

social_net_ads

February 1, 2022

https://raw.githubusercontent.com/shivang98/Social-Network-ads-Boost/master/Social_Network_Ads.csv

Raw Data : https://github.com/shivang98/Social-Network-ads-Boost/blob/master/Social_Network_Ads.csv

```
[ ]: !pip3 install numpy
      !pip3 install pandas
      !pip3 install matplotlib
      !pip3 install seaborn
      !pip3 install sklearn
```

Requirement already satisfied: numpy in ./assign5_venv/lib/python3.8/site-packages (1.22.1)

Requirement already satisfied: pandas in ./assign5_venv/lib/python3.8/site-packages (1.4.0)

Requirement already satisfied: python-dateutil>=2.8.1 in ./assign5_venv/lib/python3.8/site-packages (from pandas) (2.8.2)

Requirement already satisfied: pytz>=2020.1 in ./assign5_venv/lib/python3.8/site-packages (from pandas) (2021.3)

Requirement already satisfied: numpy>=1.18.5; platform_machine != "aarch64" and platform_machine != "arm64" and python_version < "3.10" in ./assign5_venv/lib/python3.8/site-packages (from pandas) (1.22.1)

Requirement already satisfied: six>=1.5 in ./assign5_venv/lib/python3.8/site-packages (from python-dateutil>=2.8.1->pandas) (1.16.0)

Requirement already satisfied: matplotlib in ./assign5_venv/lib/python3.8/site-packages (3.5.1)

Requirement already satisfied: fonttools>=4.22.0 in ./assign5_venv/lib/python3.8/site-packages (from matplotlib) (4.29.0)

Requirement already satisfied: numpy>=1.17 in ./assign5_venv/lib/python3.8/site-packages (from matplotlib) (1.22.1)

Requirement already satisfied: cycler>=0.10 in ./assign5_venv/lib/python3.8/site-packages (from matplotlib) (0.11.0)

Requirement already satisfied: pillow>=6.2.0 in ./assign5_venv/lib/python3.8/site-packages (from matplotlib) (9.0.0)

Requirement already satisfied: python-dateutil>=2.7 in ./assign5_venv/lib/python3.8/site-packages (from matplotlib) (2.8.2)

Requirement already satisfied: kiwisolver>=1.0.1 in ./assign5_venv/lib/python3.8/site-packages (from matplotlib) (1.3.2)

Requirement already satisfied: packaging>=20.0 in

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./assign5_venv/lib/python3.8/site-packages (from matplotlib) (21.3)
Requirement already satisfied: pyparsing>=2.2.1 in
./assign5_venv/lib/python3.8/site-packages (from matplotlib) (3.0.7)
Requirement already satisfied: six>=1.5 in ./assign5_venv/lib/python3.8/site-
packages (from python-dateutil>=2.7->matplotlib) (1.16.0)
Requirement already satisfied: seaborn in ./assign5_venv/lib/python3.8/site-
packages (0.11.2)
Requirement already satisfied: pandas>=0.23 in
./assign5_venv/lib/python3.8/site-packages (from seaborn) (1.4.0)
Requirement already satisfied: matplotlib>=2.2 in
./assign5_venv/lib/python3.8/site-packages (from seaborn) (3.5.1)
Requirement already satisfied: scipy>=1.0 in ./assign5_venv/lib/python3.8/site-
packages (from seaborn) (1.7.3)
Requirement already satisfied: numpy>=1.15 in ./assign5_venv/lib/python3.8/site-
packages (from seaborn) (1.22.1)
Requirement already satisfied: python-dateutil>=2.8.1 in
./assign5_venv/lib/python3.8/site-packages (from pandas>=0.23->seaborn) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
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Requirement already satisfied: kiwisolver>=1.0.1 in
./assign5_venv/lib/python3.8/site-packages (from matplotlib>=2.2->seaborn)
(1.3.2)
Requirement already satisfied: cycycler>=0.10 in
./assign5_venv/lib/python3.8/site-packages (from matplotlib>=2.2->seaborn)
(0.11.0)
Requirement already satisfied: six>=1.5 in ./assign5_venv/lib/python3.8/site-
packages (from python-dateutil>=2.8.1->pandas>=0.23->seaborn) (1.16.0)
Requirement already satisfied: sklearn in ./assign5_venv/lib/python3.8/site-
packages (0.0)
Requirement already satisfied: scikit-learn in
./assign5_venv/lib/python3.8/site-packages (from sklearn) (1.0.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
./assign5_venv/lib/python3.8/site-packages (from scikit-learn->sklearn) (3.0.0)
Requirement already satisfied: joblib>=0.11 in
./assign5_venv/lib/python3.8/site-packages (from scikit-learn->sklearn) (1.1.0)
Requirement already satisfied: numpy>=1.14.6 in

```

```
./assign5_venv/lib/python3.8/site-packages (from scikit-learn->sklearn) (1.22.1)
Requirement already satisfied: scipy>=1.1.0 in
./assign5_venv/lib/python3.8/site-packages (from scikit-learn->sklearn) (1.7.3)
```

