In [145…

```
import numpy as np
import numpy.random as rd
import pandas as pd
import matplotlib.pyplot as plt
import plotly as pt
import seaborn as sns
from scipy.stats import norm
import warnings
warnings.filterwarnings("ignore")
import ipywidgets as w
from IPython.display import display
```

Importing Dataset

In [146…

```
df=
pd.read_csv("https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/00
1641285094")
```

In [147…

```
df
```

Out[147]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Ma
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 [148…

```
df.shape
```

Out[148]:
```
(550068, 10)
```

In [149…
```
for i in df.columns:
  print(i,':',df[i].nunique())
```

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

In [150…
```
df.dtypes
```

Out[150]:
```
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 [151…
```
df.isnull().sum()
# No Null values found
```

Out[151]:
```
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
```

Checking Value Counts for Categorical Columns

In [152…
```
df['Product_ID'].value_counts()
```

Out[152]:
```
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 [153…

```python
df['Gender'].value_counts()
```

Out[153]:

```
M    414259
F    135809
Name: Gender, dtype: int64
```

In [154…

```python
df['Marital_Status'].value_counts()
```

Out[154]:

```
0    324731
1    225337
Name: Marital_Status, dtype: int64
```

In [155…

```python
df['Product_Category'].value_counts()
```

Out[155]:

```
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 [156…

```python
df['Occupation'].value_counts()
```

Out[156]:

```
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 [157…

```
df['Stay_In_Current_City_Years'].value_counts()
```

Out[157]:

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

In [158…

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

Out[158]:

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

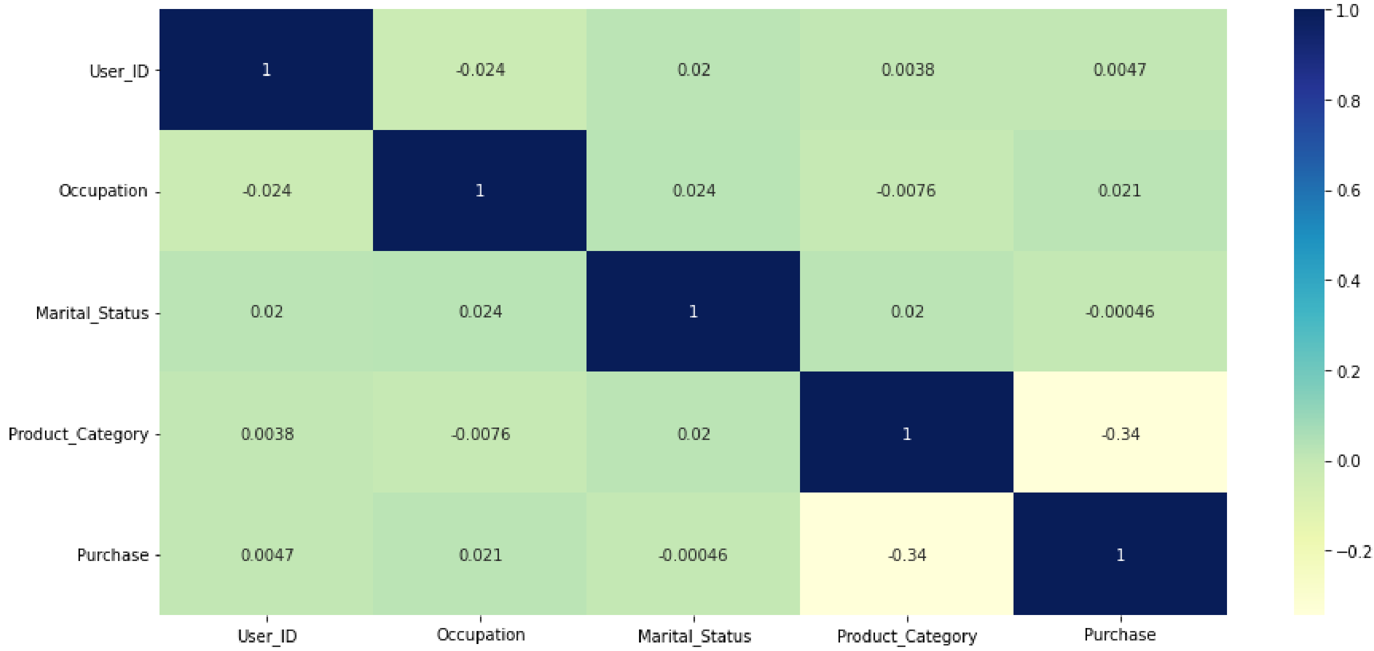
Corelating Plot in Heatmap

In [159…

```
df_copy = df.copy().corr()
```

In [160…

```
# Correlation plot as Heatmap

plt.figure(figsize=(15,7))
sns.heatmap(df_copy, cmap="YlGnBu" , annot=True)
plt.show()
```



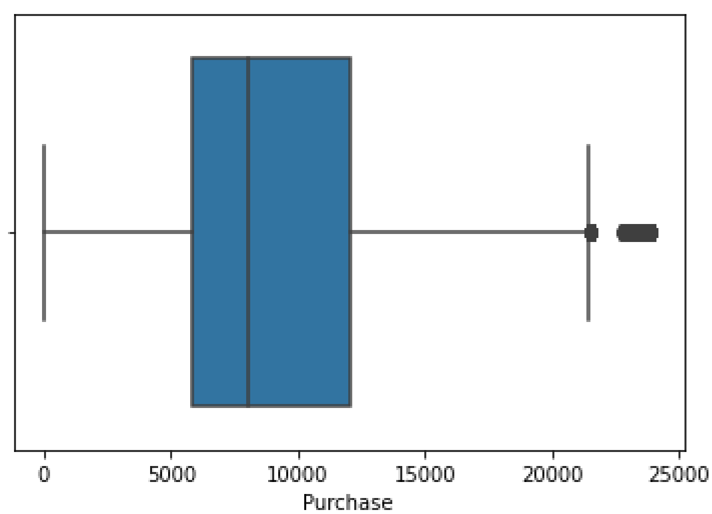
Correlation:

1. We can see clear correlation between Product_Category and Marital_status
2. And Also Purchase and occupation also has high correlation

Observing Outliers of Occupation

In [161…

```
ax= sns.boxplot(data=df, x="Purchase", orient='h')
plt.show()
```



In [162…

```
# There are outliers present , and hence , we can delete the rows having
purchase greater than 20000
df = df[df["Purchase"]<20000]
```

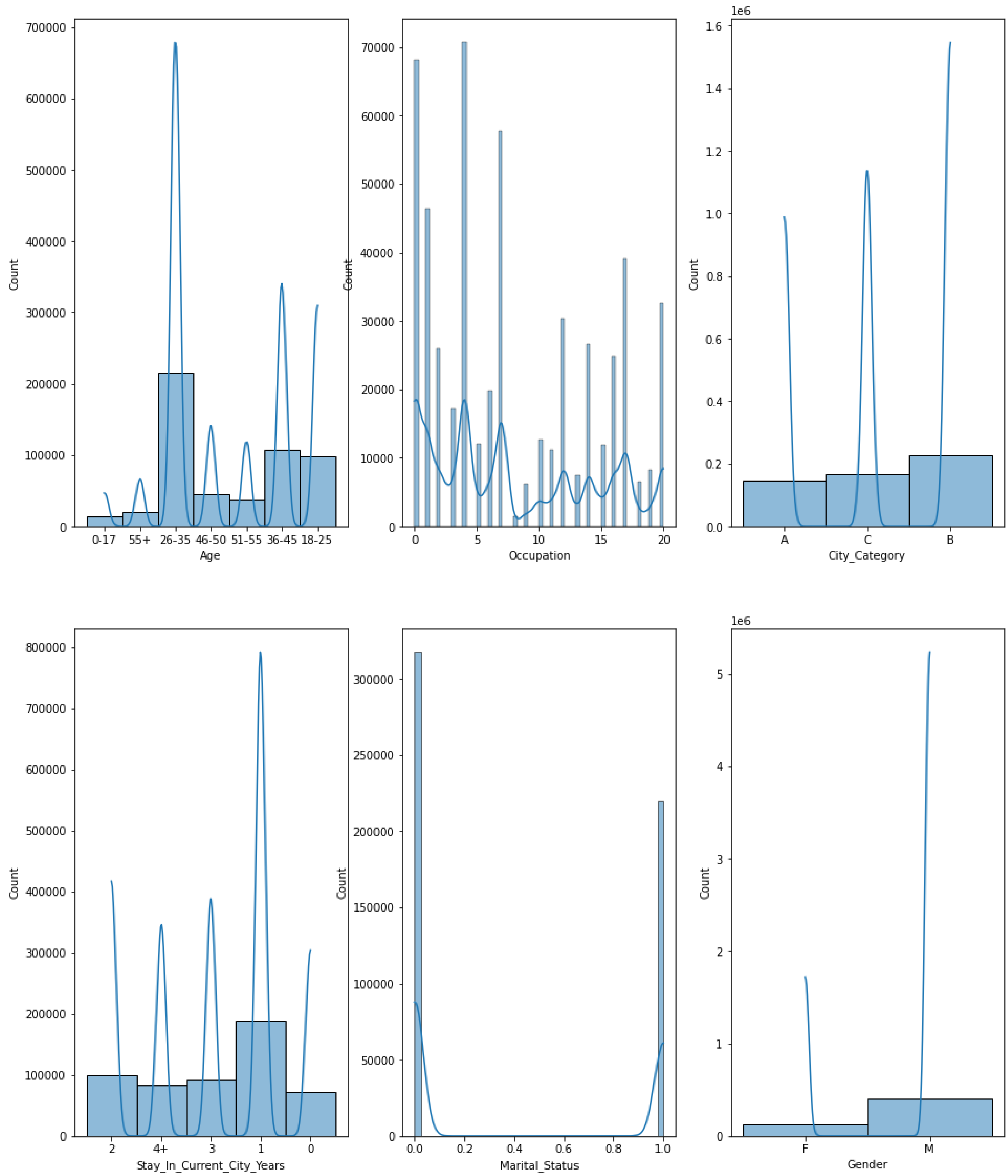
In [163…

```
fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(15, 13))
fig.subplots_adjust(top=1.2)
sns.histplot(data=df, x="Age", kde=True, ax=axis[0,0])
sns.histplot(data=df, x="Occupation", kde=True, ax=axis[0,1])
```

```
sns.histplot(data=df, x="City_Category", kde=True, ax=axis[0,2])
sns.histplot(data=df, x="Stay_In_Current_City_Years", kde=True, ax=axis[1,0])
sns.histplot(data=df, x="Marital_Status", kde=True, ax=axis[1,1])
sns.histplot(data=df, x="Gender", kde=True, ax=axis[1,2])
```

Out[163]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f061f3675d0>
```



Observations:

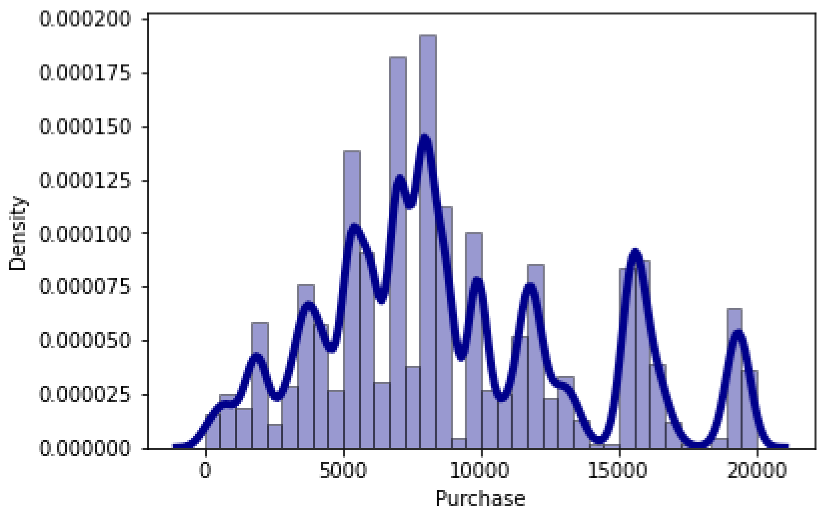
- 26-35 age category has done more number of purchases and least is 0-17
- 4th occupation category has done more purchases and least is 9

- City category B has done more purchases and least by A city category
- More number of purchases done by 1 year stay in current city
- Single person purchased more than married
- We can clearly see More male person purchased than female

Distplot for Analysis of Continuous Variable

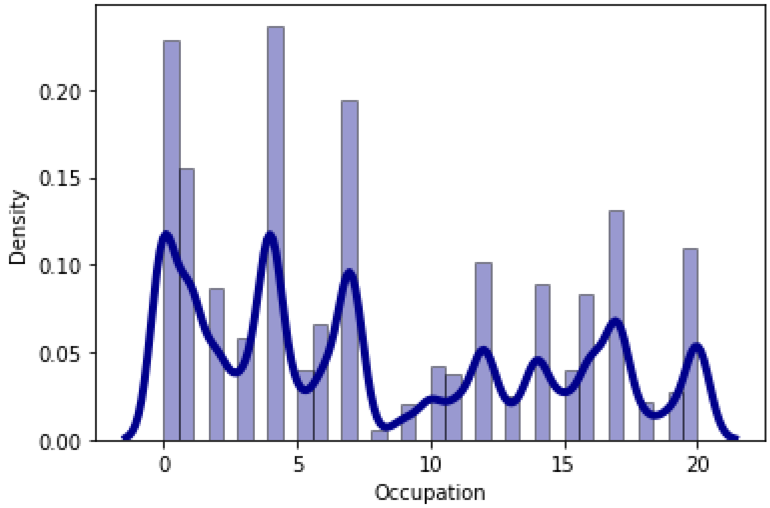
In [207…

```
# Distplot for purchase

sns.distplot(df['Purchase'], hist=True, kde= True,
            bins =int(36), color ='darkblue',
            hist_kws={'edgecolor':'black'},
            kde_kws={'linewidth':4})
plt.show()
```



In [205…

```
#Distplot for Occupation
sns.distplot(df['Occupation'], hist=True, kde= True,
            bins =int(36), color ='darkblue',
            hist_kws={'edgecolor':'black'},
            kde_kws={'linewidth':4})
plt.show()
```



In [166…

```
# Finding the purchase power of wallmart customers
df['Purchase'].describe()
```

Out[166]:

```
count    537371.000000
mean       8984.494781
std        4733.938413
min          12.000000
25%        5466.000000
50%        8003.000000
75%       11879.000000
max       19999.000000
Name: Purchase, dtype: float64
```

In [167…

```
# Finding the no of city categroy
df['City_Category'].nunique()
```

Out[167]:

```
3
```

In [168…

```
# Also finding the unique Product category
df['Product_Category'].nunique()
```

Out[168]:

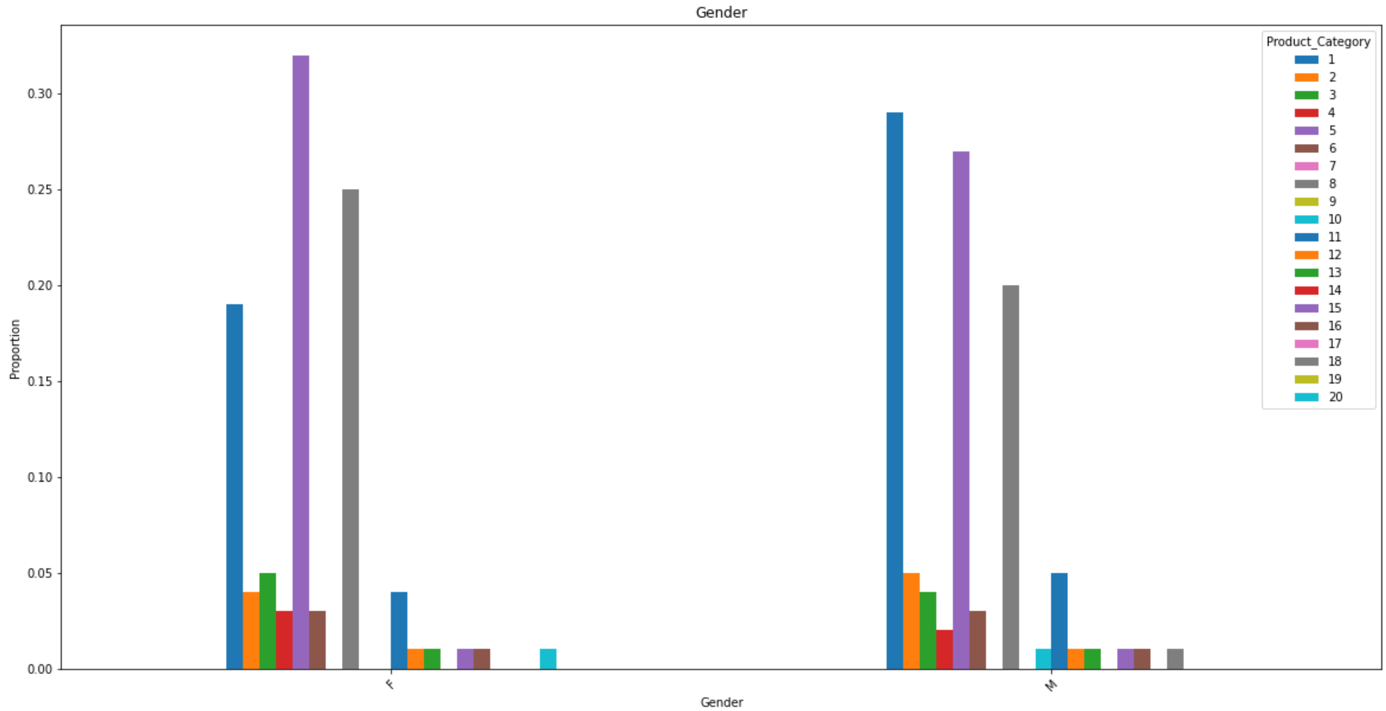
```
20
```

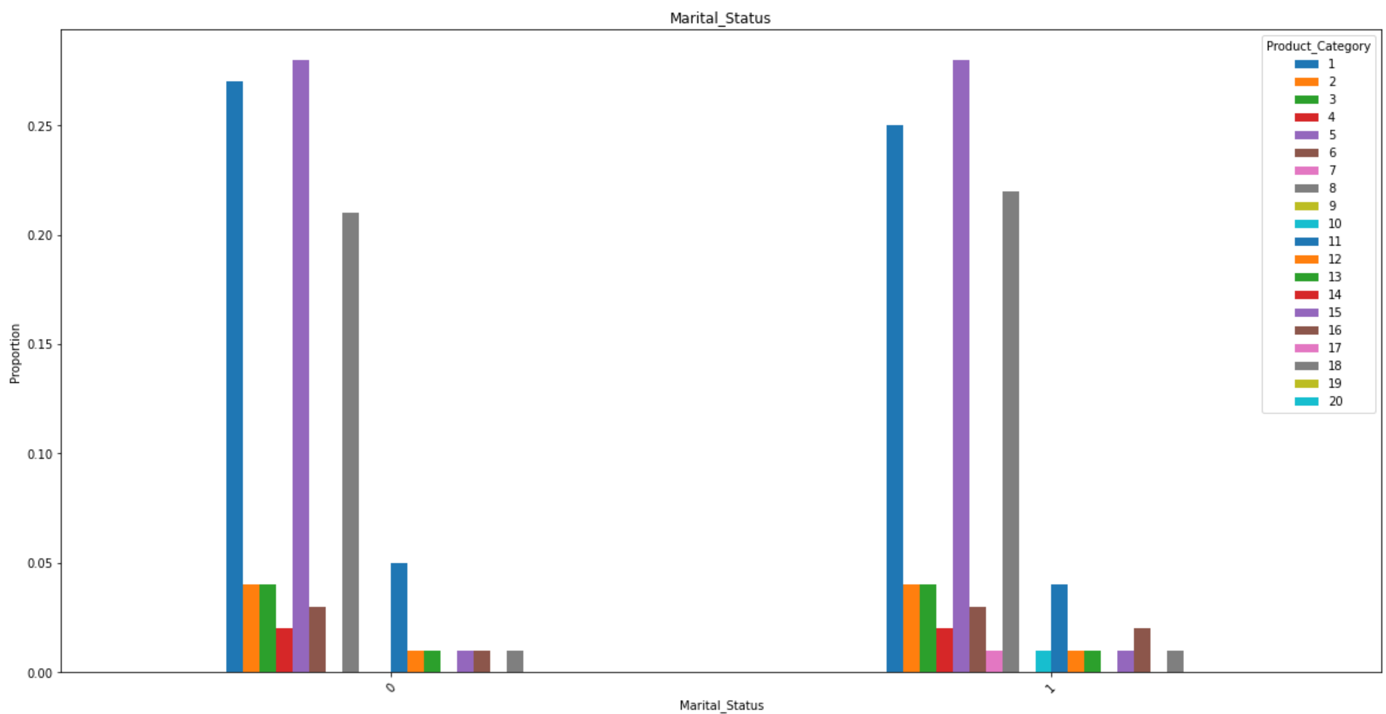
Crosstabs

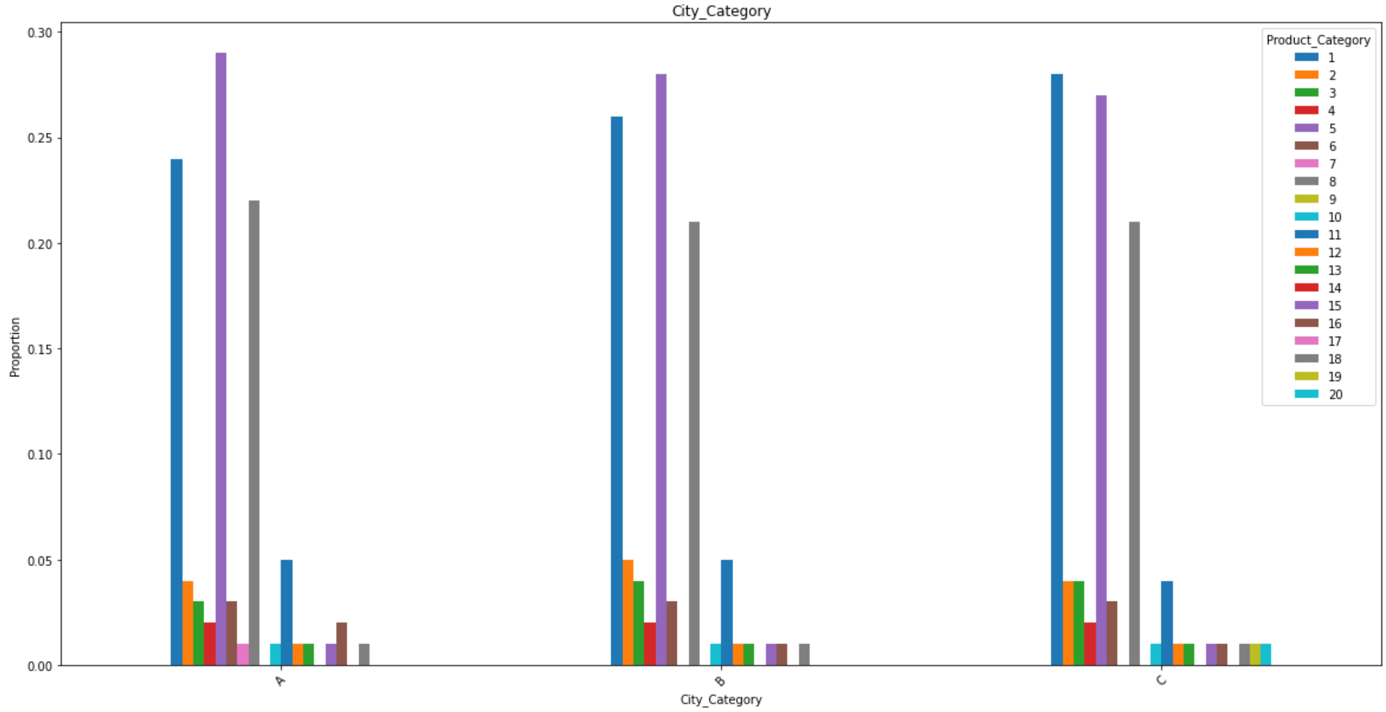
In [169…

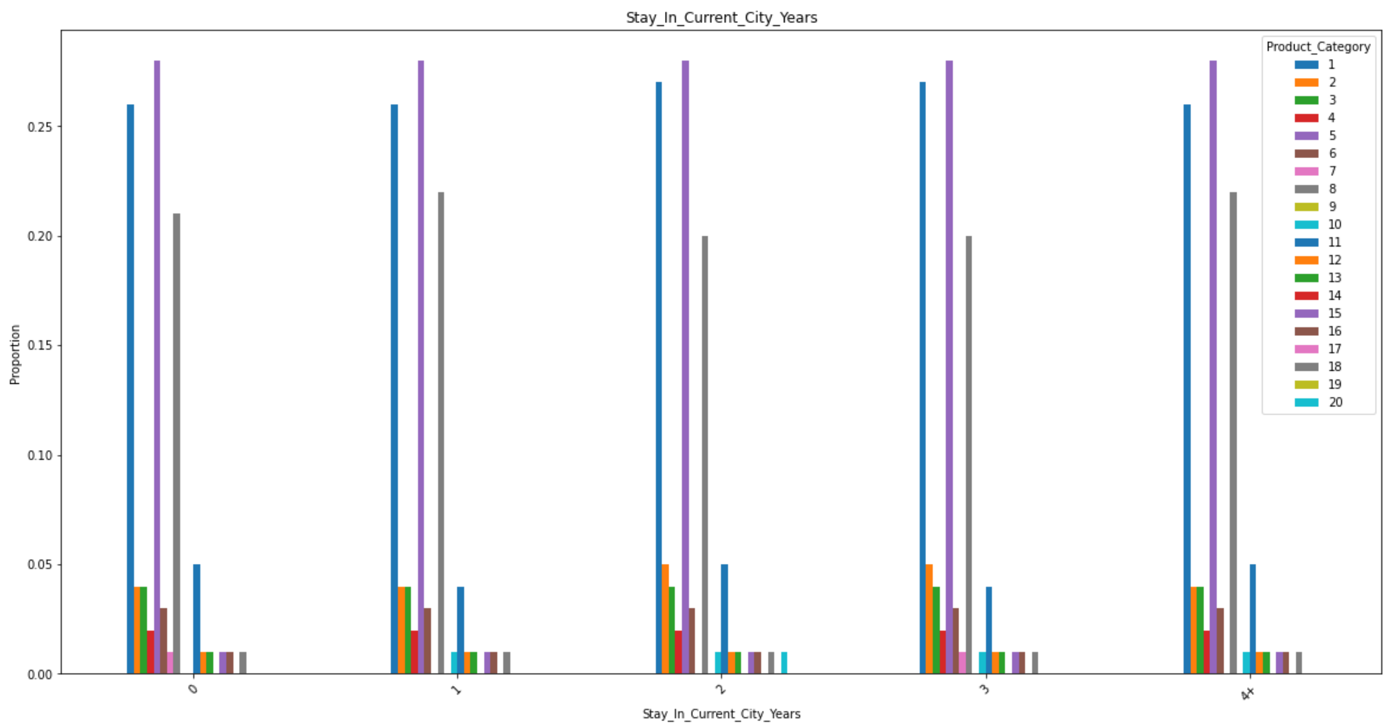
```
cat_cols= ['Gender',
'Marital_Status','City_Category','Stay_In_Current_City_Years','Age']
for i in cat_cols:
  other= round(pd.crosstab(df[df[i].notnull()][i],
df['Product_Category']).div(pd.crosstab(df[df[i].notnull()]
[i],df['Product_Category']).apply(sum,1),0),2)
  ax=other.plot(kind='bar', title = i, figsize =(20,10))
  ax.set_xlabel(i)
  ax.set_ylabel('Proportion')
```

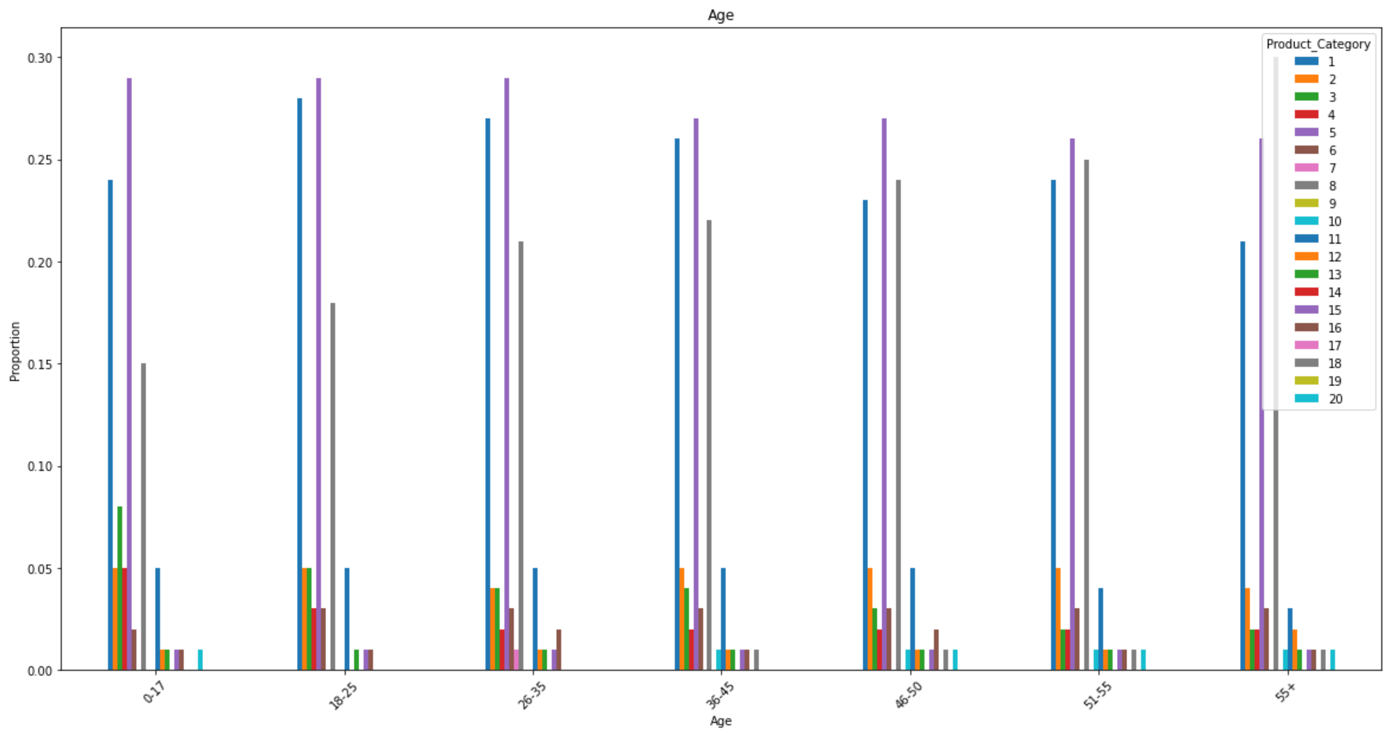
```
plt.xticks (rotation=45)
plt.show()
```






City_Category
Proportion
0.00
0.05
0.10
0.15
0.20
0.25
0.30
A
B
C
City_Category
Product_Category
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20


Stay_In_Current_City_Years
Proportion
0.00
0.05
0.10
0.15
0.20
0.25
0
1
2
3
4+
Stay_In_Current_City_Years
Product_Category
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20



In [170…

```
## Tracking the amount spent by male and female
print("Males:: \n")
print("The Total Amount puchases made by males :",df[df['Gender']=="M"]
['Purchase'].sum())
print("The Mean of total amount puchases made by males
:",round(df[df['Gender']=="M"]['Purchase'].mean(),2))

print("Females:: \n")
print("The Total Amount puchases made by males :",df[df['Gender']=="F"]
['Purchase'].sum())
print("The Mean of total amount puchases made by males :
",round(df[df['Gender']=="F"]['Purchase'].mean(),2))
```

```
Males::

The Total Amount puchases made by males : 3701342147
The Mean of total amount puchases made by males : 9153.02
Females::

The Total Amount puchases made by males : 1126664798
The Mean of total amount puchases made by males :  8472.06
```

Observations on Categorical plots

1. Total mean of male is more than Female
2. Category 5 is most purchased by male and product category 1 is most purchased by female
3. But Category 1 and 5 are most purchased product category and being favourite among all other product category
4. Married and unmarried person also preferred to buy product category 5

5. While A and B City Category people prefers to buy produt category 5 and c prefers Product category 1 , the most
6. As Seen for Stay in current years vs Product category , all of them preferred product category the most

Probabilites

In [171…

```
pd.crosstab(df['Gender'],columns=df['Product_Category'], margins=True)
```

Out[171]:

Product_Category	1	2	3	4	5	6	7	8	9	10	...	12	
Gender													
F	24831	5658	6006	3639	41961	3376	631	33558	56	638	...	1532	14
M	115547	18206	14207	8114	108972	11556	1832	80367	279	2212	...	2415	40
All	140378	23864	20213	11753	150933	14932	2463	113925	335	2850	...	3947	55

3 rows × 21 columns

In [172…

```
pd.crosstab(df['Gender'],columns=df['Product_Category'], margins=True,
normalize=True)*100
```

Out[172]:

Product_Category	1	2	3	4	5	6	7	8
Gender								
F	4.620830	1.052904	1.117664	0.677186	7.808572	0.628244	0.117424	6.244848
M	21.502277	3.387976	2.643797	1.509944	20.278727	2.150470	0.340919	14.955589
All	26.123107	4.440880	3.761461	2.187130	28.087299	2.778713	0.458343	21.200437

3 rows × 21 columns

In [173…

```
pd.crosstab(df['Gender'],columns=df['Product_Category'], margins=True,
normalize="index")
```

Out[173]:

Product_Category	1	2	3	4	5	6	7	8	
Gender									
F	0.186719	0.042546	0.045163	0.027364	0.315529	0.025386	0.004745	0.252342	0.0
M	0.285735	0.045021	0.035132	0.020065	0.269476	0.028577	0.004530	0.198739	0.0
All	0.261231	0.044409	0.037615	0.021871	0.280873	0.027787	0.004583	0.212004	0.0

Population Mean and Population Standard deviation

In [174…

```
## Tracking the amount spent by male and female
print("Males:: \n")
```

```
male_mean=round(df[df['Gender']=="M"]['Purchase'].mean(),2)
print("The Mean of total amount puchases made by males :",male_mean)
print("The Standard deviation amount puchases made by males
:",df[df['Gender']=="M"]['Purchase'].std())

print("Females:: \n")
female_mean= round(df[df['Gender']=="F"]['Purchase'].mean(),2)
print("The Mean of total amount puchases made by females : ",female_mean)
print("The Standard deviation amount puchases made by females
:",df[df['Gender']=="F"]['Purchase'].std())
```

```
Males::

The Mean of total amount puchases made by males : 9153.02
The Standard deviation amount puchases made by males : 4809.692761778849
Females::

The Mean of total amount puchases made by females :  8472.06
The Standard deviation amount puchases made by females : 4456.787969134718
```

In [175…

```
## Tracking the amount spent by Married  and Single
print("Married:: \n")

Married_mean=round(df[df['Marital_Status']==1]['Purchase'].mean(),2)
print("The Mean of total amount puchases made by married :",Married_mean)
print("The Standard deviation amount puchases made by married
:",df[df['Marital_Status']==1]['Purchase'].std())

print("Single:: \n")
Single_mean= round(df[df['Marital_Status']==0]['Purchase'].mean(),2)
print("The Mean of total amount puchases made by Single : ",female_mean)
print("The Standard deviation amount puchases made by Single
:",df[df['Marital_Status']==0]['Purchase'].std())
```

```
Married::

The Mean of total amount puchases made by married : 8976.64
The Standard deviation amount puchases made by married : 4719.617936141523
Single::

The Mean of total amount puchases made by Single :  8472.06
The Standard deviation amount puchases made by Single : 4743.844815795029
```

Sample mean Histogram

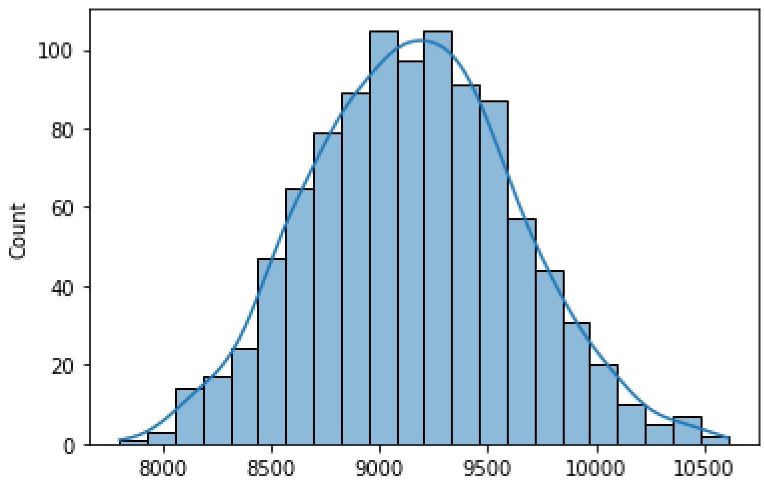
In [176…

```
# Sample mean histogram for purchase made by Male,Female, Married , Single
```

In [177…

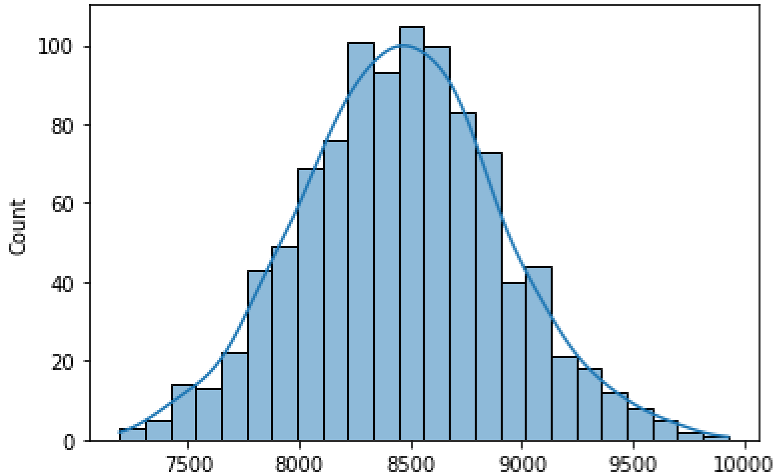
```
#MALE
```

```python
sample_size = 100

collect_sample_means_male = []

for person in range(1000):
    sample_mean = df[df['Gender']=="M"]
["Purchase"].sample(sample_size).mean()
    collect_sample_means_male.append(sample_mean)

sns.histplot(collect_sample_means_male, kde=True)

# Collecting a random sample mean
m_male = collect_sample_means_male[0]
```



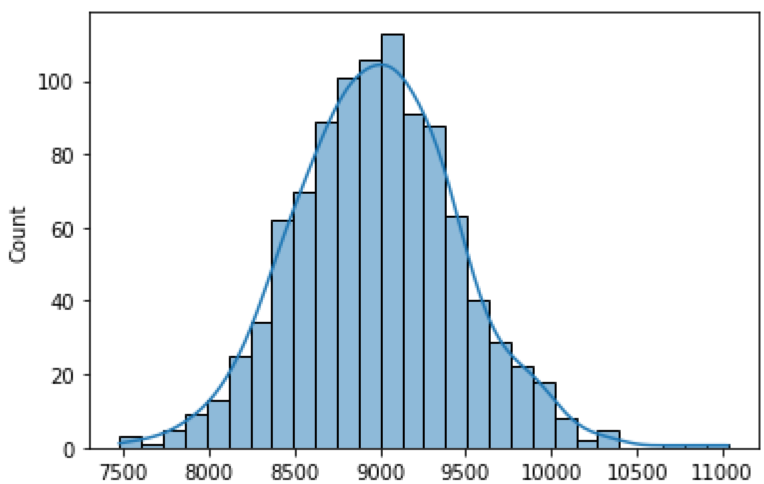
In [178…

```python
# FEMALE

sample_size = 100
collect_sample_means_female = []
for person in range(1000):
    sample_mean = df[df['Gender']=="F"]
["Purchase"].sample(sample_size).mean()
    collect_sample_means_female.append(sample_mean)
sns.histplot(collect_sample_means_female, kde=True)

# Collecting a random sample mean
m_female=collect_sample_means_female[0]
```



In [179…

```
# Married

sample_size = 100
collect_sample_means_married = []
for person in range(1000):
    sample_mean = df[df['Marital_Status']==1]
["Purchase"].sample(sample_size).mean()
    collect_sample_means_married.append(sample_mean)
sns.histplot(collect_sample_means_married, kde=True)
m_married=collect_sample_means_married[0]
```



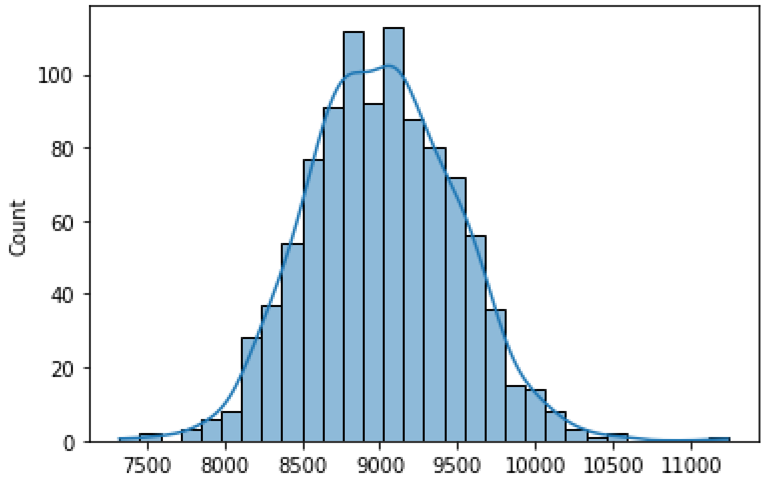
In [179…

```
```

In [180…

```
# SINGLE

sample_size = 100
collect_sample_means_single = []
for person in range(1000):
    sample_mean = df[df['Marital_Status']==0]
["Purchase"].sample(sample_size).mean()
    collect_sample_means_single.append(sample_mean)
```

```
sns.histplot(collect_sample_means_single, kde=True)
m_single=collect_sample_means_single[0]
```



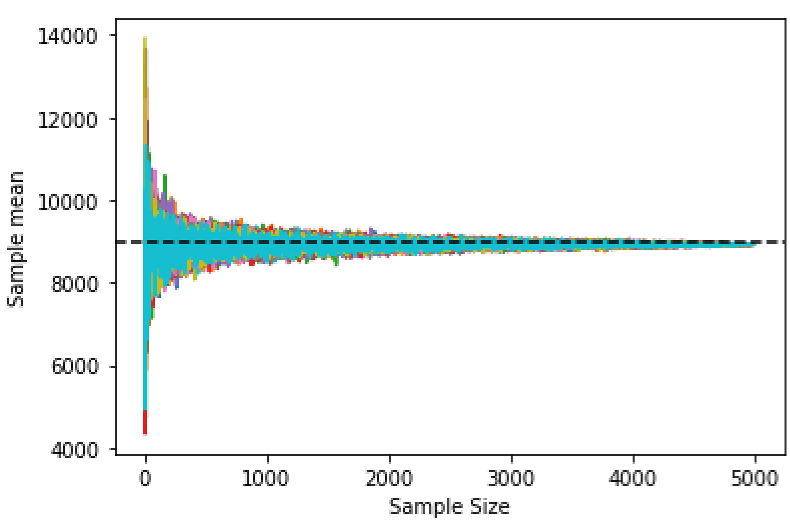
Sample Mean Trend

In [181…

```
# Getting sample of 5000 from overall purchase
dfs= df.sample(5000)
me_purchase=df['Purchase'].mean()
for person in range(20):
    sample_mean_trend = []
    for num_samples in range(5, len(dfs)):
        sample = dfs["Purchase"].sample(num_samples)
        sample_mean = np.mean(sample)
        sample_mean_trend.append(sample_mean)
    plt.plot(sample_mean_trend)

plt.xlabel("Sample Size")
plt.ylabel("Sample mean")
plt.axhline(y = me_purchase, linestyle = '--', color = 'black')
```

Out[181]:

```
&lt;matplotlib.lines.Line2D at 0x7f061e4299d0&gt;
```



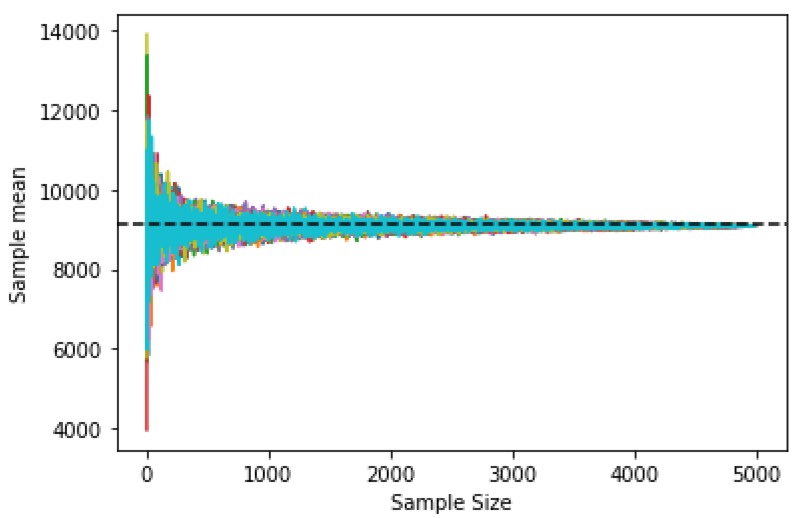
We Can see , that the mean of samples reaches close to population mean , when sample size increases

In [182…

```
# Getting sample of 5000 for Male Purchase
dfs= df[df["Gender"]=="M"].sample(5000)
me_male=df[df["Gender"]=="M"]["Purchase"].mean()
for person in range(20):
    sample_mean_trend = []
    for num_samples in range(5, len(dfs)):
        sample = dfs["Purchase"].sample(num_samples)
        sample_mean = np.mean(sample)
        sample_mean_trend.append(sample_mean)
    plt.plot(sample_mean_trend)

plt.xlabel("Sample Size")
plt.ylabel("Sample mean")
plt.axhline(y = me_male, linestyle = '--', color = 'black')
```

Out[182]:

```
<matplotlib.lines.Line2D at 0x7f061e3f2790>
```



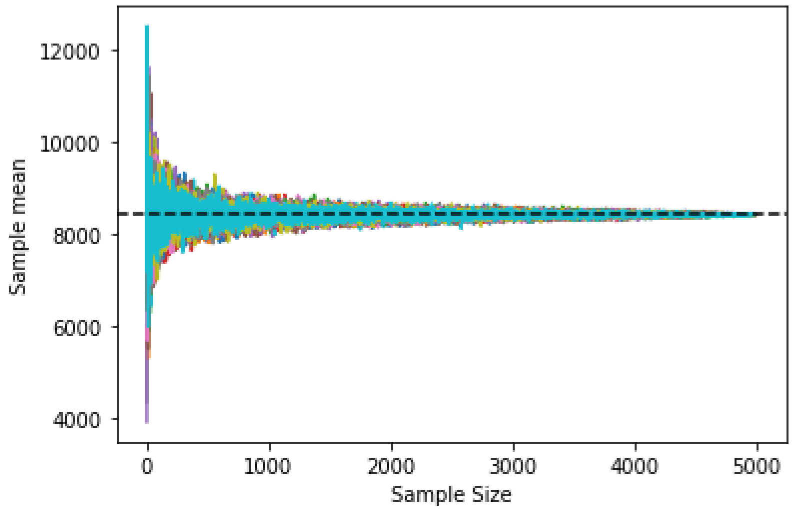
In [183…

```
# Getting sample of 5000 for Female Purchas

dfs= df[df["Gender"]=="F"].sample(5000)
me_female=df[df["Gender"]=="F"]["Purchase"].mean()
for person in range(20):
    sample_mean_trend = []
    for num_samples in range(5, len(dfs)):
        sample = dfs["Purchase"].sample(num_samples)
        sample_mean = np.mean(sample)
        sample_mean_trend.append(sample_mean)
    plt.plot(sample_mean_trend)

plt.xlabel("Sample Size")
```

```python
plt.ylabel("Sample mean")
plt.axhline(y = me_female, linestyle = '--', color = 'black')
```

Out[183]:

```
<matplotlib.lines.Line2D at 0x7f061e351590>
```

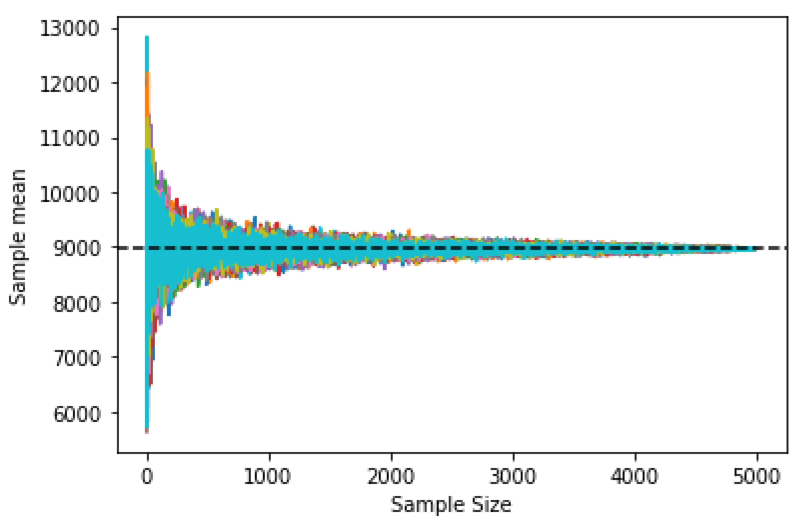


In [184…

```python
# Getting sample of 5000 for Married Purchase

dfs= df[df["Marital_Status"]==1].sample(5000)
me_married=df[df["Marital_Status"]==1]["Purchase"].mean()
for person in range(20):
    sample_mean_trend = []
    for num_samples in range(5, len(dfs)):
        sample = dfs["Purchase"].sample(num_samples)
        sample_mean = np.mean(sample)
        sample_mean_trend.append(sample_mean)
    plt.plot(sample_mean_trend)

plt.xlabel("Sample Size")
plt.ylabel("Sample mean")
plt.axhline(y = me_married, linestyle = '--', color = 'black')
```

Out[184]:

```
<matplotlib.lines.Line2D at 0x7f061e202390>
```

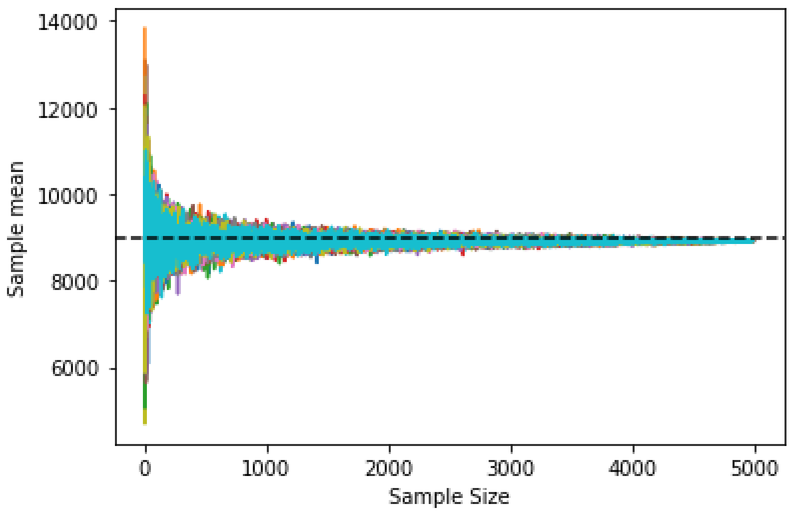


In [185…

```
# Getting sample of 5000 for Single Purchase

dfs= df[df["Marital_Status"]==0].sample(5000)
me_single=df[df["Marital_Status"]==0]["Purchase"].mean()
for person in range(20):
    sample_mean_trend = []
    for num_samples in range(5, len(dfs)):
        sample = dfs["Purchase"].sample(num_samples)
        sample_mean = np.mean(sample)
        sample_mean_trend.append(sample_mean)
    plt.plot(sample_mean_trend)

plt.xlabel("Sample Size")
plt.ylabel("Sample mean")
plt.axhline(y = me_single, linestyle = '--', color = 'black')
```

Out[185]:

```
<matplotlib.lines.Line2D at 0x7f061e148110>
```



Confidence Interval (95 , 99%) - for Gender and Marital status.

In [186…

```
# 95% Confidence - Male

Zl= norm.ppf(0.025)
Zr= norm.ppf(0.975)

left = m_male + Zl * male_mean / np.sqrt(sample_size)
right = m_male + Zr * male_mean / np.sqrt(sample_size)
print(f"95% confidence that the population mean of male purchases is in
[{np.round(left,2)}, {np.round(right,2)}]")

# 99 % Confidence - Male
```

```
z= 2.57

left = m_male - z * male_mean / np.sqrt(sample_size)
right = m_male + z * male_mean / np.sqrt(sample_size)
print(f"99% confidence that the population mean of male purchases is in
[{np.round(left,2)}, {np.round(right,2)}]")


# 95% Confidence - Female

Zl= norm.ppf(0.025)
Zr= norm.ppf(0.975)

left = m_female + Zl * female_mean / np.sqrt(sample_size)
right = m_female + Zr * female_mean / np.sqrt(sample_size)
print(f"95% confidence that the population mean of Female purchases is in
[{np.round(left,2)}, {np.round(right,2)}]")

# 99 % Confidence - Female

z= 2.576

left = m_female - z * female_mean / np.sqrt(sample_size)
right = m_female + z * female_mean / np.sqrt(sample_size)
print(f"99% confidence that the population mean of Female purchases is in
[{np.round(left,2)}, {np.round(right,2)}]")

# 95% Confidence - Married

Zl= norm.ppf(0.025)
Zr= norm.ppf(0.975)

left = m_married + Zl * Married_mean / np.sqrt(sample_size)
right = m_married + Zr * Married_mean / np.sqrt(sample_size)
print(f"95% confidence that the population mean of Married person purchases
is in [{np.round(left,2)}, {np.round(right,2)}]")

# 99 % Confidence - Married

z= 2.576

left = m_married - z * Married_mean / np.sqrt(sample_size)
right = m_married + z * Married_mean / np.sqrt(sample_size)
print(f"99% confidence that the population mean of Married person purchases
```

```
is in [{np.round(left,2)}, {np.round(right,2)}]")


# 95% Confidence - Unmarried

Zl= norm.ppf(0.025)
Zr= norm.ppf(0.975)

left = m_single + Zl * Single_mean / np.sqrt(sample_size)
right = m_married + Zr * Single_mean / np.sqrt(sample_size)
print(f"95% confidence that the population mean of Unmarried person is in
[{np.round(left,2)}, {np.round(right,2)}]")

# 99 % Confidence - Unmarried

z= 2.576

left = m_married - z * Single_mean / np.sqrt(sample_size)
right = m_married + z * Single_mean / np.sqrt(sample_size)
print(f"99% confidence that the population mean of Unmarried person purchases
is in [{np.round(left,2)}, {np.round(right,2)}]")
```

```
95% confidence that the population mean of male purchases is in [8440.23, 12028.15]
99% confidence that the population mean of male purchases is in [7881.86, 12586.52]
95% confidence that the population mean of Female purchases is in [6238.67, 9559.65]
99% confidence that the population mean of Female purchases is in [5716.76, 10081.56]
95% confidence that the population mean of Married person purchases is in [6859.22, 1037
8.0]
99% confidence that the population mean of Married person purchases is in [6306.23, 1093
0.99]
95% confidence that the population mean of Unmarried person is in [8227.67, 10380.61]
99% confidence that the population mean of Unmarried person purchases is in [6302.8, 109
34.42]
```

Observations

There is considerable overlap for Male and Female , and Married and unmarried person. So there is no much difference in their mean significance.

Business Insights

1. There are more males than female in dataset
2. More records of Married person than singles present in dataset
3. Product Category 5 is the most purchased product and least purchases category is 9
4. There are more number of 4th category occupation present in dataset and 8th category occupation is least.
5. One year of stay in current city category is more in dataset

6. Age Category - 26 to 35 has purchased more number of product and the count is high in dataset
7. There are outliers present in purchase amount greater than 20000
8. Mean Purchases made by male is 9437 and by female is 5092
9. Mean purchases made by married person is 9261 and by single person is 8734

Recommendations

1. As checked in dataset, we infer , Married person purchase more than single , and there is a difference of 1000 in mean purchase, So , product category liked by single person , can be sell more to attract singles
2. Least purchased product category 9 , can be marketed more to boost up the sales
3. More purchases made by 26-35 , and hence products related that category can be sold
4. Since the purchases by City Category A is least, more specific city offers can be given to boost up the sales
5. Product category 1 is most brought by males, so more products can be released with respect to that category.
6. Second and third most purchased category is 1 and 8. More offers can be given on that product category to increase the sales , since it might also be a essential day-to-day used product