# Implementation of Logistic Regression using Python

# **Import Libraries**

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

## Import and View Dataset

```
data_set = pd.read_csv('LogisticRegressionDataset.csv')
data_set.head()
```

	Age	Salary	Purchased
0	19	19000	0
1	35	20000	0
2	26	43000	0
3	27	57000	0
4	19	76000	0

```
data_set.describe()
```

	Age	Salary	Purchased
count	400.000000	400.000000	400.000000
mean	37.655000	69742.500000	0.357500
std	10.482877	34096.960282	0.479864
min	18.000000	15000.000000	0.000000
25%	29.750000	43000.000000	0.000000
50%	37.000000	70000.000000	0.000000
75%	46.000000	88000.000000	1.000000
max	60.000000	150000.000000	1.000000

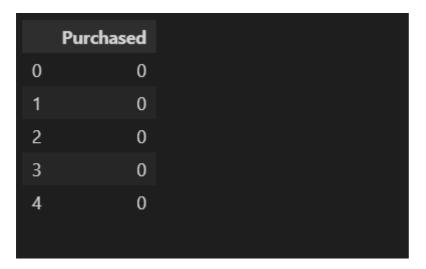
```
data_set.info()
```

## Defining Independent (X) and Dependent (y) variables

```
X = data_set.iloc[:,:-1]
X.head()
```

	Age	Salary
0	19	19000
1	35	20000
2	26	43000
3	27	57000
4	19	76000

```
y = data_set.iloc[:,-1:]
y.head()
```



#### Data Visulization (Bar Plot)

```
# Import Libraries for Data Visulization
import plotly.graph_objects as go

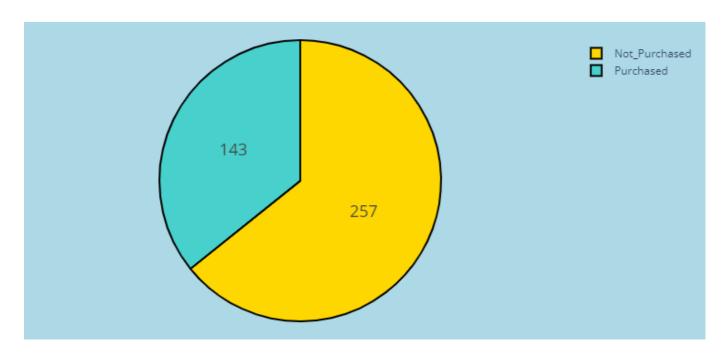
# Count the total outputs (0 and 1) from "Purchased" column
purchased = data_set['Purchased'].value_counts().reset_index()

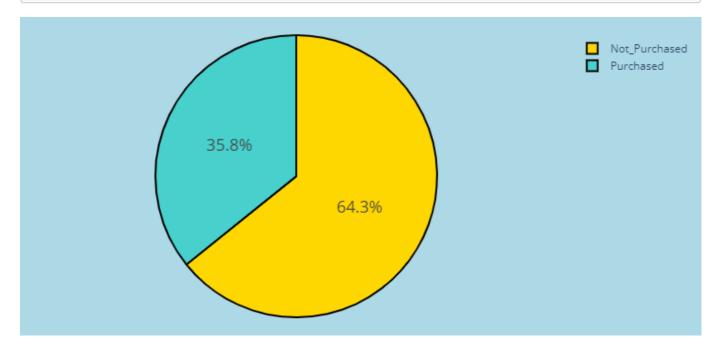
# Divide the output classes into two sections
fig = go.Figure(data=[go.Bar(x = ['not-purchased', 'purchased'], y =
purchased['Purchased'], text=purchased['Purchased'], textposition='auto')])

# Customize aspect
fig.update_layout(margin=dict(l=10, r=10, t=20, b=20),
paper_bgcolor="LightSteelBlue")
fig.update_traces(marker_color='rgb(160,202,225)',
marker_line_color='rgb(8,48,107)', marker_line_width=1.5, opacity=1)
fig.update_layout(autosize=False, width=750, height=350)
fig.show()
```



#### Datavisualization (pi chart)





# Train and Test Logistic Regression Model

# Spliting the Data

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)
```

#### Feature Scaling

Now, let's apply the scaling method to the independent data so that the outliers would not affect the predicting class.

```
from sklearn.preprocessing import StandardScaler

scale_X = StandardScaler()
X_train = scale_X.fit_transform(X_train)
X_test = scale_X.fit_transform(X_test)
```

#### Model Training (Binary Classification)

```
from sklearn.linear_model import LogisticRegression

model = LogisticRegression()
model.fit(X_train, y_train)
```

### Calculating model accuracy

```
# testing the model
y_pred = model.predict(X_test)

# calculating model accuracy

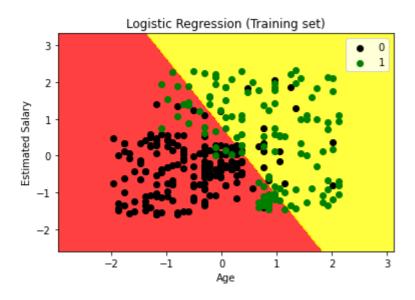
from sklearn.metrics import accuracy_score

score = accuracy_score(y_test, y_pred)*100
print("Accuracy Score of Model is %.2f percent" %score)
```

```
Accuracy Score of Model is 88.75 percent
```

## Visualizing training dataset

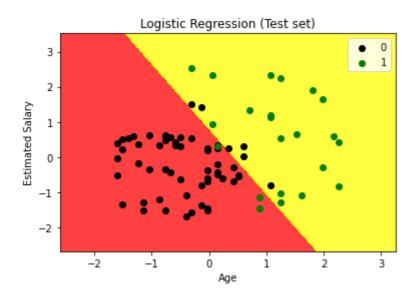
```
# import libraries
from matplotlib.colors import ListedColormap
# setting x_train and y_train
x_set, y_set = X_train, y_train
x1, x2 = np.meshgrid(np.arange(start=x_set[:, 0].min()-1, stop = x_set[:,
0].max()+1, step=0.01),
np.arange(start=x_set[:, 1].min()-1, stop=x_set[:, 1].max()+1, step=0.01))
# ploting
plt.contourf(x1, x2, model.predict(np.array([x1.ravel(),
x2.ravel()]).T).reshape(x1.shape), alpha = 0.75, cmap =
ListedColormap(('red', 'yellow')))
plt.xlim(x1.min(), x1.max())
plt.ylim(x2.min(), x2.max())
# for-loop for data iteration
y_set_one_dimension = y_set.iloc[:,0]
for i, j in enumerate(np.unique(y_set)):
    plt.scatter(x_set[y_set_one_dimension == j, 0], x_set[y_set_one_dimension ==
j, 1], c = ListedColormap(('black', 'green'))(i), label = j)
# labeling the graph
plt.title('Logistic Regression (Training set)')
plt.xlabel('Age')
plt.ylabel('Estimated Salary')
plt.legend()
plt.show()
```



#### Visualizing test dataset

```
# import libraries
from matplotlib.colors import ListedColormap
# setting x_test and y_test
```

```
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))
# ploting
plt.contourf(x1, x2, model.predict(np.array([x1.ravel(),
x2.ravel()]).T).reshape(x1.shape), alpha = 0.75, cmap =
ListedColormap(('red', 'yellow')))
plt.xlim(x1.min(), x1.max())
plt.ylim(x2.min(), x2.max())
# for-loop for data iteration
y_set_one_dimension = y_set.iloc[:,0]
for i, j in enumerate(np.unique(y_set)):
    plt.scatter(x_set[y_set_one_dimension == j, 0], x_set[y_set_one_dimension ==
j, 1], c = ListedColormap(('black', 'green'))(i), label = j)
# labeling the graph
plt.title('Logistic Regression (Test set)')
plt.xlabel('Age')
plt.ylabel('Estimated Salary')
plt.legend()
plt.show()
```



# Evaluation of Logistic Regression algorithm for binary classification

#### Calculate confusion matrix parameters

```
y_actual = y_test.iloc[:,0]
# initializing the values with zero value
```

```
TP = 0
FP = 0
TN = 0
FN = 0
# iterating through the values
for i in range(len(y_pred)):
    if y_actual.iloc[i]==y_pred[i]==1:
           TP += 1
    if y_pred[i]==1 and y_actual.iloc[i]!=y_pred[i]:
           FP += 1
    if y_actual.iloc[i]==y_pred[i]==0:
           TN += 1
    if y_pred[i]==0 and y_actual.iloc[i]!=y_pred[i]:
           FN += 1
# printing the values
print("True Positive: ", TP)
print("False Positive:", FP)
print("True Negative: ", TN)
print("False Negative: ", FN)
```

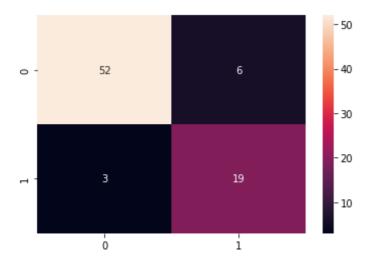
```
True Positive: 19
False Positive: 6
True Negative: 52
False Negative: 3
```

#### Visualize confusion matrix

```
# importing the required modules
import seaborn as sns
from sklearn.metrics import confusion_matrix

# passing actual and predicted values
cm = confusion_matrix(y_test, y_pred, labels=model.classes_)

# write data values in each cell of the matrix
sns.heatmap(cm,annot=True)
#plt.savefig('confusion.png')
```



# Classification report

```
# importing classification report
from sklearn.metrics import classification_report
# printing the report
```

print(classification\_report(y\_test, y\_pred))

	precision	recall	f1-score	support	
0	0.95	0.90	0.92	58	
1	0.76	0.86	0.81	22	
accuracy			0.89	80	
macro avg	0.85	0.88	0.86	80	
weighted avg	0.89	0.89	0.89	80	