ohd5udrk2

March 24, 2023

[174]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[175]:
```python
df = pd.read_csv('walmart_data.csv')
df
```

[175]:
```
        User_ID Product_ID Gender    Age  Occupation City_Category  \
0       1000001  P00069042      F   0-17        10.0             A
1       1000001  P00248942      F   0-17        10.0             A
2       1000001  P00087842      F   0-17        10.0             A
3       1000001  P00085442      F   0-17        10.0             A
4       1000002  P00285442      M    55+        16.0             C
…           …          …      …     …           …
375654  1003822  P00116742      M  46-50        20.0             C
375655  1003822  P00182142      M  46-50        20.0             C
375656  1003823  P00112442      M    55+         7.0             B
375657  1003823  P00182342      M    55+         7.0             B
375658  1003823        P00    NaN    NaN         NaN           NaN

       Stay_In_Current_City_Years  Marital_Status  Product_Category  Purchase
0                               2             0.0               3.0    8370.0
1                               2             0.0               1.0   15200.0
2                               2             0.0              12.0    1422.0
3                               2             0.0              12.0    1057.0
4                              4+             0.0               8.0    7969.0
…                              …               …                 …       …
375654                          1             0.0              11.0    6092.0
375655                          1             0.0               1.0   11581.0
375656                          1             0.0               6.0   20414.0
375657                          1             0.0               1.0   19696.0
375658                        NaN             NaN               NaN       NaN

[375659 rows x 10 columns]
```

1 Defining Problem Statement and Analyzing basic metrics

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

1.1 Observations on shape of data, data types of all the attributes, conversion of categorical attributes to 'category' (If required), statistical summary

[176]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 375659 entries, 0 to 375658
Data columns (total 10 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   User_ID                     375659 non-null  int64
 1   Product_ID                  375659 non-null  object
 2   Gender                      375658 non-null  object
 3   Age                         375658 non-null  object
 4   Occupation                  375658 non-null  float64
 5   City_Category               375658 non-null  object
 6   Stay_In_Current_City_Years  375658 non-null  object
 7   Marital_Status              375658 non-null  float64
 8   Product_Category            375658 non-null  float64
 9   Purchase                    375658 non-null  float64
dtypes: float64(4), int64(1), object(5)
memory usage: 28.7+ MB
```

[177]:
```
df.isna().sum()
```

[177]:
```
User_ID                       0
Product_ID                    0
Gender                        1
Age                           1
Occupation                    1
City_Category                 1
Stay_In_Current_City_Years    1
Marital_Status                1
Product_Category              1
Purchase                      1
dtype: int64
```

[178]:
```
# Their is only one row with Nan value so better to drop it
df = df.dropna(axis = 0)
```

```
#Change the data types of - Occupation, Marital_Status, Product_Category

cols = ['Occupation', 'Marital_Status', 'Product_Category']
df[cols] = df[cols].astype('object')
```

```
<ipython-input-178-367352d48f10>:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df[cols] = df[cols].astype('object')
```

[179]:
```
df.isna().sum()
```

[179]:
```
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
```

[180]:
```
df.describe()
```

[180]:

	User_ID	Purchase
count	3.756580e+05	375658.000000
mean	1.002955e+06	9326.964489
std	1.714878e+03	4976.730193
min	1.000001e+06	185.000000
25%	1.001456e+06	5866.000000
50%	1.002967e+06	8061.000000
75%	1.004381e+06	12067.000000
max	1.006040e+06	23961.000000

[181]:
```
df[['Occupation', 'Marital_Status', 'Product_Category', "Product_ID", "Age",␣
↪"City_Category", "Stay_In_Current_City_Years"]].describe()
```

[181]:

	Occupation	Marital_Status	Product_Category	Product_ID	Age	\
count	375658.0	375658.0	375658.0	375658	375658	
unique	21.0	2.0	18.0	3560	7	
top	4.0	0.0	5.0	P00265242	26-35	
freq	49774.0	221740.0	103990.0	1257	149645	

```
       City_Category Stay_In_Current_City_Years
count         375658                     375658
unique             3                          5
top                B                          1
freq          158354                     132090
```

1.2 Non-Graphical Analysis: Value counts and unique attributes

[182]:
```python
#␣
↪User_ID         Occupation         Marital_Status         Product_Category         Purchase
df['User_ID'].value_counts()
```

[182]:
```
1001680    741
1004277    631
1001941    629
1001181    605
1000889    603
          …
1004178      4
1005110      3
1004527      3
1002111      3
1005391      3
Name: User_ID, Length: 5891, dtype: int64
```

[183]:
```python
df['User_ID'].unique()
```

[183]:
```
array([1000001, 1000002, 1000003, …, 1004113, 1005391, 1001529])
```

[184]:
```python
df['Occupation'].value_counts()
```

[184]:
```
4.0     49774
0.0     47660
7.0     40414
1.0     32075
17.0    27327
20.0    23071
12.0    21119
14.0    18642
2.0     18116
16.0    17207
6.0     13900
3.0     12104
10.0     8870
15.0     8256
5.0      8240
```

```
11.0     8004
19.0     5815
13.0     5326
18.0     4387
9.0      4315
8.0      1036
Name: Occupation, dtype: int64
```

[185]:
```
df['Occupation'].unique()
```

[185]:
```
array([10.0, 16.0, 15.0, 7.0, 20.0, 9.0, 1.0, 12.0, 17.0, 0.0, 3.0, 4.0,
       11.0, 8.0, 19.0, 2.0, 18.0, 5.0, 14.0, 13.0, 6.0], dtype=object)
```

[186]:
```
df['Marital_Status'].value_counts()
```

[186]:
```
0.0    221740
1.0    153918
Name: Marital_Status, dtype: int64
```

[187]:
```
df['Marital_Status'].unique()
```

[187]:
```
array([0.0, 1.0], dtype=object)
```

[188]:
```
df['Product_Category'].value_counts()
```

[188]:
```
5.0     103990
1.0      96500
8.0      78520
11.0     16677
2.0      16449
3.0      13946
6.0      13934
4.0       8142
16.0      6765
15.0      4350
13.0      3783
10.0      3527
12.0      2695
7.0       2582
18.0      2096
14.0      1037
17.0       397
9.0        268
Name: Product_Category, dtype: int64
```

[189]:
```
df['Product_Category'].unique()
```

[189]: array([3.0, 1.0, 12.0, 8.0, 5.0, 4.0, 2.0, 6.0, 14.0, 11.0, 13.0, 15.0,
       7.0, 16.0, 18.0, 10.0, 17.0, 9.0], dtype=object)

[190]:
```
df['Purchase'].value_counts()
```

[190]:
```
7193.0     140
7027.0     136
7093.0     136
7089.0     135
6928.0     131
          …
16965.0      1
18603.0      1
21493.0      1
17314.0      1
8928.0       1
Name: Purchase, Length: 17266, dtype: int64
```

[191]:
```
df['Purchase'].unique()
```

[191]: array([8370., 15200., 1422., …, 13832., 13945., 8928.])

[192]:
```
df['Gender'].value_counts()
```

[192]:
```
M    283187
F     92471
Name: Gender, dtype: int64
```

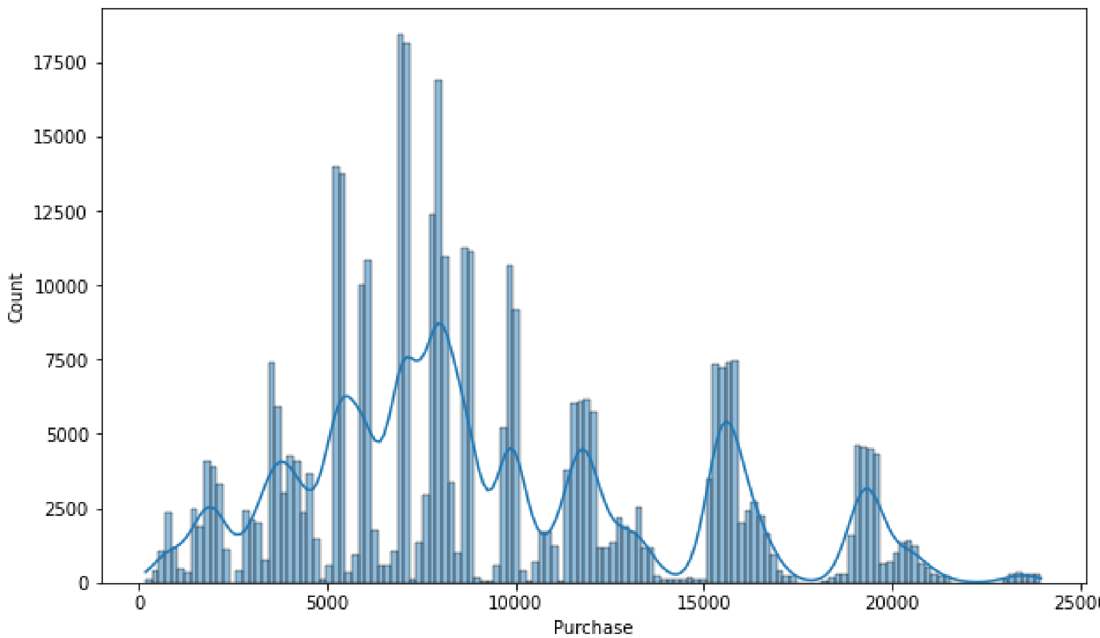
[193]:
```
df['Gender'].unique()
```

[193]: array(['F', 'M'], dtype=object)

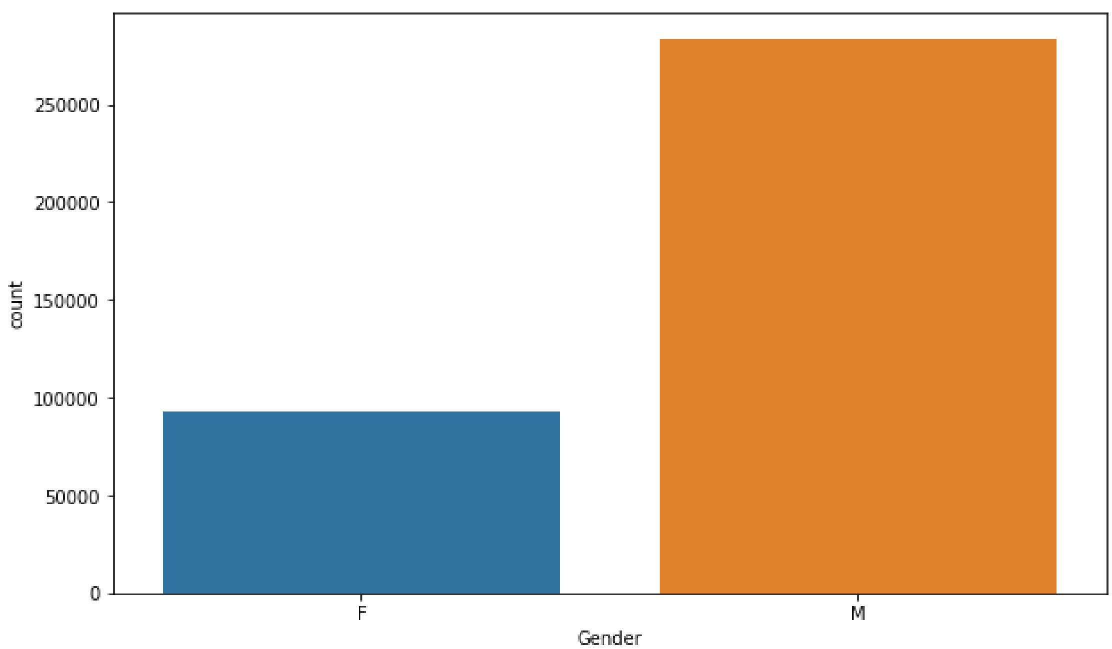
1.3 Visual Analysis - Univariate & Bivariate

For continuous variable(s): Distplot, countplot, histogram for univariate analysis

[194]:
```
#␣
↪User_ID         Occupation         Marital_Status         Product_Category         Purchase

plt.figure(figsize = (10, 6))
sns.histplot(x = 'Purchase', data = df, kde = True)
plt.show()
```

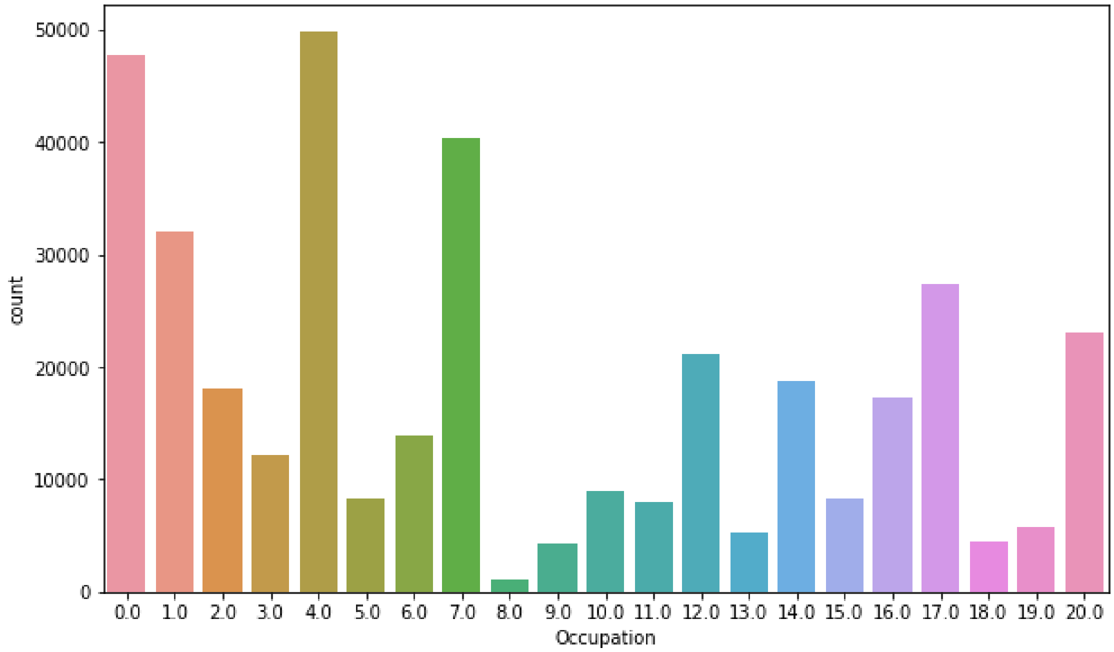


[195]:
```
plt.figure(figsize = (10, 6))
sns.countplot(x = 'Gender', data = df)
plt.show()
```



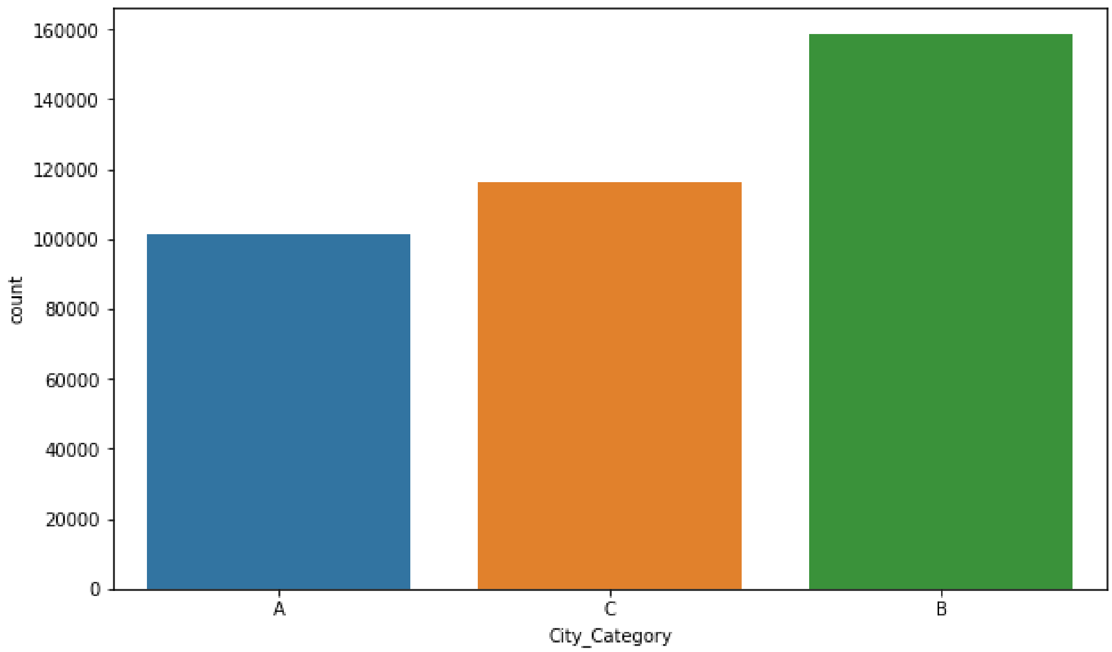
[196]:

```
plt.figure(figsize = (10, 6))
sns.countplot(x = 'Occupation', data = df)
plt.show()
```

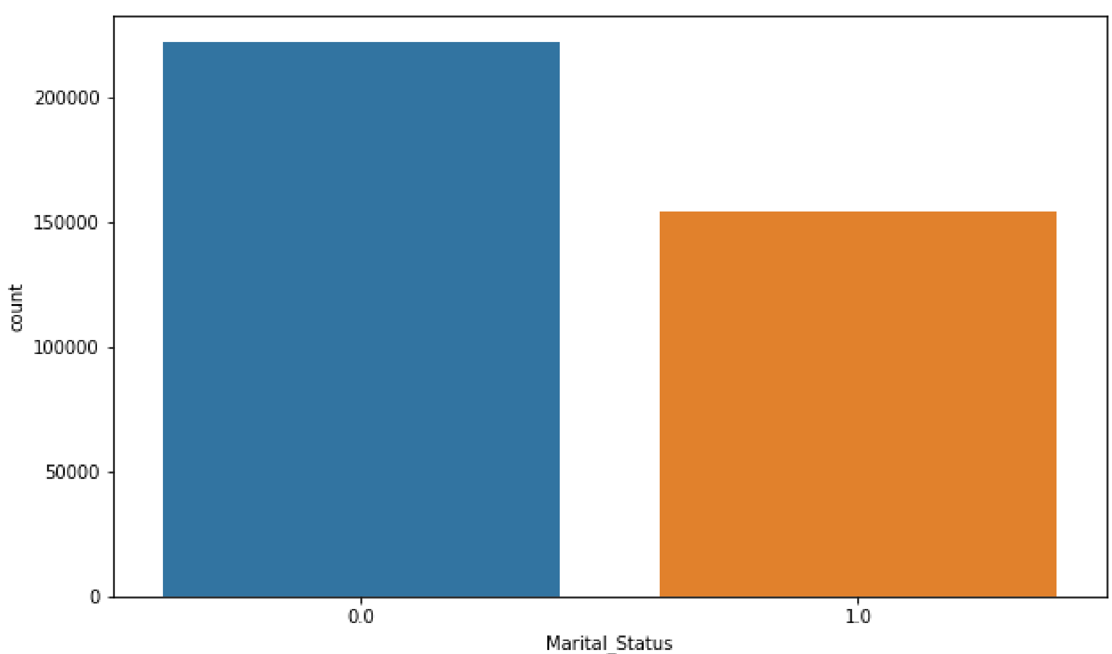


[197]:

```
plt.figure(figsize = (10, 6))
sns.countplot(x = 'City_Category', data = df)
plt.show()
```

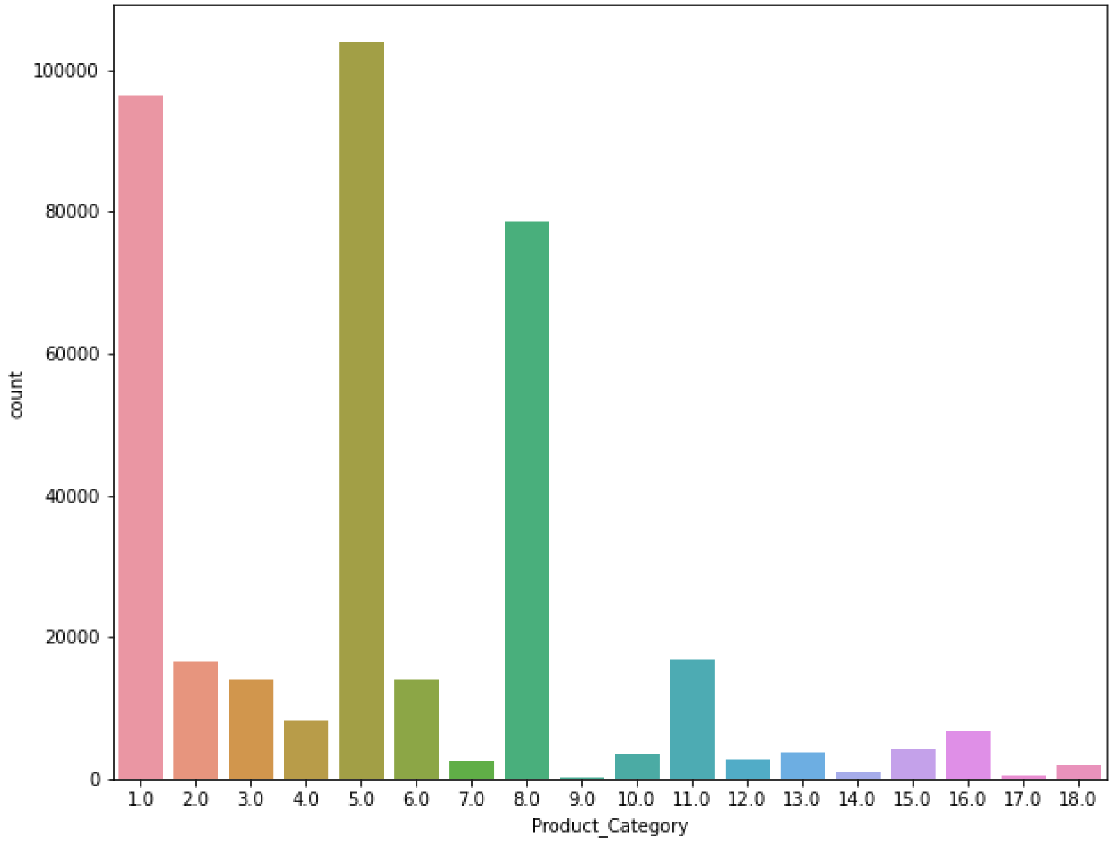


[198]:
```
plt.figure(figsize = (10, 6))
sns.countplot(x = 'Marital_Status', data = df)
plt.show()
```



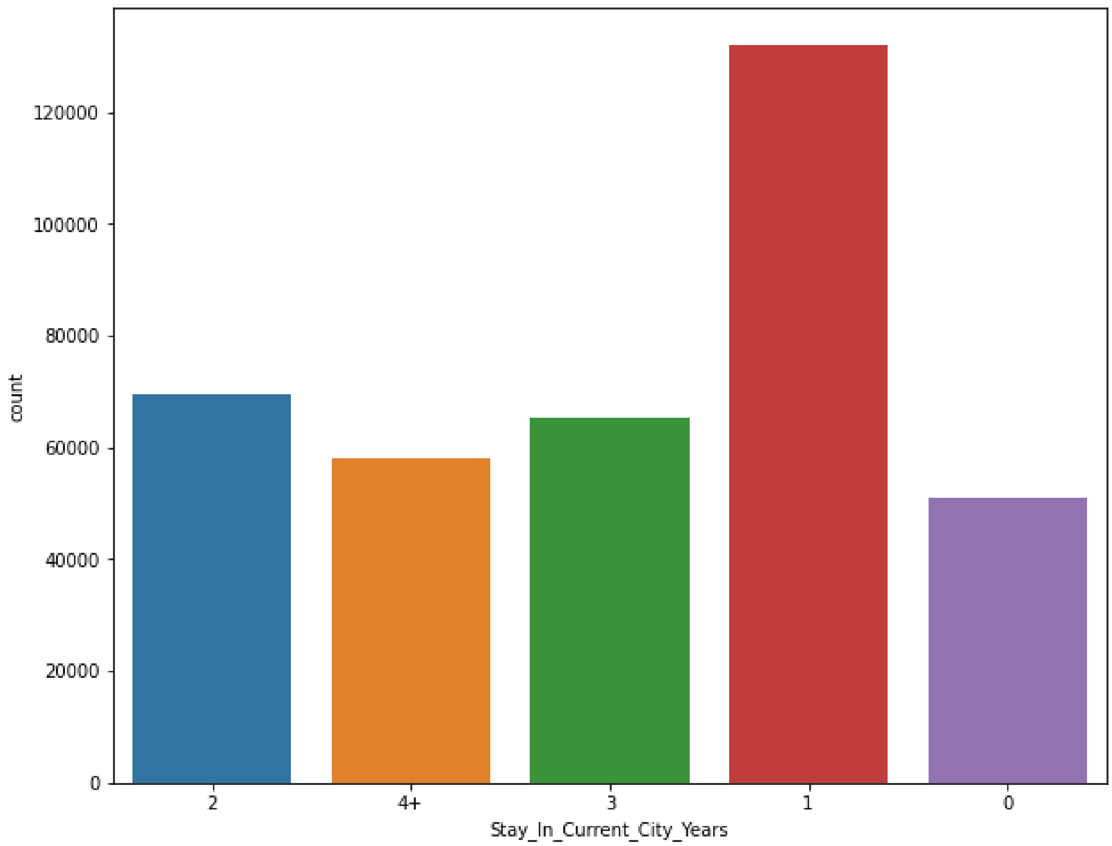
[199]:

