DSBDAL Assignment 09 - Data Analytics 2

1. Implement logistic regression using Python/R to perform classification on Social_Network_Ads.csv dataset.
2. Compute Confusion matrix to find TP, FP, TN, FN, Accuracy, Error rate, Precision, Recall on the given dataset

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
import numpy as np
import pandas as pd
import seaborn as sns
```

```
ds = pd.read_csv('/content/drive/My Drive/DSBDL/Assignment9/data.csv')
ds
```

	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
...	...	...	...	...	...
395	15691863	Female	46	41000	1
396	15706071	Male	51	23000	1
397	15654296	Female	50	20000	1
398	15755018	Male	36	33000	0
399	15594041	Female	49	36000	1

400 rows × 5 columns

Next steps: Generate code with ds View recommended plots

```
ds.dtypes
```

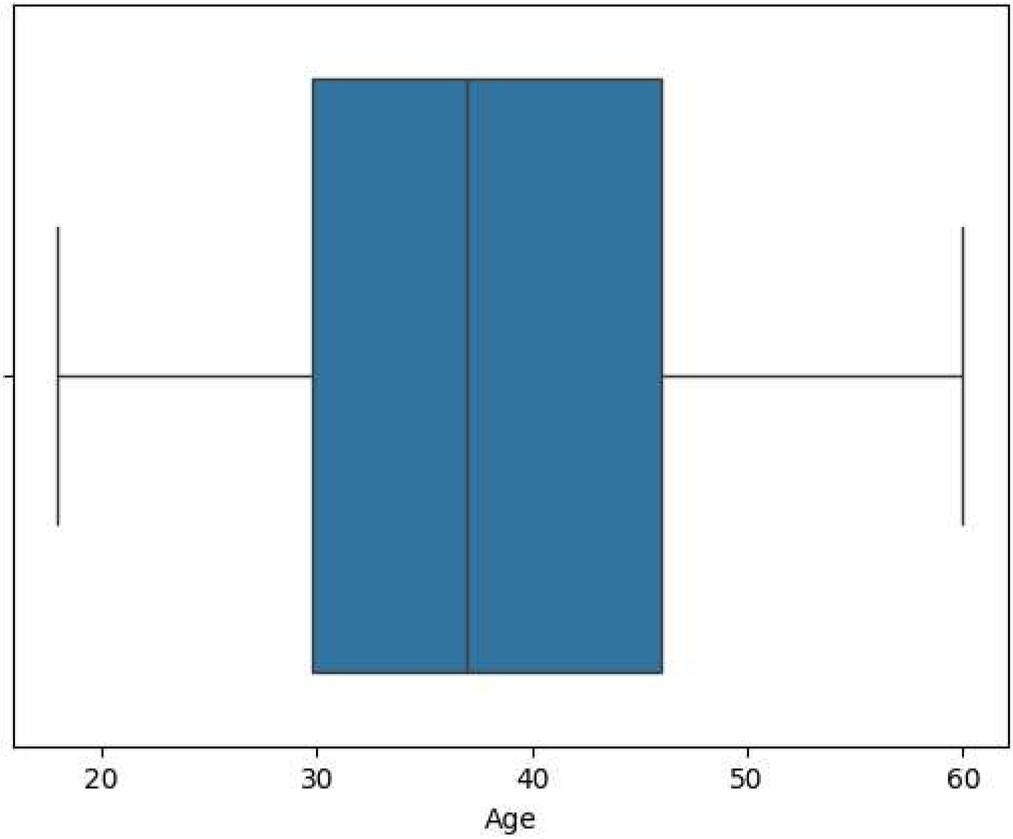
```
User ID             int64
Gender             object
Age                 int64
EstimatedSalary     int64
Purchased           int64
dtype: object
```

