Importing required libraries

In [115…

```
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
from matplotlib import pyplot as plt
from matplotlib.colors import ListedColormap
import numpy as np
import pickle
import pandas as pd
import seaborn as sns
```

Reading data from dataset

In [63]:

```
dataset = pd.read_csv('Social_Network_Ads.csv')
X = dataset.iloc[:, :-1].values #all the numerical features
y = dataset.iloc[:, -1].values #label (or target)
```

In [64]:

```
#dataset information
dataset.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
```

In [65]:

```
dataset.head()
```

Out[65]:

	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

In [66]:
```
dataset.tail()
```

Out[66]:

	User ID	Gender	Age	EstimatedSalary	Purchased
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

Data Preprosessing

In [67]:
```
print(dataset.describe())
#Missing Data Check
print(dataset.isnull().sum())
```

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

This dataset does not have any missing data

In [68]:
```
#Checking for duplicated values
dataset.duplicated().sum()
```

Out[68]: 0

There are no duplicate values

In [69]:
```
# Dropping Unecessary columns
dataset.drop('User ID',axis=1,inplace=True)
dataset.head()
```

Out[69]:

	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

In [83]:
```
#Converting Categorical data to numeric data
dataset['Gender'].replace(to_replace=['Male', 'Female'], value=[1,2], inplace=True)
```

Correlation between the features/variables are

In [84]:
```
cor = dataset.corr()
cor
```

Out[84]:

	Gender	Age	EstimatedSalary	Purchased
Gender	1.000000	0.073741	0.060435	0.042469
Age	0.073741	1.000000	0.155238	0.622454
EstimatedSalary	0.060435	0.155238	1.000000	0.362083
Purchased	0.042469	0.622454	0.362083	1.000000

In [85]:
```
dataset['Purchased'].value_counts()
```

Out[85]:
```
Purchased
0    257
1    143
Name: count, dtype: int64
```

In [86]:
```
dataset.Age.describe()
```

Out[86]:
```
count    400.000000
mean      37.655000
std       10.482877
min       18.000000
25%       29.750000
50%       37.000000
75%       46.000000
max       60.000000
Name: Age, dtype: float64
```

Average age of the considered population is around 37

In [87]:
```
dataset.EstimatedSalary.describe()
```

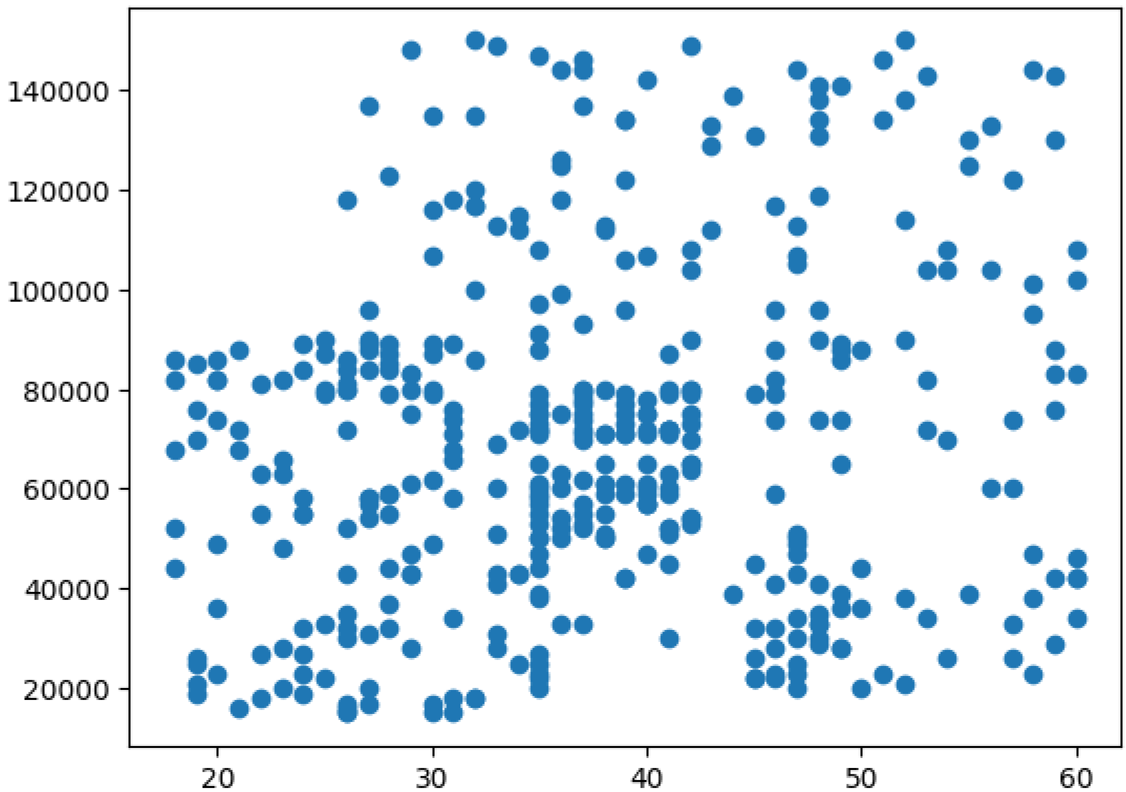
Out[87]:
```
count       400.000000
mean      69742.500000
std       34096.960282
min       15000.000000
25%       43000.000000
50%       70000.000000
75%       88000.000000
max      150000.000000
Name: EstimatedSalary, dtype: float64
```

Average Salary of the population is around 70000

Checking if there is any relation between Age and Estimated salary

In [88]:
```
plt.scatter(dataset.Age, dataset.EstimatedSalary)
```

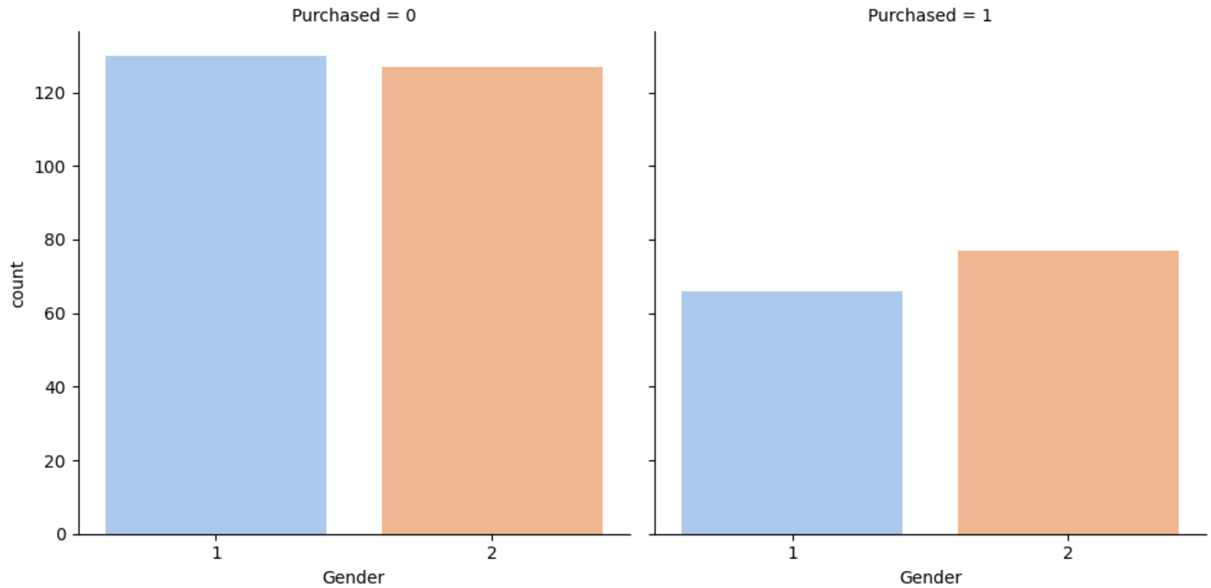
Out[88]: <matplotlib.collections.PathCollection at 0x27e38479950>



We do not observe any major dependencies between Age and Salaries

In [89]:
```
sns.catplot(x="Gender",col='Purchased', data=dataset, kind = 'count', palette='past
```

Out[89]: <seaborn.axisgrid.FacetGrid at 0x27e36a4f950>



In [90]:
```
dataset.head()
```

Out[90]:

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

Training

In [136…
```
#Determining the columns that drive the decision of the "To purchase or not"
feature_cols = ['Gender','Age','EstimatedSalary']
X = dataset[feature_cols]
Y = dataset['Purchased']
```

In [92]:
```
#splitting dataset into training and testing sets(75% training and 25% for testing)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_
X_test
```

Out[92]:

	Gender	Age	EstimatedSalary
132	1	30	87000
309	2	38	50000
341	1	35	75000
196	2	30	79000
246	2	35	50000
...	...	...	...
146	2	27	96000
135	1	23	63000
390	1	48	33000
264	1	48	90000
364	1	42	104000

100 rows × 3 columns

In [93]:
```
X_train
```

Out[93]:

	Gender	Age	EstimatedSalary
250	2	44	39000
63	1	32	120000
312	2	38	50000
159	2	32	135000
283	2	52	21000
...	...	...	...
323	2	48	30000
192	1	29	43000
117	1	36	52000
47	2	27	54000
172	2	26	118000

300 rows × 3 columns

In [94]:
```
y_train
```

Out[94]:
```
array([0, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1,
       0, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0,
       0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0,
       0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 0, 0,
       1, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1,
       0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0,
       1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0,
       0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0,
       1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1,
       0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0,
       0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0,
       1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1,
       1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0,
       0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0], dtype=int64)
```

In [95]:
```
X_test
```

Out[95]:

	Gender	Age	EstimatedSalary
132	1	30	87000
309	2	38	50000
341	1	35	75000
196	2	30	79000
246	2	35	50000
...	...	...	...
146	2	27	96000
135	1	23	63000
390	1	48	33000
264	1	48	90000
364	1	42	104000

100 rows × 3 columns

Decision Tree Classifier

In [106…
```
from sklearn import tree

tr = tree.DecisionTreeClassifier()
tr.fit(X_train, y_train)
y_pred = tr.predict(X_test)
y_pred
```

Out[106]:
```
array([0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0,
       0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1,
       0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1,
       1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 1], dtype=int64)
```

Feature Scaling is required to normalize the data from within a specified minimum and maximum range

This step is needed to normalize the range of independent vavriables/features from a minimum to a maximum range

Training the model and implementing the Test set

In [108…
```
from sklearn import model_selection
kfold = model_selection.KFold(n_splits = 10)
tr = tree.DecisionTreeClassifier()
tr.fit(X_train, y_train)
results = model_selection.cross_val_score(tr, X_train, y_train, cv = kfold)
results
```

Out[108]:
```
array([0.8       , 0.8       , 0.76666667, 0.76666667, 0.93333333,
       0.7       , 0.9       , 0.86666667, 0.93333333, 0.9       ])
```

In [109…
```
tr_train_score = tr.score(X_train, y_train)

tr_test_score= tr.score(X_test, y_test)


print('Decision Tree Classifier Train Score is : ' , tr_train_score)

print('Decision Tree Classifier Test Score is : ' , tr_test_score)
```

```
Decision Tree Classifier Train Score is :  1.0
Decision Tree Classifier Test Score is :  0.91
```

Accuracy of the Classifier

In [110…
```
from sklearn.metrics import accuracy_score

tr_acc = accuracy_score(y_test, y_pred)
print('accuracy_score : ', tr_acc)
```

```
accuracy_score :  0.91
```

In [111…
```
from sklearn import  metrics

tr_acc = 100*tr.score(X_test, y_test)
print('Decision Tree Classifier Predictions: \n', tr.predict(X_test), '\n Accuracy:
```

```
Decision Tree Classifier Predictions:
 [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 1 0 1 0 0 0 0 0 0 1 0 0 0 0
 0 0 1 0 0 0 0 1 0 0 0 0 1 1 0 0 1 1 1 0 0 1 0 0 1 0 1 0 1 0 0 0 1 1 0 0 1
 0 0 0 0 1 1 1 1 0 0 1 0 1 1 1 0 0 1 0 0 0 1 0 1 1 1]
 Accuracy: 91.0 %
```

Confusion Matrix

In [141…

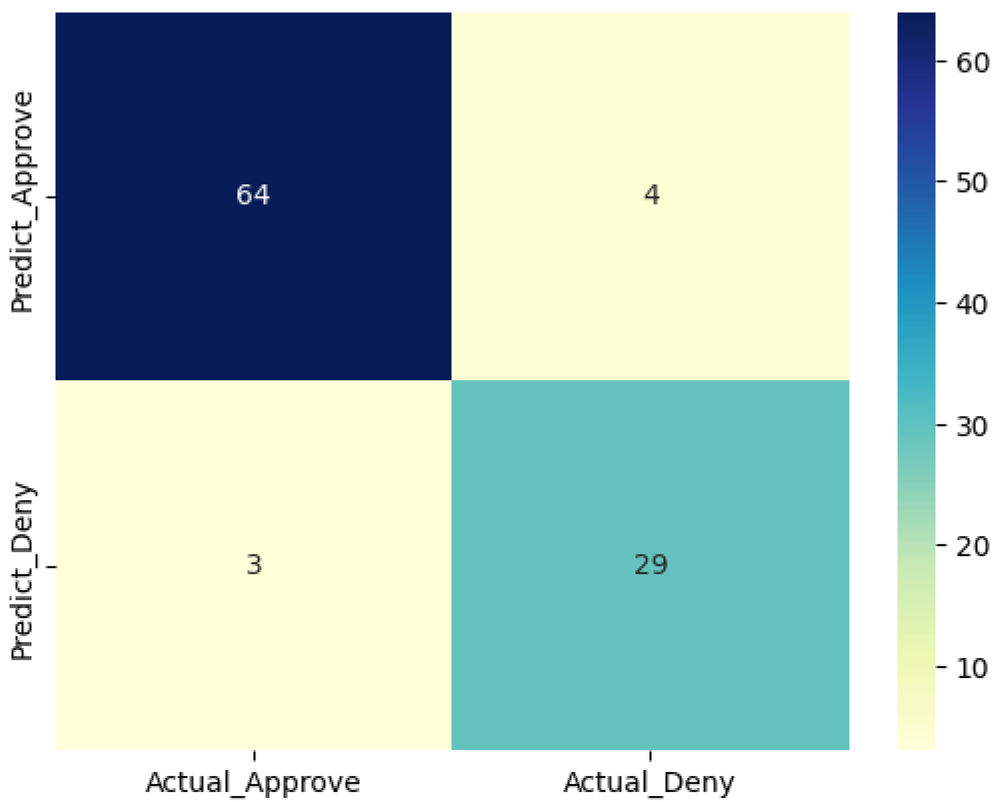
```python
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
[[64  4]
 [ 3 29]]
```

In [151…

```python
from sklearn.metrics import confusion_matrix
cm_matrix = pd.DataFrame(data=cm, columns=['Actual_Approve', 'Actual_Deny'],
                                 index=['Predict_Approve', 'Predict_Deny'])
sns.heatmap(cm_matrix, annot=True, fmt='d', cmap='YlGnBu')
```

Out[151]: <Axes: >



Verification

In [124…

```python
cross_check = pd.DataFrame({'Actual' : y_test, 'Predicted' : y_pred})
cross_check
```

Out[124]:

	Actual	Predicted
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0
...	...	...
95	1	1
96	0	0
97	1	1
98	1	1
99	1	1

100 rows × 2 columns

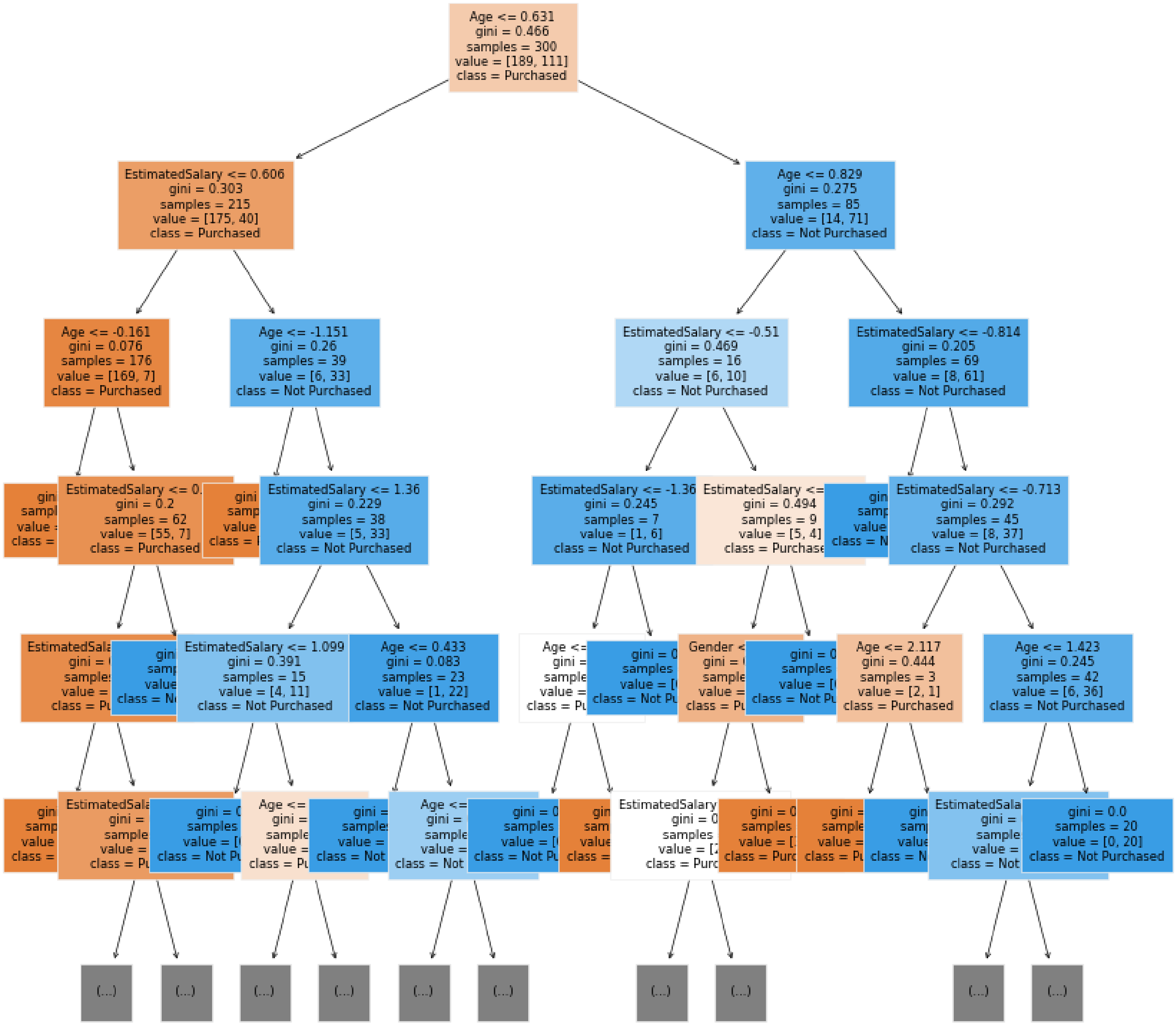
In [132…

```
from sklearn.datasets import load_iris
from matplotlib import pyplot as plt
from sklearn import datasets,tree
from sklearn.tree import DecisionTreeClassifier
iris = load_iris()
#Prepare the data
x = iris.data
y = iris.target
clf = DecisionTreeClassifier(random_state=1234)
model = clf.fit(x, y)
```

Plotting the decision tree

In [174…

```
fn=['Gender', 'Age', 'EstimatedSalary']
cn=['Purchased', 'Not Purchased']
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (10,10), dpi=100)
tree.plot_tree(tr,
               feature_names = fn,
               class_names=cn,
               fontsize=6,
               max_depth = 5,
               filled = True);
```



KNN Model

In [137…
```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train_scaled = sc.fit_transform(X_train)
X_test_scaled  = sc.transform(X_test)
```

In [138…
```
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2)
classifier.fit(X_train_scaled, y_train)
```

Out[138]:
```
▾ KNeighborsClassifier
KNeighborsClassifier()
```

In [139…
```
y_pred = classifier.predict(X_test_scaled)
print(np.concatenate((y_pred.reshape(len(y_pred),1), y_test.reshape(len(y_test),1))
```

```
[[0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [1 1]
 [0 0]
 [1 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [1 0]
 [0 0]
 [0 0]
 [1 1]
 [0 0]
 [0 0]
 [1 1]
 [0 0]
 [1 1]
 [0 0]
 [1 1]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 1]
 [1 1]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [1 1]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [1 1]
 [0 0]
 [0 0]
 [1 1]
 [0 0]
 [1 1]
 [1 1]
 [0 0]
 [0 0]
 [1 0]
 [1 1]
 [1 1]
```

```
 [0 0]
 [0 0]
 [1 1]
 [0 0]
 [0 0]
 [1 1]
 [0 0]
 [1 1]
 [0 0]
 [1 1]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [1 1]
 [0 0]
 [0 0]
 [1 1]
 [0 0]
 [0 0]
 [0 0]
 [0 0]
 [1 1]
 [1 1]
 [1 1]
 [1 0]
 [0 0]
 [0 0]
 [1 1]
 [0 1]
 [0 0]
 [1 1]
 [1 1]
 [0 0]
 [0 0]
 [1 1]
 [0 0]
 [0 0]
 [0 0]
 [0 1]
 [0 0]
 [1 1]
 [1 1]
 [1 1]]
```

In [140…

```python
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

```
[[64  4]
 [ 3 29]]
```

Out[140]: 0.93

Confusion Matrix

In [145…

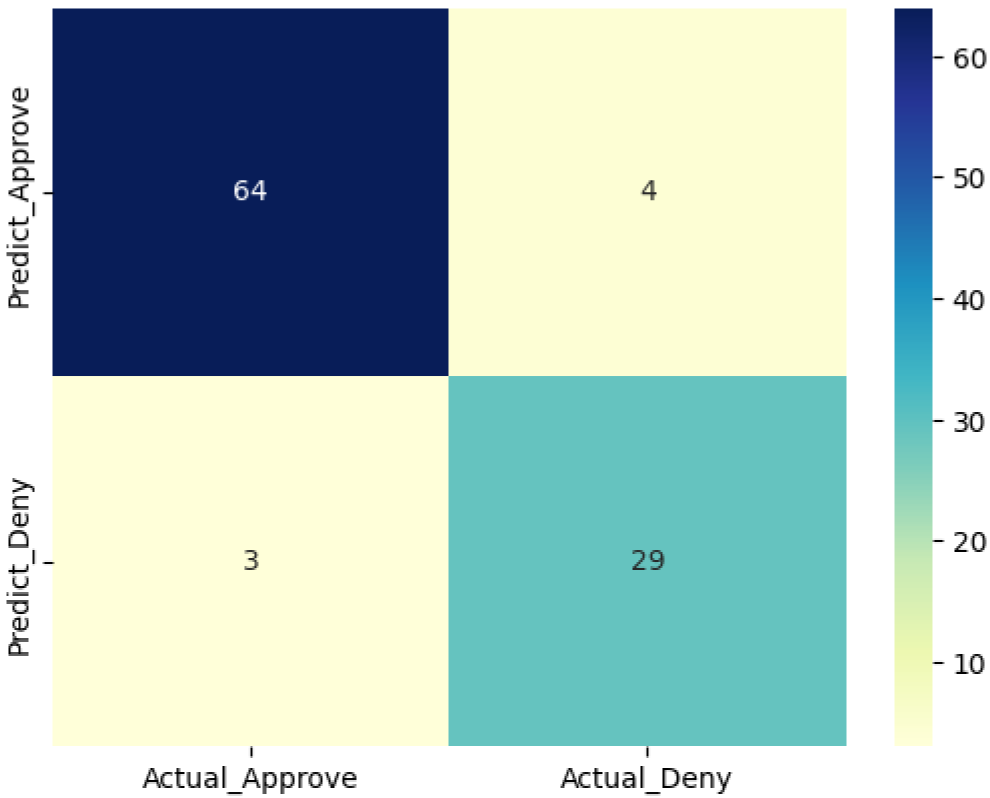
```
from sklearn.metrics import classification_report,confusion_matrix
print(confusion_matrix(y_test, y_pred))
```

