Walmart: Confidence Interval and CLT Business Case

Problem Statement

The Management team at Walmart Inc. wants to analyze the customer purchase behavior (specifically, purchase amount) against the customer's gender and the various other factors to help the business make better decisions. They want to understand if the spending habits differ between male and female customers: Do women spend more on Black Friday than men? (Assume 50 million customers are male and 50 million are female).

In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

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

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

Out[ ]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marit
0	1000001	P00069042	F	0-17	10	A	2	
1	1000001	P00248942	F	0-17	10	A	2	
2	1000001	P00087842	F	0-17	10	A	2	
3	1000001	P00085442	F	0-17	10	A	2	
4	1000002	P00285442	M	55+	16	C	4+	

In [ ]:
```
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
```

From the above cell we can see that Occupation , Marital Staus and Product Category are integers. Since these mentioned columns are categorical lets convert them to objects

In [ ]:
```
columns = ["Occupation","Marital_Status","Product_Category"]
df[columns]=df[columns].astype("object")
```

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

Out[ ]:

	User_ID	Purchase
count	5.500680e+05	550068.000000
mean	1.003029e+06	9263.968713
std	1.727592e+03	5023.065394
min	1.000001e+06	12.000000
25%	1.001516e+06	5823.000000
50%	1.003077e+06	8047.000000
75%	1.004478e+06	12054.000000
max	1.006040e+06	23961.000000

In [ ]:
```
df.isnull().sum()
```

Out[ ]:
```
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
```

In [ ]:
```
#> The dataset doesnt have any null/missing values
#> For Purchase Amount : the mean and median values has a difference of 1220 approximately
```

In [ ]:
```
#Lets do some Non - Graphical Analysis
```

In [ ]:
```
df.nunique()
```

Out[ ]:
```
User_ID                        5891
Product_ID                     3631
Gender                            2
Age                               7
Occupation                       21
City_Category                     3
Stay_In_Current_City_Years        5
Marital_Status                    2
Product_Category                 20
Purchase                      18105
dtype: int64
```

In [ ]:
```
categorical_columns = ['Gender', 'Age', 'Occupation', 'City_Category','Stay_In_Current_City
df[categorical_columns].melt().groupby(['variable','value'])[['value']].count()/len(df)
```

Out[ ]:

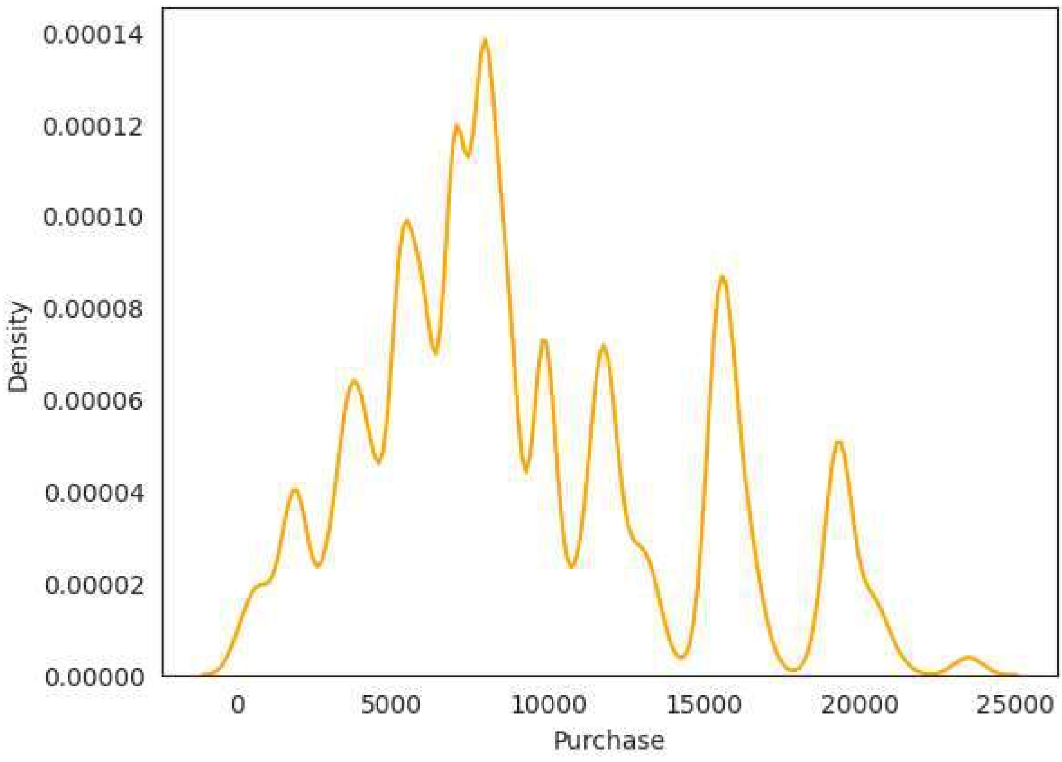
variable	value	value
Age	0-17	0.027455
	18-25	0.181178
	26-35	0.399200
	36-45	0.199999
	46-50	0.083082
	51-55	0.069993
	55+	0.039093
City_Category	A	0.268549
	B	0.420263
	C	0.311189
Gender	F	0.246895
	M	0.753105
Marital_Status	0	0.590347
	1	0.409653
Occupation	0	0.126599
	1	0.086218
	2	0.048336
	3	0.032087
	4	0.131453
	5	0.022137
	6	0.037005
	7	0.107501
	8	0.002811
	9	0.011437
	10	0.023506
	11	0.021063
	12	0.056682
	13	0.014049
	14	0.049647
	15	0.022115
	16	0.046123
	17	0.072796
	18	0.012039
	19	0.015382
	20	0.061014
Product_Category	1	0.255201

		value
variable	value	
	2	0.043384
	3	0.036746
	4	0.021366
	5	0.274390
	6	0.037206
	7	0.006765
	8	0.207111
	9	0.000745
	10	0.009317
	11	0.044153
	12	0.007175
	13	0.010088
	14	0.002769
	15	0.011435
	16	0.017867
	17	0.001051
	18	0.005681
	19	0.002914
	20	0.004636
Stay_In_Current_City_Years	0	0.135252
	1	0.352358
	2	0.185137
	3	0.173224
	4+	0.154028

