Step - 1 : Import Libraries

```
# Import Necessary Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# to avoid warnings
import warnings
warnings.filterwarnings('ignore')
```

Step - 2 : Read the Data

```
# Read the data
ads = pd.read_csv('/content/social_ads.csv')
ads.head()
```

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

Next steps: Generate code with ads View recommended plots

Step - 3 : Explore the Data

```
# Shape of data
ads.shape
```

```
(400, 3)
```

```
# Information about the data
ads.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 3 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Age              400 non-null    int64
 1   EstimatedSalary  400 non-null    int64
 2   Purchased        400 non-null    int64
dtypes: int64(3)
memory usage: 9.5 KB
```

```
# Checking for null values
ads.isna().sum()
```

```
Age                0
EstimatedSalary    0
Purchased          0
dtype: int64
```

```
# Checkimg for duplicated data
ads.duplicated()
```

```
0      False
1      False
2      False
3      False
4      False
       ...
395    False
396    False
397    False
398    False
399    False
Length: 400, dtype: bool
```

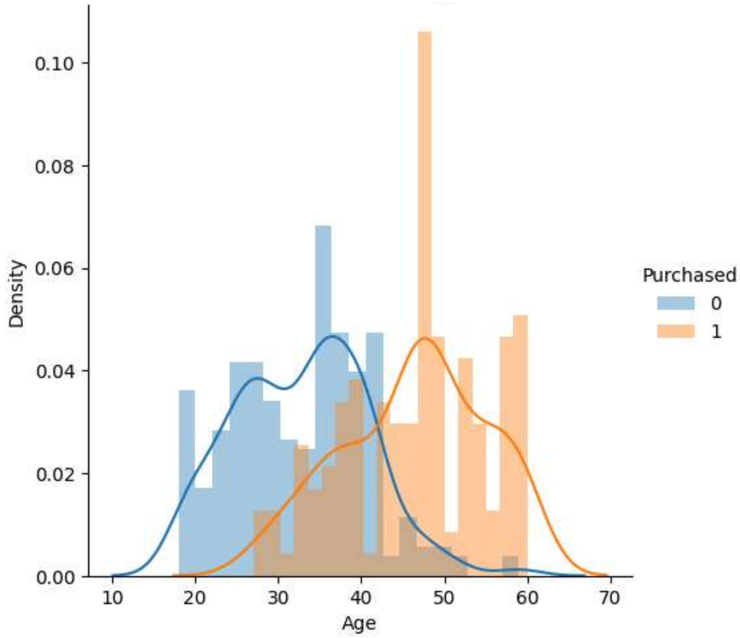
```
# The Summary of Data
ads.describe().T
```

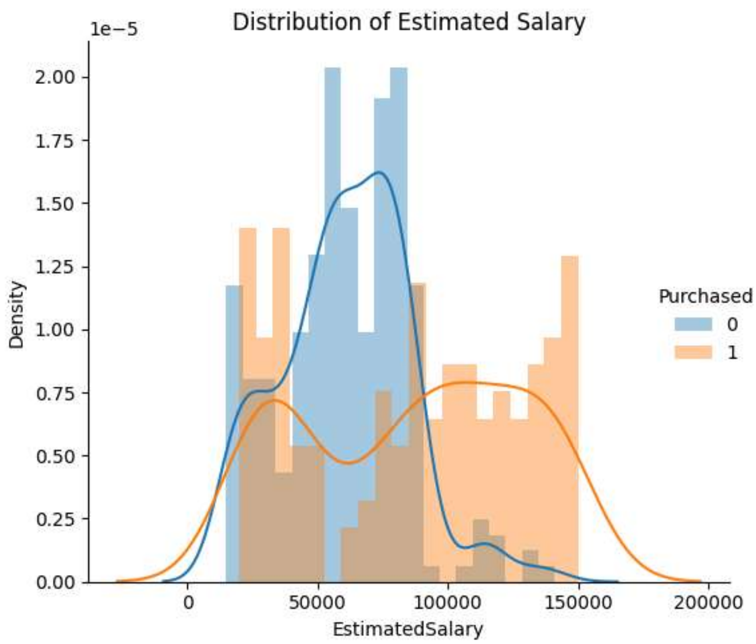
	count	mean	std	min	25%	50%	75%
Age	400.0	37.6550	10.482877	18.0	29.75	37.0	46.0
EstimatedSalary	400.0	69742.5000	34096.960282	15000.0	43000.00	70000.0	88000.0
Purchased	400.0	0.3575	0.479864	0.0	0.00	0.0	1.0

Step - 4 : Data Visulization

Distplot : Salary & Age

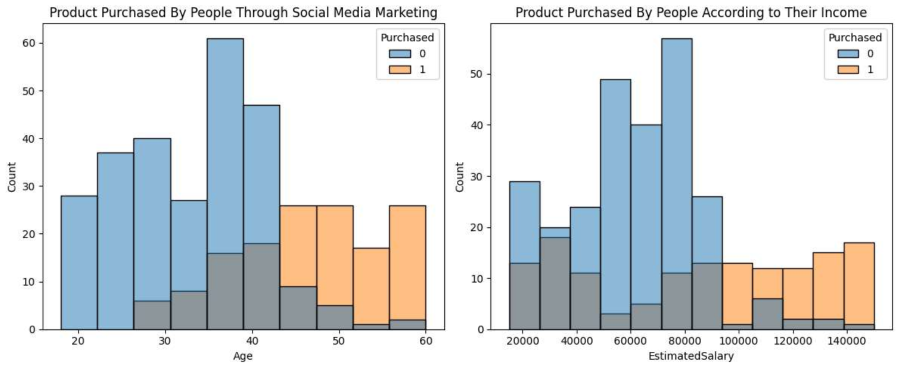
```
# Plotting the first subplot for 'Age'

sns.FacetGrid(ads, hue='Purchased', height=5) \
    .map(sns.distplot, 'Age', bins=20, kde=True) \
    .add_legend()
plt.title("Distribution of Age")

# Plotting the second subplot for 'EstimatedSalary'

sns.FacetGrid(ads, hue='Purchased', height=5) \
    .map(sns.distplot, 'EstimatedSalary', bins=20, kde=True) \
    .add_legend()
plt.title("Distribution of Estimated Salary")

# Display the entire figure with both subplots
plt.tight_layout()  # Adjust subplot parameters for better layout
plt.show()
;
```





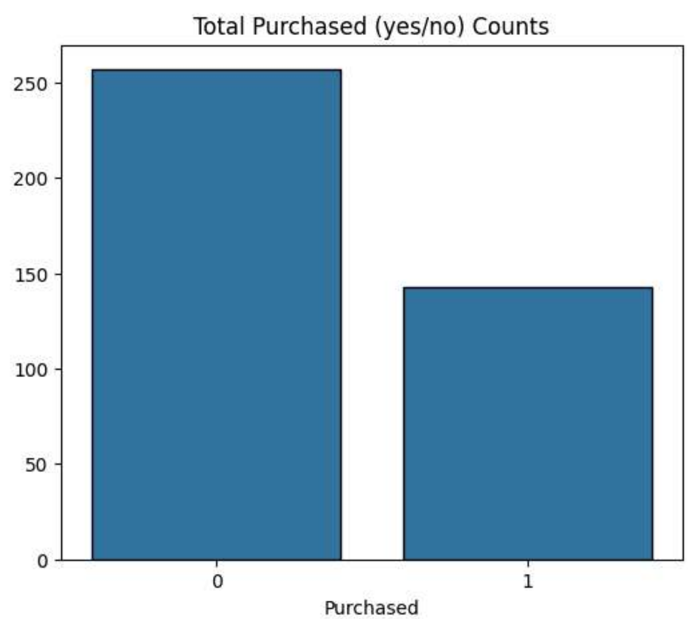
Histplot : Age & EstimatedSalary

```
# Set the default figure size
plt.rcParams['figure.figsize'] = (12, 5)  # Adjust figure size as needed

plt.subplot(1,2,1)
sns.histplot(x="Age", hue="Purchased", data=ads)
plt.title("Product Purchased By People Through Social Media Marketing")

plt.subplot(1,2,2)
plt.title("Product Purchased By People According to Their Income")
sns.histplot(x="EstimatedSalary", hue="Purchased", data=ads)
plt.tight_layout()
plt.show();
```



