the sigmoid function.
- $z_{\mathbf{w},b}(\mathbf{x}^{(i)}) = \mathbf{w} \cdot \mathbf{x^{(i)}} + b$

`count_cost` function implementing equation (3) and (4) to calculate total cost

```
def count_cost(x, y, w, b) :
  total_cost = 0
  for i in range(m):
    z_wb = np.dot(w,x[i]) + b
    f_wb = sigmoid(z_wb)

    loss = ((-1 * y[i]) * math.log(f_wb) - (1-y[i]) * math.log(1 - f_wb))
    total_cost = total_cost + loss

  total_cost = total_cost/m

  return total_cost
```

Gradient for logistic regression

In this section, there will be implementation of the gradient for logistic regression.

The gradient descent algorithm is:

$$\begin{aligned}
&\text{repeat until convergence: } \{ \\
&b := b - \alpha \frac{\partial J(\mathbf{w},b)}{\partial b} \\
&w_j := w_j - \alpha \frac{\partial J(\mathbf{w},b)}{\partial w_j} \qquad\qquad \text{for j := 0..n-1} \\
&\}
\end{aligned} \tag{5}$$

where:

$$\frac{\partial J(\mathbf{w},b)}{\partial b} = \frac{1}{m} \sum_{i=0}^{m-1} (f_{\mathbf{w},b}(\mathbf{x}^{(i)}) - \mathbf{y}^{(i)}) \tag{6}$$

$$\frac{\partial J(\mathbf{w},b)}{\partial w_j} = \frac{1}{m} \sum_{i=0}^{m-1} (f_{\mathbf{w},b}(\mathbf{x}^{(i)}) - \mathbf{y}^{(i)}) x_j^{(i)} \tag{7}$$

Note that parameters b and w_j are all updated simultaneously

`gradient` function implementing equation (6) and (7) to calculate gradient descent algorithm

```
def gradient(x,y,w,b,*argv):
  dj_db = 0.
  dj_dw = np.zeros(n)

  for i in range(m):
    z_wb = np.dot(w,x[i]) + b
    f_wb = sigmoid(z_wb)
    err_i = f_wb - y[i]

    # dj db
    dj_db = dj_db + err_i

    # dj dw
    for j in range(n):
      dj_dw[j] = dj_dw[j] + err_i * x[i][j]

  dj_dw = dj_dw / m
  dj_db = dj_db / m

  return dj_db, dj_dw
```

Intiate the Model

Here is a brief explanation the logic of `compute_model` function that ultilize all fuctions:

- w , and b value will be intiated at random value
- $alpha$ is the learning rate of the algorithm
- equation (5) implemented in function below to update w , and b value to produce the lowest cost
- `list_` will stores all counted cost of every w , and b value for graph visualization

```
def compute_model(x,y,w,b,list_,iters,alpha):
  for i in range(iters):
    cost = count_cost(x_train, y_train, w, b)
    list_.append(cost)
```

```
    b_update,w_update = gradient(x,y,w,b)
    b = b - (alpha*b_update)
    for j in range(n):
      w[j] = w[j] - (alpha*w_update[j])

  return w,b
```

Run the function

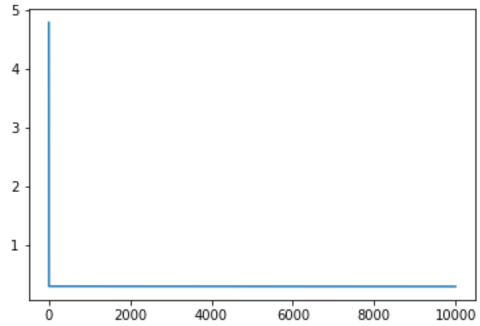
- counted cost will be stored in `cost_list`
- alpha set to 0.001
- program will iters for number of `iters`

```
cost_list = []
w = 0.01 * (np.random.rand(2) - 0.5)
b = -8
alpha = 0.001
iters = 10000

w,b = compute_model(x_train,y_train,w,b,cost_list,iters,alpha)
print(f'Final w value is: {w}\nFinal b value is: {b}\n')
print(f'Total cost for correspondents w and b is: {count_cost(x_train,y_train,w,b)}')
```

```
Final w value is: [0.07125349 0.06482881]
Final b value is: -8.188615085400823

Total cost for correspondents w and b is: 0.30186821266597186
```

```
plt.plot(cost_list)
```

```
[<matplotlib.lines.Line2D at 0x7f057e38e310>]
```

