WALMART BUSINESS CASE STUDY

PROBLEM STATEMENT : Walmart Black Friday Purchase Analysis

Objective: Analyze customer purchase behavior during Black Friday to understand spending patterns across different segments.

Gender Focus: Determine whether women spend more than men per transaction.

Other Segments: Examine how marital status (married vs unmarried) and age groups influence purchase amounts.

Methodology: Use transactional data to compute average spending, confidence intervals, and segment-wise trends.

Business Impact: Provide actionable insights to help Walmart optimize marketing strategies, promotions, and inventory planning for better business decisions.

MODULES' IMPORT

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
import warnings
```

DATA IMPORT

```
!wget https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/293/original/walmart_data.csv?1641285094
```

```
--2025-09-29 11:47:43--  https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/293/original/walmart_data.csv?1641285094
Resolving d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)... 108.157.172.173, 108.157.172.183, 108.157.172.176, ...
Connecting to d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)|108.157.172.173|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 23027994 (22M) [text/plain]
Saving to: ‘walmart_data.csv?1641285094’

walmart_data.csv?16 100%[===================>]  21.96M   141MB/s    in 0.2s

2025-09-29 11:47:43 (141 MB/s) - ‘walmart_data.csv?1641285094’ saved [23027994/23027994]
```

```
df = pd.read_csv('walmart_data.csv?1641285094')
df.sample(5)
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purchase
310776	1005889	P00256642	M	51-55	20	C	1	1	5	5443
350998	1000033	P00273442	M	46-50	3	A	1	1	12	1395
242567	1001383	P00214142	F	26-35	7	A	1	0	8	5853
282537	1001519	P00116842	M	18-25	4	C	1	0	2	16498
407846	1002811	P0097742	M	26-35	19	B	1	0	8	5922

We observe a population of ~550k male and female customers. Considering this as a substantially large population, inferences from the samples are valid provided they are random and independent.

EXPLORATORY DATA ANALYTICS

Data Overview

```
df.shape
```

```
(550068, 10)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067
Data columns (total 10 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
```

```
 0   User_ID                     550068 non-null  int64 
 1   Product_ID                  550068 non-null  object
 2   Gender                      550068 non-null  object
 3   Age                         550068 non-null  object
 4   Occupation                  550068 non-null  int64 
 5   City_Category               550068 non-null  object
 6   Stay_In_Current_City_Years  550068 non-null  object
 7   Marital_Status              550068 non-null  int64 
 8   Product_Category            550068 non-null  int64 
 9   Purchase                    550068 non-null  int64 
dtypes: int64(5), object(5)
memory usage: 42.0+ MB
```

```
df.isnull().sum() # NO NULL VALUES
```

	0
User_ID	0
Product_ID	0
Gender	0
Age	0
Occupation	0
City_Category	0
Stay_In_Current_City_Years	0
Marital_Status	0
Product_Category	0
Purchase	0

dtype: int64

```
df[df.duplicated()].shape # NO DUPLICATE ROWS
```

```
(0, 10)
```

```
df['Gender'].unique(),df['Occupation'].unique(),df['City_Category'].unique(),df['Marital_Status'].unique(),df['Product_Category'].unique()
```

```
(array(['F', 'M'], dtype=object),
 array([10, 16, 15,  7, 20,  9,  1, 12, 17,  0,  3,  4, 11,  8, 19,  2, 18,
         5, 14, 13,  6]),
 array(['A', 'C', 'B'], dtype=object),
 array([0, 1]),
 array([ 3,  1, 12,  8,  5,  4,  2,  6, 14, 11, 13, 15,  7, 16, 18, 10, 17,
         9, 20, 19]))
```

Converting categories to category dtype:

```
df['Gender'] = df['Gender'].astype('category')
df['Occupation'] = df['Occupation'].astype('category')
df['City_Category'] = df['City_Category'].astype('category')
df['Marital_Status'] = df['Marital_Status'].astype('category')
df['Product_Category'] = df['Product_Category'].astype('category')
```

```
print("Gender codes: ",df["Gender"].cat.codes.unique())
print("Occupation codes: ",df["Occupation"].cat.codes.unique())
print("City_Category codes: ",df["City_Category"].cat.codes.unique())
print("Marital_Status codes: ",df["Marital_Status"].cat.codes.unique())
print("Product_Category codes: ",df["Product_Category"].cat.codes.unique())
```

```
Gender codes:  [0 1]
Occupation codes:  [10 16 15  7 20  9  1 12 17  0  3  4 11  8 19  2 18  5 14 13  6]
City_Category codes:  [0 2 1]
Marital_Status codes:  [0 1]
Product_Category codes:  [ 2  0 11  7  4  3  1  5 13 10 12 14  6 15 17  9 16  8 19 18]
```

Converting Age to ordered categorical dtype: Sorting will follow life stages, not alphabet (string values)

```
print(df['Age'].unique())
df['Age'].dtype
```

```
['0-17' '55+' '26-35' '46-50' '51-55' '36-45' '18-25']
dtype('O')
```

```
age_order = ["0-17", "18-25", "26-35", "36-45", "46-50", "51-55", "55+"]
df['Age'] = pd.Categorical(df['Age'], categories=age_order, ordered=True)
```

```
print("Age codes: ",df["Age"].cat.codes.unique())
```

```
Age codes:  [0 6 2 4 5 3 1]
```

Statistical Summary

```
df.describe().T
```

	count	mean	std	min	25%	50%	75%	max
User_ID	550068.0	1.003029e+06	1727.591586	1000001.0	1001516.0	1003077.0	1004478.0	1006040.0
Purchase	550068.0	9.263969e+03	5023.065394	12.0	5823.0	8047.0	12054.0	23961.0

```
cat_cols = ['Gender','Age','City_Category','Marital_Status']
df[cat_cols].melt().groupby(['variable','value'])[['value']].count()/len(df)*100
```

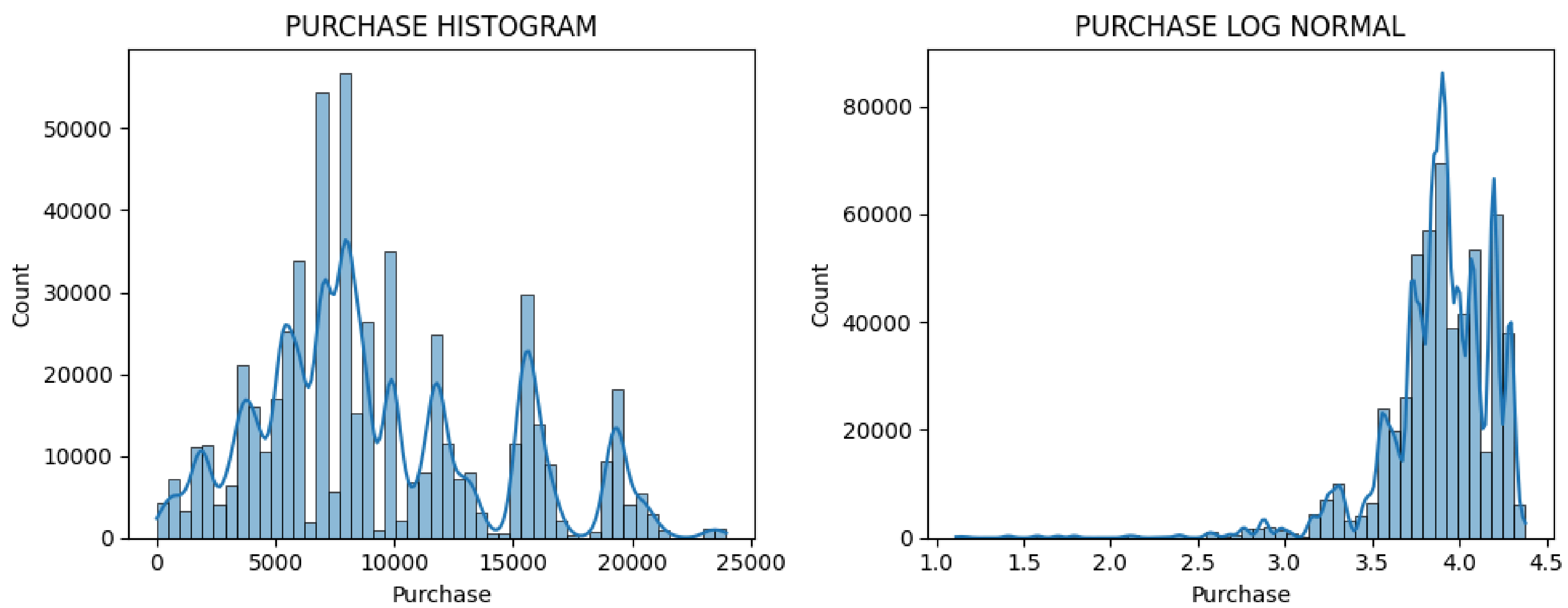
variable	value	value
Age	**0-17**	2.745479
	18-25	18.117760
	26-35	39.919974
	36-45	19.999891
	46-50	8.308246
	51-55	6.999316
	55+	3.909335
City_Category	**A**	26.854862
	B	42.026259
	C	31.118880
Gender	**F**	24.689493
	M	75.310507
Marital_Status	**0**	59.034701
	1	40.965299

- 60% of the users fall within the age bracket of 26–45 years, which shows that the majority of Walmart's customers are young to middle-aged adults.
- 42% of the users belong to City Category B, suggesting that this city type contributes the largest share of customers.
- 75% of the users are male, indicating that the customer base is heavily dominated by men.
- 60% of the users are single, highlighting that unmarried individuals form the majority of Walmart's customer base.

Visualizing Univariate Distributions

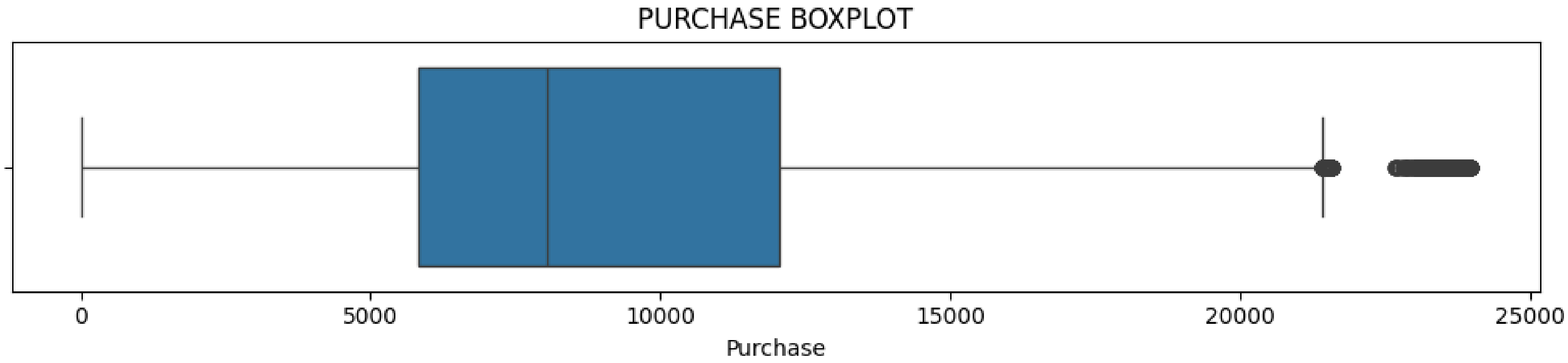
Visualizing Continuous Variables

```
fig,axis = plt.subplots(1,2,figsize=(10,4))
sns.histplot(data=df,x='Purchase',ax=axis[0],bins=50,kde=True)
axis[0].set_title('PURCHASE HISTOGRAM')
sns.histplot(np.log10(df['Purchase']+1),ax=axis[1],bins=50,kde=True)
axis[1].set_title('PURCHASE LOG NORMAL')
plt.tight_layout()
plt.show()
```




```
fig,axis = plt.subplots(1,1,figsize=(10,2.5))
sns.boxplot(x=df['Purchase'])
```

```
plt.title('PURCHASE BOXPLOT')
plt.tight_layout()
plt.show()
```




```
q1 = df['Purchase'].quantile(0.25)
q3 = df['Purchase'].quantile(0.75)
iqr = q3 - q1

lower_bound = q1 - 1.5 * iqr
upper_bound = q3 + 1.5 * iqr

outliers = df[(df['Purchase'] < lower_bound) | (df['Purchase'] > upper_bound)]

print("Number of outliers:",len(outliers))
print("Percentage of outliers:",(len(outliers)/len(df))*100)
```

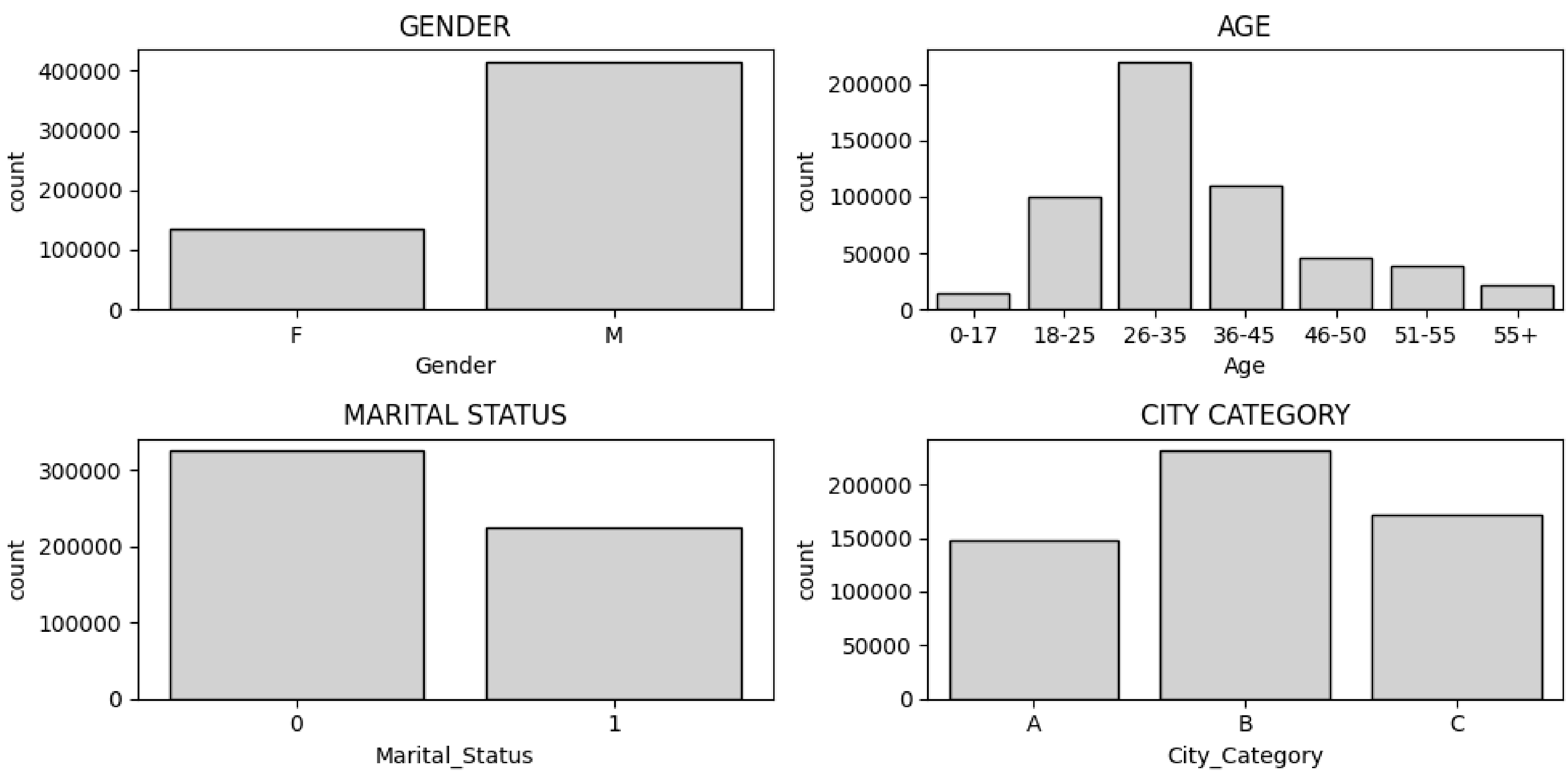
```
Number of outliers: 2677
Percentage of outliers: 0.4866671029763593
```

Visualizing Categorical Variables

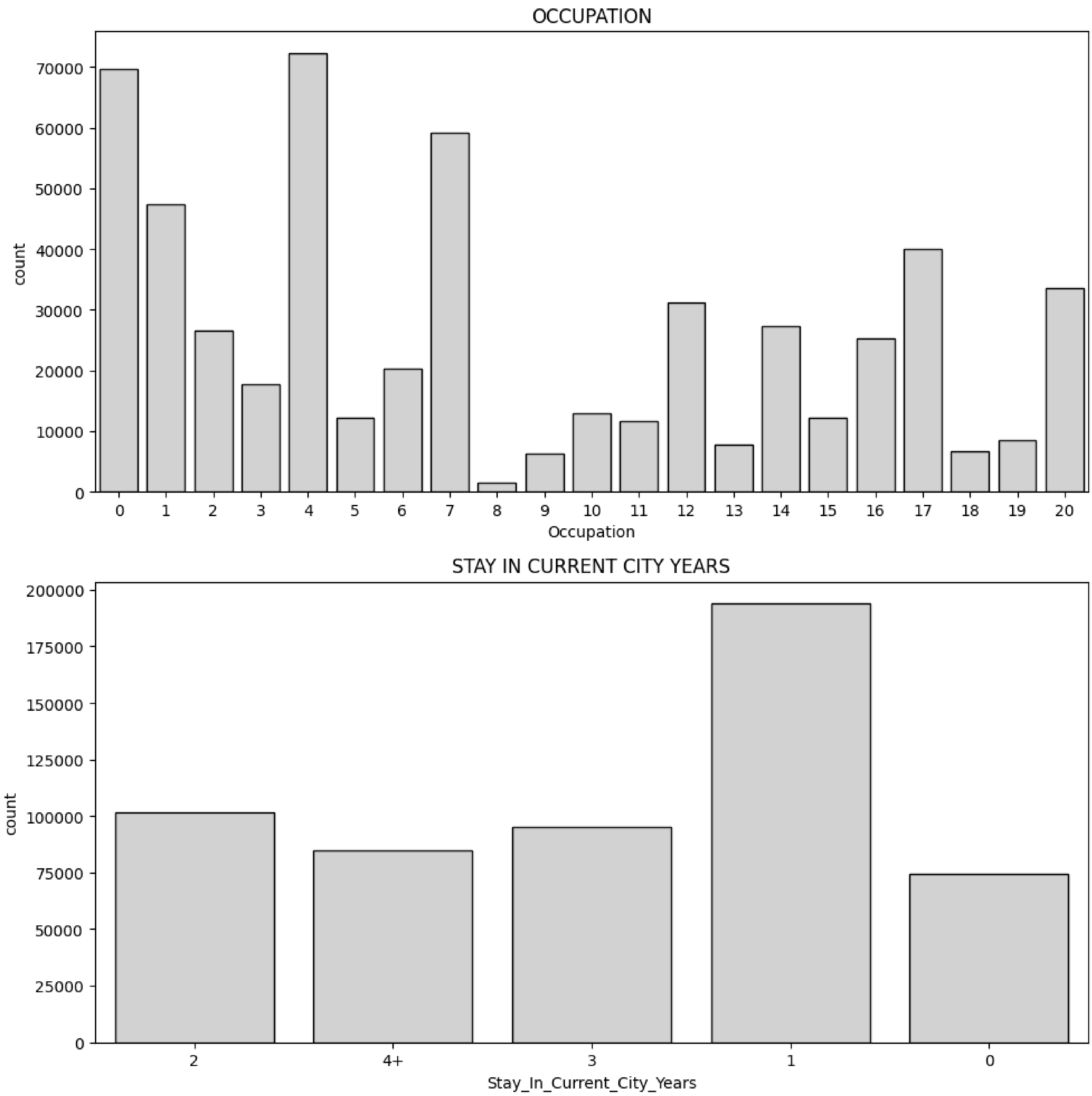
```
df.columns
```

```
Index(['User_ID', 'Product_ID', 'Gender', 'Age', 'Occupation', 'City_Category',
       'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Category',
       'Purchase'],
      dtype='object')
```

```
fig,axis = plt.subplots(2,2,figsize=(10,5))
sns.countplot(data=df,x='Gender',ax=axis[0,0],color='lightgrey',edgecolor='black')
axis[0,0].set_title('GENDER')
sns.countplot(data=df,x='Age',ax=axis[0,1],color='lightgrey',edgecolor='black')
axis[0,1].set_title('AGE')
sns.countplot(data=df,x='Marital_Status',ax=axis[1,0],color='lightgrey',edgecolor='black')
axis[1,0].set_title('MARITAL STATUS')
sns.countplot(data=df,x='City_Category',ax=axis[1,1],color='lightgrey',edgecolor='black')
axis[1,1].set_title('CITY CATEGORY')
plt.tight_layout()
plt.show()
```



```
fig,axis = plt.subplots(2,1,figsize=(10,10))
sns.countplot(data=df,x='Occupation',ax=axis[0],color='lightgrey',edgecolor='black')
axis[0].set_title('OCCUPATION')
sns.countplot(data=df,x='Stay_In_Current_City_Years',ax=axis[1],color='lightgrey',edgecolor='black')
axis[1].set_title('STAY IN CURRENT CITY YEARS')
plt.tight_layout()
plt.show()
```



Bivariate Analysis

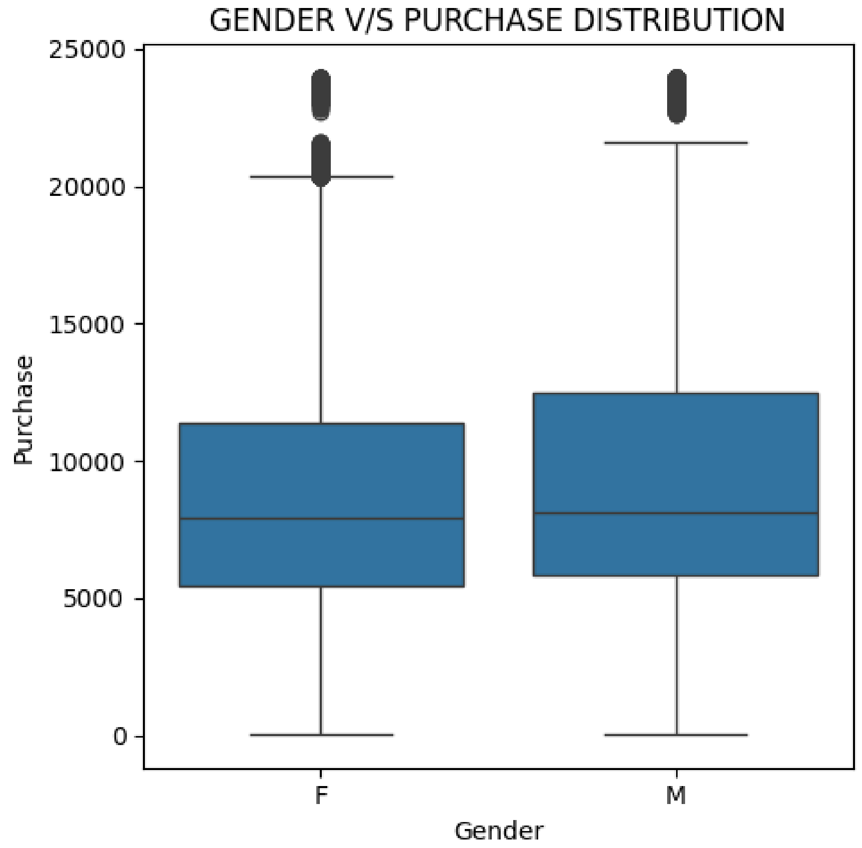
Purchase vis-a-vis Gender

```
df.groupby('Gender')['Purchase'].describe()
```

```
/tmp/ipython-input-1243678314.py:1: FutureWarning: The default of observed=False is deprecated and will be changed to True in a future version
  df.groupby('Gender')['Purchase'].describe()
```

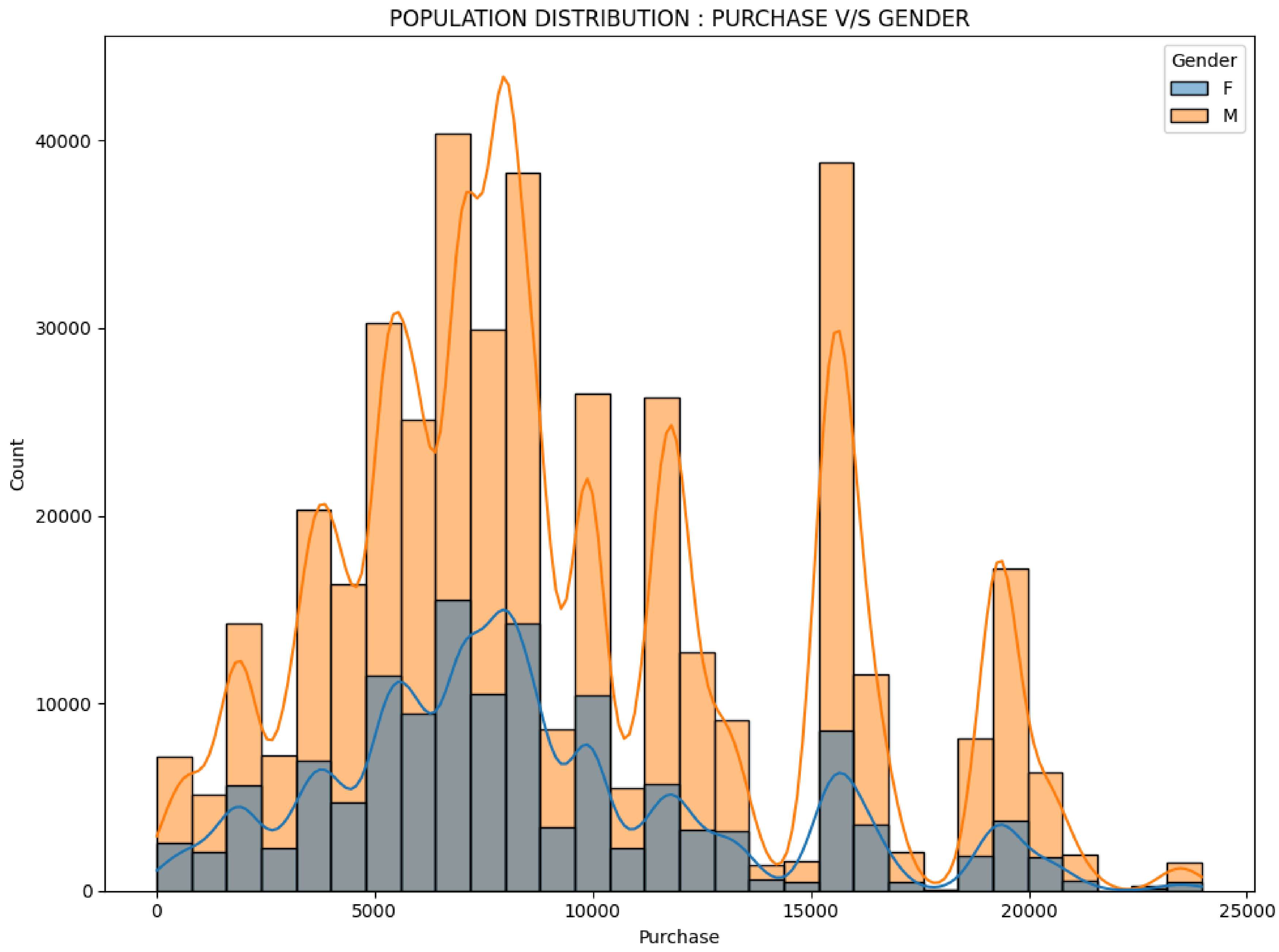
Gender	count	mean	std	min	25%	50%	75%	max
F	135809.0	8734.565765	4767.233289	12.0	5433.0	7914.0	11400.0	23959.0
M	414259.0	9437.526040	5092.186210	12.0	5863.0	8098.0	12454.0	23961.0

```
fig,axis = plt.subplots(1,1,figsize=(5,5))
sns.boxplot(data=df,x='Gender',y='Purchase',ax=axis)
axis.set_title('GENDER V/S PURCHASE DISTRIBUTION')
plt.tight_layout()
plt.show()
```



Population Distribution Analysis

```
fig,axis = plt.subplots(1,1,figsize=(10,7.5))
sns.histplot(data=df,x='Purchase',bins=30,kde=True,hue='Gender',ax=axis)
plt.title('POPULATION DISTRIBUTION : PURCHASE V/S GENDER')
plt.tight_layout()
plt.show()
```

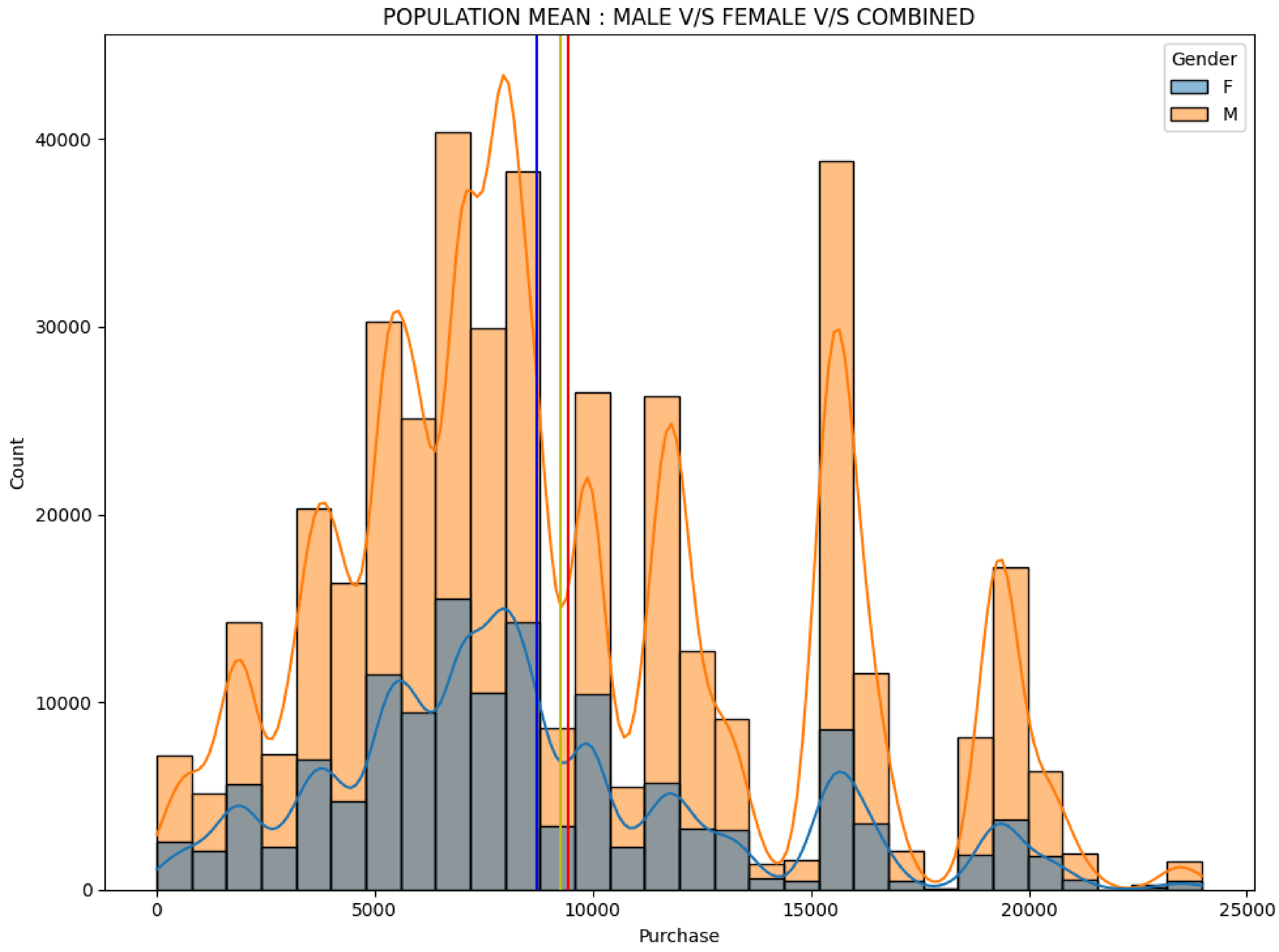


Notes: The distribution appears roughly normal, though an outlier is evident around 15,000

Population Mean Analysis

```
fig,axis = plt.subplots(1,1,figsize=(10,7.5))
sns.histplot(data=df,x='Purchase',bins=30,kde=True,hue='Gender',ax=axis)
plt.axvline(x=df['Purchase'].mean(),color='y')
plt.axvline(x=df[df['Gender']=='M']['Purchase'].mean(),color='r')
plt.axvline(x=df[df['Gender']=='F']['Purchase'].mean(),color='b')
plt.title('POPULATION MEAN : MALE V/S FEMALE V/S COMBINED')
```

```
plt.tight_layout()
plt.show()
```



Notes: The mean spending for males, females, and the overall sample is similar, with females spending slightly less

SAMPLE-DERIVED GENDER-CENTRIC ANALYSIS USING 1000 SAMPLE POINTS

FEMALES

```
df_f = df[df['Gender']=='F']
print("Mean of Purchase Amount by Females:",df_f['Purchase'].mean())
print("Standard Deviation of Purchase Amount by Females:",df_f['Purchase'].std())
```

```
Mean of Purchase Amount by Females: 8734.565765155476
Standard Deviation of Purchase Amount by Females: 4767.233289291444
```

```
sample_mean_of_purchase_by_females = []
for i in range(1000):
  sample_f = df_f['Purchase'].sample(n=7500)
  sample_f_mean = sample_f.mean()
  sample_mean_of_purchase_by_females.append(sample_f_mean)
sample_mean_of_purchase_by_females = np.array(sample_mean_of_purchase_by_females)

sample_mean_of_purchase_by_females[:10]
```

```
array([8775.50546667, 8680.09173333, 8838.23413333, 8733.1336    ,
       8767.11706667, 8769.03186667, 8776.6692    , 8729.47586667,
       8778.35293333, 8807.84386667])
```

MALES

```
df_m = df[df['Gender']=='M']
print("Mean of Purchase Amount by Males:",df_m['Purchase'].mean())
print("Standard Deviation of Purchase Amount by Males:",df_m['Purchase'].std())
```

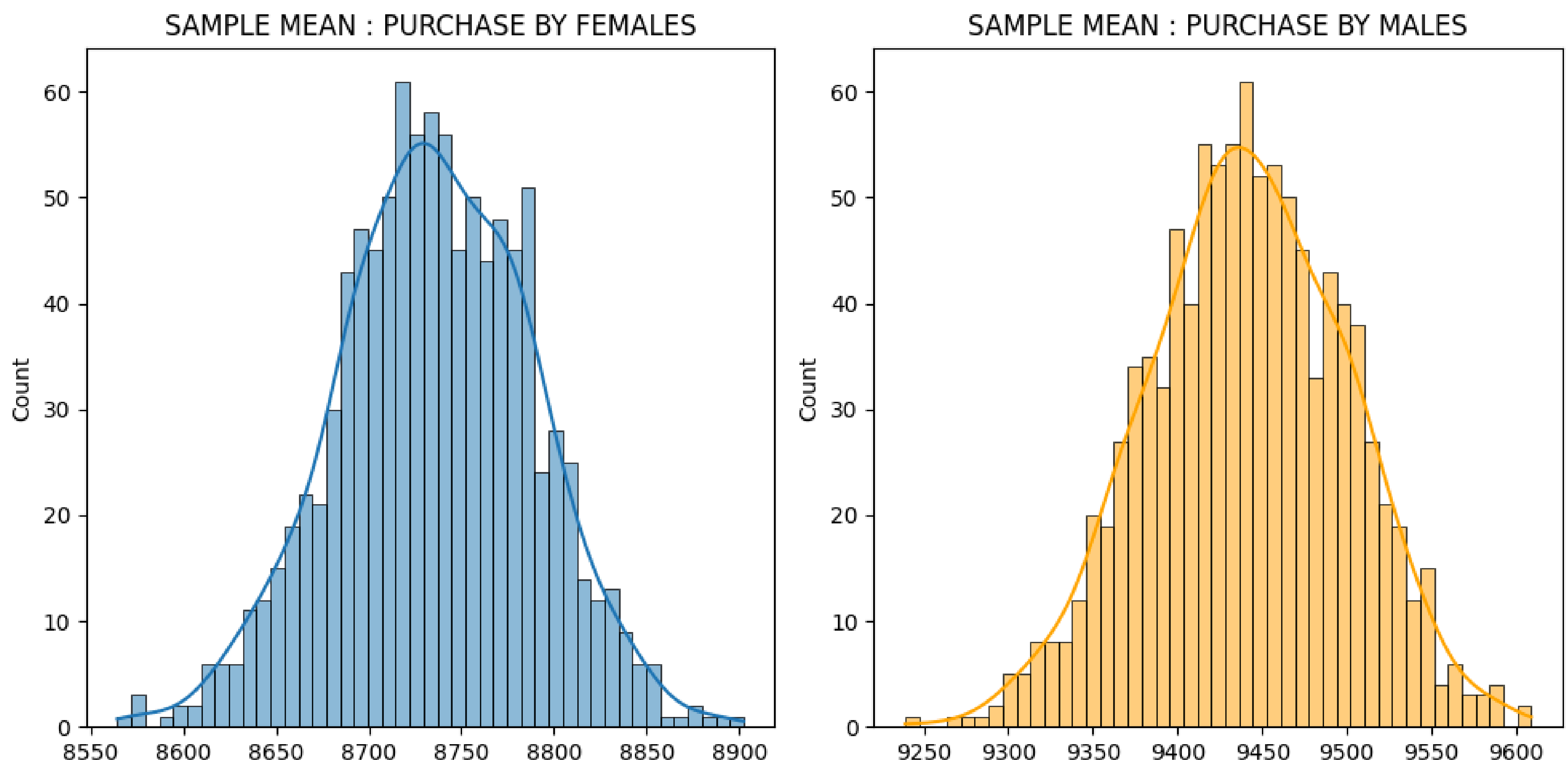
```
Mean of Purchase Amount by Males: 9437.526040472265
Standard Deviation of Purchase Amount by Males: 5092.186209777949
```

```
sample_mean_of_purchase_by_males = []
for i in range(1000):
  sample_m = df_m['Purchase'].sample(n=7500)
  sample_m_mean = sample_m.mean()
  sample_mean_of_purchase_by_males.append(sample_m_mean)
sample_mean_of_purchase_by_males = np.array(sample_mean_of_purchase_by_males)
```

```
sample_mean_of_purchase_by_males[:10]
```

```
array([9342.21493333, 9356.6844    , 9512.2004    , 9471.31453333,
       9380.058     , 9461.36      , 9456.962     , 9415.81666667,
       9466.61493333, 9436.20933333])
```

```
fig,axis = plt.subplots(1,2,figsize=(10,5))
sns.histplot(data=sample_mean_of_purchase_by_females,bins=45,kde=True,ax=axis[0])
axis[0].set_title('SAMPLE MEAN : PURCHASE BY FEMALES')
sns.histplot(data=sample_mean_of_purchase_by_males,bins=45,kde=True,ax=axis[1],color='orange')
axis[1].set_title('SAMPLE MEAN : PURCHASE BY MALES')
plt.tight_layout()
plt.show()
```



SAMPLE DISTRIBUTION MEANS:

```
print("Sample Mean of Purchase Amount by Females:",sample_mean_of_purchase_by_females.mean())
print("Sample Mean of Purchase Amount by Males:",sample_mean_of_purchase_by_males.mean())
```

```
Sample Mean of Purchase Amount by Females: 8735.427967733334
Sample Mean of Purchase Amount by Males: 9440.581635066666
```

The mean of this sampling distribution was found to be very close to the original population mean.

Females

- Population mean = 8734.56
- Sampling distribution mean = 8735.42

Males

- Population mean = 9437.52
- Sampling distribution mean = 9440.58

This justifies the first property of the Central Limit Theorem: Sampling Distribution Mean

≈

Population Mean

ESTIMATION OF THE 95% CONFIDENCE INTERVAL

```
from scipy.stats import norm
```

FEMALES

```
mu = df_f['Purchase'].mean()
sigma = df_f['Purchase'].std()
n = len(df_f)
alpha = 0.05
se = sigma/np.sqrt(n)
z1 = norm.ppf(alpha/2)
z2 = norm.ppf(1-alpha/2)
x1 = z1*se + mu
x2 = z2*se + mu
print("Confidence Interval for Females:",(x1,x2))
```

```
Confidence Interval for Females: (np.float64(8709.21154714068), np.float64(8759.919983170272))
```

MALES

```
mu = df_m['Purchase'].mean()
sigma = df_m['Purchase'].std()
n = len(df_m)
alpha = 0.05
se = sigma/np.sqrt(n)
z1 = norm.ppf(alpha/2)
z2 = norm.ppf(1-alpha/2)
x1 = z1*se + mu
x2 = z2*se + mu
print("Confidence Interval for Males:",(x1,x2))
```

```
Confidence Interval for Males: (np.float64(9422.01944736257), np.float64(9453.032633581959))
```

The **95% confidence intervals** in each case included the true population values — **consistent with the Central Limit Theorem**.

Numerical column v/s categorical column with two unique entries => Independent Samples T-test

```
from scipy.stats import ttest_ind
```

```
# H0 : Purchase amount in independent of Gender
# H1 : Purchase amount in dependent on Gender

sample_size = 10000

male_sample = df[df['Gender'] == 'M']['Purchase'].sample(n=sample_size, random_state=42)
female_sample = df[df['Gender'] == 'F']['Purchase'].sample(n=sample_size, random_state=42)

result = ttest_ind(male_sample, female_sample, alternative='two-sided')
alpha = 0.05

if result.pvalue < alpha:
    print("Reject Null Hypothesis")
    print("Gender has a significant impact on Purchase Amount\n")
else:
    print("Fail to Reject Null Hypothesis")
    print("Gender has no significant impact on Purchase Amount\n")

result
```

```
Reject Null Hypothesis
Gender has a significant impact on Purchase Amount

TtestResult(statistic=np.float64(10.842139195163371), pvalue=np.float64(2.5889036301871065e-27), df=np.float64(19998.0))
```

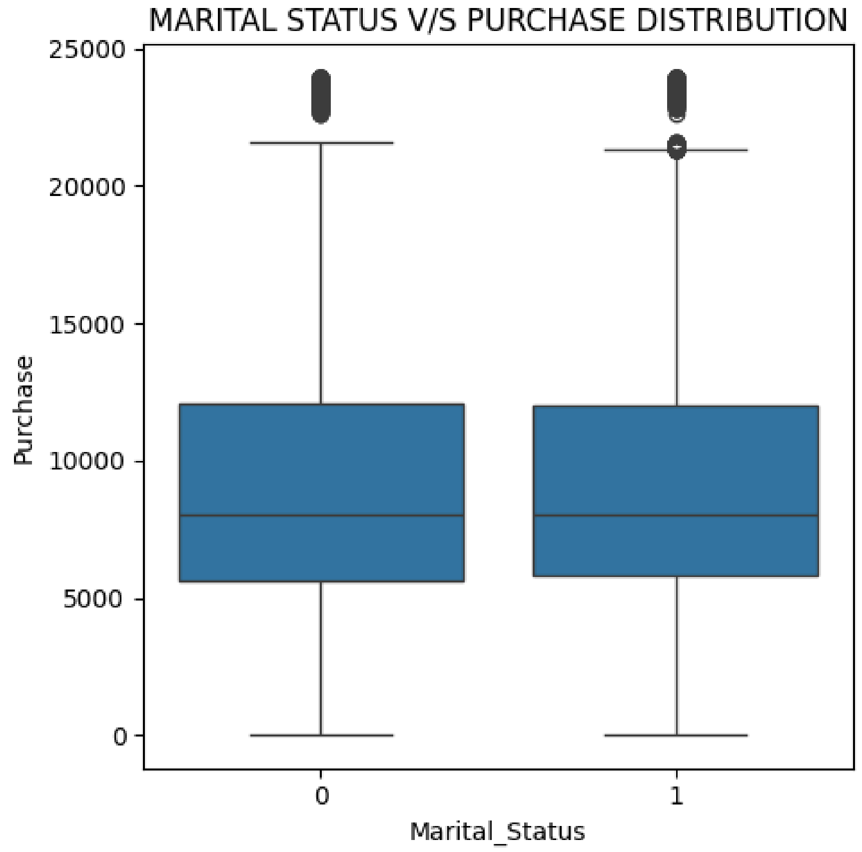
Purchase vis-a-vis Marital Status

```
df.groupby('Marital_Status')['Purchase'].describe()
```

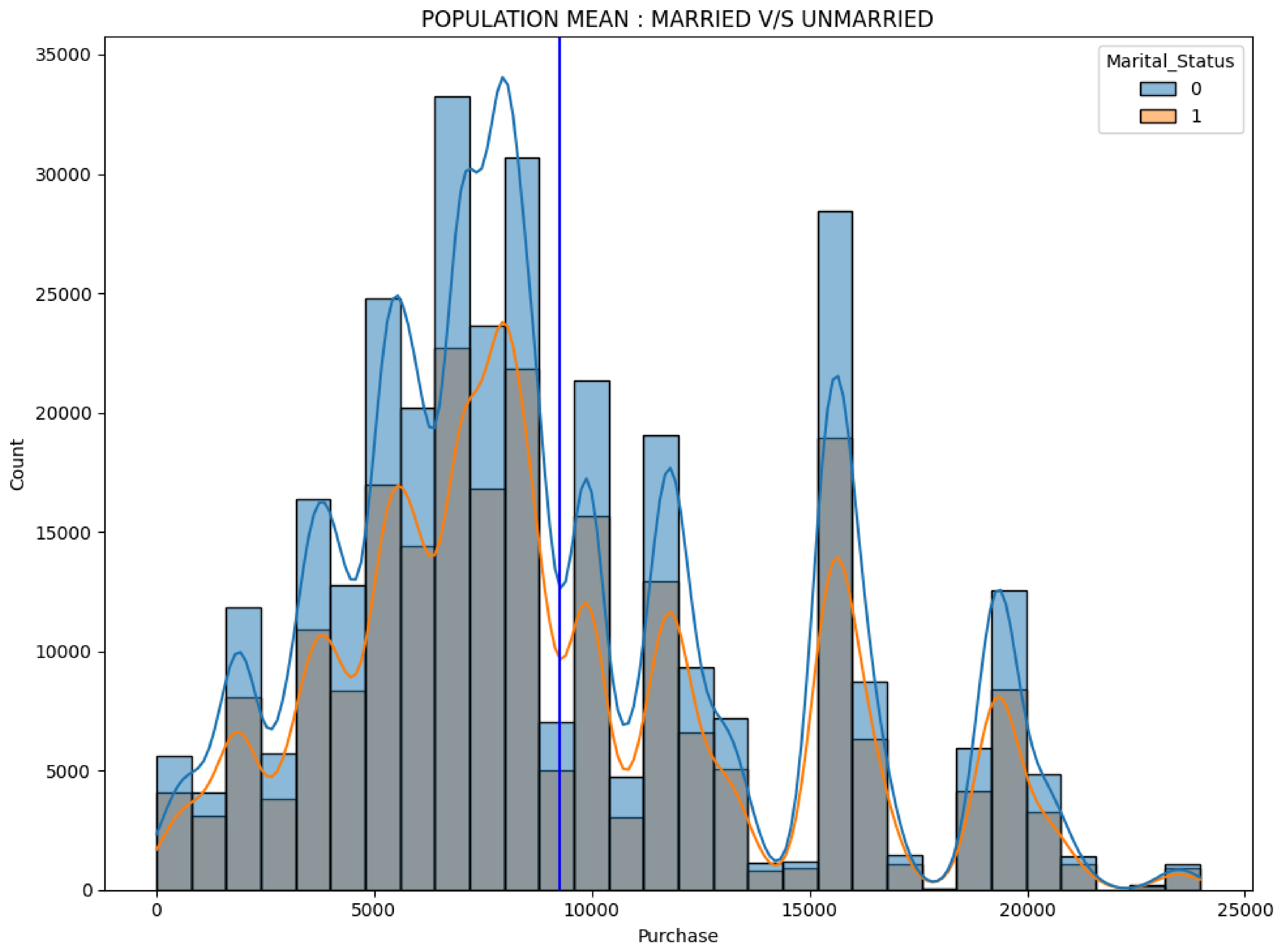
```
/tmp/ipython-input-3740306556.py:1: FutureWarning: The default of observed=False is deprecated and will be changed to True in a future version
  df.groupby('Marital_Status')['Purchase'].describe()
```

Marital_Status	count	mean	std	min	25%	50%	75%	max
0	324731.0	9265.907619	5027.347859	12.0	5605.0	8044.0	12061.0	23961.0
1	225337.0	9261.174574	5016.897378	12.0	5843.0	8051.0	12042.0	23961.0

```
fig,axis = plt.subplots(1,1,figsize=(5,5))
sns.boxplot(data=df,x='Marital_Status',y='Purchase',ax=axis)
axis.set_title('MARITAL STATUS V/S PURCHASE DISTRIBUTION')
plt.tight_layout()
plt.show()
```




```
fig,axis = plt.subplots(1,1,figsize=(10,7.5))
sns.histplot(data=df,x='Purchase',bins=30,kde=True,hue='Marital_Status',ax=axis)
plt.axvline(x=df['Purchase'].mean(),color='y')
plt.axvline(x=df[df['Marital_Status']==0]['Purchase'].mean(),color='r')
plt.axvline(x=df[df['Marital_Status']==1]['Purchase'].mean(),color='b')
plt.title('POPULATION MEAN : MARRIED V/S UNMARRIED')
plt.tight_layout()
plt.show()
```



Notes: The distribution appears roughly normal, though outliers are evident around 15,000 and 20,000

SAMPLE-DERIVED GENDER-CENTRIC ANALYSIS USING 1000 SAMPLE POINTS

MARRIED

```
df_married = df[df['Marital_Status']==1]
print("Mean of Purchase Amount by Married People:",df_married['Purchase'].mean())
print("Standard Deviation of Purchase Amount by Married People:",df_married['Purchase'].std())
```

```
sample_mean_of_purchase_by_married = []
for i in range(1000):
  sample_m = df_married['Purchase'].sample(n=7500)
  sample_m_mean = sample_m.mean()
  sample_mean_of_purchase_by_married.append(sample_m_mean)
sample_mean_of_purchase_by_married = np.array(sample_mean_of_purchase_by_married)

sample_mean_of_purchase_by_married[:5]
```

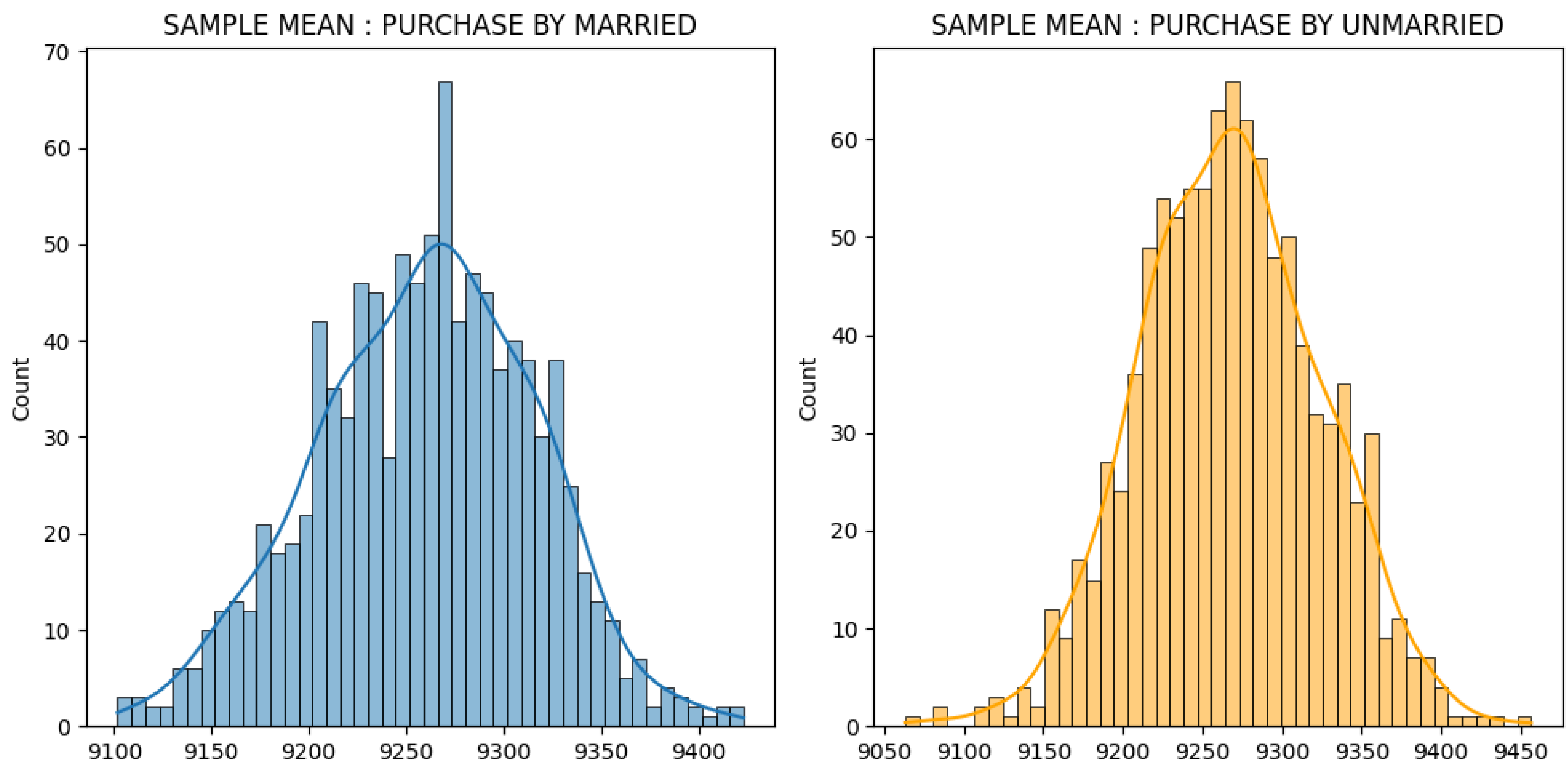
```
Mean of Purchase Amount by Married People: 9261.174574082374
Standard Deviation of Purchase Amount by Married People: 5016.89737779313
array([9307.33933333, 9249.242     , 9216.6016    , 9236.61186667,
       9303.73493333])
```

UNMARRIED

```
df_unmarried = df[df['Marital_Status']==0]
print("Mean of Purchase Amount by Unmarried People:",df_unmarried['Purchase'].mean())
print("Standard Deviation of Purchase Amount by Unmarried People:",df_unmarried['Purchase'].std())

sample_mean_of_purchase_by_unmarried = []
for i in range(1000):
  sample_u = df_unmarried['Purchase'].sample(n=7500)
  sample_u_mean = sample_u.mean()
  sample_mean_of_purchase_by_unmarried.append(sample_u_mean)
sample_mean_of_purchase_by_unmarried = np.array(sample_mean_of_purchase_by_unmarried)

sample_mean_of_purchase_by_unmarried[:5]
```

```
Mean of Purchase Amount by Unmarried People: 9265.907618921507
Standard Deviation of Purchase Amount by Unmarried People: 5027.347858674457
array([9259.70173333, 9303.49693333, 9296.08226667, 9255.4528    ,
       9273.15533333])
```

```
fig,axis = plt.subplots(1,2,figsize=(10,5))
sns.histplot(data=sample_mean_of_purchase_by_married,bins=45,kde=True,ax=axis[0])
axis[0].set_title('SAMPLE MEAN : PURCHASE BY MARRIED')
sns.histplot(data=sample_mean_of_purchase_by_unmarried,bins=45,kde=True,ax=axis[1],color='orange')
axis[1].set_title('SAMPLE MEAN : PURCHASE BY UNMARRIED')
plt.tight_layout()
plt.show()
```



SAMPLE DISTRIBUTION MEANS:

```
print("Sample Mean of Purchase Amount by the Married:",sample_mean_of_purchase_by_married.mean())
print("Sample Mean of Purchase Amount by the Unmarried:",sample_mean_of_purchase_by_unmarried.mean())
```

```
Sample Mean of Purchase Amount by the Married: 9259.6269848
Sample Mean of Purchase Amount by the Unmarried: 9267.197437333334
```

The mean of this sampling distribution was found to be very close to the original population mean.

Married

- Population mean = 9261.17
- Sampling distribution mean = 9259.62

Unmarried

- Population mean = 9265.90

- Sampling distribution mean = 9267.19

This justifies the first property of the Central Limit Theorem: Sampling Distribution Mean ≈ Population Mean

---

ESTIMATION OF THE 95% CONFIDENCE INTERVAL

```
from scipy.stats import norm
```

MARRIED

```
mu = df_married['Purchase'].mean()
sigma = df_married['Purchase'].std()
n = len(df_married)
alpha = 0.05
se = sigma/np.sqrt(n)
z1 = norm.ppf(alpha/2)
z2 = norm.ppf(1-alpha/2)
x1 = z1*se + mu
x2 = z2*se + mu
print("Confidence Interval for the Married:",(x1,x2))
```

```
Confidence Interval for the Married: (np.float64(9240.460427057078), np.float64(9281.888721107669))
```

UNMARRIED

```
mu = df_unmarried['Purchase'].mean()
sigma = df_unmarried['Purchase'].std()
n = len(df_unmarried)
alpha = 0.05
se = sigma/np.sqrt(n)
z1 = norm.ppf(alpha/2)
z2 = norm.ppf(1-alpha/2)
x1 = z1*se + mu
x2 = z2*se + mu
print("Confidence Interval for the Unmarried:",(x1,x2))
```

```
Confidence Interval for the Unmarried: (np.float64(9248.61641818668), np.float64(9283.198819656332))
```

The **95% confidence intervals** in each case included the true population values — **consistent with the Central Limit Theorem**.

```
# H0 : Purchase amount in independent of Marital Status
# H1 : Purchase amount in dependent on Marital Status

sample_size = 10000

unmarried_group = df[df['Marital_Status'] == 0]['Purchase'].sample(n=sample_size, random_state=42)
married_group = df[df['Marital_Status'] == 1]['Purchase'].sample(n=sample_size, random_state=42)

result = ttest_ind(unmarried_group, married_group, alternative='two-sided')
alpha = 0.05

if result.pvalue < alpha:
    print("Reject Null Hypothesis")
    print("Marital Status has a significant impact on Purchase Amount\n")
else:
    print("Fail to Reject Null Hypothesis")
    print("Marital Status has no significant impact on Purchase Amount\n")

result
```

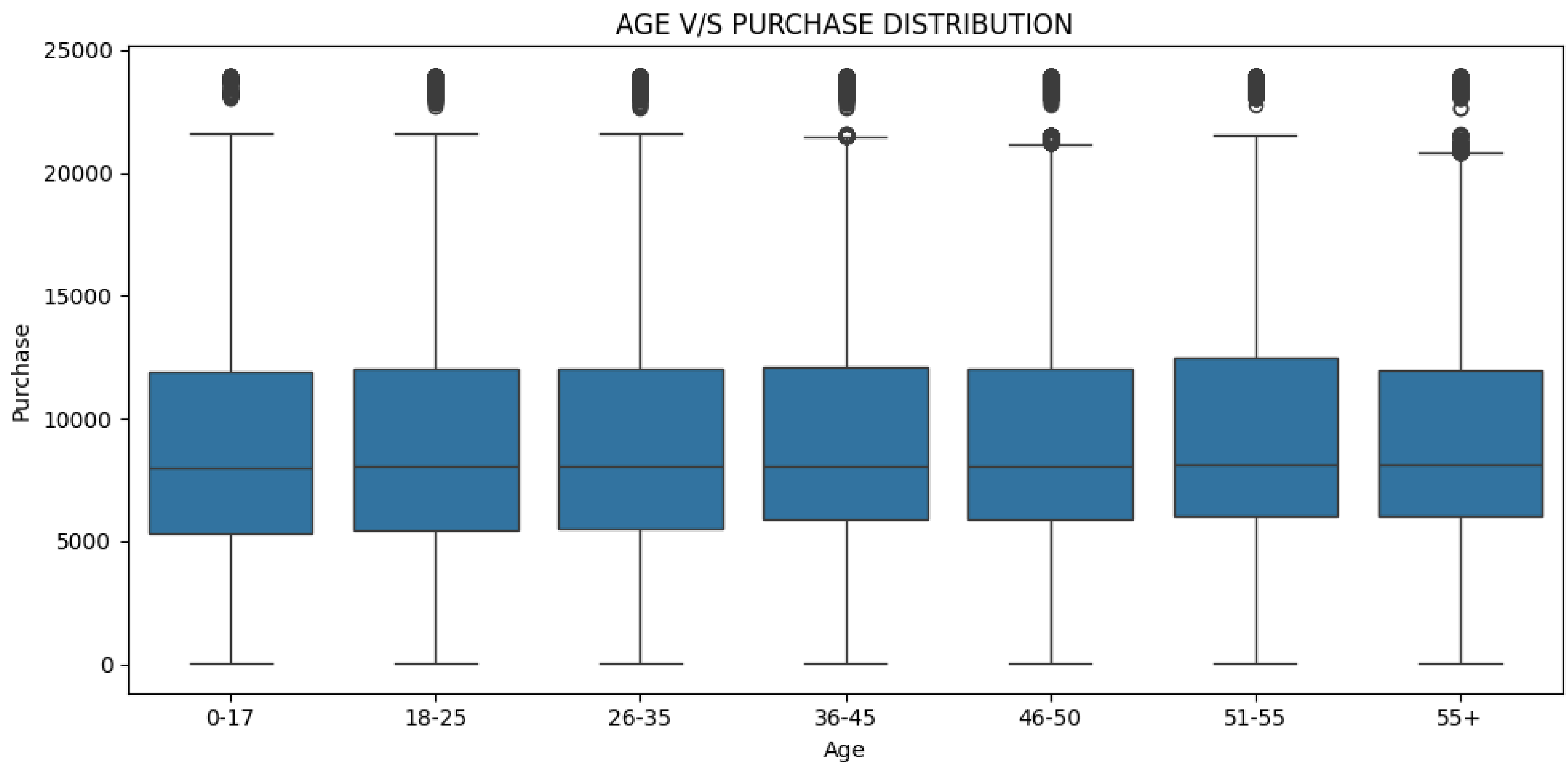
```
Fail to Reject Null Hypothesis
Marital Status has no significant impact on Purchase Amount

TtestResult(statistic=np.float64(0.5349013930718557), pvalue=np.float64(0.5927239922085221), df=np.float64(19998.0))
```

Purchase vis-a-vis Age

```
df.groupby('Age')['Purchase'].describe()
```

	count	mean	std	min	25%	50%	75%	max
Age								
0-17	15102.0	8933.464640	5111.114046	12.0	5328.0	7986.0	11874.0	23955.0
18-25	99660.0	9169.663606	5034.321997	12.0	5415.0	8027.0	12028.0	23958.0
26-35	219587.0	9252.690633	5010.527303	12.0	5475.0	8030.0	12047.0	23961.0
36-45	110013.0	9331.350695	5022.923879	12.0	5876.0	8061.0	12107.0	23960.0
46-50	45701.0	9208.625697	4967.216367	12.0	5888.0	8036.0	11997.0	23960.0
51-55	38501.0	9534.808031	5087.368080	12.0	6017.0	8130.0	12462.0	23960.0
55+	21504.0	9336.280459	5011.493996	12.0	6018.0	8105.5	11932.0	23960.0

```
fig,axis = plt.subplots(1,1,figsize=(10,5))
sns.boxplot(data=df,x='Age',y='Purchase',ax=axis)
axis.set_title('AGE V/S PURCHASE DISTRIBUTION')
plt.tight_layout()
plt.show()
```



- The largest group is 26–35 years, followed by 18–25 years => Mid-career and young adults dominate the dataset
- Mean values rise with age up to the 51–55 group (9534.81, the highest) => Older adults tend to spend more on average
- Standard deviation is roughly the same across all groups (~5000)

```
from scipy.stats import f_oneway
```

```
# H0 : Purchase amount in independent of Age
# H1 : Purchase amount in dependent on Age

age_groups = [df[df['Age']==age_group]['Purchase'] for age_group in df['Age'].unique()]

result = f_oneway(*age_groups)
# The * before 'age_groups' in the function call unpacks the list of group arrays so that each group is passed as a separate argument
alpha = 0.05

if result.pvalue < alpha:
    print("Reject Null Hypothesis")
    print("Age has a significant impact on Purchase Amount\n")
else:
    print("Fail to Reject Null Hypothesis")
    print("Age has no significant impact on Purchase Amount\n")

result
```

```
Reject Null Hypothesis
Age has a significant impact on Purchase Amount

F_onewayResult(statistic=np.float64(40.57579909450407), pvalue=np.float64(1.053563939251671e-49))
```

BUSINESS TAKEAWAY & ACTIONABLE INSIGHTS

- Target marketing and high-value promotions primarily toward **male and older adult segments** where spending is higher.
- Prioritize **City Category B** for inventory, ads, and store events due to its large customer share.

- **Marital status** can be **deprioritized** in segmentation, as its effect on purchase size is negligible.
- **Age-based marketing (especially for 36+ years)** may yield greater basket sizes and overall sales uplift.

These insights support more precise segmentation for Walmart's marketing and inventory planning, enhancing effectiveness during future Black Friday and major sales events.