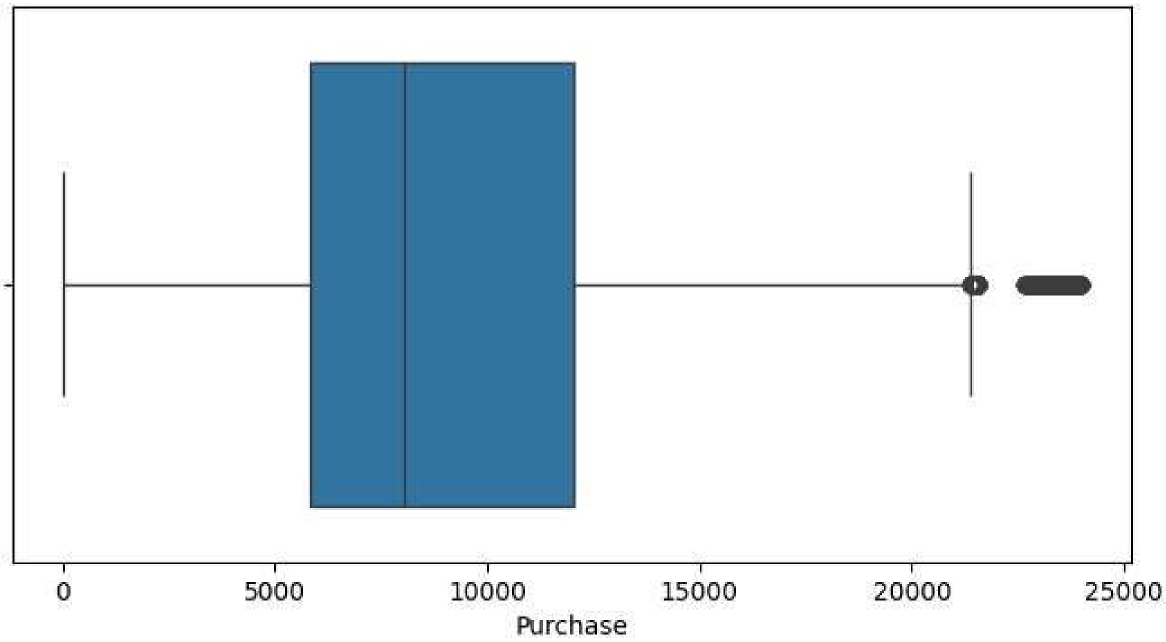
Some Observations

- 60% Single, 40% Married
- 80% of the users are between the age 18-50 (40%: 26-35, 18%: 18-25, 20%: 36-45)
- 75% of the users are Male and 24.6% are Female
- 35% Staying in the city from 1 year, 18% from 2 years, 17% from 3 years
- Total of 20 product categories are there
- There are 20 different types of occupations in the city

In [ ]:
```
sns.kdeplot(data=df, x='Purchase',color="Orange")
plt.show()
```



In [ ]:
```
plt.figure(figsize=(8,4))
sns.boxplot(data=df,x="Purchase")
plt.show()
```

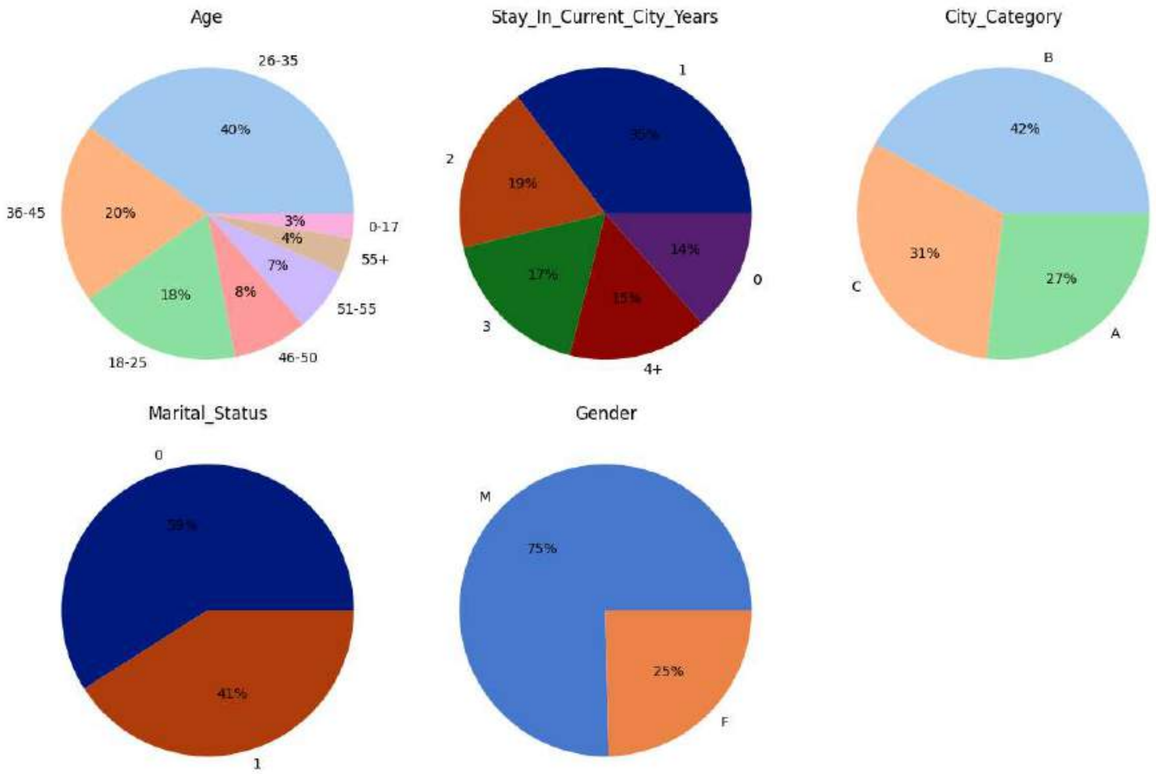


We can see from the above graph that purchase has outliers

For Categorical columns lets use pie charts and countplot to understand the distribution of data

