Wallmart Case

In [ ]:
```
# import libraries
import pandas as pd
import numpy as np
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
```

In [ ]:
```
df_walmart = pd.read_csv("/Users/mojo/ML/Scaler/Projects/Wallmart/walmart_da
df_walmart.head()
```

Out[ ]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years
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+

Missing Values, Data types and Shape of data

In [ ]:
```
# Shape and size of data
df_walmart.shape
```

Out[ ]:
```
(550068, 10)
```

In [ ]:
```
# Missing Value
df_walmart.isna().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 [ ]:
```
df_walmart.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
```

- No missing values
- We can see that there are 5 numerical and 5 categorical features
- Numericals: User_ID, Occupation,Marital_Status,Product_Category and Purchase
- Categorical: Product_ID, Gender, Age(represents age group), City_Category, Stay_In_Current_City_Years
- Looking at the data we can see that the Purchase is the only column which should be in numerical.
- User_ID, Occupation,Marital_Status,Product_Category : These all should be changed into categorical data.
- We are going to change all of variables as categorical form for consistancy reasons.

In [ ]:
```
for col in df_walmart.columns:
    if col!='Purchase':
        # print(col)
        df_walmart[col] = df_walmart[col].astype('category')
df_walmart.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  category
 1   Product_ID                  550068 non-null  category
 2   Gender                      550068 non-null  category
 3   Age                         550068 non-null  category
 4   Occupation                  550068 non-null  category
 5   City_Category               550068 non-null  category
 6   Stay_In_Current_City_Years  550068 non-null  category
 7   Marital_Status              550068 non-null  category
 8   Product_Category            550068 non-null  category
 9   Purchase                    550068 non-null  int64
dtypes: category(9), int64(1)
memory usage: 10.3 MB
```

Non-Graphical Analysis: Value counts and unique attributes

In [ ]:
```
df_walmart.describe(include='all').T
```

Out[ ]:

	count	unique	top	freq	mean	std
User_ID	550068.0	5891.0	1001680.0	1026.0	NaN	NaN
Product_ID	550068	3631	P00265242	1880	NaN	NaN
Gender	550068	2	M	414259	NaN	NaN
Age	550068	7	26-35	219587	NaN	NaN
Occupation	550068.0	21.0	4.0	72308.0	NaN	NaN
City_Category	550068	3	B	231173	NaN	NaN
Stay_In_Current_City_Years	550068	5	1	193821	NaN	NaN
Marital_Status	550068.0	2.0	0.0	324731.0	NaN	NaN
Product_Category	550068.0	20.0	5.0	150933.0	NaN	NaN
Purchase	550068.0	NaN	NaN	NaN	9263.968713	5023.065394

- We can see the unique values of all the columns in the above table.
- We can see that in purchase mean is to the right of the median then we can say that the data is slightly right skewed.
- There are total 20 types of products.
- There are 21 types occupation available in the state.

In [ ]:
```
attr = ['Gender', 'Age', 'City_Category','Stay_In_Current_City_Years','Marit
for col in attr:
    print(df_walmart[col].value_counts(normalize=True)*100)
    print("*"*50)
```

```
M    75.310507
F    24.689493
Name: Gender, dtype: float64
**************************************************
26-35    39.919974
36-45    19.999891
18-25    18.117760
46-50     8.308246
51-55     6.999316
55+       3.909335
0-17      2.745479
Name: Age, dtype: float64
**************************************************
B    42.026259
C    31.118880
A    26.854862
Name: City_Category, dtype: float64
**************************************************
1     35.235825
2     18.513711
3     17.322404
4+    15.402823
0     13.525237
Name: Stay_In_Current_City_Years, dtype: float64
**************************************************
0    59.034701
1    40.965299
Name: Marital_Status, dtype: float64
**************************************************
```

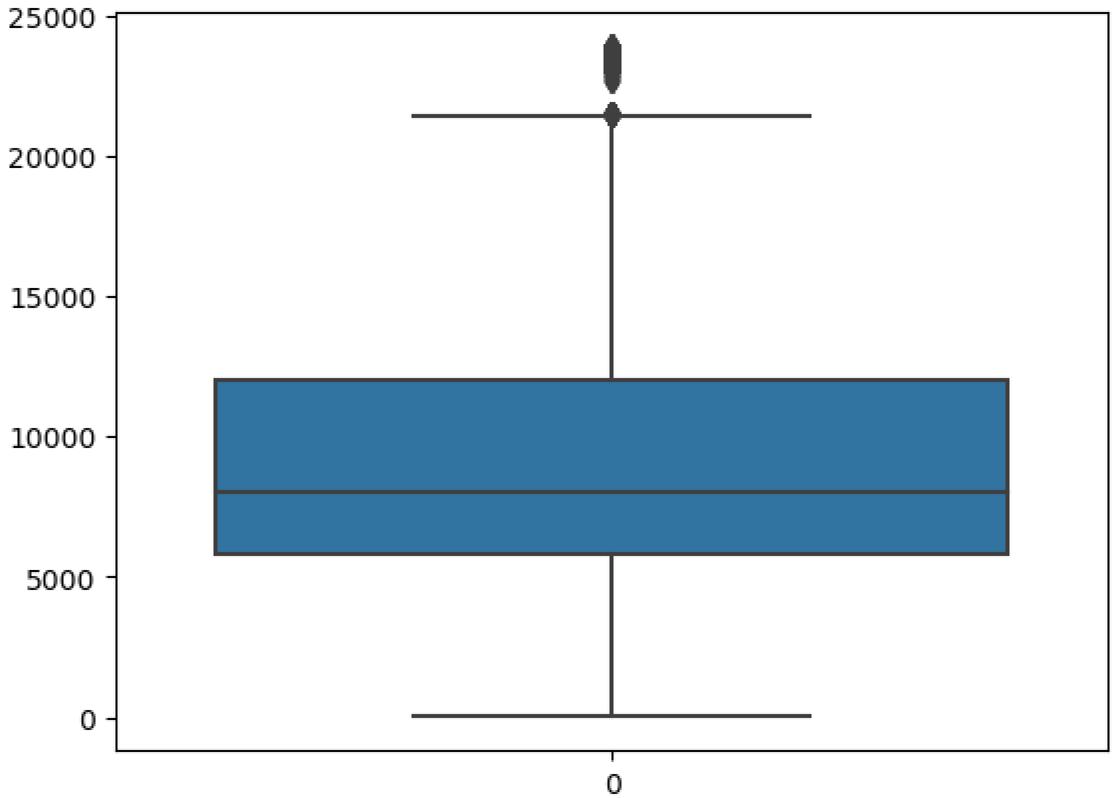
Observations:

- Unlike the popular belief 25% of the users are female and 75% are male. Need to explore more on it
- Users in age Group 26-35 takes ~40% and kids(<18) and old people are only~ 6.75%.
- We can notice a downward trend after the age of 35.
- 35% Staying in the city from 1 year, 18% from 2 years, 17% from 3 years
- 59% of the users are single and 41 % of the users are Married.

Univariate Analysis

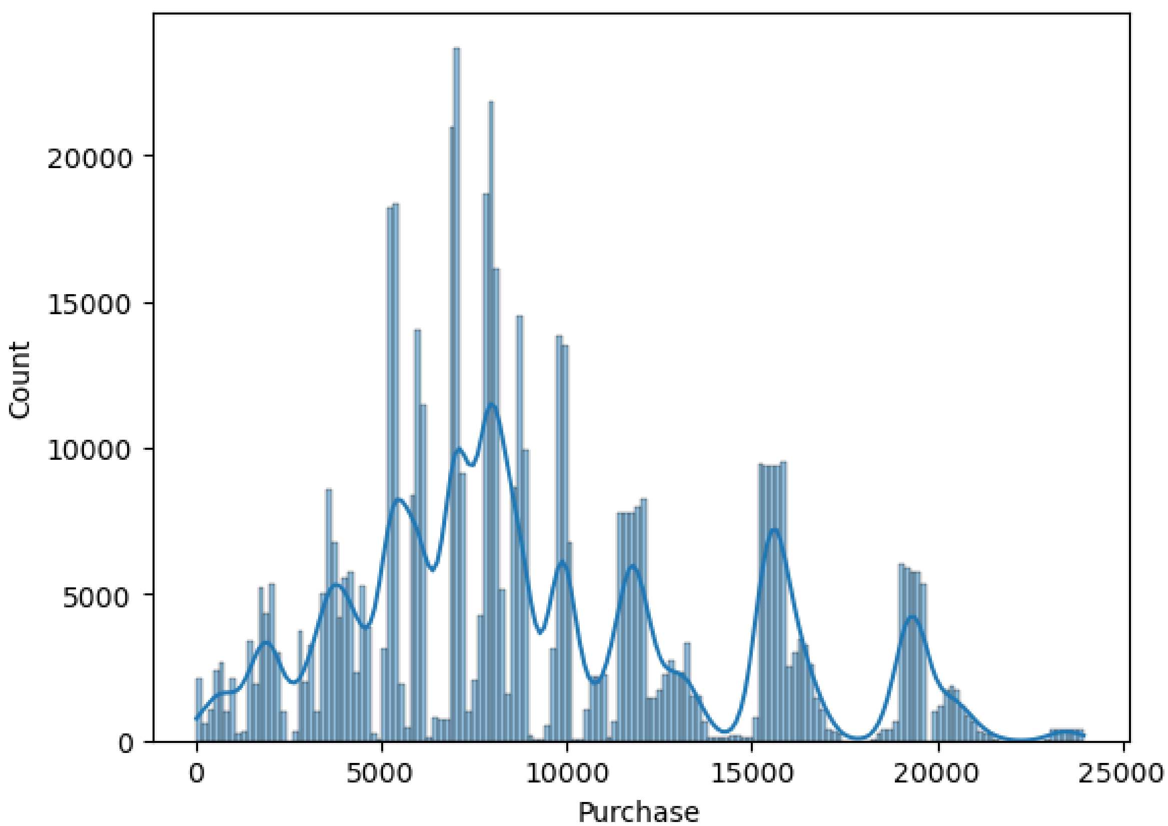
Outlier detection

In [ ]:
```
## Outlier detection
sns.boxplot(df_walmart['Purchase']);
```



We can see that there are lots of out liers in purchase amount.

In [ ]:
```
sns.histplot(df_walmart.Purchase, kde=True);
```



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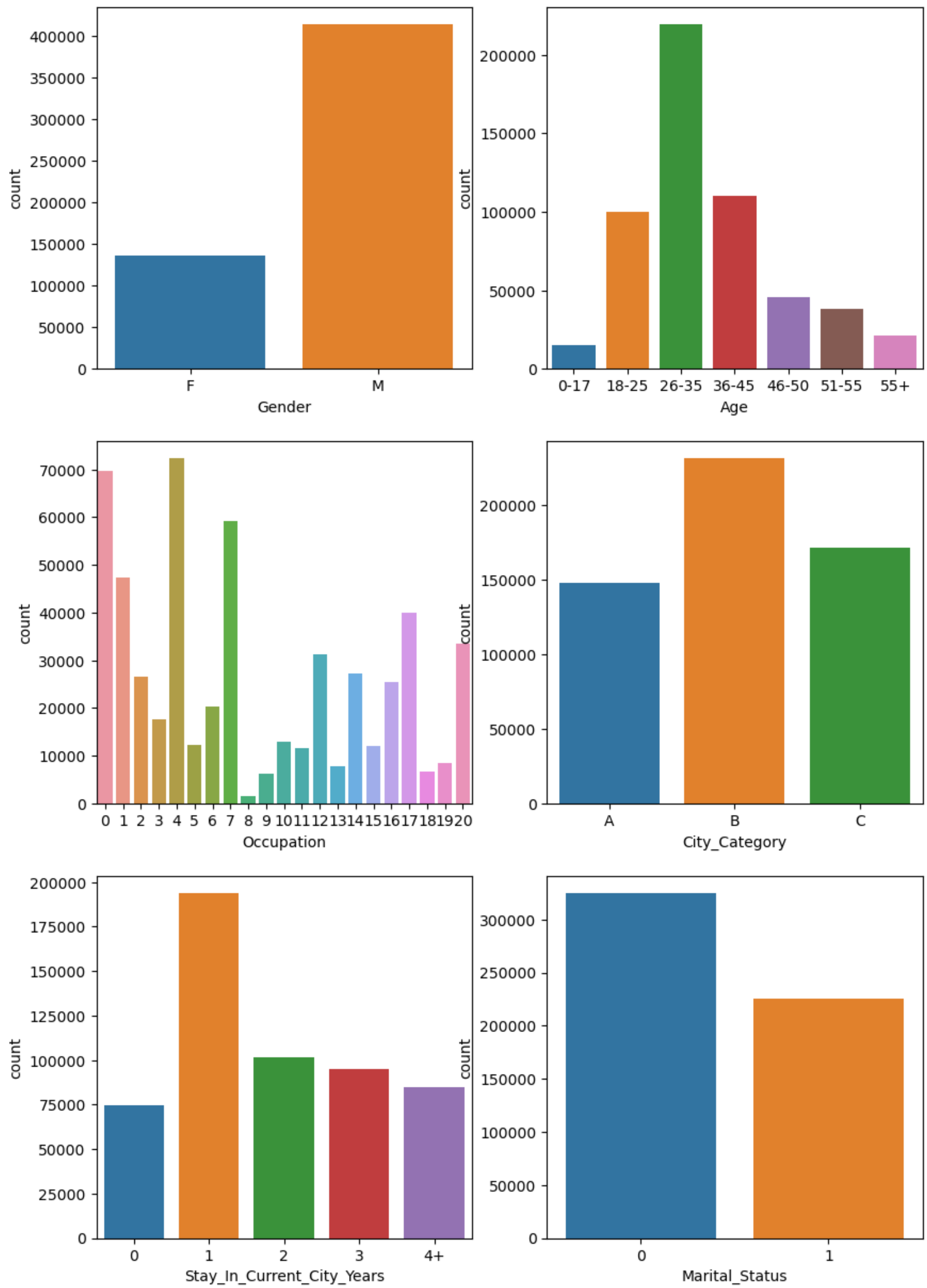
- Categorical variables can only be seen as count plot

In [ ]:
```
fig, axs = plt.subplots(nrows=3, ncols=2, figsize=(10,15))
sns.countplot(data=df_walmart, x='Gender', ax=axs[0,0])
sns.countplot(data=df_walmart, x='Age', ax=axs[0,1])
sns.countplot(data=df_walmart, x='Occupation', ax=axs[1,0])
sns.countplot(data=df_walmart, x='City_Category', ax=axs[1,1])
sns.countplot(data=df_walmart, x='Stay_In_Current_City_Years', ax=axs[2,0])
sns.countplot(data=df_walmart, x='Marital_Status', ax=axs[2,1])
plt.show()
sns.countplot(data=df_walmart, x='Product_Category')
plt.show()
```



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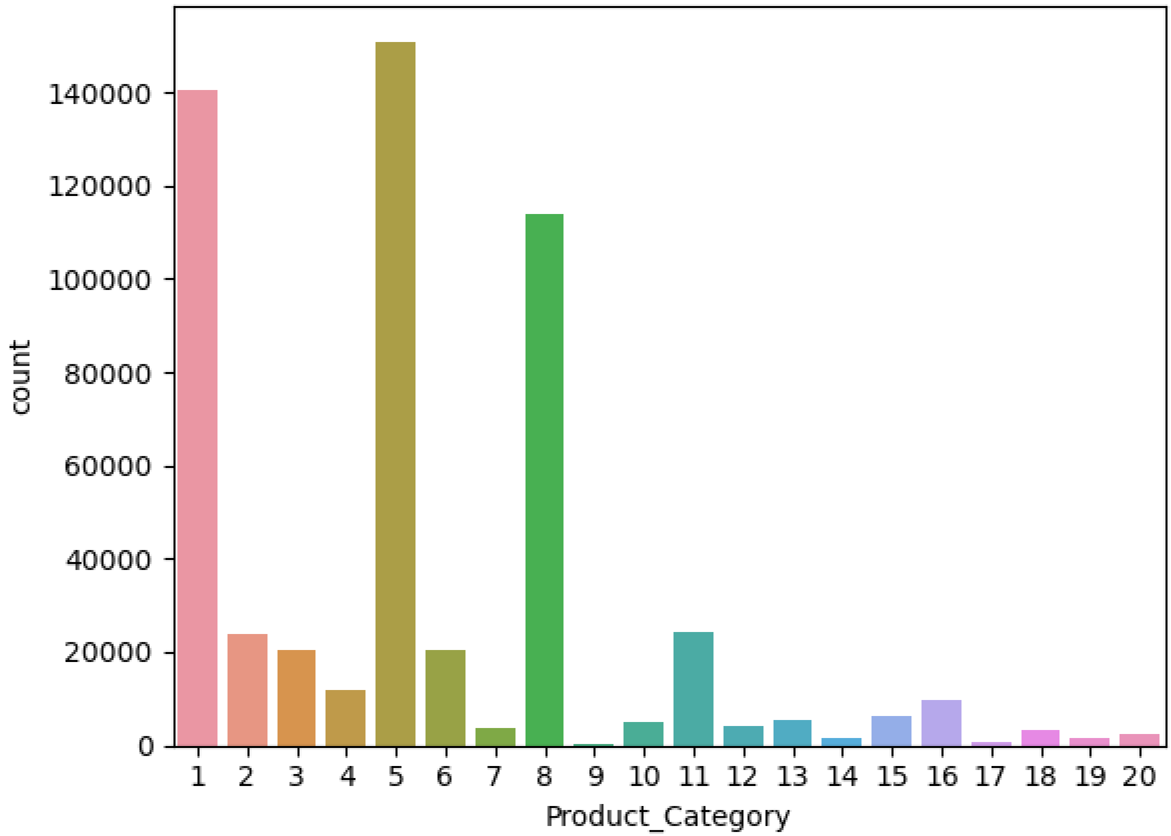

Observations:

- Unlike the popular belief 25% of the users are female and 75% are male. Need to explore more on it
- Users in age Group 26-35 takes ~40% and kids(<18) and old people are only~ 6.75%.
- We can notice a downward trend after the age of 35.
- 35% Staying in the city from 1 year, 18% from 2 years, 17% from 3 years
- 59% of the users are single and 41 % of the users are Married.
- Most of the users belogs to City_category B.
- Single users are more as compared to married people.
- Top 3 Product_Category: 1,5 and 11

Bivariate Analysis

We have 1- Numerical and 9 categorical Variables. For these features following plots can be drawn and anaalysed:

- boxplots, voilonplot,and barplot
- countplot with hue

Boxplot


