Q3 - Part 1 : Manipulate data as necessary & create a scatter plot using any plotting library

Solution:

Importing Required Libraries & Reading the datafile

In [6]:
```
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import seaborn as sb

# reading data file
dataset = pd.read_csv('https://raw.githubusercontent.com/DrUzair/MachineLear
```

In [ ]:
```
```

Understanding the Data

1. Number of Rows and Columns
2. Duplicates
3. Missing or null values
4. Datatypes of features
5. Statistics

1. Number of Rows and Columns

In [11]:
```
# number of rows and columns in the dataset. \
dataset.shape
```

Out[11]:
```
(99, 3)
```

In [ ]:
```
```

2. Duplicates

In [12]:
```
# How many duplicate rows and columns do we have in our dataset?
dataset.duplicated().sum()
```

Out[12]:
```
0
```

In [ ]:
```
```

3. Missing or null values

In [60]:
```
dataset.isnull().sum()
```

Out[60]:
```
-0.590911854382    0
0.221097787545     0
0                  0
dtype: int64
```

In [ ]:

4. Datatypes of features

In [13]:
```
info=dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99 entries, 0 to 98
Data columns (total 3 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   -0.590911854382  99 non-null     float64
 1   0.221097787545   99 non-null     float64
 2   0                99 non-null     int64  
dtypes: float64(2), int64(1)
memory usage: 2.4 KB
```

In [ ]:

5.Statistics

In [14]:
```
dataset.describe()
```

Out[14]:

	-0.590911854382	0.221097787545	0
count	99.000000	99.000000	99.000000
mean	3.972875	5.075990	0.505051
std	3.119784	3.321910	0.502519
min	-0.651939	-0.552670	0.000000
25%	0.999647	1.913945	0.000000
50%	4.655505	4.836154	1.000000
75%	6.927850	8.156762	1.000000
max	9.811431	11.771933	1.000000

In [ ]:

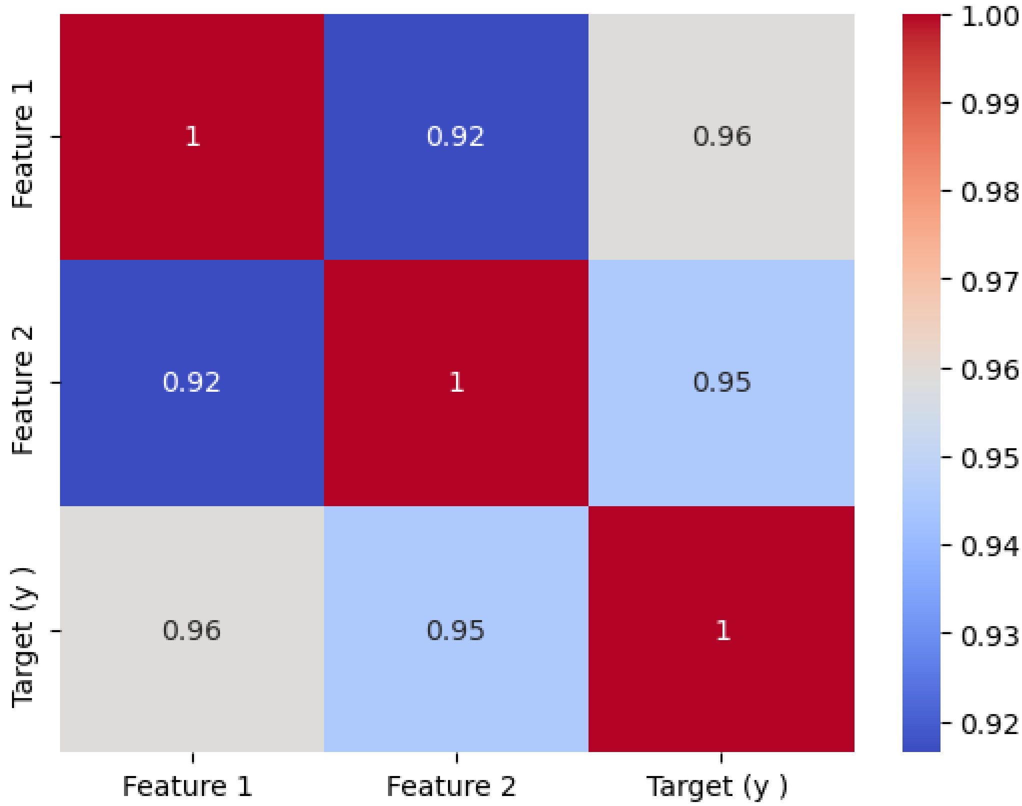
we see the column names do not make sense, lets rename them to Feature 1 (x1) , Feature 2(x2) , Target (y)

In [15]:
```
dataset.columns = ['Feature 1 ', 'Feature 2 ', 'Target (y ) ']
```

In [ ]:

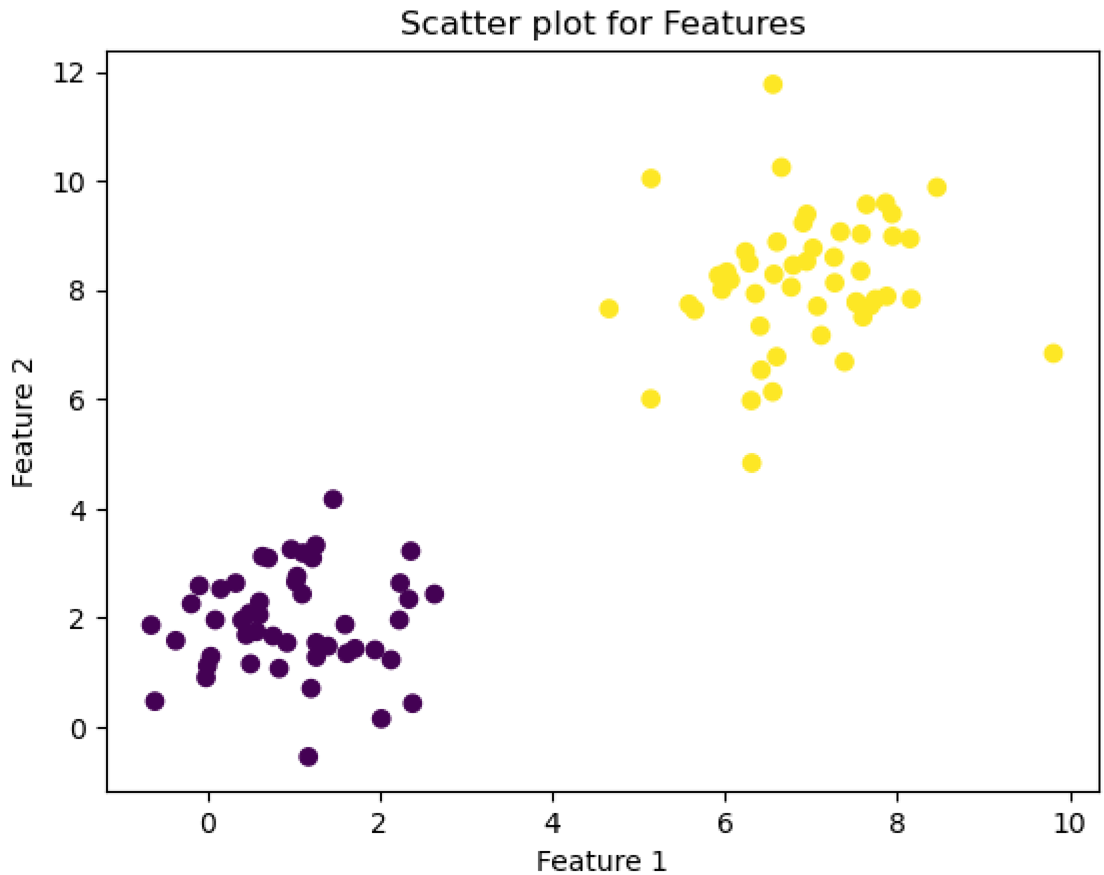
Creating a correlation matrix to understand the correlation between Features and target variable

In [16]:
```
# Correlation Heatmap for Features 1 , Fatures 2 , Target Variable y
corr = dataset[['Feature 1 ', 'Feature 2 ','Target (y ) ']].corr()
sb.heatmap(corr, annot=True, cmap='coolwarm')
plt.show()
```



Plotting a scatter graph

In [17]:
```
plt.scatter(data=dataset, x= "Feature 1 ", y="Feature 2 ",  c= dataset["Targ
plt.xlabel("Feature 1")
plt.ylabel("Feature 2")
plt.title("Scatter plot for Features")
plt.show()
```



In [ ]:

PART 2- Use the following class definition as skeleton of your code

Using the formulas for pi, mu0, mu1, sigma as below

$$\phi = \frac{1}{m}\sum_{i=1}^{m} 1\{y^{(i)} = 1\}$$

$$\mu_0 = \frac{\sum_{i=1}^{m} 1\{y^{(i)} = 0\}x^{(i)}}{\sum_{i=1}^{m} 1\{y^{(i)} = 0\}}$$

$$\mu_1 = \frac{\sum_{i=1}^{m} 1\{y^{(i)} = 1\}x^{(i)}}{\sum_{i=1}^{m} 1\{y^{(i)} = 1\}}$$

$$\sum = \frac{1}{m}\sum_{i=1}^{m} (x^{(i)} - \mu_k)(x^{(i)} - \mu_k)^T \text{ where } k = 1\{y^{(i)} = 1\}$$

In [2]:

```
#we are using 4 paramters :
#mu0,mu1 - mean of the 2 classes y=1 and y=0
#sigma - covariance of both classes , we are taking same
#pi - probability estimate

class GDA():

    #For initialising the 4 paramaters
    def __init__(self):
        self.pi = None
        self.mu0 = None
        self.mu1 = None
        self.sigma = None
        self.sigma_inv = None


        #  "train" function is used Training the model , estimating GDA Para
    def train(self, x, y):

        #pi = mean of y values
        self.pi = np.mean(y)

        # mu0, mu1
        self.mu0 = np.mean(X[y==0], axis=0)
        self.mu1 = np.mean(X[y==1], axis=0)

        # coviariance calculations
        n_x = x[y== 0] - self.mu0
        p_x = x[y== 1] - self.mu1


        #covariance
        self.sigma = ((n_x.T).dot(n_x) + (p_x.T).dot(p_x))/X.shape[0]
        print("self.sigma", self.sigma)


        #covariance inverse
        self.sigma_inv = np.linalg.inv(self.sigma)


        # "predict" function returns a prediction vector which is based on G
        # calculates likelihood of datapoint belonging to a class . Uses Gau

    def predict(self, x):
        p0 = np.sum(np.dot((x-self.mu0),self.sigma_inv)*(x-self.mu0),axis=1)
        p1 = np.sum(np.dot((x-self.mu1),self.sigma_inv)*(x-self.mu1),axis=1)
        return p1 >= p0

    # To make it Normal Distribution
    def normal_distribution(self, x, mu, sigma):
        n = x.shape[1]
        return (1 / (2 * np.pi) * ((n + 1) / 2) / np.sqrt(np.linalg.det(sigm
            -0.5 * np.sum(np.dot((x - mu), np.linalg.inv(self.sigma)) * (x -
```

In [ ]:

PART 3 - Write a function to draw the decision boundary and contours of each class along with the data points

The aim of this function is to create a scatter plot of data points, plot the decision boundary & visualize the contour of the data points (gaussian distribution)

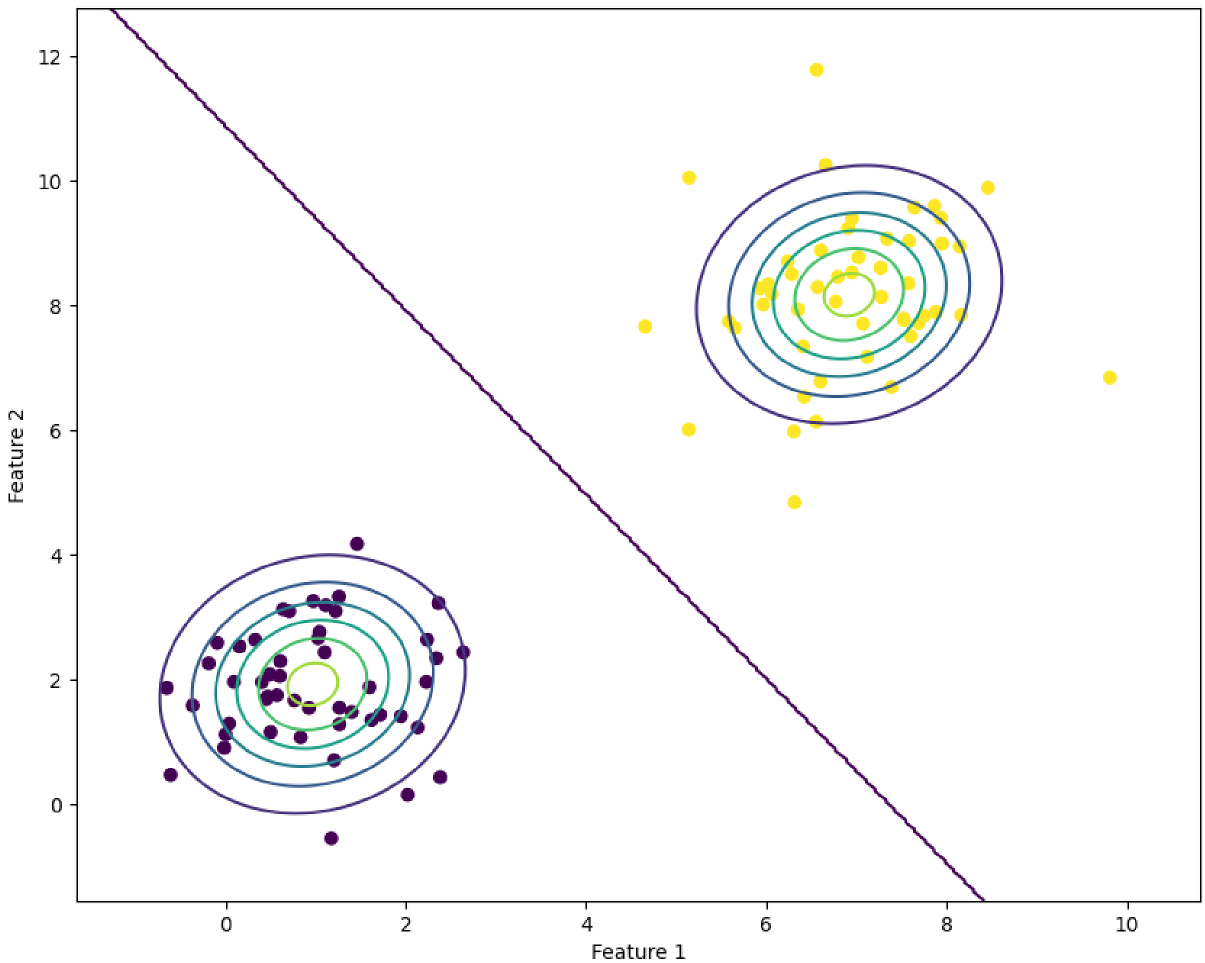
In [73]:

```
def contour_plot(gda_model, X, y):

    #size of plot
    plt.figure(figsize=(10, 8))

    # Creating a Scatter Plot
    plt.scatter(X[:, 0], X[:, 1], c=y)
    plt.xlabel("Feature 1")
    plt.ylabel("Feature 2")

    #why min and max values - to ensure a proper graph is plotted without ar
    #plot can b properly scaled
    x1_min = X[:, 0].min()
    x2_min = X[:, 1].min()
    x1_max = X[:, 0].max()
    x2_max = X[:, 1].max()

    # Defining range for x and y values
    x1_value = np.linspace(x1_min-1, x1_max+1,400)
    x2_value = np.linspace(x2_min-1, x2_max+1,400)

    # Why Meshgrid? Say, we want a grid where there's a point at every int v
    # It will create a rectangular grid with every combination of x&y value.
    x1_meshgrid, x2_meshgrid = np.meshgrid(x1_value, x2_value)

    # RAVEL: transform these 2D arrays into 1D arrays
    grid = np.c_[x1_meshgrid.ravel(), x2_meshgrid.ravel()]

    output = gda_model.predict(grid)
    output = output.reshape(x1_meshgrid.shape)

    # plotting the decision boundary
    plt.contour(x1_meshgrid, x2_meshgrid, output)


    #contour Plot y=0 class
    y0=gda_model.normal_distribution(grid,gda_model.mu0, gda_model.sigma)
    y0=y0.reshape(x1_meshgrid.shape)
    cplot0=plt.contour(x1_meshgrid,x2_meshgrid,y0)


    #contour Plot y=1 class
```

```
    y1=gda_model.normal_distribution(grid,gda_model.mu1, gda_model.sigma)
    y1=y1.reshape(x2_meshgrid.shape)
    cplot1=plt.contour(x1_meshgrid,x2_meshgrid,y1)
```

In [79]:
```
#Why are we slicing ?
# X and y are 0-d arr, which are not suitable for doing algebra operations
# So, we've to makesure X,y arr passed to the train function (GDA class) are


X = dataset.iloc[:, :-1].values
gda = GDA()

y = dataset.iloc[:, -1].values
gda.train(X, y)

contour_plot(gda, X, y)

plt.show()
```

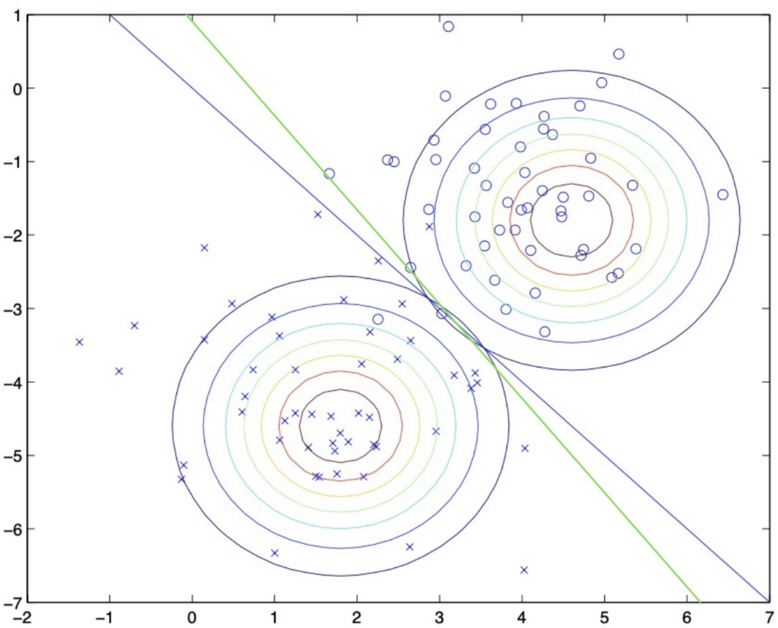
```
self.sigma [[0.77865383 0.10462239]
 [0.10462239 1.16332662]]
```



In [ ]:

Part 4- Explain the difference between GDA and Logistic Regression as a classifier ?

Comparison of GDA Vs Logisitc Regression (Picture courtsey - Andrew NG Notes)



1. **Modelling** -

> Logistic Regression is a Discriminative Algorithm which directly model conditional probability of the class labels P(y|x) from the training dataset. As the name suggests, "discriminative" models can discriminate bw the data points.

> GDA is a Generative Algorithms which model joint probability P(x|y) and P(y). As the name suggests, "generative" models can generate new datapoints.

2. **Decision Boundary**

> Logistic Regression has decision boundary based on linear functions- it just segregates the 2 classes from each other. It does not have the ability to generate new data.

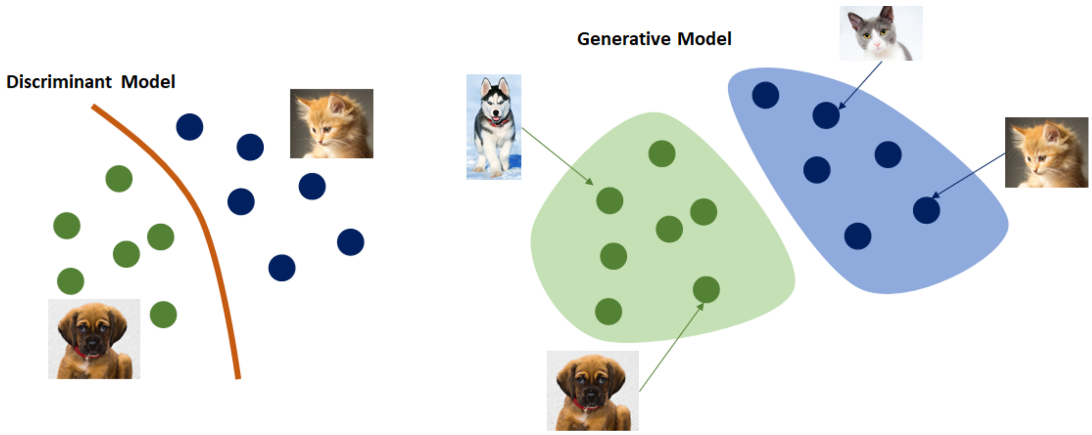
> GDA has a decision boundary which can capture more complex information about the feature. It has ability to generate new data.

3. **Assumption**

> Logistic Regression doesnt make any assumption about distribution of the features

> while GDA makes assumptions that features in every class follow a Gaussian distribution & covariance matrix for all class are equivalent

Note: When dataset in not Gaussian and it is large, in practise we use Logistic Regression more commonly than we use GDA becuase Logistic Regression will perform better



In [153…

In [ ]:

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