```
[[64  4]
 [ 3 29]]
```

In [152…

```
cm_matrix = pd.DataFrame(data=cm, columns=['Actual_Approve', 'Actual_Deny'],
                                  index=['Predict_Approve', 'Predict_Deny'])
sns.heatmap(cm_matrix, annot=True, fmt='d', cmap='YlGnBu')
```

Out[152]: <Axes: >



Plotting for K values ranging from 1 to 30

In [168…

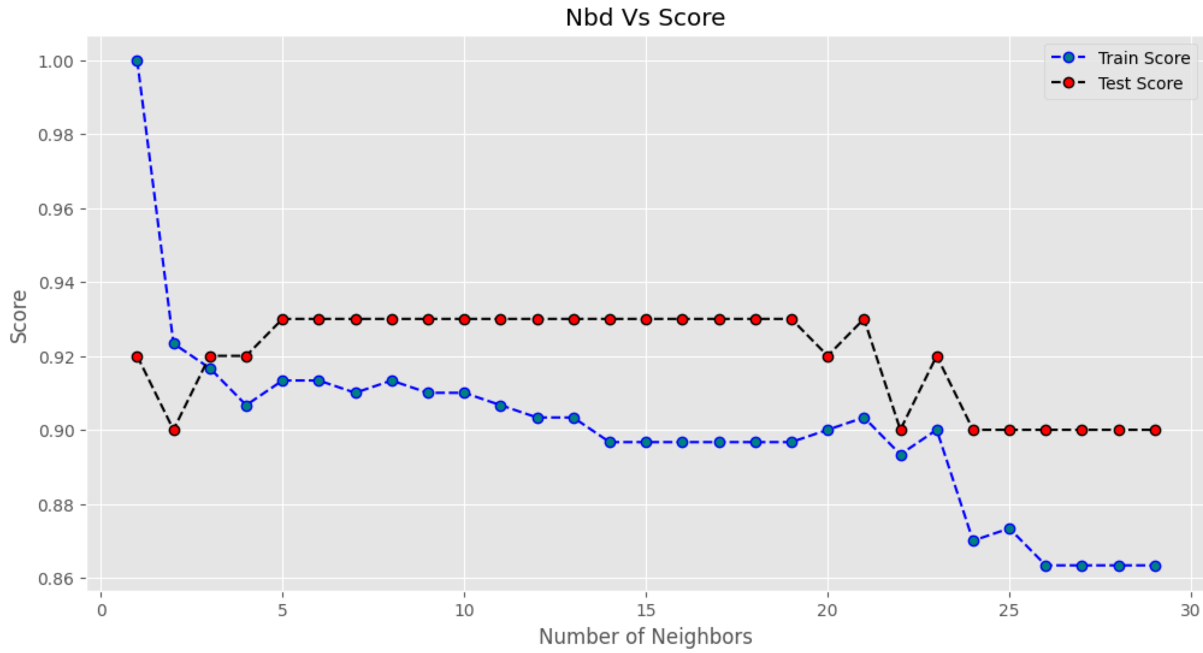
```
testAccuracy = []
trainAccuracy = []
for k in range(1,30):
    model=KNeighborsClassifier(n_neighbors=k)
    model.fit(X_train,y_train)
    trainAccuracy.append(model.score(X_train,y_train))
    testAccuracy.append(model.score(X_test,y_test))
```

In [166…

```
from matplotlib import pyplot as plt,style
style.use('ggplot')
```

In [169…

```
#create a plot using the information from the above loop
plt.figure(figsize=(12,6))
plt.plot(range(1,30),trainAccuracy,label="Train Score",marker="o",markerfacecolor="
plt.plot(range(1,30),testAccuracy,label="Test Score",marker="o",markerfacecolor="re
plt.legend()
plt.xlabel("Number of Neighbors")
plt.ylabel("Score")
plt.title("Nbd Vs Score")
plt.show()
```



The optimal value hence obtained is 4

Creating a model using K = 4

In [171…

```
from sklearn.pipeline import Pipeline
model_steps_20=[('sipStanderise',StandardScaler()),('shipModel',KNeighborsClassifie
pipelineModel=Pipeline(steps=model_steps_20)
pipelineModel.fit(X_train,y_train)
print("score is:"+ str(pipelineModel.score(X_train,y_train)))
print("********************************")
pipelineModel.score(X_test,y_test)
predic_test_y=pipelineModel.predict(X_train)
print(pd.crosstab(y_train,predic_test_y))
```

```
score is:0.9133333333333333
********************************
col_0    0    1
row_0
0      174   15
1       11  100
```

In [ ]: