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

In [2]:
```
wal=pd.read_csv(r"D:\Scaler projects\walmart\walmart.csv")
```

In [3]:
```
wal
```

Out[3]:

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

550068 rows × 10 columns

In [4]:
```
wal.shape
```

Out[4]:
```
(550068, 10)
```

In [5]:
```
wal.describe()
```

Out[5]:

	User_ID	Occupation	Marital_Status	Product_Category	Purchase
count	5.500680e+05	550068.000000	550068.000000	550068.000000	550068.000000
mean	1.003029e+06	8.076707	0.409653	5.404270	9263.968713
std	1.727592e+03	6.522660	0.491770	3.936211	5023.065394
min	1.000001e+06	0.000000	0.000000	1.000000	12.000000
25%	1.001516e+06	2.000000	0.000000	1.000000	5823.000000
50%	1.003077e+06	7.000000	0.000000	5.000000	8047.000000
75%	1.004478e+06	14.000000	1.000000	8.000000	12054.000000
max	1.006040e+06	20.000000	1.000000	20.000000	23961.000000

In [6]:
```
wal.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
```

In [7]:
```
wal.isnull().sum()
```

Out[7]:
```
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 [9]:
```
wal["Occupation"].value_counts()
```

Out[9]:
```
4     72308
0     69638
7     59133
1     47426
17    40043
20    33562
12    31179
14    27309
2     26588
16    25371
6     20355
3     17650
10    12930
5     12177
15    12165
11    11586
19     8461
13     7728
18     6622
9      6291
8      1546
Name: Occupation, dtype: int64
```

In [10]:
```
wal["Gender"].value_counts()
```

Out[10]:
```
M    414259
F    135809
Name: Gender, dtype: int64
```

In [11]:
```
#% of data consists of Males
wal["Gender"].value_counts(normalize=True)*100
```

Out[11]:
```
M    75.310507
F    24.689493
Name: Gender, dtype: float64
```

In [12]:
```
wal["Marital_Status"].value_counts()
```

Out[12]:
```
0    324731
1    225337
Name: Marital_Status, dtype: int64
```

In [13]:
```
#% of data consists of married
wal["Marital_Status"].value_counts(normalize=True)*100
```

Out[13]:
```
0    59.034701
1    40.965299
Name: Marital_Status, dtype: float64
```

In [14]:
```
wal["Product_Category"].value_counts()
```

Out[14]:
```
5     150933
1     140378
8     113925
11     24287
2      23864
6      20466
3      20213
4      11753
16      9828
15      6290
13      5549
10      5125
12      3947
7       3721
18      3125
20      2550
19      1603
14      1523
17       578
9        410
Name: Product_Category, dtype: int64
```

In [15]:
```
#% of most selling product category
wal["Product_Category"].value_counts(normalize=True)*100
```

Out[15]:
```
5     27.438971
1     25.520118
8     20.711076
11     4.415272
2      4.338373
6      3.720631
3      3.674637
4      2.136645
16     1.786688
15     1.143495
13     1.008784
10     0.931703
12     0.717548
7      0.676462
18     0.568112
20     0.463579
19     0.291419
14     0.276875
17     0.105078
9      0.074536
Name: Product_Category, dtype: float64
```

In [16]:
```
wal["Gender"].value_counts()
```

Out[16]:
```
M    414259
F    135809
Name: Gender, dtype: int64
```

In [17]:
```
wal["Age"].value_counts()
```

Out[17]:
```
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 [18]:
```
wal["Stay_In_Current_City_Years"].value_counts()
```

Out[18]:
```
1     193821
2     101838
3      95285
4+     84726
0      74398
Name: Stay_In_Current_City_Years, dtype: int64
```

In [19]:
```
wal["City_Category"].value_counts()
```

Out[19]:
```
B    231173
C    171175
A    147720
Name: City_Category, dtype: int64
```

In [20]:
```
wal["Product_ID"].value_counts()
```

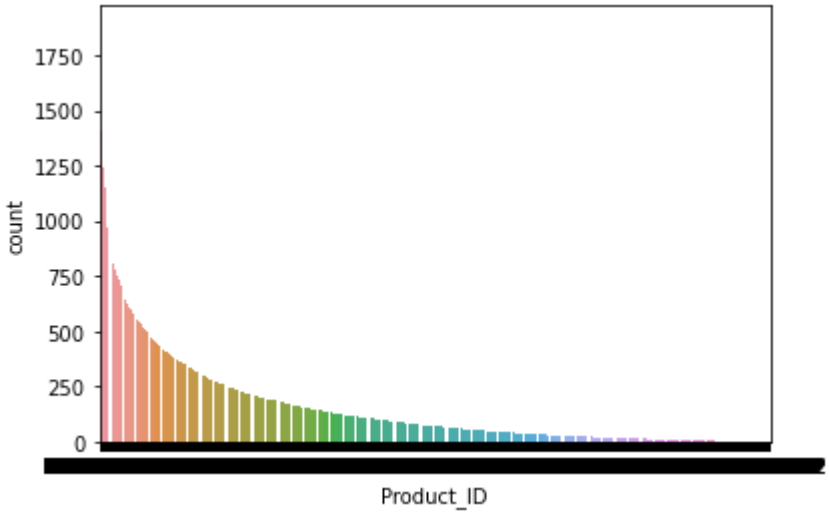
Out[20]:
```
P00265242    1880
P00025442    1615
P00110742    1612
P00112142    1562
P00057642    1470
             ...
P00314842       1
P00298842       1
P00231642       1
P00204442       1
P00066342       1
Name: Product_ID, Length: 3631, dtype: int64
```

In [21]:
```
wal["Product_ID"].nunique()
```

Out[21]:
```
3631
```

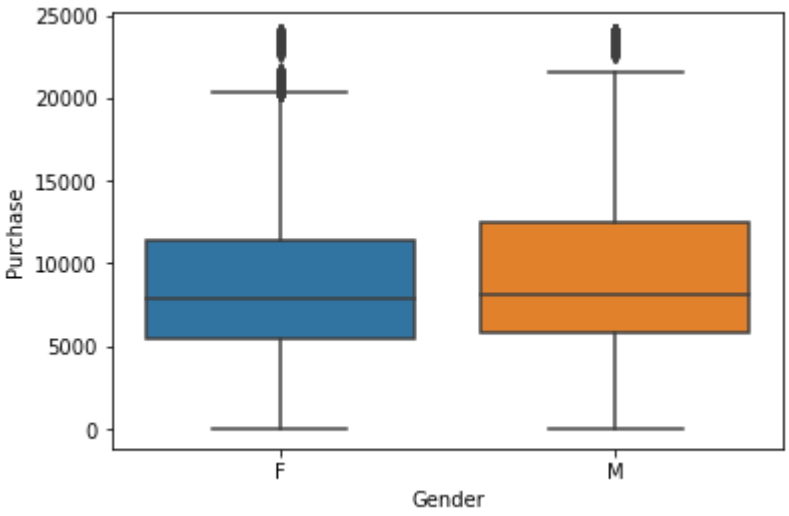
In [22]:
```
sns.countplot(data=wal,x="Product_ID", order=wal["Product_ID"].value_counts().index)
```

Out[22]:
```
<AxesSubplot:xlabel='Product_ID', ylabel='count'>
```



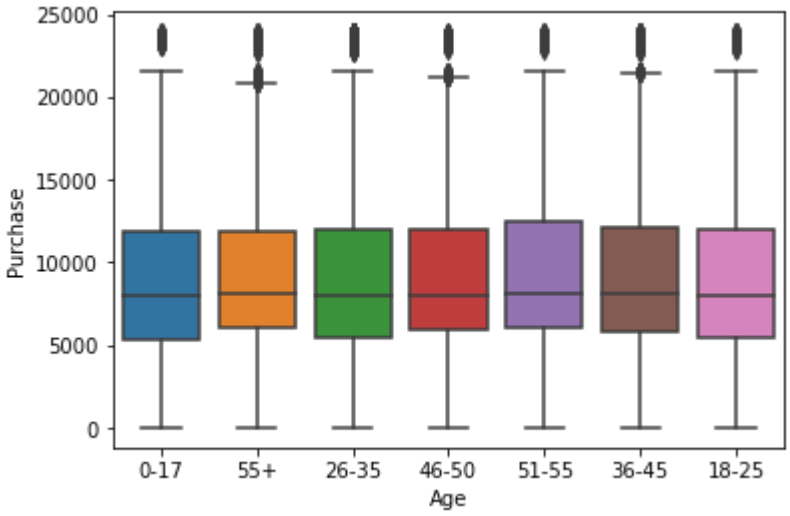
In [23]:
```
# bivariate analysis
#Purchase amount Vs Gender
sns.boxplot(data=wal,y="Purchase",x="Gender")
```

Out[23]:
```
<AxesSubplot:xlabel='Gender', ylabel='Purchase'>
```



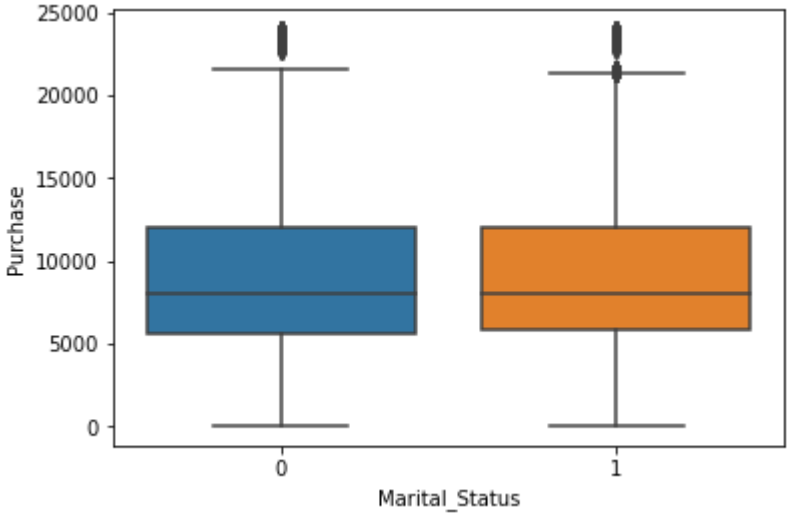
In [24]:
```
#Purchase amount Vs Age
sns.boxplot(data=wal,y="Purchase",x="Age")
```

Out[24]:
```
<AxesSubplot:xlabel='Age', ylabel='Purchase'>
```



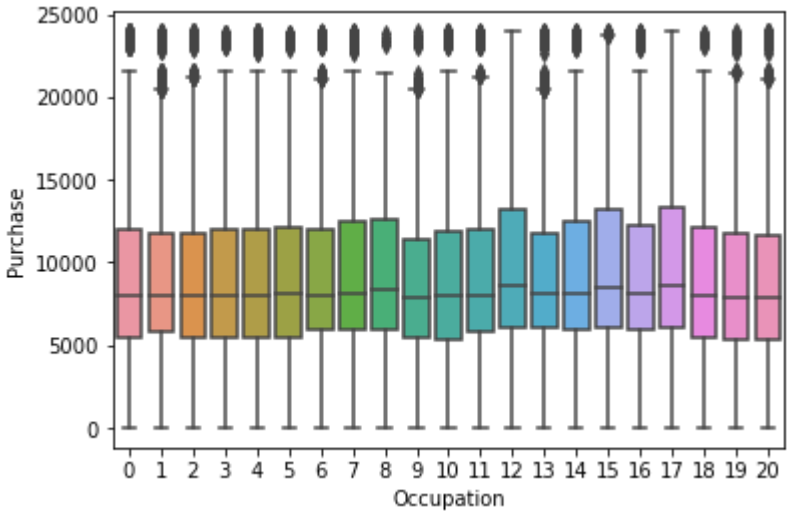
In [25]:
```
#Purchase amount Vs Marital_Status
sns.boxplot(data=wal,y="Purchase",x="Marital_Status")
```

Out[25]:
```
<AxesSubplot:xlabel='Marital_Status', ylabel='Purchase'>
```



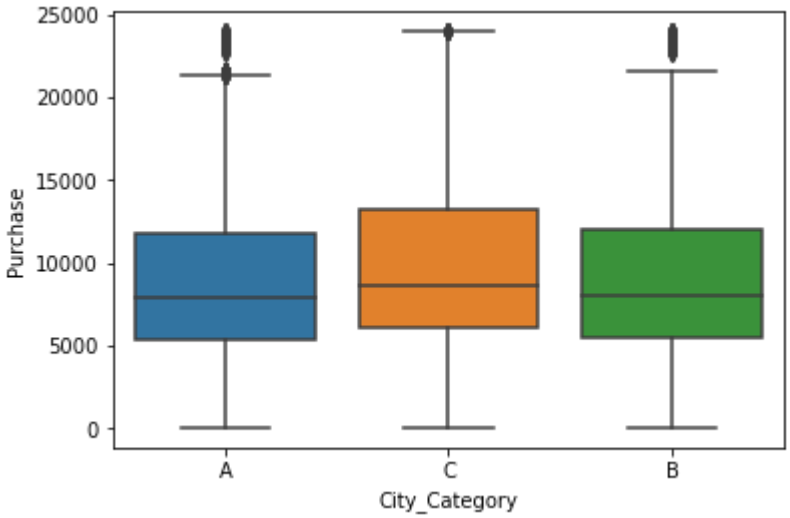
In [26]:
```
#Purchase amount Vs Occupation
sns.boxplot(data=wal,y="Purchase",x="Occupation")
```

Out[26]:
```
<AxesSubplot:xlabel='Occupation', ylabel='Purchase'>
```



In [27]:
```
#Purchase amount Vs City_Category
sns.boxplot(data=wal,y="Purchase",x="City_Category")
```

Out[27]:
```
<AxesSubplot:xlabel='City_Category', ylabel='Purchase'>
```



In [28]:
```
#Categoriacal vs categorical
#product_categorey Vs various attributes
```

In [29]:
```
df_wal=wal.groupby(["Product_Category","Gender"]).size().reset_index().pivot(columns='
```

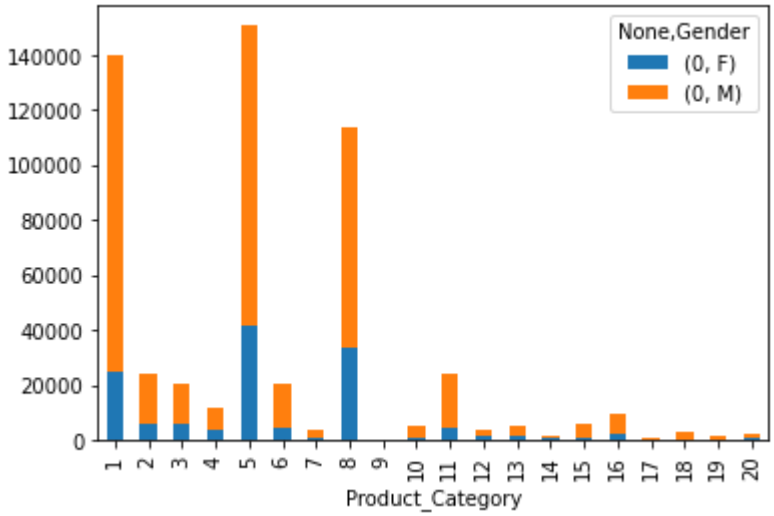
In [30]:
```
df_wal
```

Out[30]:

	0	
Gender	F	M
Product_Category		
1	24831	115547
2	5658	18206
3	6006	14207
4	3639	8114
5	41961	108972
6	4559	15907
7	943	2778
8	33558	80367
9	70	340
10	1162	3963
11	4739	19548
12	1532	2415
13	1462	4087
14	623	900
15	1046	5244
16	2402	7426
17	62	516
18	382	2743
19	451	1152
20	723	1827

In [31]:
```
df_wal.plot(kind="bar",stacked=True)
```

Out[31]:
```
<AxesSubplot:xlabel='Product_Category'>
```



In [32]:
```
df_wal=wal.groupby(["Product_Category","Marital_Status"]).size().reset_index().pivot(c
```

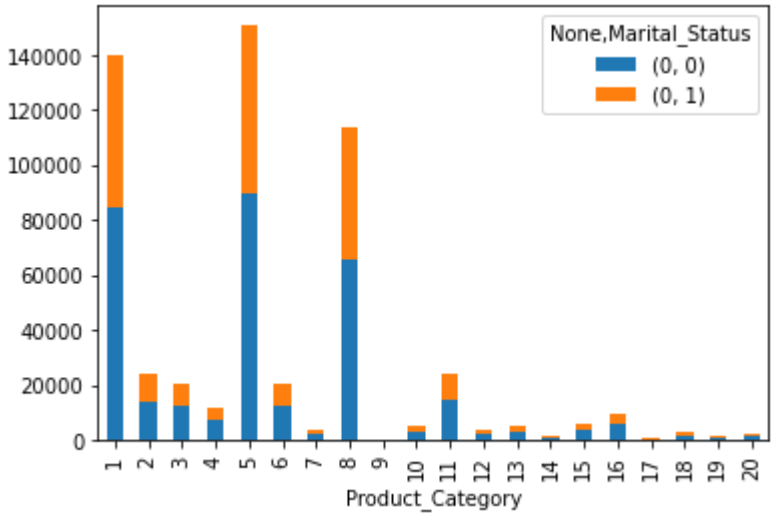
In [33]:
```
df_wal
```

Out[33]:

	0	
Marital_Status	**0**	**1**
Product_Category		
1	84375	56003
2	14138	9726
3	12359	7854
4	7177	4576
5	89656	61277
6	12139	8327
7	2040	1681
8	65411	48514
9	247	163
10	2778	2347
11	14668	9619
12	2034	1913
13	3162	2387
14	846	677
15	3623	2667
16	5713	4115
17	298	280
18	1641	1484
19	946	657
20	1480	1070

In [34]:
```
df_wal.plot(kind="bar",stacked=True)
```

Out[34]:
```
<AxesSubplot:xlabel='Product_Category'>
```



In [35]:
```
df_wal2=wal.groupby(["Product_Category","City_Category"]).size().reset_index().pivot(c
```

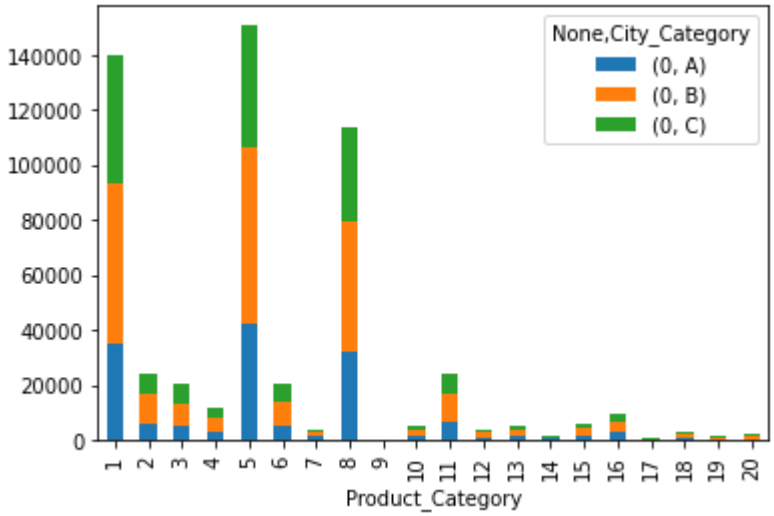
In [36]:
```
df_wal2
```

Out[36]:

	0		
City_Category	A	B	C
Product_Category			
1	35081	58253	47044
2	6141	10444	7279
3	4943	8587	6683
4	3050	5226	3477
5	42211	64138	44584
6	5507	8526	6433
7	1226	1599	896
8	32179	47553	34193
9	110	174	126
10	1333	2063	1729
11	6601	10485	7201
12	1063	1675	1209
13	1614	2271	1664
14	481	632	410
15	1717	2638	1935
16	2848	4038	2942
17	121	267	190
18	753	1389	983
19	273	462	868
20	468	753	1329

In [37]:
```
df_wal2.plot(kind="bar",stacked=True)
```

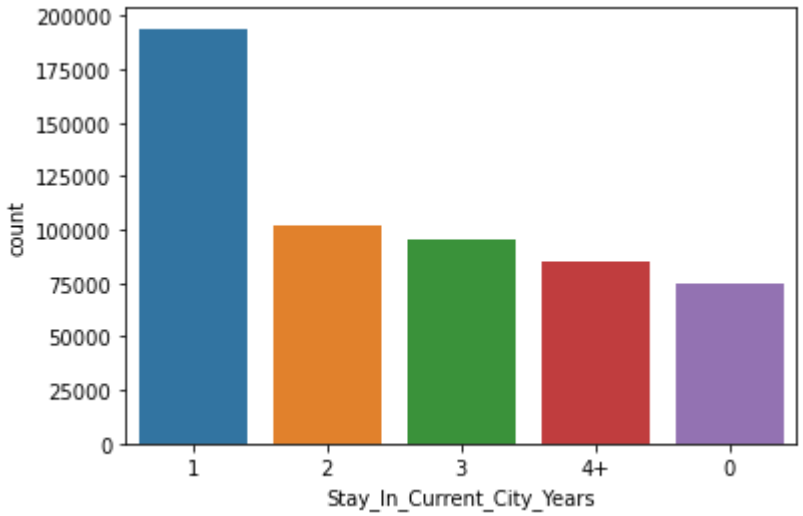
Out[37]:
```
<AxesSubplot:xlabel='Product_Category'>
```



In [38]:
```
#Stay_In_Current_City_Years
```

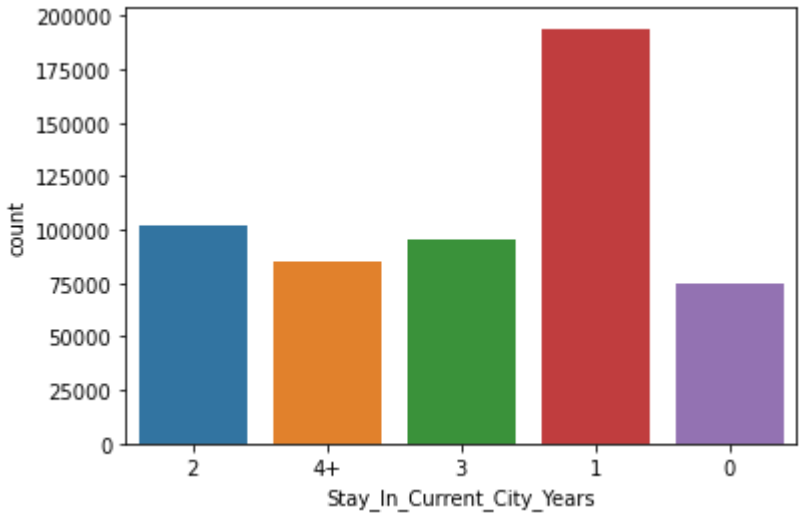
In [39]:
```
sns.countplot(data=wal,x="Stay_In_Current_City_Years", order=wal["Stay_In_Current_City
```

Out[39]:
```
<AxesSubplot:xlabel='Stay_In_Current_City_Years', ylabel='count'>
```



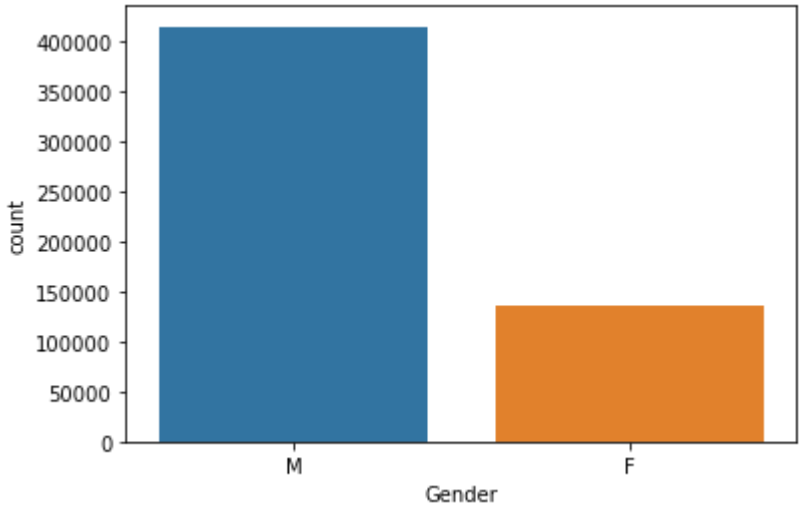
In [40]:
```
sns.countplot(data=wal,x="Stay_In_Current_City_Years")
```

Out[40]:
```
<AxesSubplot:xlabel='Stay_In_Current_City_Years', ylabel='count'>
```



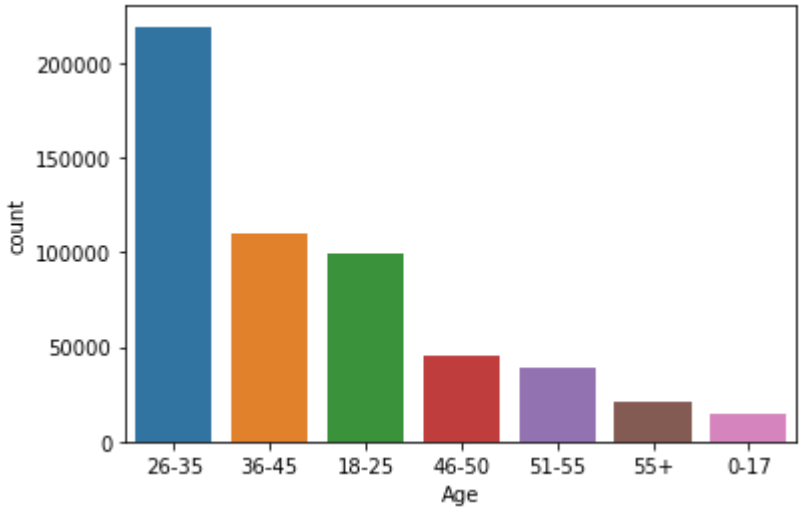
In [41]:
```
sns.countplot(data=wal,x="Gender", order=wal["Gender"].value_counts().index)
```

Out[41]:
```
<AxesSubplot:xlabel='Gender', ylabel='count'>
```



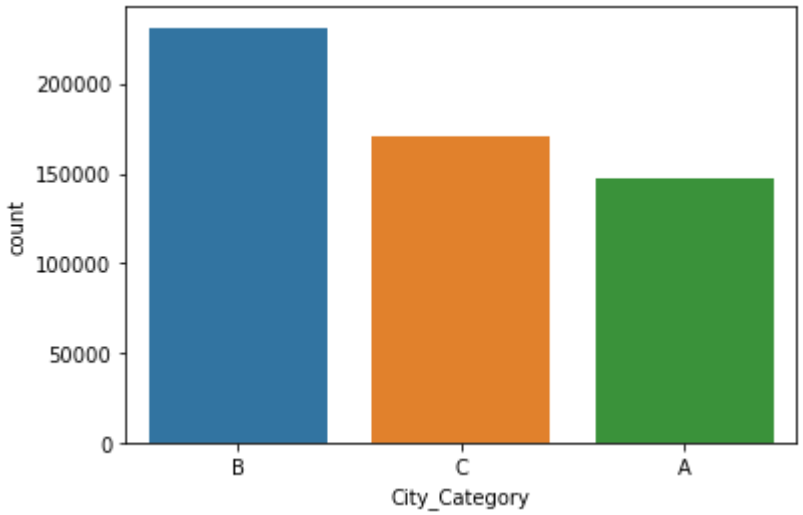
In [42]:
```
sns.countplot(data=wal,x="Age", order=wal["Age"].value_counts().index)
```

Out[42]:
```
<AxesSubplot:xlabel='Age', ylabel='count'>
```



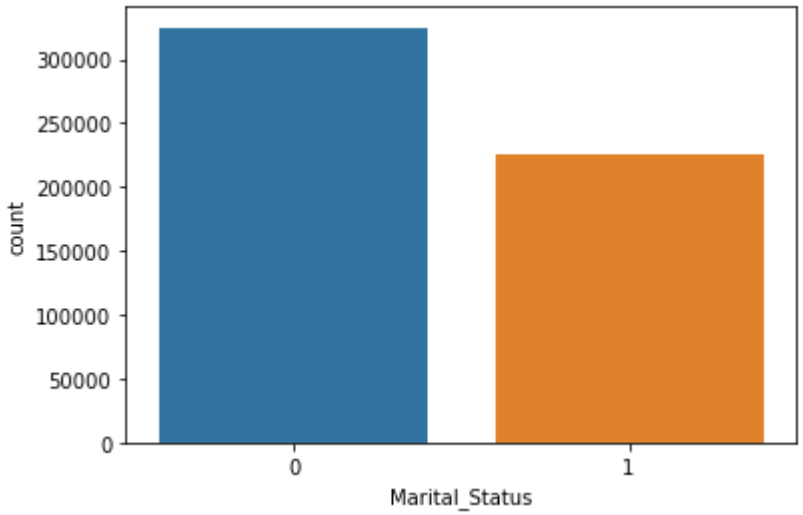
In [43]:
```
sns.countplot(data=wal,x="City_Category", order=wal["City_Category"].value_counts().ir
```

Out[43]:
```
<AxesSubplot:xlabel='City_Category', ylabel='count'>
```



In [44]:
```
sns.countplot(data=wal,x="Marital_Status", order=wal["Marital_Status"].value_counts().
```

Out[44]:
```
<AxesSubplot:xlabel='Marital_Status', ylabel='count'>
```



In [45]:
```
#Probability Analysis
```

In [46]:
```
pd.crosstab(index=wal["Product_Category"],columns=wal["Gender"],margins=True,normalize
```

Out[46]:

Gender	F	M	All
Product_Category			
1	4.514169	21.005948	25.520118
2	1.028600	3.309773	4.338373
3	1.091865	2.582772	3.674637
4	0.661555	1.475090	2.136645
5	7.628330	19.810642	27.438971
6	0.828807	2.891824	3.720631
7	0.171433	0.505028	0.676462
8	6.100700	14.610375	20.711076
9	0.012726	0.061811	0.074536
10	0.211247	0.720456	0.931703
11	0.861530	3.553742	4.415272
12	0.278511	0.439037	0.717548
13	0.265785	0.742999	1.008784
14	0.113259	0.163616	0.276875
15	0.190158	0.953337	1.143495
16	0.436673	1.350015	1.786688
17	0.011271	0.093807	0.105078
18	0.069446	0.498666	0.568112
19	0.081990	0.209429	0.291419
20	0.131438	0.332141	0.463579
All	24.689493	75.310507	100.000000

In [47]:
```
pd.crosstab(index=wal["Product_Category"],columns=wal["Age"],margins=True,normalize=Tr
```

Out[47]:

Age	0-17	18-25	26-35	36-45	46-50	51-55	55+	All
Product_Category								
1	0.651738	4.901576	10.589418	5.026288	1.904128	1.645069	0.801901	25.520118
2	0.146346	0.804991	1.623072	0.892981	0.382680	0.323778	0.164525	4.338373
3	0.218155	0.856258	1.392919	0.700641	0.250151	0.167979	0.088535	3.674637
4	0.137801	0.447763	0.762088	0.427947	0.179978	0.123257	0.057811	2.136645
5	0.787175	5.185177	11.175527	5.340612	2.176276	1.798505	0.975698	27.438971
6	0.072536	0.681552	1.542537	0.708821	0.294873	0.263604	0.156708	3.720631
7	0.009635	0.087444	0.300145	0.147073	0.059447	0.048358	0.024361	0.676462
8	0.410495	3.256143	8.045551	4.235113	1.937215	1.697972	1.128588	20.711076
9	0.002909	0.011453	0.027997	0.019452	0.005999	0.005272	0.001454	0.074536
10	0.020179	0.109623	0.324869	0.224518	0.094534	0.094352	0.063628	0.931703
11	0.134529	0.835715	1.795051	0.900434	0.382498	0.265058	0.101987	4.415272
12	0.022724	0.079808	0.199248	0.180705	0.094534	0.078718	0.061811	0.717548
13	0.020361	0.137438	0.381044	0.227245	0.100169	0.087807	0.054721	1.008784
14	0.007090	0.041813	0.102533	0.056720	0.027088	0.027997	0.013635	0.276875
15	0.029087	0.186159	0.431219	0.253605	0.109441	0.092352	0.041631	1.143495
16	0.041631	0.290510	0.748635	0.355411	0.159798	0.122167	0.068537	1.786688
17	0.001091	0.007454	0.023088	0.024542	0.017271	0.019452	0.012180	0.105078
18	0.004908	0.061629	0.189431	0.127621	0.063810	0.076900	0.043813	0.568112
19	0.010726	0.049994	0.102351	0.058175	0.027088	0.024361	0.018725	0.291419
20	0.016362	0.085262	0.163253	0.091989	0.041268	0.036359	0.029087	0.463579
All	2.745479	18.117760	39.919974	19.999891	8.308246	6.999316	3.909335	100.000000

In [48]:
```
pd.crosstab(index=wal["Product_Category"],columns=wal["Marital_Status"],margins=True,r
```

Out[48]:

Marital_Status	0	1	All
Product_Category			
1	15.339013	10.181105	25.520118
2	2.570228	1.768145	4.338373
3	2.246813	1.427823	3.674637
4	1.304748	0.831897	2.136645
5	16.299076	11.139895	27.438971
6	2.206818	1.513813	3.720631
7	0.370863	0.305599	0.676462
8	11.891439	8.819637	20.711076
9	0.044904	0.029633	0.074536
10	0.505028	0.426675	0.931703
11	2.666579	1.748693	4.415272
12	0.369772	0.347775	0.717548
13	0.574838	0.433946	1.008784
14	0.153799	0.123076	0.276875
15	0.658646	0.484849	1.143495
16	1.038599	0.748089	1.786688
17	0.054175	0.050903	0.105078
18	0.298327	0.269785	0.568112
19	0.171979	0.119440	0.291419
20	0.269058	0.194521	0.463579
All	59.034701	40.965299	100.000000

In [49]:
```
pd.crosstab(index=wal["Product_Category"],columns=wal["City_Category"],margins=True,nc
```

Out[49]:

City_Category	A	B	C	All
Product_Category				
1	6.377575	10.590145	8.552397	25.520118
2	1.116407	1.898674	1.323291	4.338373
3	0.898616	1.561080	1.214941	3.674637
4	0.554477	0.950064	0.632104	2.136645
5	7.673779	11.660013	8.105180	27.438971
6	1.001149	1.549990	1.169492	3.720631
7	0.222882	0.290691	0.162889	0.676462
8	5.850004	8.644931	6.216141	20.711076
9	0.019998	0.031632	0.022906	0.074536
10	0.242334	0.375045	0.314325	0.931703
11	1.200033	1.906128	1.309111	4.415272
12	0.193249	0.304508	0.219791	0.717548
13	0.293418	0.412858	0.302508	1.008784
14	0.087444	0.114895	0.074536	0.276875
15	0.312143	0.479577	0.351775	1.143495
16	0.517754	0.734091	0.534843	1.786688
17	0.021997	0.048539	0.034541	0.105078
18	0.136892	0.252514	0.178705	0.568112
19	0.049630	0.083990	0.157799	0.291419
20	0.085080	0.136892	0.241606	0.463579
All	26.854862	42.026259	31.118880	100.000000

In [50]:
```
wal_male=wal[wal["Gender"]=="M"]
wal_male
```

Out[50]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	M
4	1000002	P00285442	M	55+	16	C	4+	
5	1000003	P00193542	M	26-35	15	A	3	
6	1000004	P00184942	M	46-50	7	B	2	
7	1000004	P00346142	M	46-50	7	B	2	
8	1000004	P0097242	M	46-50	7	B	2	
...	...	...	...	...	...	...	...	
550057	1006023	P00370853	M	26-35	0	C	2	
550058	1006024	P00372445	M	26-35	12	A	0	
550060	1006026	P00371644	M	36-45	6	C	1	
550062	1006032	P00372445	M	46-50	7	A	3	
550063	1006033	P00372445	M	51-55	13	B	1	

414259 rows × 10 columns

In [51]:
```
wal_female=wal[wal["Gender"]=="F"]
wal_female
```

Out[51]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	M
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	
14	1000006	P00231342	F	51-55	9	A	1	
...	...	...	...	...	...	...	...	
550061	1006029	P00372445	F	26-35	1	C	1	
550064	1006035	P00375436	F	26-35	1	C	3	
550065	1006036	P00375436	F	26-35	15	B	4+	
550066	1006038	P00375436	F	55+	1	C	2	
550067	1006039	P00371644	F	46-50	0	B	4+	

135809 rows × 10 columns

In [52]:
```
wal_male.describe()
```

Out[52]:

	User_ID	Occupation	Marital_Status	Product_Category	Purchase
count	4.142590e+05	414259.00000	414259.000000	414259.000000	414259.00000
mean	1.002996e+06	8.51475	0.406386	5.301512	9437.52604
std	1.706494e+03	6.55379	0.491159	4.006275	5092.18621
min	1.000002e+06	0.00000	0.000000	1.000000	12.00000
25%	1.001505e+06	3.00000	0.000000	1.000000	5863.00000
50%	1.003041e+06	7.00000	0.000000	5.000000	8098.00000
75%	1.004411e+06	15.00000	1.000000	8.000000	12454.00000
max	1.006040e+06	20.00000	1.000000	20.000000	23961.00000

In [53]:
```
wal_male["Purchase"].mean()
```

Out[53]:
```
9437.526040472265
```

In [60]:
```
np.mean(wal_male["Purchase"].sample(5))
```

Out[60]:
```
6532.6
```

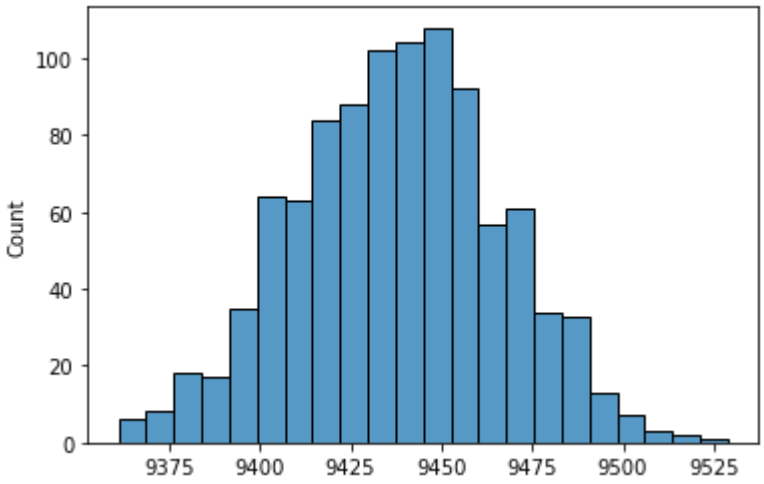
In [61]:
```
np.mean(wal_male["Purchase"].sample(30000))
```

Out[61]:
```
9417.574233333333
```

In [91]:
```
sample_mean_male=[(np.mean(wal_male["Purchase"].sample(30000))) for i in range(1000)]
```

In [92]:
```
sns.histplot(sample_mean_male)
```

Out[92]:
```
<AxesSubplot:ylabel='Count'>
```



In [93]:
```
n=30000
st_dev_male=np.std(wal_male["Purchase"])
st_dev_male
```

Out[93]:
```
5092.180063635943
```

In [94]:
```
std_err_male=st_dev_male/np.sqrt(n)
```

In [95]:
```
from scipy.stats import norm
#for 90% confidence interval
z=norm.ppf(0.95)
x1=9437.52-z*std_err_male
x2=9437.52+z*std_err_male
x1,x2
```

Out[95]:
```
(9389.161771649193, 9485.878228350808)
```

In [73]:
```
# female analysis
wal_female["Purchase"].mean()
```

Out[73]:
```
8734.565765155476
```

In [74]:
```
wal_female.describe()
```

Out[74]:

	User_ID	Occupation	Marital_Status	Product_Category	Purchase
count	1.358090e+05	135809.000000	135809.000000	135809.000000	135809.000000
mean	1.003130e+06	6.740540	0.419619	5.717714	8734.565765
std	1.786631e+03	6.239639	0.493498	3.696752	4767.233289
min	1.000001e+06	0.000000	0.000000	1.000000	12.000000
25%	1.001569e+06	1.000000	0.000000	3.000000	5433.000000
50%	1.003159e+06	4.000000	0.000000	5.000000	7914.000000
75%	1.004765e+06	11.000000	1.000000	8.000000	11400.000000
max	1.006039e+06	20.000000	1.000000	20.000000	23959.000000

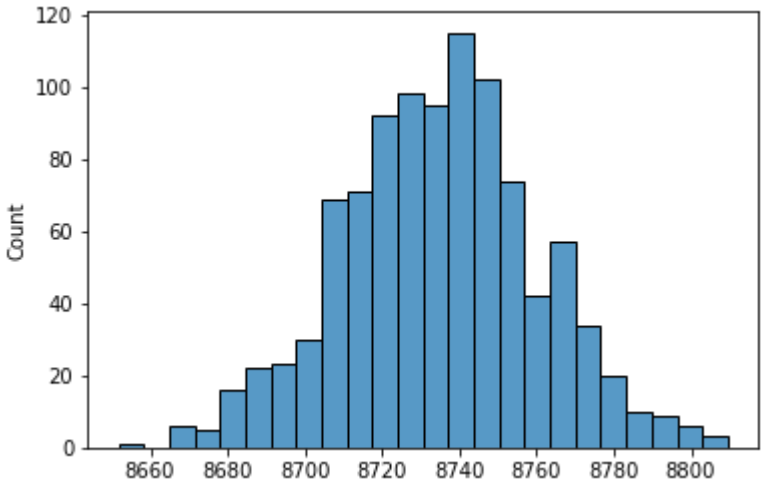
In [76]:
```
np.mean(wal_female["Purchase"].sample(30000))
```

Out[76]:
```
8765.002833333334
```

In [77]:
```
sample_mean_female=[(np.mean(wal_female["Purchase"].sample(30000))) for i in range(100
```

In [78]:
```
sns.histplot(sample_mean_female)
```

Out[78]:
```
<AxesSubplot:ylabel='Count'>
```



In [79]:
```
np.mean(sample_mean_female)
```

Out[79]:
```
8734.801626200002
```

In [96]:
```
n=30000
st_dev_female=np.std(wal_female["Purchase"])
std_err_female=st_dev_female/np.sqrt(n)
#for 90% confidence interval
z=norm.ppf(0.95)
x1=8734.80-z*std_err_female
x2=8734.80+z*std_err_female
x1,x2
```

Out[96]:
```
(8689.527817089016, 8780.072182910983)
```

In [ ]:
```
# for 95% confidence interval
```

In [97]:
```
#for Males
n=30000
st_dev_male=np.std(wal_male["Purchase"])
std_err_male=st_dev_male/np.sqrt(n)
#for 90% confidence interval
z=norm.ppf(0.975)
x1=9437.52-z*std_err_male
x2=9437.52+z*std_err_male
x1,x2
```

Out[97]:
```
(9379.897616846425, 9495.142383153576)
```

In [98]:
```
# for females
n=30000
st_dev_female=np.std(wal_female["Purchase"])
std_err_female=st_dev_female/np.sqrt(n)
#for 90% confidence interval
z=norm.ppf(0.975)
x1=8734.80-z*std_err_female
x2=8734.80+z*std_err_female
x1,x2
```

Out[98]:
```
(8680.854866795966, 8788.745133204033)
```

In [ ]:
```
# for 99% confidence interval
```

In [99]:
```
#for Males
n=30000
st_dev_male=np.std(wal_male["Purchase"])
std_err_male=st_dev_male/np.sqrt(n)
#for 90% confidence interval
z=norm.ppf(0.995)
x1=9437.52-z*std_err_male
x2=9437.52+z*std_err_male
x1,x2
```

Out[99]:
```
(9361.791351801328, 9513.248648198673)
```

In [100…
```
# for females
n=30000
st_dev_female=np.std(wal_female["Purchase"])
std_err_female=st_dev_female/np.sqrt(n)
#for 90% confidence interval
z=norm.ppf(0.975)
x1=8734.80-z*std_err_female
x2=8734.80+z*std_err_female
x1,x2
```

Out[100]:
```
(8680.854866795966, 8788.745133204033)
```

In [106…
```
#Analysis for Married and Unmarried
wal_mar=wal[wal["Marital_Status"]==1]
wal_mar.describe()
```

Out[106]:

	User_ID	Occupation	Marital_Status	Product_Category	Purchase
count	2.253370e+05	225337.000000	225337.0	225337.000000	225337.000000
mean	1.003071e+06	8.266823	1.0	5.498245	9261.174574
std	1.765091e+03	6.687118	0.0	3.968868	5016.897378
min	1.000004e+06	0.000000	1.0	1.000000	12.000000
25%	1.001506e+06	2.000000	1.0	2.000000	5843.000000
50%	1.003093e+06	7.000000	1.0	5.000000	8051.000000
75%	1.004647e+06	14.000000	1.0	8.000000	12042.000000
max	1.006039e+06	20.000000	1.0	20.000000	23961.000000

In [107…

```
wal_unmar=wal[wal["Marital_Status"]==0]
wal_unmar.describe()
```

Out[107]:

	User_ID	Occupation	Marital_Status	Product_Category	Purchase
count	3.247310e+05	324731.000000	324731.0	324731.000000	324731.000000
mean	1.002999e+06	7.944782	0.0	5.339059	9265.907619
std	1.700466e+03	6.402753	0.0	3.912070	5027.347859
min	1.000001e+06	0.000000	0.0	1.000000	12.000000
25%	1.001524e+06	3.000000	0.0	1.000000	5605.000000
50%	1.003065e+06	7.000000	0.0	5.000000	8044.000000
75%	1.004386e+06	14.000000	0.0	8.000000	12061.000000
max	1.006040e+06	20.000000	0.0	20.000000	23961.000000

In [114…

```
np.mean(wal_mar["Purchase"].sample(30000))
sample_mean_mar=[(np.mean(wal_mar["Purchase"].sample(30000))) for i in range(1000)]
n=30000
st_dev_mar=np.std(wal_mar["Purchase"])
std_err_mar=st_dev_mar/np.sqrt(n)
#for 90% confidence interval
mean_mar=np.mean(wal_mar["Purchase"])
z=norm.ppf(0.95)
x1=mean_mar-z*std_err_mar
x2=mean_mar+z*std_err_mar
x1,x2
```

Out[114]:

```
(9213.531378505573, 9308.817769659174)
```

In [115…

```
np.mean(wal_unmar["Purchase"].sample(30000))
sample_mean_unmar=[(np.mean(wal_unmar["Purchase"].sample(30000))) for i in range(1000)
n=30000
st_dev_unmar=np.std(wal_unmar["Purchase"])
std_err_unmar=st_dev_unmar/np.sqrt(n)
mean_unmar=np.mean(wal_unmar["Purchase"])
#for 90% confidence interval
z=norm.ppf(0.95)
```

```
x1=mean_unmar-z*std_err_unmar
x2=mean_unmar+z*std_err_unmar
x1,x2
```

Out[115]:
```
(9218.165147449665, 9313.650090393348)
```

In [116…
```
np.mean(wal_mar["Purchase"].sample(30000))
sample_mean_mar=[(np.mean(wal_mar["Purchase"].sample(30000))) for i in range(1000)]
n=30000
st_dev_mar=np.std(wal_mar["Purchase"])
std_err_mar=st_dev_mar/np.sqrt(n)
#for 95% confidence interval
mean_mar=np.mean(wal_mar["Purchase"])
z=norm.ppf(0.975)
x1=mean_mar-z*std_err_mar
x2=mean_mar+z*std_err_mar
x1,x2
```

Out[116]:
```
(9204.404205030149, 9317.944943134598)
```

In [117…
```
np.mean(wal_unmar["Purchase"].sample(30000))
sample_mean_unmar=[(np.mean(wal_unmar["Purchase"].sample(30000))) for i in range(1000)
n=30000
st_dev_unmar=np.std(wal_unmar["Purchase"])
std_err_unmar=st_dev_unmar/np.sqrt(n)
mean_unmar=np.mean(wal_unmar["Purchase"])
#for 95% confidence interval
z=norm.ppf(0.975)
x1=mean_unmar-z*std_err_unmar
x2=mean_unmar+z*std_err_unmar
x1,x2
```

Out[117]:
```
(9209.018955344087, 9322.796282498926)
```

In [119…
```
np.mean(wal_mar["Purchase"].sample(30000))
sample_mean_mar=[(np.mean(wal_mar["Purchase"].sample(30000))) for i in range(1000)]
n=30000
st_dev_mar=np.std(wal_mar["Purchase"])
std_err_mar=st_dev_mar/np.sqrt(n)
#for 99% confidence interval
mean_mar=np.mean(wal_mar["Purchase"])
z=norm.ppf(0.995)
x1=mean_mar-z*std_err_mar
x2=mean_mar+z*std_err_mar
x1,x2
```

Out[119]:
```
(9186.565662218964, 9335.783485945783)
```

In [120…
```
np.mean(wal_unmar["Purchase"].sample(30000))
sample_mean_unmar=[(np.mean(wal_unmar["Purchase"].sample(30000))) for i in range(1000)
n=30000
st_dev_unmar=np.std(wal_unmar["Purchase"])
std_err_unmar=st_dev_unmar/np.sqrt(n)
mean_unmar=np.mean(wal_unmar["Purchase"])
#for 99% confidence interval
z=norm.ppf(0.995)
x1=mean_unmar-z*std_err_unmar
```

```
x2=mean_unmar+z*std_err_unmar
x1,x2
```

Out[120]:
```
(9191.143241699116, 9340.671996143898)
```

In [ ]:
```
# Analysis for age
```

In [162…
```
age0_17=wal[wal["Age"]=="0-17"]
age18_25=wal[wal["Age"]=="18-25"]
age26_35=wal[wal["Age"]=="26-35"]
age36_50=pd.concat([wal[wal["Age"]=="36-45"] , wal[wal["Age"]=="46-50" ]])
age50plus=pd.concat([wal[wal["Age"]=="51-55"] , wal[wal["Age"]=="55+" ]])
```

In [154…
```
#90% confidence interval analysis
```

In [155…
```
np.mean(age0_17["Purchase"].sample(3000))
sample_mean_age0_17=[(np.mean(age0_17["Purchase"].sample(3000))) for i in range(1000)]
n=3000
st_dev_age0_17=np.std(age0_17["Purchase"])
std_err_age0_17=st_dev_age0_17/np.sqrt(n)
mean_age0_17=np.mean(age0_17["Purchase"])
#for 90% confidence interval
z=norm.ppf(0.95)
x1=mean_age0_17-z*std_err_age0_17
x2=mean_age0_17+z*std_err_age0_17
x1,x2
```

Out[155]:
```
(8779.978974850774, 9086.950306039174)
```

In [156…
```
age18_25.shape
```

Out[156]:
```
(99660, 10)
```

In [157…
```
#for age range 18_25
np.mean(age18_25["Purchase"].sample(3000))
sample_mean_age18_25=[(np.mean(age18_25["Purchase"].sample(3000))) for i in range(1000
n=3000
st_dev_age18_25=np.std(age18_25["Purchase"])
std_err_age18_25=st_dev_age18_25/np.sqrt(n)
mean_age18_25=np.mean(age18_25["Purchase"])
#for 90% confidence interval
z=norm.ppf(0.95)
x1=mean_age18_25-z*std_err_age18_25
x2=mean_age18_25+z*std_err_age18_25
x1,x2
```

Out[157]:
```
(9018.47974249923, 9320.847470023347)
```

In [158…
```
#for age range 26_35
np.mean(age26_35["Purchase"].sample(30000))
sample_mean_age26_35=[(np.mean(age26_35["Purchase"].sample(30000))) for i in range(100
n=30000
st_dev_age26_35=np.std(age26_35["Purchase"])
std_err_age26_35=st_dev_age26_35/np.sqrt(n)
mean_age26_35=np.mean(age26_35["Purchase"])
#for 90% confidence interval
z=norm.ppf(0.95)
```

```
x1=mean_age26_35-z*std_err_age26_35
x2=mean_age26_35+z*std_err_age26_35
x1,x2
```

Out[158]:
```
(9205.10793376461, 9300.273331975166)
```

In [159…
```
age36_50.shape
```

Out[159]:
```
(155714, 10)
```

In [160…
```
#for age range 36_50
np.mean(age36_50["Purchase"].sample(30000))
sample_mean_age36_50=[(np.mean(age36_50["Purchase"].sample(30000))) for i in range(100
n=30000
st_dev_age36_50=np.std(age36_50["Purchase"])
std_err_age36_50=st_dev_age36_50/np.sqrt(n)
mean_age36_50=np.mean(age36_50["Purchase"])
#for 90% confidence interval
z=norm.ppf(0.95)
x1=mean_age36_50-z*std_err_age36_50
x2=mean_age36_50+z*std_err_age36_50
x1,x2
```

Out[160]:
```
(9247.78320900821, 9342.880276612863)
```

In [163…
```
#for age range 50plus
np.mean(age50plus["Purchase"].sample(30000))
sample_mean_age50plus=[(np.mean(age50plus["Purchase"].sample(30000))) for i in range(1
n=30000
st_dev_age50plus=np.std(age50plus["Purchase"])
std_err_age50plus=st_dev_age50plus/np.sqrt(n)
mean_age50plus=np.mean(age50plus["Purchase"])
#for 90% confidence interval
z=norm.ppf(0.95)
x1=mean_age50plus-z*std_err_age50plus
x2=mean_age50plus+z*std_err_age50plus
x1,x2
```

Out[163]:
```
(9415.598420431128, 9511.724935955841)
```

In [ ]:
```

```

In [ ]:
```
#95% confidence interval analysis
```

In [165…
```
np.mean(age0_17["Purchase"].sample(3000))
sample_mean_age0_17=[(np.mean(age0_17["Purchase"].sample(3000))) for i in range(1000)]
n=3000
st_dev_age0_17=np.std(age0_17["Purchase"])
std_err_age0_17=st_dev_age0_17/np.sqrt(n)
mean_age0_17=np.mean(age0_17["Purchase"])
#for 95% confidence interval
z=norm.ppf(0.975)
x1=mean_age0_17-z*std_err_age0_17
x2=mean_age0_17+z*std_err_age0_17
x1,x2
```

Out[165]: (8750.575189506208, 9116.35409138374)

In [166…
```
#for age range 18_25
np.mean(age18_25["Purchase"].sample(30000))
sample_mean_age18_25=[(np.mean(age18_25["Purchase"].sample(30000))) for i in range(100
n=30000
st_dev_age18_25=np.std(age18_25["Purchase"])
std_err_age18_25=st_dev_age18_25/np.sqrt(n)
mean_age18_25=np.mean(age18_25["Purchase"])
#for 95% confidence interval
z=norm.ppf(0.975)
x1=mean_age18_25-z*std_err_age18_25
x2=mean_age18_25+z*std_err_age18_25
x1,x2
```

Out[166]: (9112.696222544599, 9226.630989977979)

In [167…
```
#for age range 26_35
np.mean(age26_35["Purchase"].sample(30000))
sample_mean_age26_35=[(np.mean(age26_35["Purchase"].sample(30000))) for i in range(100
n=30000
st_dev_age26_35=np.std(age26_35["Purchase"])
std_err_age26_35=st_dev_age26_35/np.sqrt(n)
mean_age26_35=np.mean(age26_35["Purchase"])
#for 95% confidence interval
z=norm.ppf(0.975)
x1=mean_age26_35-z*std_err_age26_35
x2=mean_age26_35+z*std_err_age26_35
x1,x2
```

Out[167]: (9195.99234980965, 9309.388915930125)

In [168…
```
#for age range 36_50
np.mean(age36_50["Purchase"].sample(30000))
sample_mean_age36_50=[(np.mean(age36_50["Purchase"].sample(30000))) for i in range(100
n=30000
st_dev_age36_50=np.std(age36_50["Purchase"])
std_err_age36_50=st_dev_age36_50/np.sqrt(n)
mean_age36_50=np.mean(age36_50["Purchase"])
#for 95% confidence interval
z=norm.ppf(0.975)
x1=mean_age36_50-z*std_err_age36_50
x2=mean_age36_50+z*std_err_age36_50
x1,x2
```

Out[168]: (9238.674170219734, 9351.989315401339)

In [169…
```
#for age range 50plus
np.mean(age50plus["Purchase"].sample(30000))
sample_mean_age50plus=[(np.mean(age50plus["Purchase"].sample(30000))) for i in range(1
n=30000
st_dev_age50plus=np.std(age50plus["Purchase"])
std_err_age50plus=st_dev_age50plus/np.sqrt(n)
mean_age50plus=np.mean(age50plus["Purchase"])
#for 95% confidence interval
z=norm.ppf(0.975)
x1=mean_age50plus-z*std_err_age50plus
```

```
x2=mean_age50plus+z*std_err_age50plus
x1,x2
```

Out[169]:
```
(9406.390774174824, 9520.932582212145)
```

In [ ]:
```
```

In [170…
```
#99% confidence interval analysis
```

In [172…
```
np.mean(age0_17["Purchase"].sample(3000))
sample_mean_age0_17=[(np.mean(age0_17["Purchase"].sample(3000))) for i in range(1000)]
n=3000
st_dev_age0_17=np.std(age0_17["Purchase"])
std_err_age0_17=st_dev_age0_17/np.sqrt(n)
mean_age0_17=np.mean(age0_17["Purchase"])
#for 99% confidence interval
z=norm.ppf(0.995)
x1=mean_age0_17-z*std_err_age0_17
x2=mean_age0_17+z*std_err_age0_17
x1,x2
```

Out[172]:
```
(8693.107159004521, 9173.822121885427)
```

In [173…
```
#for age range 18_25
np.mean(age18_25["Purchase"].sample(30000))
sample_mean_age18_25=[(np.mean(age18_25["Purchase"].sample(30000))) for i in range(100
n=30000
st_dev_age18_25=np.std(age18_25["Purchase"])
std_err_age18_25=st_dev_age18_25/np.sqrt(n)
mean_age18_25=np.mean(age18_25["Purchase"])
#for 99% confidence interval
z=norm.ppf(0.995)
x1=mean_age18_25-z*std_err_age18_25
x2=mean_age18_25+z*std_err_age18_25
x1,x2
```

Out[173]:
```
(9094.795773239142, 9244.531439283435)
```

In [174…
```
#for age range 26_35
np.mean(age26_35["Purchase"].sample(30000))
sample_mean_age26_35=[(np.mean(age26_35["Purchase"].sample(30000))) for i in range(100
n=30000
st_dev_age26_35=np.std(age26_35["Purchase"])
std_err_age26_35=st_dev_age26_35/np.sqrt(n)
mean_age26_35=np.mean(age26_35["Purchase"])
#for 99% confidence interval
z=norm.ppf(0.995)
x1=mean_age26_35-z*std_err_age26_35
x2=mean_age26_35+z*std_err_age26_35
x1,x2
```

Out[174]:
```
(9178.176458058791, 9327.204807680984)
```

In [175…
```
#for age range 36_50
np.mean(age36_50["Purchase"].sample(30000))
sample_mean_age36_50=[(np.mean(age36_50["Purchase"].sample(30000))) for i in range(100
n=30000
```

```
st_dev_age36_50=np.std(age36_50["Purchase"])
std_err_age36_50=st_dev_age36_50/np.sqrt(n)
mean_age36_50=np.mean(age36_50["Purchase"])
#for 99% confidence interval
z=norm.ppf(0.995)
x1=mean_age36_50-z*std_err_age36_50
x2=mean_age36_50+z*std_err_age36_50
x1,x2
```

Out[175]: (9220.87107062549, 9369.792414995583)

In [176…

```
#for age range 50plus
np.mean(age50plus["Purchase"].sample(30000))
sample_mean_age50plus=[(np.mean(age50plus["Purchase"].sample(30000))) for i in range(1
n=30000
st_dev_age50plus=np.std(age50plus["Purchase"])
std_err_age50plus=st_dev_age50plus/np.sqrt(n)
mean_age50plus=np.mean(age50plus["Purchase"])
#for 99% confidence interval
z=norm.ppf(0.995)
x1=mean_age50plus-z*std_err_age50plus
x2=mean_age50plus+z*std_err_age50plus
x1,x2
```

Out[176]: (9388.394951878296, 9538.928404508673)

In [ ]: