Product Buyed or Not

Import Necessary Libraries

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

Import Dataset

In [2]:

```
df=pd.read_csv("Social_Network_Ads.csv")
```

In [3]:

```
df
```

Out[3]:

	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

Data Exploration

Summary of Data

In [4]:

```
df.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
```

Descriptive Summary of Data

In [5]:

```
df.describe()
```

Out[5]:

	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

Check for any Null Values

In [6]:

```
df.isna().sum()
```

Out[6]:

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

Check for any Duplicate Values

In [7]:

```
df.duplicated().sum()
```

Out[7]:

```
0
```

Check for Imbalanced Data

In [8]:

```
zeros=df[df["Purchased"]==0]
ones=df[df["Purchased"]==1]
```

In [9]:

```
len(zeros),len(ones)
```

Out[9]:

```
(257, 143)
```

In [10]:

```
from sklearn.utils import resample
```

In [11]:

```
ones_resample=resample(ones,replace=True,n_samples=len(zeros),random_state=42)
```

In [12]:

```
ones_resample
```

Out[12]:

	User ID	Gender	Age	EstimatedSalary	Purchased
340	15588080	Female	53	104000	1
320	15774872	Female	52	138000	1
48	15727696	Male	30	135000	1
347	15768151	Female	54	108000	1
283	15663249	Female	52	21000	1
...	...	...	...	...	...
364	15654456	Male	42	104000	1
20	15649487	Male	45	22000	1
331	15589715	Female	48	119000	1
373	15708791	Male	59	130000	1
223	15593715	Male	60	102000	1

257 rows × 5 columns

In [13]:

```
df=pd.concat([ones_resample,zeros])
```

In [14]:

```
df
```

Out[14]:

	User ID	Gender	Age	EstimatedSalary	Purchased
340	15588080	Female	53	104000	1
320	15774872	Female	52	138000	1
48	15727696	Male	30	135000	1
347	15768151	Female	54	108000	1
283	15663249	Female	52	21000	1
...	...	...	...	...	...
377	15800215	Female	42	53000	0
380	15683758	Male	42	64000	0
387	15627220	Male	39	71000	0
394	15757632	Female	39	59000	0
398	15755018	Male	36	33000	0

514 rows × 5 columns

In [15]:

```
zeros=df[df["Purchased"]==0]
ones=df[df["Purchased"]==1]
```

In [16]:

```
len(zeros),len(ones)
```

Out[16]:

```
(257, 257)
```

In [17]:

```
df=df.sample(frac=1)
```

In [18]:

```
df
```

Out[18]:

	User ID	Gender	Age	EstimatedSalary	Purchased
31	15729054	Female	27	137000	1
197	15680243	Female	20	36000	0
32	15573452	Female	21	16000	0
299	15747043	Male	46	117000	1
337	15612465	Male	35	79000	0
...	...	...	...	...	...
397	15654296	Female	50	20000	1
17	15617482	Male	45	26000	1
129	15792102	Female	26	84000	0
245	15722061	Female	51	146000	1
128	15722758	Male	30	17000	0

514 rows × 5 columns

In [19]:

```
df=df.reset_index()
```

In [20]:

```
df.drop("index",axis=1,inplace=True)
```

In [21]:

```
df
```

Out[21]:

	User ID	Gender	Age	EstimatedSalary	Purchased
0	15729054	Female	27	137000	1
1	15680243	Female	20	36000	0
2	15573452	Female	21	16000	0
3	15747043	Male	46	117000	1
4	15612465	Male	35	79000	0
...	...	...	...	...	...
509	15654296	Female	50	20000	1
510	15617482	Male	45	26000	1
511	15792102	Female	26	84000	0
512	15722061	Female	51	146000	1
513	15722758	Male	30	17000	0

514 rows × 5 columns

Convert Categorical Columns to Numericals

In [22]:

```
from sklearn.preprocessing import LabelEncoder
```

In [23]:

```
encoder=LabelEncoder()
```

In [24]:

```
df["Sex"]=encoder.fit_transform(df[["Gender"]])
```

In [25]:

```
df
```

Out[25]:

	User ID	Gender	Age	EstimatedSalary	Purchased	Sex
0	15729054	Female	27	137000	1	0
1	15680243	Female	20	36000	0	0
2	15573452	Female	21	16000	0	0
3	15747043	Male	46	117000	1	1
4	15612465	Male	35	79000	0	1
...	...	...	...	...	...	...
509	15654296	Female	50	20000	1	0
510	15617482	Male	45	26000	1	1
511	15792102	Female	26	84000	0	0
512	15722061	Female	51	146000	1	0
513	15722758	Male	30	17000	0	1

514 rows × 6 columns

EDA

Check for Outliers

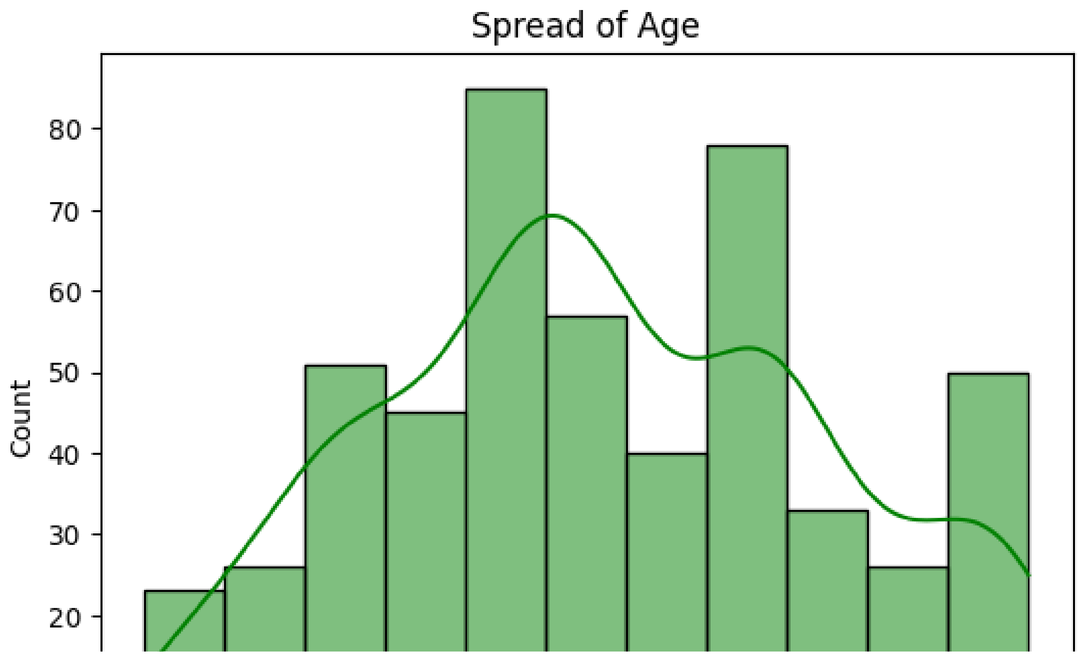
In [26]:

```
for i in df.columns:
    if i not in ["User ID","Gender"]:
        sns.boxplot(df[i],color="y")
        plt.title("Outliers in "+str(i))
        plt.show()
```

Check the Spread of the Data

In [27]:

```
for i in df.columns:
    if i not in ["User ID","Gender"]:
        sns.histplot(df[i],kde=True,color="g")
        plt.title("Spread of "+str(i))
        plt.show()
```



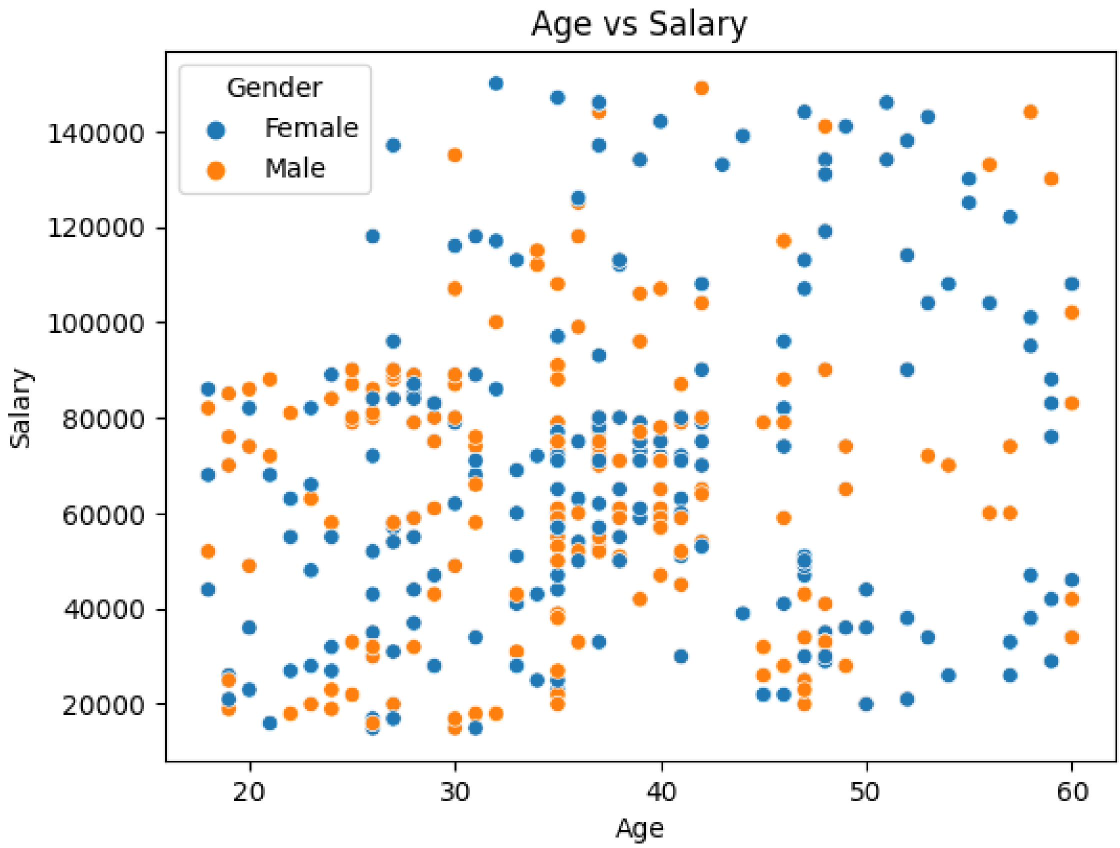
Releationship between Age and Estimated salary W.R.T Gender

In [28]:

```
sns.scatterplot(x=df["Age"],y=df["EstimatedSalary"],hue=df["Gender"])
plt.xlabel("Age")
plt.ylabel("Salary")
plt.title("Age vs Salary")
```

Out[28]:

```
Text(0.5, 1.0, 'Age vs Salary')
```



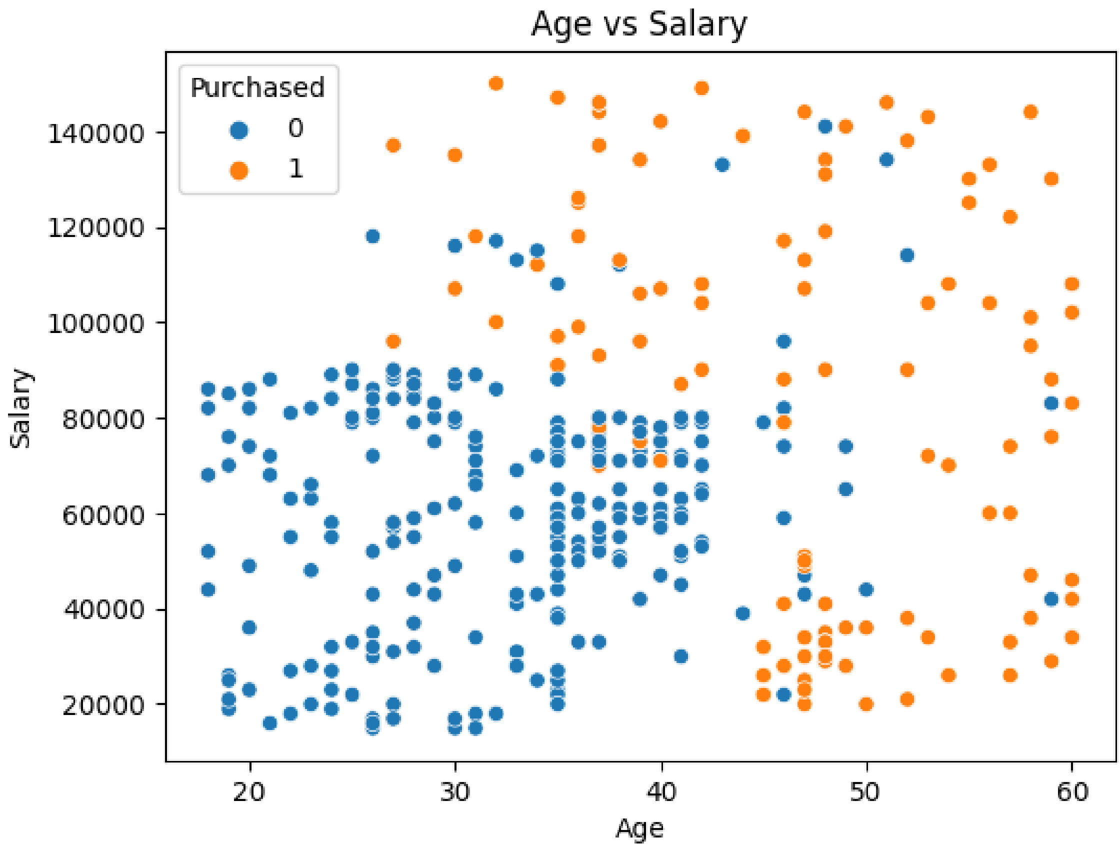
Releationship between Age and Estimated salary W.R.T Gender

In [29]:

```
sns.scatterplot(x=df["Age"],y=df["EstimatedSalary"],hue=df["Purchased"])
plt.xlabel("Age")
plt.ylabel("Salary")
plt.title("Age vs Salary")
```

Out[29]:

```
Text(0.5, 1.0, 'Age vs Salary')
```



Observations:

- If Age is more or If salary is more, then Purchasing power Presents

Feature Engineering

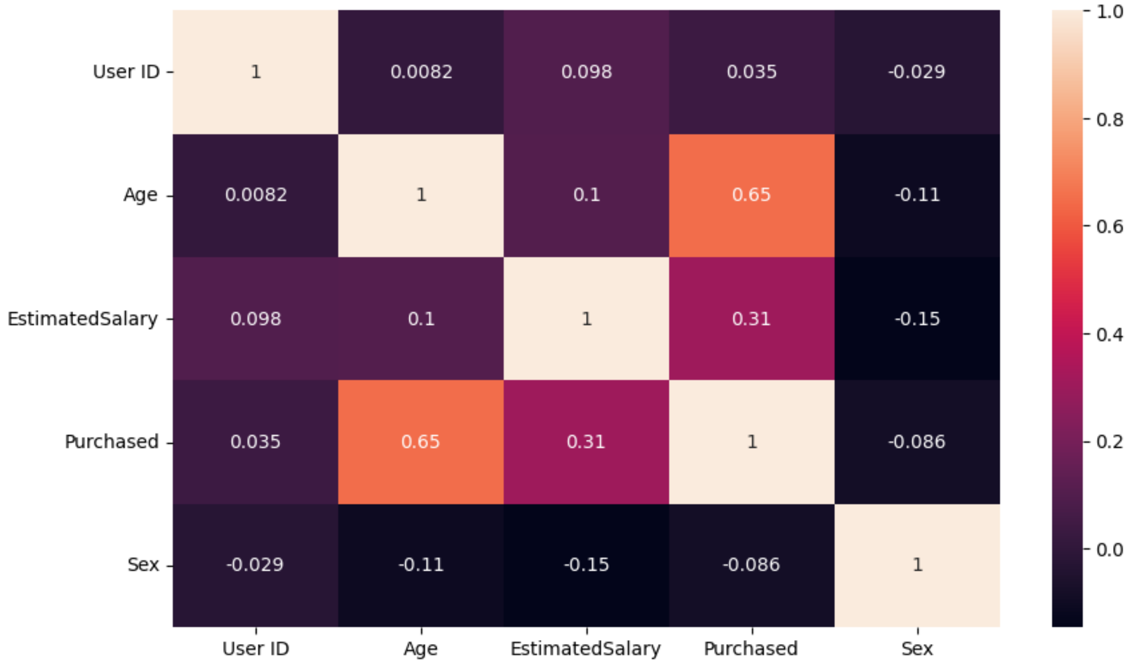
Check Co Releations and drop unnecessary columns

In [30]:

```
plt.figure(figsize=(10,6))
sns.heatmap(df.corr(method="spearman"),annot=True)
```

Out[30]:

```
<Axes: >
```



Observations:

- Sex and User ID doesn't impact Purchasing, so we can remove them.

In [31]:

```
df.drop(["Gender","Sex","User ID"],axis=1,inplace=True)
```

In [32]:

```
df
```

Out[32]:

	Age	EstimatedSalary	Purchased
0	27	137000	1
1	20	36000	0
2	21	16000	0
3	46	117000	1
4	35	79000	0
...	...	...	...
509	50	20000	1
510	45	26000	1
511	26	84000	0
512	51	146000	1
513	30	17000	0

514 rows × 3 columns

Split Data between Independent and Dependent Features

X Data ¶

In [33]:

```
x=df.drop("Purchased",axis=1)
```

In [34]:

```
x.head()
```

Out[34]:

	Age	EstimatedSalary
0	27	137000
1	20	36000
2	21	16000
3	46	117000
4	35	79000

Scale X Data

In [35]:

```
from sklearn.preprocessing import MinMaxScaler
```

In [36]:

```
scaler=MinMaxScaler()
```

In [37]:

```
x_new=scaler.fit_transform(x)
```

In [38]:

```
x_new
```

Out[38]:

```
array([[0.21428571, 0.9037037 ],
       [0.04761905, 0.15555556],
       [0.07142857, 0.00740741],
       ...,
       [0.19047619, 0.51111111],
       [0.78571429, 0.97037037],
       [0.28571429, 0.01481481]])
```

In [39]:

```
x=pd.DataFrame(x_new,columns=x.columns)
```

In [40]:

```
x
```

Out[40]:

	Age	EstimatedSalary
0	0.214286	0.903704
1	0.047619	0.155556
2	0.071429	0.007407
3	0.666667	0.755556
4	0.404762	0.474074
...	...	...
509	0.761905	0.037037
510	0.642857	0.081481
511	0.190476	0.511111
512	0.785714	0.970370
513	0.285714	0.014815

514 rows × 2 columns

Save scaler to use it in Flask web API

In [41]:

```
import pickle
pickle.dump(scaler,open("scaler_purchase.pkl","wb"))
```

Y Data

In [42]:

```
y=df["Purchased"]
```

In [43]:

```
y
```

Out[43]:

```
0      1
1      0
2      0
3      1
4      0
      ..
509    1
510    1
511    0
512    1
513    0
Name: Purchased, Length: 514, dtype: int64
```

Split the Data into Train and Test

In [44]:

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

In [45]:

```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25)
```

In [46]:

```
x_train.shape,y_train.shape,x_test.shape,y_test.shape
```

Out[46]:

```
((385, 2), (385,), (129, 2), (129,))
```

Build the Model

In [47]:

```
from sklearn.svm import SVC
```

In [48]:

```
model=SVC()
```

In [49]:

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

Out[49]:

```
SVC()
```

In [50]:

```
y_pred=model.predict(x_test)
```

In [51]:

```
y_pred
```

Out[51]:

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

Accuracy Metrics

In [52]:

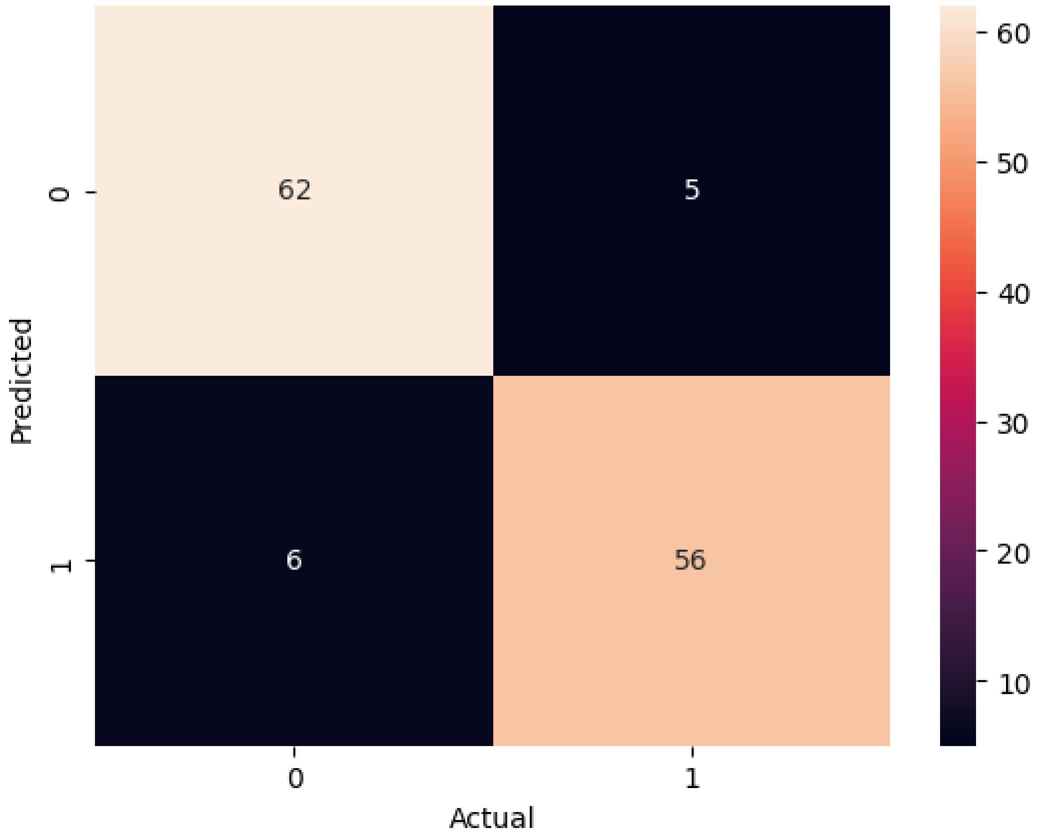
```
from sklearn.metrics import confusion_matrix,classification_report
```

In [53]:

```
sns.heatmap(confusion_matrix(y_test,y_pred),annot=True)
plt.xlabel("Actual")
plt.ylabel("Predicted")
```

Out[53]:

```
Text(50.722222222222214, 0.5, 'Predicted')
```



In [54]:

```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.91      0.93      0.92        67
           1       0.92      0.90      0.91        62

    accuracy                           0.91       129
   macro avg       0.91      0.91      0.91       129
weighted avg       0.91      0.91      0.91       129
```

Hyperparameter Tuning

In [55]:

```
grid={
    "degree":[3,6,9,12],
    "gamma":("scale","auto"),
    "shrinking":[True,False],
    "probability":[True,False],
    "random_state":[1,5,10,15,25],
    "coef0":[0.0,1.2,3.4,5.6,77.3]
}
```

In [56]:

```
from sklearn.model_selection import GridSearchCV
```

In [57]:

```
model=SVC()
```

In [58]:

```
clf=GridSearchCV(model,param_grid=grid,cv=6)
```

In [59]:

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

Out[59]:

```
GridSearchCV(cv=6, estimator=SVC(),
             param_grid={'coef0': [0.0, 1.2, 3.4, 5.6, 77.3],
                         'degree': [3, 6, 9, 12], 'gamma': ('scale', 'aut
o'),
                         'probability': [True, False],
                         'random_state': [1, 5, 10, 15, 25],
                         'shrinking': [True, False]})
```

In [60]:

```
clf.best_params_
```

Out[60]:

```
{'coef0': 0.0,
 'degree': 3,
 'gamma': 'scale',
 'probability': True,
 'random_state': 1,
 'shrinking': True}
```

In [61]:

```
model=SVC(degree=3,gamma="scale",probability=True,shrinking=True,random_state=1,coef0=0.
```

In [62]:

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

Out[62]:

```
SVC(probability=True, random_state=1)
```

In [63]:

```
y_pred=model.predict(x_test)
```

In [64]:

```
y_pred
```

Out[64]:

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

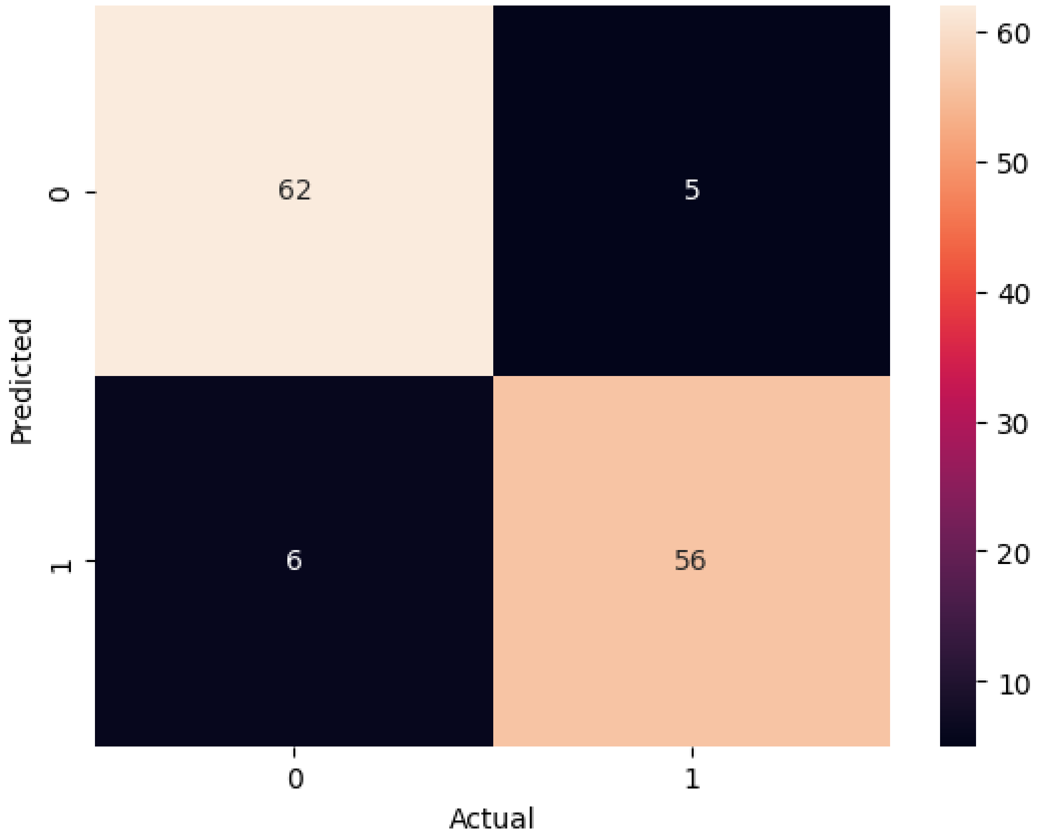
Accuracy Metrics

In [65]:

```
sns.heatmap(confusion_matrix(y_test,y_pred),annot=True)
plt.xlabel("Actual")
plt.ylabel("Predicted")
```

Out[65]:

```
Text(50.722222222222214, 0.5, 'Predicted')
```



In [66]:

```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.91      0.93      0.92        67
           1       0.92      0.90      0.91        62

    accuracy                           0.91       129
   macro avg       0.91      0.91      0.91       129
weighted avg       0.91      0.91      0.91       129
```

Observation:

- Our Default Parameters were the Best Parameters

Save our Model

In [67]:

```
pickle.dump(model,open("model_purchase.pkl","wb"))
```