```
import sklearn
import pandas
import seaborn
import matplotlib
%matplotlib inline


from sklearn import model_selection
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.preprocessing import StandardScaler


data_set = pandas.read_csv ('suv_data.csv')


data_set.head (20)
```

	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
10	15570769	Female	26	80000	0
11	15606274	Female	26	52000	0
12	15746139	Male	20	86000	0
13	15704987	Male	32	18000	0
14	15628972	Male	18	82000	0
15	15697686	Male	29	80000	0
16	15733883	Male	47	25000	1
17	15617482	Male	45	26000	1
18	15704583	Male	46	28000	1
19	15621083	Female	48	29000	1

```
data_set.shape
```

```
(400, 5)
```

```
data_set.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
```

```
data_set.groupby ('Purchased').size()
```

```
Purchased
0    257
1    143
dtype: int64
```

```
cleaned_data_set = data_set.drop (columns = ['User ID'], axis = '1')
cleaned_data_set.head ()
```

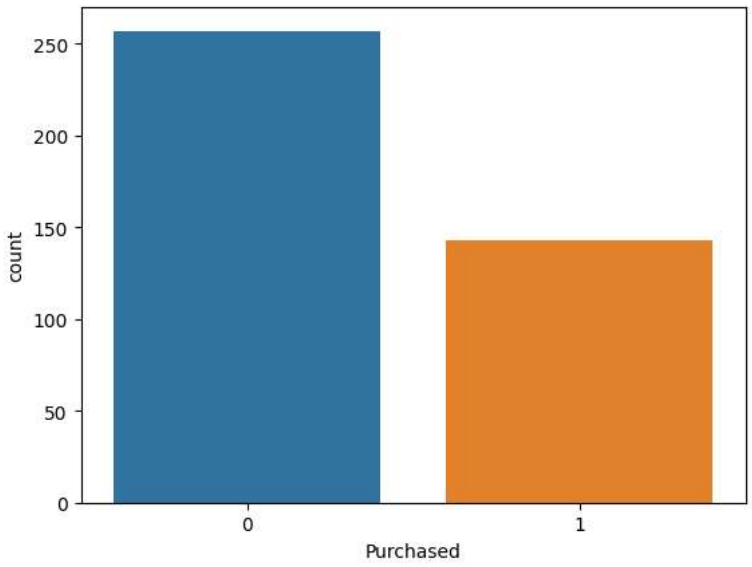
	Gender	Age	EstimatedSalary	Purchased
0	Male	19	19000	0
1	Male	35	20000	0
2	Female	26	43000	0
3	Female	27	57000	0
4	Male	19	76000	0

```
cleaned_data_set.describe ()
```

	Age	EstimatedSalary	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

```
seaborn.countplot (x = 'Purchased', data = cleaned_data_set)
```

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

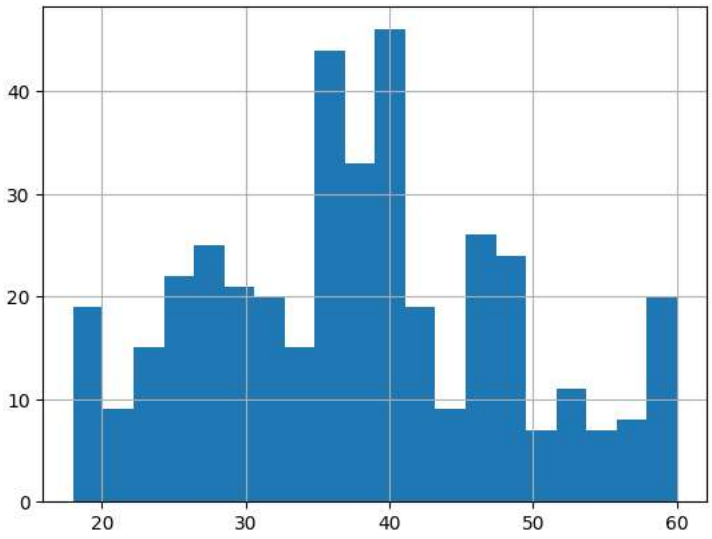



```
seaborn.countplot ( x = 'Purchased', hue = 'Gender', data = cleaned_data_set)
```

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


```
data_set ['Age'].hist(bins = 20)
```

```
<Axes: >
```




```
age_category = []
for i in range (0, len  (data_set ['Age'])):
    if cleaned_data_set ['Age'][i] <= 20:
        age_category.append ('A');
    elif 20 < cleaned_data_set ['Age'][i] <= 26:
        age_category.append ('B');
    elif 26 < cleaned_data_set ['Age'][i] <= 30:
        age_category.append ('C');
    elif 30 < cleaned_data_set ['Age'][i] <= 40:
        age_category.append ('D');
    elif 40 < cleaned_data_set ['Age'][i] <= 50:
        age_category.append ('E');
    else:
        age_category.append ('F');

age_data_frame = pandas.DataFrame (data = age_category, columns = ['AgeCategory'])
augmented_data_set = pandas.concat([cleaned_data_set, age_data_frame], axis = 1)
augmented_data_set.head()
```

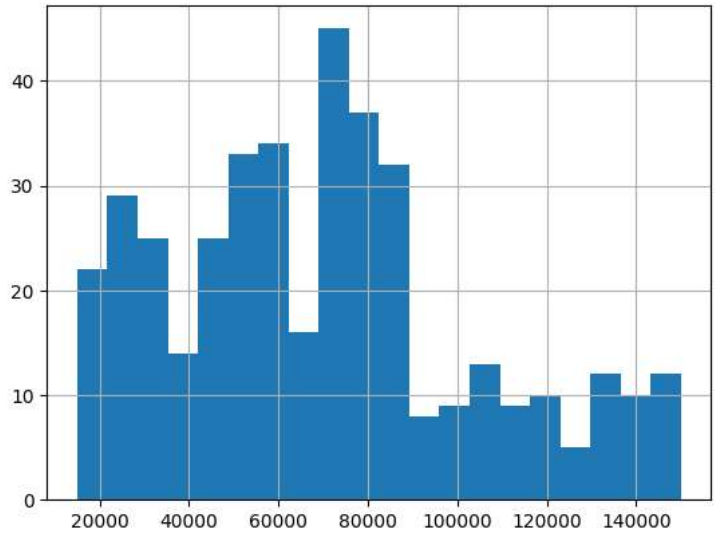
	Gender	Age	EstimatedSalary	Purchased	AgeCategory
0	Male	19	19000	0	A
1	Male	35	20000	0	D
2	Female	26	43000	0	B
3	Female	27	57000	0	C
4	Male	19	76000	0	A

```
seaborn.countplot ( x = 'Purchased', hue = 'AgeCategory', data = augmented_data_set)
```

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


```
data_set ['EstimatedSalary'].hist(bins = 20)
```

```
<Axes: >
```



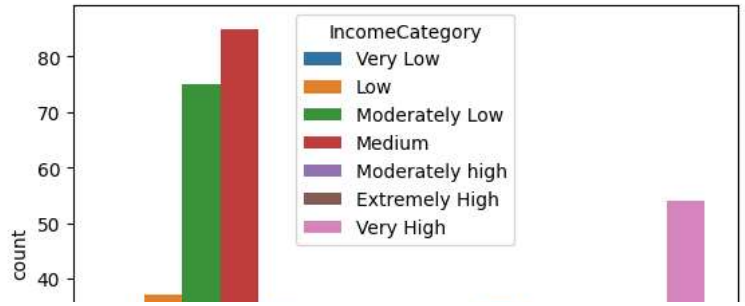

```
income_category = []
for i in range (0, len  (data_set ['EstimatedSalary'])):
    if cleaned_data_set ['EstimatedSalary'][i] <= 19500:
        income_category.append ('Very Low');
    elif 19500 < cleaned_data_set ['EstimatedSalary'][i] <= 40000:
        income_category.append ('Low');
    elif 40000 < cleaned_data_set ['EstimatedSalary'][i] <= 60000:
        income_category.append ('Moderately Low');
    elif 60000 < cleaned_data_set ['EstimatedSalary'][i] <= 80000:
        income_category.append ('Medium');
    elif 80000 < cleaned_data_set ['EstimatedSalary'][i] <= 100000:
        income_category.append ('Moderately high');
    elif 100000 < cleaned_data_set ['EstimatedSalary'][i] <= 130000:
        income_category.append ('Very High');
    elif 130000 < cleaned_data_set ['EstimatedSalary'][i] <= 145000:
        income_category.append ('Very High');
    else:
        income_category.append ('Extremely High');

income_data_frame = pandas.DataFrame (data = income_category, columns = ['IncomeCategory'])
augmented_data_set_2 = pandas.concat([augmented_data_set, income_data_frame], axis = 1)
augmented_data_set_2.head()
```

	Gender	Age	EstimatedSalary	Purchased	AgeCategory	IncomeCategory
0	Male	19	19000	0	A	Very Low
1	Male	35	20000	0	D	Low
2	Female	26	43000	0	B	Moderately Low
3	Female	27	57000	0	C	Moderately Low
4	Male	19	76000	0	A	Medium

```
seaborn.countplot ( x = 'Purchased', hue = 'IncomeCategory', data = augmented_data_set_2)
```

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




```
binary_gender = pandas.get_dummies (augmented_data_set_2 ['Gender'],drop_first = True)
binary_gender.head ()
```

	Male
0	1
1	1
2	0
3	0
4	1

```
binary_age = pandas.get_dummies (augmented_data_set_2 ['AgeCategory'])
binary_age.head ()
```

	A	B	C	D	E	F
0	1	0	0	0	0	0
1	0	0	0	1	0	0
2	0	1	0	0	0	0
3	0	0	1	0	0	0
4	1	0	0	0	0	0

```
binary_income = pandas.get_dummies (augmented_data_set_2 ['IncomeCategory'])
binary_income.head ()
```

	Extremely High	Low	Medium	Moderately Low	Moderately high	Very High	Very Low
0	0	0	0	0	0	0	1
1	0	1	0	0	0	0	0
2	0	0	0	1	0	0	0
3	0	0	0	1	0	0	0
4	0	0	1	0	0	0	0

```
final_data_set  = pandas.concat ([augmented_data_set_2, binary_age, binary_gender, binary_income], axis = 1)
final_data_set_1 = final_data_set.drop (columns = ['Age', 'Gender', 'EstimatedSalary', 'IncomeCategory', 'AgeCategory'], axis = 1)
final_data_set_1.head ()
```

	Purchased	A	B	C	D	E	F	Male	Extremely High	Low	Medium	Moderately Low	Moderately high	Very High	Very Low
0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	1
1	0	0	0	0	1	0	0	1	0	1	0	0	0	0	0
2	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0
3	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0
4	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0

```
Y = final_data_set_1 ['Purchased']
X = final_data_set_1.drop (columns = ['Purchased'], axis = 1)
```

```
X.head()
```

	A	B	C	D	E	F	Male	Extremely High	Low	Medium	Moderately Low	Moderately high	Very High	Very Low
0	1	0	0	0	0	0	1	0	0	0	0	0	0	1
1	0	0	0	1	0	0	1	0	1	0	0	0	0	0
2	0	1	0	0	0	0	0	0	0	0	1	0	0	0
3	0	0	1	0	0	0	0	0	0	0	1	0	0	0

```
Y.head()
```

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

```
test_set_size = 0.2
seed = 0
X_train, X_test, Y_train, Y_test = model_selection.train_test_split (X,Y, test_size = test_set_size, random_state = seed)
model = LogisticRegression (solver = 'liblinear')
model.fit (X_train, Y_train)
```

```
LogisticRegression(solver='liblinear')
```

```
predictions = model.predict (X_test)
```

```
Y = data_set.iloc [:, 4]
X = data_set.iloc [:, 2:4]
```

```
print (X.head())
```

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

```
print (Y.head())
```

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

```
test_set_size = 0.2
seed = 0
X_train, X_test, Y_train, Y_test = model_selection.train_test_split (X,Y, test_size = test_set_size, random_state = seed)
```

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

```
classifier = LogisticRegression (random_state = seed, solver = 'liblinear')
classifier.fit (X_train, Y_train)
```

```
LogisticRegression(random_state=0, solver='liblinear')
```

```
predictions = classifier.predict (X_test)
```

```
report = classification_report (Y_test, predictions)
print (report)
```

```
              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
```

```
accuracy_score (Y_test, predictions)
```

```
0.8875
```