Classification using Logistic Regression & K-NN Classifier

import libs

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

import dataset

```
# from google.colab import files
# uploaded = files.upload()
# D8data1.csv

import os
os.chdir(r'C:\Users\surya\Downloads\PG-DBDA-Mar23\Datasets')
os.getcwd()
```

```
'C:\\Users\\surya\\Downloads\\PG-DBDA-Mar23\\Datasets'
```

```
data = pd.read_csv('D8data1.csv')
data.head()
```

	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

```
data.shape
```

```
(400, 5)
```

```
data.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

```
data.info()
```

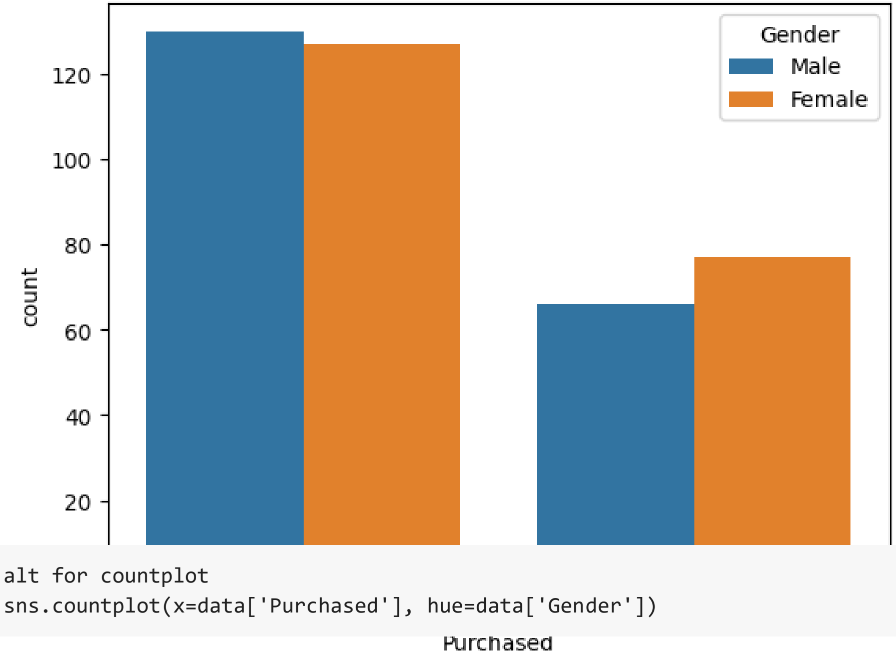
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 5 columns):
 #   Column           Non-Null Count  Dtype 
---  ------           --------------  ----- 
 0   User ID          400 non-null    int64 
 1   Gender           400 non-null    object
 2   Age              400 non-null    int64 
 3   EstimatedSalary  400 non-null    int64 
 4   Purchased        400 non-null    int64 
dtypes: int64(4), object(1)
memory usage: 15.8+ KB
```

EDA

count for Gender column

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

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

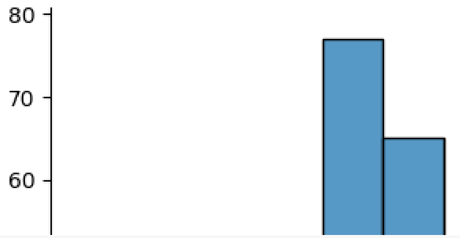



```
1 # alt for countplot
2 # sns.countplot(x=data['Purchased'], hue=data['Gender'])
```

dist for Age column

```
1 sns.displot(data['Age'])
```

```
c:\users\surya\appdata\local\programs\python\python39\lib\site-packages\seaborn\axisgrid.p
  self._figure.tight_layout(*args, **kwargs)
<seaborn.axisgrid.FacetGrid at 0x222bd492340>
```

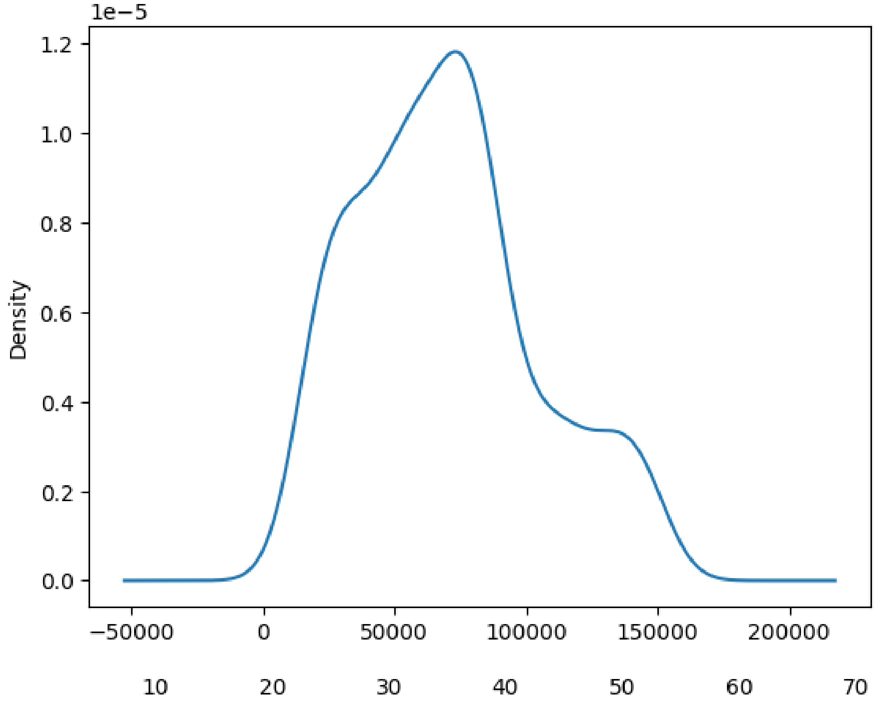



```
1 sns.distplot(data['Age'])
```

dist for EstimatedSalary column

```
data['EstimatedSalary'].plot(kind='kde')
# kernel density plot
```

```
<Axes: ylabel='Density'>
```



identify X & Y

```
x = data[['Age', 'EstimatedSalary']]
x[:5]
```

	Age	EstimatedSalary
0	19	19000

```
y = data['Purchased']
y[:5]
```

```
0    0
1    0
2    0
3    0
4    0
Name: Purchased, dtype: int64
```

Splitting

```
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=0)
```

```
x_train.head()
```

	Age	EstimatedSalary
250	44	39000
63	32	120000
312	38	50000
159	32	135000
283	52	21000

```
x_test.head()
```

```
Age  EstimatedSalary
```

```
x_train.describe()
# to get an idea of min & max for scaling values
```

	Age	EstimatedSalary
count	300.000000	300.000000
mean	38.126667	69583.333333
std	10.114592	34548.541619
min	18.000000	15000.000000
25%	30.750000	43000.000000
50%	38.000000	69500.000000
75%	46.000000	88000.000000
max	60.000000	150000.000000

Preprocessing

Feature Scaling

```
from sklearn.preprocessing import StandardScaler
```

```
scaler = StandardScaler()
```

```
x_train = scaler.fit_transform(x_train)
x_train[:5]
```

```
array([[ 0.58164944, -0.88670699],
       [-0.60673761,  1.46173768],
       [-0.01254409, -0.5677824 ],
       [-0.60673761,  1.89663484],
       [ 1.37390747, -1.40858358]])
```

```
x_test = scaler.fit_transform(x_test)
x_test[:5]
```

```
array([[-0.54748976,  0.5130727 ],
       [ 0.15442019, -0.61825566],
       [-0.10879604,  0.14615539],
       [-0.54748976,  0.26846116],
       [-0.10879604, -0.61825566]])
```

Logistic Regression Classification

```
from sklearn.linear_model import LogisticRegression
```

Modeling

```
model = LogisticRegression()
```

Training

```
model.fit(x_train, y_train)
```

```
▾ LogisticRegression
LogisticRegression()
```

Prediction

```
prediction = model.predict(x_test)
# generating prediction
prediction[:5]
```

```
array([0, 0, 0, 0, 0], dtype=int64)
```

Evaluation

- checking performance using evaluation metrics

confusion_matrix

```
from sklearn.metrics import confusion_matrix
```

```
confusion_matrix(y_test, prediction)
```

```
array([[63,  5],
       [ 8, 24]], dtype=int64)
```

classification_report

```
from sklearn.metrics import classification_report
```

```
print(classification_report(y_test, prediction))
```

```
              precision    recall  f1-score   support

           0       0.89      0.93      0.91        68
           1       0.83      0.75      0.79        32

    accuracy                           0.87       100
   macro avg       0.86      0.84      0.85       100
weighted avg       0.87      0.87      0.87       100
```

accuracy_score

```
from sklearn.metrics import accuracy_score
```

```
accuracy_score(y_test, prediction)
```

```
0.87
```

precision_score

```
from sklearn.metrics import precision_score
```

```
precision_score(y_test, prediction)
```

```
0.8275862068965517
```

recall_score

```
from sklearn.metrics import recall_score
```

```
recall_score(y_test, prediction)
```

```
0.75
```

K-Nearest Neighbor (KNN) Classification

Modeling

```
from sklearn.neighbors import KNeighborsClassifier
```

```
knn_model = KNeighborsClassifier(n_neighbors=5)
```

Training

```
knn_model.fit(x_train, y_train)
```

```
▾ KNeighborsClassifier
KNeighborsClassifier()
```

Prediction

```
knn_predictions = knn_model.predict(x_test)
knn_predictions[:5]
```

```
array([0, 0, 0, 0, 0], dtype=int64)
```

Evaluation

confusion_matrix

```
from sklearn.metrics import confusion_matrix
```

```
confusion_matrix(y_test, knn_predictions)
```

```
array([[64,  4],
       [ 3, 29]], dtype=int64)
```

classification_report

```
from sklearn.metrics import classification_report
```

```
print(classification_report(y_test, knn_predictions))
```

```
              precision    recall  f1-score   support

           0       0.96      0.94      0.95        68
           1       0.88      0.91      0.89        32

    accuracy                           0.93       100
   macro avg       0.92      0.92      0.92       100
weighted avg       0.93      0.93      0.93       100
```

accuracy_score

```
from sklearn.metrics import accuracy_score
```

```
accuracy_score(y_test, knn_predictions)
```

```
0.93
```

precision_score

```
from sklearn.metrics import precision_score
```

```
precision_score(y_test, knn_predictions)
```

```
0.8787878787878788
```

recall_score

```
from sklearn.metrics import recall_score
```

```
recall_score(y_test, knn_predictions)
```

```
0.90625
```

Observation Note

- Note that K-NN model has more accuracy than Logistic, so K-NN performs better than Logistic regression

HW:

- conditional probability
- Bayes Theorem

```

```