```
[ ]: import numpy as NP
import pandas as PD
import seaborn as SNS
import matplotlib.pyplot as MPlot
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import mean_absolute_error
from sklearn.preprocessing import MinMaxScaler
```

```
[ ]: DF = PD.read_csv("https://raw.githubusercontent.com/shivang98/
↳Social-Network-ads-Boost/master/Social_Network_Ads.csv")
print("Shape :",DF.shape)
print("Size :",DF.size)
DF.sample    (10)
```

```
Shape : (400, 5)
Size : 2000
```

```
[ ]:      User ID  Gender  Age  EstimatedSalary  Purchased
355  15606472   Male   60           34000           1
34   15724858   Male   27           90000           0
2    15668575  Female   26           43000           0
173  15581654  Female   34           43000           0
273  15589449   Male   39          106000           1
127  15745232   Male   26           32000           0
281  15685536   Male   35           61000           0
20   15649487   Male   45           22000           1
376  15596984  Female   46           74000           0
317  15684861   Male   35           55000           0
```

```
[ ]: DF.dtypes
```

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

```
[ ]: DF.describe()
```

```
[ ]:      Gender      Age  EstimatedSalary  Purchased
count  400.000000  400.000000      400.000000  400.000000
```

mean	0.490000	37.655000	69742.500000	0.357500
std	0.500526	10.482877	34096.960282	0.479864
min	0.000000	18.000000	15000.000000	0.000000
25%	0.000000	29.750000	43000.000000	0.000000
50%	0.000000	37.000000	70000.000000	0.000000
75%	1.000000	46.000000	88000.000000	1.000000
max	1.000000	60.000000	150000.000000	1.000000

```
[ ]: DF.isna().sum()
```

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

```
[ ]: DF.isnull().sum()
```

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

0.0.1 Dropping unwanted Information

We will drop User ID Column as it is not useful in classification

```
[ ]: DF.drop(columns=['User ID'], inplace=True)
      DF.sample(10)
```

```
[ ]:      Gender  Age  EstimatedSalary  Purchased
      317    Male   35           55000           0
      282    Male   37           70000           1
      31   Female   27          137000           1
      372  Female   39           73000           0
      342  Female   38           65000           0
      341    Male   35           75000           0
      109  Female   38           80000           0
      94   Female   29           83000           0
      36   Female   33           28000           0
      174  Female   34           72000           0
```

0.0.2 Converting Data to Category

Gender == Categorical Data -> So will convert into number (encoding)

```
[ ]: DF.dtypes
```

```
[ ]: Gender      object
Age            int64
EstimatedSalary int64
Purchased      int64
dtype: object
```

```
[ ]: DF['Gender'] = DF['Gender'].astype('category')
DF.dtypes
```

```
[ ]: Gender      category
Age            int64
EstimatedSalary int64
Purchased      int64
dtype: object
```

```
[ ]: DF['Gender'] = DF['Gender'].cat.codes
DF.sample(10)
```

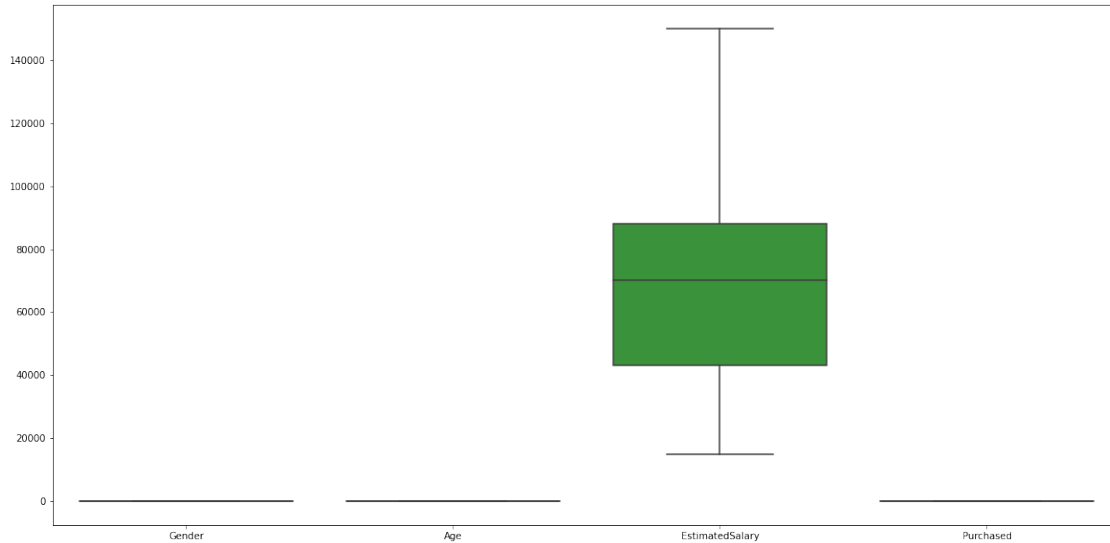
```
[ ]:      Gender  Age  EstimatedSalary  Purchased
381         1   48           33000           1
22          1   48           41000           1
382         0   44          139000           1
36          0   33           28000           0
82          1   20           49000           0
364         1   42          104000           1
161         1   25           90000           0
335         0   36           54000           0
334         1   57           60000           1
359         1   42           54000           0
```

0.0.3 Removing Outliers

Now will detect and remove outliers

```
[ ]: fig, ax = MPLOT.subplots(figsize=(20,10))
     SNS.boxplot(data=DF, ax=ax)
```

```
[ ]: <AxesSubplot:>
```



```
[ ]: def Remove_Outlier(DataFrame, Col_Name) :
    Upper_Threshold = DataFrame[Col_Name].mean() + 3*DataFrame[Col_Name].std()
    Lower_Threshold = DataFrame[Col_Name].mean() - 3*DataFrame[Col_Name].std()
    Count = DataFrame[(DataFrame[Col_Name] >= Upper_Threshold ) |
    ↪(DataFrame[Col_Name] <= Lower_Threshold)][Col_Name].count()
    print("[ * ] In", str(Col_Name), "->", "High :",Upper_Threshold, "| Low :
    ↪", Lower_Threshold, "| -> Outliers Detected :", Count)
    return DataFrame[((DataFrame[Col_Name] >= Lower_Threshold ) &
    ↪(DataFrame[Col_Name] <= Upper_Threshold))]
```

```
[ ]: Remove_Outlier( DF, 'Gender' )
Remove_Outlier( DF, 'Age' )
Remove_Outlier( DF, 'EstimatedSalary' )
Remove_Outlier( DF, 'Purchased' )
```

```
[ * ] In Gender -> High : 1.991578117217104 | Low : -1.0115781172171041 | ->
Outliers Detected : 0
[ * ] In Age -> High : 69.10362979192374 | Low : 6.206370208076258 | -> Outliers
Detected : 0
[ * ] In EstimatedSalary -> High : 172033.38084727435 | Low :
-32548.380847274355 | -> Outliers Detected : 0
[ * ] In Purchased -> High : 1.797091890790607 | Low : -1.0820918907906072 | ->
Outliers Detected : 0
```

```
[ ]:      Gender  Age  EstimatedSalary  Purchased
0         1    19         19000         0
1         1    35         20000         0
2         0    26         43000         0
3         0    27         57000         0
```

```

4          1   19          76000          0
..      ...  ...          ...      ...
395         0   46          41000          1
396         1   51          23000          1
397         0   50          20000          1
398         1   36          33000          0
399         0   49          36000          1

```

[400 rows x 4 columns]

1 Corelation Matrix

```
[ ]: fig, ax = MPlot.subplots(figsize=(15,10))
     sns.heatmap(Df.corr(), annot = True, ax=ax)
```

```
[ ]: <AxesSubplot:>
```



2 Train Model

```
[ ]: X = DF[['Age', 'EstimatedSalary']]
      Y = DF['Purchased']

      X_TRAIN, X_TEST, Y_TRAIN, Y_TEST = train_test_split(
          X,
          Y,
          test_size=0.2,
          random_state=42)

      model = LogisticRegression()
      model.fit(X_TRAIN, Y_TRAIN)
      output = model.predict(X_TEST)

      print("Mean Absolute Error :", mean_absolute_error(Y_TEST, output))
      print("Model Score (Accuracy) :", model.score(X_TEST, Y_TEST))
```

Mean Absolute Error : 0.35
Model Score (Accuracy) : 0.65

3 Data Normalization and Training Model

```
[ ]: DF.describe()
```

```
[ ]:
```

	Gender	Age	EstimatedSalary	Purchased
count	400.000000	400.000000	400.000000	400.000000
mean	0.490000	37.655000	69742.500000	0.357500
std	0.500526	10.482877	34096.960282	0.479864
min	0.000000	18.000000	15000.000000	0.000000
25%	0.000000	29.750000	43000.000000	0.000000
50%	0.000000	37.000000	70000.000000	0.000000
75%	1.000000	46.000000	88000.000000	1.000000
max	1.000000	60.000000	150000.000000	1.000000

```
[ ]: X = DF[['Age', 'EstimatedSalary']]
      Y = DF['Purchased']

      X_TRAIN, X_TEST, Y_TRAIN, Y_TEST = train_test_split(X, Y, test_size=0.2,
          ↪random_state=42)

      # fit scaler on training data
      norm = MinMaxScaler().fit(X_TRAIN)
```



```
# transform training data
X_TRAIN = norm.transform(X_TRAIN)

# fit scaler on training data
norm = MinMaxScaler().fit(X_TEST)

# transform training data
X_TEST = norm.transform(X_TEST)

model = LogisticRegression()
model.fit(X_TRAIN, Y_TRAIN)
output = model.predict(X_TEST)

print("Mean Absolute Error :", mean_absolute_error(Y_TEST, output))
print("Model Score (Accuracy) :", model.score(X_TEST, Y_TEST))
```

Mean Absolute Error : 0.125

Model Score (Accuracy) : 0.875