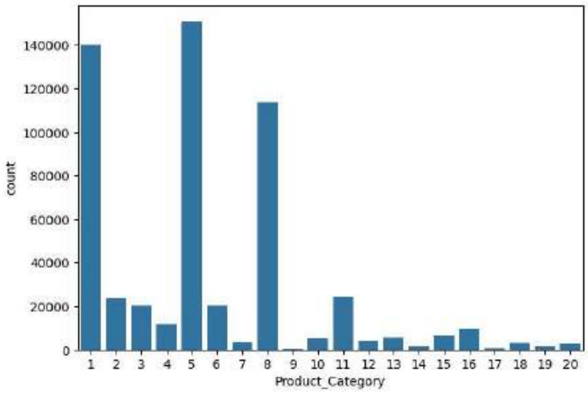
In [ ]:
```
fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(12, 8))

c1=sns.color_palette('pastel')
c2=sns.color_palette('dark')
c3=sns.color_palette('muted')

data = df['Age'].value_counts(normalize=True)*100
axis[0,0].pie(x=data.values, labels=data.index, autopct='%.0f%%',colors=c1)
axis[0,0].set_title("Age")
```

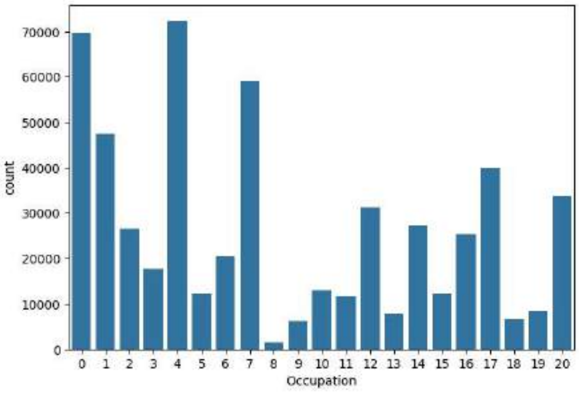
```python
data = df['Stay_In_Current_City_Years'].value_counts(normalize=True)*100
axis[0,1].pie(x=data.values, labels=data.index, autopct='%.0f%%',colors=c2)
axis[0,1].set_title("Stay_In_Current_City_Years")

data = df['City_Category'].value_counts(normalize=True)*100
axis[0,2].pie(x=data.values, labels=data.index, autopct='%.0f%%',colors=c1)
axis[0,2].set_title("City_Category")

data = df['Marital_Status'].value_counts(normalize=True)*100
axis[1,0].pie(x=data.values, labels=data.index, autopct='%.0f%%',colors=c2)
axis[1,0].set_title("Marital_Status")

data = df['Gender'].value_counts(normalize=True)*100
axis[1,1].pie(x=data.values, labels=data.index, autopct='%.0f%%',colors=c3)
axis[1,1].set_title("Gender")


axis[1, 2].axis('off')

plt.tight_layout()
```



In [ ]:

```python
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(16, 5))
sns.countplot(data=df, x='Product_Category', ax=axs[0])
sns.countplot(data=df, x='Occupation', ax=axs[1])
plt.show()
```





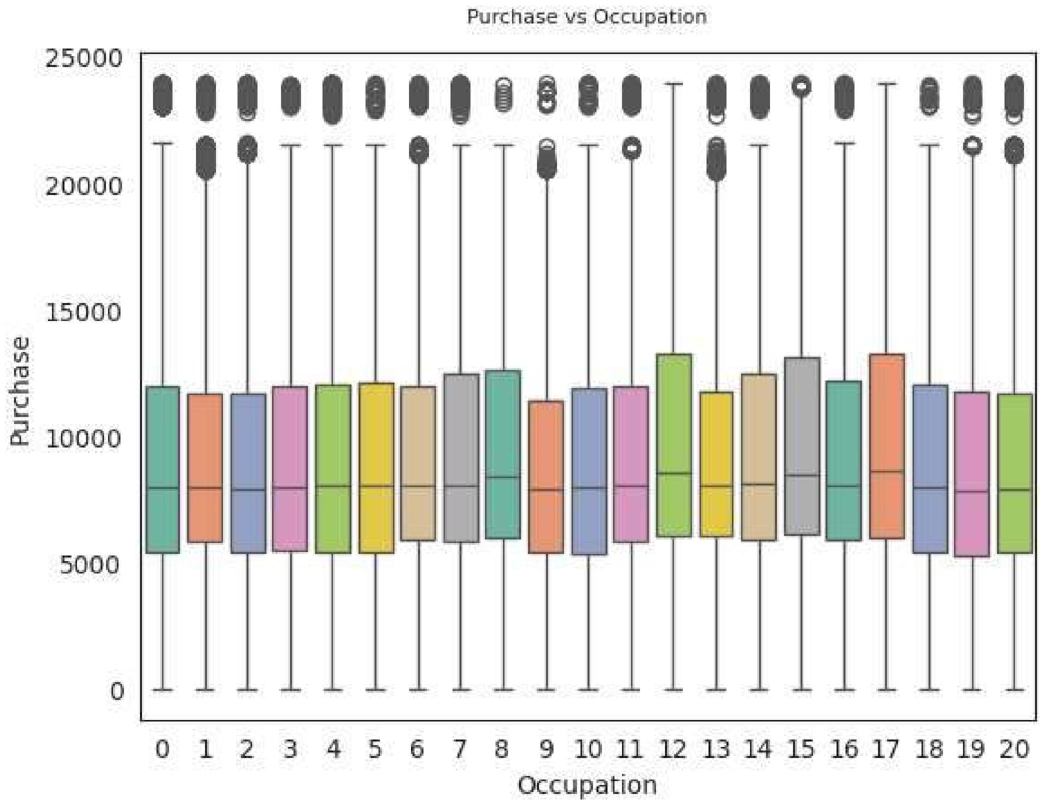
Observations :

- Majority of the people are in the age of 26-35
- Most of the users are single
- Most of the users are Male
- There are 20 different types of occupation and product category
- City B has majority no of users

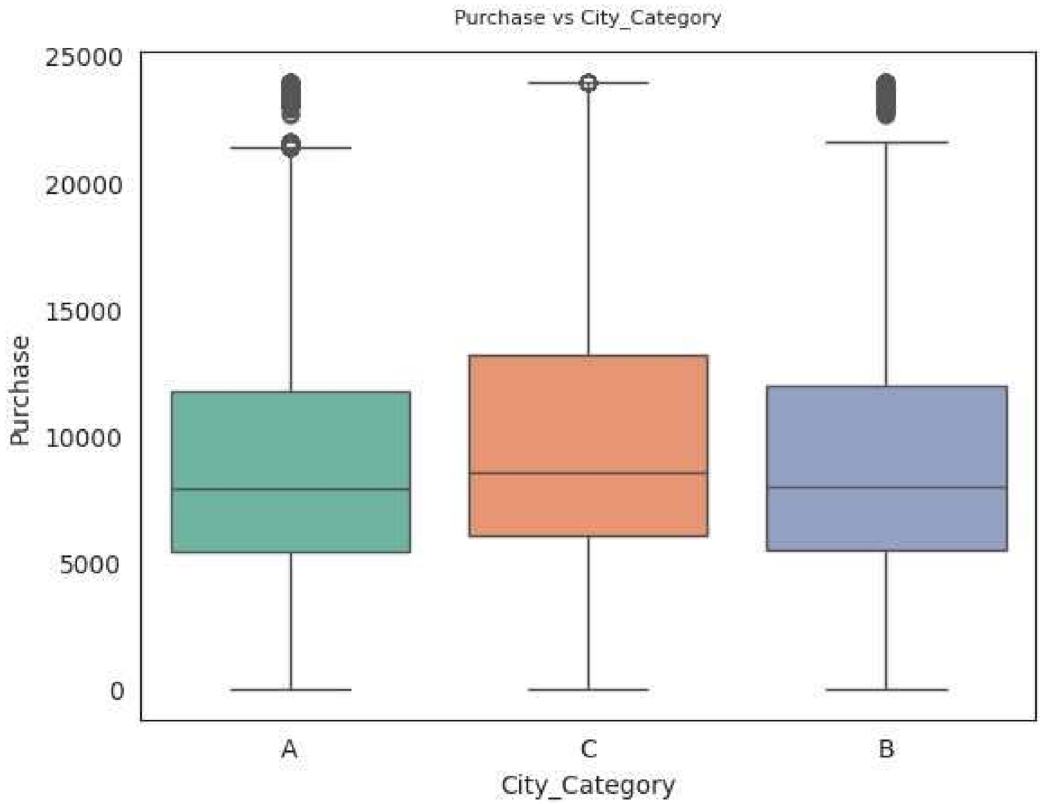
In [ ]:

```
categories = ['Occupation', 'City_Category','Stay_In_Current_City_Years', 'Product_Category
sns.set_style("white")

sns.boxplot(data=df, y='Purchase', x=categories[0], palette='Set2')
plt.title(f"Purchase vs {categories[0]}", pad=12,fontsize=8)
plt.show()

sns.boxplot(data=df, y='Purchase', x=categories[1], palette='Set2')
plt.title(f"Purchase vs {categories[1]}", pad=12,fontsize=8)
plt.show()

sns.boxplot(data=df, y='Purchase', x=categories[2], palette='Set2')
plt.title(f"Purchase vs {categories[2]}", pad=12,fontsize=8)
plt.show()

plt.figure(figsize=(10, 8))
sns.boxplot(data=df, y='Purchase', x=categories[-1], palette='Set3')
plt.show()
```

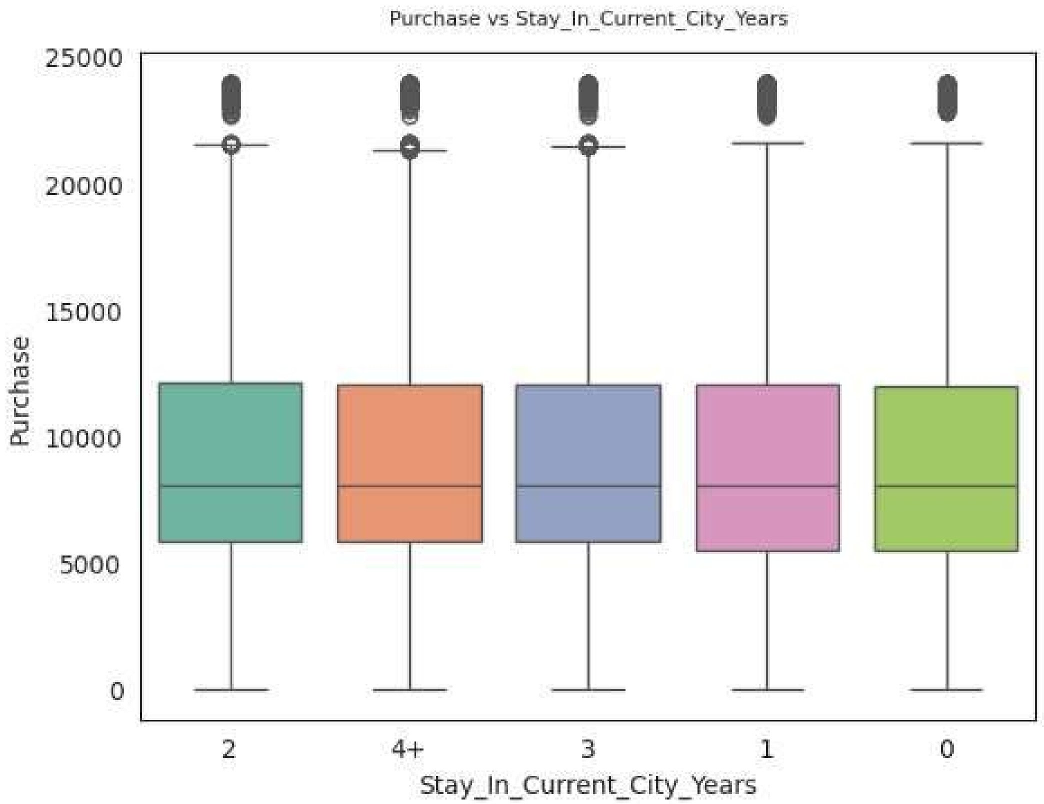
```
<ipython-input-18-0be016ae8583>:4: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assi
gn the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.boxplot(data=df, y='Purchase', x=categories[0], palette='Set2')
```