```
plt.figure(figsize=(10, 8))
sns.countplot(data=df, x='Product_Category')
plt.show()
```

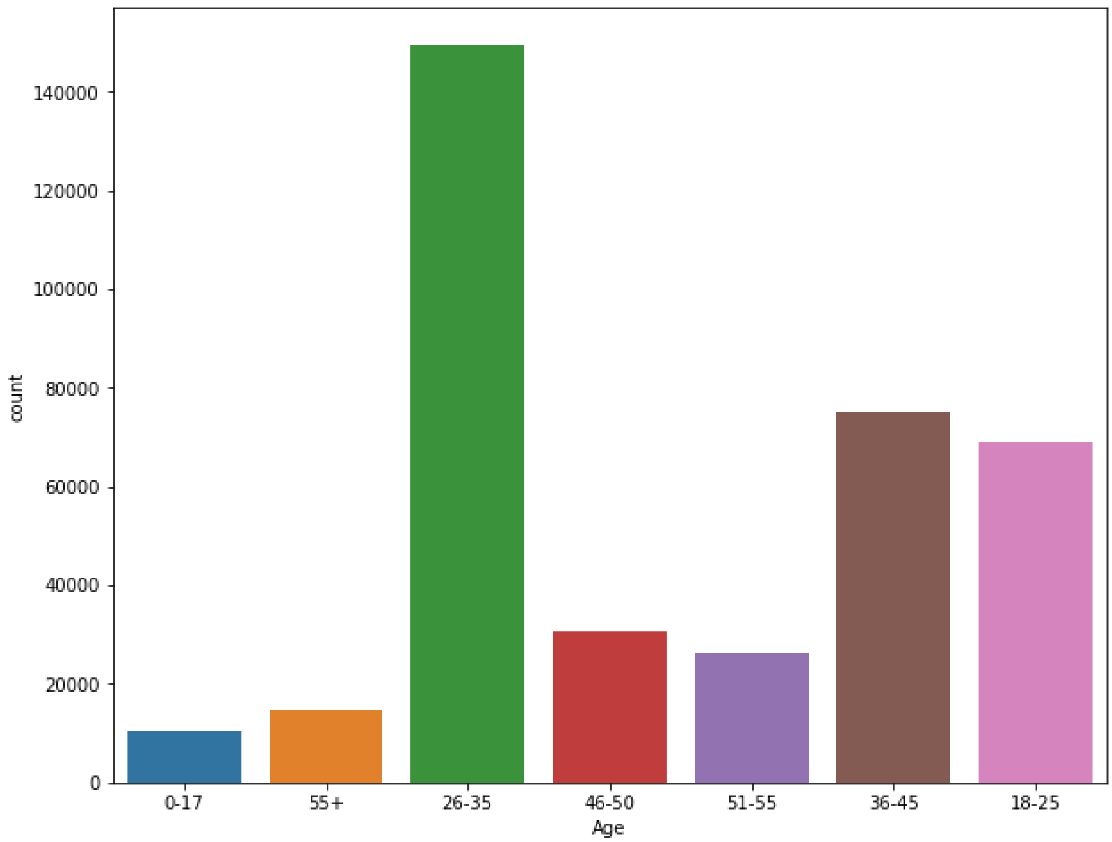


[200]:

```
plt.figure(figsize=(10, 8))
sns.countplot(data=df, x='Stay_In_Current_City_Years')
plt.show()
```

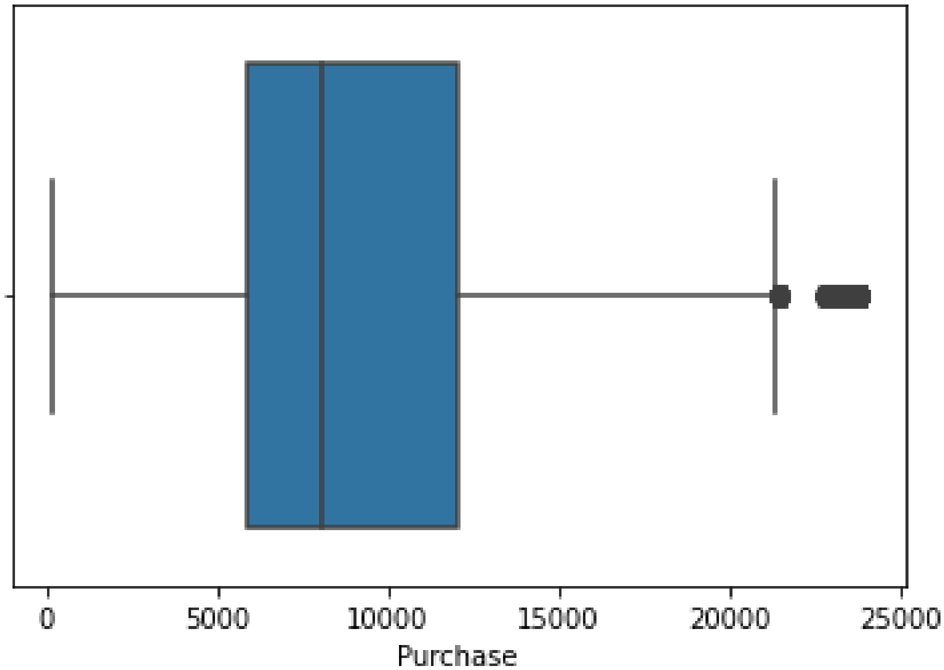


[201]:
```
plt.figure(figsize=(10, 8))
sns.countplot(data=df, x='Age')
plt.show()
```

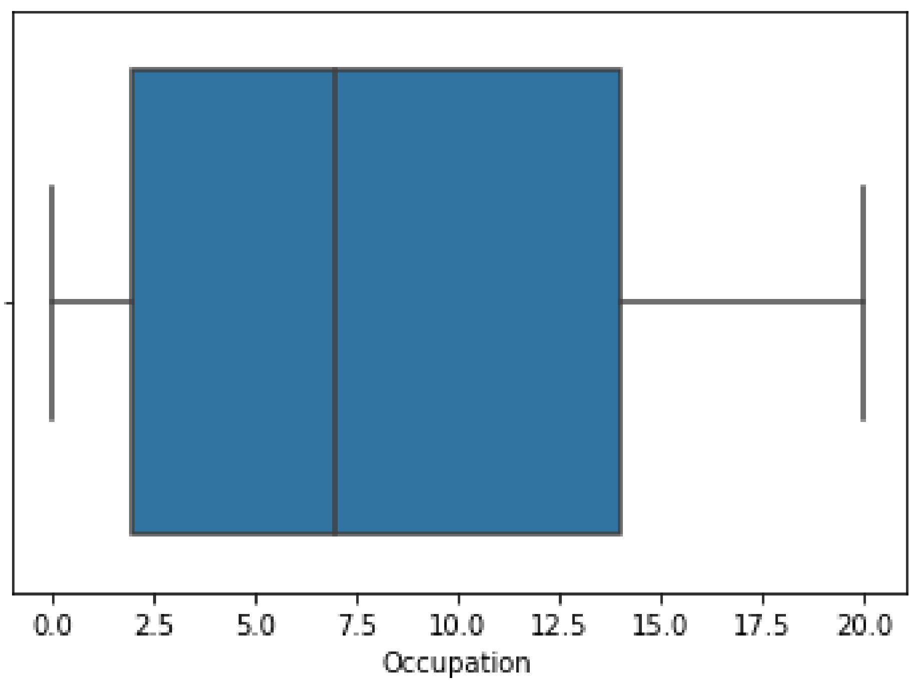


For categorical variable(s): Boxplot

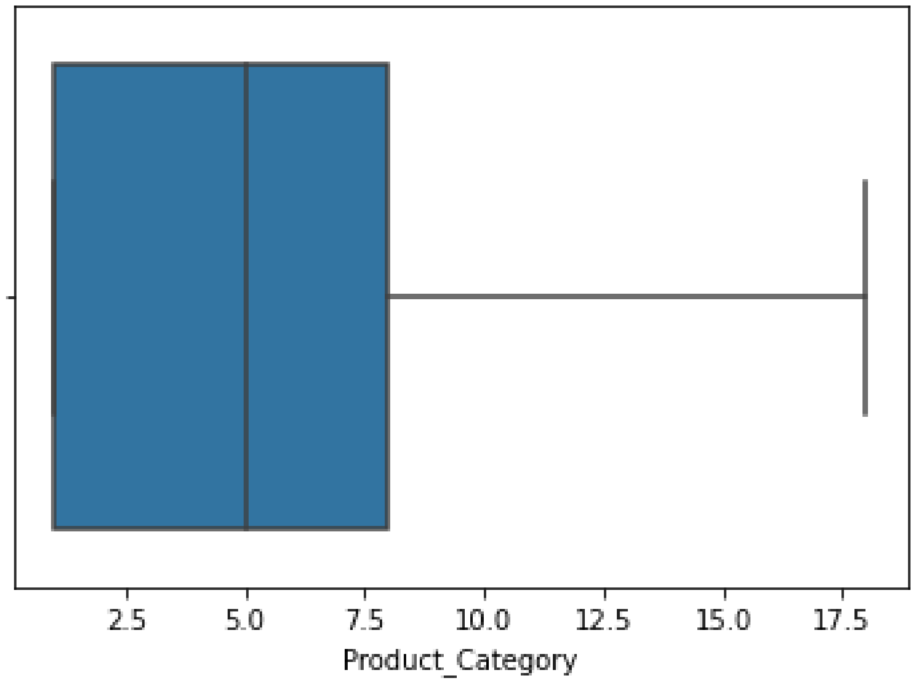
[202]:
```
sns.boxplot(data=df, x='Purchase', orient='h')
plt.show()
```



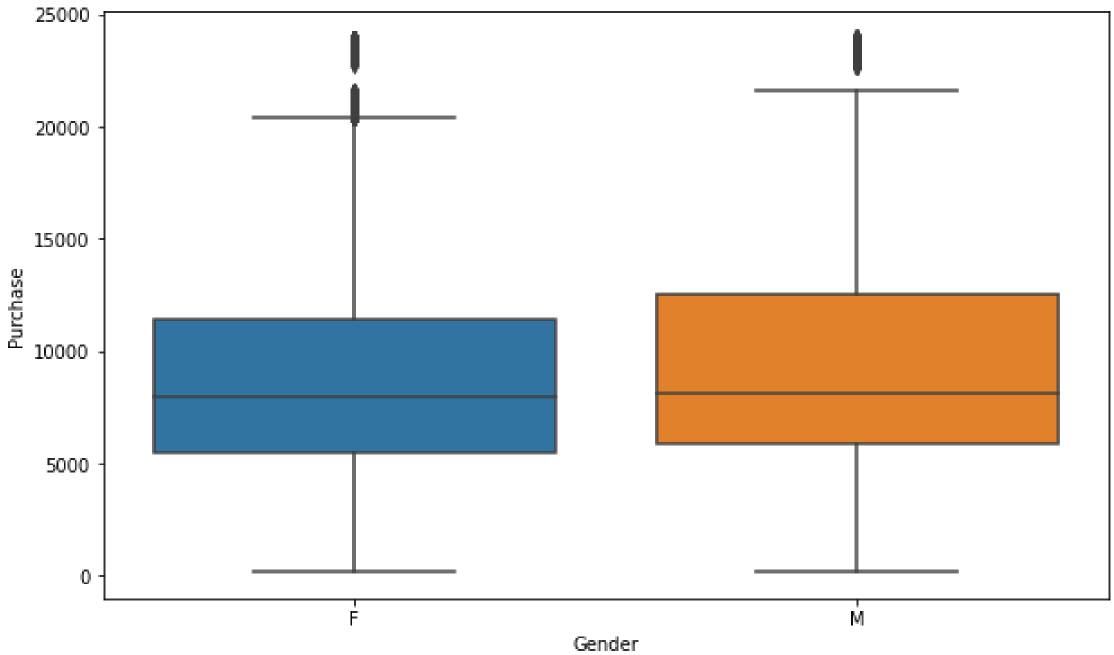
[203]:
```
sns.boxplot(data=df, x='Occupation', orient='h')
plt.show()
```



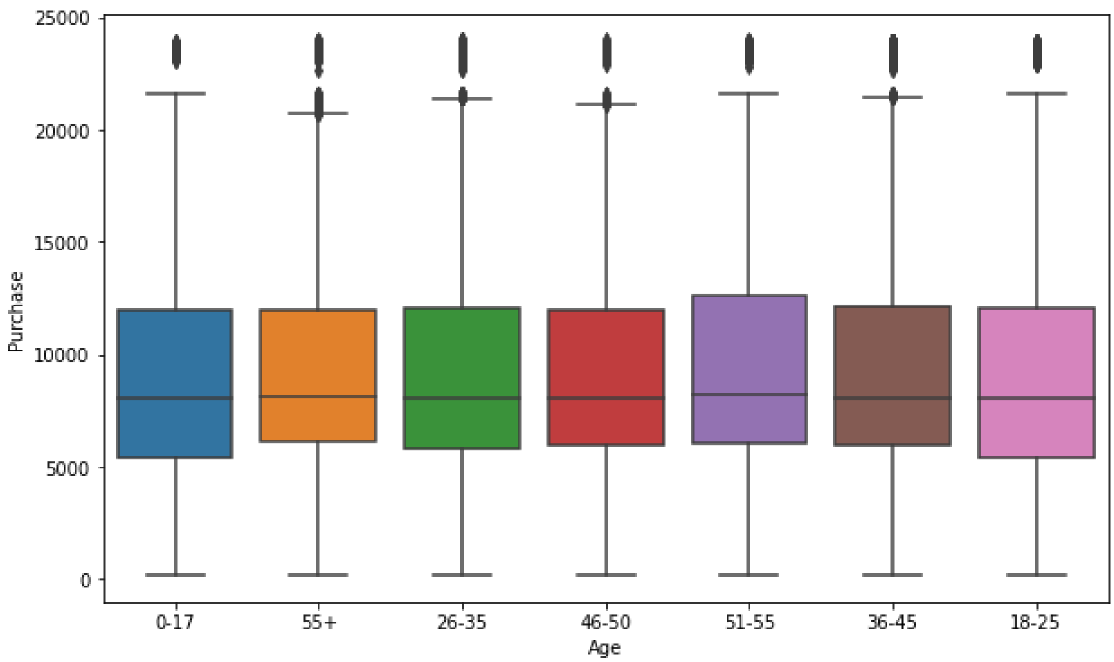
[204]:
```
sns.boxplot(data=df, x='Product_Category', orient='h')
plt.show()
```



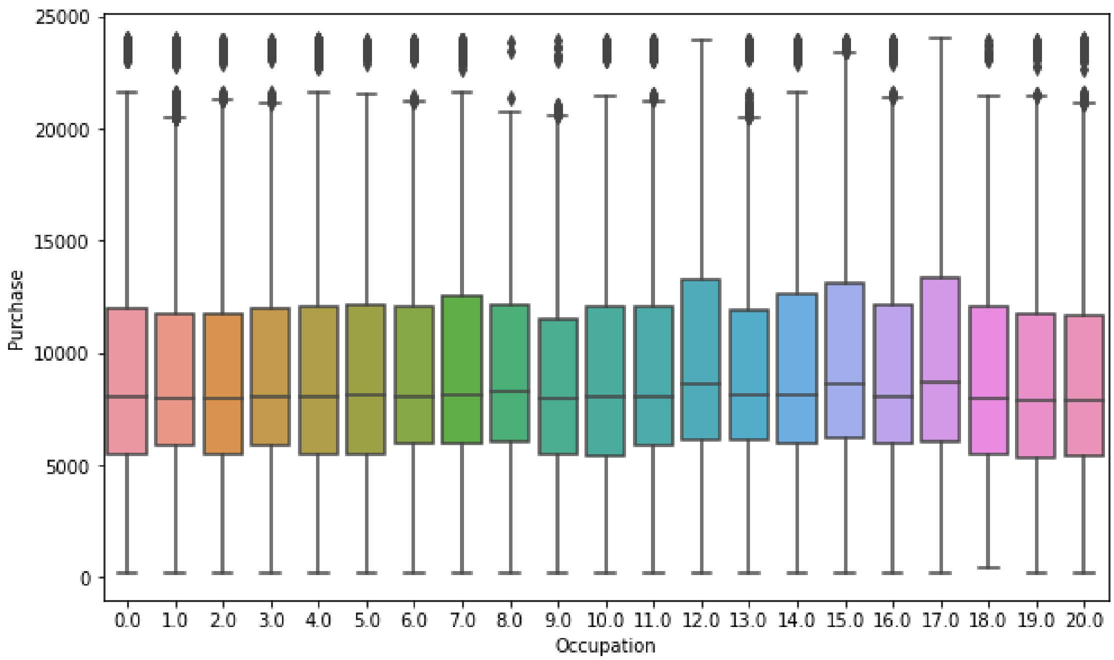
[205]:
```
plt.figure(figsize = (10, 6))
sns.boxplot(data = df, x = 'Gender', y = 'Purchase')
plt.show()
```



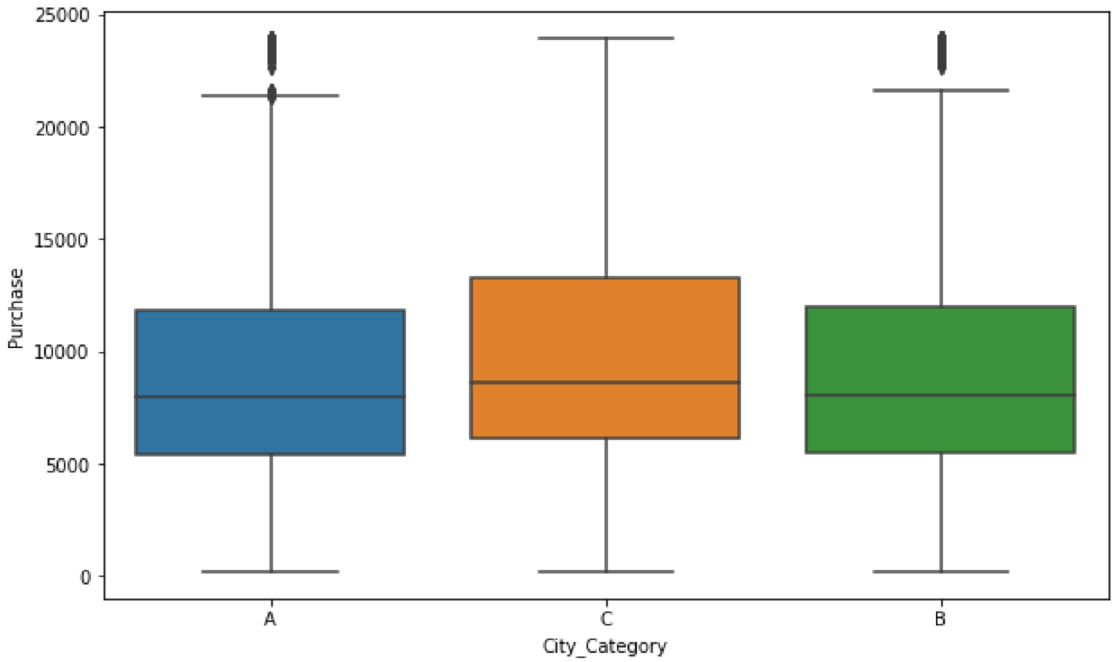
[206]:
```
plt.figure(figsize = (10, 6))
sns.boxplot(data = df, x = 'Age', y = 'Purchase')
plt.show()
```



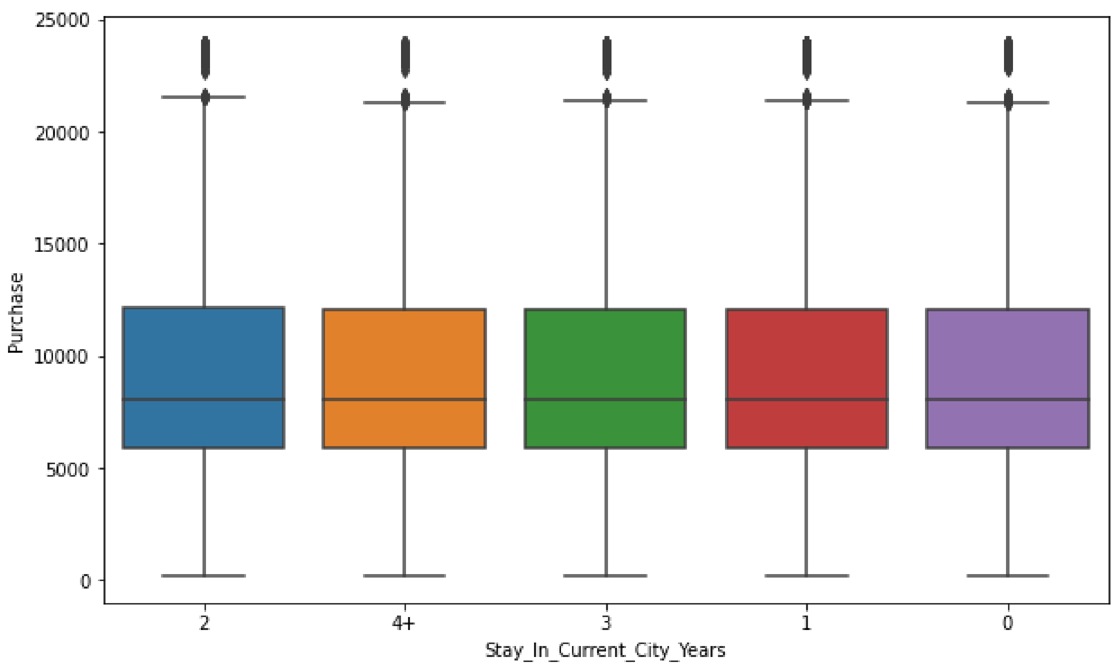
[207]:
```
plt.figure(figsize = (10, 6))
sns.boxplot(data = df, x = 'Occupation', y = 'Purchase')
plt.show()
```



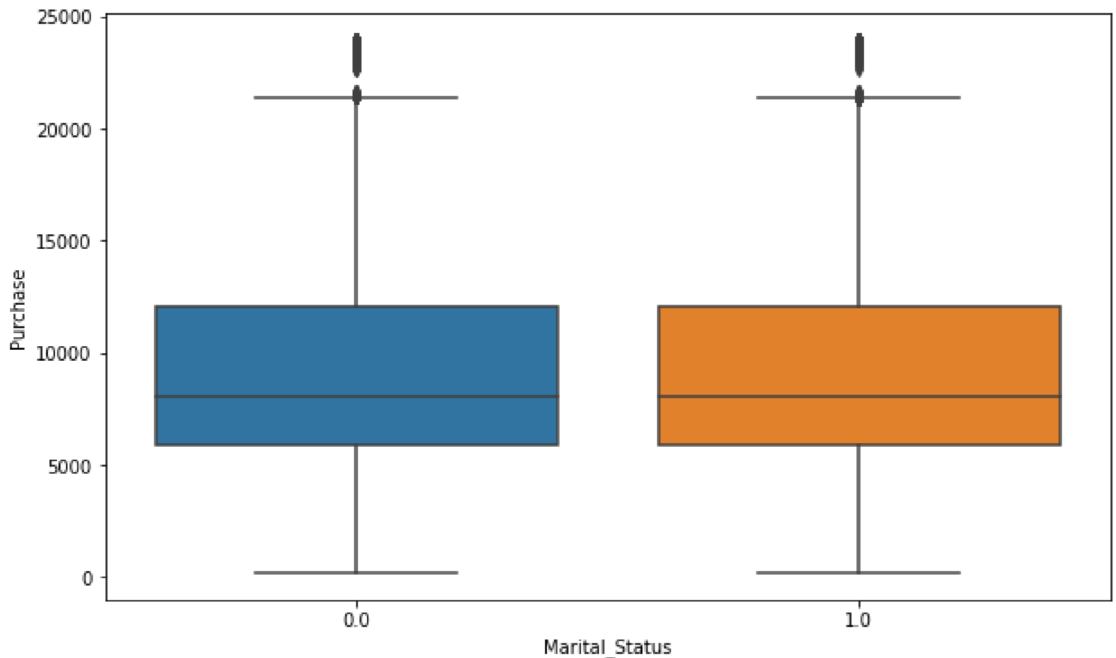
[208]:
```
plt.figure(figsize = (10, 6))
sns.boxplot(data = df, x = 'City_Category', y = 'Purchase')
plt.show()
```



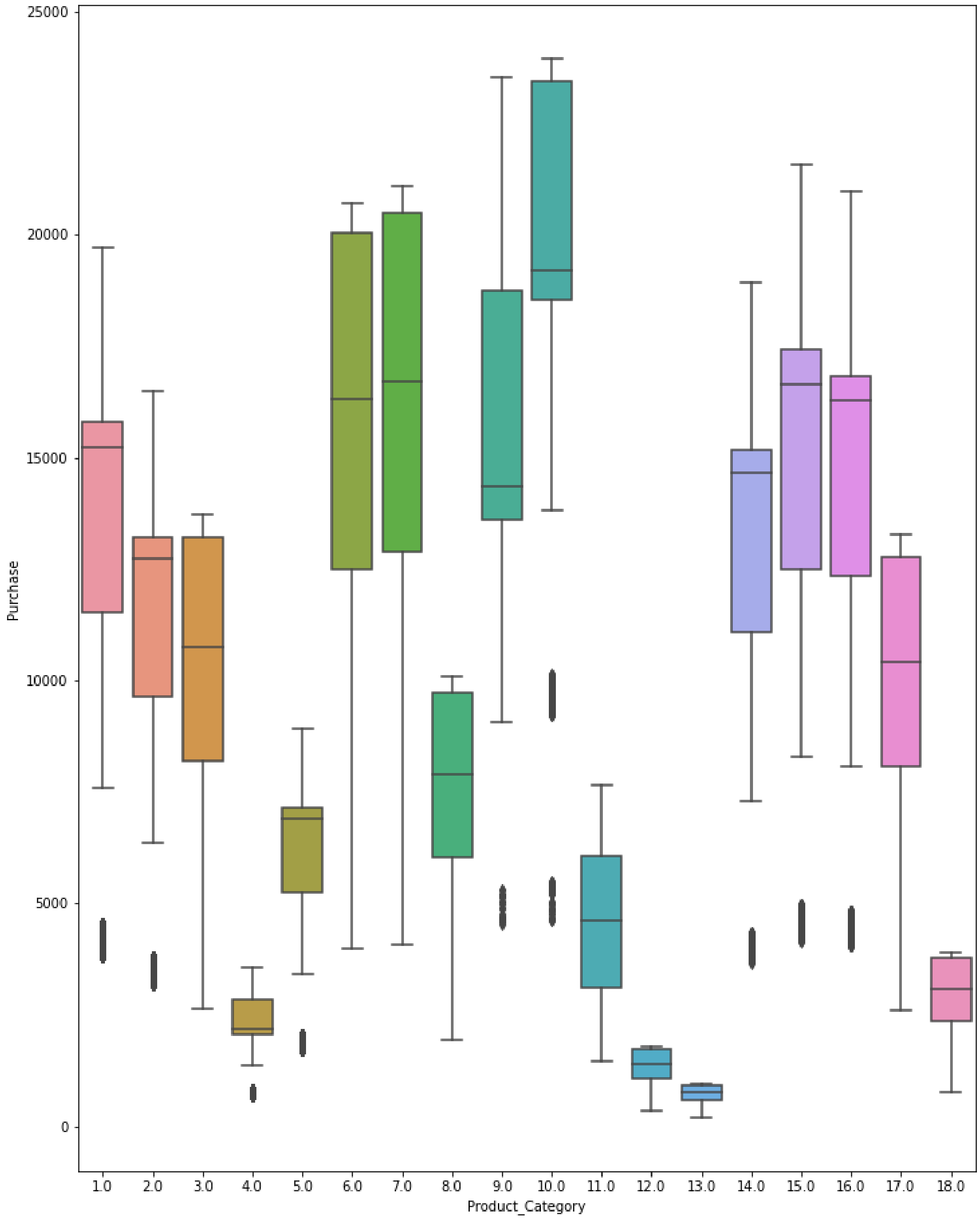
[209]:
```
plt.figure(figsize = (10, 6))
sns.boxplot(data = df, x = 'Stay_In_Current_City_Years', y = 'Purchase')
plt.show()
```



[210]:
```
plt.figure(figsize = (10, 6))
sns.boxplot(data = df, x = 'Marital_Status', y = 'Purchase')
plt.show()
```

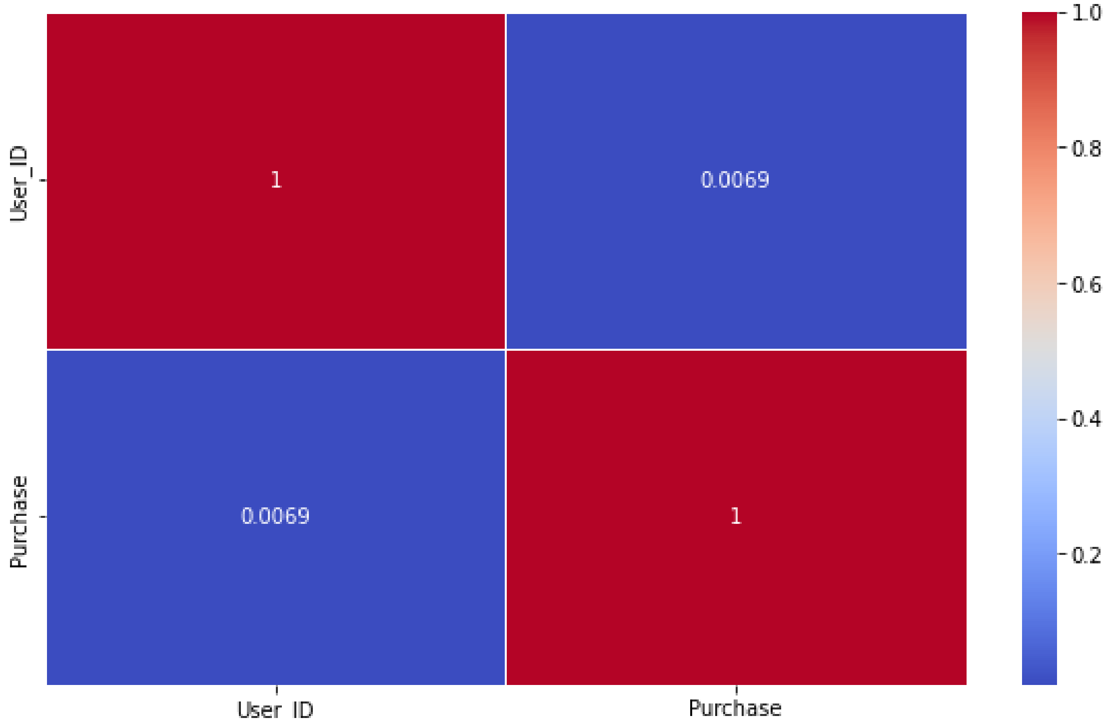


[211]:
```
plt.figure(figsize = (12, 16))
sns.boxplot(data = df, x = 'Product_Category', y = 'Purchase')
plt.show()
```



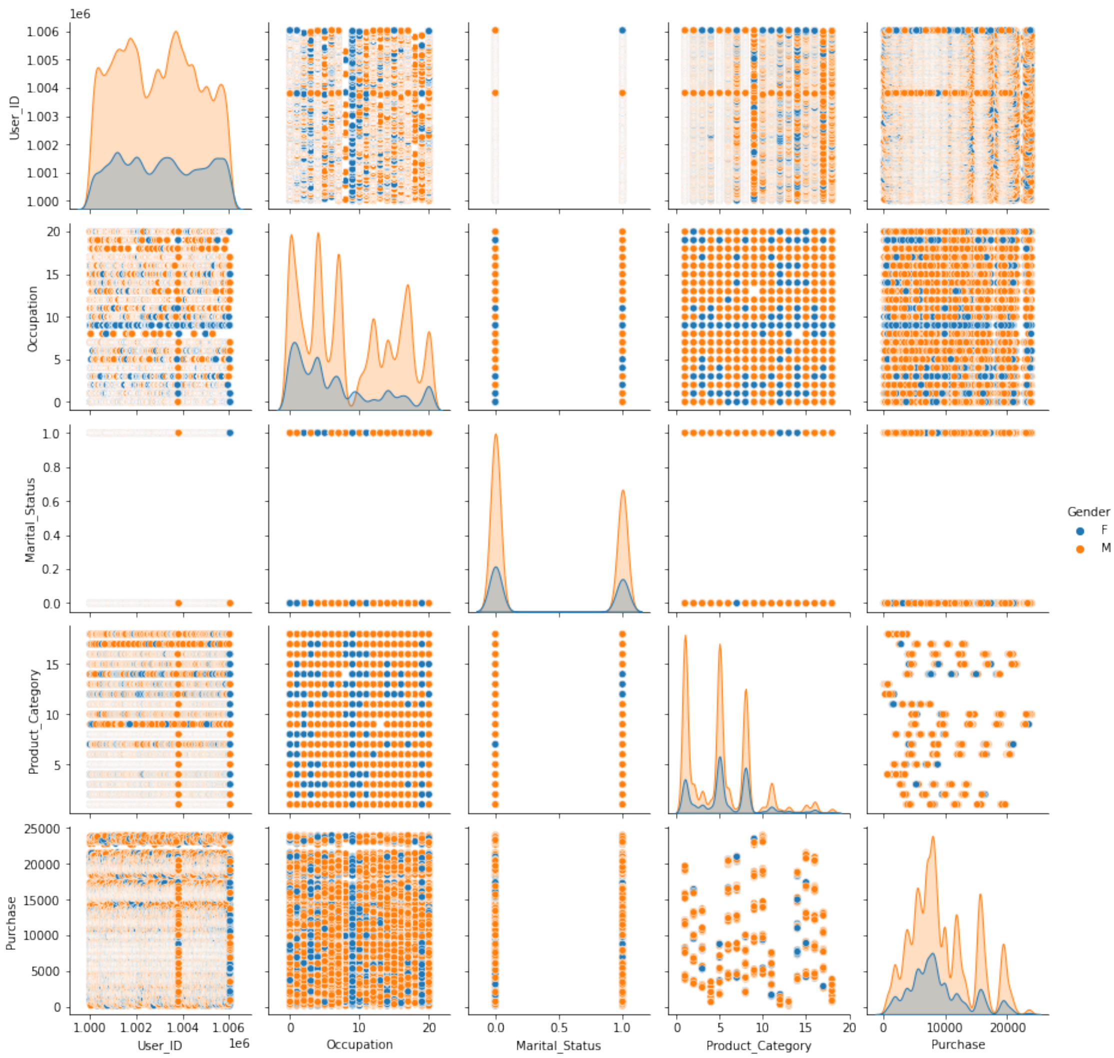
For correlation: Heatmaps, Pairplots

[212]:
```
plt.figure(figsize = (10, 6))
sns.heatmap( df.corr() , annot=True,linewidth = 0.5 , cmap = 'coolwarm')
plt.show()
```



[213]:
```
sns.pairplot(df, hue = 'Gender')
```

[213]: <seaborn.axisgrid.PairGrid at 0x7fe1699292e0>



2 Missing Value & Outlier Detection

[214]:
```
df.isna().sum()
```

[214]:
```
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
```

Their are no missing values

[215]:
```
data = []

for Att in ["User_ID", "Occupation", "Marital_Status", "Product_Category",␣
↪"Purchase"]:
  for model in df['Gender'].unique():

    obj = {}

    q1 = df.loc[df['Gender'] == model, Att].quantile(.25)
    q3 = df.loc[df['Gender'] == model, Att].quantile(.75)

    iqr = q3 - q1
    upper_w = q3 + 1.5*iqr
    lower_w = q1 - 1.5*iqr if q1 - 1.5*iqr > 0 else 0
    outliers = len(df.loc[(df['Gender'] == model) & (df[Att] > upper_w)]) +␣
↪len(df.loc[(df['Gender'] == model) & (df[Att] < lower_w)])

    obj['Attributes'] = Att
    obj['Gender'] = "Male" if model == 'M' else "Female"
    obj['Upper_Whisker'] = upper_w
    obj['Inter Quartile Range'] = iqr
    obj['Lower_Whisker'] = lower_w
    obj['Outliers'] = outliers

    data.append(obj)
pd.DataFrame(data)
```

[215]:
```
         Attributes  Gender  Upper_Whisker  Inter Quartile Range  \
0           User_ID  Female      1009375.5                3171.0
1           User_ID    Male      1008592.0                2854.0
2        Occupation  Female           26.0                  10.0
3        Occupation    Male           33.0                  12.0
4    Marital_Status  Female            2.5                   1.0
5    Marital_Status    Male            2.5                   1.0
6  Product_Category  Female           15.5                   5.0
7  Product_Category    Male           18.5                   7.0
8          Purchase  Female        20413.0                5982.0
9          Purchase    Male        22434.5                6613.0

   Lower_Whisker  Outliers
0       996691.5         0
1       997176.0         0
2            0.0         0
```

```
3              0.0          0
4              0.0          0
5              0.0          0
6              0.0       1970
7              0.0          0
8              0.0       1317
9              0.0       1273
```

3 Business Insights based on Non- Graphical and Visual Analysis

3.1 Comments on the range of attributes

[218]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 375658 entries, 0 to 375657
Data columns (total 10 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   User_ID                     375658 non-null  int64
 1   Product_ID                  375658 non-null  object
 2   Gender                      375658 non-null  object
 3   Age                         375658 non-null  object
 4   Occupation                  375658 non-null  object
 5   City_Category               375658 non-null  object
 6   Stay_In_Current_City_Years  375658 non-null  object
 7   Marital_Status              375658 non-null  object
 8   Product_Category            375658 non-null  object
 9   Purchase                    375658 non-null  float64
dtypes: float64(1), int64(1), object(8)
memory usage: 39.6+ MB
```

[221]:
```
# For Non Categorical Values

data = []
for att in df.columns:
  if df[att].dtype == 'int64':

    obj = {}

    obj['Attributes'] = att
    obj['Min_Value'] = df[att].min()
    obj['Mean'] = df[att].mean()
    obj['Max_Value'] = df[att].max()

    data.append(obj)
```

```
pd.DataFrame(data)
```

[221]:

	Attributes	Min_Value	Mean	Max_Value
0	User_ID	1000001	1.002955e+06	1006040

[226]:

```
df['Occupation']
```

[226]:

```
0         10.0
1         10.0
2         10.0
3         10.0
4         16.0
          …
375653    20.0
375654    20.0
375655    20.0
375656     7.0
375657     7.0
Name: Occupation, Length: 375658, dtype: object
```

[228]:

```
# For categorical Values

data = []

for att in df.columns:
  if df[att].dtype == 'object':
    obj = {}

    # print(att, str(df[att][0])[0].isdigit())
    if str(df[att][0])[0].isdigit():
      most_freq = df[att].value_counts().index[0], max(df[att].value_counts())
      less_freq = df[att].value_counts().index[-1], min(df[att].value_counts())
    else:
      most_freq = df[att].value_counts().index[0], df[att].value_counts()[0]
      less_freq = df[att].value_counts().index[-1], df[att].value_counts()[-1]


    obj['Attributes'] = att
    obj['Most Frequent'] = most_freq
    obj['Less Frequent'] = less_freq

    data.append(obj)

pd.DataFrame(data)
```

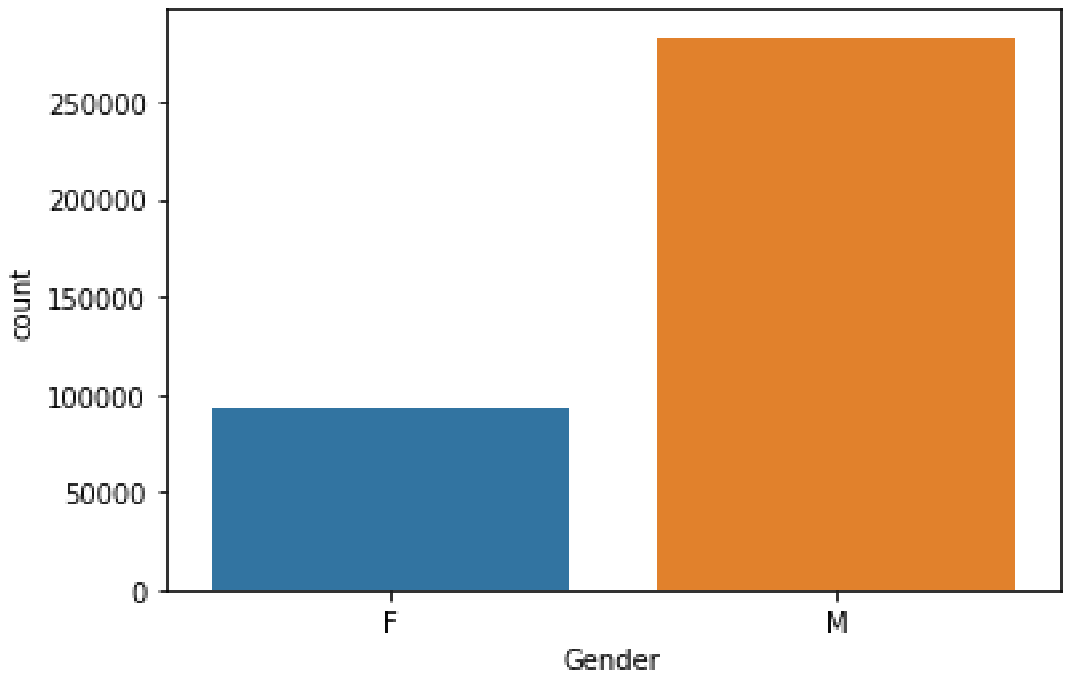
[228]:

	Attributes	Most Frequent	Less Frequent
0	Product_ID	(P00265242, 1257)	(P00315242, 1)

```
1                       Gender        (M, 283187)       (F, 92471)
2                          Age    (26-35, 149645)    (0-17, 10325)
3                   Occupation       (4.0, 49774)      (8.0, 1036)
4                City_Category        (B, 158354)      (A, 101246)
5   Stay_In_Current_City_Years        (1, 132090)       (0, 50839)
6               Marital_Status      (0.0, 221740)    (1.0, 153918)
7             Product_Category      (5.0, 103990)       (9.0, 268)
```

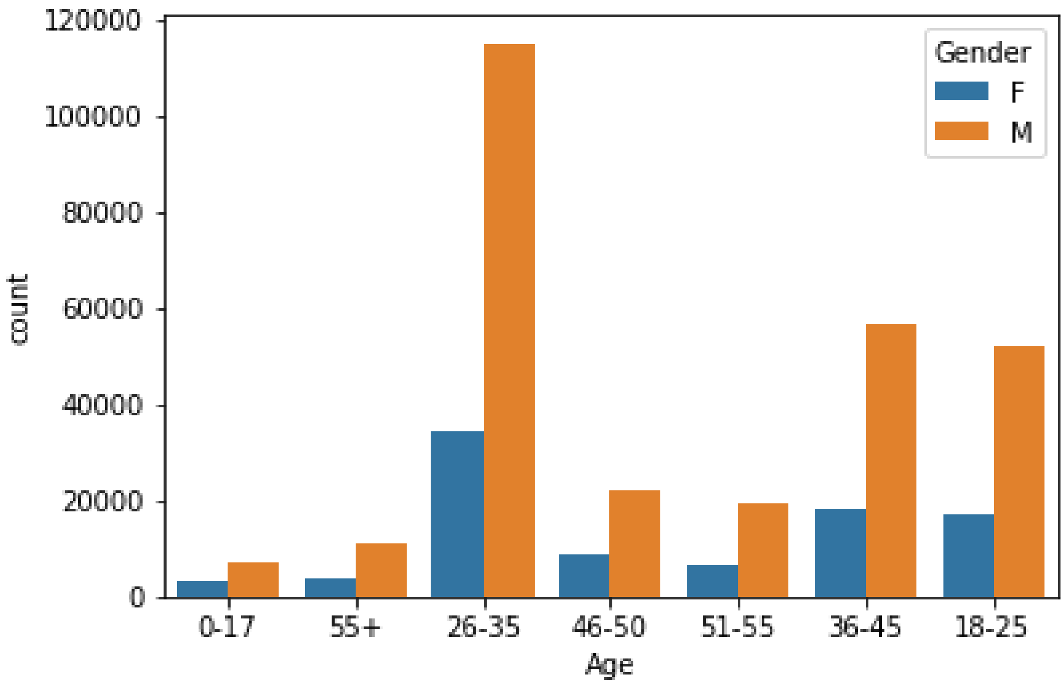
3.2 Comments on the distribution of the variables and relationship between them AND Comments for each univariate and bivariate plot

[229]:
```
sns.countplot(x = 'Gender', data = df)
plt.show()
```



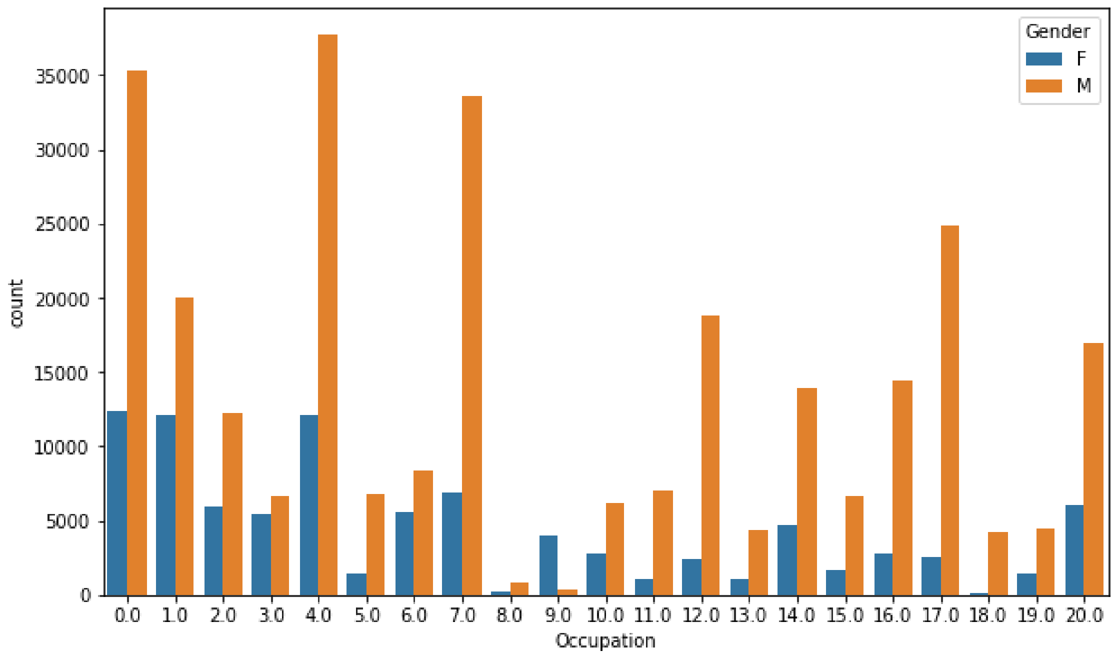
1. Male customers are more as compared to female

[230]:
```
sns.countplot(x = 'Age', data = df, hue = 'Gender')
plt.show()
```



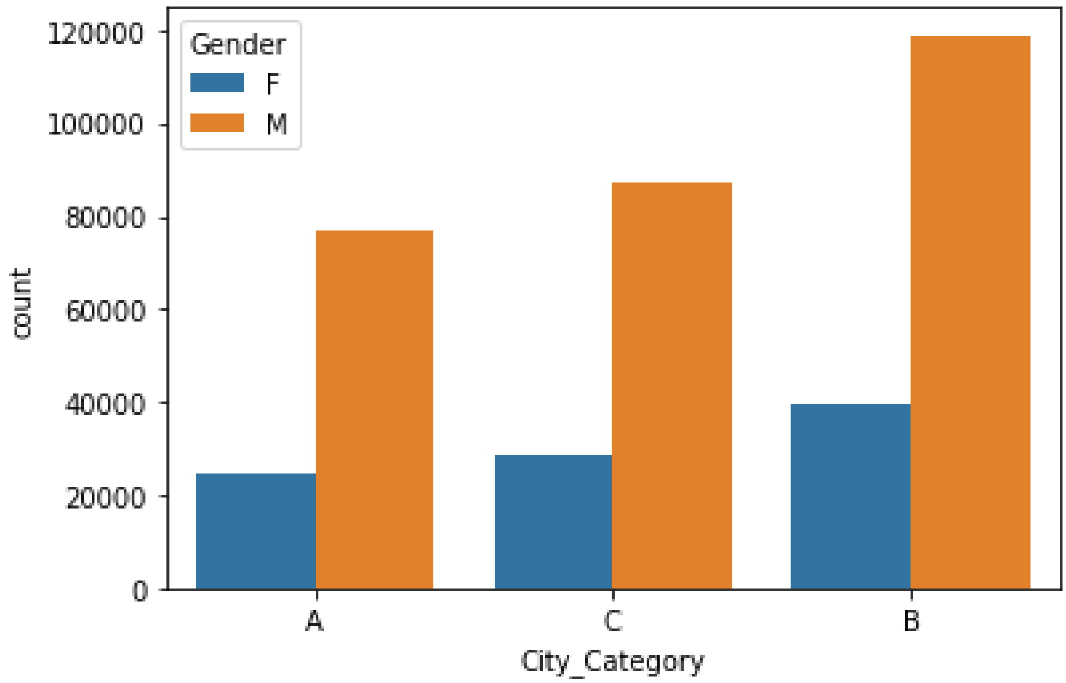
1. Male group with age between 26 -35 are heighest among shopping
2. Female group with age between 26 -35 are heighest among shopping
3. Male group with age between 0-17 are least among shopping
4. Female group with age 55+ are least among shopping

[231]:
```
plt.figure(figsize = (10, 6))
sns.countplot(x = 'Occupation', data = df, hue = 'Gender')
plt.show()
```



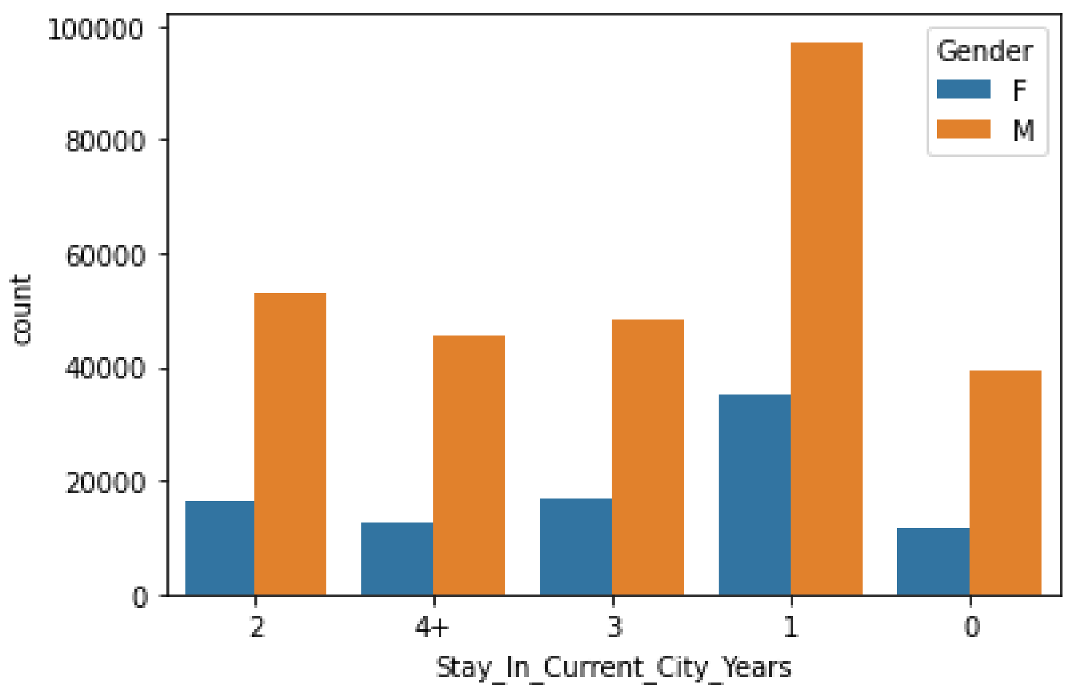
1. Occupation 4 has heighest number of males
2. Occupation 0, 1, 4 have relatively same number of females
3. Occupation 9 has least number of males
4. Occupation 8, 18 has least number of females

[232]:
```
sns.countplot(x = 'City_Category', data = df, hue = 'Gender')
plt.show()
```



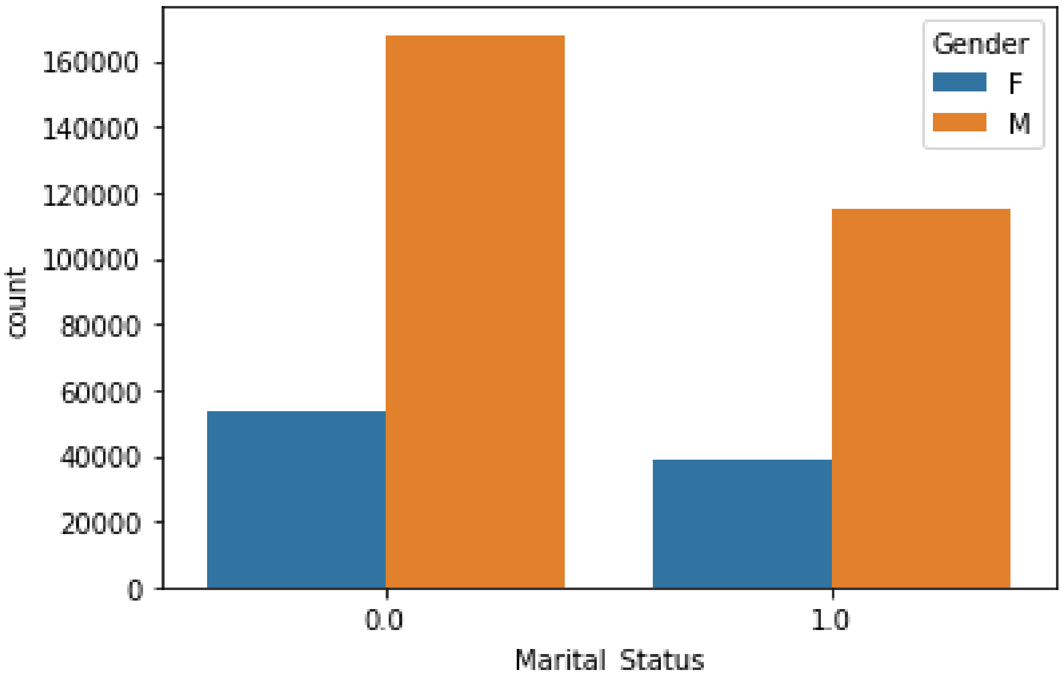
1. City Category of B has heighest number of Males
2. City Category of B has heighest number of females

[233]:
```
sns.countplot(x = 'Stay_In_Current_City_Years', data = df, hue = 'Gender')
plt.show()
```



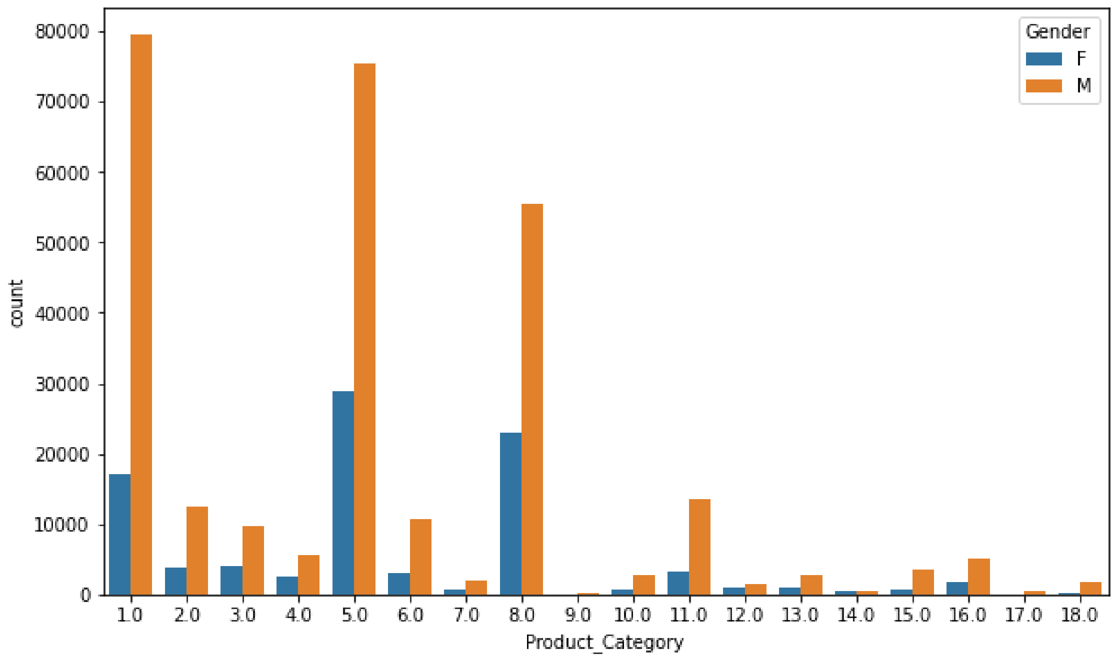
1. Male with residence nearly 1 year are more
2. Male with residence 0 years are less
3. female with residence nearly 1 year are more
4. female with residence 0 years are less

[234]:
```
sns.countplot(x = 'Marital_Status', data = df, hue = 'Gender')
plt.show()
```



1. Unmarreid males are high compared to married mles
2. Unmarreid females are high compared to married Femles

[235]:
```
plt.figure(figsize = (10, 6))
sns.countplot(x = 'Product_Category', data = df, hue = 'Gender')
plt.show()
```



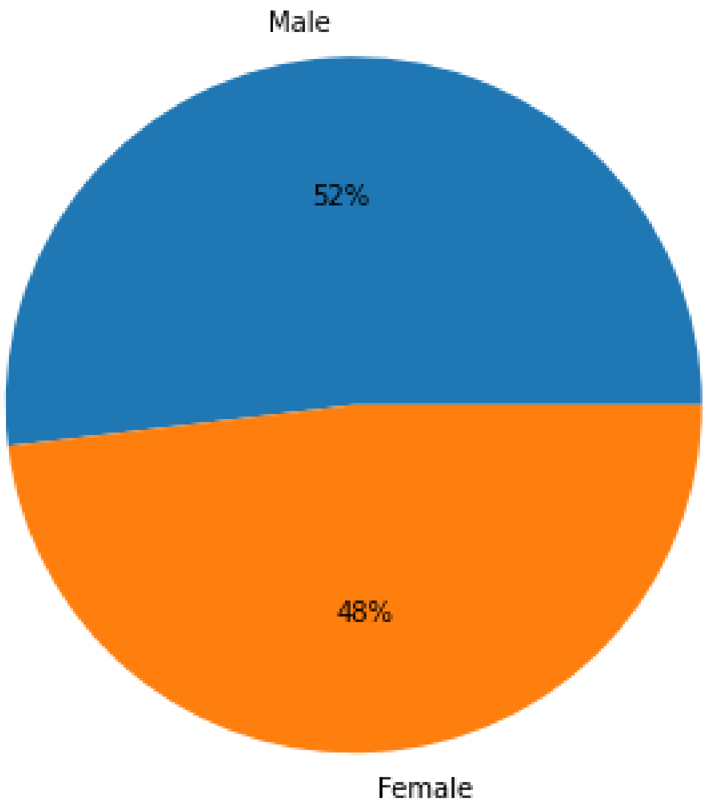
1. Males tends to buys product category 1 more
2. Females tends to buy product category 5 more
3. Males tends to buy product category 19 least
4. Females tends to buy product category 10, 15 least

4 Answering questions

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

[236]:
```
avg_men_spend_per_transaction = df[df['Gender'] == 'M']['Purchase'].sum() /␣
 ↪df[df['Gender'] == 'M']['Purchase'].count()
avg_women_spend_per_transaction = df[df['Gender'] == 'F']['Purchase'].sum() /␣
 ↪df[df['Gender'] == 'F']['Purchase'].count()

print(df[df['Gender'] == 'M']['Purchase'].sum() / df[df['Gender'] ==␣
 ↪'M']['Purchase'].count(),
      df[df['Gender'] == 'F']['Purchase'].sum() / df[df['Gender'] ==␣
 ↪'F']['Purchase'].count())
plt.figure(figsize = (10, 6))
plt.pie([avg_men_spend_per_transaction, avg_women_spend_per_transaction],␣
 ↪labels = ['Male', 'Female'], autopct = '%.0f%%')
plt.show()
```

```
9496.310826415054 8808.351288512074
```



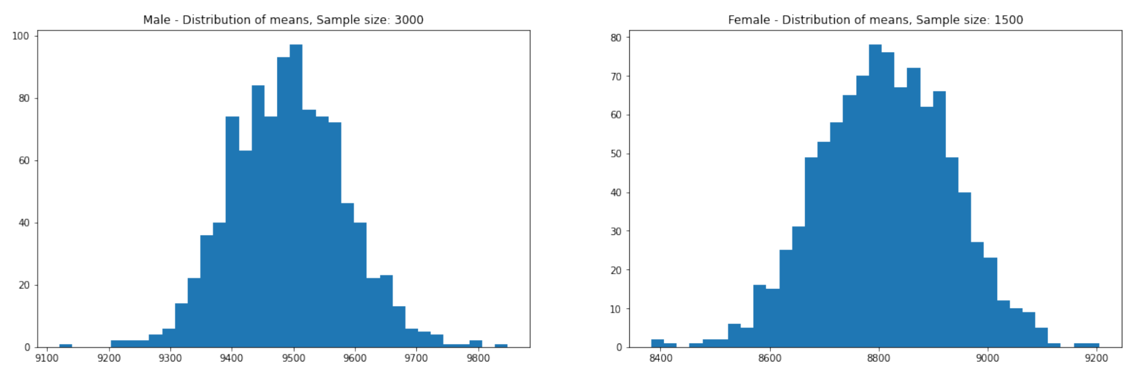
Avg Women spending per transaction is 8735 and Avg Men spending per 9437. So clearly Men are spending more than women

1. Possibility of the products that are available attracts Men more than women
2. Their is very less data of Female Purchase as compared to men
3. Possibility of Product Cost of Female Items are high
4. Possibility that women wait for the events where the price becomes low like christmas, new year etc..
5. Possibility of Product Cost of Male Items are low.

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

[237]:
```
male_df = df.loc[df['Gender']=='M', ['Gender', 'Purchase']]
female_df = df.loc[df['Gender']=='F', ['Gender', 'Purchase']]


genders = ["M", "F"]

male_sample_size = 3000
```

```
female_sample_size = 1500
num_repitions = 1000
male_means = []
female_means = []

for _ in range(num_repitions):
    male_mean = male_df.sample(male_sample_size, replace=True)['Purchase'].
 ↪mean()
    female_mean = female_df.sample(female_sample_size,␣
 ↪replace=True)['Purchase'].mean()

    male_means.append(male_mean)
    female_means.append(female_mean)
fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))

axis[0].hist(male_means, bins=35)
axis[1].hist(female_means, bins=35)
axis[0].set_title("Male - Distribution of means, Sample size: 3000")
axis[1].set_title("Female - Distribution of means, Sample size: 1500")

plt.show()
```




```
[238]: print("Population mean - Mean of sample means of amount spend for Male: {:.2f}".
 ↪format(np.mean(male_means)))
print("Population mean - Mean of sample means of amount spend for Female: {:.
 ↪2f}".format(np.mean(female_means)))

print("\nMale - Sample mean: {:.2f} Sample std: {:.2f}".
 ↪format(male_df['Purchase'].mean(), male_df['Purchase'].std()))
print("Female - Sample mean: {:.2f} Sample std: {:.2f}".
 ↪format(female_df['Purchase'].mean(), female_df['Purchase'].std()))
```

```
Population mean - Mean of sample means of amount spend for Male: 9491.17
Population mean - Mean of sample means of amount spend for Female: 8812.27
```

```
Male - Sample mean: 9496.31 Sample std: 5046.36
Female - Sample mean: 8808.35 Sample std: 4719.53
```

[239]:
```
male_margin_of_error_clt = 1.96*male_df['Purchase'].std()/np.sqrt(len(male_df))
male_sample_mean = male_df['Purchase'].mean()
male_lower_lim = male_sample_mean - male_margin_of_error_clt
male_upper_lim = male_sample_mean + male_margin_of_error_clt

female_margin_of_error_clt = 1.96*female_df['Purchase'].std()/np.
 ↪sqrt(len(female_df))
female_sample_mean = female_df['Purchase'].mean()
female_lower_lim = female_sample_mean - female_margin_of_error_clt
female_upper_lim = female_sample_mean + female_margin_of_error_clt

print("Male confidence interval of means: ({:.2f}, {:.2f})".
 ↪format(male_lower_lim, male_upper_lim))
print("Female confidence interval of means: ({:.2f}, {:.2f})".
 ↪format(female_lower_lim, female_upper_lim))
```

```
Male confidence interval of means: (9477.72, 9514.90)
Female confidence interval of means: (8777.93, 8838.77)
```

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

[240]:
```
data_df = pd.DataFrame({
    "Lower" : [male_lower_lim, female_lower_lim],
    "Upper": [male_upper_lim, female_upper_lim]
})
data_df.index = ['Male', 'Female']

data_df
```

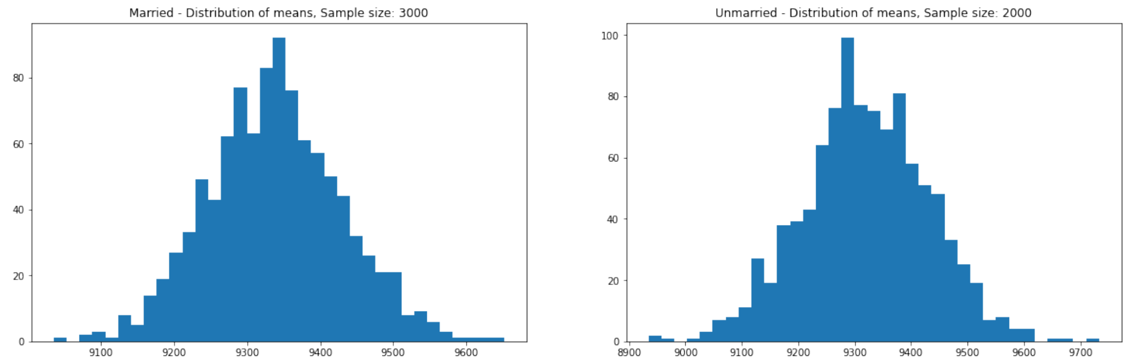
[240]:

	Lower	Upper
Male	9477.724320	9514.897333
Female	8777.931789	8838.770788

Confidence intervals of avg male and female are not overlapping 1. Walmart can try to make a combo pack that could limit between confidence Intervals 2. Try to maintain the product ranges between the 9422 - 9453 for men 3. Try to maintain the product ranges between the 8709 - 8759 for women 4. Try to make combos of products that are highly sold and products with low sales

4.4 Results when the same activity is performed for Married vs Unmarried

[241]:
```
marid_samp_size = 3000
unmarid_sample_size = 2000
num_repitions = 1000
marid_means = []
unmarid_means = []

for _ in range(num_repitions):
    marid_mean = df[df['Marital_Status']==1].sample(marid_samp_size,␣
 ↪replace=True)['Purchase'].mean()
    unmarid_mean = df[df['Marital_Status']==0].sample(unmarid_sample_size,␣
 ↪replace=True)['Purchase'].mean()

    marid_means.append(marid_mean)
    unmarid_means.append(unmarid_mean)


fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))

axis[0].hist(marid_means, bins=35)
axis[1].hist(unmarid_means, bins=35)
axis[0].set_title("Married - Distribution of means, Sample size: 3000")
axis[1].set_title("Unmarried - Distribution of means, Sample size: 2000")

plt.show()

print("Population mean - Mean of sample means of amount spend for Married: {:.
 ↪2f}".format(np.mean(marid_means)))
print("Population mean - Mean of sample means of amount spend for Unmarried: {:.
 ↪2f}".format(np.mean(unmarid_means)))

print("\nMarried - Sample mean: {:.2f} Sample std: {:.2f}".
 ↪format(df[df['Marital_Status']==1]['Purchase'].mean(),␣
 ↪df[df['Marital_Status']==1]['Purchase'].std()))
print("Unmarried - Sample mean: {:.2f} Sample std: {:.2f}".
 ↪format(df[df['Marital_Status']==0]['Purchase'].mean(),␣
 ↪df[df['Marital_Status']==0]['Purchase'].std()))
```




```
Population mean - Mean of sample means of amount spend for Married: 9338.19
Population mean - Mean of sample means of amount spend for Unmarried: 9320.29

Married - Sample mean: 9337.07 Sample std: 4969.72
Unmarried - Sample mean: 9319.95 Sample std: 4981.59
```

[242]:
```python
for val in ["Married", "Unmarried"]:

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

    new_df = df[df['Marital_Status']==new_val]

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

    print("{} confidence interval of means: ({:.2f}, {:.2f})".format(val,␣
 ↪lower_lim, upper_lim))
```

```
Married confidence interval of means: (9312.24, 9361.90)
Unmarried confidence interval of means: (9299.22, 9340.69)
```

4.5 Results when the same activity is performed for Age

[243]:
```python
sample_size = 200
num_repitions = 1000

all_means = {}

age_intervals = ['26-35', '36-45', '18-25', '46-50', '51-55', '55+', '0-17']
for age_interval in age_intervals:
    all_means[age_interval] = []
```

```
for age_interval in age_intervals:
    for _ in range(num_repitions):
        mean = df[df['Age']==age_interval].sample(sample_size,␣
 ↪replace=True)['Purchase'].mean()
        all_means[age_interval].append(mean)
```

[244]:
```
for val in ['26-35', '36-45', '18-25', '46-50', '51-55', '55+', '0-17']:

    new_df = df[df['Age']==val]

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

    print("For age {} --> confidence interval of means: ({:.2f}, {:.2f})".
 ↪format(val, lower_lim, upper_lim))
```

```
For age 26-35 --> confidence interval of means: (9280.73, 9331.09)
For age 36-45 --> confidence interval of means: (9367.13, 9438.39)
For age 18-25 --> confidence interval of means: (9182.20, 9256.76)
For age 46-50 --> confidence interval of means: (9213.91, 9323.29)
For age 51-55 --> confidence interval of means: (9567.23, 9689.16)
For age 55+ --> confidence interval of means: (9361.14, 9519.91)
For age 0-17 --> confidence interval of means: (8946.05, 9142.44)
```

5 Final Insights - Illustrate the insights based on exploration and CLT

5.1 Comments on the distribution of the variables and relationship between them

1. Product_Category - 1, 5, 8, & 11 have highest purchasing frequency.
2. There are 20 differnent types of occupations in the city
3. 35% Staying in the city from 1 year, 18% from 2 years, 17% from 3 years
4. More users are Single as compare to Married
5. Most of the users are Male
6. 60% Single, 40% Married

1. Total of 20 product categories are there
2. More users belong to B City_Category
3. There are 20 different types of Occupation and Product_Category
4. 75% of the users are Male and 25% are Female

5. ~ 80% of the users are between the age 18-50 (40%: 26-35, 18%: 18-25, 20%: 36-45)

1. Average amount spend by Male customers: 925344.40
2. Average amount spend by Female customers: 712024.39

5.2 Comments for each univariate and bivariate plots

Confidence Interval by Marital_Status

1. Married confidence interval of means: (806668.83, 880384.76)
2. Unmarried confidence interval of means: (848741.18, 912410.38)

Confidence Interval by Age

1. For age 26-35 –> confidence interval of means: (945034.42, 1034284.21)
2. For age 36-45 –> confidence interval of means: (823347.80, 935983.62)
3. For age 18-25 –> confidence interval of means: (801632.78, 908093.46)
4. For age 46-50 –> confidence interval of means: (713505.63, 871591.93)
5. For age 51-55 –> confidence interval of means: (692392.43, 834009.42)
6. For age 55+ –> confidence interval of means: (476948.26, 602446.23)
7. For age 0-17 –> confidence interval of means: (527662.46, 710073.17)

5.3 Comments on different variables when generalizing it for Population

Confidence Interval by Gender Now using the Central Limit Theorem for the population:

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

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

1. Average amount spend by male customer will lie in between: (895617.83, 955070.97)
2. Average amount spend by female customer will lie in between: (673254.77, 750794.02)

6 Recommendations

- Actionable items for business. No technical jargon. No complications. Simple action items that everyone can understand

1. Men spent more money than women, Hence Focus more on Men products
2. Product_Category - 1, 5, 8, & 11 have highest purchasing frequency. it means these are the products in these categories are liked more by customers. Company can focus on selling more of these products or selling more of the products which are purchased less.
3. Unmarried customers spend more money than married customers, So walmart should focus on acquisition of Unmarried customers.
4. Customers in the age 18-45 spend more money than the others, So company should focus on acquisition of customers who are in the age 18-45
5. Male customers living in City_Category C spend more money than other male customers living in B or C, Selling more products in the City_Category C will help the company increase the revenue.