Business Case: Walmart - Confidence Interval and CLT

Importing libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib as mpl
import seaborn as sns
import scipy.stats as spy
```

Loading the dataset

In [2]:
```
df = pd.read_csv(r"https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/293/original/walmart_data.csv
```

shape of data

In [3]:
```
df.shape
```

Out[3]:
```
(550068, 10)
```

columns present in the data

In [4]:
```
df.columns
```

Out[4]:
```
Index(['User_ID', 'Product_ID', 'Gender', 'Age', 'Occupation', 'City_Category',
       'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Category',
       'Purchase'],
      dtype='object')
```

datatype of the each column

In [5]:
```
df.dtypes
```

Out[5]:
```
User_ID                        int64
Product_ID                    object
Gender                        object
Age                           object
Occupation                     int64
City_Category                 object
Stay_In_Current_City_Years    object
Marital_Status                 int64
Product_Category               int64
Purchase                       int64
dtype: object
```

In [6]:
```
df.head()
```

Out[6]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purchase
0	1000001	P00069042	F	0-17	10	A	2	0	3	8370
1	1000001	P00248942	F	0-17	10	A	2	0	1	15200
2	1000001	P00087842	F	0-17	10	A	2	0	12	1422
3	1000001	P00085442	F	0-17	10	A	2	0	12	1057
4	1000002	P00285442	M	55+	16	C	4+	0	8	7969

In [7]:
```
df.tail()
```

Out[7]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Purchas
550063	1006033	P00372445	M	51-55	13	B	1	1	20	36
550064	1006035	P00375436	F	26-35	1	C	3	0	20	37
550065	1006036	P00375436	F	26-35	15	B	4+	1	20	13
550066	1006038	P00375436	F	55+	1	C	2	0	20	36
550067	1006039	P00371644	F	46-50	0	B	4+	1	20	49

Is there any missing value in the dataset?

In [8]:
```
np.any(df.isna())
```

Out[8]: False

Is there any duplicate value in the dataset ?

In [9]:
```
np.any(df.duplicated())
```

Out[9]: False

Basic information about the dataset

In [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
```

Memory Optimization

Converting User_ID column datatype to int32

In [11]:
```
df['User_ID'] = df['User_ID'].astype('int32')
```

Updating 'Marital_Status' column

In [12]:
```
df['Marital_Status'] = df['Marital_Status'].apply(lambda x: 'Married' if x == 1 else 'Single')
```

In [13]:
```
df['Marital_Status'] = df['Marital_Status'].astype('category')
```

Converting 'Age' column datatype to category

In [14]:
```
df['Age'] = df['Age'].astype('category')
```

Converting 'Product_Category' column datatype to int8

In [15]:
```python
df['Product_Category'] = df['Product_Category'].astype('int8')
```

Converting 'Occupation' column's datatype to int8

In [16]:
```python
df['Occupation'] = df['Occupation'].astype('int8')
```

Converting 'City_Category' column's datatype to category

In [17]:
```python
df['City_Category'] = df['City_Category'].astype('category')
```

Converting 'Stay_In_Current_City_Years' column's datatype to category

In [18]:
```python
df['Stay_In_Current_City_Years'] = df['Stay_In_Current_City_Years'].astype('category')
```

In [19]:
```python
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  int32
 1   Product_ID                  550068 non-null  object
 2   Gender                      550068 non-null  object
 3   Age                         550068 non-null  category
 4   Occupation                  550068 non-null  int8
 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  int8
 9   Purchase                    550068 non-null  int64
dtypes: category(4), int32(1), int64(1), int8(2), object(2)
memory usage: 17.8+ MB
```

Earlier the dataframe took 42.0+ MB of memory but the memory usage is reduced to 17.8+ MB (57.62% reduction in the memory usage).

Basic statistical description of the dataset

In [20]:
```python
# For measurable quantities
df.describe()
```

Out[20]:

	User_ID	Occupation	Product_Category	Purchase
count	5.500680e+05	550068.000000	550068.000000	550068.000000
mean	1.003029e+06	8.076707	5.404270	9263.968713
std	1.727592e+03	6.522660	3.936211	5023.065394
min	1.000001e+06	0.000000	1.000000	12.000000
25%	1.001516e+06	2.000000	1.000000	5823.000000
50%	1.003077e+06	7.000000	5.000000	8047.000000
75%	1.004478e+06	14.000000	8.000000	12054.000000
max	1.006040e+06	20.000000	20.000000	23961.000000

In [21]:
```python
# description of columns with 'object' datatype
df.describe(include = 'object')
```

Out[21]:

	Product_ID	Gender
count	550068	550068
unique	3631	2
top	P00265242	M
freq	1880	414259

value_counts and unique attributes

In [22]:
```
# Total number of transactions made by each gender
np.round(df['Gender'].value_counts(normalize = True) * 100, 2)
```

Out[22]:
```
M    75.31
F    24.69
Name: Gender, dtype: float64
```

It is clear from the above that out of every four transactions, three are made by males.

In [23]:
```
np.round(df['Occupation'].value_counts(normalize = True) * 100, 2).cumsum()
```

Out[23]:
```
4     13.15
0     25.81
7     36.56
1     45.18
17    52.46
20    58.56
12    64.23
14    69.19
2     74.02
16    78.63
6     82.33
3     85.54
10    87.89
5     90.10
15    92.31
11    94.42
19    95.96
13    97.36
18    98.56
9     99.70
8     99.98
Name: Occupation, dtype: float64
```

It can be inferred from the above that 82.33 % of the total transactions are made by the customers belonging to 11 occupations. These are 4, 0, 7, 1, 17, 20, 12, 14, 2, 16, 6 (Ordered in descending order of the total transactions' share.)

In [24]:
```
np.round(df['Stay_In_Current_City_Years'].value_counts(normalize = True) * 100, 2)
```

Out[24]:
```
1     35.24
2     18.51
3     17.32
4+    15.40
0     13.53
Name: Stay_In_Current_City_Years, dtype: float64
```

From the above result, it is clear that majority of the transactions (53.75 % of total transactions) are made by the customers having 1 or 2 years of stay in the current city.

In [25]:
```
np.round(df['Product_Category'].value_counts(normalize = True).head(10) * 100, 2).cumsum()
```

Out[25]:
```
5     27.44
1     52.96
8     73.67
11    78.09
2     82.43
6     86.15
3     89.82
4     91.96
16    93.75
15    94.89
Name: Product_Category, dtype: float64
```

It can be inferred from the above result that 82.43% of the total transactions are made for only 5 Product Categories. These are, 5, 1, 8, 11 and 2.

How many unique customers are there for each gender

In [26]:
```
df_gender_dist = pd.DataFrame(df.groupby(by = ['Gender'])['User_ID'].nunique()).reset_index().rename(columns = {'U
df_gender_dist['percent_share'] = np.round(df_gender_dist['unique_customers'] / df_gender_dist['unique_customers']
df_gender_dist
```

Out[26]:

	Gender	unique_customers	percent_share
0	F	1666	28.28
1	M	4225	71.72

How many transactions are made by each gender category ?

In [27]:
```
df.groupby(by = ['Gender'])['User_ID'].count()
```

Out[27]:
```
Gender
F    135809
M    414259
Name: User_ID, dtype: int64
```

In [28]:
```
print('Average number of transactions made by each Male on Black Friday is', round(414259 / 4225))
print('Average number of transactions made by each Female on Black Friday is', round(135809 / 1666))
```

```
Average number of transactions made by each Male on Black Friday is 98
Average number of transactions made by each Female on Black Friday is 82
```

What is the total Revenue generated by Walmart from each Gender ?

In [29]:
```
df_gender_revenue = df.groupby(by = ['Gender'])['Purchase'].sum().to_frame().sort_values(by = 'Purchase', ascendin
df_gender_revenue['percent_share'] = np.round((df_gender_revenue['Purchase'] / df_gender_revenue['Purchase'].sum()
df_gender_revenue
```

Out[29]:

	Gender	Purchase	percent_share
0	M	3909580100	76.72
1	F	1186232642	23.28

What is the average total purchase made by each user in each gender ?

In [30]:
```
df1 = pd.DataFrame(df.groupby(by = ['Gender', 'User_ID'])['Purchase'].sum()).reset_index().rename(columns = {'Purc
df1.groupby(by = 'Gender')['Average_Purchase'].mean()
```

Out[30]:
```
Gender
F    712024.394958
M    925344.402367
Name: Average_Purchase, dtype: float64
```

```
On an average each male makes a total purchase of 712024.394958.
On an average each female makes a total purchase of 925344.402367.
```

What is the Average Revenue generated by Walmart from each Gender per transaction ?

In [31]:
```
pd.DataFrame(df.groupby(by = 'Gender')['Purchase'].mean()).reset_index().rename(columns = {'Purchase' : 'Average_Pu
```

Out[31]:

	Gender	Average_Purchase
0	F	8734.565765
1	M	9437.526040

How many unique customers are there for each Marital Status ?

In [32]:
```
df_marital_status_dist = pd.DataFrame(df.groupby(by = ['Marital_Status'])['User_ID'].nunique()).reset_index().renai
df_marital_status_dist['percent_share'] = np.round(df_marital_status_dist['unique_customers'] / df_marital_status_(
df_marital_status_dist
```

Out[32]:

	Marital_Status	unique_customers	percent_share
0	Married	2474	42.0
1	Single	3417	58.0

How many transactions are made by each Marital Status category ?

In [33]:
```
df.groupby(by = ['Marital_Status'])['User_ID'].count()
```

Out[33]:
```
Marital_Status
Married    225337
Single     324731
Name: User_ID, dtype: int64
```

In [34]:
```
print('Average number of transactions made by each user with marital status Married is', round(225337 / 2474))
print('Average number of transactions made by each with marital status Single is', round(324731 / 3417))
```

```
Average number of transactions made by each user with marital status Married is 91
Average number of transactions made by each with marital status Single is 95
```

What is the total Revenue generated by Walmart from each Marital Status ?

In [35]:
```
df_marital_status_revenue = df.groupby(by = ['Marital_Status'])['Purchase'].sum().to_frame().sort_values(by = 'Pur
df_marital_status_revenue['percent_share'] = np.round((df_marital_status_revenue['Purchase'] / df_marital_status_r
df_marital_status_revenue
```

Out[35]:

	Marital_Status	Purchase	percent_share
0	Single	3008927447	59.05
1	Married	2086885295	40.95

What is the average total purchase made by each user in each marital status ?

In [36]:
```
df1 = pd.DataFrame(df.groupby(by = ['Marital_Status', 'User_ID'])['Purchase'].sum()).reset_index().rename(columns
df1.groupby(by = 'Marital_Status')['Average_Purchase'].mean()
```

Out[36]:
```
Marital_Status
Married    354249.753013
Single     510766.838737
Name: Average_Purchase, dtype: float64
```

```
On an average each Married customer makes a total purchase of 843526.796686.
On an average each Single customer makes a total purchase of 880575.781972.
```

In [37]:
```
df_age_dist = pd.DataFrame(df.groupby(by = ['Age'])['User_ID'].nunique()).reset_index().rename(columns = {'User_ID
df_age_dist['percent_share'] =  np.round(df_age_dist['unique_customers'] / df_age_dist['unique_customers'].sum() *
df_age_dist['cumulative_percent'] =  df_age_dist['percent_share'].cumsum()
df_age_dist
```

Out[37]:

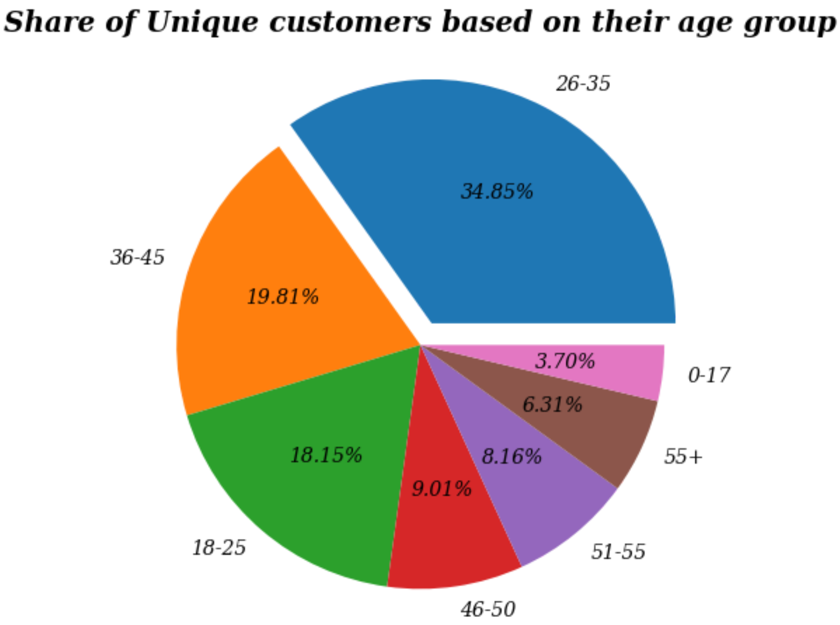
	Age	unique_customers	percent_share	cumulative_percent
2	26-35	2053	34.85	34.85
3	36-45	1167	19.81	54.66
1	18-25	1069	18.15	72.81
4	46-50	531	9.01	81.82
5	51-55	481	8.16	89.98
6	55+	372	6.31	96.29
0	0-17	218	3.70	99.99

```
Majority of the transactions are made by the customers between 26 and 45 years of age.
```

```
About 81.82% of the total transactions are made by customers of age between 18 and 50 years.
```

In [38]:
```
plt.figure(figsize = (8, 8))
plt.title('Share of Unique customers based on their age group', fontdict = {'fontsize' : 20,
                    'fontstyle' : 'oblique',
                    'fontfamily' : 'serif',
                    'fontweight' : 600} )
plt.pie(x = df_age_dist['percent_share'], labels = df_age_dist['Age'],
        explode = [0.1] + [0] * 6, autopct = '%.2f%%',
       textprops = {'fontsize' : 14,
                    'fontstyle' : 'oblique',
                    'fontfamily' : 'serif',
                    'fontweight' : 500})
plt.plot()
```

Out[38]:
```
[]
```



In [39]:
```
df['Age'].value_counts()
```

Out[39]:
```
26-35    219587
36-45    110013
18-25     99660
46-50     45701
51-55     38501
55+       21504
0-17      15102
Name: Age, dtype: int64
```

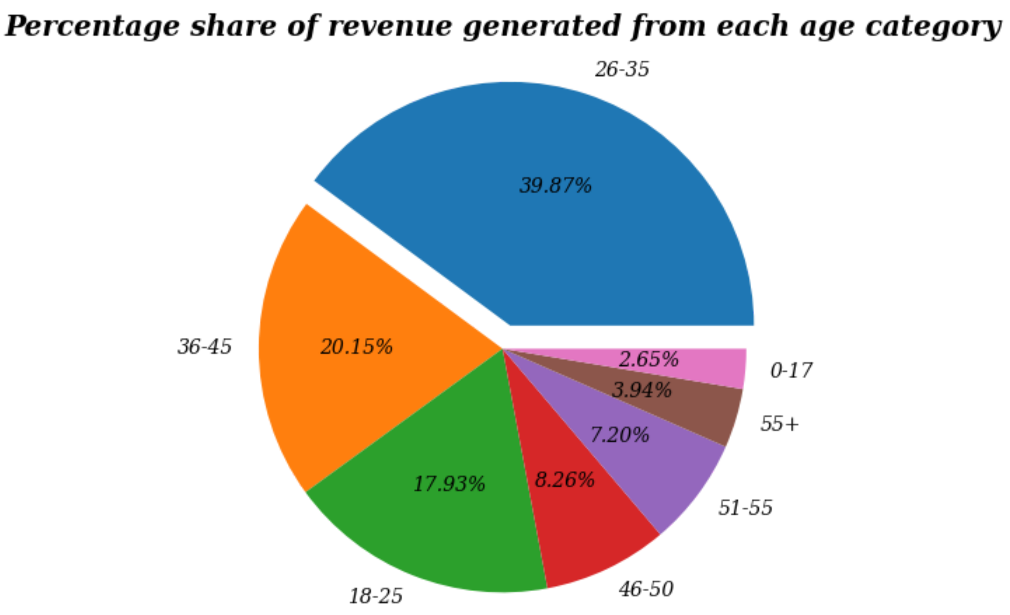
In [40]:
```
df_age_revenue = pd.DataFrame(df.groupby(by = 'Age', as_index = False)['Purchase'].sum()).sort_values(by = 'Purcha
df_age_revenue['percent_share'] = np.round((df_age_revenue['Purchase'] / df_age_revenue['Purchase'].sum()) * 100,
df_age_revenue['cumulative_percent_share'] = df_age_revenue['percent_share'].cumsum()
df_age_revenue
```

Out[40]:

	Age	Purchase	percent_share	cumulative_percent_share
2	26-35	2031770578	39.87	39.87
3	36-45	1026569884	20.15	60.02
1	18-25	913848675	17.93	77.95
4	46-50	420843403	8.26	86.21
5	51-55	367099644	7.20	93.41
6	55+	200767375	3.94	97.35
0	0-17	134913183	2.65	100.00

In [41]:
```
plt.figure(figsize = (8, 8))
plt.title('Percentage share of revenue generated from each age category', fontdict = {'fontsize' : 20,
                   'fontstyle' : 'oblique',
                   'fontfamily' : 'serif',
                   'fontweight' : 600} )
plt.pie(x = df_age_revenue['percent_share'], labels = df_age_revenue['Age'],
        explode = [0.1] + [0] * 6, autopct = '%.2f%%',
       textprops = {'fontsize' : 14,
                   'fontstyle' : 'oblique',
                   'fontfamily' : 'serif',
                   'fontweight' : 500})
plt.plot()
```

Out[41]: []



In [42]:
```
df_city_dist = pd.DataFrame(df.groupby(by = ['City_Category'])['User_ID'].nunique()).reset_index().rename(columns
df_city_dist['percent_share'] = np.round((df_city_dist['unique_customers'] / df_city_dist['unique_customers'].sum(
df_city_dist['cumulative_percent_share'] = df_city_dist['percent_share'].cumsum()
df_city_dist
```

Out[42]:

	City_Category	unique_customers	percent_share	cumulative_percent_share
0	A	1045	17.74	17.74
1	B	1707	28.98	46.72
2	C	3139	53.28	100.00

```
Majority of the total unique customers belong to the city C.
82.26 % of the total unique customers belong to city C and B.
```

In [43]:
```
df['City_Category'].value_counts()
```

Out[43]:
```
B    231173
C    171175
A    147720
Name: City_Category, dtype: int64
```

What is the revenue generated from different cities ?

In [44]:
```
df_city_revenue = df.groupby(by = ['City_Category'])['Purchase'].sum().to_frame().sort_values(by = 'Purchase', asc
df_city_revenue['percent_share'] = np.round((df_city_revenue['Purchase'] / df_city_revenue['Purchase'].sum()) * 10
df_city_revenue['cumulative_percent_share'] = df_city_revenue['percent_share'].cumsum()
df_city_revenue
```

Out[44]:

	City_Category	Purchase	percent_share	cumulative_percent_share
0	B	2115533605	41.52	41.52
1	C	1663807476	32.65	74.17
2	A	1316471661	25.83	100.00

In [45]:
```
df.groupby(by = ['Product_Category'])['Product_ID'].nunique()
```

Out[45]:
```
Product_Category
1      493
2      152
3       90
4       88
5      967
6      119
7      102
8     1047
9        2
10      25
11     254
12      25
13      35
14      44
15      44
16      98
17      11
18      30
19       2
20       3
Name: Product_ID, dtype: int64
```

What is the revenue generated from different product categories ?

In [46]:
```
df_product_revenue = df.groupby(by = ['Product_Category'])['Purchase'].sum().to_frame().sort_values(by = 'Purchase
df_product_revenue['percent_share'] = np.round((df_product_revenue['Purchase'] / df_product_revenue['Purchase'].su
df_product_revenue['cumulative_percent_share'] = df_product_revenue['percent_share'].cumsum()
df_product_revenue
```

Out[46]:

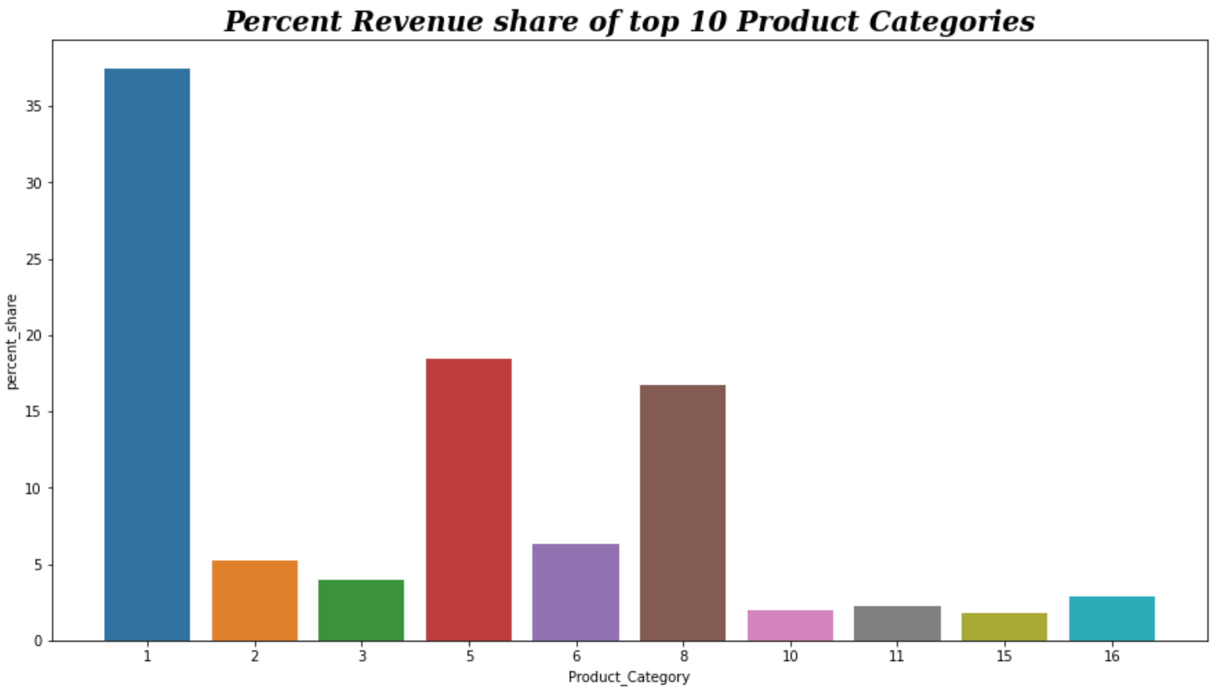
	Product_Category	Purchase	percent_share	cumulative_percent_share
0	1	1910013754	37.48	37.48
1	5	941835229	18.48	55.96
2	8	854318799	16.77	72.73
3	6	324150302	6.36	79.09
4	2	268516186	5.27	84.36
5	3	204084713	4.00	88.36
6	16	145120612	2.85	91.21
7	11	113791115	2.23	93.44
8	10	100837301	1.98	95.42
9	15	92969042	1.82	97.24
10	7	60896731	1.20	98.44
11	4	27380488	0.54	98.98
12	14	20014696	0.39	99.37
13	18	9290201	0.18	99.55
14	9	6370324	0.13	99.68
15	17	5878699	0.12	99.80
16	12	5331844	0.10	99.90
17	13	4008601	0.08	99.98
18	20	944727	0.02	100.00
19	19	59378	0.00	100.00

In [47]:
```
top5 = df_product_revenue.head(5)['Purchase'].sum() /  df_product_revenue['Purchase'].sum()
top5 = np.round(top5 * 100, 2)
print(f'Top 5 product categories from which Walmart makes {top5} % of total revenue are : {list(df_product_revenue
```

```
Top 5 product categories from which Walmart makes 84.36 % of total revenue are : [1, 5, 8, 6, 2]
```

In [48]:
```
plt.figure(figsize = (15, 8))
plt.title('Percent Revenue share of top 10 Product Categories', fontsize = 20, fontweight = 600, fontfamily = 'ser
sns.barplot(data = df_product_revenue, x = df_product_revenue.head(10)['Product_Category'], y = df_product_revenue
plt.plot()
```

Out[48]: []



What is the total Revenue generated by Walmart from each Gender ?

In [49]:
```
df_gender_revenue = df.groupby(by = ['Gender'])['Purchase'].sum().to_frame().sort_values(by = 'Purchase', ascendin
df_gender_revenue['percent_share'] = np.round((df_gender_revenue['Purchase'] / df_gender_revenue['Purchase'].sum()
df_gender_revenue
```

Out[49]:

	Gender	Purchase	percent_share
0	M	3909580100	76.72
1	F	1186232642	23.28

What is the Average Revenue generated by Walmart from each Gender per transaction ?

In [50]:
```
pd.DataFrame(df.groupby(by = 'Gender')['Purchase'].mean()).reset_index().rename(columns = {'Purchase' : 'Average_P
```

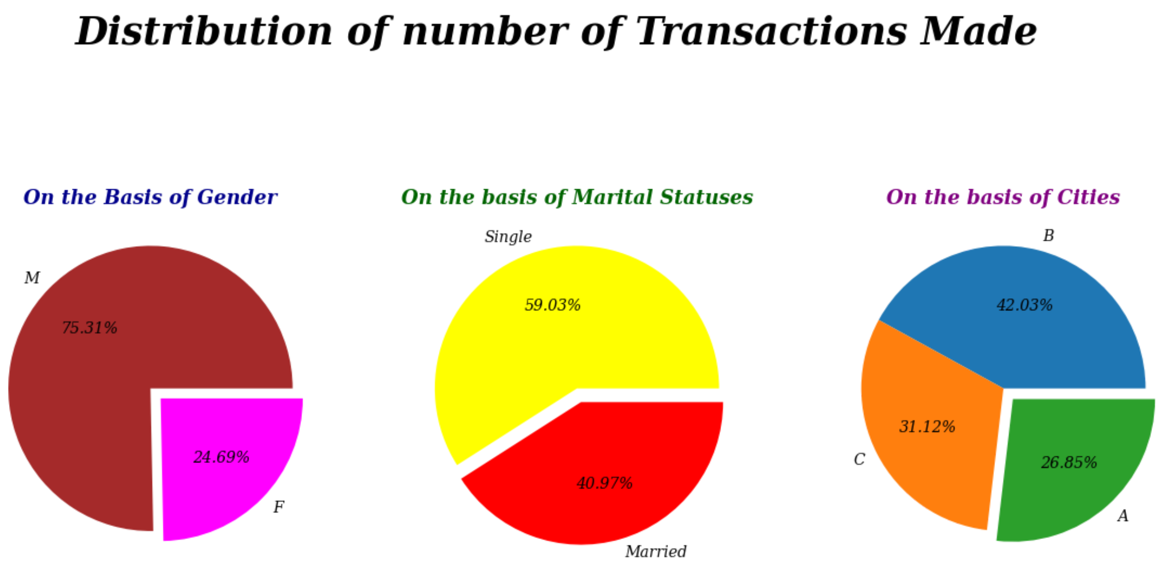
Out[50]:

	Gender	Average_Purchase
0	F	8734.565765
1	M	9437.526040

Distribution of number of Transactions :

In [51]:
```
plt.figure(figsize = (20, 10))
plt.suptitle('Distribution of number of Transactions Made', fontsize = 35, fontweight = 600, fontfamily = 'serif',
plt.subplot(1, 3, 1)
plt.title('On the Basis of Gender', color = 'darkblue', fontdict = {'fontsize' : 18,
                                                'fontweight' : 600,
                                                'fontstyle' : 'oblique',
                                                'fontfamily' : 'serif'})
df_gender_dist = np.round(df['Gender'].value_counts(normalize = True) * 100, 2)
plt.pie(x = df_gender_dist.values, labels = df_gender_dist.index,
        explode = [0, 0.1], autopct = '%.2f%%',
       textprops = {'fontsize' : 14,
                    'fontstyle' : 'oblique',
                    'fontfamily' : 'serif',
                    'fontweight' : 500},
       colors = ['brown', 'magenta'])
plt.plot()
plt.subplot(1, 3, 2)
plt.title('On the basis of Marital Statuses', color = 'darkgreen', fontdict = {'fontsize' : 18,
                                                'fontweight' : 600,
                                                'fontstyle' : 'oblique',
                                                'fontfamily' : 'serif'})
df_Marital_Status_dist = np.round(df['Marital_Status'].value_counts(normalize = True) * 100, 2)
plt.pie(x = df_Marital_Status_dist.values, labels = df_Marital_Status_dist.index,
        explode = [0, 0.1], autopct = '%.2f%%',
       textprops = {'fontsize' : 14,
                    'fontstyle' : 'oblique',
                    'fontfamily' : 'serif',
                    'fontweight' : 500},
       colors = ['yellow', 'red'])
plt.plot()
plt.subplot(1, 3, 3)
plt.title("On the basis of Cities", color = 'purple', fontdict = {'fontsize' : 18,
                                                'fontweight' : 555,
                                                'fontstyle' : 'oblique',
                                                'fontfamily' : 'serif'})
df_City_Category_dist = np.round(df['City_Category'].value_counts(normalize = True) * 100, 2)
plt.pie(x = df_City_Category_dist.values, labels = df_City_Category_dist.index,
        explode = [0, 0, 0.1], autopct = '%.2f%%',
       textprops = {'fontsize' : 14,
                    'fontstyle' : 'oblique',
                    'fontfamily' : 'serif',
                    'fontweight' : 500})
plt.plot()
```

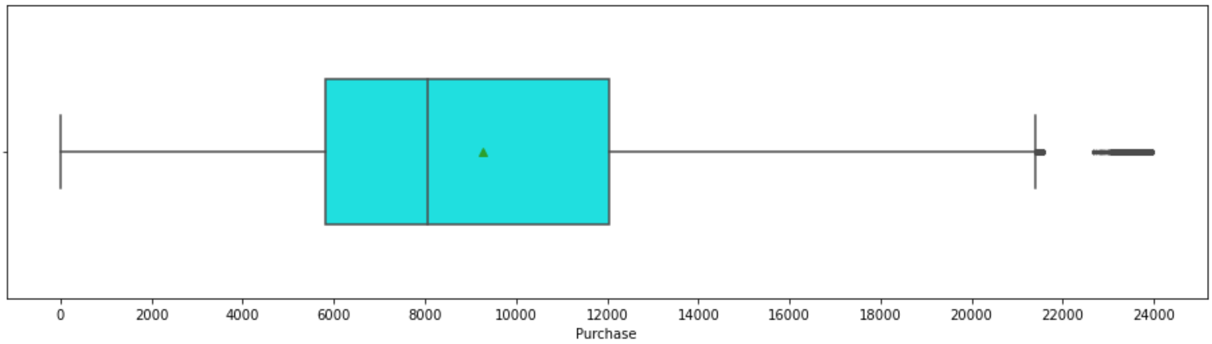
Out[51]: []



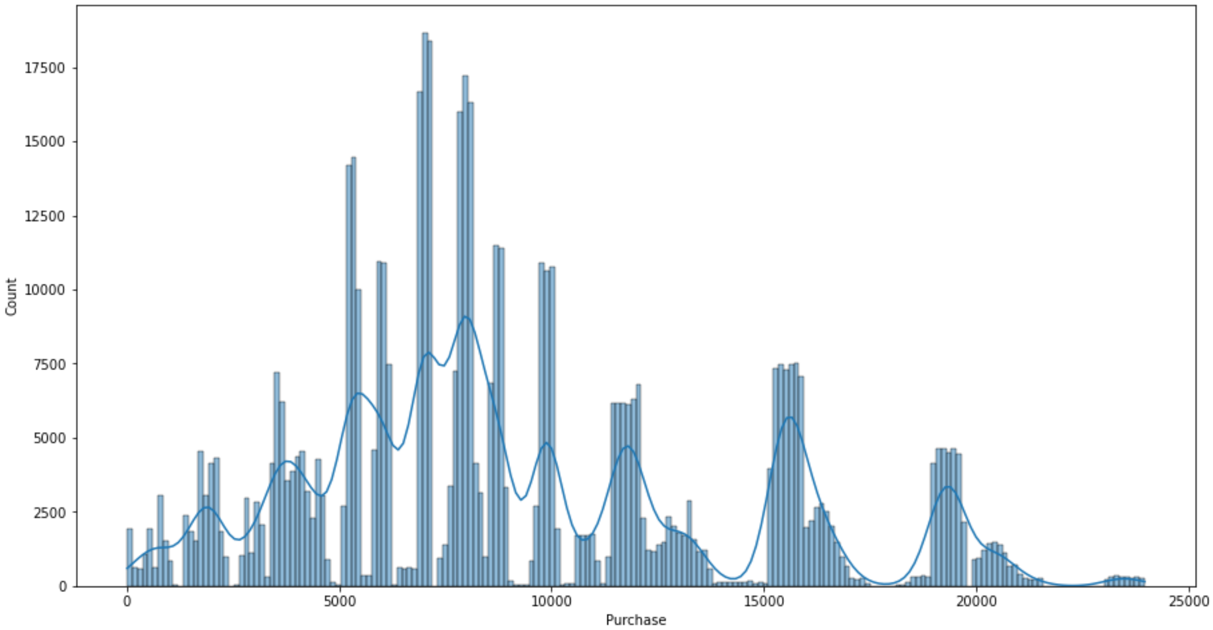
Univariate Analysis

In [52]:
```
plt.figure(figsize = (16, 4))
sns.boxplot(data = df,
            x = 'Purchase',
            showmeans = True,
            fliersize = 2,
            width = 0.5,
            color = np.random.choice(['magenta', 'lightgreen', 'cyan']))
plt.xticks(np.arange(0, 25001, 2000))
plt.plot()
```

Out[52]: []

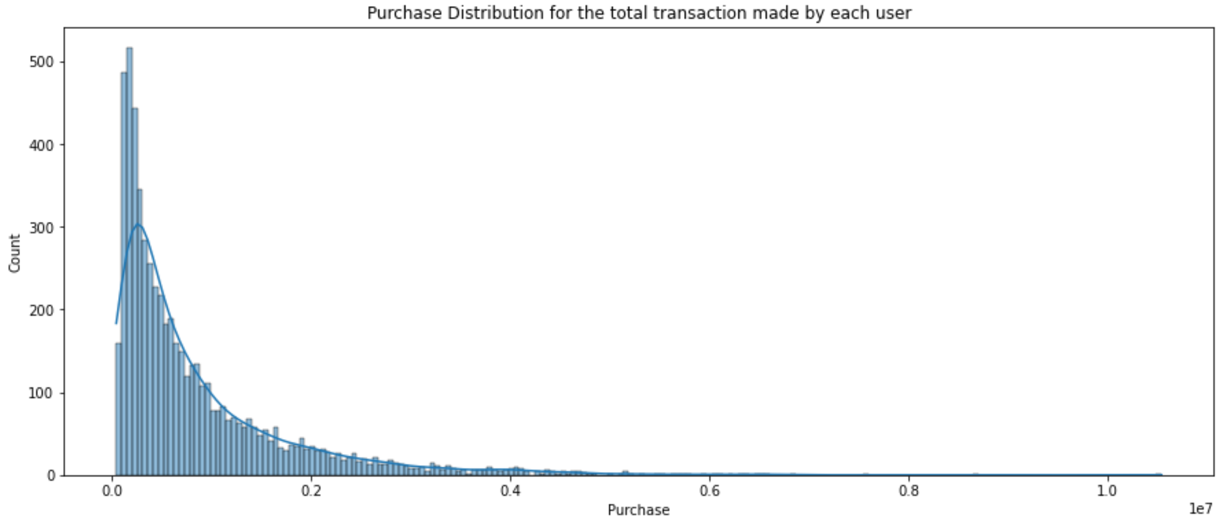


In [53]:
```
plt.figure(figsize = (15, 8))
sns.histplot(data = df, x = 'Purchase', kde = True, bins = 200)
plt.show()
```

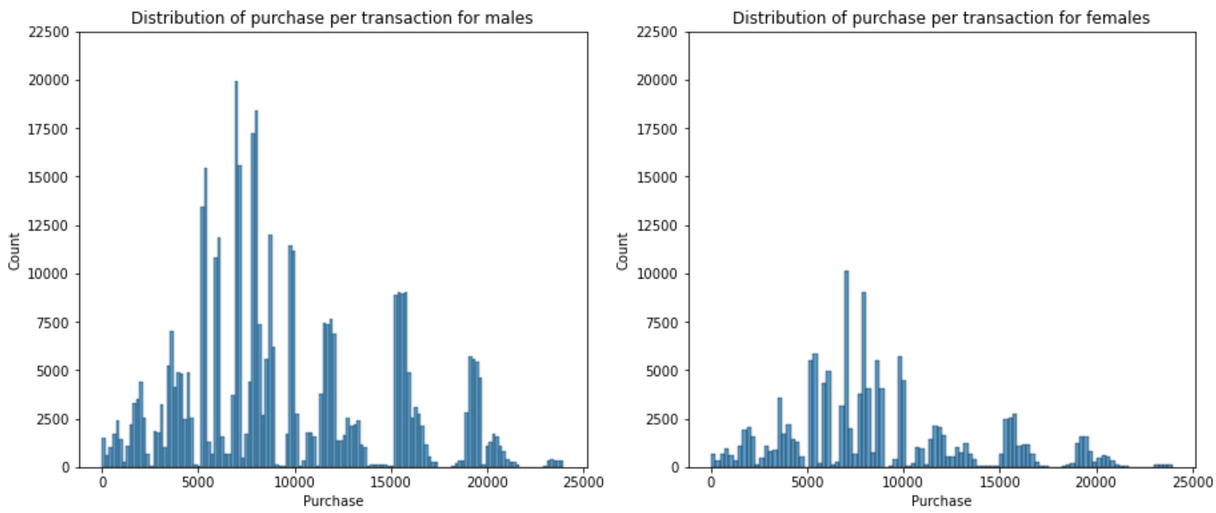


In [54]:
```
plt.figure(figsize = (15, 6))
plt.title('Purchase Distribution for the total transaction made by each user')
df_customer = df.groupby(by = 'User_ID')['Purchase'].sum()
sns.histplot(data = df_customer, kde = True, bins = 200)
plt.plot()
```

Out[54]: []



In [55]:
```
plt.figure(figsize = (15, 6))
plt.subplot(1, 2, 1)
plt.title('Distribution of purchase per transaction for males')
df_male = df[df['Gender'] == 'M']
sns.histplot(data = df_male, x = 'Purchase')
plt.yticks(np.arange(0, 22550, 2500))
plt.subplot(1, 2 ,2)
plt.title('Distribution of purchase per transaction for females')
df_female = df[df['Gender'] == 'F']
sns.histplot(data = df_female, x = 'Purchase')
plt.yticks(np.arange(0, 22550, 2500))
plt.show()
```



In [56]:
```
df_cust_gender = pd.DataFrame(df.groupby(by = ['Gender', 'User_ID'])['Purchase'].sum()).reset_index().rename(colum
df_cust_gender
```

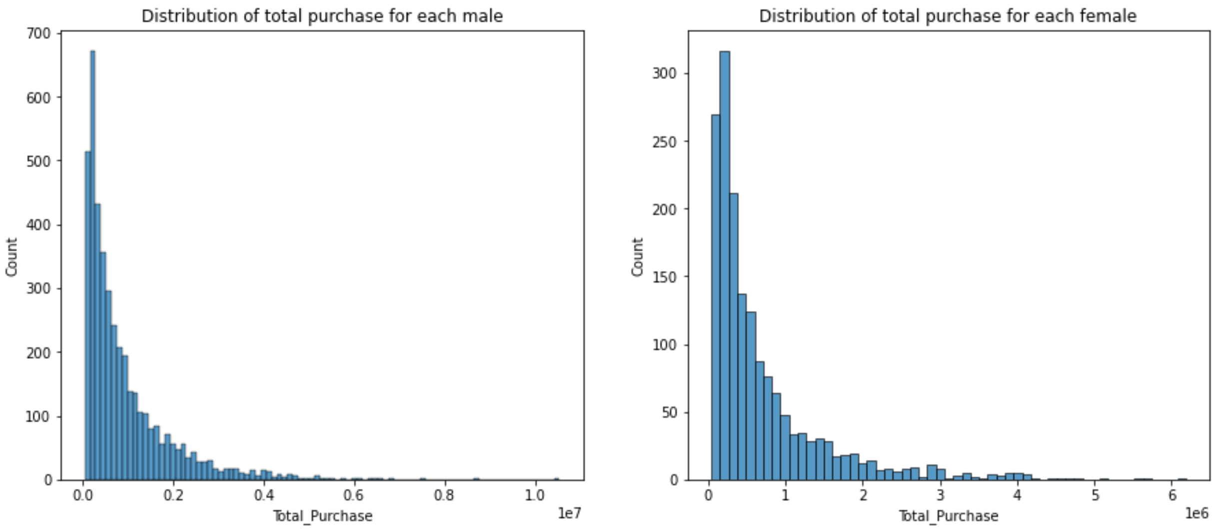
Out[56]:

	Gender	User_ID	Total_Purchase
0	F	1000001	334093
1	F	1000006	379930
2	F	1000010	2169510
3	F	1000011	557023
4	F	1000016	150490
...	...	...	...
5886	M	1006030	737361
5887	M	1006032	517261
5888	M	1006033	501843
5889	M	1006034	197086
5890	M	1006040	1653299

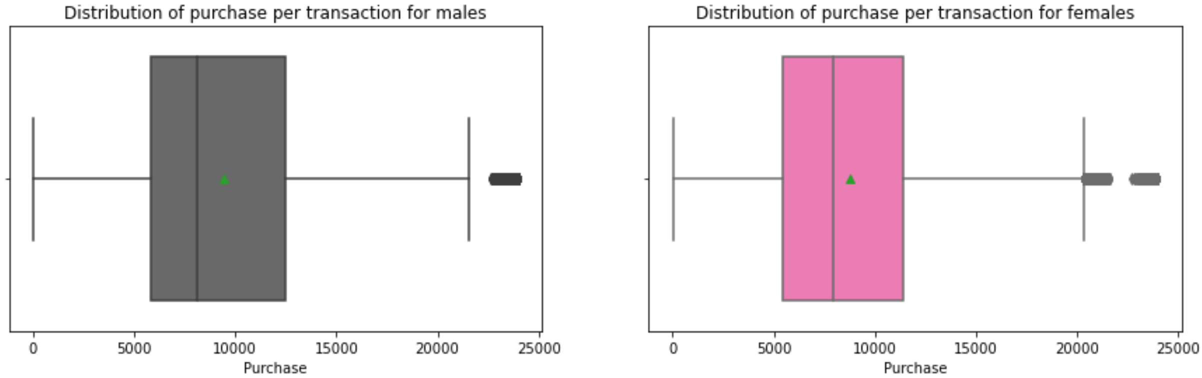
5891 rows × 3 columns

In [57]:
```
df_male_customer = df_cust_gender.loc[df_cust_gender['Gender'] == 'M']
df_female_customer = df_cust_gender.loc[df_cust_gender['Gender'] == 'F']
```

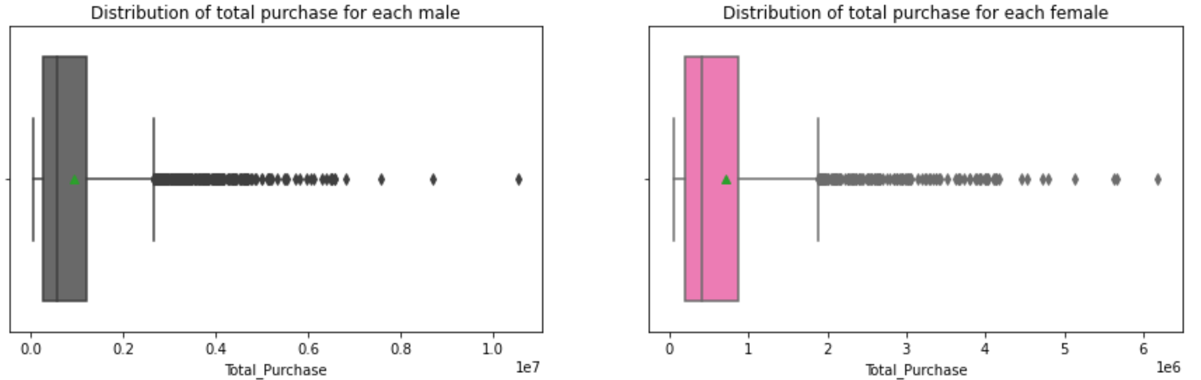
In [58]:
```
plt.figure(figsize = (15, 6))
plt.subplot(1, 2, 1)
plt.title('Distribution of total purchase for each male')
sns.histplot(data = df_male_customer, x = 'Total_Purchase')
plt.subplot(1, 2 ,2)
plt.title('Distribution of total purchase for each female')
df_female = df[df['Gender'] == 'F']
sns.histplot(data = df_female_customer, x = 'Total_Purchase')
plt.show()
```



In [59]:
```
plt.figure(figsize = (15, 4))
plt.subplot(1, 2, 1)
plt.title('Distribution of purchase per transaction for males')
sns.boxplot(data = df_male, x = 'Purchase', showmeans = True, color = 'dimgray')
plt.subplot(1, 2 ,2)
plt.title('Distribution of purchase per transaction for females')
sns.boxplot(data = df_female, x = 'Purchase', showmeans = True, color = 'hotpink')
plt.show()
```



In [60]:
```
plt.figure(figsize = (15, 4))
plt.subplot(1, 2, 1)
plt.title('Distribution of total purchase for each male')
sns.boxplot(data = df_male_customer, x = 'Total_Purchase', showmeans = True, color = 'dimgray')
plt.subplot(1, 2 ,2)
plt.title('Distribution of total purchase for each female')
sns.boxplot(data = df_female_customer, x = 'Total_Purchase', showmeans = True, color = 'hotpink')
plt.show()
```

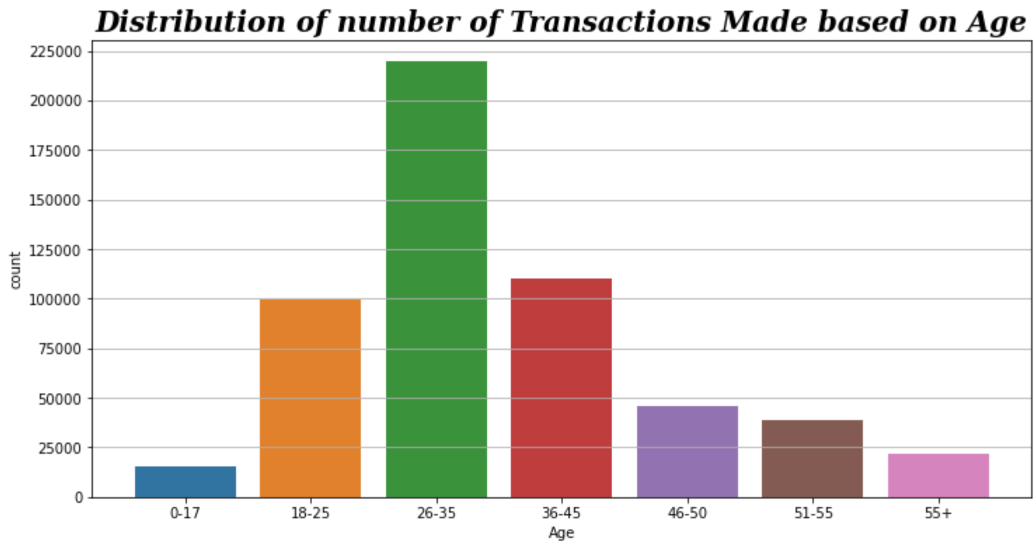


In [61]:
```
df['Age'].unique()
```

Out[61]:
```
['0-17', '55+', '26-35', '46-50', '51-55', '36-45', '18-25']
Categories (7, object): ['0-17', '18-25', '26-35', '36-45', '46-50', '51-55', '55+']
```

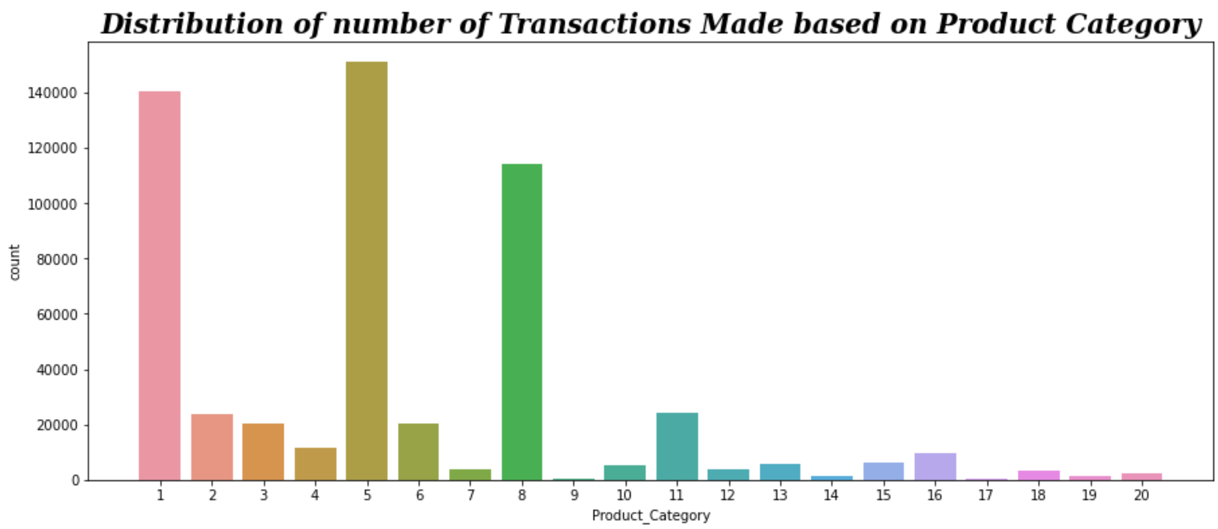
In [62]:
```
plt.figure(figsize = (12, 6))
plt.title('Distribution of number of Transactions Made based on Age',
          fontsize = 20,
          fontweight = 600,
          fontstyle = 'oblique',
          fontfamily = 'serif')
plt.yticks(np.arange(0, 250001, 25000))
plt.grid('y')
sns.countplot(data = df, x = 'Age',
              order = ['0-17', '18-25', '26-35', '36-45', '46-50', '51-55', '55+'])
plt.plot()
```

Out[62]: []



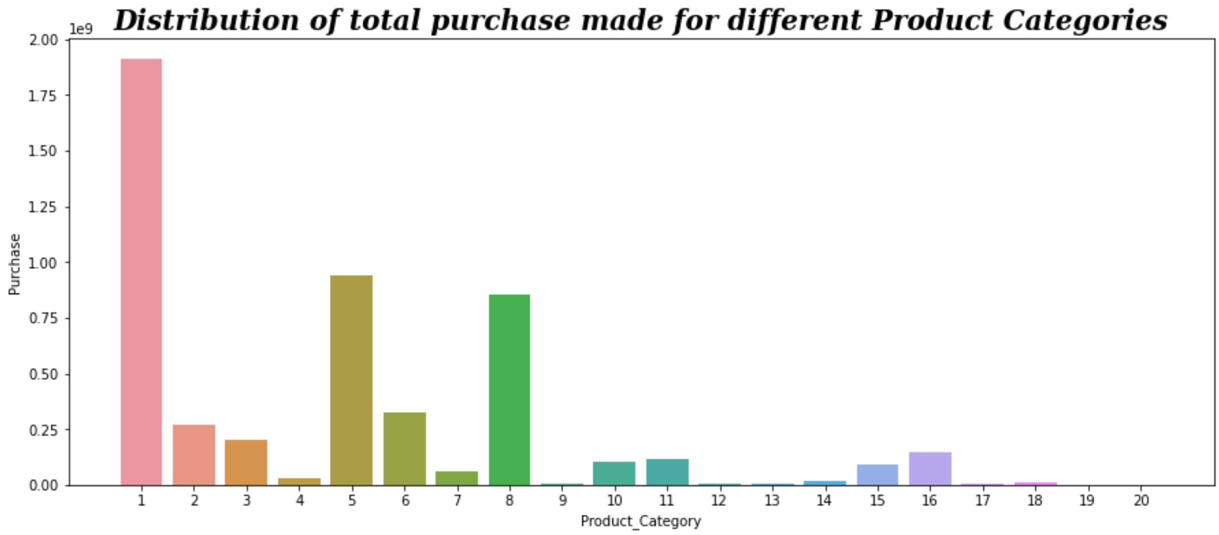
In [63]:
```
plt.figure(figsize = (15, 6))
plt.title('Distribution of number of Transactions Made based on Product Category', fontsize = 20, fontweight = 600
sns.countplot(data = df, x = 'Product_Category')
plt.plot()
```

Out[63]: []



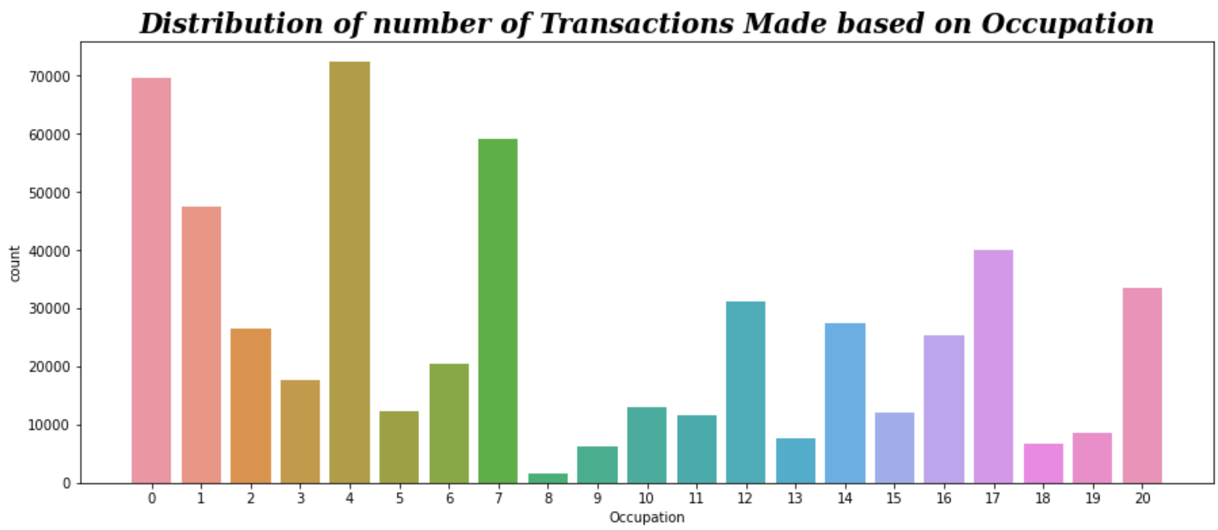
```
In [64]: df_product_category = df.groupby(by = 'Product_Category')['Purchase'].sum().to_frame().reset_index()
         plt.figure(figsize = (15, 6))
         plt.title('Distribution of total purchase made for different Product Categories',
                   fontsize = 20,
                   fontweight = 600,
                   fontstyle = 'oblique',
                   fontfamily = 'serif')
         sns.barplot(data = df_product_category, x = 'Product_Category', y = 'Purchase')
         plt.plot()

Out[64]: []
```



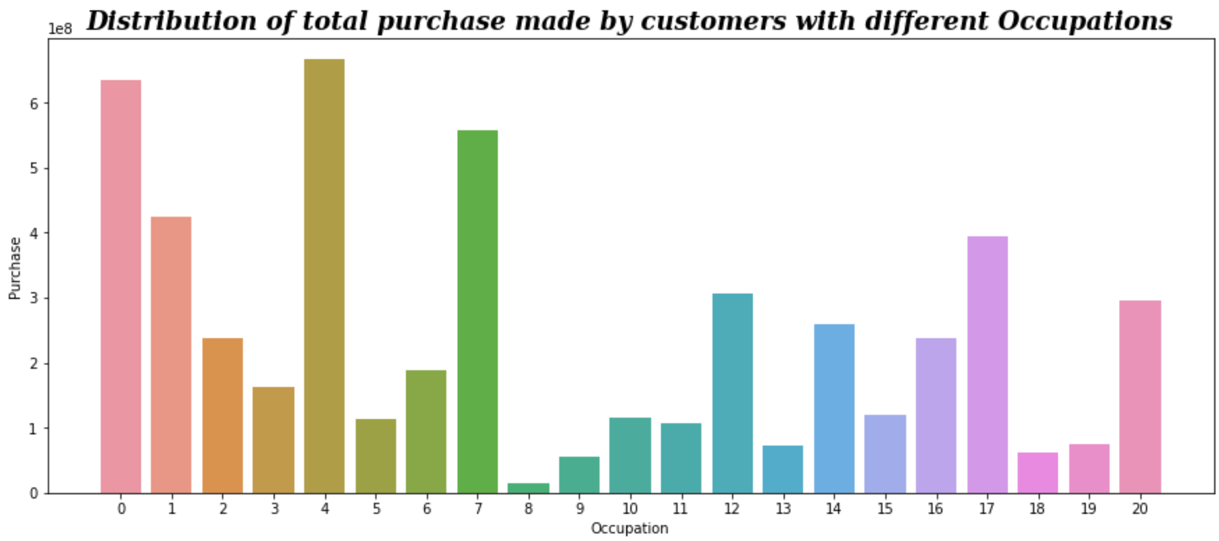

```
In [65]: plt.figure(figsize = (15, 6))
         plt.title('Distribution of number of Transactions Made based on Occupation',
                   fontsize = 20,
                   fontweight = 600,
                   fontstyle = 'oblique',
                   fontfamily = 'serif')
         sns.countplot(data = df, x = 'Occupation')
         plt.plot()

Out[65]: []
```



In [66]:
```
df_occupation = df.groupby(by = 'Occupation')['Purchase'].sum().to_frame().reset_index()
plt.figure(figsize = (15, 6))
plt.title('Distribution of total purchase made by customers with different Occupations',
          fontsize = 18,
          fontweight = 600,
          fontstyle = 'oblique',
          fontfamily = 'serif')
sns.barplot(data = df_occupation, x = 'Occupation', y = 'Purchase')
plt.plot()
```

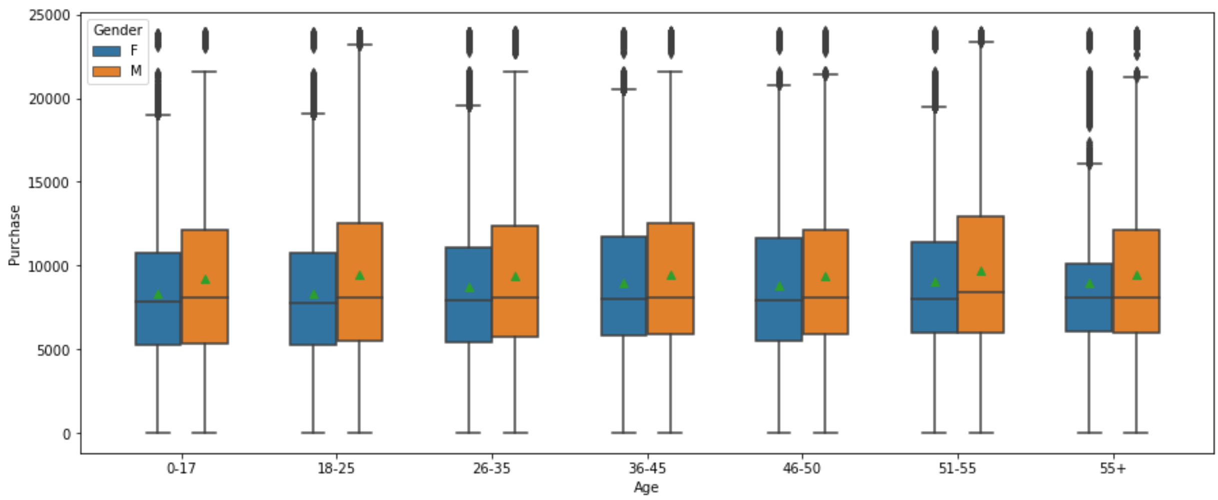
Out[66]: []



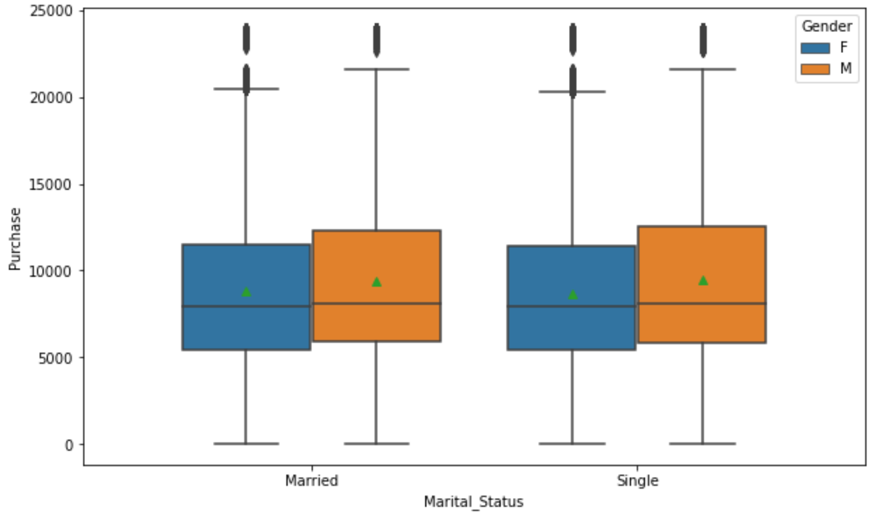
Bivariate Analysis

In [67]:
```
plt.figure(figsize = (15, 6))
sns.boxplot(data = df, x = 'Age', y = 'Purchase', hue = 'Gender', showmeans = True, width = 0.6)
plt.plot()
```

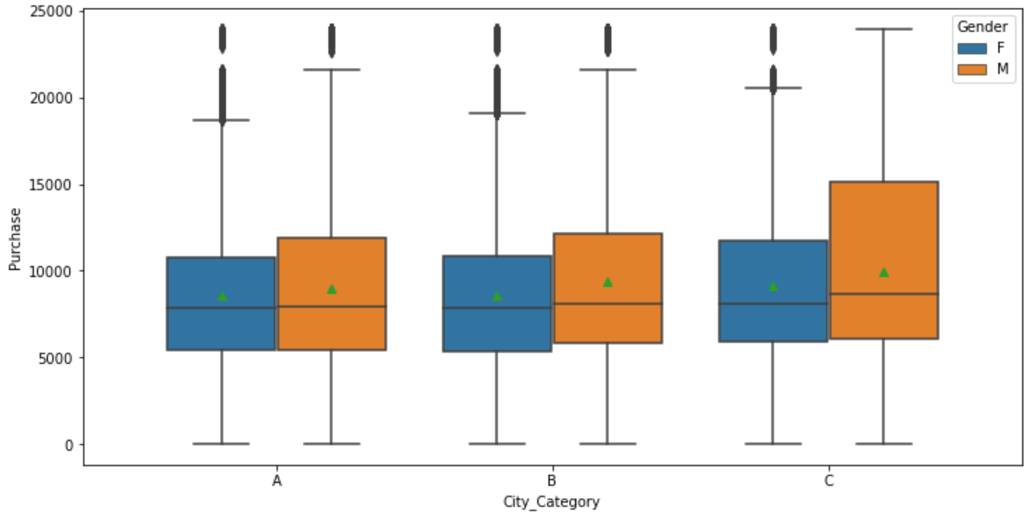
Out[67]: []



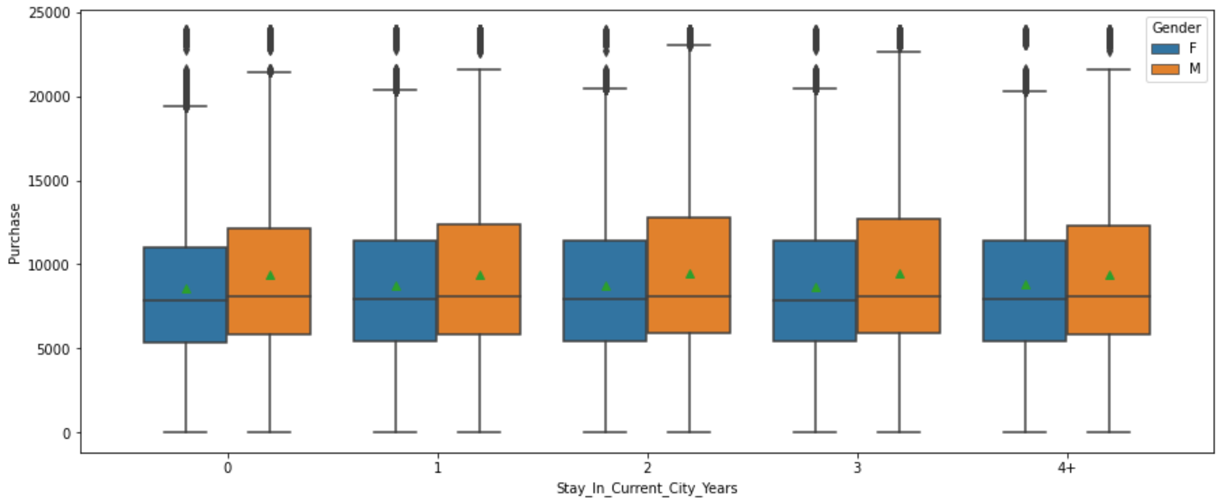
In [68]:
```
plt.figure(figsize = (10, 6))
sns.boxplot(data = df, x = 'Marital_Status', y = 'Purchase', hue = 'Gender', showmeans = True, width  = 0.8)
plt.plot()
```
Out[68]: []



In [69]:
```
plt.figure(figsize = (12, 6))
sns.boxplot(data = df, x = 'City_Category', y = 'Purchase', hue = 'Gender', showmeans = True)
plt.plot()
```
Out[69]: []



In [70]:
```
plt.figure(figsize = (15, 6))
sns.boxplot(data = df, x = 'Stay_In_Current_City_Years', y = 'Purchase', hue = 'Gender', showmeans = True)
plt.plot()
```
Out[70]: []



Determining the mean purchase made by each user

For Males

How the deviations vary for different sample sizes ?

In [71]:
```
df_male_customer
```

Out[71]:

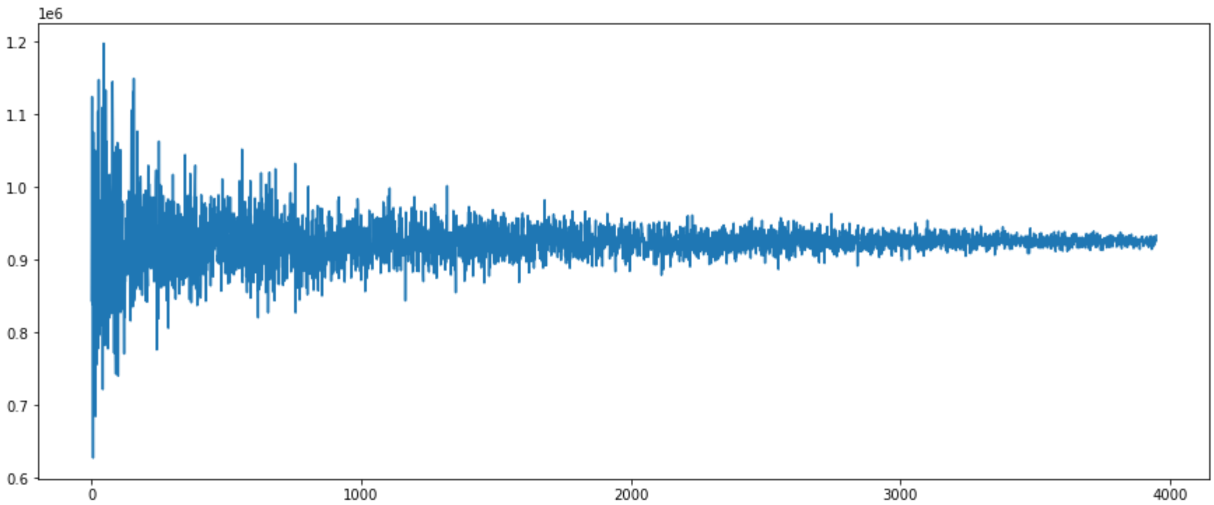
	Gender	User_ID	Total_Purchase
1666	M	1000002	810472
1667	M	1000003	341635
1668	M	1000004	206468
1669	M	1000005	821001
1670	M	1000007	234668
...	...	...	...
5886	M	1006030	737361
5887	M	1006032	517261
5888	M	1006033	501843
5889	M	1006034	197086
5890	M	1006040	1653299

4225 rows × 3 columns

In [72]:
```
mean_purchases = []
for sample_size in range(50, 4000):
    sample_mean = df_male_customer['Total_Purchase'].sample(sample_size).mean()
    mean_purchases.append(sample_mean)
```

In [73]:
```
plt.figure(figsize = (15, 6))
plt.plot(mean_purchases)
plt.xticks(np.arange(0, 10001, 1000))
plt.plot()
```

Out[73]: []



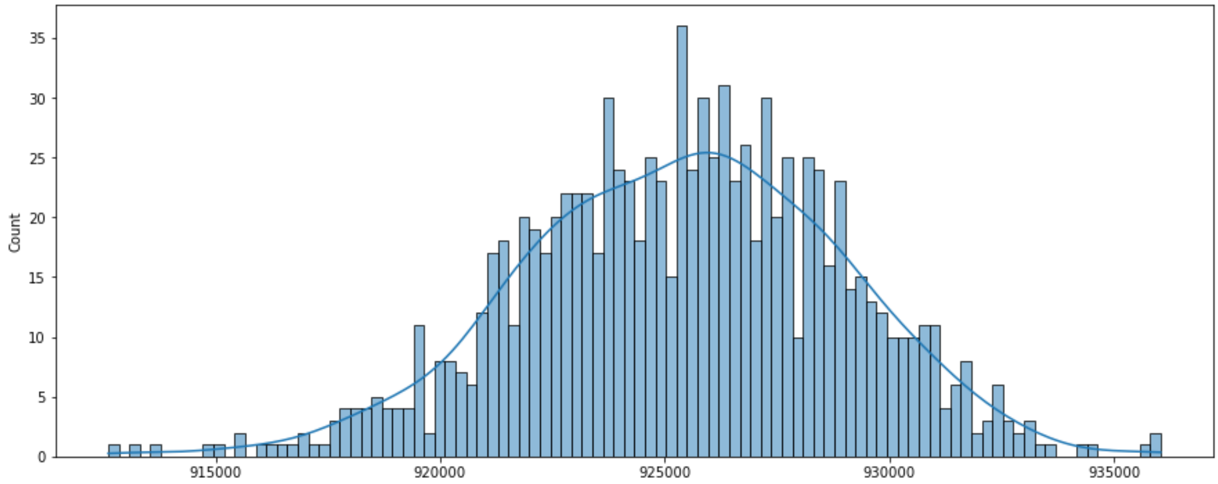

```
It can be inferred from the above plot that as the sample size is small the deviations are fairly high.
As the sample size increases, the deviation becomes smaller and smaller.
The deviations will be small if the sample size taken is greater than 2000.
```

For conservative analysis, sample size of 4000 is taken 1000 times

In [74]:
```python
means = []
for sample_size in range(1000):
    sample_mean = df_male_customer['Total_Purchase'].sample(4000).mean()
    means.append(sample_mean)
```

In [75]:
```python
plt.figure(figsize = (15, 6))
sns.histplot(means, kde = True, bins = 100)
plt.plot()
```

Out[75]: []




```
For males sample of size 4000 is taken 1000 times and the frequency of the sample means are plotted, it has
resulted in an approximate
normal distribution curve with mean of approximately 925463.09 and a standard deviation of about 9275.75.
```

Determining Mean Purchase made by males with 90% Confidence

In [76]:
```python
sample_mean = np.mean(means)
sample_std = np.std(means)
sample_mean, sample_std
```

Out[76]: (925383.920298, 3544.8882100823002)

In [77]:
```python
sample_mean + spy.norm.ppf(0.05)* sample_std, sample_mean + spy.norm.ppf(0.95)* sample_std
```

Out[77]: (919553.0980685086, 931214.7425274914)

Determining Mean Purchase made by males with 95% Confidence

In [78]:
```python
sample_mean + spy.norm.ppf(0.025)* sample_std, sample_mean + spy.norm.ppf(0.975)* sample_std
```

Out[78]: (918436.067077018, 932331.773518982)

Determining Mean Purchase made by males with 99% Confidence

In [79]:
```python
sample_mean + spy.norm.ppf(0.005)* sample_std, sample_mean + spy.norm.ppf(0.995)* sample_std
```

Out[79]: (916252.893368665, 934514.947227335)

For Females

How the deviations vary for different sample sizes ?

In [80]:
```
df_female_customer
```

Out[80]:

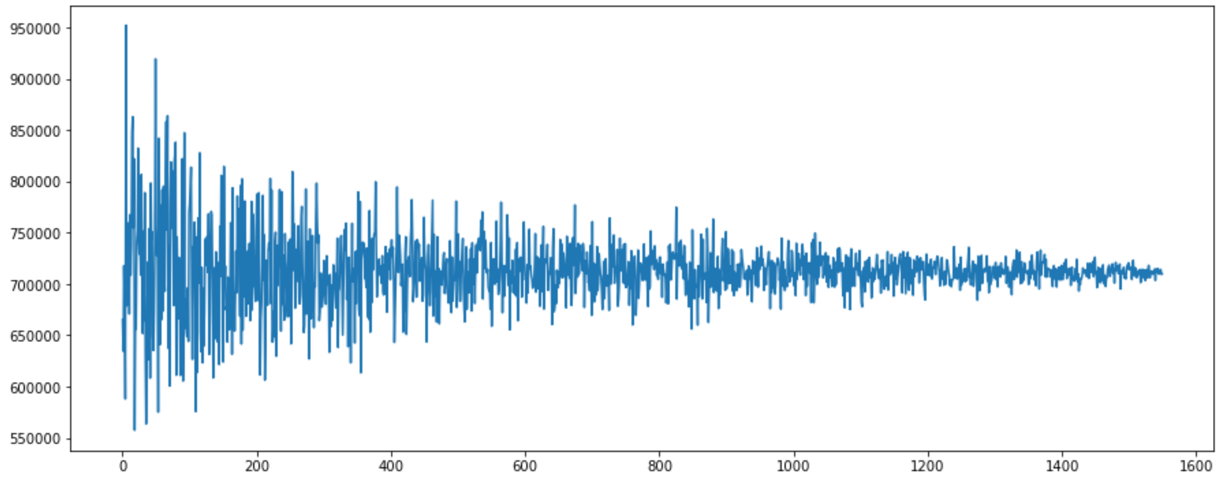
	Gender	User_ID	Total_Purchase
0	F	1000001	334093
1	F	1000006	379930
2	F	1000010	2169510
3	F	1000011	557023
4	F	1000016	150490
...	...	...	...
1661	F	1006035	956645
1662	F	1006036	4116058
1663	F	1006037	1119538
1664	F	1006038	90034
1665	F	1006039	590319

1666 rows × 3 columns

In [81]:
```
mean_purchases = []
for sample_size in range(50, 1600):
    sample_mean = df_female_customer['Total_Purchase'].sample(sample_size).mean()
    mean_purchases.append(sample_mean)
```

In [82]:
```
plt.figure(figsize = (15, 6))
plt.plot(mean_purchases)
plt.plot()
```

Out[82]: []



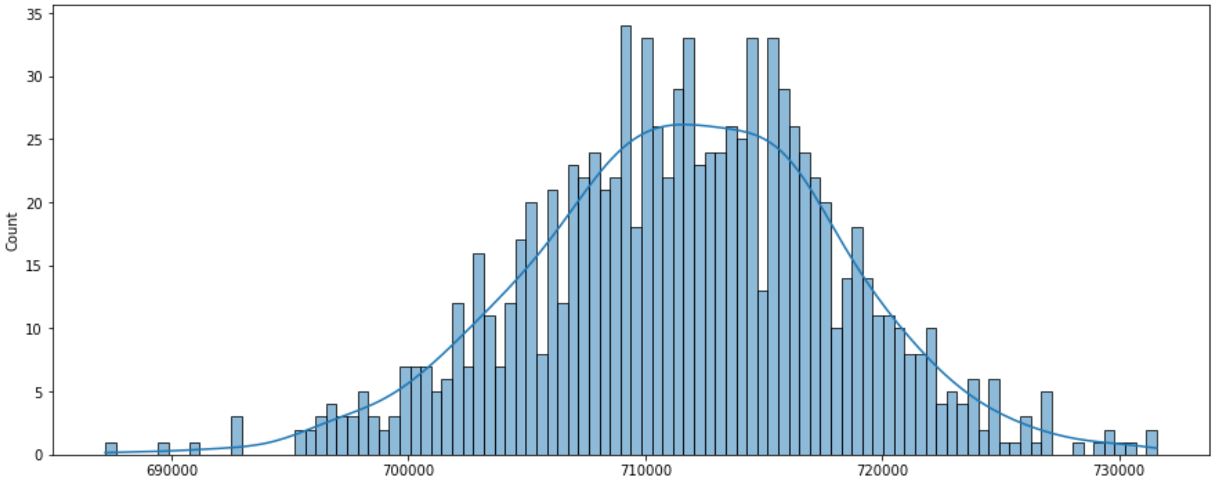

```
It can be inferred from the above plot that as the sample size is small the deviations are fairly high.
As the sample size increases, the deviation becomes smaller and smaller.
The deviations will be small if the sample size taken is greater than 1000.
```

For conservative analysis, sample size of 1500 is taken 1000 times

In [83]:
```
means = []
for sample_size in range(1000):
    sample_mean = df_female_customer['Total_Purchase'].sample(1500).mean()
    means.append(sample_mean)
```

In [84]:
```
plt.figure(figsize = (15, 6))
sns.histplot(means, kde = True, bins = 100)
plt.plot()
```

Out[84]: []




```
For males sample of size 1500 is taken 1000 times and the frequency of the sample means are plotted, it has
resulted in an approximate
normal distribution curve with mean of approximately 712459.92 and a standard deviation of about 6460.07.
```

Determining Mean Purchase made by females with 90% Confidence

In [85]:
```
sample_mean = np.mean(means)
sample_std = np.std(means)
sample_mean, sample_std
```

Out[85]: (711685.0669833333, 6578.864117043024)

In [86]:
```
sample_mean + spy.norm.ppf(0.05)* sample_std, sample_mean + spy.norm.ppf(0.95)* sample_std
```

Out[86]: (700863.7984791942, 722506.3354874725)

Determining Mean Purchase made by females with 95% Confidence

In [87]:
```
sample_mean + spy.norm.ppf(0.025)* sample_std, sample_mean + spy.norm.ppf(0.975)* sample_std
```

Out[87]: (698790.730254746, 724579.4037119206)

Determining Mean Purchase made by females with 99% Confidence

In [88]:
```
sample_mean + spy.norm.ppf(0.005)* sample_std, sample_mean + spy.norm.ppf(0.995)* sample_std
```

Out[88]: (694739.0360065876, 728631.0979600791)

Determining the mean purchase made by each user belonging to different Marital Status per transaction

In [89]:
```
df_single = df.loc[df['Marital_Status'] == 'Single']
df_married = df.loc[df['Marital_Status'] == 'Married']
```

In [90]:
```
df_single = df_single.groupby('User_ID')['Purchase'].sum().to_frame().reset_index().rename(columns = {'Purchase' :
df_married = df_married.groupby('User_ID')['Purchase'].sum().to_frame().reset_index().rename(columns = {'Purchase'
```

For Singles

In [91]:
```
df_single
```

Out[91]:

	User_ID	Total_Purchase
0	1000001	334093
1	1000002	810472
2	1000003	341635
3	1000006	379930
4	1000009	594099
...	...	...
3412	1006034	197086
3413	1006035	956645
3414	1006037	1119538
3415	1006038	90034
3416	1006040	1653299

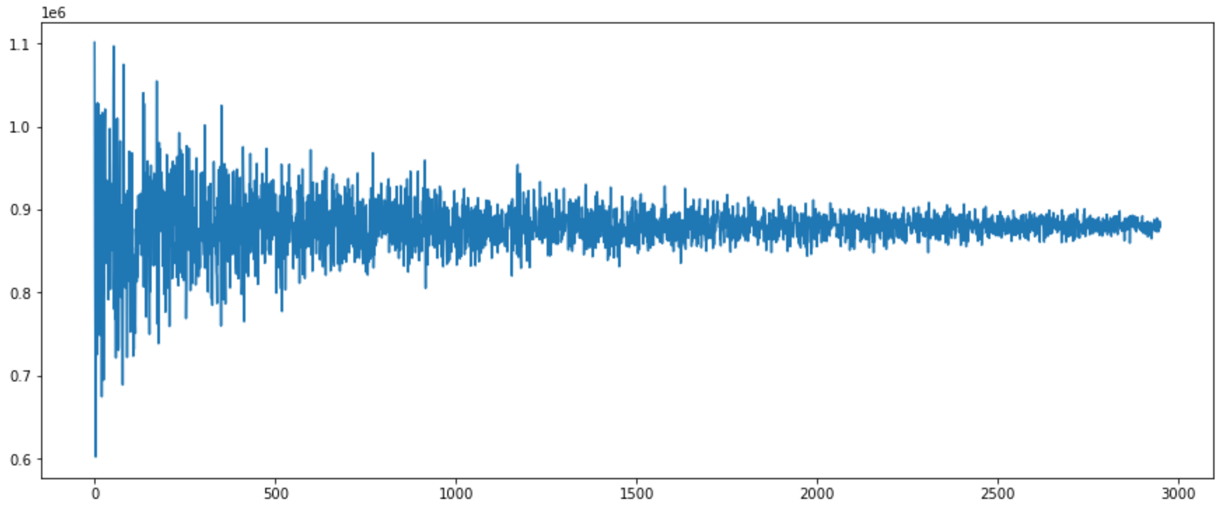
3417 rows × 2 columns

How the deviations vary for different sample sizes ?

In [92]:
```
mean_purchases = []
for sample_size in range(50, 3000):
    sample_mean = df_single['Total_Purchase'].sample(sample_size).mean()
    mean_purchases.append(sample_mean)
```

In [93]:
```
plt.figure(figsize = (15, 6))
plt.plot(mean_purchases)
plt.plot()
```

Out[93]: []



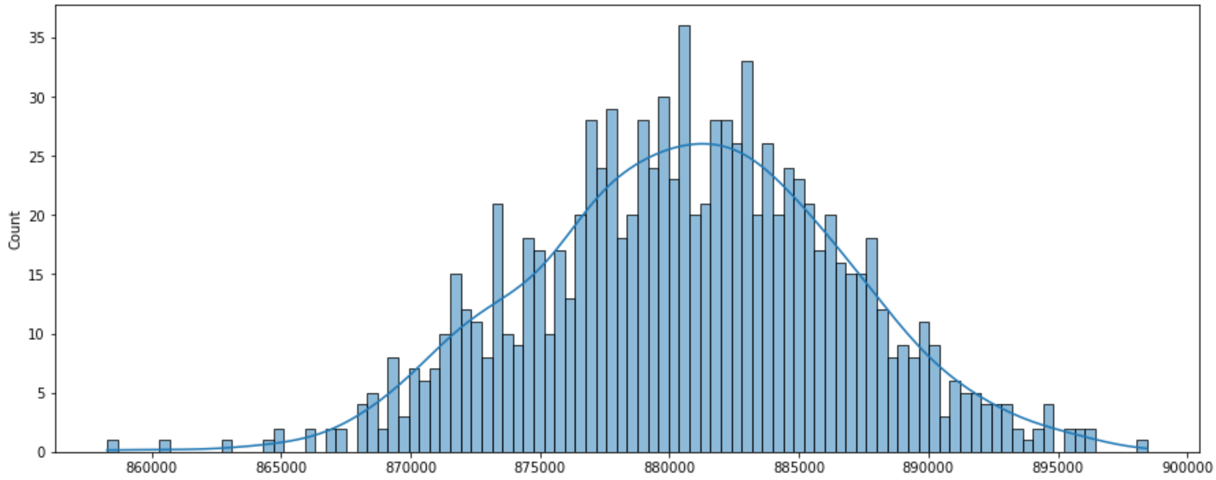

```
It can be inferred from the above plot that as the sample size is small the deviations are fairly high.
As the sample size increases, the deviation becomes smaller and smaller.
The deviations will be small if the sample size taken is greater than 2000.
```

For conservative analysis, sample size of 3000 is taken 1000 times

In [94]:
```
means = []
for sample_size in range(1000):
    sample_mean = df_single['Total_Purchase'].sample(3000).mean()
    means.append(sample_mean)
```

In [95]:
```
plt.figure(figsize = (15, 6))
sns.histplot(means, kde = True, bins = 100)
plt.plot()
```

Out[95]: []



Determining Mean Total Purchase made by singles with 90% Confidence

In [96]:
```
sample_mean = np.mean(means)
sample_std = np.std(means)
sample_mean, sample_std
```

Out[96]: (880688.4894113333, 5970.6722656699985)

In [97]:
```
sample_mean + spy.norm.ppf(0.05)* sample_std, sample_mean + spy.norm.ppf(0.95)* sample_std
```

Out[97]: (870867.6074798075, 890509.3713428592)

Determining Mean Total Purchase made by singles with 95% Confidence

In [98]:
```
sample_mean + spy.norm.ppf(0.025)* sample_std, sample_mean + spy.norm.ppf(0.975)* sample_std
```

Out[98]: (868986.186807128, 892390.7920155387)

Determining Mean Total Purchase made by singles with 99% Confidence

In [99]:
```
sample_mean + spy.norm.ppf(0.005)* sample_std, sample_mean + spy.norm.ppf(0.995)* sample_std
```

Out[99]: (865309.0568275339, 896067.9219951328)

For Marrieds

In [100]:
```
df_married
```

Out[100]:

	User_ID	Total_Purchase
0	1000004	206468
1	1000005	821001
2	1000007	234668
3	1000008	796593
4	1000010	2169510
...	...	...
2469	1006029	157436
2470	1006030	737361
2471	1006033	501843
2472	1006036	4116058
2473	1006039	590319

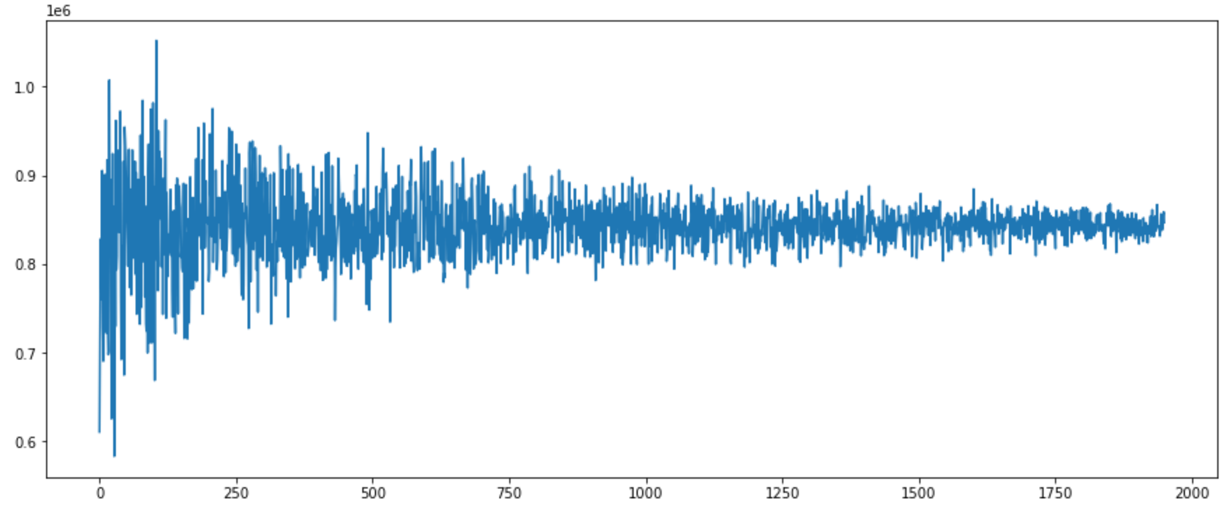
2474 rows × 2 columns

How the deviations vary for different sample sizes ?

In [101]:
```
mean_purchases = []
for sample_size in range(50, 2000):
    sample_mean = df_married['Total_Purchase'].sample(sample_size).mean()
    mean_purchases.append(sample_mean)
```

In [102]:
```
plt.figure(figsize = (15, 6))
plt.plot(mean_purchases)
plt.plot()
```

Out[102]: []



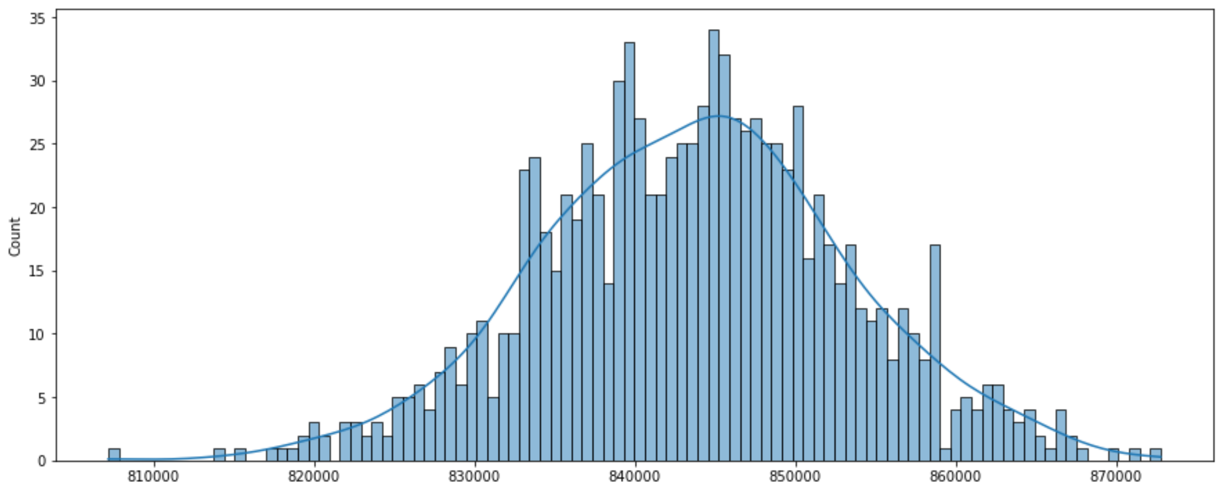

```
It can be inferred from the above plot that as the sample size is small the deviations are fairly high.
As the sample size increases, the deviation becomes smaller and smaller.
The deviations will be small if the sample size taken is greater than 1500.
```

For conservative analysis, sample size of 2000 is taken 1000 times

In [103]:
```
means = []
for sample_size in range(1000):
    sample_mean = df_married['Total_Purchase'].sample(2000).mean()
    means.append(sample_mean)
```

In [104]:
```
plt.figure(figsize = (15, 6))
sns.histplot(means, kde = True, bins = 100)
plt.plot()
```

Out[104]: []



Determining Mean Total Purchase made by marrieds with 90% Confidence

In [105]:
```
sample_mean = np.mean(means)
sample_std = np.std(means)
sample_mean, sample_std
```
Out[105]:
```
(843626.2500895, 9599.537769255468)
```
In [106]:
```
sample_mean + spy.norm.ppf(0.05)* sample_std, sample_mean + spy.norm.ppf(0.95)* sample_std
```
Out[106]:
```
(827836.4155726825, 859416.0846063175)
```
Determining Mean Total Purchase made by marrieds with 95% Confidence

In [107]:
```
sample_mean + spy.norm.ppf(0.025)* sample_std, sample_mean + spy.norm.ppf(0.975)* sample_std
```
Out[107]:
```
(824811.5017935273, 862440.9983854727)
```
Determining Mean Total Purchase made by marrieds with 99% Confidence

In [108]:
```
sample_mean + spy.norm.ppf(0.005)* sample_std, sample_mean + spy.norm.ppf(0.995)* sample_std
```
Out[108]:
```
(818899.4794029273, 868353.0207760726)
```
In [ ]:
```

```
Determining the mean purchase made by each user per transaction based on their age groups :

In [109]:
```
df['Age'].unique()
```
Out[109]:
```
['0-17', '55+', '26-35', '46-50', '51-55', '36-45', '18-25']
Categories (7, object): ['0-17', '18-25', '26-35', '36-45', '46-50', '51-55', '55+']
```
In [110]:
```
df_age_0_to_17 = df.loc[df['Age'] == '0-17']
df_age_18_to_25 = df.loc[df['Age'] == '18-25']
df_age_26_to_35 = df.loc[df['Age'] == '26-35']
df_age_36_to_45 = df.loc[df['Age'] == '36-45']
df_age_46_to_50 = df.loc[df['Age'] == '46-50']
df_age_51_to_55 = df.loc[df['Age'] == '51-55']
df_age_above_55 = df.loc[df['Age'] == '55+']
```
In [111]:
```
df_age_0_to_17 = df_age_0_to_17.groupby(by = 'User_ID')['Purchase'].sum().to_frame().reset_index().rename(columns
df_age_18_to_25 = df_age_18_to_25.groupby(by = 'User_ID')['Purchase'].sum().to_frame().reset_index().rename(column
df_age_26_to_35 = df_age_26_to_35.groupby(by = 'User_ID')['Purchase'].sum().to_frame().reset_index().rename(column
df_age_36_to_45 = df_age_36_to_45.groupby(by = 'User_ID')['Purchase'].sum().to_frame().reset_index().rename(column
df_age_46_to_50 = df_age_46_to_50.groupby(by = 'User_ID')['Purchase'].sum().to_frame().reset_index().rename(column
df_age_51_to_55 = df_age_51_to_55.groupby(by = 'User_ID')['Purchase'].sum().to_frame().reset_index().rename(column
df_age_above_55 = df_age_above_55.groupby(by = 'User_ID')['Purchase'].sum().to_frame().reset_index().rename(column
```

For Age Group 0 - 17 years

In [112]:
```
df_age_0_to_17
```

Out[112]:

	User_ID	Total_Purchase
0	1000001	334093
1	1000019	1458069
2	1000051	200772
3	1000075	1035584
4	1000086	294063
...	...	...
213	1005844	476231
214	1005953	629161
215	1005973	270475
216	1005989	466195
217	1006006	514919

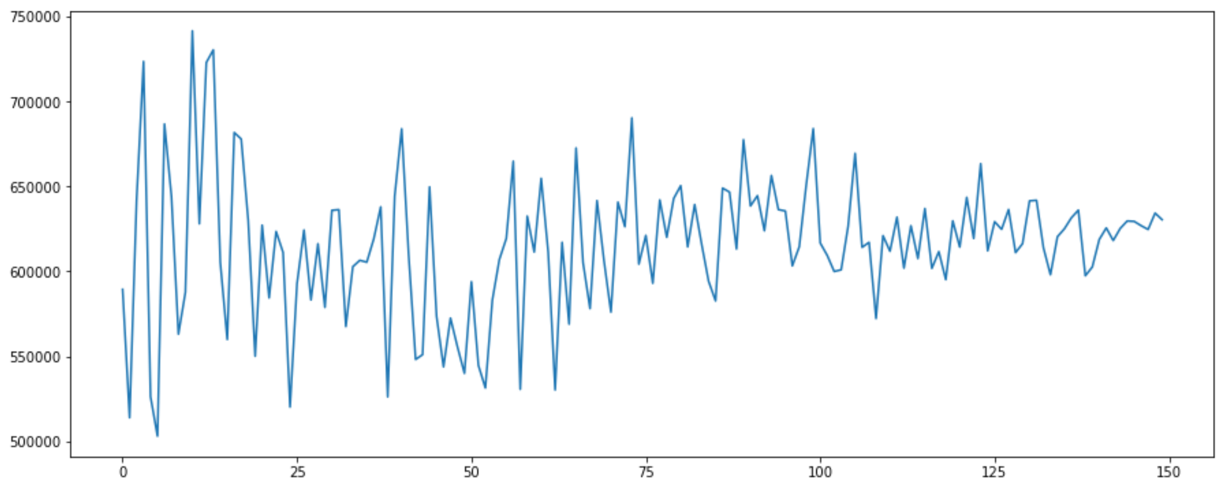
218 rows × 2 columns

How the deviations vary for different sample sizes ?

In [113]:
```
mean_purchases = []
for sample_size in range(50, 200):
    sample_mean = df_age_0_to_17['Total_Purchase'].sample(sample_size).mean()
    mean_purchases.append(sample_mean)
```

In [114]:
```
plt.figure(figsize = (15, 6))
plt.plot(mean_purchases)
plt.xticks(np.arange(0, 201, 25))
plt.plot()
```

Out[114]: []



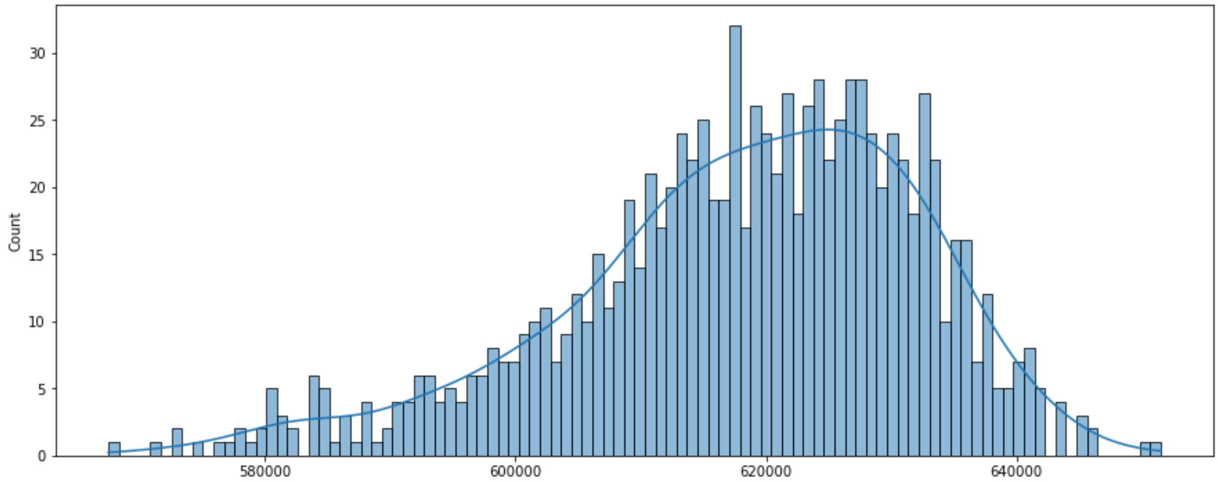

```
It can be inferred from the above plot that as the sample size is small the deviations are fairly high.
As the sample size increases, the deviation becomes smaller and smaller.
The deviations will be small if the sample size taken is greater than 150.
```

For conservative analysis, sample size of 200 is taken 1000 times

In [115]:
```
means = []
for sample_size in range(1000):
    sample_mean = df_age_0_to_17['Total_Purchase'].sample(200).mean()
    means.append(sample_mean)
```

In [116]:
```
plt.figure(figsize = (15, 6))
sns.histplot(means, kde = True, bins = 100)
plt.plot()
```

Out[116]: []



Determining Mean Total Purchase made by Age Group 0 - 17 with 90% Confidence

In [117]:
```
sample_mean = np.mean(means)
sample_std = np.std(means)
sample_mean, sample_std
```

Out[117]: (618064.71096, 14071.046507229506)

In [118]:
```
sample_mean + spy.norm.ppf(0.05)* sample_std, sample_mean + spy.norm.ppf(0.95)* sample_std
```

Out[118]: (594919.8990775808, 641209.5228424193)

Determining Mean Total Purchase made by Age Group 0 - 17 with 95% Confidence

In [119]:
```
sample_mean + spy.norm.ppf(0.025)* sample_std, sample_mean + spy.norm.ppf(0.975)* sample_std
```

Out[119]: (590485.966581042, 645643.455338958)

Determining Mean Total Purchase made by Age Group 0 - 17 with 99% Confidence

In [120]:
```
sample_mean + spy.norm.ppf(0.005)* sample_std, sample_mean + spy.norm.ppf(0.995)* sample_std
```

Out[120]: (581820.0970350789, 654309.3248849212)

For Age Group 18 - 25 years

In [121]:
```
df_age_18_to_25
```

Out[121]:

	User_ID	Total_Purchase
0	1000018	1979047
1	1000021	127099
2	1000022	1279914
3	1000025	534706
4	1000034	807983
...	...	...
1064	1005998	702901
1065	1006008	266306
1066	1006027	265201
1067	1006028	362972
1068	1006031	286374

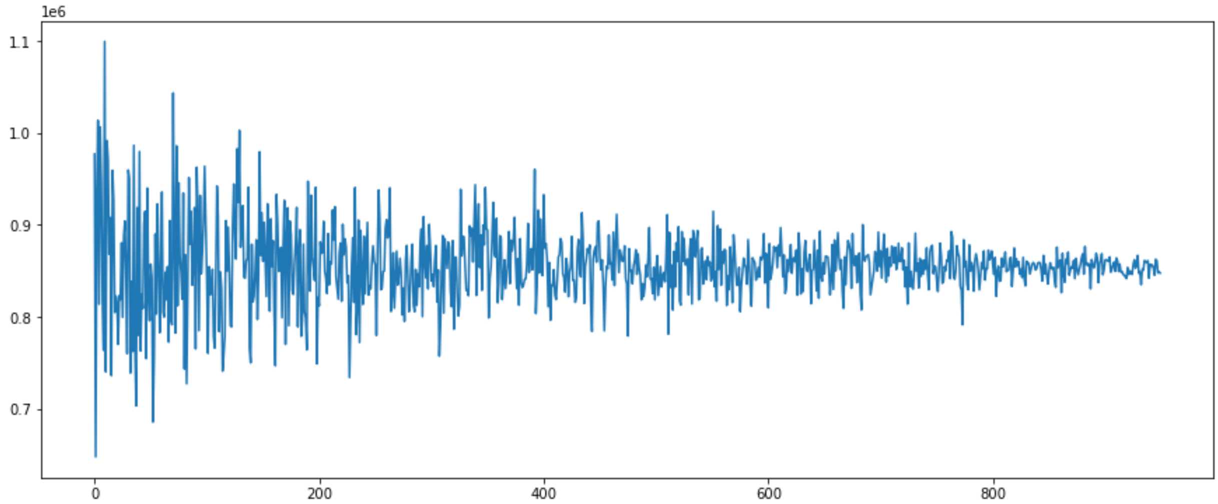
1069 rows × 2 columns

How the deviations vary for different sample sizes ?

In [122]:
```
mean_purchases = []
for sample_size in range(50, 1000):
    sample_mean = df_age_18_to_25['Total_Purchase'].sample(sample_size).mean()
    mean_purchases.append(sample_mean)
```

In [123]:
```
plt.figure(figsize = (15, 6))
plt.plot(mean_purchases)
plt.plot()
```

Out[123]: []



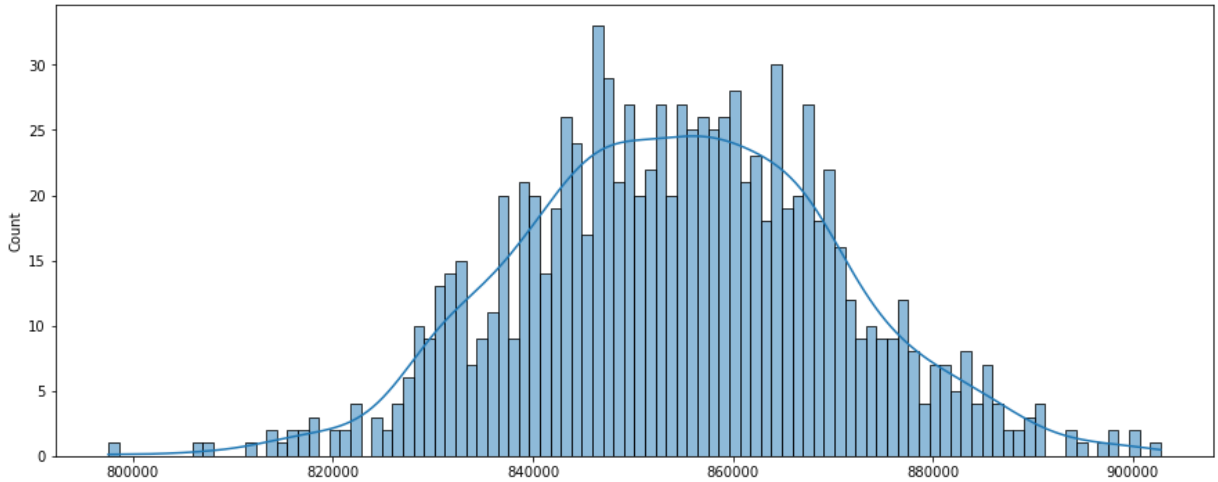

```
It can be inferred from the above plot that as the sample size is small the deviations are fairly high.
As the sample size increases, the deviation becomes smaller and smaller.
The deviations will be small if the sample size taken is greater than 600.
```

For conservative analysis, sample size of 800 is taken 1000 times

In [124]:
```
means = []
for sample_size in range(1000):
    sample_mean = df_age_18_to_25['Total_Purchase'].sample(800).mean()
    means.append(sample_mean)
```

In [125]:
```
plt.figure(figsize = (15, 6))
sns.histplot(means, kde = True, bins = 100)
plt.plot()
```

Out[125]: []



Determining Mean Total Purchase made by Age Group 18 - 25 with 90% Confidence

In [126]:
```
sample_mean = np.mean(means)
sample_std = np.std(means)
sample_mean, sample_std
```

Out[126]: (854503.3011287501, 15877.065310191889)

In [127]:
```
sample_mean + spy.norm.ppf(0.05)* sample_std, sample_mean + spy.norm.ppf(0.95)* sample_std
```

Out[127]: (828387.8526679355, 880618.7495895646)

Determining Mean Total Purchase made by Age Group 18 - 25 with 95% Confidence

In [128]:
```
sample_mean + spy.norm.ppf(0.025)* sample_std, sample_mean + spy.norm.ppf(0.975)* sample_std
```

Out[128]: (823384.8249405837, 885621.7773169165)

Determining Mean Total Purchase made by Age Group 18 - 25 with 99% Confidence

In [129]:
```
sample_mean + spy.norm.ppf(0.005)* sample_std, sample_mean + spy.norm.ppf(0.995)* sample_std
```

Out[129]: (813606.6910483981, 895399.911209102)

For Age Group 26 - 35 years

In [130]:
```
df_age_26_to_35
```

Out[130]:

	User_ID	Total_Purchase
0	1000003	341635
1	1000005	821001
2	1000008	796593
3	1000009	594099
4	1000011	557023
...	...	...
2048	1006030	737361
2049	1006034	197086
2050	1006035	956645
2051	1006036	4116058
2052	1006040	1653299

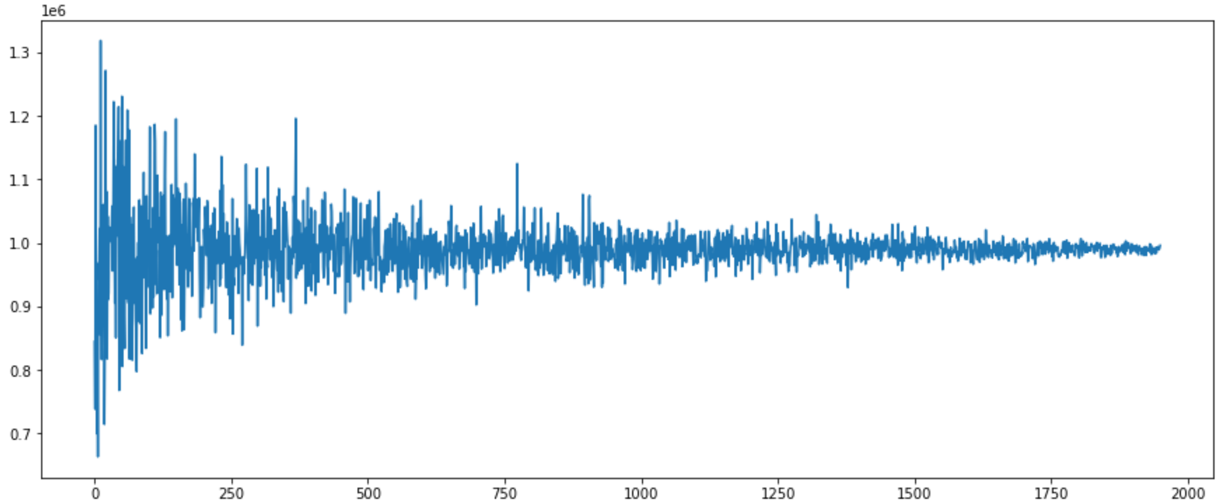
2053 rows × 2 columns

How the deviations vary for different sample sizes ?

In [131]:
```
mean_purchases = []
for sample_size in range(50, 2000):
    sample_mean = df_age_26_to_35['Total_Purchase'].sample(sample_size).mean()
    mean_purchases.append(sample_mean)
```

In [132]:
```python
plt.figure(figsize = (15, 6))
plt.plot(mean_purchases)
plt.plot()
```

Out[132]: []



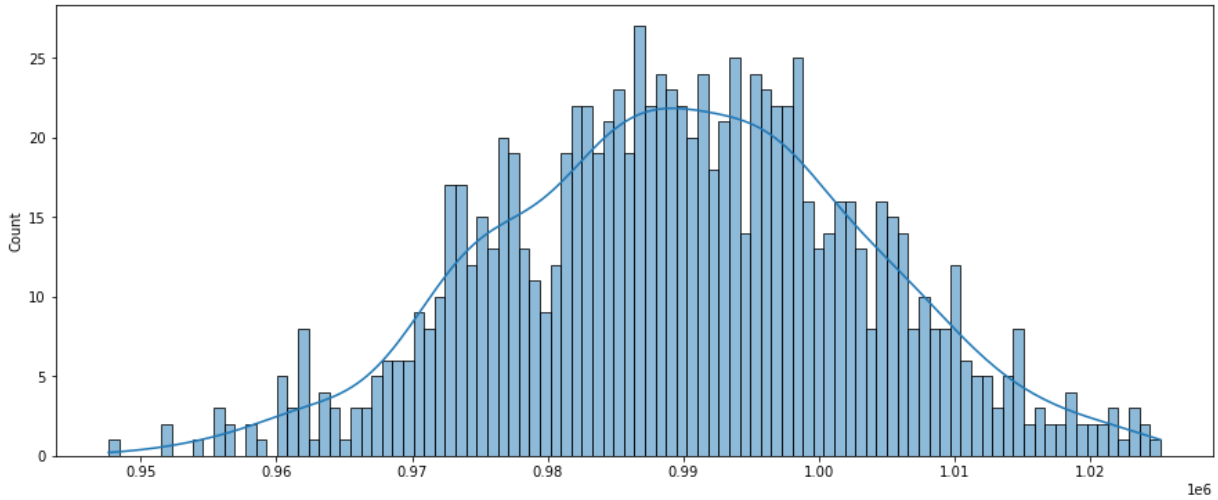

```
It can be inferred from the above plot that as the sample size is small the deviations are fairly high.
As the sample size increases, the deviation becomes smaller and smaller.
The deviations will be small if the sample size taken is greater than 1250.
```

For conservative analysis, sample size of 1500 is taken 1000 times

In [133]:
```python
means = []
for sample_size in range(1000):
    sample_mean = df_age_26_to_35['Total_Purchase'].sample(1500).mean()
    means.append(sample_mean)
```

In [134]:
```python
plt.figure(figsize = (15, 6))
sns.histplot(means, kde = True, bins = 100)
plt.plot()
```

Out[134]: []



Determining Mean Total Purchase made by Age Group 26 - 35 with 90% Confidence

In [135]:
```python
sample_mean = np.mean(means)
sample_std = np.std(means)
sample_mean, sample_std
```

Out[135]: (989828.22563, 13506.091315595819)

In [136]:
```python
sample_mean + spy.norm.ppf(0.05)* sample_std, sample_mean + spy.norm.ppf(0.95)* sample_std
```

Out[136]: (967612.6823436044, 1012043.7689163956)

Determining Mean Total Purchase made by Age Group 26 - 35 with 95% Confidence

In [137]:
```
sample_mean + spy.norm.ppf(0.025)* sample_std, sample_mean + spy.norm.ppf(0.975)* sample_std
```

Out[137]:
```
(963356.773079523, 1016299.678180477)
```

Determining Mean Total Purchase made by Age Group 26 - 35 with 99% Confidence

In [138]:
```
sample_mean + spy.norm.ppf(0.005)* sample_std, sample_mean + spy.norm.ppf(0.995)* sample_std
```

Out[138]:
```
(955038.839842881, 1024617.611417119)
```

For Age Group 36 - 45 years

In [139]:
```
df_age_36_to_45
```

Out[139]:

	User_ID	Total_Purchase
0	1000007	234668
1	1000010	2169510
2	1000014	127629
3	1000016	150490
4	1000023	1670998
...	...	...
1162	1006011	1198714
1163	1006012	127920
1164	1006017	160230
1165	1006018	975585
1166	1006026	490768

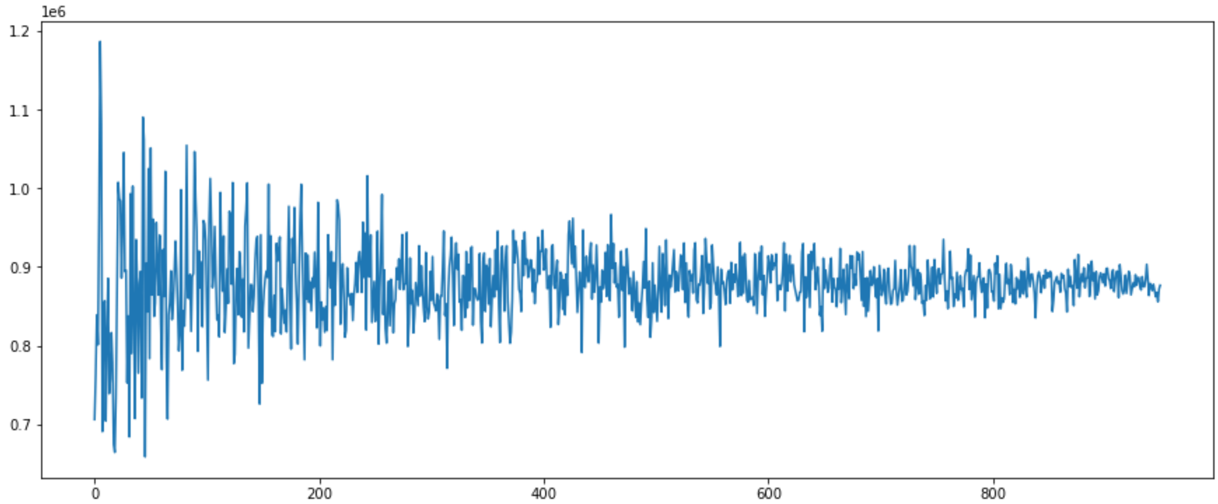
1167 rows × 2 columns

How the deviations vary for different sample sizes ?

In [140]:
```
mean_purchases = []
for sample_size in range(50, 1000):
    sample_mean = df_age_36_to_45['Total_Purchase'].sample(sample_size).mean()
    mean_purchases.append(sample_mean)
```

In [141]:
```
plt.figure(figsize = (15, 6))
plt.plot(mean_purchases)
plt.plot()
```

Out[141]: []




```
It can be inferred from the above plot that as the sample size is small the deviations are fairly high.
As the sample size increases, the deviation becomes smaller and smaller.
```

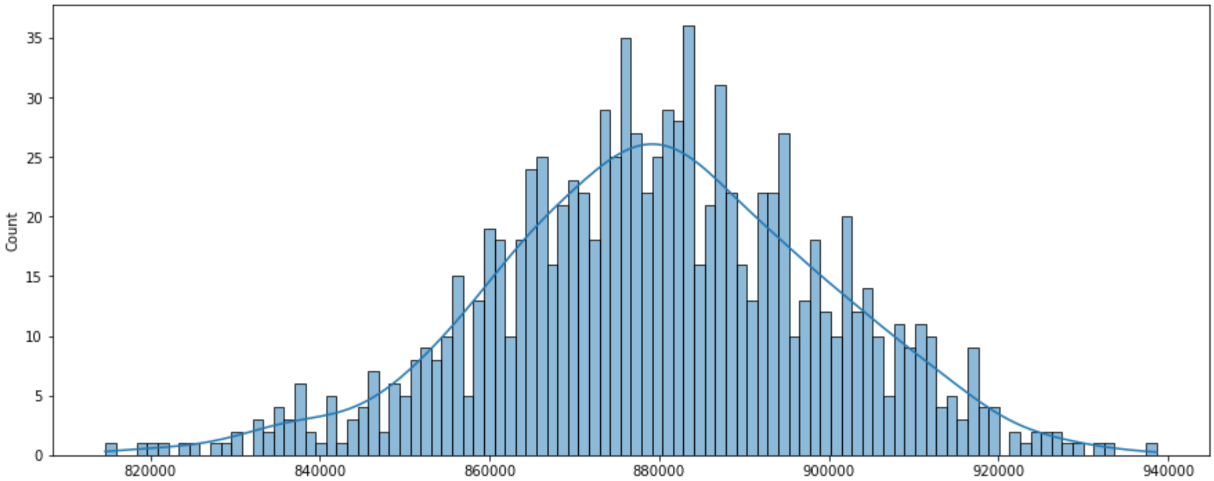
```
The deviations will be small if the sample size taken is greater than 600.
```

For conservative analysis, sample size of 800 is taken 1000 times

In [142]:
```
means = []
for sample_size in range(1000):
    sample_mean = df_age_36_to_45['Total_Purchase'].sample(800).mean()
    means.append(sample_mean)
```

In [143]:
```
plt.figure(figsize = (15, 6))
sns.histplot(means, kde = True, bins = 100)
plt.plot()
```

Out[143]: []



Determining Mean Total Purchase made by Age Group 36 - 45 with 90% Confidence

In [144]:
```
sample_mean = np.mean(means)
sample_std = np.std(means)
sample_mean, sample_std
```

Out[144]: (879908.27735, 19545.13193847692)

In [145]:
```
sample_mean + spy.norm.ppf(0.05)* sample_std, sample_mean + spy.norm.ppf(0.95)* sample_std
```

Out[145]: (847759.3961917511, 912057.1585082489)

Determining Mean Total Purchase made by Age Group 36 - 45 with 95% Confidence

In [146]:
```
sample_mean + spy.norm.ppf(0.025)* sample_std, sample_mean + spy.norm.ppf(0.975)* sample_std
```

Out[146]: (841600.5226775017, 918216.0320224983)

Determining Mean Total Purchase made by Age Group 36 - 45 with 99% Confidence

In [147]:
```
sample_mean + spy.norm.ppf(0.005)* sample_std, sample_mean + spy.norm.ppf(0.995)* sample_std
```

Out[147]: (829563.3537611417, 930253.2009388583)

For Age Group 46 - 50 years

In [148]:
```
df_age_46_to_50
```

Out[148]:

	User_ID	Total_Purchase
0	1000004	206468
1	1000013	713927
2	1000033	1940418
3	1000035	821303
4	1000044	1180380
...	...	...
526	1006014	528238
527	1006016	3770970
528	1006032	517261
529	1006037	1119538
530	1006039	590319

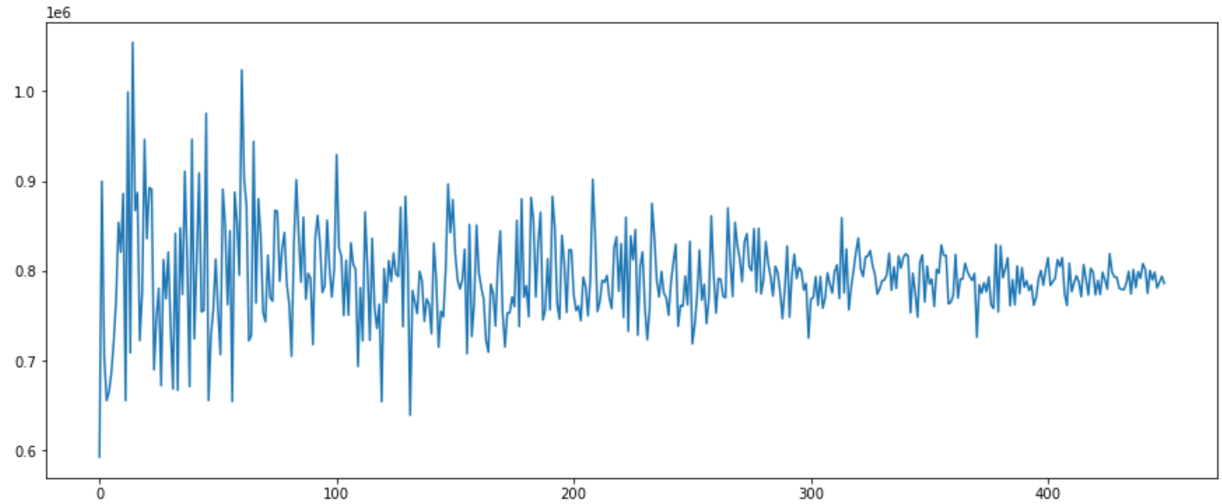
531 rows × 2 columns

How the deviations vary for different sample sizes ?

In [149]:
```
mean_purchases = []
for sample_size in range(50, 500):
    sample_mean = df_age_46_to_50['Total_Purchase'].sample(sample_size).mean()
    mean_purchases.append(sample_mean)
```

In [150]:
```
plt.figure(figsize = (15, 6))
plt.plot(mean_purchases)
plt.plot()
```

Out[150]: []



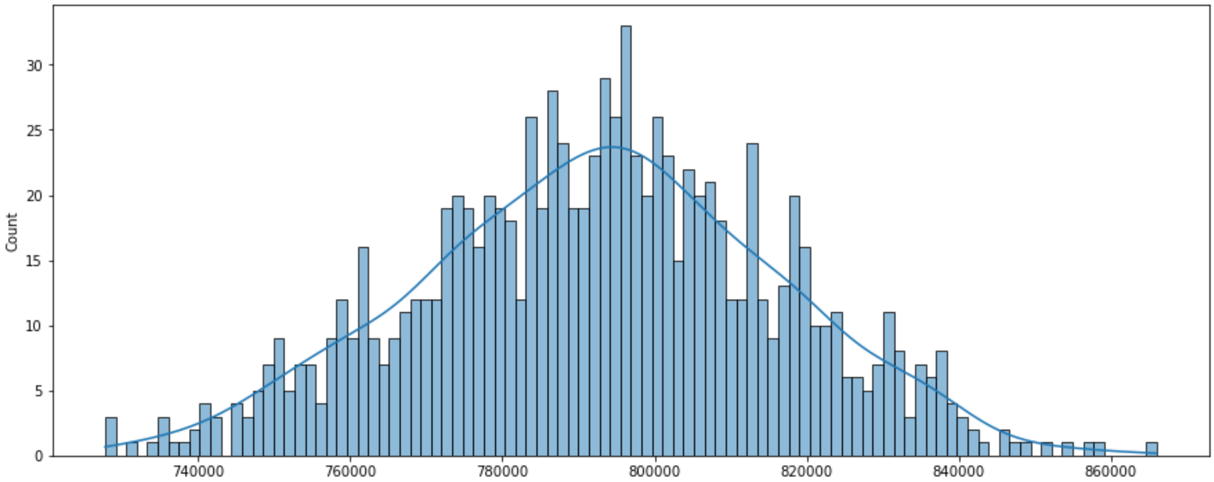

```
It can be inferred from the above plot that as the sample size is small the deviations are fairly high.
As the sample size increases, the deviation becomes smaller and smaller.
The deviations will be small if the sample size taken is greater than 300.
```

For conservative analysis, sample size of 400 is taken 1000 times

In [151]:
```
means = []
for sample_size in range(1000):
    sample_mean = df_age_46_to_50['Total_Purchase'].sample(400).mean()
    means.append(sample_mean)
```

In [152]:
```
plt.figure(figsize = (15, 6))
sns.histplot(means, kde = True, bins = 100)
plt.plot()
```

Out[152]: []



Determining Mean Total Purchase made by Age Group 46 - 50 with 90% Confidence

In [153]:
```
sample_mean = np.mean(means)
sample_std = np.std(means)
sample_mean, sample_std
```

Out[153]: (792491.2072975, 23514.53425376348)

In [154]:
```
sample_mean + spy.norm.ppf(0.05)* sample_std, sample_mean + spy.norm.ppf(0.95)* sample_std
```

Out[154]: (753813.2403441225, 831169.1742508775)

Determining Mean Total Purchase made by Age Group 46 - 50 with 95% Confidence

In [155]:
```
sample_mean + spy.norm.ppf(0.025)* sample_std, sample_mean + spy.norm.ppf(0.975)* sample_std
```

Out[155]: (746403.5670468902, 838578.8475481098)

Determining Mean Total Purchase made by Age Group 46 - 50 with 99% Confidence

In [156]:
```
sample_mean + spy.norm.ppf(0.005)* sample_std, sample_mean + spy.norm.ppf(0.995)* sample_std
```

Out[156]: (731921.7809073516, 853060.6336876483)

Actionable insights

- Out of every four transactions made on Black Friday in the Walmart stores, three are made by the males and one is made by the females.
- 82.33 % of the total transactions are made by the customers belonging to 11 occupations. These are 4, 0, 7, 1, 17, 20, 12, 14, 2, 16, 6 (Ordered in descending order of the total transactions' share.)
- Majority of the transactions (53.75 % of total transactions) are made by the customers having 1 or 2 years of stay in the current city.
- 82.43% of the total transactions are made for only 5 Product Categories. These are, 5, 1, 8, 11 and 2.
- There are 1666 unique female customers and 4225 unique male customers. Average number of transactions made by each Male on Black Friday is 98 while for Female it is 82.
- On an average each male makes a total purchase of 712024.394958 on Black Friday while for each female the figure is 925344.402367.
- 76.72 % of the total revenue is generated from males.
- Out of 5891 unique customers, 42 % of them are Married and 58 % of them are Single.
- Average number of transactions made by each user with marital status Married is 91 and for Single it is 95.
- On an average each Married customer makes a total purchase of 843526.796686 on Black Friday while for each Single customer the figure is 880575.781972.
- 59.05 % of the total revenue is generated from the customers who are Single.
- Majority of the transactions are made by the customers whose age is between 26 and 45 years.
- About 81.82% of the total transactions are made by customers of age between 18 and 50 years.
- 81.82 % of total unique customers have age between 18 and 50 years.
- Out of all unique customers, 35.85 % belong to the age group of 26 - 35 years, 19.81 % belong to the age group of 36 - 45 years, 18.15 % belong to the age group of 18 - 25 years, 9.01 % belong to the age group of 46 - 50 years.

- Walmart generated 86.21 % of total revenue from customers in range 18 to 50 years on Black Friday.
- 39.87 % of the total revenue is generated from the customers having age group of 26 - 35 years, 20.15 % is generated from 36 - 45 years, 17.93 % from 18 - 25 years, 8.26 % from 46 - 50 years.
- Majority of the total unique customers belong to the city C. 82.26 % of the total unique customers belong to city C and B.
- Walmart generated 41.52 % of the total revenue from the customers belonging to the city B, 32.65 % from city C and 25.83 % from city A on Black Friday.
- Top 5 product categories from which Walmart made 84.36 % of total revenue on Black Friday are 1, 5, 8, 6 and 2.
- Mean Total Purchase made by males lies in the 90% Confidence Interval of (919449.38, 931427.31), 95% Confidence Interval of (918302.05, 932574.64), 99% Confidence Interval of (901570.35, 949355.85) for sample size of 4000 taken 1000 times.
- Mean Total Purchase made by females lies in the 90% Confidence Interval of (701674.04, 722233.84), 95% Confidence Interval of (699704.69, 724203.20), 99% Confidence Interval of (695855.69, 728052.19) for sample size of 1500 taken 1000 times.
- Mean Total Purchase made by singles lies in the 90% Confidence Interval of (870556.09, 890708.94), 95% Confidence Interval of (868625.72, 892639.32), 99% Confidence Interval of (864852.91, 896412.13) for sample size of 3000 taken 1000 times.
- Mean Total Purchase made by marrieds lies in the 90% Confidence Interval of (858757.213, 903452.27), 95% Confidence Interval of (854476.02, 907733.47), 99% Confidence Interval of (846108.67, 916100.82) for sample size of 2000 taken 1000 times.

Recommendations

- Since the average total purchase made by males is greater than females, Walmart should give special attention to their choices of products so as to retain them.
- Since 82.33 % of the total transactions are made by the customers belonging to the occupations 4, 0, 7, 1, 17, 20, 12, 14, 2, 16, 6, Walmart should keep on adding new quality products related to their field of work.
- Since 82.43% of the total transactions are made for the Product Categories 5, 1, 8, 11 and 2, Walmart can earn more profits if they add new products in these product categories.
- Since 76.72 % of the total revenue is generated from males, Walmart should give special discounts to males on occasions like International Men's Day (19th Nov).
- Since 59.05 % of the total revenue is generated from the customers who are Single, special discounts should be given on the occasions like Single's Day. Moreover, Walmart should focus on acquisition of Unmarried customers.
- Since Walmart generated 41.52 % of the total revenue from the customers belonging to the city B and 32.65 % from city C, customers belonging to such cities should be given special priority.
- As 39.87 % of the total revenue is generated from the customers having age group of 26 - 35 years and 20.15 % is generated from 36 - 45 years, Walmart should focus on acquisition of customers whose age is in between 26 and 45 years.

```
In [ ]:
```