LOGISTIC REGRESSION

In [3]:

```
#importing libararies

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

The Data

The data is related with social network ads. The classification goal is to predict if they purchased (1/0) a term deposit (variable y).

In [9]:

```
data=pd.read_csv('E:\\Social_Network_Ads.csv')
```

In [46]:

```
data.head(10)
```

Out[46]:

	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	Male	19	19000	0
1	15810944	Male	35	20000	0
2	15668575	Female	26	43000	0
3	15603246	Female	27	57000	0
4	15804002	Male	19	76000	0
5	15728773	Male	27	58000	0
6	15598044	Female	27	84000	0
7	15694829	Female	32	150000	1
8	15600575	Male	25	33000	0
9	15727311	Female	35	65000	0

In [12]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 400 entries, 0 to 399
Data columns (total 5 columns):
 #   Column           Non-Null Count  Dtype 
---  ------           --------------  ----- 
 0   User ID          400 non-null    int64 
 1   Gender           400 non-null    object
 2   Age              400 non-null    int64 
 3   EstimatedSalary  400 non-null    int64 
 4   Purchased        400 non-null    int64 
dtypes: int64(4), object(1)
memory usage: 18.8+ KB
```

In [34]:

```
df.describe()
```

Out[34]:

	User ID	Age	EstimatedSalary	Purchased
count	4.000000e+02	400.000000	400.000000	400.000000
mean	1.569154e+07	37.655000	69742.500000	0.357500
std	7.165832e+04	10.482877	34096.960282	0.479864
min	1.556669e+07	18.000000	15000.000000	0.000000
25%	1.562676e+07	29.750000	43000.000000	0.000000
50%	1.569434e+07	37.000000	70000.000000	0.000000
75%	1.575036e+07	46.000000	88000.000000	1.000000
max	1.581524e+07	60.000000	150000.000000	1.000000

In [35]:

```
df.isnull().sum()
```

Out[35]:

```
User ID            0
Gender             0
Age                0
EstimatedSalary    0
Purchased          0
dtype: int64
```

In this dataset purchased is the dependent feature where are "userid, Gender, Age and EstimatedSalary" is the independent feature. We will not consider userid and gender in our model building as this is not expressing much with dependent variable.

In [36]:

```
#Split X and y

X=df.iloc[:,2:4]
y=df['Purchased']
print(X.shape)
print(y.shape)
```

```
(400, 2)
(400,)
```

In [37]:

```
#Split X and y into train and test
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.25,random_state=21)
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(300, 2)
(100, 2)
(300,)
(100,)
```

In [38]:

```
#Now we perfouniquethe feature scalling as Age and Estimated salary both having different r
#Estimated salary will do dominent Age feature when the model finds the nearest neighbour t

from sklearn.preprocessing import StandardScaler
SC=StandardScaler()
X_train=SC.fit_transform(X_train)
X_test=SC.fit_transform(X_test)
```

In [39]:

```
#Finally we make the model using logistic regression
from sklearn.linear_model import LogisticRegression
model_lr=LogisticRegression()
model_lr.fit(X_train,y_train)
print(model_lr.intercept_)
print(model_lr.coef_)
```

```
[-0.93722653]
[[2.04534306 1.18128442]]
```

In [40]:

```
#Validate the model with X test and check the performance of the model using confusion metr
from sklearn.metrics import confusion_matrix
y_predict=model_lr.predict(X_test)
print("Confusion Metrix for this model is: ")
print(confusion_matrix(y_test,y_predict))
```

```
Confusion Metrix for this model is: 
[[58  9]
 [ 6 27]]
```

In [41]:

```
from sklearn.metrics import accuracy_score
print(f"Accuracy Score is {accuracy_score(y_test,y_predict)}")
```

```
Accuracy Score is 0.85
```

In [42]:

```
#Now we have to visualize the performance of our model test dataset
from matplotlib.colors import ListedColormap
x_set,y_set=X_test,y_test
X1,X2=np.meshgrid(np.arange(start=x_set[:,0].min()-1,stop=x_set[:,0].max()+1,step=0.01),
np.arange(start=x_set[:,1].min()-1,stop=x_set[:,1].max()+1,step=0.01))

plt.contourf(X1,X2,model_lr.predict(
             np.array([X1.ravel(), X2.ravel()]).T).reshape(
             X1.shape), alpha = 0.75, cmap = ListedColormap(('red', 'green')))
plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())

for i, j in enumerate(np.unique(y_set)):
    plt.scatter(x_set[y_set == j, 0], x_set[y_set == j, 1],
                c = ListedColormap(('black', 'white'))(i), label = j)

plt.title('Classifier (Test set)')
plt.xlabel('Age')
plt.ylabel('Estimated Salary')
plt.legend()
plt.show()
```

```
*c* argument looks like a single numeric RGB or RGBA sequence, which should
be avoided as value-mapping will have precedence in case its length matches
with *x* & *y*.  Please use the *color* keyword-argument or provide a 2-D ar
ray with a single row if you intend to specify the same RGB or RGBA value fo
r all points.
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with *x* & *y*.  Please use the *color* keyword-argument or provide a 2-D ar
ray with a single row if you intend to specify the same RGB or RGBA value fo
r all points.
```

In [43]:

```
#Now we have to visualize the performance of our model train dataset

from matplotlib.colors import ListedColormap
x_set,y_set=X_train,y_train
X1,X2=np.meshgrid(np.arange(start=x_set[:,0].min()-1,stop=x_set[:,0].max()+1,step=0.01),
np.arange(start=x_set[:,1].min()-1,stop=x_set[:,1].max()+1,step=0.01))

plt.contourf(X1,X2,model_lr.predict(
             np.array([X1.ravel(), X2.ravel()]).T).reshape(
             X1.shape), alpha = 0.75, cmap = ListedColormap(('red', 'green')))
plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())

for i, j in enumerate(np.unique(y_set)):
    plt.scatter(x_set[y_set == j, 0], x_set[y_set == j, 1],
                c = ListedColormap(('black', 'white'))(i), label = j)

plt.title('Classifier (Train set)')
plt.xlabel('Age')
plt.ylabel('Estimated Salary')
plt.legend()
plt.show()
```

```
*c* argument looks like a single numeric RGB or RGBA sequence, which should
be avoided as value-mapping will have precedence in case its length matches
with *x* & *y*.  Please use the *color* keyword-argument or provide a 2-D ar
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with *x* & *y*.  Please use the *color* keyword-argument or provide a 2-D ar
ray with a single row if you intend to specify the same RGB or RGBA value fo
r all points.
```

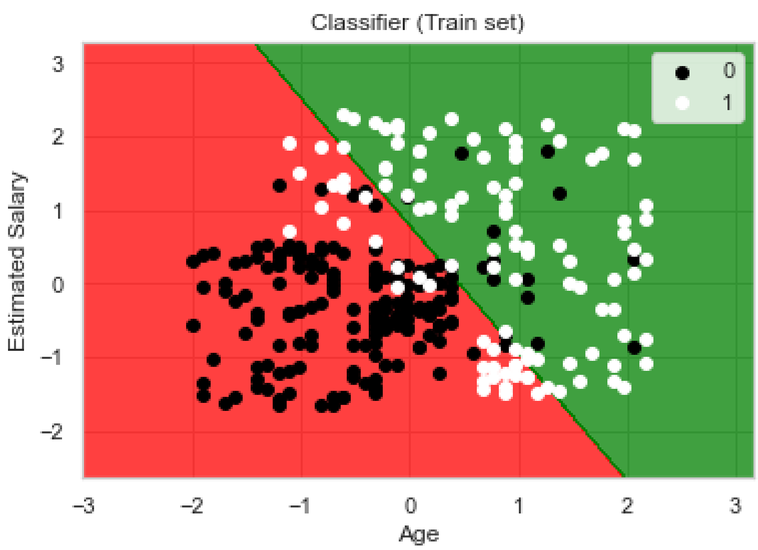

From the above graph it is clear visible the line which divides green and red line.

Green Line : Purchased SUV cars

red Line : Didn't purchase SUV cars

Here X-axis gives Age and Y-axis gives the esimated salary. The graph plots the dependent variable data point purchased based on this two independent variables

Data Points lies on green area is purchased SUV car. Where are data points lies on red area is not purchased SUV car.

Older age is having high estimated salary purchased more SUV where as younger age having less salary is not purchased SUV car.

Here few black points are lying on red area and few white points are lying on green area. That means few younger age people having high estimated salary and purchased SUV where as few older age people having less salary is not purchasing SUV

In [ ]: