In [75]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from mlxtend.plotting import plot_confusion_matrix
from sklearn.metrics import confusion_matrix, classification_report, accuracy_
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

In [2]:
```
df = pd.read_csv("Social_Network_Ads.csv")
```

In [3]:
```
df.head()
```

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

In [6]:
```
df.shape
```

Out[6]:
```
(400, 5)
```

In [7]:
```
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
```

In [8]:
```
df.describe()
```

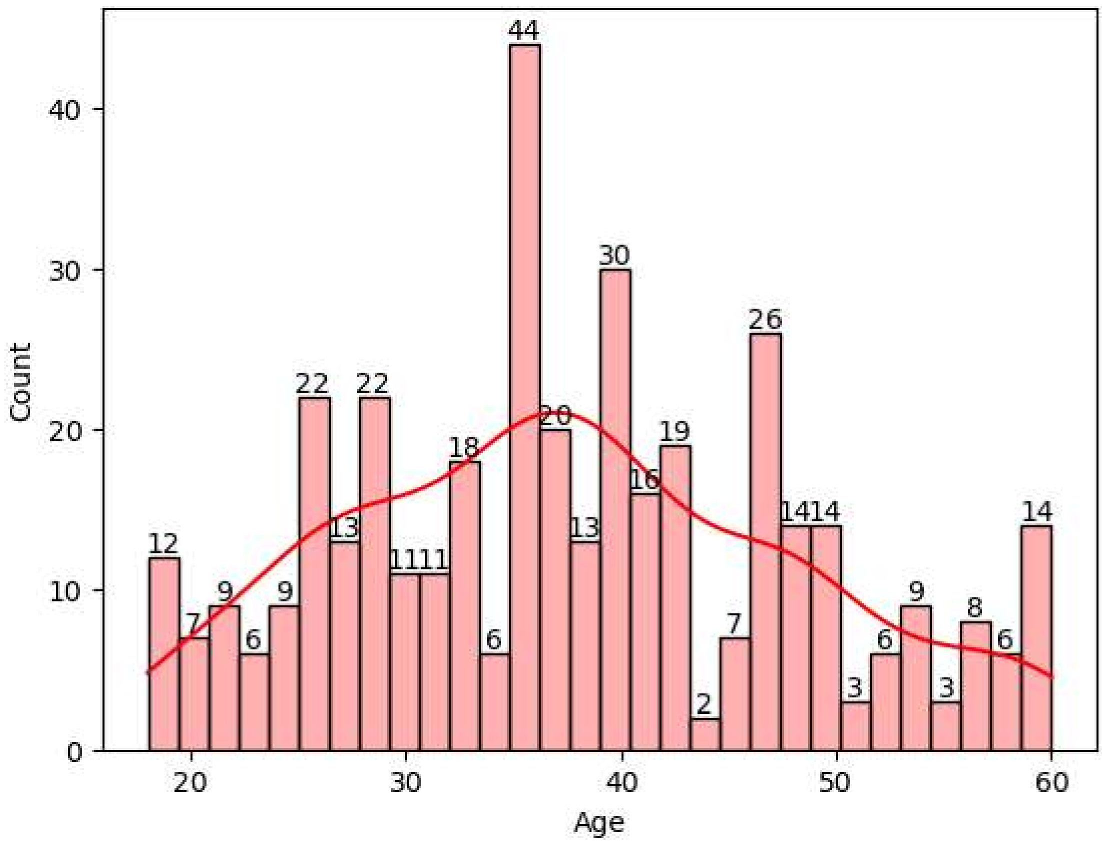
Out[8]:

	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

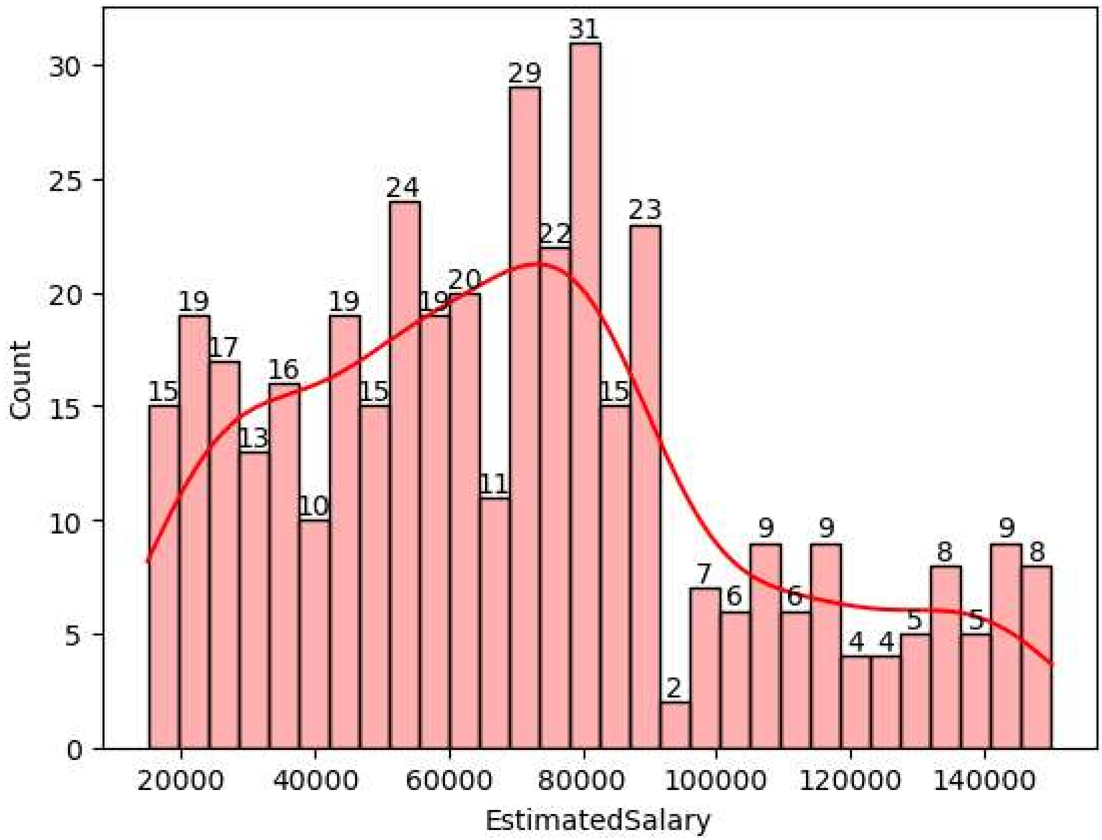
In [21]:
```
df.isna().sum()
```

Out[21]:
```
User ID            0
Gender             0
Age                0
EstimatedSalary    0
Purchased          0
dtype: int64
```

In [16]:
```
histplot = sns.histplot(df['Age'], kde=True, bins=30, color='red', alpha=0.3)
for i in histplot.containers:
    histplot.bar_label(i,)
plt.show()
```



In [19]:
```
histplot = sns.histplot(df['EstimatedSalary'], kde=True, bins=30, color='red',
for i in histplot.containers:
    histplot.bar_label(i,)
plt.show()
```



In [20]:
```
df["Gender"].value_counts()
```

Out[20]:
```
Female    204
Male      196
Name: Gender, dtype: int64
```

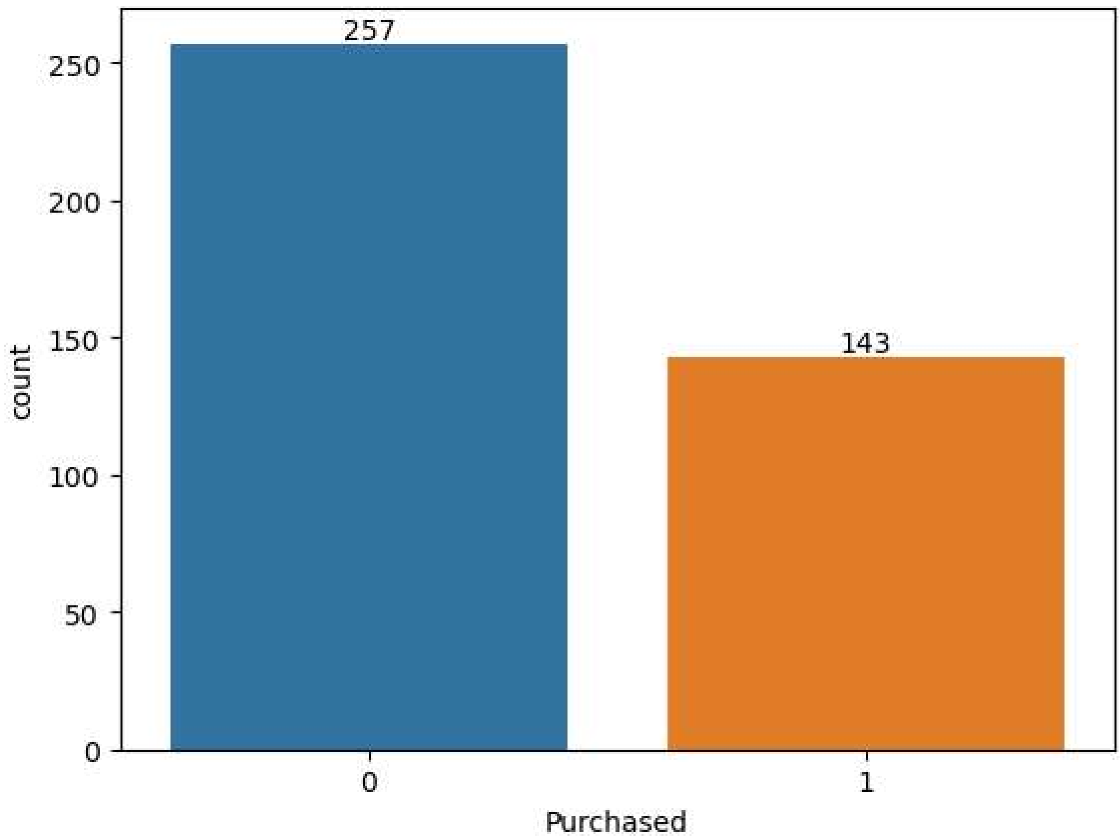
In [23]:
```
def gender_encoder(value):
    if (value == "Male"):
        return 1
    elif (value == "Female"):
        return 0
    else:
        return -1
```

In [24]:
```
df["Gender"] = df["Gender"].apply(gender_encoder)
```

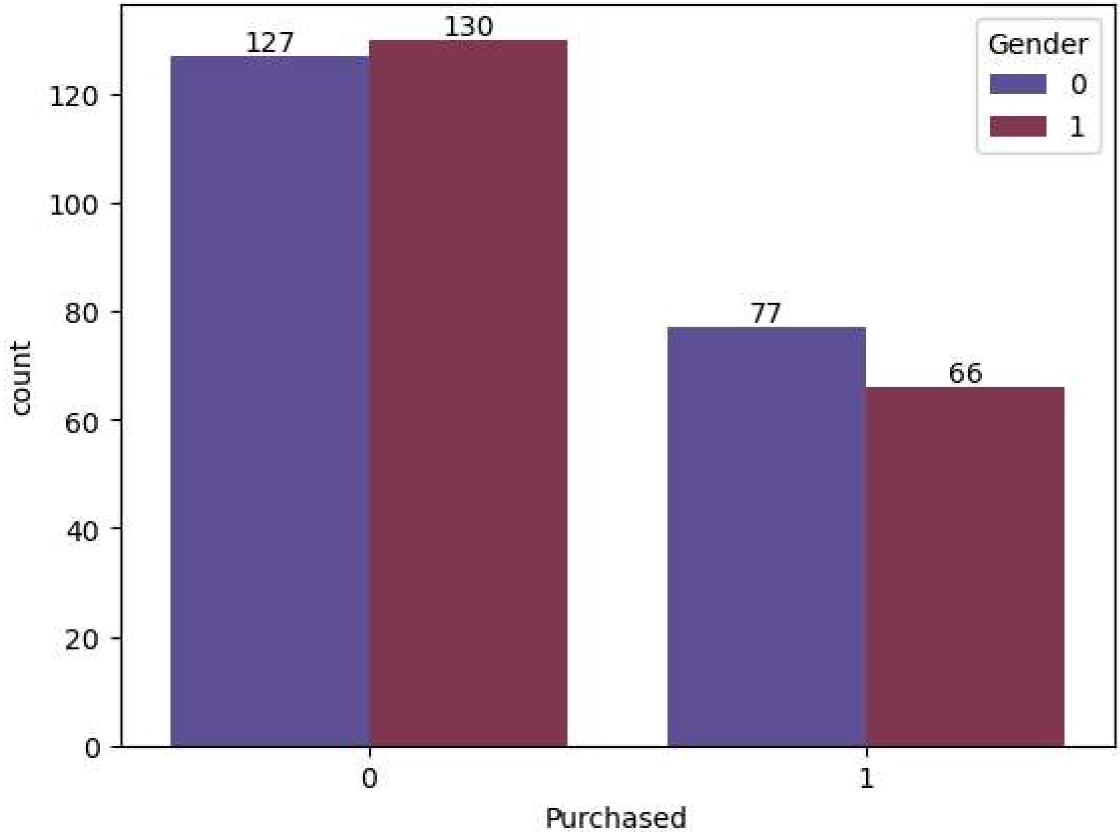
In [25]:
```
df["Purchased"].value_counts()
```

Out[25]:
```
0    257
1    143
Name: Purchased, dtype: int64
```

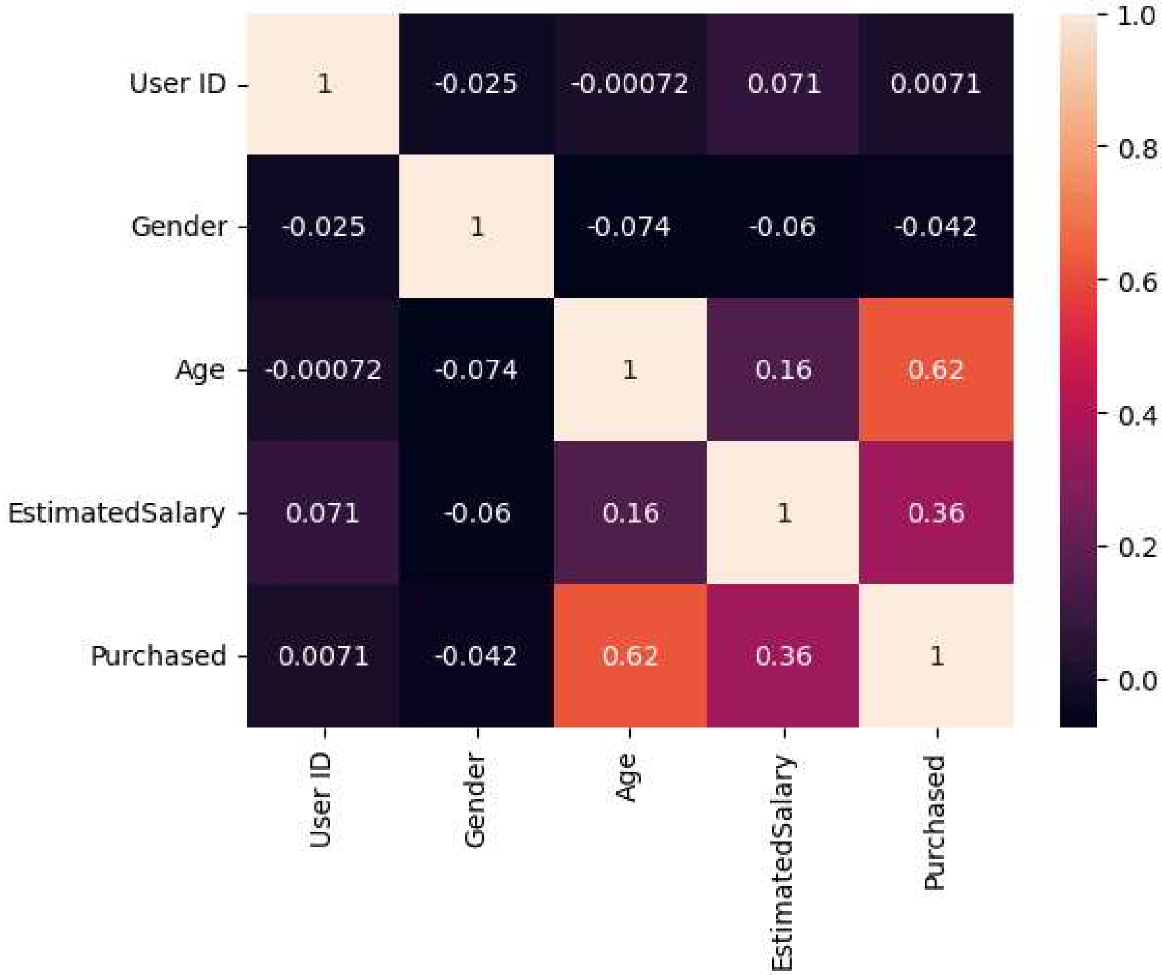
In [29]:
```
countplot = sns.countplot(df["Purchased"])
for i in countplot.containers:
    countplot.bar_label(i,)
plt.show()
```



In [48]:
```
countplot = sns.countplot(df["Purchased"], hue=df["Gender"], palette="twilight
for i in countplot.containers:
    countplot.bar_label(i,)
plt.show()
```



In [49]:
```
sns.heatmap(df.corr(), annot=True)
plt.show()
```



Data preparation

In [50]:
```
x = df[["Age", "EstimatedSalary"]]
y = df["Purchased"]
```

In [51]:
```
scaler = StandardScaler()
x = scaler.fit_transform(x)
```

In [64]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, rando
```

In [65]:
```
x_train.shape, x_test.shape, y_train.shape, y_test.shape
```

Out[65]:
```
((320, 2), (80, 2), (320,), (80,))
```

Model building

In [66]:
```
model = LogisticRegression(n_jobs=-1)
```

In [67]:
```
model.fit(x_train, y_train)
```

Out[67]:
```
LogisticRegression(n_jobs=-1)
```

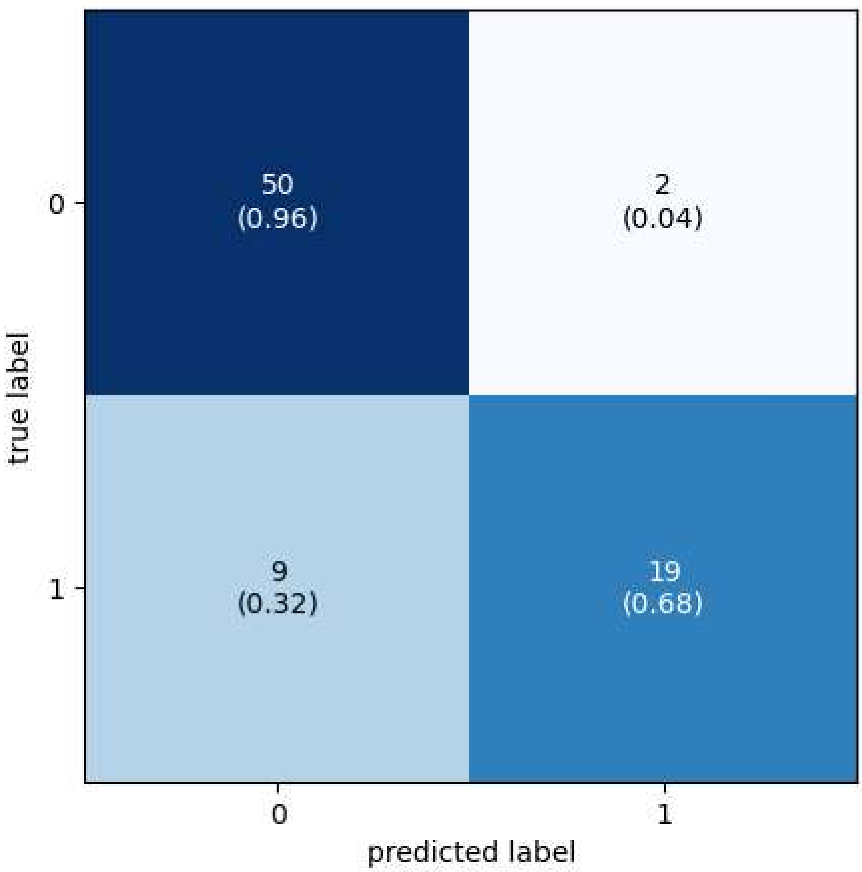
In [68]:
```
y_pred = model.predict(x_test)
```

Evalutation

In [69]:
```
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
[[50  2]
 [ 9 19]]
```

In [70]:
```
plot_confusion_matrix(conf_mat=cm, figsize=(5,5), show_normed=True)
plt.show()
```



In [71]:
```
print(f"TN value is {cm[0][0]}")
print(f"FP value is {cm[0][1]}")
print(f"FN value is {cm[1][0]}")
print(f"TP value is {cm[1][1]}")
```

```
TN value is 50
FP value is 2
FN value is 9
TP value is 19
```

In [73]:
```
print(f"Accuracy score is {accuracy_score(y_test, y_pred)}")
```

```
Accuracy score is 0.8625
```

In [76]:
```
print(f"Error rate is {1-accuracy_score(y_test, y_pred)}")
```

```
Error rate is 0.13749999999999996
```

In [77]:
```
print(f"Precision score is {precision_score(y_test, y_pred)}")
```

```
Precision score is 0.9047619047619048
```

In [78]:
```
print(f"Recall score is {recall_score(y_test, y_pred)}")
```

```
Recall score is 0.6785714285714286
```

In [79]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.85      0.96      0.90        52
           1       0.90      0.68      0.78        28

    accuracy                           0.86        80
   macro avg       0.88      0.82      0.84        80
weighted avg       0.87      0.86      0.86        80
```