```
lmart.columns[2:-1].to_list() # consist all of the features exc
```

```
fig, axs = plt.subplots(nrows=3, ncols=2, figsize=(10,15))
count = 0
for row in range(3):
    for col in range(2):
        sns.boxplot(data=df_walmart, x=attrs[count], y='Purchase', ax= axs[r
        count+=1
plt.show()

sns.boxplot(data=df_walmart, y='Purchase', x=attrs[-1])
plt.show()
```

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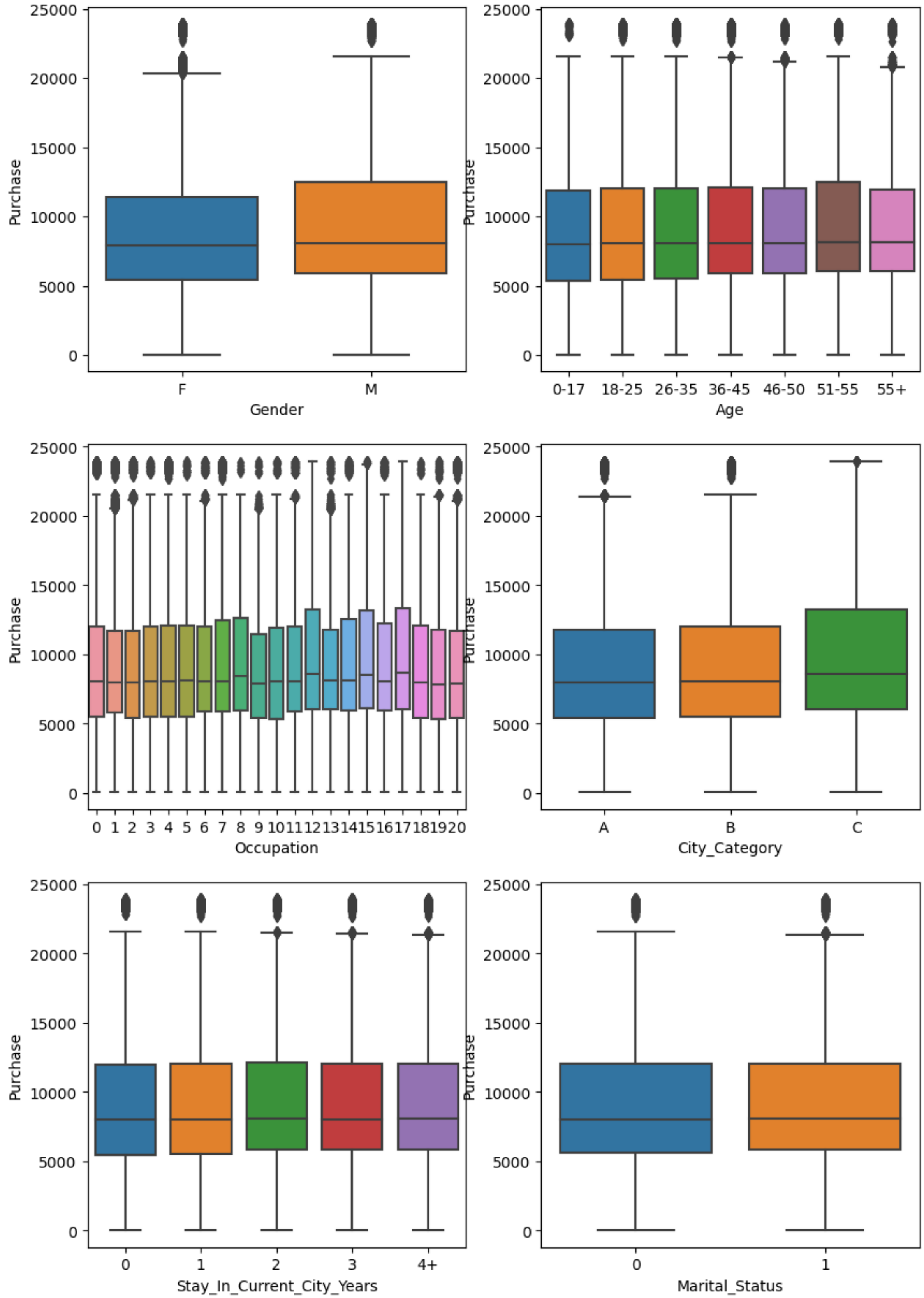

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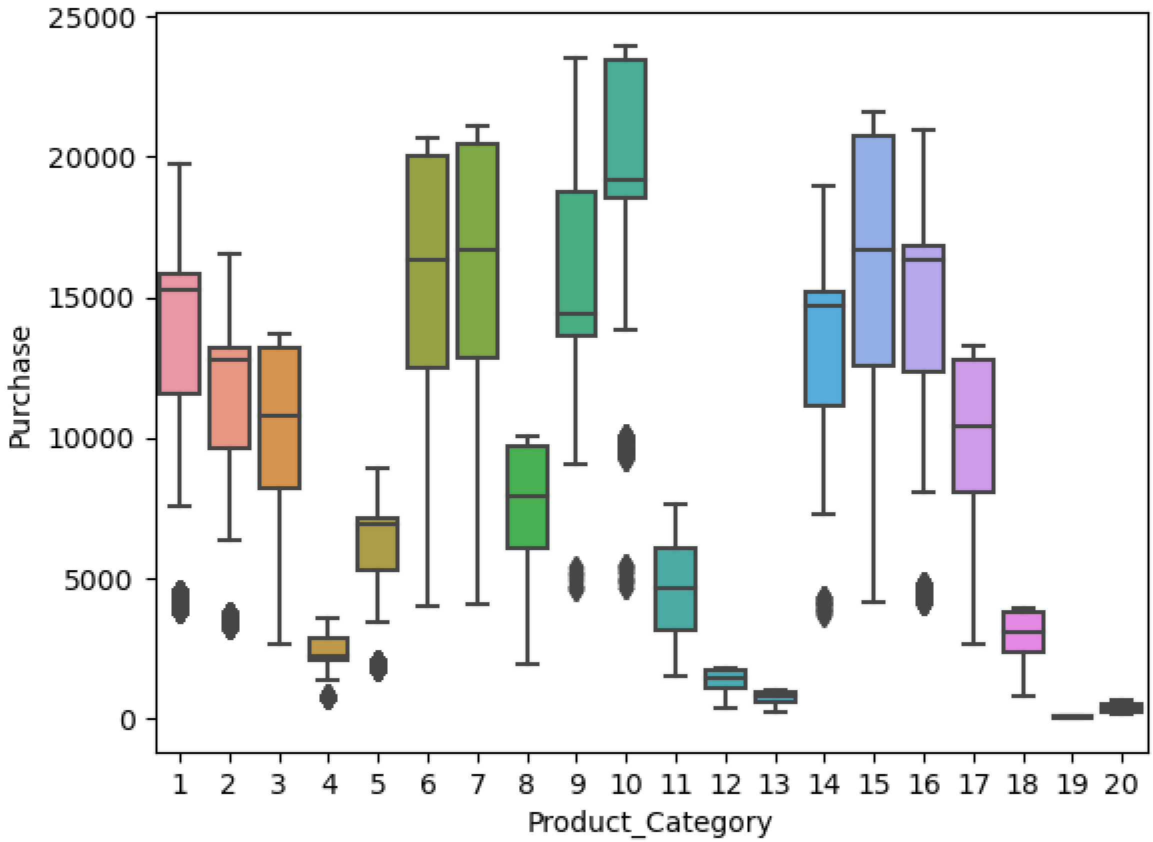

- we can see that there are outlier in all of the factors when we are comparing with respect to the Purchase amount.
- In all of the features the outliers are in the top section except the product category.
- In product category, the outliers are in bottom side of the section.

Violin plot

In [ ]:
```
fig, axs = plt.subplots(nrows=3, ncols=2, figsize=(13,18))
count = 0
for row in range(3):
    for col in range(2):
        sns.violinplot(data=df_walmart, x=attrs[count], y='Purchase', ax= ax
        count+=1
plt.show()

sns.violinplot(data=df_walmart, y='Purchase', x=attrs[-1])
plt.show()
```

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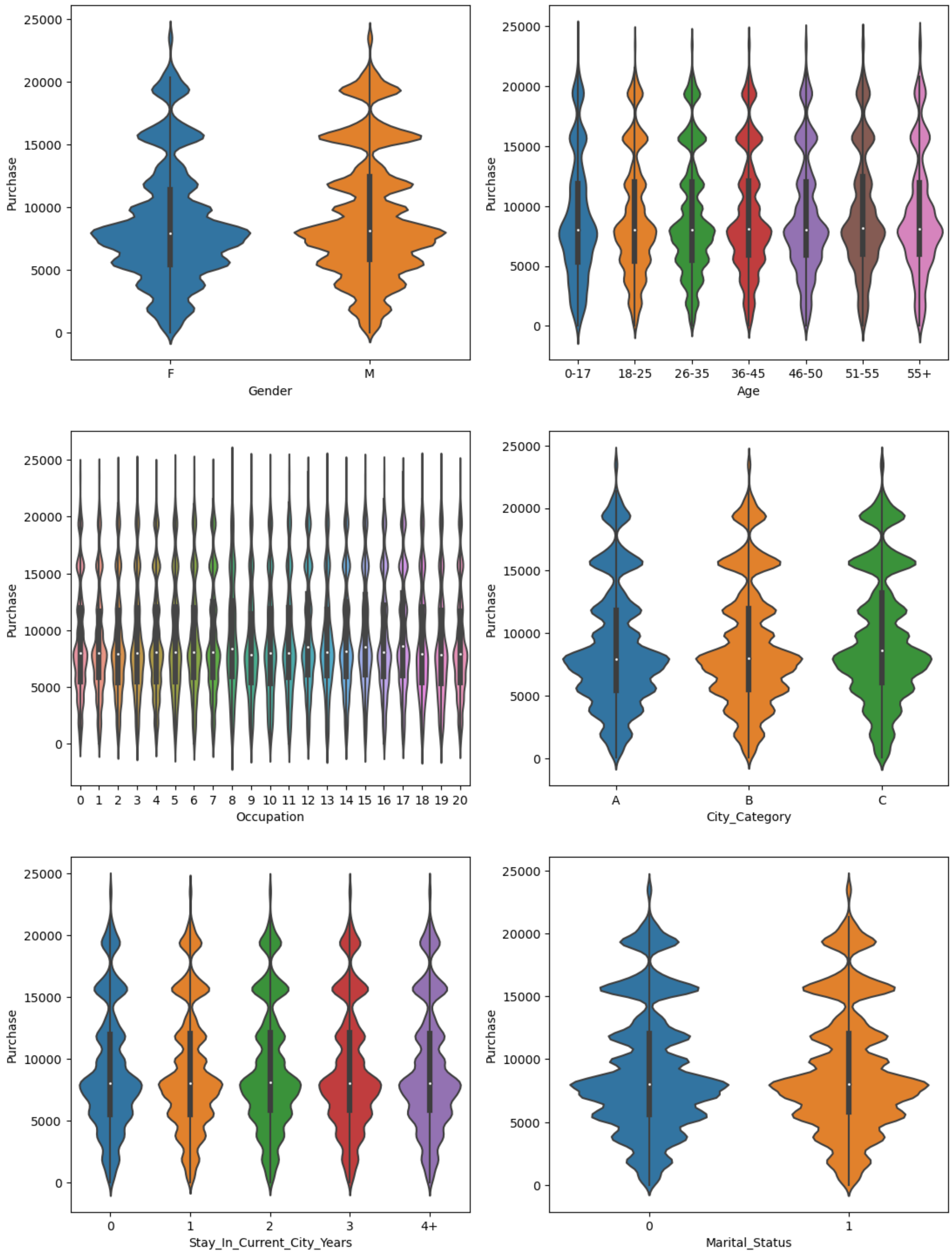
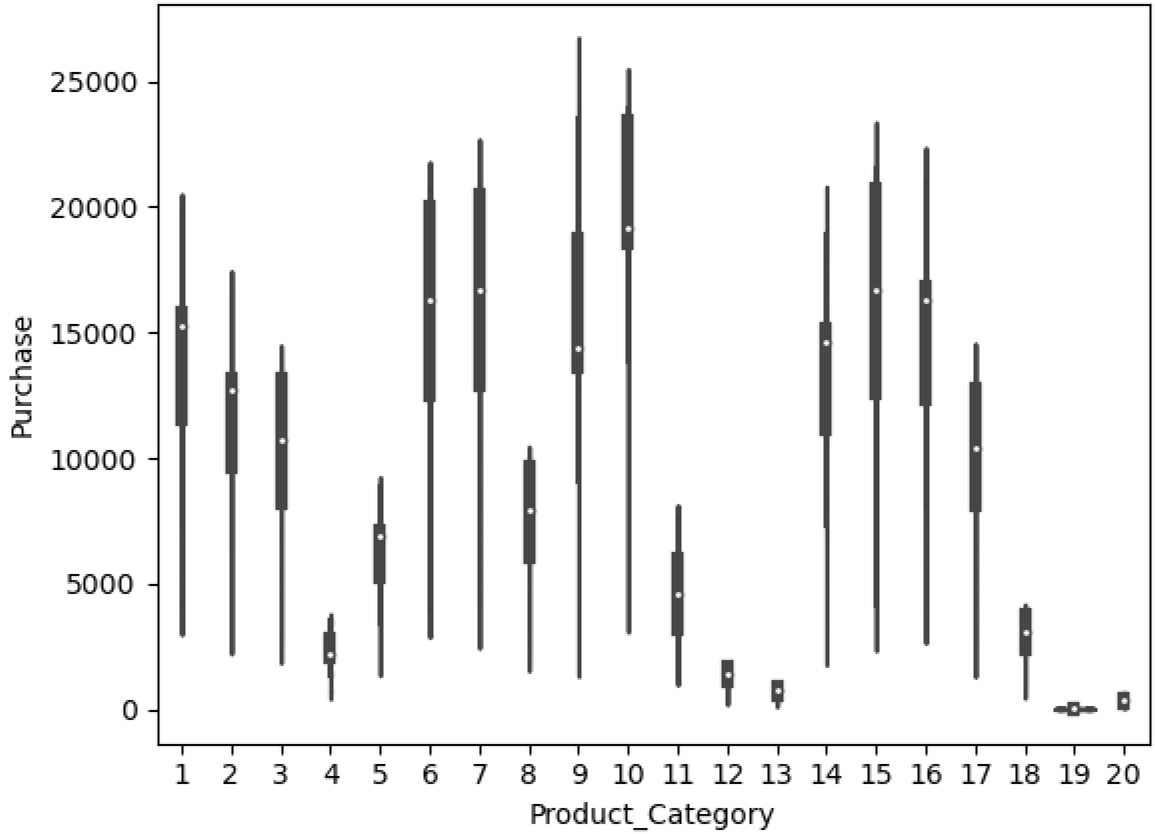

Purchase
0
5000
10000
15000
20000
25000
F
M
Gender
0-17
18-25
26-35
36-45
46-50
51-55
55+
Age
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Occupation
A
B
C
City_Category
0
1
2
3
4+
Stay_In_Current_City_Years
0
1
Marital_Status



- We can notice that the distribution of all the details(e.g. male/female) of all the features are the same.
- Product category has very les distrubiton unable to identify as well.
- The outliers are responsible for a significant amount of purchase. This can be noticed in distribution in all the outliers and purchase.

Bar plots

In [ ]:
```
fig, axs = plt.subplots(nrows=3, ncols=2, figsize=(13,18))
count = 0
for row in range(3):
    for col in range(2):
        sns.barplot(data=df_walmart, x=attrs[count], y='Purchase', ax= axs[r
        count+=1
plt.show()

sns.barplot(data=df_walmart, y='Purchase', x=attrs[-1])
plt.show()
```

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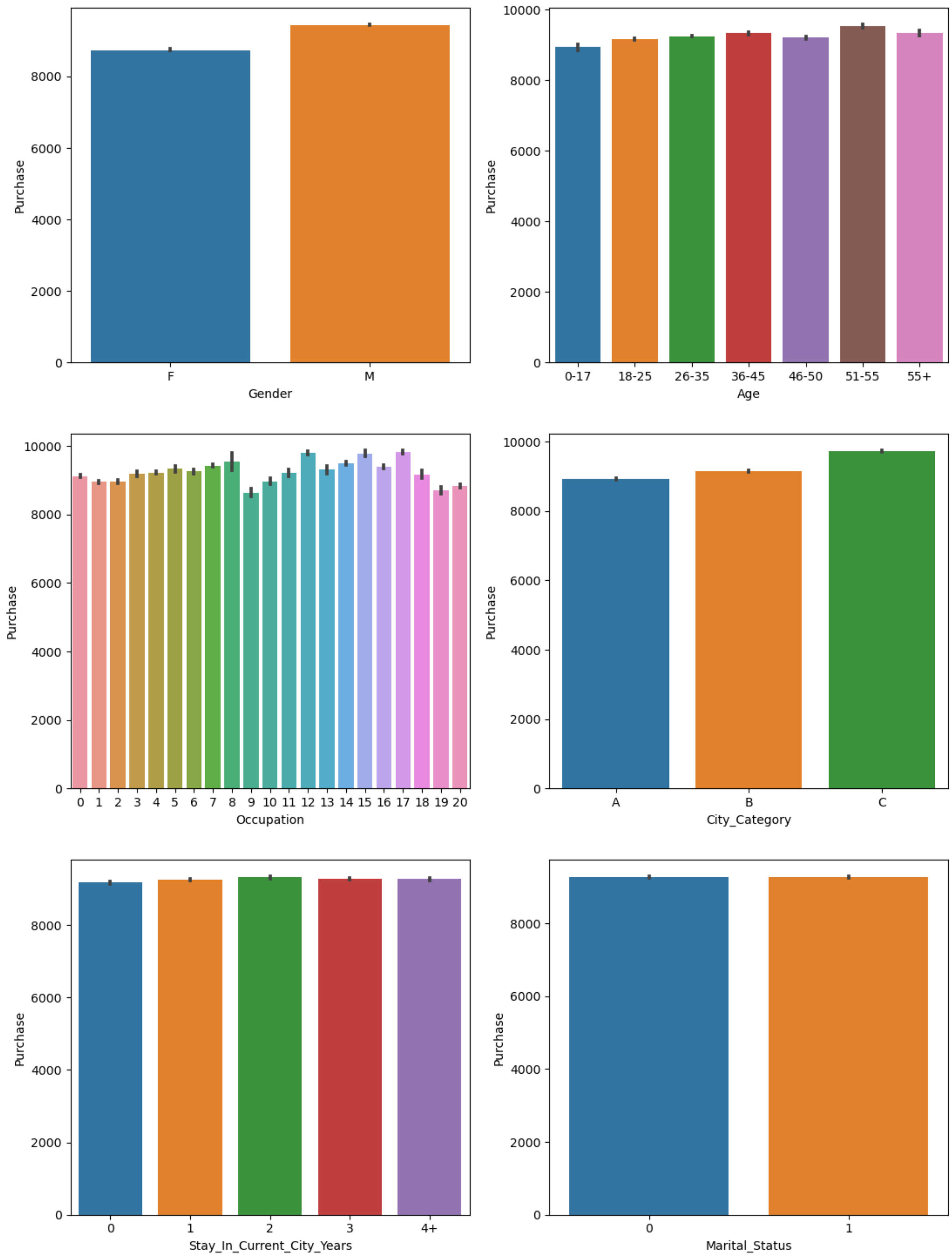
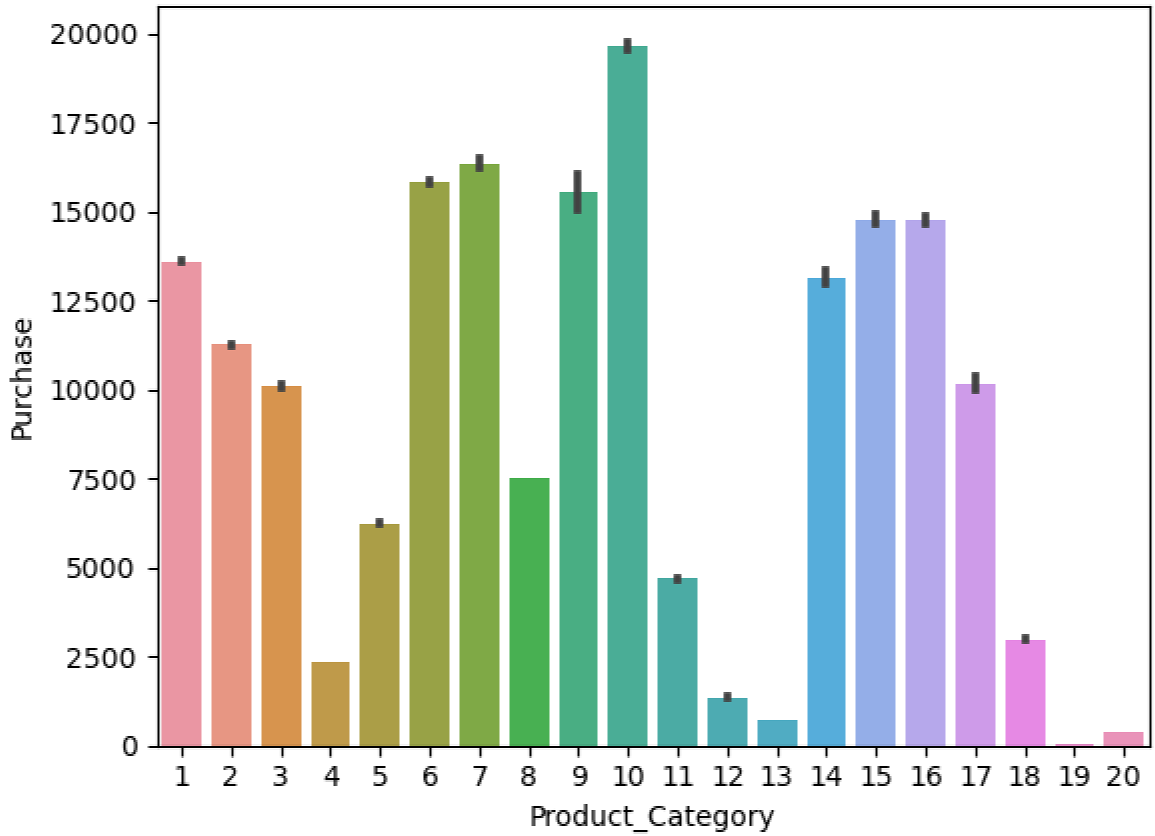

Purchase
0
2000
4000
6000
8000
F
M
Gender
Purchase
0
2000
4000
6000
8000
10000
0-17
18-25
26-35
36-45
46-50
51-55
55+
Age
Purchase
0
2000
4000
6000
8000
10000
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Occupation
Purchase
0
2000
4000
6000
8000
10000
A
B
C
City_Category
Purchase
0
2000
4000
6000
8000
0
1
2
3
4+
Stay_In_Current_City_Years
Purchase
0
2000
4000
6000
8000
0
1
Marital_Status



- Males are purchasing more in comparison to female
- Most purchases are made among product category 10.
- Lowest pruchases are in Product category: 19, 20, 12, and 13.
- Almost all of Age segments are purchasing in stores.
- Occupation 9, 19 and 20 are the ones who purchase the lowest in the stores.
- Order of Purchase City Category wise si C>B>A. This can be because of multiple factors which can be looked into more depth.
- Marital Status and # of years a person is staying in the city doesn't make any difference in this data. Which is a bit odd because if a person is married he will buy more as he lives with family.

Pair Plots

In [ ]:

```
# We can see that pair plots wouldn't make any sense because we have only 1
sns.pairplot(data=df_walmart);
```

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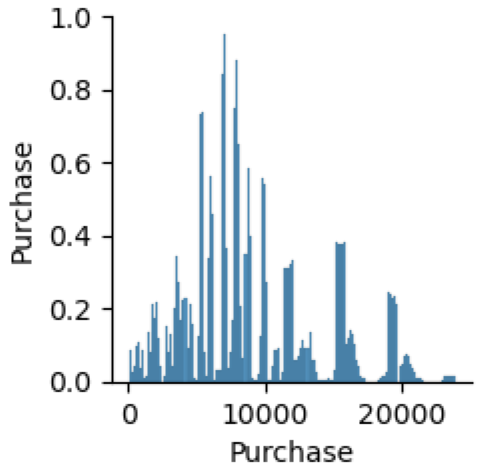


Heat map

- Heat Maps wouldn't make any sense because there is no numerical data

Answering questions

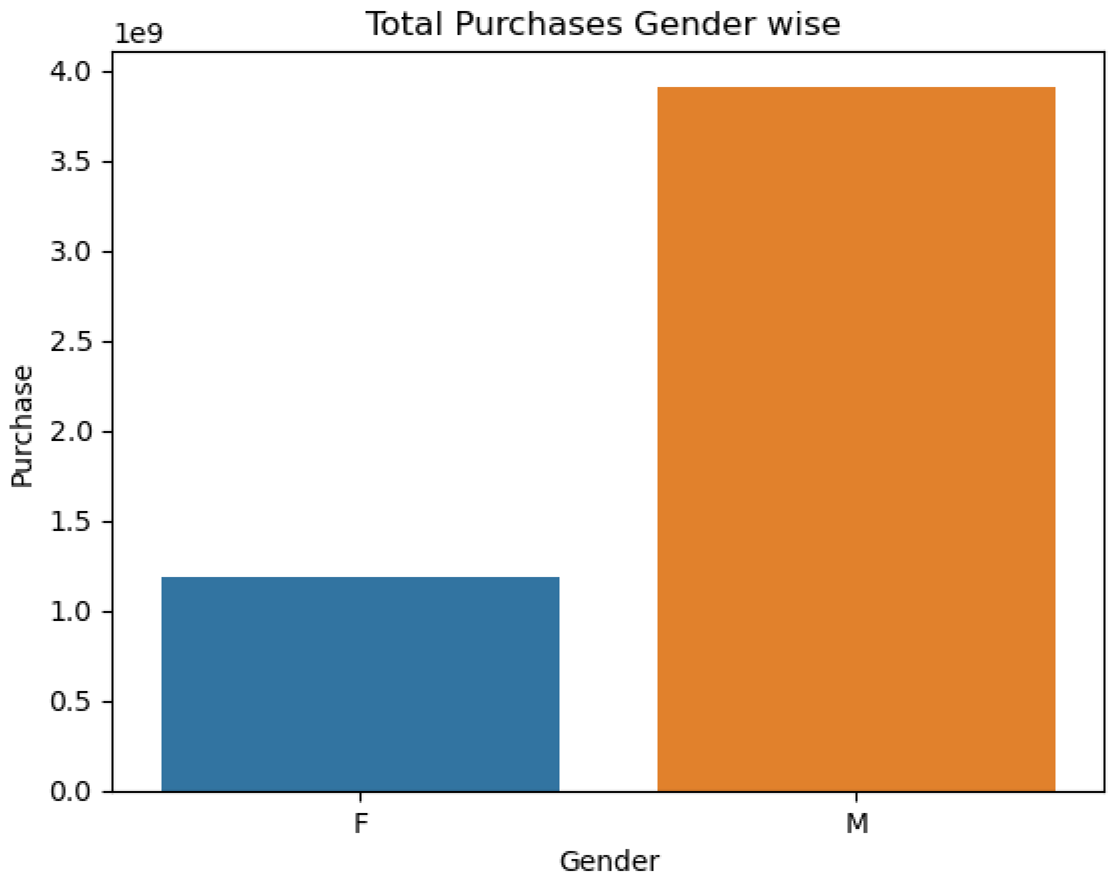
Q1:Are women spending more money per transaction than men? Why or Why not?

In [ ]:
```
df1 = df_walmart.groupby('Gender')['Purchase'].sum().reset_index()
df1
```

Out[ ]:

	Gender	Purchase
0	F	1186232642
1	M	3909580100

In [ ]:
```
# sum of mal
sns.barplot(data = pd.DataFrame(df1), x='Gender', y='Purchase')
plt.title("Total Purchases Gender wise ")
plt.show()
```



In [ ]:
```
df2 = df_walmart.groupby('Gender')['Purchase'].mean().reset_index()
df2
```

Out[ ]:

	Gender	Purchase
0	F	8734.565765
1	M	9437.526040

In [ ]:
```
# sum of mal
sns.barplot(data = pd.DataFrame(df2), x='Gender', y='Purchase')
plt.title("Average of Purchases Gender wise")
plt.show()
```

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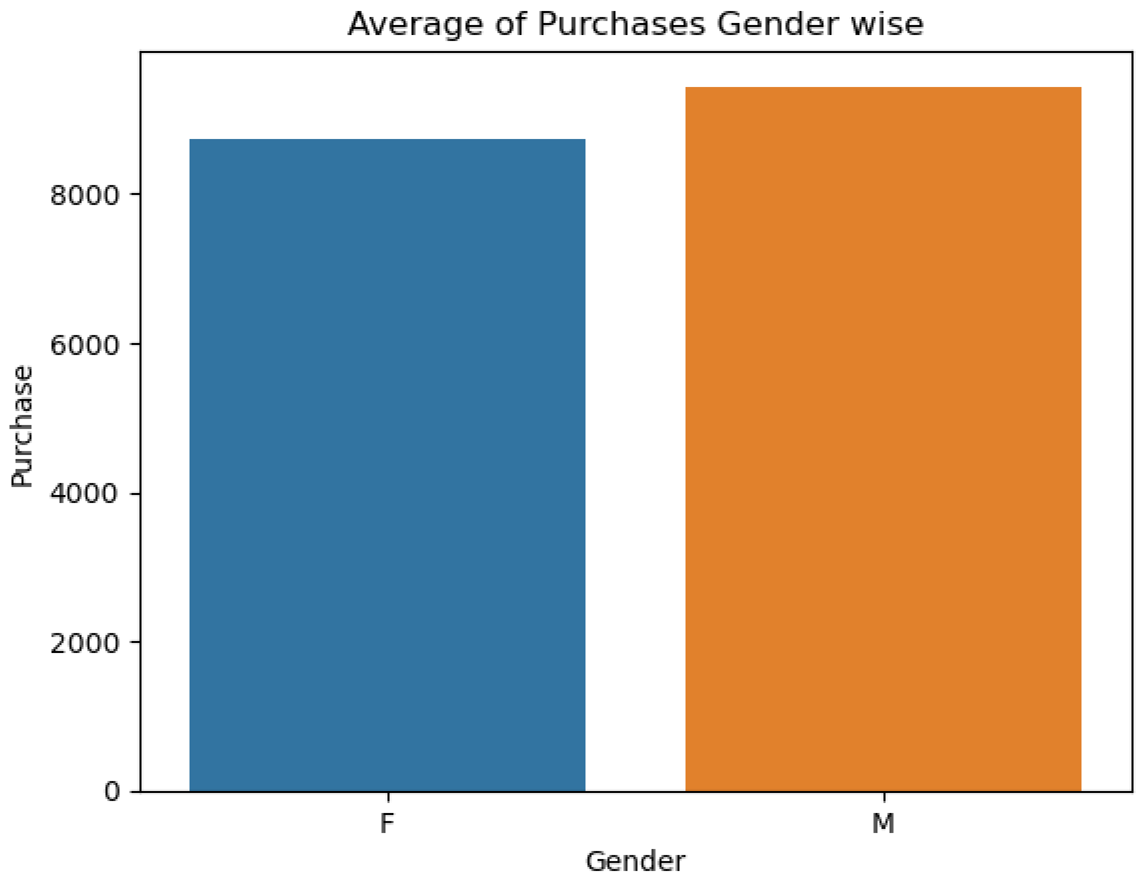
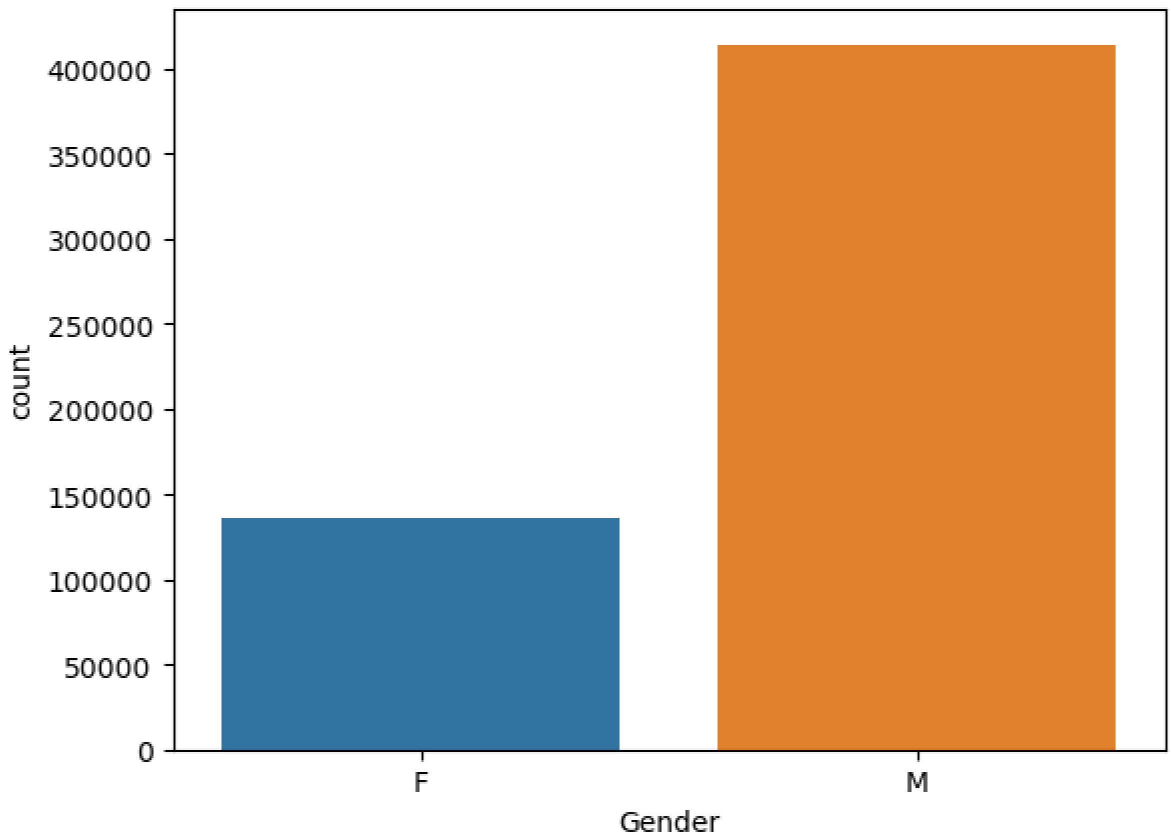


In [ ]:
```
print(df_walmart['Gender'].value_counts(normalize=True)*100)
sns.countplot(data=df_walmart, x='Gender');
```

```
M    75.310507
F    24.689493
Name: Gender, dtype: float64
```



- We can see that most of purchases are made by men in our data.
- This is because of the fact that proportions of female to male is 25%: 75% in our data.
- So we can conclude that females purchase more than males as females with 25% of population has an average of 8734.56 and males with 75% of population has averge 9437.52.

Q2: Confidence intervals and distribution of the mean of the expenses by female and male customers

In [ ]:
```
# number of male and female population
df_walmart['Gender'].value_counts()
```

Out[ ]:
```
M    414259
F    135809
Name: Gender, dtype: int64
```

In [ ]:
```
# df_walmart.groupby(['User_ID', 'Gender'])['Purchase'].nunique(),
df_walmart['User_ID'].nunique()
```

Out[ ]:
```
5891
```

In [ ]:
```
df = pd.DataFrame(df_walmart.groupby(['User_ID', 'Gender'])['Purchase'].sum(
df_purchase_user_wise=df[df['Purchase']!=0][['Gender','Purchase']] # Droping
df_purchase_user_wise
```

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Out[ ]:

	Gender	Purchase
0	F	334093
3	M	810472
5	M	341635
7	M	206468
9	M	821001
...	...	...
11772	F	4116058
11774	F	1119538
11776	F	90034
11778	F	590319
11781	M	1653299

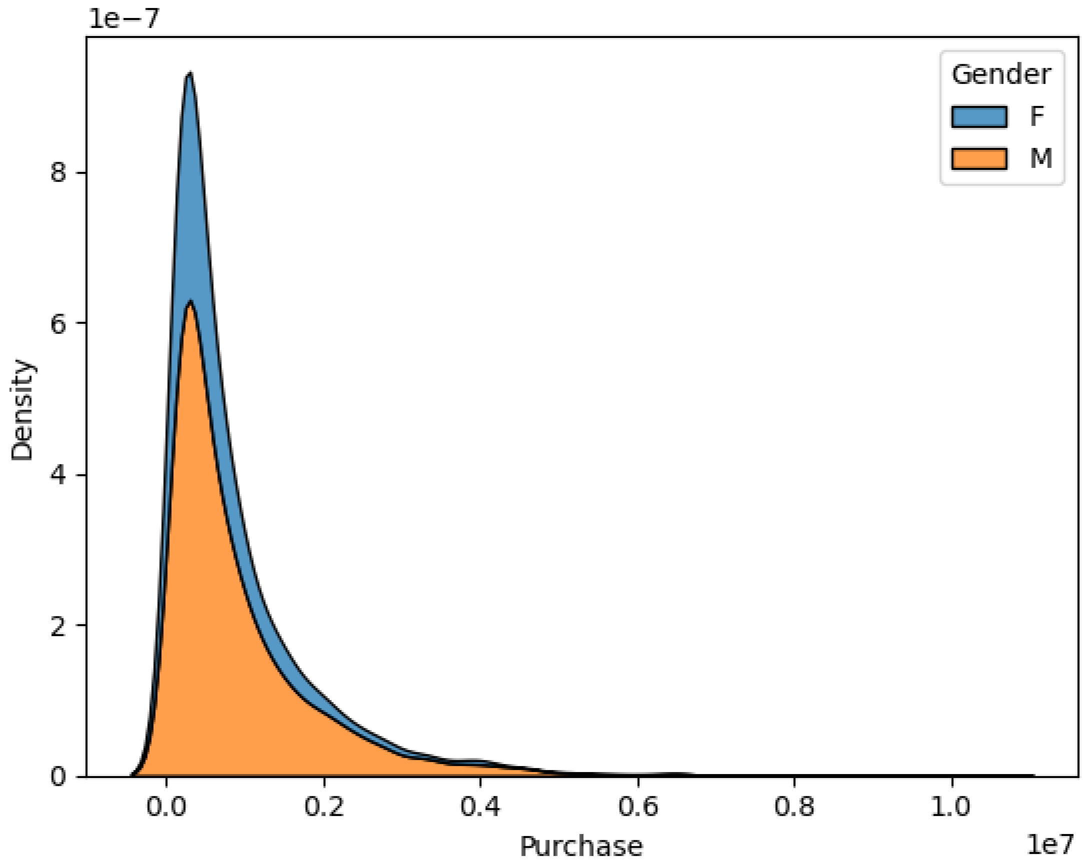
5891 rows × 2 columns

In [ ]:
```
df_purchase_user_wise['Gender'].value_counts()
```

Out[ ]:
```
M    4225
F    1666
Name: Gender, dtype: int64
```

- We can notice that we have only 5891 unique users. These consist of our male and female.

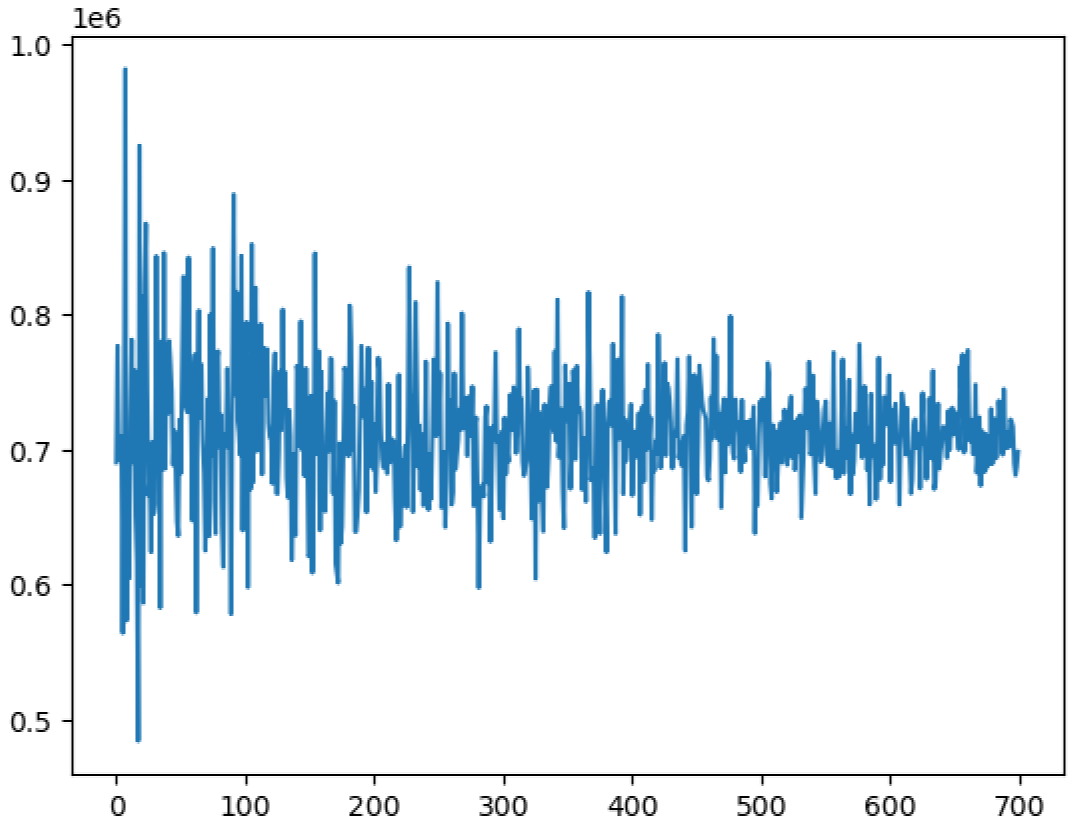
In [ ]:
```
sns.kdeplot(data=df_purchase_user_wise, x='Purchase', hue='Gender', multiple
```



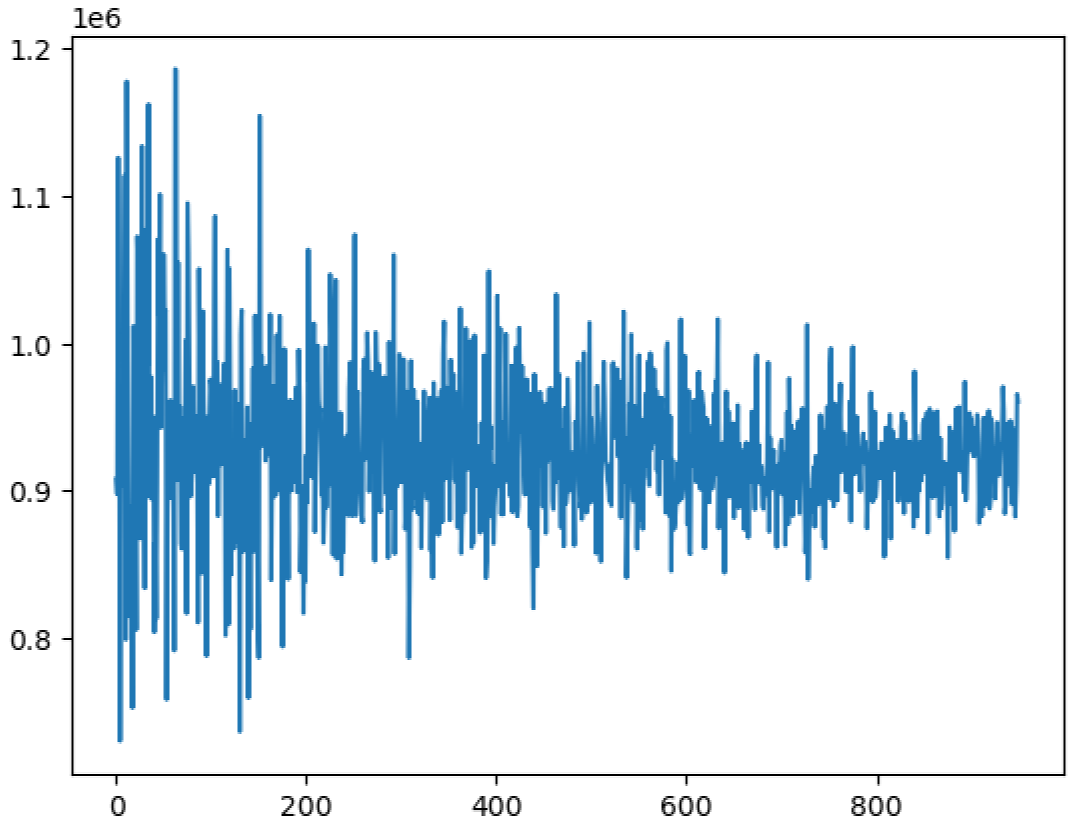
- We can notice that we have only 5891 unique users. These consist of our male and female.
- Female and Male purchases are right Skewed.
- Data being right skewed also points to that we have outlier in expesive purchases. This has been noticed in the above bar plots and violin plots
- We can see that there are only 4225 Males and 1666 Females.

In [ ]:
```
# Creating seperate df to making counfidence interval and population mean
df_female = df_purchase_user_wise[df_purchase_user_wise['Gender']=='F']
df_male = df_purchase_user_wise[df_purchase_user_wise['Gender']=='M']
```

In [ ]:
```
# Trying to find best sample size for female data size
sample_mean_trend = []
for i in np.arange(50,750):
    sample =df_female['Purchase'].sample(i)
    sample_mean_trend.append(np.mean(sample))
plt.plot(sample_mean_trend)
plt.show()
```



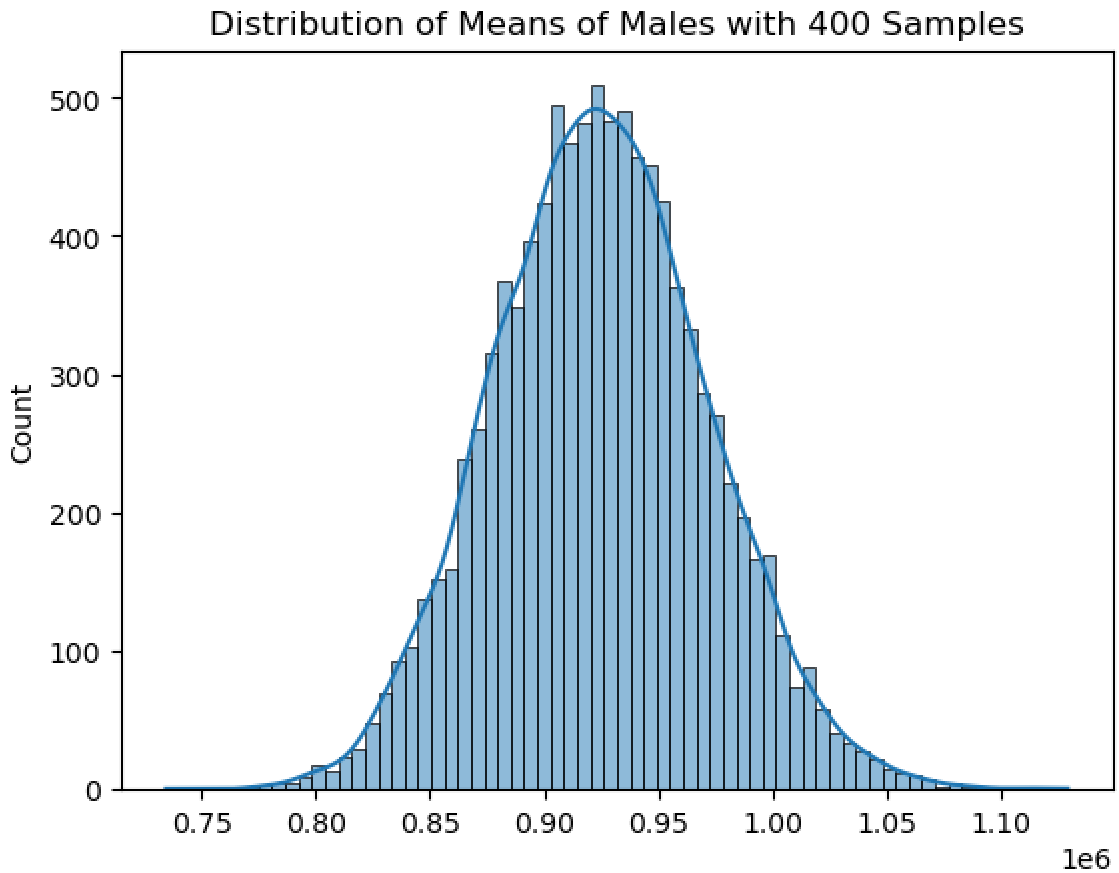
In [ ]:
```
# Trying to find best sample size for male data size
sample_mean_trend = []
for i in np.arange(50,1000):
    sample =df_male['Purchase'].sample(i)
    sample_mean_trend.append(np.mean(sample))
plt.plot(sample_mean_trend);
```



- There is not much change after 400 for both male and female. Hence Taking 400 as sample size for male and female.

Plotting 400 samples and trying to predict population mean

In [ ]:
```
num_samples = 400
female_collect_sample_means = []
for person in range(10000):
    sample_mean = df_male['Purchase'].sample(num_samples).mean()
    female_collect_sample_means.append(sample_mean)
sns.histplot(female_collect_sample_means, kde=True)
plt.title("Distribution of Means of Males with 400 Samples");
```



In [ ]:

```
num_samples = 400
male_collect_sample_means = []
for person in range(10000):
    sample_mean = df_female['Purchase'].sample(num_samples).mean()
    male_collect_sample_means.append(sample_mean)
sns.histplot(male_collect_sample_means, kde=True)
plt.title("Distribution of Means of Females with 400 Samples");
```

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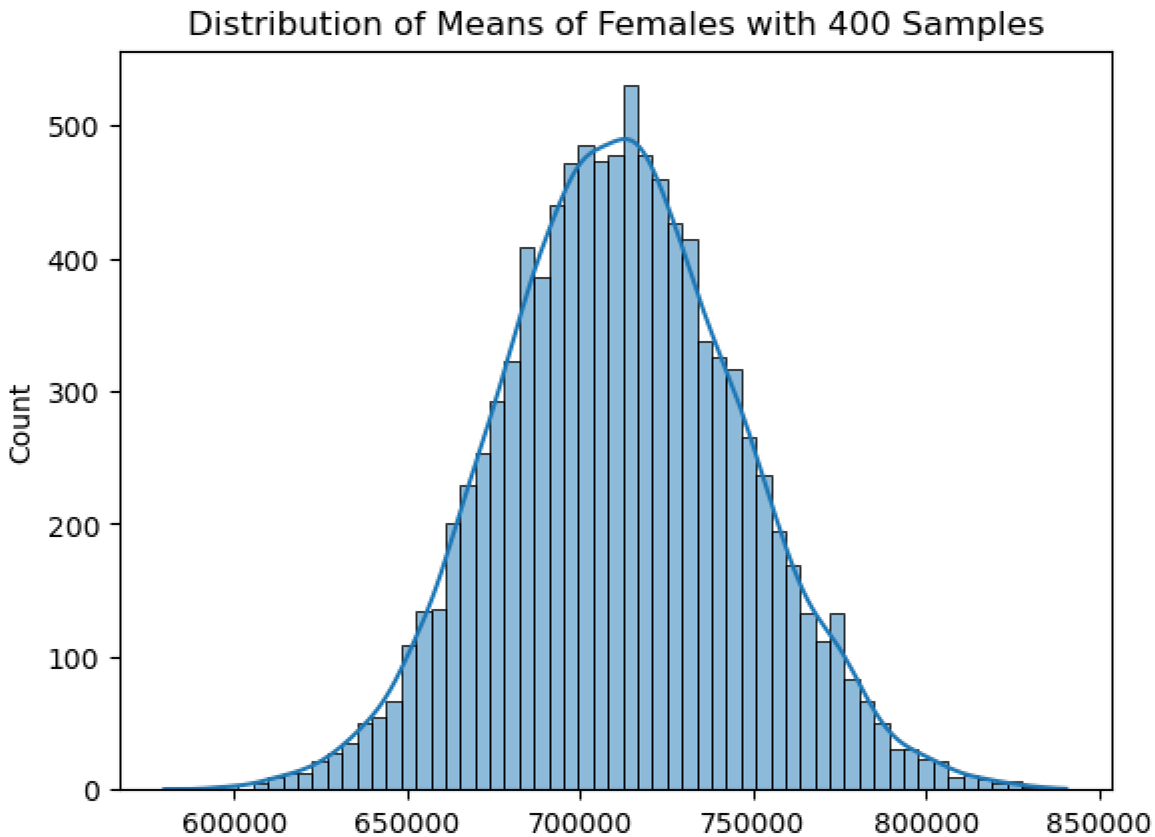

- We can notice here that the Central Limit Theoram has been proved right. The deistribution with 400 samples is gaussian in the end.

In [ ]:
```
np.mean(male_collect_sample_means), np.mean(female_collect_sample_means)
print(f"Predicted Population means of the males: ${np.round(np.mean(male_col
print(f"Predicted Population means of the females: ${np.round(np.mean(female
```

```
Predicted Population means of the males: $711775.68
Predicted Population means of the females: $924637.31
```

In [ ]:
```
m_upper = np.round(np.percentile(male_collect_sample_means, 97.5),2)
m_lower = np.round(np.percentile(male_collect_sample_means, 2.5),2)
f_upper = np.round(np.percentile(female_collect_sample_means, 97.5),2)
f_lower = np.round(np.percentile(female_collect_sample_means, 2.5),2)
print(f"95% Confidence Interval Population means of the males: ({m_upper}, {
print(f"95% Confidence Interval Population means of the females: ({f_upper},
```

```
95% Confidence Interval Population means of the males: (781561.77, 645098.
8)
95% Confidence Interval Population means of the females: (1018094.65, 83511
4.76)
```

Q3: Are confidence intervals of average male and female spending overlapping? How can Walmart leverage this conclusion to make changes or improvements?

In [ ]:
```
fig, axs =plt.subplots()
```

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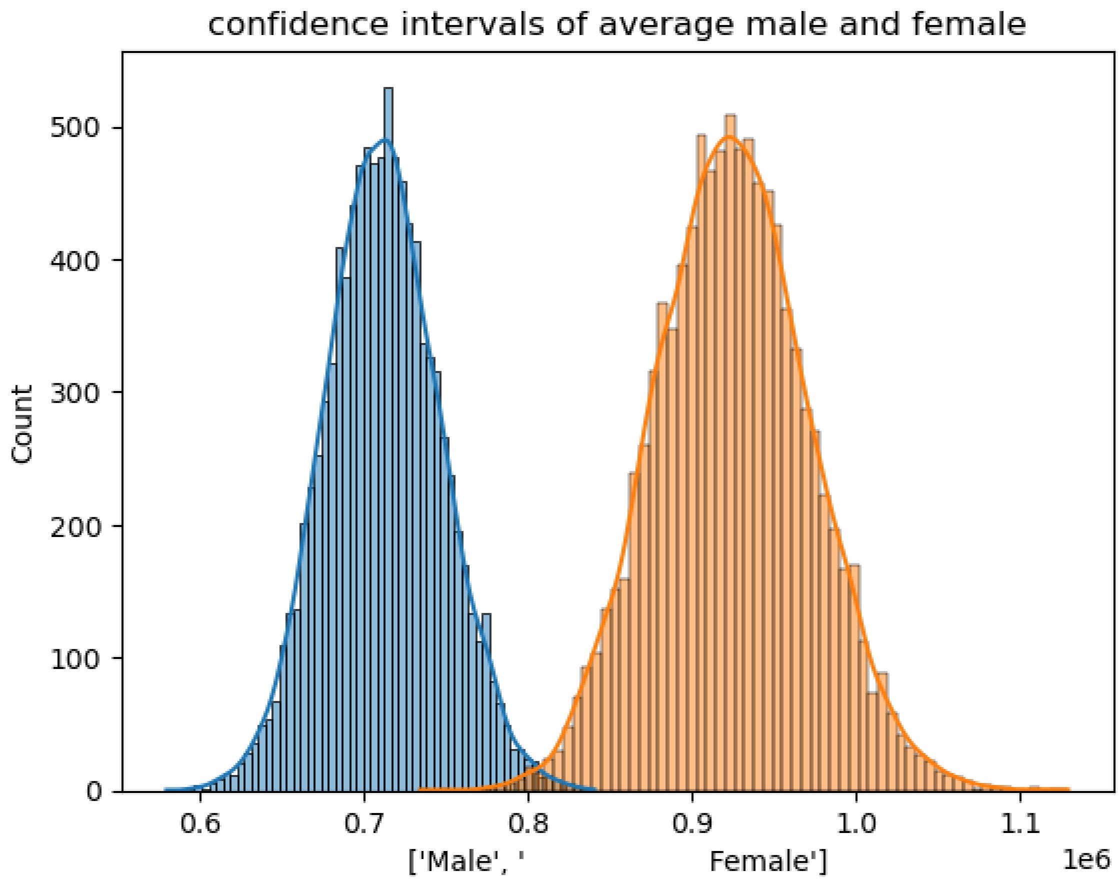
```
sns.histplot(male_collect_sample_means, kde=True, legend=True)
sns.histplot(female_collect_sample_means, kde=True,legend=True)

plt.title("confidence intervals of average male and female")
plt.xlabel(['Male',"                     "'Female']);
```



- We can clearly see that the confidence interval of Males and Females doesn't overlap.
- 95% Confidence Interval Population means of the males: (782751.49, 645250.8)
- 95% Confidence Interval Population means of the females: (1020105.31, 834682.2)
- It is very beneficial for the wallmart as male and female can be easily targeted audiances are different. So walmart can easily dedicate the product in the price range as per the data. For example the females tend to spend more and they female products can be priced accordingly.

Q4: Married vs Unmarried

Are Married spending more money per transaction than unmarried? Why or Why not?

In [ ]:
```
df1 = df_walmart.groupby('Marital_Status')['Purchase'].sum().reset_index()
```

In [ ]:
```
# sum of mal
sns.barplot(data = pd.DataFrame(df1), x='Marital_Status', y='Purchase')
```

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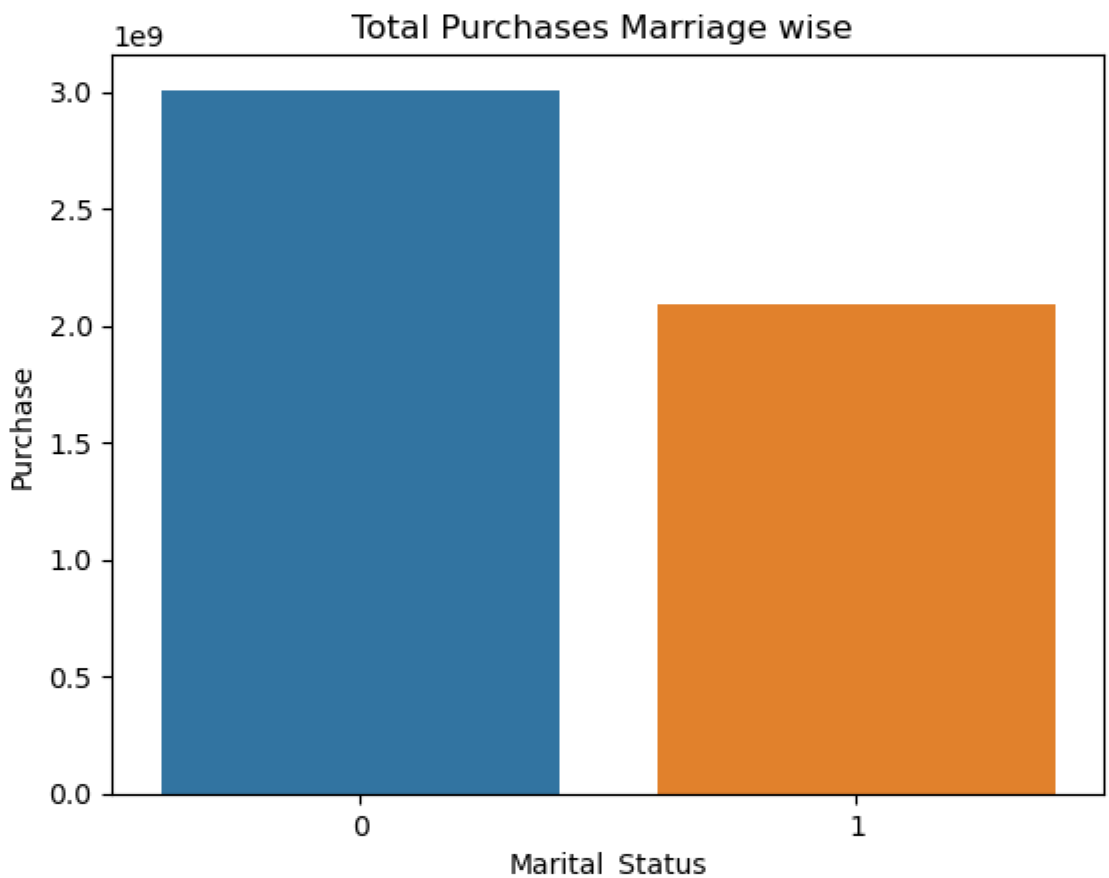
```
plt.title("Total Purchases Marriage wise ")
plt.show()
```



In [ ]:
```
df2 = df_walmart.groupby('Marital_Status')['Purchase'].mean().reset_index()
df2
```

Out[ ]:

	Marital_Status	Purchase
0	0	9265.907619
1	1	9261.174574

In [ ]:
```
sns.barplot(data = pd.DataFrame(df2), x='Marital_Status', y='Purchase')
plt.title("Average of Purchases Marital_Status wise")
plt.show()
```

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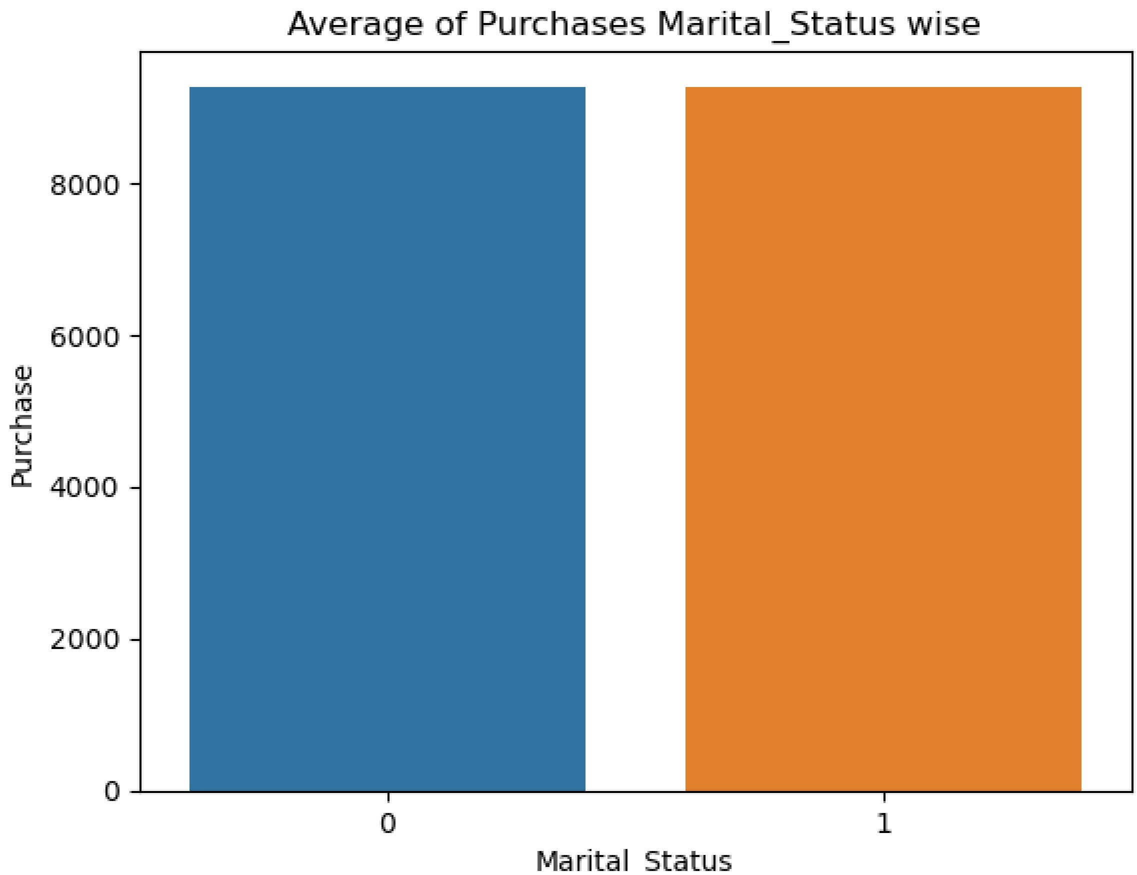

In [ ]:
```
print(df_walmart['Marital_Status'].value_counts(normalize=True)*100)
sns.countplot(data=df_walmart, x='Marital_Status');
```

```
0    59.034701
1    40.965299
Name: Marital_Status, dtype: float64
```

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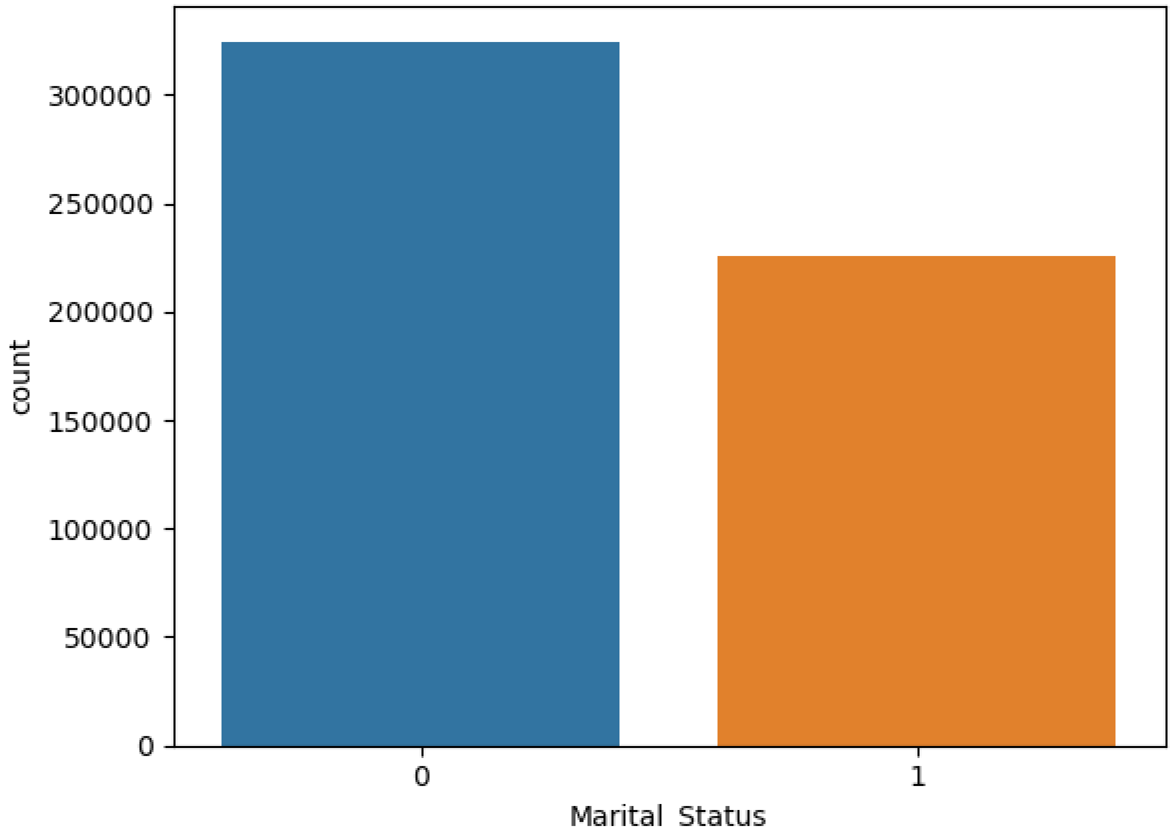

- Unmarried People has done more Purchases than married people.
- Average sales comes to be almost equal.

Confidence intervals and distribution of the mean of the expenses by Marital Status wise customers

In [ ]:
```
# number of people Marital_Status wise
df_walmart['Marital_Status'].value_counts()
```

Out[ ]:
```
0    324731
1    225337
Name: Marital_Status, dtype: int64
```

In [ ]:
```
df = pd.DataFrame(df_walmart.groupby(['User_ID', 'Marital_Status'])['Purchas
df_purchase_marital_status_wise=df[df['Purchase']!=0][['Marital_Status','Pur
df_purchase_marital_status_wise
```

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Out[ ]:

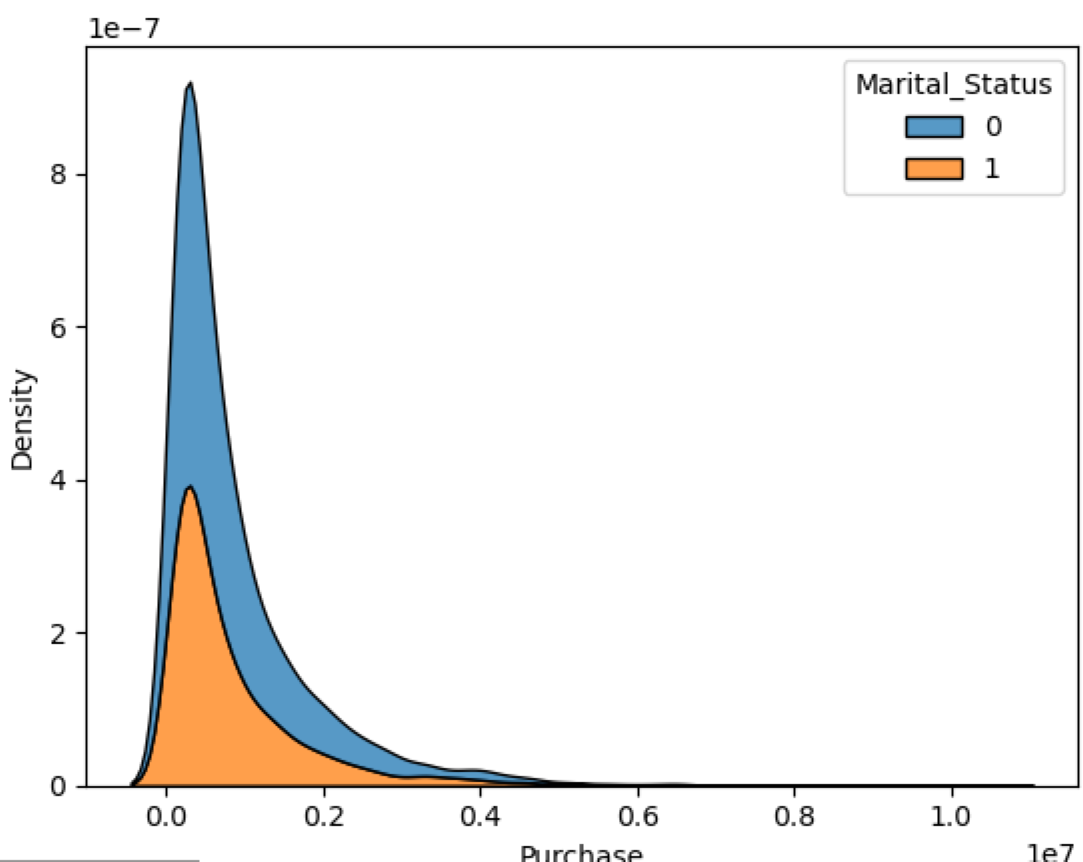
	Marital_Status	Purchase
0	0	334093
2	0	810472
4	0	341635
7	1	206468
9	1	821001
...	...	...
11773	1	4116058
11774	0	1119538
11776	0	90034
11779	1	590319
11780	0	1653299

5891 rows × 2 columns

In [ ]:
```
df_purchase_marital_status_wise['Marital_Status'].value_counts()
```

Out[ ]:
```
0    3417
1    2474
Name: Marital_Status, dtype: int64
```

In [ ]:
```
sns.kdeplot(data=df_purchase_marital_status_wise, x='Purchase', hue='Marital
```



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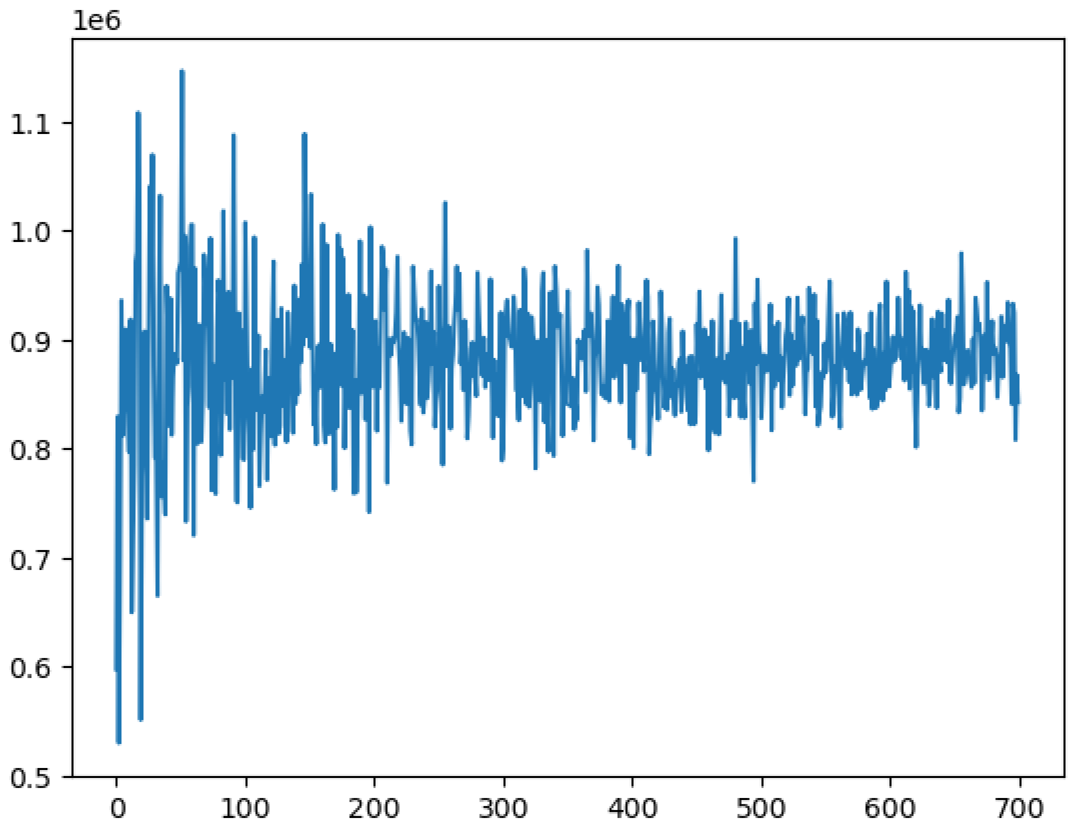
- There are 3417 unmarried and 2474 married people
- Data being right skewed also points to that we have outlier in expesive purchases. This has been noticed in the above bar plots and violin plots

In [ ]:
```
# Creating seperate df to making counfidence interval and population mean
df_unmarried = df_purchase_marital_status_wise[df_purchase_marital_status_wi
df_married = df_purchase_marital_status_wise[df_purchase_marital_status_wise
```

In [ ]:
```
# Trying to find best sample size for unmarried data size
sample_mean_trend = []
for i in np.arange(50,750):
    sample =df_unmarried['Purchase'].sample(i)
    sample_mean_trend.append(np.mean(sample))
plt.plot(sample_mean_trend)
plt.show()
```



In [ ]:
```
# Trying to find best sample size for married data size
sample_mean_trend = []
for i in np.arange(50,750):
    sample =df_married['Purchase'].sample(i)
    sample_mean_trend.append(np.mean(sample))
plt.plot(sample_mean_trend)
plt.show()
```

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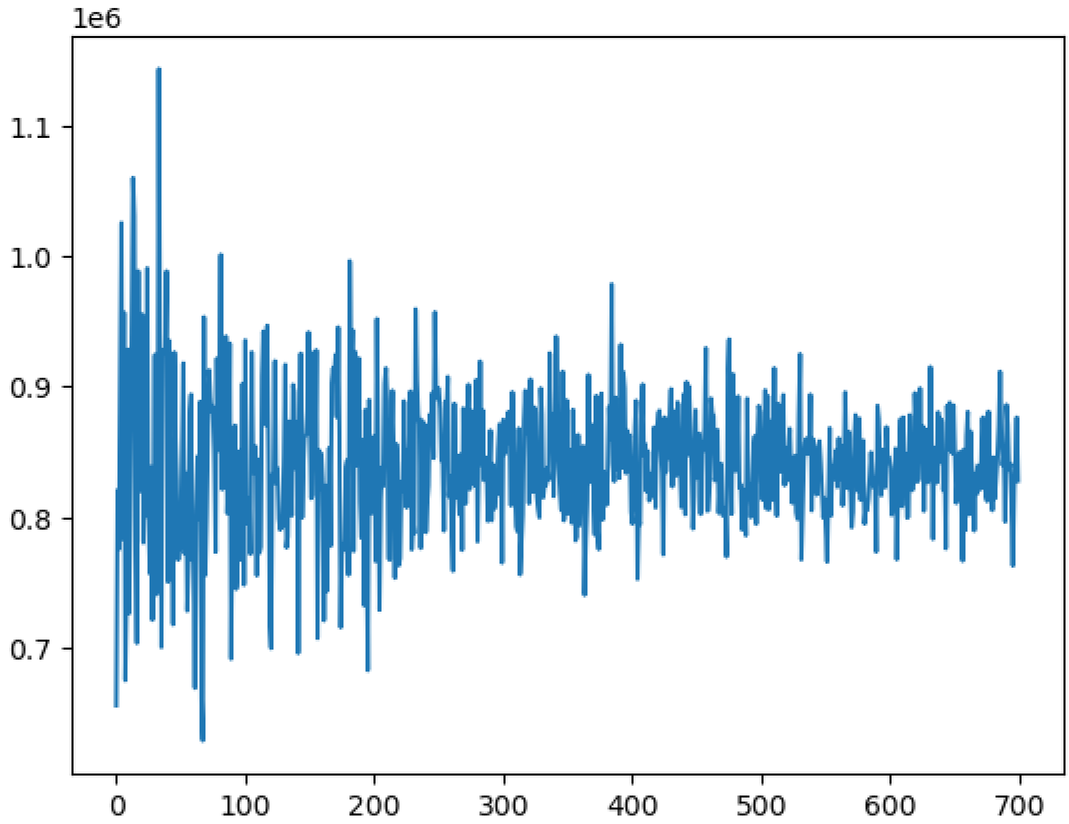
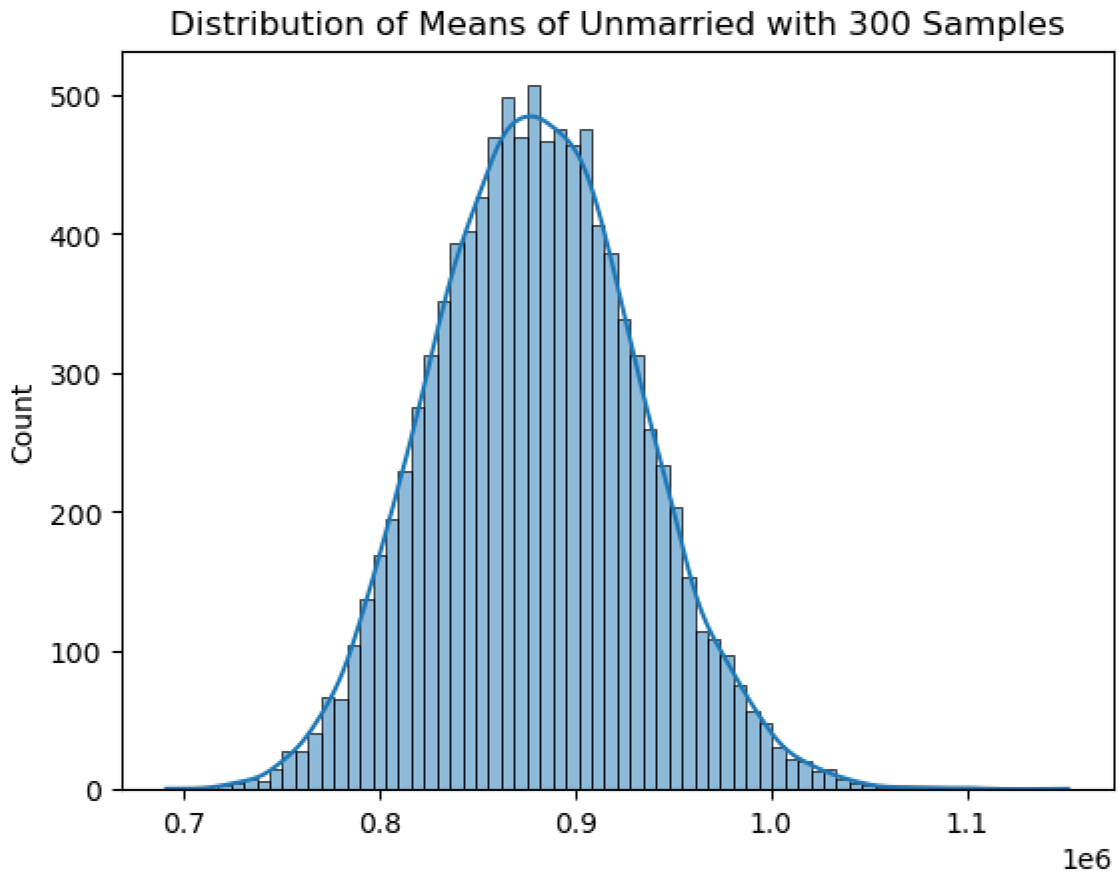


- We can see that 300 sample size seems to be perfect

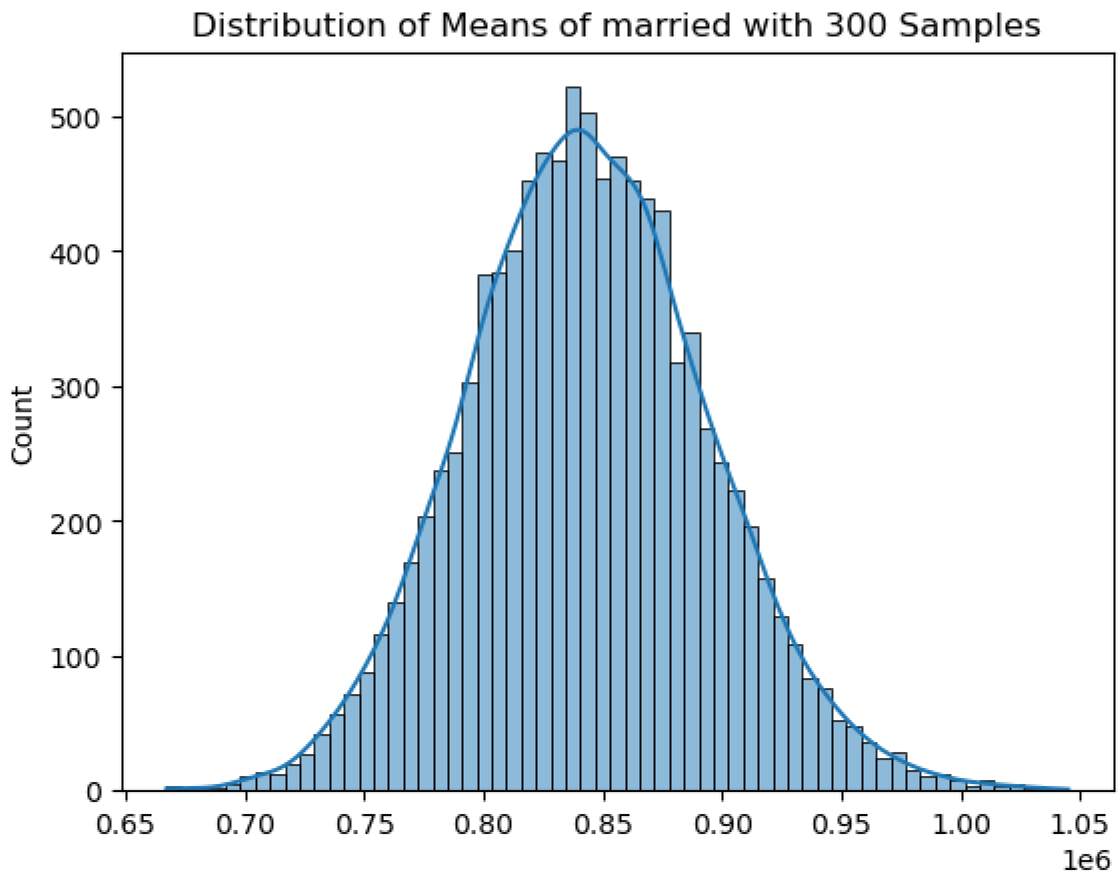
Plotting 300 samples and trying to predict population mean

In [ ]:
```
num_samples = 300
unmarried_collect_sample_means = []
for person in range(10000):
    sample_mean = df_unmarried['Purchase'].sample(num_samples).mean()
    unmarried_collect_sample_means.append(sample_mean)
sns.histplot(unmarried_collect_sample_means, kde=True)
plt.title("Distribution of Means of Unmarried with 300 Samples");
```



In [ ]:

```
num_samples = 300
married_collect_sample_means = []
for person in range(10000):
    sample_mean = df_married['Purchase'].sample(num_samples).mean()
    married_collect_sample_means.append(sample_mean)
sns.histplot(married_collect_sample_means, kde=True)
plt.title("Distribution of Means of married with 300 Samples");
```



In [ ]:
```
np.mean(unmarried_collect_sample_means), np.mean(married_collect_sample_mear
print(f"Predicted Population means of the Unmarried: ${np.round(np.mean(unma
print(f"Predicted Population means of the Married: ${np.round(np.mean(marrie
```

```
Predicted Population means of the Unmarried: $880286.01
Predicted Population means of the Married: $843560.42
```

In [ ]:
```
upper1 = np.round(np.percentile(married_collect_sample_means, 97.5),2)
lower1 = np.round(np.percentile(married_collect_sample_means, 2.5),2)
upper2 = np.round(np.percentile(unmarried_collect_sample_means, 97.5),2)
lower2 = np.round(np.percentile(unmarried_collect_sample_means, 2.5),2)
print(f"95% Confidence Interval Population means of the Married: ({upper1},
print(f"95% Confidence Interval Population means of the Unmarried: ({upper2}
```

```
95% Confidence Interval Population means of the Married: (946621.04, 74616
6.04)
95% Confidence Interval Population means of the Unmarried: (985301.35, 7818
27.96)
```

Are confidence intervals of average married and unmarried spending overlapping? How can Walmart leverage this conclusion to make changes or improvements?

In [ ]:
```
fig, axs =plt.subplots()
sns.histplot(married_collect_sample_means, kde=True, legend=True)
sns.histplot(unmarried_collect_sample_means, kde=True,legend=True)
plt.title("confidence intervals of average married and unmarried")
plt.xlabel(['Married',"                    "'Unmarried']);
```

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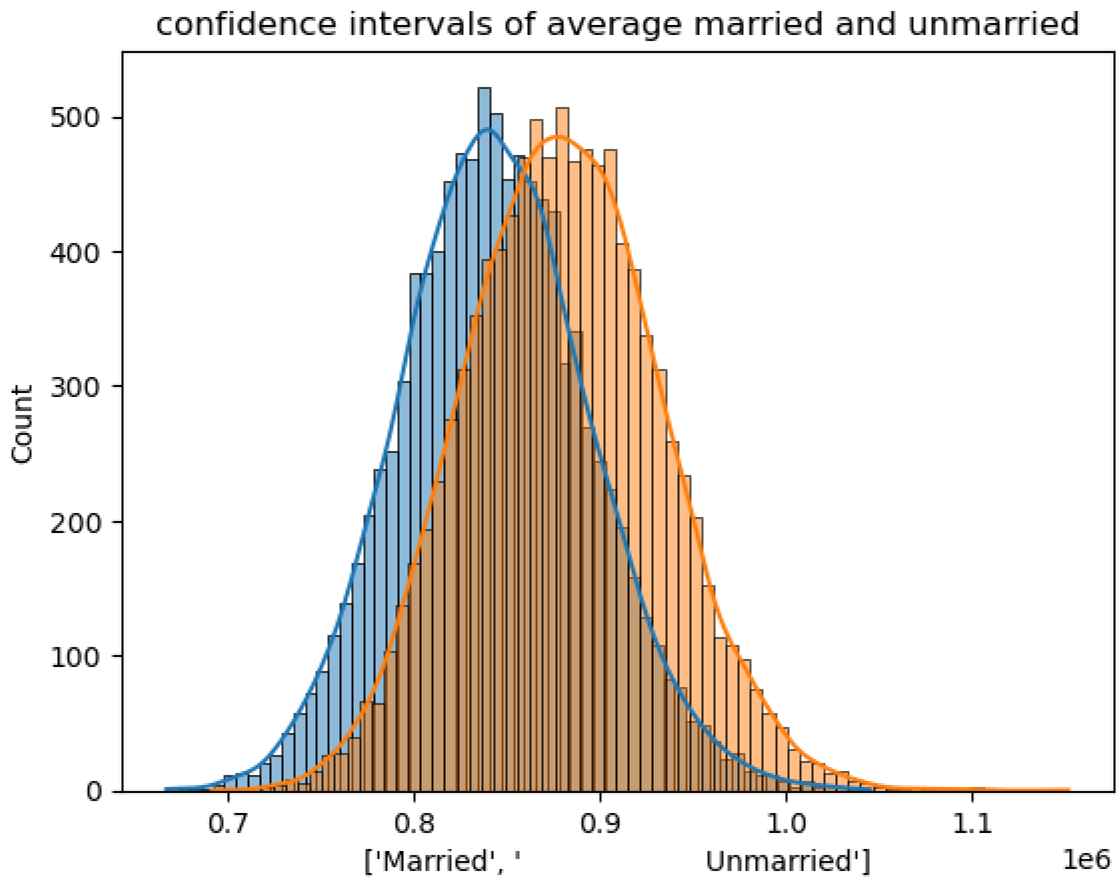

- Confidence interval of Married and unmarried people coincide. Which means that company can targert both type of people as company is doing good to attract both of them.
- 95% Confidence Interval Population means of the Married: (946621.04, 746166.04)
- 95% Confidence Interval Population means of the Unmarried: (985301.35, 781827.96)

Q5: Results when the same activity is performed for Age

In [ ]:
```
df1 = df_walmart.groupby('Age')['Purchase'].sum().reset_index()
df1
```

Out[ ]:

	Age	Purchase
0	0-17	134913183
1	18-25	913848675
2	26-35	2031770578
3	36-45	1026569884
4	46-50	420843403
5	51-55	367099644
6	55+	200767375

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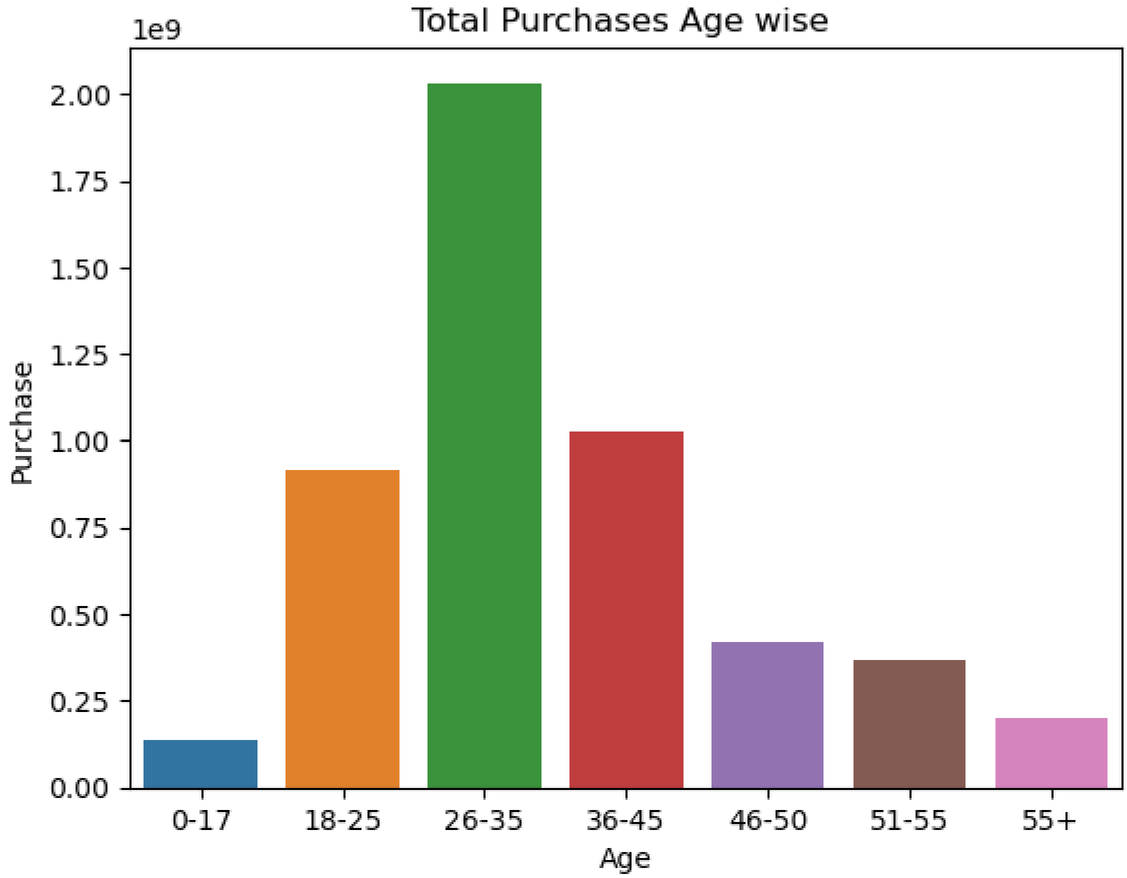
In [ ]:
```
# sum of mal
sns.barplot(data = pd.DataFrame(df1), x='Age', y='Purchase')
plt.title("Total Purchases Age wise ")
plt.show()
```

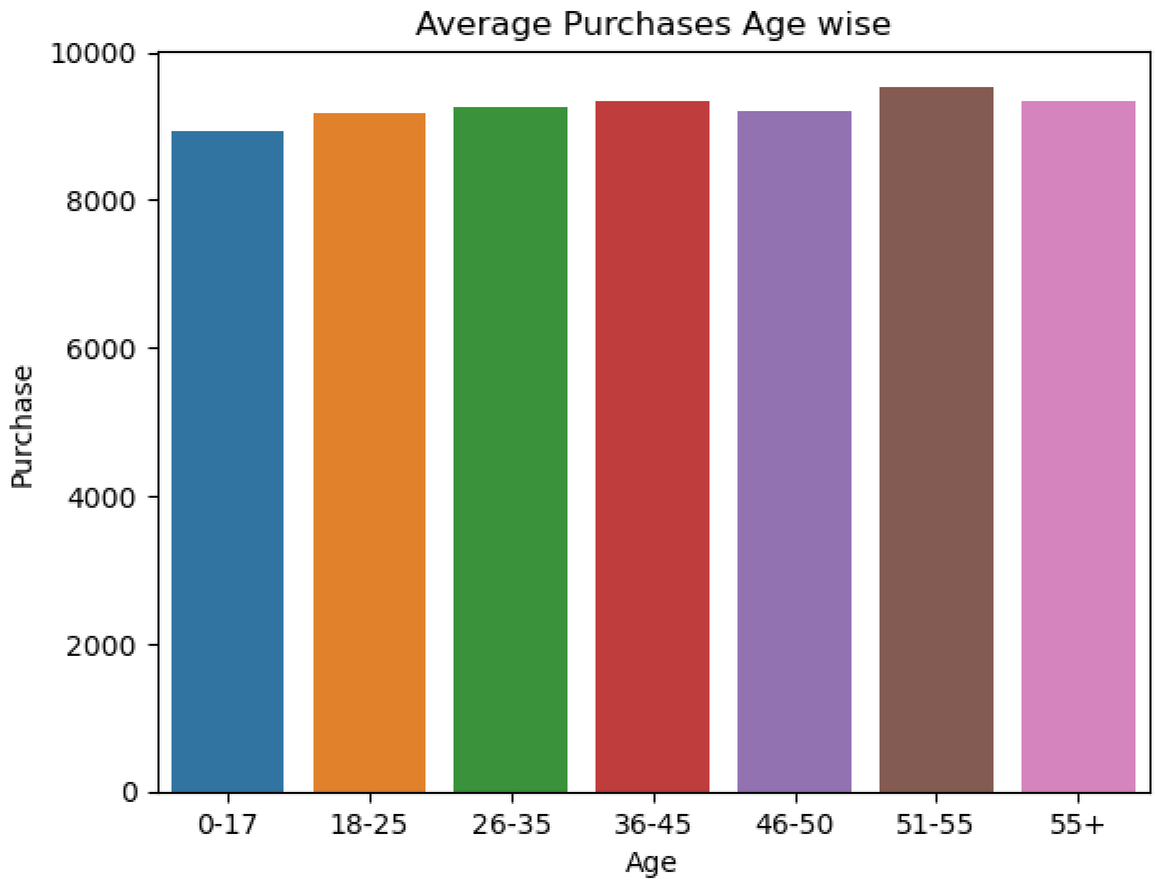


In [ ]:
```
df2 = df_walmart.groupby('Age')['Purchase'].mean().reset_index()
df2
```

Out[ ]:

	Age	Purchase
0	0-17	8933.464640
1	18-25	9169.663606
2	26-35	9252.690633
3	36-45	9331.350695
4	46-50	9208.625697
5	51-55	9534.808031
6	55+	9336.280459

In [ ]:
```
# sum of mal
sns.barplot(data = pd.DataFrame(df2), x='Age', y='Purchase')
plt.title("Average Purchases Age wise")
plt.show()
```




```
In [ ]: print(df_walmart['Age'].value_counts(normalize=True)*100)
        sns.countplot(data=df_walmart, x='Age');
```

```
26-35    39.919974
36-45    19.999891
18-25    18.117760
46-50     8.308246
51-55     6.999316
55+       3.909335
0-17      2.745479
Name: Age, dtype: float64
```

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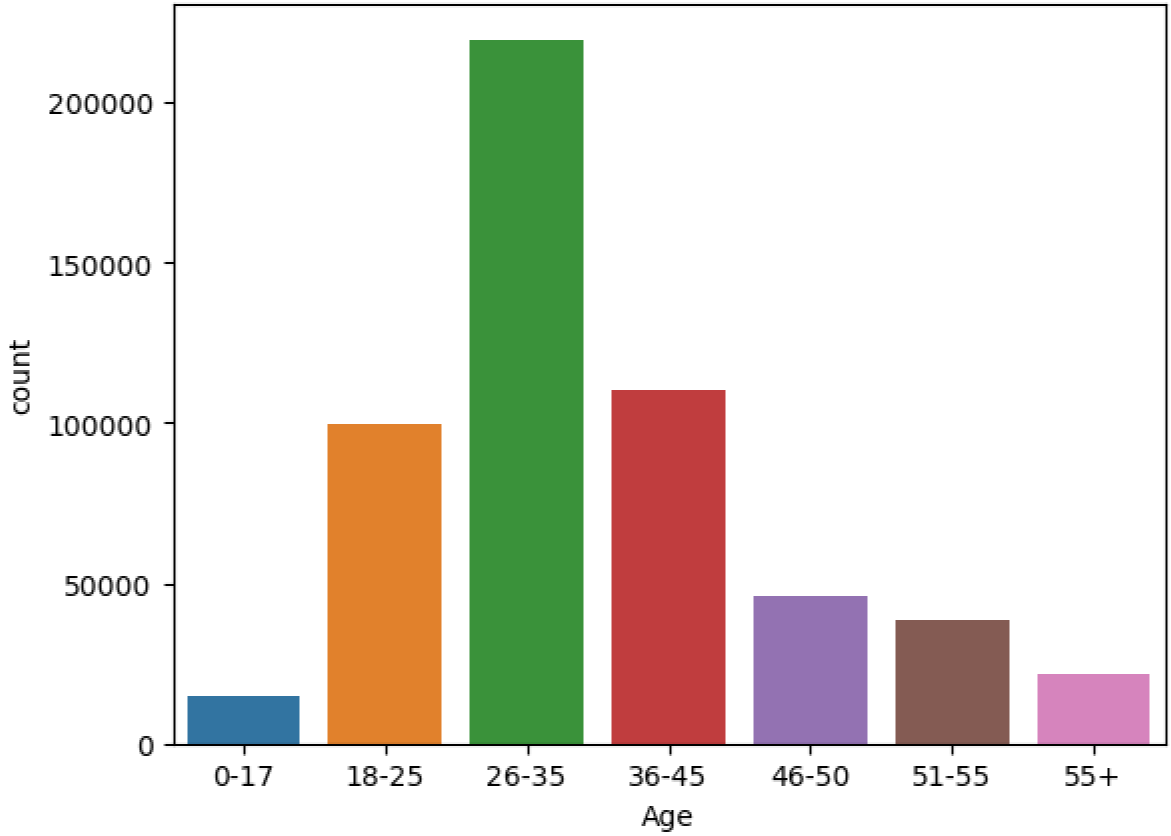

- Most Purchases are Made by 26-35 age group then followed by 36-45 and 18-25.

Confidence intervals and distribution of the mean of the expenses Age of the Customers

In [ ]:
```
# number of cusotmers age wise
df_walmart['Age'].value_counts()
```

Out[ ]:
```
26-35    219587
36-45    110013
18-25     99660
46-50     45701
51-55     38501
55+       21504
0-17      15102
Name: Age, dtype: int64
```

In [ ]:
```
df_walmart['User_ID'].nunique()
```

Out[ ]:
```
5891
```

In [ ]:
```
df = pd.DataFrame(df_walmart.groupby(['User_ID', 'Age'])['Purchase'].sum().r
df_purchase_age_wise=df[df['Purchase']!=0][['Age','Purchase']] # Droping Use
df_purchase_age_wise
```

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Out[ ]:

	Age	Purchase
0	0-17	334093
13	55+	810472
16	26-35	341635
25	46-50	206468
30	26-35	821001
...	...	...
41204	26-35	4116058
41213	46-50	1119538
41222	55+	90034
41227	46-50	590319
41232	26-35	1653299

5891 rows × 2 columns

In [ ]:

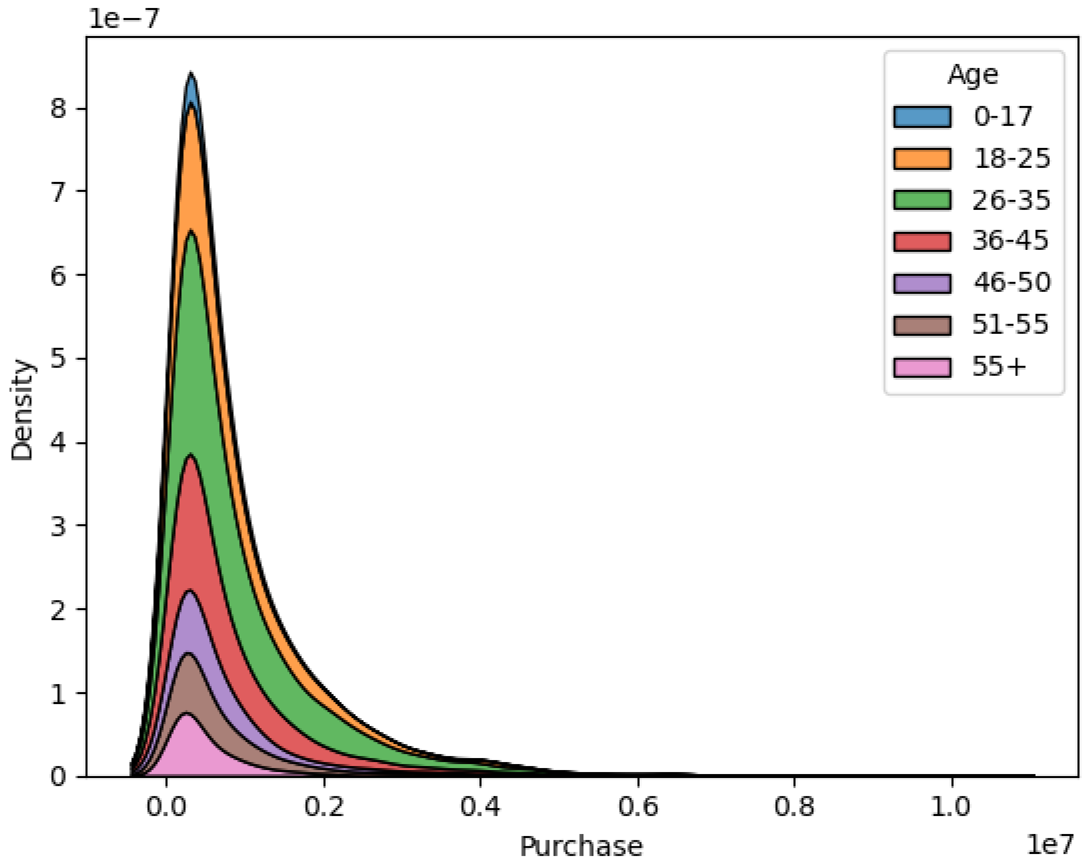
```
df_purchase_age_wise['Age'].value_counts()
```

Out[ ]:

```
26-35    2053
36-45    1167
18-25    1069
46-50     531
51-55     481
55+       372
0-17      218
Name: Age, dtype: int64
```

In [ ]:

```
sns.kdeplot(data=df_purchase_age_wise, x='Purchase', hue='Age', multiple='st
```



- We can see the see the pattern of purchase as per the age in the above graph.
- Data being right skewed also points to that we have outlier in expesive purchases. This has been noticed in the above bar plots and violin plots

In [ ]:
```
# Creating seperate df to making counfidence interval and population mean
df_0_17 = df_purchase_age_wise[df_purchase_age_wise['Age']=='0-17']
df_18_25 = df_purchase_age_wise[df_purchase_age_wise['Age']=='18-25']
df_26_35 = df_purchase_age_wise[df_purchase_age_wise['Age']=='26-35']
df_36_45 = df_purchase_age_wise[df_purchase_age_wise['Age']=='36-45']
df_46_50 = df_purchase_age_wise[df_purchase_age_wise['Age']=='46-50']
df_51_55 = df_purchase_age_wise[df_purchase_age_wise['Age']=='51-55']
df_55plus = df_purchase_age_wise[df_purchase_age_wise['Age']=='55+']
```

In [ ]:
```
# Trying to find best sample size for age: 0_17
sample_mean_trend_0_17 = []
for i in np.arange(10,170):
    sample =df_0_17['Purchase'].sample(i)
    sample_mean_trend_0_17.append(np.mean(sample))
plt.plot(sample_mean_trend_0_17)
plt.show()
```

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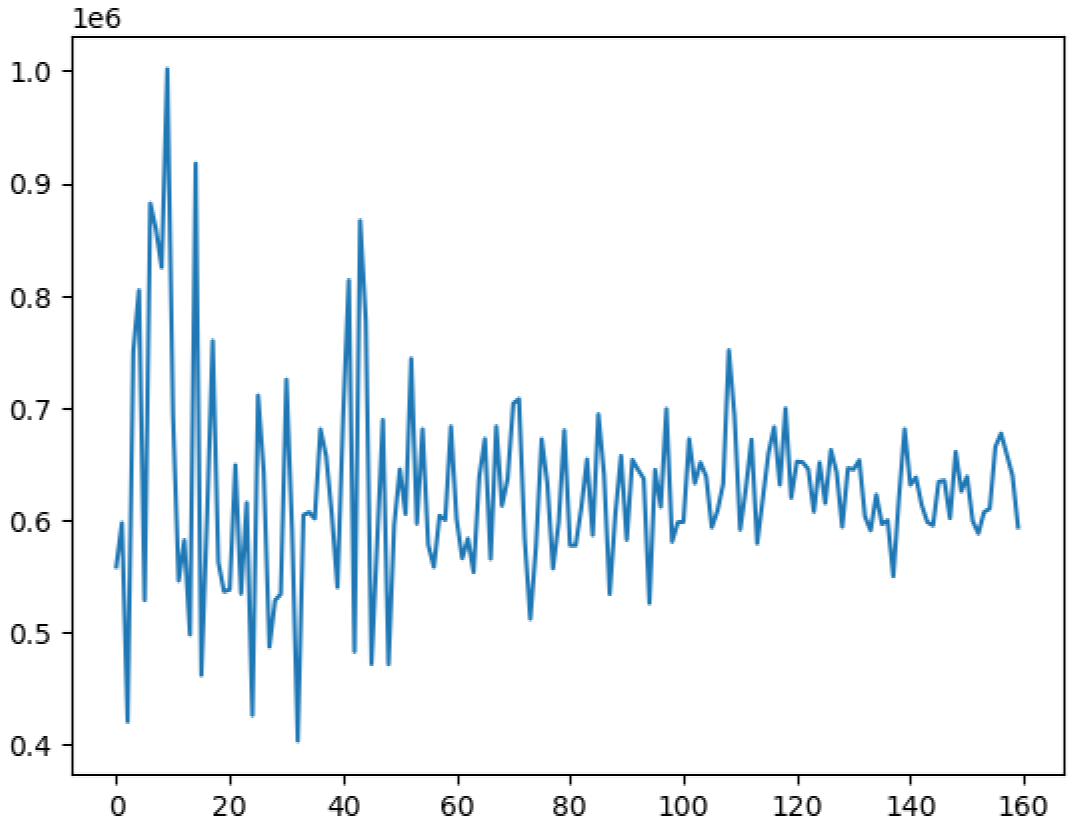
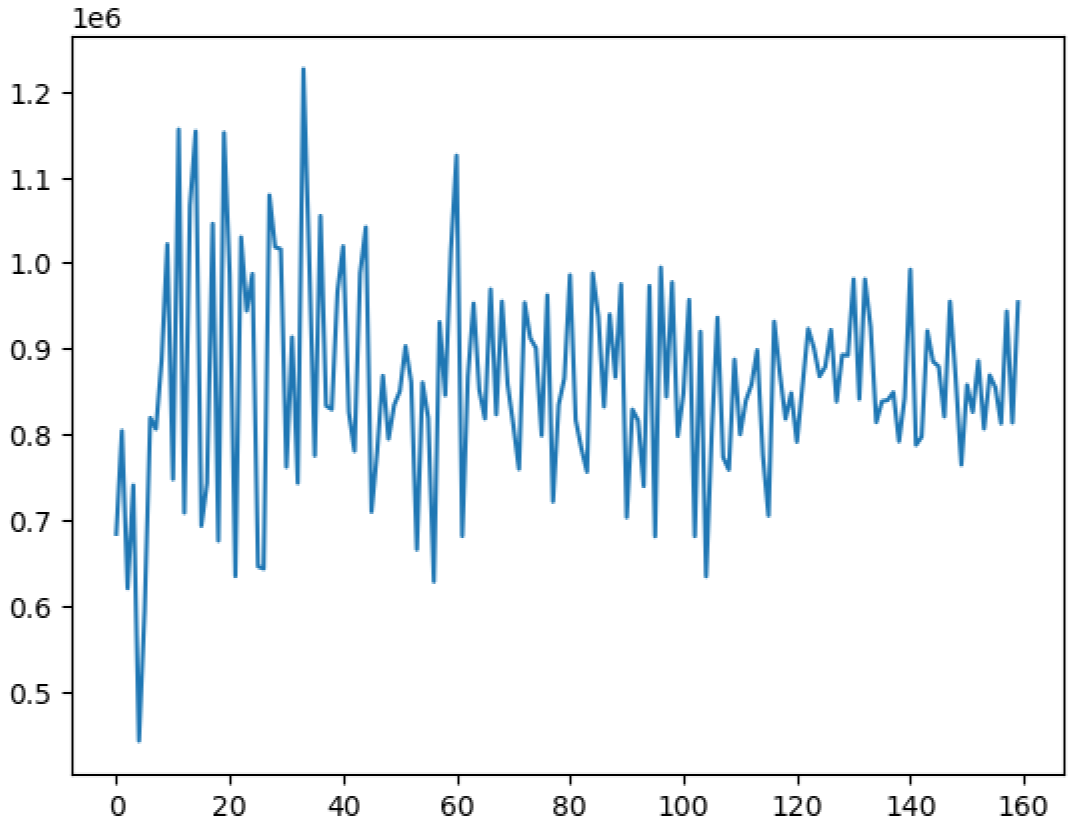


- Sample Size can be taken as 120

In [ ]:
```
# Trying to find best sample size for age: 18-25
sample_mean_trend_18_25 = []
for i in np.arange(10,170):
    sample =df_18_25['Purchase'].sample(i)
    sample_mean_trend_18_25.append(np.mean(sample))
plt.plot(sample_mean_trend_18_25)
plt.show()
```



- Sample Size can be taken as 120

In [ ]:
```
# Trying to find best sample size for age: 18-25
sample_mean_trend_26_35 = []
for i in np.arange(50,800):
    sample =df_26_35['Purchase'].sample(i)
    sample_mean_trend_26_35.append(np.mean(sample))
plt.plot(sample_mean_trend_26_35)
plt.show()
```

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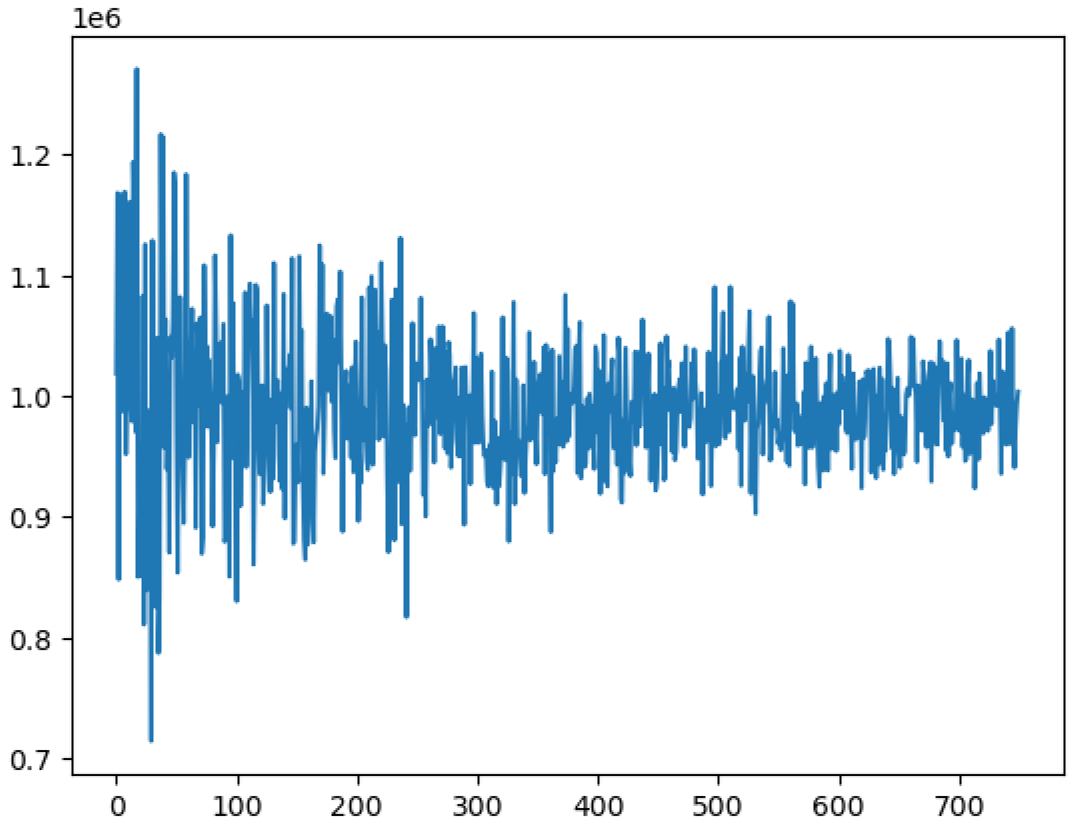
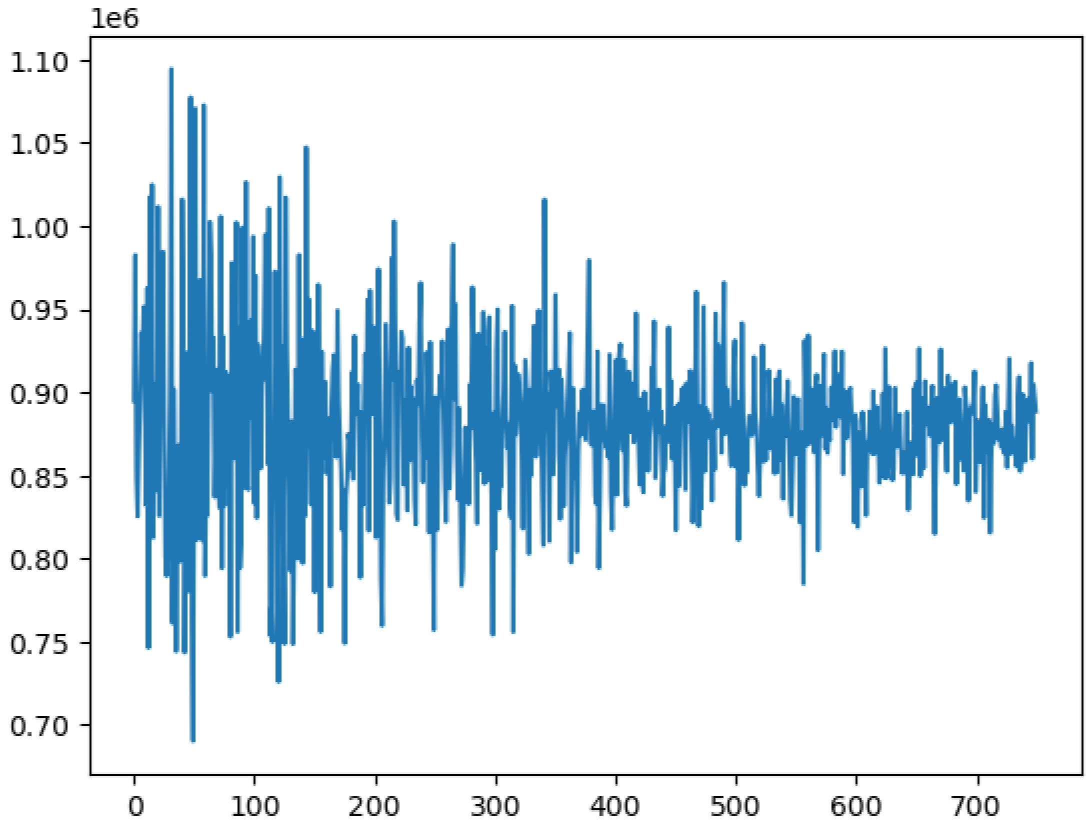


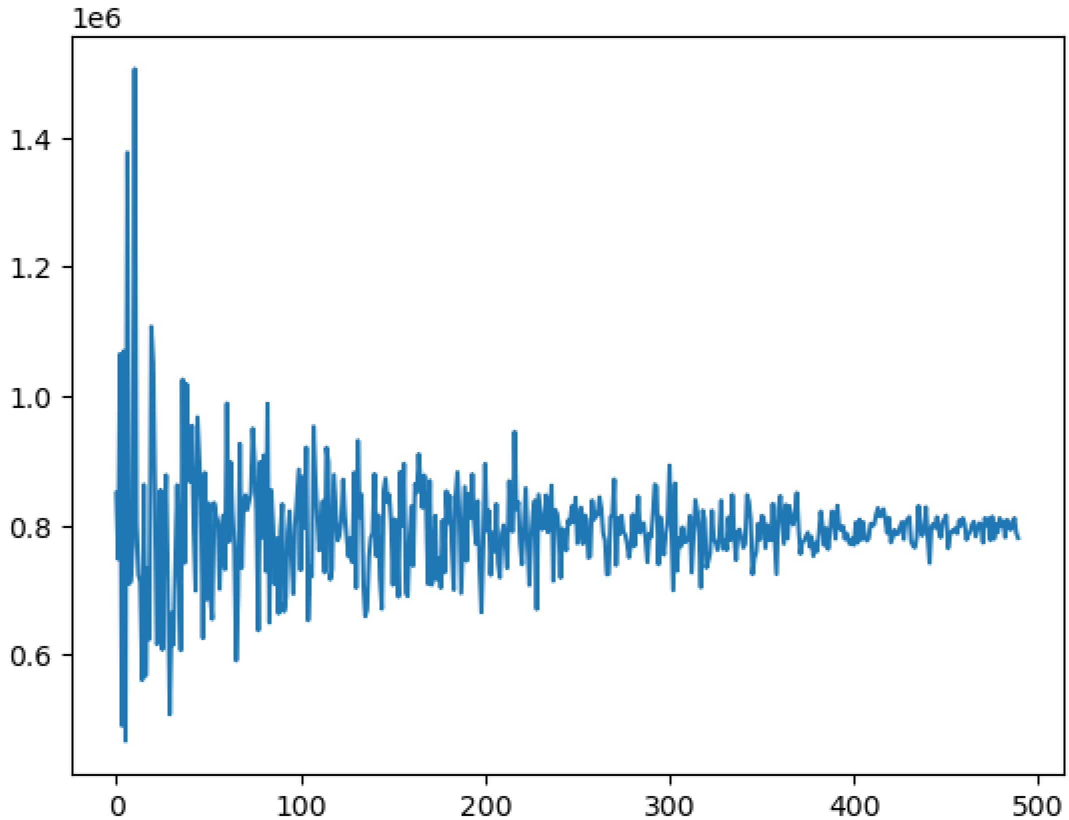
- Sample Size can be taken as 300

In [ ]:
```
# Trying to find best sample size for age: df_36_45
sample_mean_trend_36_45 = []
for i in np.arange(50,800):
    sample =df_36_45['Purchase'].sample(i)
    sample_mean_trend_36_45.append(np.mean(sample))
plt.plot(sample_mean_trend_36_45)
plt.show()
```



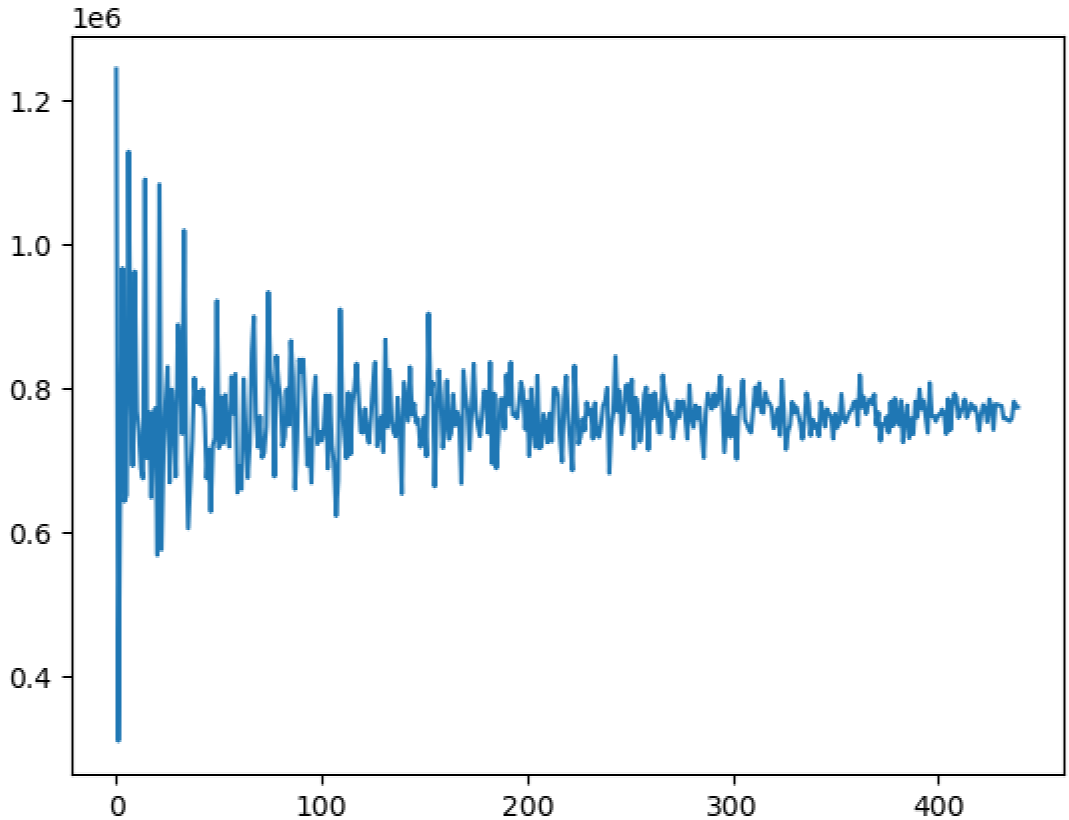
- Sample Size can be taken as 450

In [ ]:
```
# Trying to find best sample size for age: df_46_50
sample_mean_trend_46_50 = []
for i in np.arange(10,500):
    sample =df_46_50['Purchase'].sample(i)
    sample_mean_trend_46_50.append(np.mean(sample))
plt.plot(sample_mean_trend_46_50)
plt.show()
```



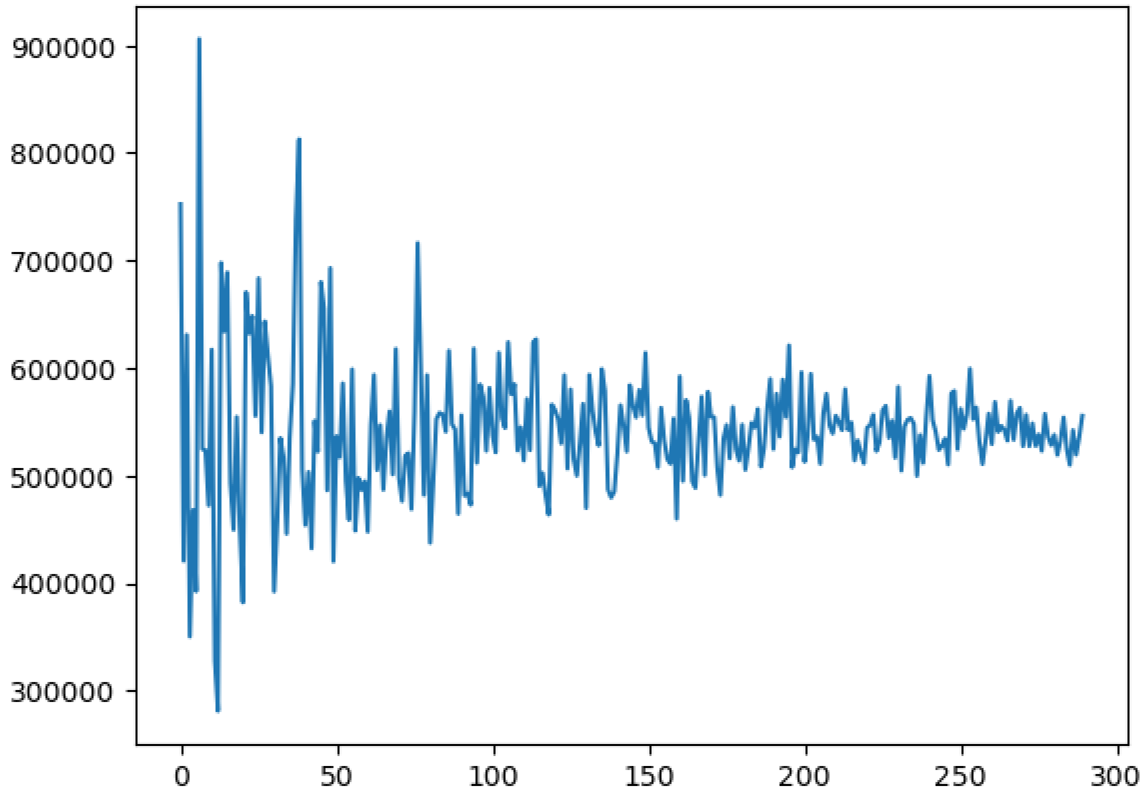
- Sample Size can be taken as 250

In [ ]:
```
# Trying to find best sample size for age: df_51_55
sample_mean_trend_51_55 = []
for i in np.arange(10,450):
    sample =df_51_55['Purchase'].sample(i)
    sample_mean_trend_51_55.append(np.mean(sample))
plt.plot(sample_mean_trend_51_55)
plt.show()
```



- Sample Size can be taken as 250

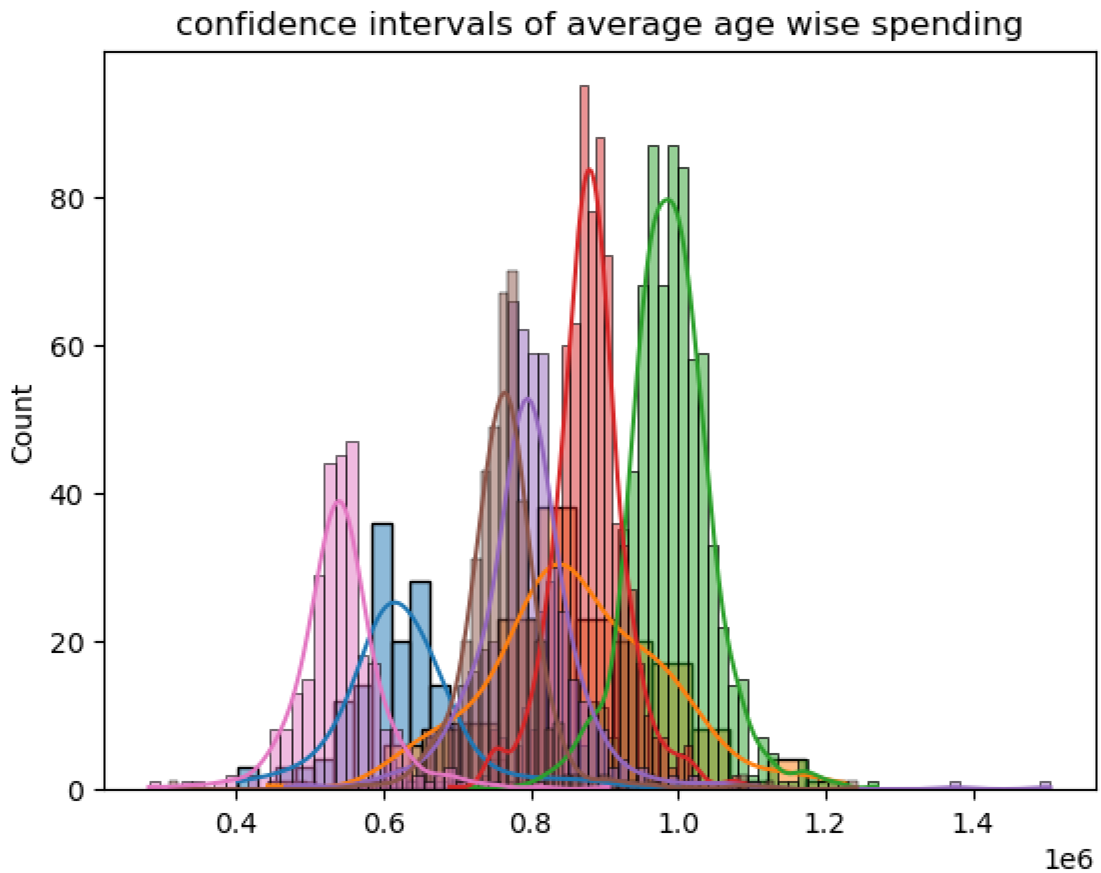
In [ ]:
```
# Trying to find best sample size for age: df_51_55
sample_mean_trend_55plus = []
for i in np.arange(10,300):
    sample =df_55plus['Purchase'].sample(i)
    sample_mean_trend_55plus.append(np.mean(sample))
plt.plot(sample_mean_trend_55plus)
plt.show()
```



- Sample Size can be taken as 150

Are confidence intervals of average age wise spending overlapping? How can Walmart leverage this conclusion to make changes or improvements?

In [ ]:
```
fig, axs =plt.subplots()
sns.histplot(sample_mean_trend_0_17, kde=True, legend=True)
sns.histplot(sample_mean_trend_18_25, kde=True,legend=True)
sns.histplot(sample_mean_trend_26_35, kde=True,legend=True)
sns.histplot(sample_mean_trend_36_45, kde=True,legend=True)
sns.histplot(sample_mean_trend_46_50, kde=True,legend=True)
sns.histplot(sample_mean_trend_51_55, kde=True,legend=True)
sns.histplot(sample_mean_trend_55plus, kde=True,legend=True)
plt.title("confidence intervals of average age wise spending");
```



- We can see the see the pattern of purchase as per the age in the above graph.
- Data being right skewed also points to that we have outlier in expesive purchases. This has been noticed in the above bar plots and violin plots
- Teh confidence interval does collide with all the ages across. but the age group of children and older people is affected ht most. Which can be a focus area for the company.

Q5: Final Insights

Observations:

- Unlike the popular belief 25% of the users are female and 75% are male. Need to explore more on it

- Users in age Group 26-35 takes ~40% and kids(<18) and old people are only~ 6.75%.

- We can notice a downward trend after the age of 35.

- 35% Staying in the city from 1 year, 18% from 2 years, 17% from 3 years

- 59% of the users are single and 41 % of the users are Married.

- Most of the users belogs to City_category B.

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- Single users are more as compared to married people.

- Top 3 Product_Category: 1,5 and 11

- we can see that there are outlier in all of the factors when we are comparing with respect to the Purchase amount.

- In all of the features the outliers are in the top section except the product category.

- In product category, the outliers are in bottom side of the section.

- We can notice that the distribution of all the details(e.g. male/female) of all the features are the same.

- Product category has very les distrubiton unable to identify as well.

- The outliers are responsible for a significant amount of purchase. This can be noticed in distribution in all the outliers and purchase.

- We can see that in purchase mean is to the right of the median then we can say that the data is slightly right skewed.

- There are total 20 types of products.

- There are 21 types occupation available in the state.

- Males are purchasing more in comparison to female
- Most purchases are made among product category 10.
- Lowest pruchases are in Product category: 19, 20, 12, and 13.
- Almost all of Age segments are purchasing in stores.
- Occupation 9, 19 and 20 are the ones who purchase the lowest in the stores.
- Order of Purchase City Category wise si C>B>A. This can be because of multiple factors which can be looked into more depth.
- Marital Status and # of years a person is staying in the city doesn't make any difference in this data. Which is a bit odd because if a person is married he will buy more as he lives with family.

- We can see that most of purchases are made by men in our data.

- This is because of the fact that proportions of female to male is 25%: 75% in our data.

- So we can conclude that females purchase more than males as females with 25% of population has an average of 8734.56 and males with 75% of population has averge 9437.52.

- We can notice that we have only 5891 unique users. These consist of our male and female.

- Female and Male purchases are right Skewed.

- Data being right skewed also points to that we have outlier in expesive purchases. This has been noticed in the above bar plots and violin plots

- We can see that there are only 4225 Males and 1666 Females.

- We can clearly see that the confidence interval of Males and Females doesn't overlap.
- 95% Confidence Interval Population means of the males: (782751.49, 645250.8)
- 95% Confidence Interval Population means of the females: (1020105.31, 834682.2)
- It is very beneficial for the wallmart as male and female can be easily targeted audiances are different. So walmart can easily dedicate the product in the price range as per the data. For example the females tend to spend more and they female products can be priced accordingly.

- Unmarried People has done more Purchases than married people.
- Average sales comes to be almost equal.

- We can see the see the pattern of purchase as per the age in the above graph.
- Data being right skewed also points to that we have outlier in expesive purchases. This has been noticed in the above bar plots and violin plots
- Teh confidence interval does collide with all the ages across. but the age group of children and older people is affected ht most. Which can be a focus area for the company.

Q6: Recommendation

- Gender wise population have diffenrent habits. This can be helpful to target specific type of people.
- Males tend to spend less so they can be attracted with cheap products and females can be attracted with expensive products.
- Children, teenager and old people doesnt' spend much this can be because of the transportation reason. Because they may not able to reach to the stor.
- Company can attract them either to some kind of online store/ help them with transportation to the nearest bus stop etc.
- There are some people who are spending way more than the average people these people. Need to look into about the rest of people why is the gap between them.
- Married and unmarried people tend to spend the same so its not much useful.

- Rest of the factors don't provide much of the information. We can dig deeper with more data.

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