```
ds.describe()
```

	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

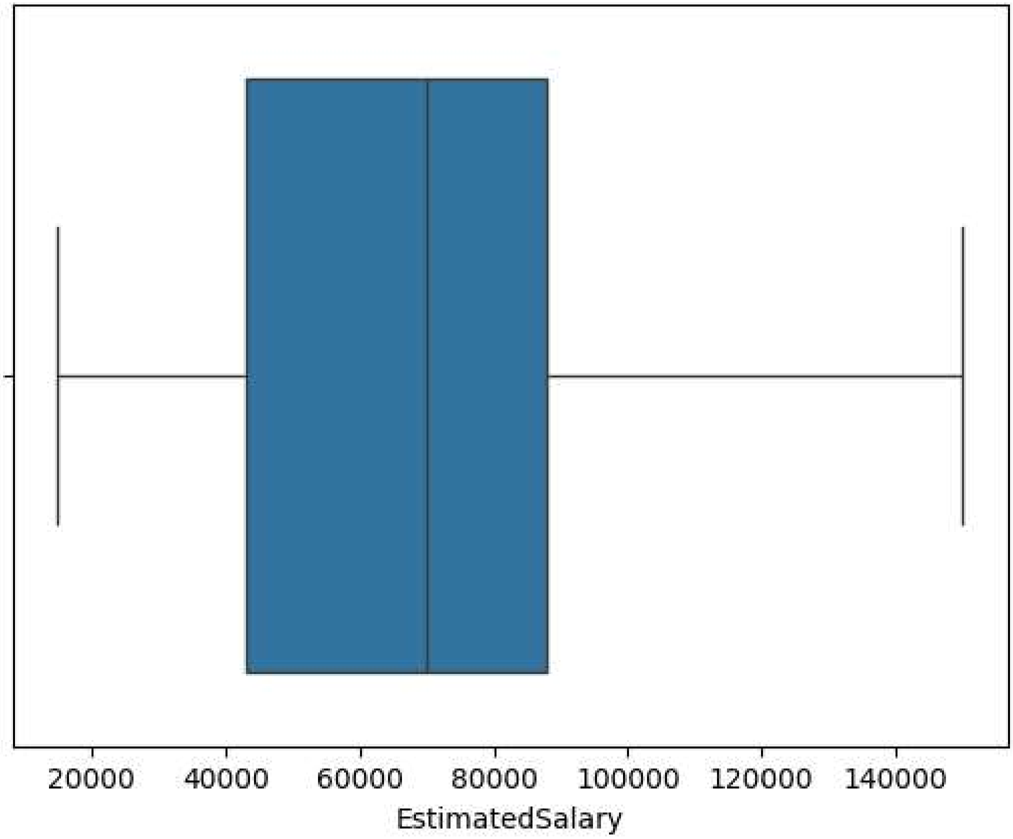
```
sns.boxplot(data = ds, x = 'Age')
```

```
<Axes: xlabel='Age'>
```




```
sns.boxplot(data = ds, x = 'EstimatedSalary')
```

```
<Axes: xlabel='EstimatedSalary'>
```

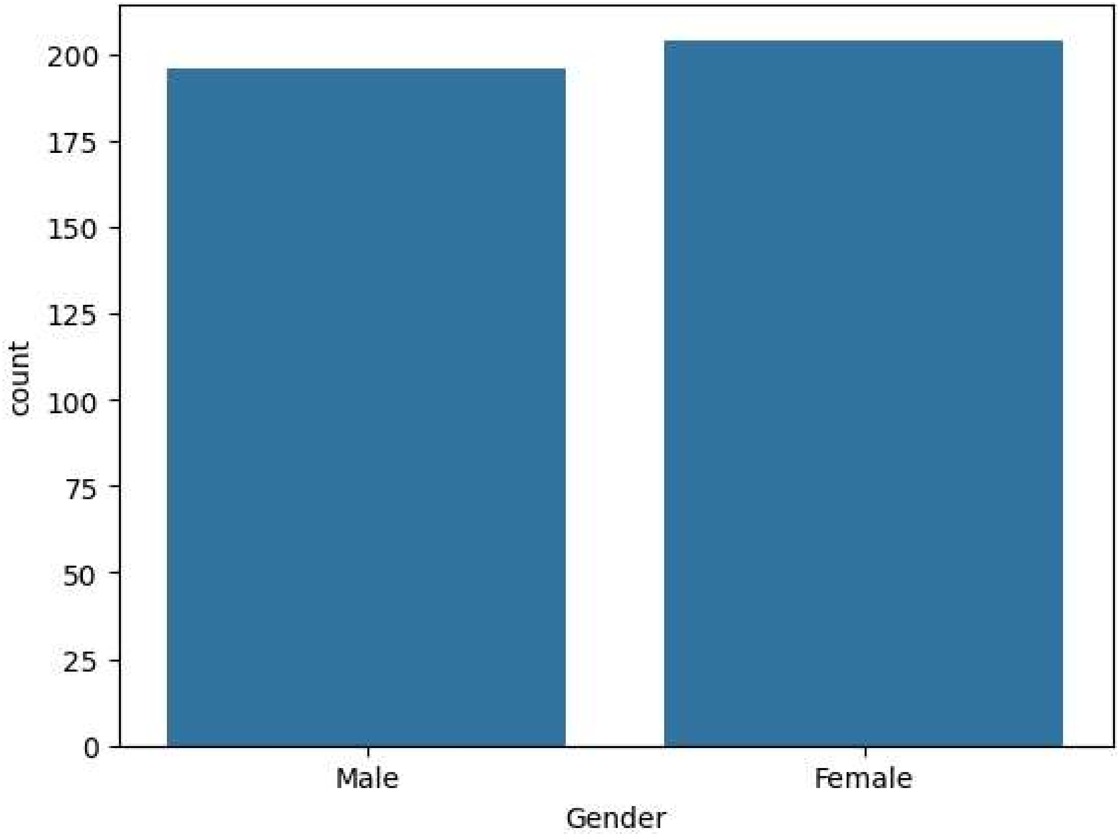



```
ds['Gender'].value_counts()
```

```
Gender
Female    204
Male      196
Name: count, dtype: int64
```

```
sns.countplot(data = ds, x = 'Gender')
```

```
<Axes: xlabel='Gender', ylabel='count'>
```

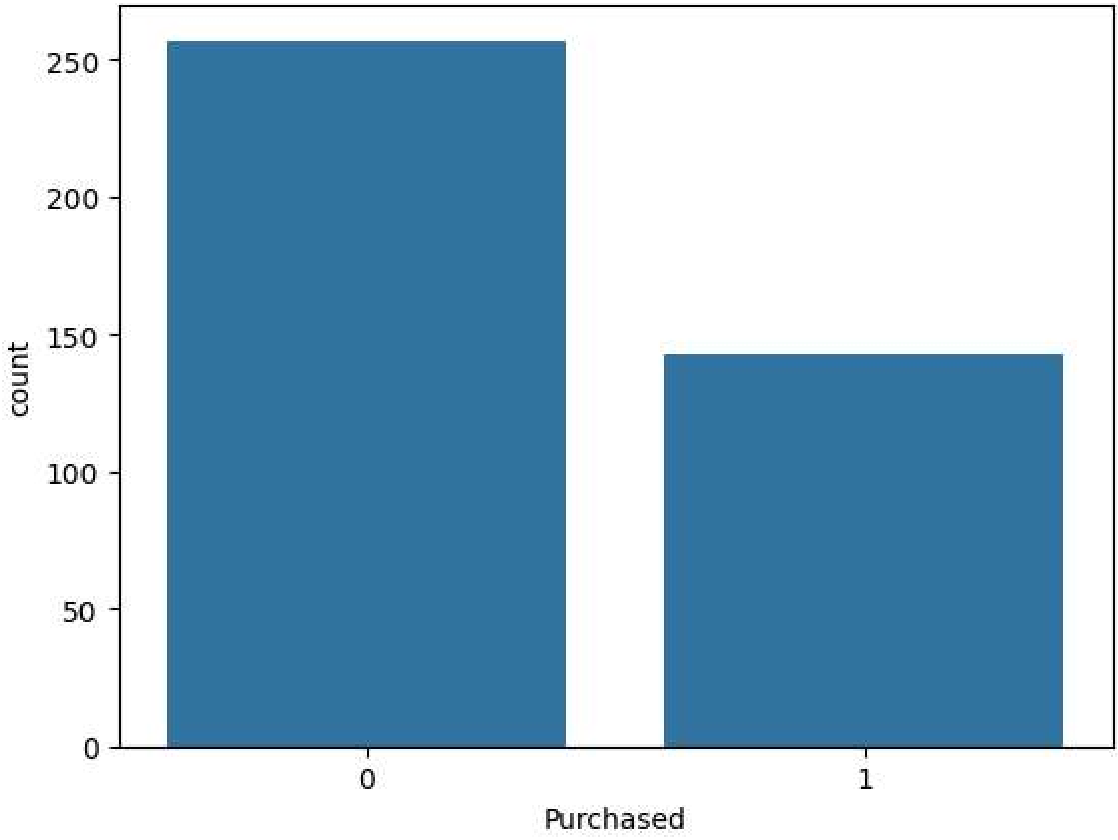



```
ds['Purchased'].value_counts()
```

```
Purchased
0    257
1    143
Name: count, dtype: int64
```

```
sns.countplot(data = ds, x = 'Purchased')
```

<Axes: xlabel='Purchased', ylabel='count'>




```
ds.isna().sum()
```

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

```
ds.loc[ds['Gender'] == 'Male', 'Gender'] = 0
ds.loc[ds['Gender'] == 'Female', 'Gender'] = 1
ds = ds.astype({'Gender' : 'int'})
ds
```

	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	0	19	19000	0
1	15810944	0	35	20000	0
2	15668575	1	26	43000	0
3	15603246	1	27	57000	0
4	15804002	0	19	76000	0
...	...	...	...	...	...
395	15691863	1	46	41000	1
396	15706071	0	51	23000	1
397	15654296	1	50	20000	1
398	15755018	0	36	33000	0
399	15594041	1	49	36000	1

400 rows × 5 columns

Next steps: Generate code with ds View recommended plots

```
ds.drop(['User ID'], axis = 1, inplace = True)
ds
```

	Gender	Age	EstimatedSalary	Purchased
0	0	19	19000	0
1	0	35	20000	0
2	1	26	43000	0
3	1	27	57000	0
4	0	19	76000	0
...	...	...	...	...
395	1	46	41000	1
396	0	51	23000	1
397	1	50	20000	1
398	0	36	33000	0
399	1	49	36000	1

400 rows × 4 columns

Next steps: Generate code with ds View recommended plots

```
def min_max_normalization(col_name):
  ds[col_name] = (ds[col_name] - ds[col_name].min()) / (ds[col_name].max() - ds[col_name]

min_max_normalization('EstimatedSalary')
min_max_normalization('Age')
ds
```

	Gender	Age	EstimatedSalary	Purchased
0	0	0.023810	0.029630	0
1	0	0.404762	0.037037	0
2	1	0.190476	0.207407	0
3	1	0.214286	0.311111	0
4	0	0.023810	0.451852	0
...	...	...	...	...
395	1	0.666667	0.192593	1
396	0	0.785714	0.059259	1
397	1	0.761905	0.037037	1
398	0	0.428571	0.133333	0
399	1	0.738095	0.155556	1

400 rows × 4 columns

Next steps: Generate code with ds View recommended plots

```
ds[['Age', 'EstimatedSalary']].skew()
ds[['Age', 'EstimatedSalary']].kurtosis()
```

```
Age                -0.622513
EstimatedSalary    -0.405878
dtype: float64
```

```
# Check for transformation with near-zero skew and kurtosis

# Reciprocal transformation
print( ( 1 / (ds["Age"] + 1e-3) ).skew() )
print( ( 1 / (ds["Age"] + 1e-3) ).kurtosis() )

# square-root transformation
print( np.sqrt( ds[ "Age" ] ).skew() )
print( np.sqrt( ds[ "Age" ] ).kurtosis() )

# cube-root transformation
print( np.cbrt( ds[ "Age" ] ).skew() )
print( np.cbrt( ds[ "Age" ] ).kurtosis() )

# log-transformation
print( np.log( ds[ "Age" ] + 1e-6 ).skew() )
print( np.log( ds[ "Age" ] + 1e-6 ).kurtosis() )
```

```
8.772648855102862
75.54534474505262
-0.6431799328732787
0.36416628386911043
-1.31598202376335
2.9087199865782374
-6.314913080205095
46.98324920534226
```

```
from scipy.stats import boxcox , skew , kurtosis

# Box-cox (power-transform)
# https://en.wikipedia.org/wiki/Power_transform
output , lmbda = boxcox( ds[ "Age" ] + 1e-4 )
print( skew(output) )
print( kurtosis(output) )
print( lmbda )
```

```
-0.2385769089771854
-0.4060057246641384
0.6805870525685984
```

```
# Box-cox transform returns the smallest skew
# and kurtosis
ds["Age"] = boxcox( ds[ "Age" ] + 1e-4 )[0]
ds["EstimatedSalary"] = boxcox( ds[ "EstimatedSalary" ] + 1e-4 )[0]
```

```
ds[ [ "Age" , "EstimatedSalary" ] ].describe()
```

	Age	EstimatedSalary
count	400.000000	400.000000
mean	-0.625744	-0.764688
std	0.335984	0.398289
min	-1.466535	-1.736617

```
from sklearn.model_selection import train_test_split
```