Barplot : Purchased(Yes/No)

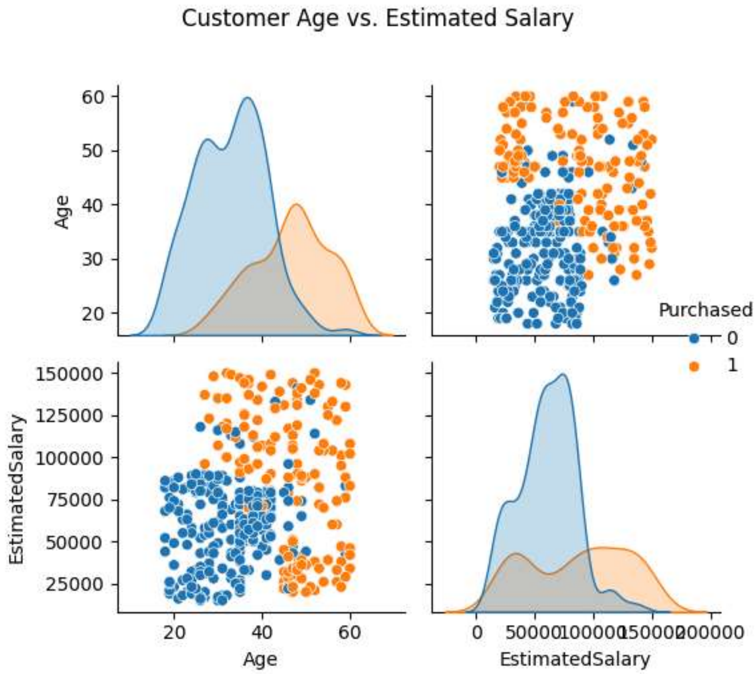
```
plt.figure(figsize=(6,5))
purchase_count=ads['Purchased'].value_counts().sort_index()
sns.barplot(x=purchase_count.index,y=purchase_count.values,edgecolor='black')
plt.title("Total Purchased (yes/no) Counts");
```



Barplot : Purchased(Yes/No) Counts

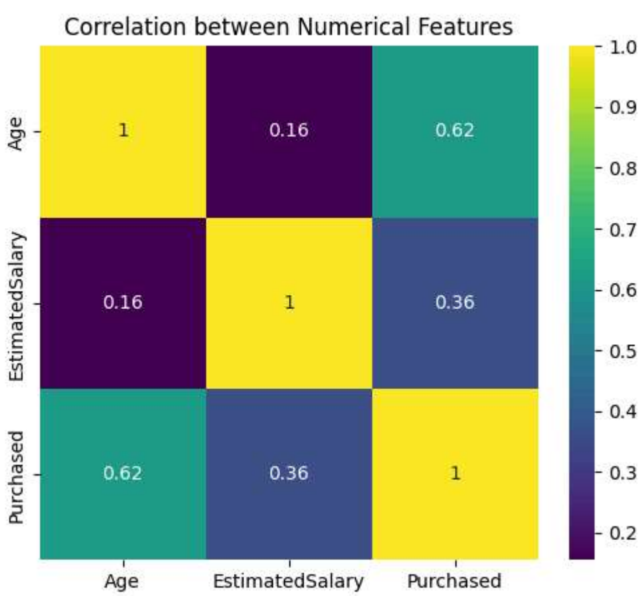
```
plt.figure(figsize=(8,6))
pairplot = sns.pairplot(ads, hue='Purchased')

# Get the figure and the axes of the pair plot
fig = pairplot.fig
fig.suptitle("Customer Age vs. Estimated Salary", y=1.02, ha='center')
plt.tight_layout()  # Adjust the bottom parameter if needed
# Show the plot
plt.show();
```

```
<Figure size 800x600 with 0 Axes>
```



Correlation between Numerical Features

```
plt.figure(figsize=(6,5))
sns.heatmap(ads.corr(),annot=True,cmap='viridis')
plt.title("Correlation between Numerical Features");
```



Observations and Insights:

Age and Purchase Behavior:

- The age distribution shows a fairly normal spread, with a wide range of ages represented in the dataset.
- There is no apparent skewness or outliers in the age distribution .
- Older individuals tend to have a stronger correlation with making purchases compared to younger individuals.
- Age can be a significant predictor of purchase behavior based on this correlation.

Estimated Salary and Purchase Behavior:

- The wide range and variability in estimated salaries suggest diverse economic backgrounds among individuals.
- Individuals with higher estimated salaries may have a higher propensity to make purchases,but this relationship needs further analysis.
- Estimated salary shows a weaker correlation with purchase behavior compared to age.
- While higher estimated salaries may be associated with a slightly higher likelihood of making purchases, the relationship is not as strong as age.

Targeting Strategies:

- Targeting strategies for social media ads could consider personalized approaches based on age and estimated salary segments.

Step 5 - : Split the data

```
# Split the data
X = ads.drop(columns=['Purchased'])
y = ads['Purchased']
```

```
from sklearn.model_selection import train_test_split,GridSearchCV
X_train,X_test,y_train,y_test=train_test_split(X,y,stratify=y,test_size=0.1,random_state=2)
```

```
#shape of spiltted data
print("The shape of X_train :",X_train.shape)
print("The shape of X_test :",X_test.shape)
print("The shape of y_train :",y_train.shape)
print("The shape of y_test :",y_test.shape)
```

```
The shape of X_train : (360, 2)
The shape of X_test : (40, 2)
The shape of y_train : (360,)
The shape of y_test : (40,)
```

Step - 6 : Train the Model

---

1. **Logistic Regression**

```
from sklearn.linear_model import LogisticRegression
logit = LogisticRegression(max_iter=500)
```

```
logit.fit(X_train,y_train)
```

```
LogisticRegression
LogisticRegression(max_iter=500)
```

```
y_pred_logit = logit.predict(X_test)
```

Step - 8 : Accuracy , Error

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

```
# Confusion Matrix
cm = confusion_matrix(y_pred_logit,y_test)
cm
```

```
array([[26, 14],
       [ 0,  0]])
```

```
# Classification Matrix
cr = classification_report(y_pred_logit,y_test)
print(cr)
```

```
              precision    recall  f1-score   support

           0       1.00      0.65      0.79        40
           1       0.00      0.00      0.00         0

    accuracy                           0.65        40
   macro avg       0.50      0.33      0.39        40
weighted avg       1.00      0.65      0.79        40
```

2. **DecisionTreeRegressor**

```
from sklearn.tree import DecisionTreeClassifier
dtc = DecisionTreeClassifier(max_depth=2)
```

```
dtc.fit(X_train,y_train)
```

```
▾ DecisionTreeClassifier
DecisionTreeClassifier(max_depth=2)
```

```
y_pred_dtc = dtc.predict(X_test)
```

```
# Confusion Matrix
cm = confusion_matrix(y_pred_dtc,y_test)
cm
```

```
array([[24,  1],
       [ 2, 13]])
```

```
# Classification Matrix
cr = classification_report(y_pred_dtc,y_test)
print(cr)
```

```
              precision    recall  f1-score   support

           0       0.92      0.96      0.94        25
           1       0.93      0.87      0.90        15

    accuracy                           0.93        40
   macro avg       0.93      0.91      0.92        40
weighted avg       0.93      0.93      0.92        40
```

Summary 📋 :

Customer Behavior Analysis for Social Media Ads

This notebook delves into an examination of customer behavior related to social media ads, utilizing data encompassing age, estimated salary, and purchase behavior (`Purchased`). Key insights derived from this analysis include:

- The dataset comprises 400 samples, detailing features such as age and estimated salary.
- Notably, age displays a moderately positive correlation 📈 (`0.622454`) with the propensity for making a purchase (`Purchased`), suggesting that older individuals exhibit a higher likelihood of purchasing