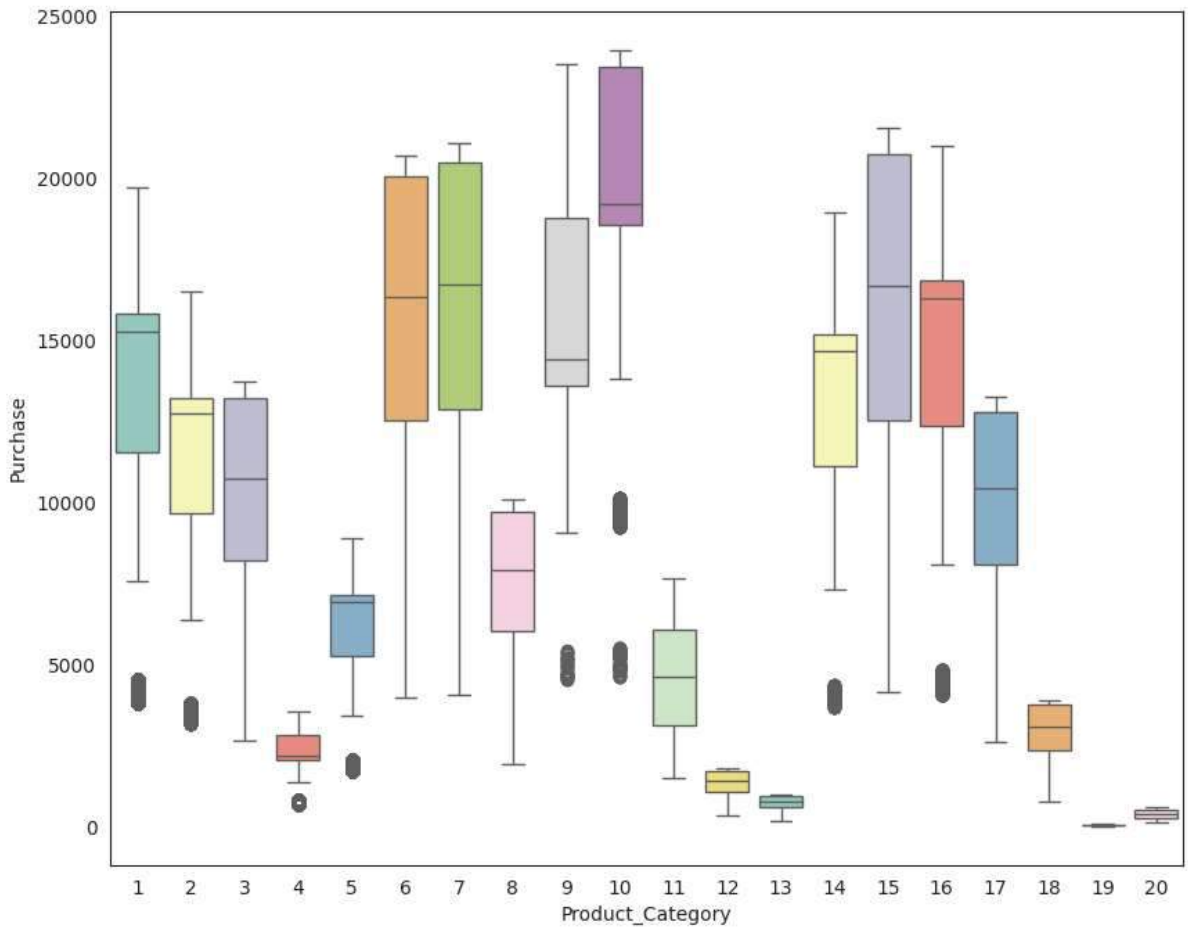

```
<ipython-input-18-0be016ae8583>:8: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assi
gn the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.boxplot(data=df, y='Purchase', x=categories[1], palette='Set2')
```




```
<ipython-input-18-0be016ae8583>:12: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assi
gn the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.boxplot(data=df, y='Purchase', x=categories[2], palette='Set2')
```




```
<ipython-input-18-0be016ae8583>:17: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assi
gn the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.boxplot(data=df, y='Purchase', x=categories[-1], palette='Set3')
```



Missing Values / Outlier Detection

In [ ]:
```
df.isnull().sum()
```

Out[ ]:
```
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
```

There is no Missing values in the dataset

In [ ]:
```
def find_outliers_IQR(df):
 q1=df.quantile(0.25)
 q3=df.quantile(0.75)
 IQR=q3-q1
 outliers = df[((df<(q1-1.5*IQR)) | (df>(q3+1.5*IQR)))]
 return outliers
```

In [ ]:
```
outliers = find_outliers_IQR(df["Purchase"])
print("Number of Outliers: "+ str(len(outliers)))
print("Maximum outlier value:"+ str(outliers.max()))
print("Minimum outlier value: "+ str(outliers.min()))
```

```
Number of Outliers: 2677
Maximum outlier value:23961
Minimum outlier value: 21401
```

Lets try to address some questions using CLT and Confidence Level Topics

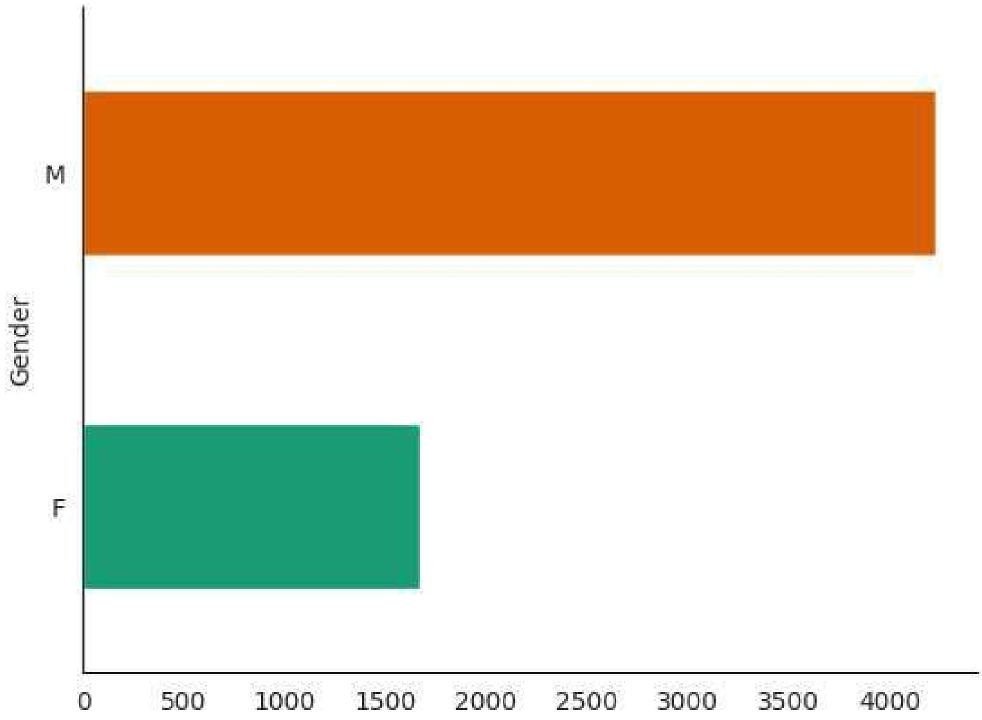
1.Are women spending more money per transaction than men? Why or Why not?

In [ ]:
```
amount_spent = df.groupby(['User_ID','Gender'])[['Purchase']].sum()
amount_spent = amount_spent.reset_index()
amount_spent.head()
```

Out[ ]:

	User_ID	Gender	Purchase
0	1000001	F	334093
1	1000002	M	810472
2	1000003	M	341635
3	1000004	M	206468
4	1000005	M	821001

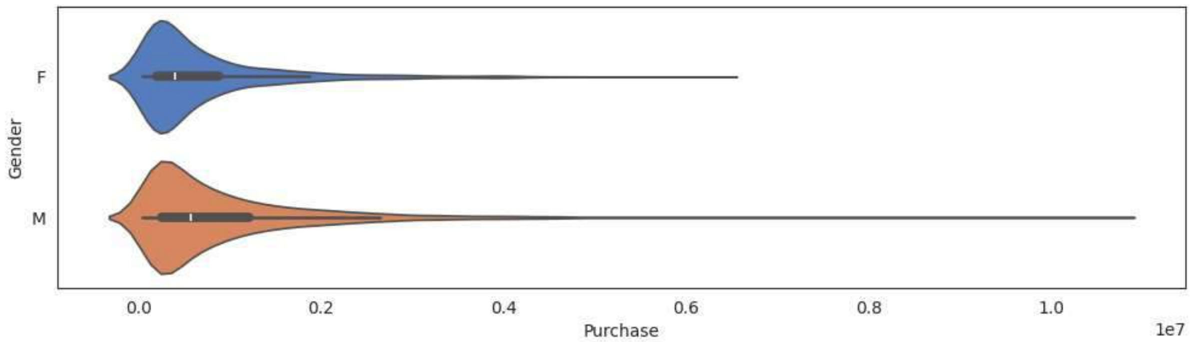
In [ ]:
```
# @title Gender wise count

from matplotlib import pyplot as plt
import seaborn as sns
amount_spent.groupby('Gender').size().plot(kind='barh', color=sns.palettes.mpl_palette('Dar
plt.gca().spines[['top', 'right',]].set_visible(False)
```



From the above graph we can see that Male purchases are about 4225 and that of Female are 1666

In [ ]:
```
# @title Gender vs Purchase Amount(in Millions)

figsize = (12, 1.5 * len(amount_spent['Gender'].unique()))
plt.figure(figsize=figsize)
sns.violinplot(amount_spent, x='Purchase', y='Gender', inner='box', palette='muted')
plt.show()
```

```
<ipython-input-24-61459af2e264>:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assi
gn the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.violinplot(amount_spent, x='Purchase', y='Gender', inner='box', palette='muted')
```

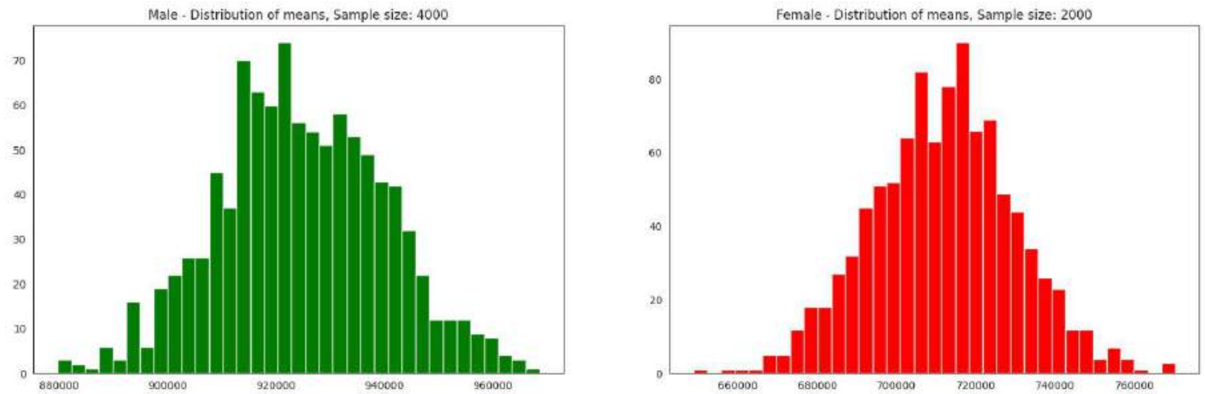


In [ ]:
```
male_avg = amount_spent[amount_spent['Gender']=='M']['Purchase'].mean()
female_avg = amount_spent[amount_spent['Gender']=='F']['Purchase'].mean()
print("Average amount spent by Male customers: {:.2f}".format(male_avg))
print("Average amount spent by Female customers: {:.2f}".format(female_avg))

# @title Male customers spend more money than female customers
```

```
Average amount spent by Male customers: 925344.40
Average amount spent by Female customers: 712024.39
```

2.Confidence intervals and distribution of the mean of the expenses by female and male customers

In [ ]:
```
male_df = amount_spent[amount_spent['Gender']=='M']
female_df = amount_spent[amount_spent['Gender']=='F']
genders = ["M", "F"]
male_sample_size = 4000
female_sample_size = 2000
number_of_repititions = 1000

male_means = []
female_means = []
for _ in range(number_of_repititions):
 male_mean = male_df.sample(male_sample_size,replace=True)['Purchase'].mean()
 female_mean = female_df.sample(female_sample_size,replace=True)['Purchase'].mean()
 male_means.append(male_mean)
 female_means.append(female_mean)

fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))
axis[0].hist(male_means, bins=35,color="Green")
axis[1].hist(female_means, bins=35,color="Red")
axis[0].set_title("Male - Distribution of means, Sample size: 4000")
axis[1].set_title("Female - Distribution of means, Sample size: 2000")
plt.show()
```



In [ ]:
```
print("Population mean - Mean of sample means of amount spent for Male: {:.4f}".format(np.m
print("Population mean - Mean of sample means of amount spent for Female: {:.4f}".format(np
print("\nMale - Sample mean: {:.4f} Sample std: {:.4f}".format(male_df['Purchase'].mean(),
print("Female - Sample mean: {:.4f} Sample std: {:.4f}".format(female_df['Purchase'].mean()
```

```
Population mean - Mean of sample means of amount spent for Male: 924528.7544
Population mean - Mean of sample means of amount spent for Female: 711721.4307

Male - Sample mean: 925344.4024 Sample std: 985830.1008
Female - Sample mean: 712024.3950 Sample std: 807370.7261
```

Now From Central Limit Theorem for the population we can say that:

1. Average amount spend by male customers is 9,26,341.86
2. Average amount spend by female customers is 7,11,704.09

3.Are confidence intervals of average male and female spending overlapping? How can Walmart leverage this conclusion to make changes or improvements?

In [ ]:
```
male_margin_of_error_clt = 1.95*male_df['Purchase'].std()/np.sqrt(len(male_df))
male_sample_mean = male_df['Purchase'].mean()
male_lower_lim = male_sample_mean - male_margin_of_error_clt
male_upper_lim = male_sample_mean + male_margin_of_error_clt
female_margin_of_error_clt = 1.95*female_df['Purchase'].std()/np.sqrt(len(female_df))
female_sample_mean = female_df['Purchase'].mean()
female_lower_lim = female_sample_mean - female_margin_of_error_clt
female_upper_lim = female_sample_mean + female_margin_of_error_clt
print("Male confidence interval of means: ({:.2f}, {:.2f})".format(male_lower_lim, male_upp
print("Female confidence interval of means: ({:.2f}, {:.2f})".format(female_lower_lim, fema
```

```
Male confidence interval of means: (895769.50, 954919.31)
Female confidence interval of means: (673452.58, 750596.21)
```

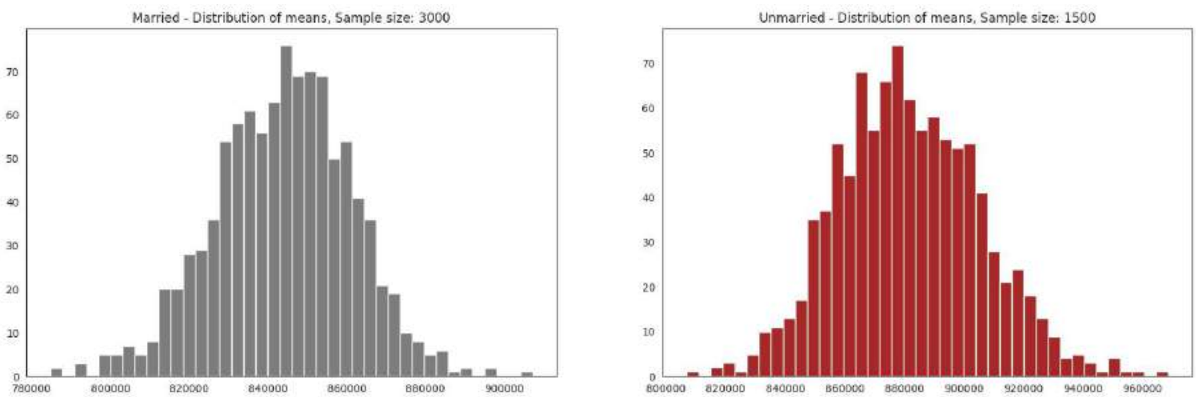
We can infer about the population that, 95% of the times:

1. Average amount spend by male customer will lie in between: (895769.50, 954919.31)
2. Average amount spend by female customer will lie in between: (673452.58, 750596.21)

The CI's of Males and Females are not overlapping.

4.Results when the same activity is performed for Married vs Unmarried

In [ ]:
```
amt_df = df.groupby(['User_ID', 'Marital_Status'])[['Purchase']].sum()
amt_df = amt_df.reset_index()
amt_df
amt_df['Marital_Status'].value_counts()
marid_samp_size = 3000
unmarid_sample_size = 1500
num_repitions = 1000
marid_means = []
unmarid_means = []
for _ in range(num_repitions):
 marid_mean =amt_df[amt_df['Marital_Status']==1].sample(marid_samp_size,replace=True)['Purc
 unmarid_mean = amt_df[amt_df['Marital_Status']==0].sample(unmarid_sample_size,replace=True
 marid_means.append(marid_mean)
 unmarid_means.append(unmarid_mean)


fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))
axis[0].hist(marid_means, bins=40,color="Grey")
axis[1].hist(unmarid_means,bins=40,color="Brown")
axis[0].set_title("Married - Distribution of means, Sample size: 3000")
axis[1].set_title("Unmarried - Distribution of means, Sample size: 1500")
plt.show()
print("Population mean - Mean of sample means of amount spend for Married: {:.2f}".format(r
print("Population mean - Mean of sample means of amount spend for Unmarried: {:.2f}".format
print("\nMarried - Sample mean: {:.2f} Sample std: {:.2f}".format(amt_df[amt_df['Marital_St
print("Unmarried - Sample mean: {:.2f} Sample std: {:.2f}".format(amt_df[amt_df['Marital_St
for val in ["Married", "Unmarried"]:

 new_val = 1 if val == "Married" else 0

 new_df = amt_df[amt_df['Marital_Status']==new_val]

 margin_of_error_clt = 1.96*new_df['Purchase'].std()/np.sqrt(len(new_df))
 sample_mean = new_df['Purchase'].mean()
 lower_lim = sample_mean - margin_of_error_clt
 upper_lim = sample_mean + margin_of_error_clt

 print("{} Confidence Interval of means: ({:.2f}, {:.2f})".format(val, lower_lim, upper_lim
```



```
Population mean - Mean of sample means of amount spend for Married: 843831.52
Population mean - Mean of sample means of amount spend for Unmarried: 881464.38

Married - Sample mean: 843526.80 Sample std: 935352.12
Unmarried - Sample mean: 880575.78 Sample std: 949436.25
Married Confidence Interval of means: (806668.83, 880384.76)
Unmarried Confidence Interval of means: (848741.18, 912410.38)
```

5.Results when the same activity is performed for Age

Calculating the average amount spent by **age**

In [ ]:
```
amt_df = df.groupby(['User_ID', 'Age'])[['Purchase']].sum()
amt_df = amt_df.reset_index()
amt_df
amt_df['Age'].value_counts()
sample_size = 200
num_repitions = 1000
all_means = {}
age_intervals = ['0-17','18-25','26-35', '36-45', '46-50', '51-55', '55+']
for age_interval in age_intervals:
 all_means[age_interval] = []
for age_interval in age_intervals:
 for _ in range(num_repitions):
  mean = amt_df[amt_df['Age']==age_interval].sample(sample_size,replace=True)['Purchase'].m
  all_means[age_interval].append(mean)

for val in ['0-17','18-25','26-35', '36-45', '46-50', '51-55', '55+']:
  new_df = amt_df[amt_df['Age']==val]
  margin_of_error_clt = 1.96*new_df['Purchase'].std()/np.sqrt(len(new_df))
  sample_mean = new_df['Purchase'].mean()
  lower_lim = sample_mean - margin_of_error_clt
  upper_lim = sample_mean + margin_of_error_clt
  print("For age {} --> confidence interval of means: ({:.2f}, {:.2f})".format(val, lower_l
```

```
For age 0-17 --> confidence interval of means: (527662.46, 710073.17)
For age 18-25 --> confidence interval of means: (801632.78, 908093.46)
For age 26-35 --> confidence interval of means: (945034.42, 1034284.21)
For age 36-45 --> confidence interval of means: (823347.80, 935983.62)
For age 46-50 --> confidence interval of means: (713505.63, 871591.93)
For age 51-55 --> confidence interval of means: (692392.43, 834009.42)
For age 55+ --> confidence interval of means: (476948.26, 602446.23)
```

Insights

1. The majority of users are male.
2. There are twenty distinct types of occupation and product categories.
3. B City_Category has a larger user base compared to other city categories.
4. Single users outnumber married users.
5. Product categories 1, 5, 8, and 11 exhibit the highest purchasing frequency.
6. When comparing purchase behavior with occupation, occupations 1, 2, 6, 9, 13, and 20 demonstrate more outliers compared to other occupations, although the median purchase amount remains consistent across all occupations.
7. In terms of purchase behavior across different city categories, while A and B city categories exhibit some outliers, the median purchase amount remains relatively consistent across all categories.
8. Purchase behavior across product categories shows significant variation in median purchase amounts. Outliers are particularly noticeable in product categories 1, 2, 5, 9, 10, 14, and 16. Using the Interquartile Range (IQR) method, a total of 2677 outliers were identified.

Recommendations

1. Men spent more money than women.So the company has to focus on attracting more women customerseither by marketing campaign's or by increasing specific product category .
2. Unmarried customers spend more money than married customers, So company can focus on acquisition of Unmarried customers.
3. From the CI of means we can see that the range of amount spent by the customers in the age of 18-45 is higher compared to other ages.So the company has to focus on acquisition of customers in this age range.
4. Since the product categories 1,5,8,11 have more buyers , the company can can improvise the stocks of these products.Since they are high selling.
5. Male customers living in City_Category C spend more money than other male customers living in B or C, Selling more products in the City_Category C will help the company increase the revenue.
6. As more users belong to City_Category B, The company allocate more resources towards this market segment, such as opening new stores or offering location-specific promotions to capitalize on the higher user base.
7. Investigate the reasons behind the outliers in city categories A and B while maintaining consistent median purchase amounts. This could involve understanding local market dynamics, consumer behavior, and competition to optimize business strategies in these regions.
8. Analyze the variations in median purchase amounts across product categories to identify potential opportunities for improvement. This could involve optimizing pricing strategies and enhancing product features.