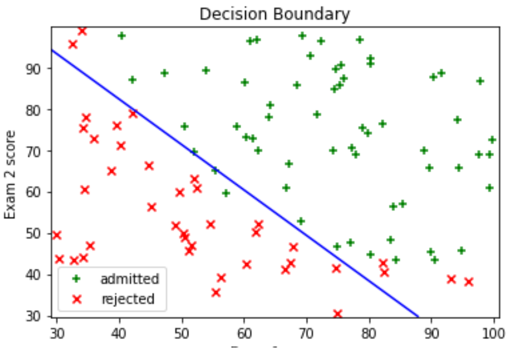


Visualize the model

After w and b value is found, let's visualize the decision boundary to actual dataset

```
# Define a grid of points that span the range of input data
x1_min, x1_max = x_train[:, 0].min() - 1, x_train[:, 0].max() + 1
x2_min, x2_max = x_train[:, 1].min() - 1, x_train[:, 1].max() + 1
xx1, xx2 = np.meshgrid(np.arange(x1_min, x1_max, 0.1), np.arange(x2_min, x2_max, 0.1))
grid = np.c_[xx1.ravel(), xx2.ravel()]

# Plot the linear decision boundary
z = np.dot(grid, w) + b
z = z.reshape(xx1.shape)
```

```
admitted = df[df['pass'] == 1]
rejected = df[df['pass'] == 0]

plt.scatter(admitted['exam 1'],admitted['exam 2'],c = 'g', label = 'admitted' , marker = '+')
plt.scatter(rejected['exam 1'],rejected['exam 2'],c = 'r', label = 'rejected' , marker = 'x')
plt.contour(xx1, xx2, z, levels=[0], colors='b')
plt.xlabel('Exam 1 score')
plt.ylabel('Exam 2 score')
plt.title('Decision Boundary')
plt.legend()
plt.show()
print()
```



> We can see that the decision boundary fit pretty wall to the actual data

Check the Accuracy

To check the accuracy of learned parameter vector w and b, we need to get a final prediction ($y^{(i)} = 0$ or $y^{(i)} = 1$) from the logistic regression model, with equation below:

$$\text{if } f(x^{(i)}) >= 0.5, \text{ predict } y^{(i)} = 1 \rightarrow \textbf{admitted} \tag{8}$$

$$\text{if } f(x^{(i)}) < 0.5, \text{ predict } y^{(i)} = 0 \rightarrow \textbf{rejected} \tag{9}$$

The program will compare the predictions (`p`) with the actual y (`y_train`) from the data set and calculate the percentage of correct predictions

```
true,false=0,0
for i in range(m):
        z_wb = np.dot(w,x_train[i]) + b
        f_wb = sigmoid(z_wb)

        if f_wb >= 0.5:
          p = 1
        elif f_wb < 0.5:
          p = 0

        if y_train[i] == p:
          true +=1
        else:
          false +=1

print(f'Number of tests = {true+false}\nCorrect Predictions = {true}\nWrong Predictions = {false}')
print(f'\nAccuracy = {true * 100 / (true+false)}%')
```

```
Number of tests = 100
Correct Predictions = 92
Wrong Predictions = 8

Accuracy = 92.0%
```

Test the Model

Now we can use the model with new data input to predict whether applicant is admitted or rejected based on equation (8) and (9)

`predict` function will be use to make the prediction

```
def predict(w,b,x1,x2):
  x = np.array([x1,x2])
  z_wb = np.dot(w,x) + b
  f_wb = sigmoid(z_wb)
  return f_wb
```

```
exam_1_score = 60 #@param {type:"slider", min:0, max:100, step:1}
exam_2_score = 65 #@param {type:"slider", min:0, max:100, step:1}
fx = predict(w,b,exam_1_score,exam_2_score)

if fx >= 0.5:
  print(f'With score:\nExam 1 = {exam_1_score}\nExam 2 = {exam_2_score}')
  print()
  print('Applicant is admitted!')
else:
  print(f'With score:\nExam 1 = {exam_1_score}\nExam 2 = {exam_2_score}')
```

exam_1_score: 60

exam_2_score: 65

```
  print()
  print('Applicant is rejected!')

print(f'\nf(x) value is = {round(fx,3)}')
```

```
With score:
Exam 1 = 60
Exam 2 = 65

Applicant is admitted!

f(x) value is = 0.575
```

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