Background

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?

Data Description

The company collected the transactional data of customers who purchased products from Walmart Stores during Black Friday. The dataset in walmart_data.csv has the following features:

`User_ID`
`Product_ID`
`Gender` - sex of a customer
`Age` - age in bins
`Occupation` (masked)
`City_Category` - category of the city [A, B, C]
`Stay_In_Current_City_Years` - number of years a customer stays in their current city
`Marital_Status`
`Product_Category` (masked)
`Purchase` - purchase amount

> For simplicity, you may assume that 50% of Walmart`s customer base are Male and the other 50% are Female.

Exploratory Data Analysis (EDA)

In [17]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
sns.set(color_codes = True)

import scipy.stats as stats
from scipy.stats import norm

# import warnings
# warnings.filterwarnings("ignore")
```

In [18]:
```
walmart_df = pd.read_csv("walmart_data.csv")
walmart_df
```

Out[18]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Curr
0	1000001	P00069042	F	0-17	10	A	
1	1000001	P00248942	F	0-17	10	A	
2	1000001	P00087842	F	0-17	10	A	
3	1000001	P00085442	F	0-17	10	A	
4	1000002	P00285442	M	55+	16	C	
...	...	...	...	...	...	...	
550063	1006033	P00372445	M	51-55	13	B	
550064	1006035	P00375436	F	26-35	1	C	
550065	1006036	P00375436	F	26-35	15	B	
550066	1006038	P00375436	F	55+	1	C	
550067	1006039	P00371644	F	46-50	0	B	

550068 rows × 10 columns

In [19]:
```
# Shape of the dataframe
walmart_df.shape
```

Out[19]:
```
(550068, 10)
```

In [20]:
```python
# Name of each column in dataframe
walmart_df.columns
```

Out[20]:
```
Index(['User_ID', 'Product_ID', 'Gender', 'Age', 'Occupation', 'City_Catego
ry',
       'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Category',
       'Purchase'],
      dtype='object')
```

In [21]:
```python
# Datatype of each column in dataframe
walmart_df.dtypes
```

Out[21]:
```
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 [23]:
```python
### Count of unique values in each column

def print_nunique_values(df):
    for column in df.columns:
        unique_values = df[column].nunique()
        print(f"\nUnique Values of {column}: ", unique_values)

print_nunique_values(walmart_df)
```

```
Unique Values of User_ID:  5891

Unique Values of Product_ID:  3631

Unique Values of Gender:  2

Unique Values of Age:  7

Unique Values of Occupation:  21

Unique Values of City_Category:  3

Unique Values of Stay_In_Current_City_Years:  5

Unique Values of Marital_Status:  2

Unique Values of Product_Category:  20

Unique Values of Purchase:  18105
```

In [24]:
```python
### Finding unique values in each column

def print_unique_values(df):
```

```
    for column in df.columns:
        unique_values = df[column].unique()
        print(f"\nUnique Values of {column}: ", unique_values)

print_unique_values(walmart_df)
```

```
Unique Values of User_ID:  [1000001 1000002 1000003 ... 1004113 1005391 1001
529]

Unique Values of Product_ID:  ['P00069042' 'P00248942' 'P00087842' ... 'P003
70293' 'P00371644'
 'P00370853']

Unique Values of Gender:  ['F' 'M']

Unique Values of Age:  ['0-17' '55+' '26-35' '46-50' '51-55' '36-45' '18-2
5']

Unique Values of Occupation:  [10 16 15  7 20  9  1 12 17  0  3  4 11  8 19
2 18  5 14 13  6]

Unique Values of City_Category:  ['A' 'C' 'B']

Unique Values of Stay_In_Current_City_Years:  ['2' '4+' '3' '1' '0']

Unique Values of Marital_Status:  [0 1]

Unique Values of Product_Category:  [ 3  1 12  8  5  4  2  6 14 11 13 15  7
16 18 10 17  9 20 19]

Unique Values of Purchase:  [ 8370 15200  1422 ...   135   123   613]
```

Data Cleaning

We'll make some changes to the data for better analysis. For example, we'll adjust the 'Stay_In_Current_City_Years' column by removing the '+' symbol and converting it to a numeric format. But first, let's look the unique values.

In [25]:
```
walmart_df.Stay_In_Current_City_Years.unique()
```

Out[25]:
```
array(['2', '4+', '3', '1', '0'], dtype=object)
```

In [27]:
```
# Removing "+" symbol
walmart_df.Stay_In_Current_City_Years=walmart_df.Stay_In_Current_City_Years.
```

In [28]:
```
walmart_df.Stay_In_Current_City_Years.unique()
```

Out[28]:
```
array(['2', '4', '3', '1', '0'], dtype=object)
```

In [ ]:
```
# Converting the datatype of Stay_In_Current_City_Years to int
walmart_df['Stay_In_Current_City_Years'] = pd.to_numeric(walmart_df['Stay_Ir
```

Statistical Summary

In [30]:
```
walmart_df.select_dtypes(include=['int64']).skew()
```

Out[30]:
```
User_ID                       0.003066
Occupation                    0.400140
Stay_In_Current_City_Years    0.317236
Marital_Status                0.367437
Product_Category              1.025735
Purchase                      0.600140
dtype: float64
```

In [31]:
```
walmart_df.describe(include = 'all').T
```

Out[31]:

	count	unique	top	freq	mean	
User_ID	550068.0	NaN	NaN	NaN	1003028.842401	
Product_ID	550068	3631	P00265242	1880	NaN	
Gender	550068	2	M	414259	NaN	
Age	550068	7	26-35	219587	NaN	
Occupation	550068.0	NaN	NaN	NaN	8.076707	
City_Category	550068	3	B	231173	NaN	
Stay_In_Current_City_Years	550068.0	NaN	NaN	NaN	1.858418	
Marital_Status	550068.0	NaN	NaN	NaN	0.409653	
Product_Category	550068.0	NaN	NaN	NaN	5.40427	
Purchase	550068.0	NaN	NaN	NaN	9263.968713	5

Observation 1

- There are no missing values in the data.
- Customers with age group of 26-35 have done more purchases (219,587) compared with others
- Customers in City_Category of B have done more purchases (231,173) compared with other City_Category
- Out of 550,068 data point, 414,259 gender is Male and rest are the Female.
- Customer with Minimum amount of Purchase is $12
- Customer with Maximum amount of Purchase is $23961
- Purchase might have outliers

Missing Values

In [32]:
```
# Missing value detection
walmart_df.isna().sum()
```

Out[32]:
```
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 [33]:
```
# Checking duplicate values in the data set
walmart_df.duplicated(subset=None,keep='first').sum()
```

Out[33]:
```
0
```

Data Visualization

In [34]:
```
walmart_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067
Data columns (total 10 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   User_ID                     550068 non-null  int64
 1   Product_ID                  550068 non-null  object
 2   Gender                      550068 non-null  object
 3   Age                         550068 non-null  object
 4   Occupation                  550068 non-null  int64
 5   City_Category               550068 non-null  object
 6   Stay_In_Current_City_Years  550068 non-null  int64
 7   Marital_Status              550068 non-null  int64
 8   Product_Category            550068 non-null  int64
 9   Purchase                    550068 non-null  int64
dtypes: int64(6), object(4)
memory usage: 42.0+ MB
```

Data Visualization with numerical features

In this part, we'll create visual representations of the numerical data. This will include graphs showing distributions of various numerical features like occupation, years in the current city, marital status, and purchase amounts. Graphs help us see patterns and trends more easily than looking at numbers alone.

In [35]:
```
[col for col in walmart_df.select_dtypes(include=['int64']).columns]
```

Out[35]:

```
['User_ID',
 'Occupation',
 'Stay_In_Current_City_Years',
 'Marital_Status',
 'Product_Category',
 'Purchase']
```

Of course from that list, we can remove User_ID amd Product_Category, because that wont contribute to our analysis.

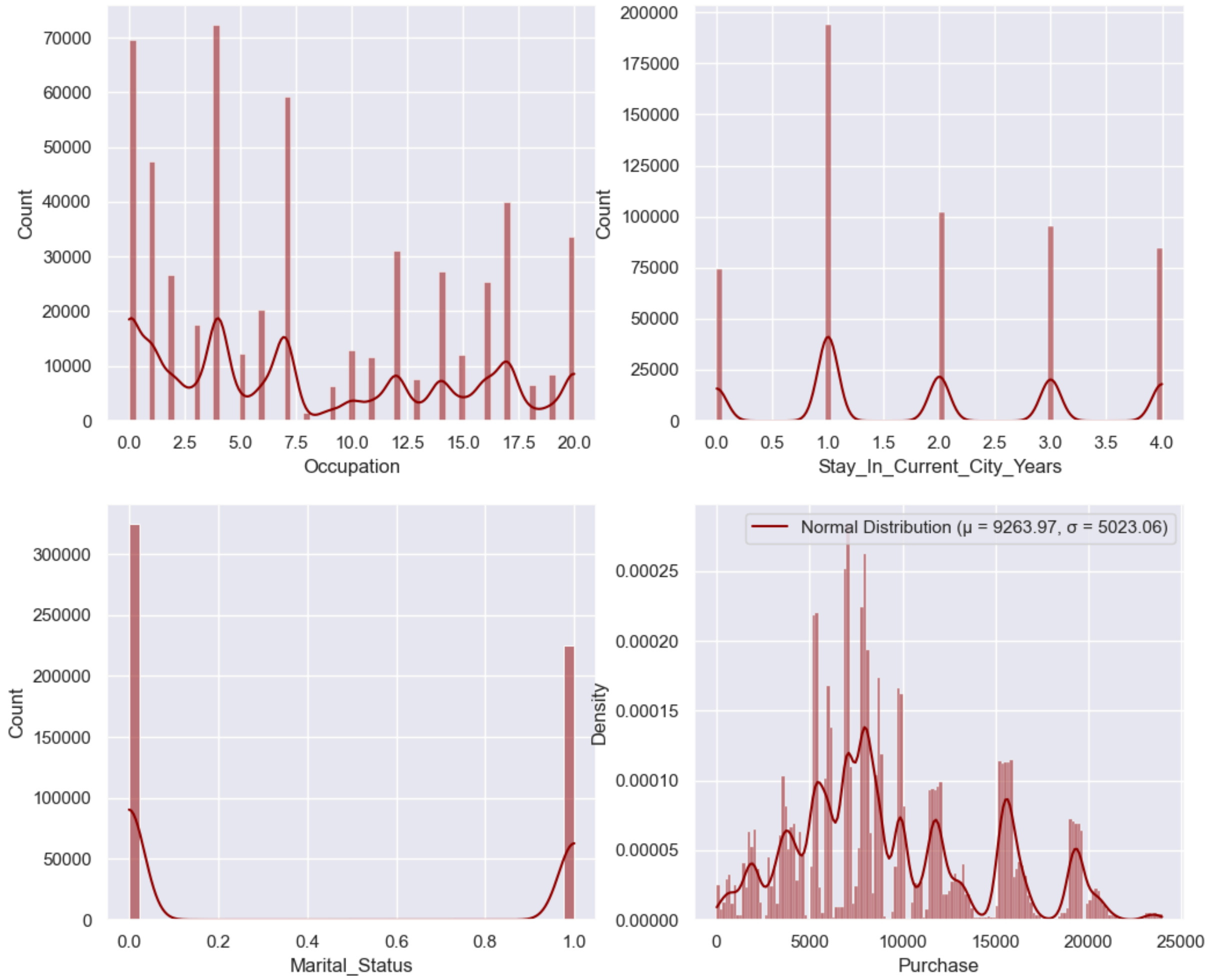
In [49]:

```
# # Create a 2x2 grid of subplots
# fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(12, 10))
# fig.subplots_adjust(top=0.9)  # Adjust the top spacing of the subplots

# # Plot distribution plots for each specified column
# sns.distplot(walmart_df['Occupation'], kde=True, ax=axis[0,0], color="#900
# sns.distplot(walmart_df['Stay_In_Current_City_Years'].astype(int), kde=Tru
# sns.distplot(walmart_df['Marital_Status'], kde=True, ax=axis[1,0], color="

# # Plotting a distribution plot for the 'Purchase' variable with normal cur
# sns.distplot(walmart_df['Purchase'], ax=axis[1,1], color="#900000", fit=no

# # Fitting the target variable to the normal curve
# mu, sigma = norm.fit(walmart_df['Purchase'])
# print("The mu (mean) is {} and sigma (standard deviation) is {} for the cu

# # Adding a legend for the 'Purchase' distribution plot
# axis[1,1].legend(['Normal Distribution (μ = {:.2f}, σ = {:.2f})'.format(mu

# # Show the plots
# plt.show()
```

In [50]:

```
# Create a 2x2 grid of subplots
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(12, 10))
fig.subplots_adjust(top=0.9)  # Adjust the top spacing of the subplots

# Plot distribution plots for each specified column
sns.histplot(walmart_df['Occupation'], kde=True, ax=axis[0,0], color="#90000
sns.histplot(walmart_df['Stay_In_Current_City_Years'].astype(int), kde=True,
sns.histplot(walmart_df['Marital_Status'], kde=True, ax=axis[1,0], color="#9

# Plotting a distribution plot for the 'Purchase' variable with normal curve
sns.histplot(walmart_df['Purchase'], ax=axis[1,1], color="#900000", kde=True

# Fitting the target variable to the normal curve
mu, sigma = norm.fit(walmart_df['Purchase'])
print("The mu (mean) is {} and sigma (standard deviation) is {} for the curv

# Adding a legend for the 'Purchase' distribution plot
axis[1,1].legend(['Normal Distribution (μ = {:.2f}, σ = {:.2f})'.format(mu,

# Show the plots
plt.show()
```

```
The mu (mean) is 9263.968712959126 and sigma (standard deviation) is 5023.06
0827959928 for the curve
```



In [43]:
```python
import plotly.graph_objects as go
from plotly.subplots import make_subplots

# Create subplots
fig = make_subplots(
    rows=4, cols=2,
    subplot_titles=("Gender", "Age", "Occupation", "City Category",
                    "Stay In Current City Years", "Marital Status", "Product
)

# Add histograms for each subplot
fig.add_trace(go.Histogram(x=walmart_df['Gender']), row=1, col=1)
fig.add_trace(go.Histogram(x=walmart_df['Age']), row=1, col=2)
fig.add_trace(go.Histogram(x=walmart_df['Occupation']), row=2, col=1)
fig.add_trace(go.Histogram(x=walmart_df['City_Category']), row=2, col=2)
fig.add_trace(go.Histogram(x=walmart_df['Stay_In_Current_City_Years']), row=
fig.add_trace(go.Histogram(x=walmart_df['Marital_Status']), row=3, col=2)
fig.add_trace(go.Histogram(x=walmart_df['Product_Category']), row=4, col=1)
fig.add_trace(go.Histogram(x=walmart_df['Purchase']), row=4, col=2)

# Update layout if needed
fig.update_layout(height=1200, width=1000, title_text="Count Plots")
fig.update_layout(showlegend=False)  # Hide the legend if not needed
```

```
# Show the figure
fig.show()
```

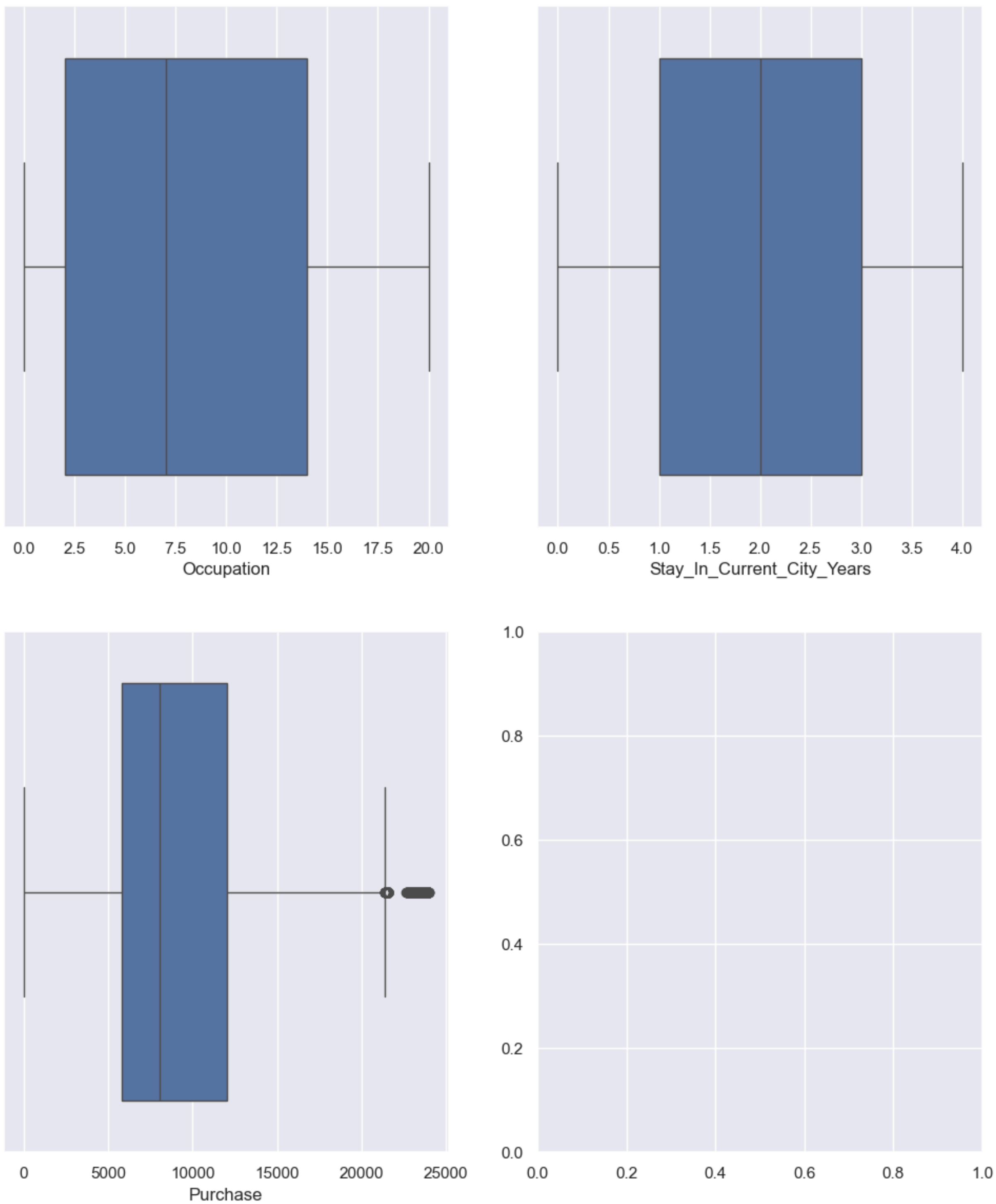
Observation 2

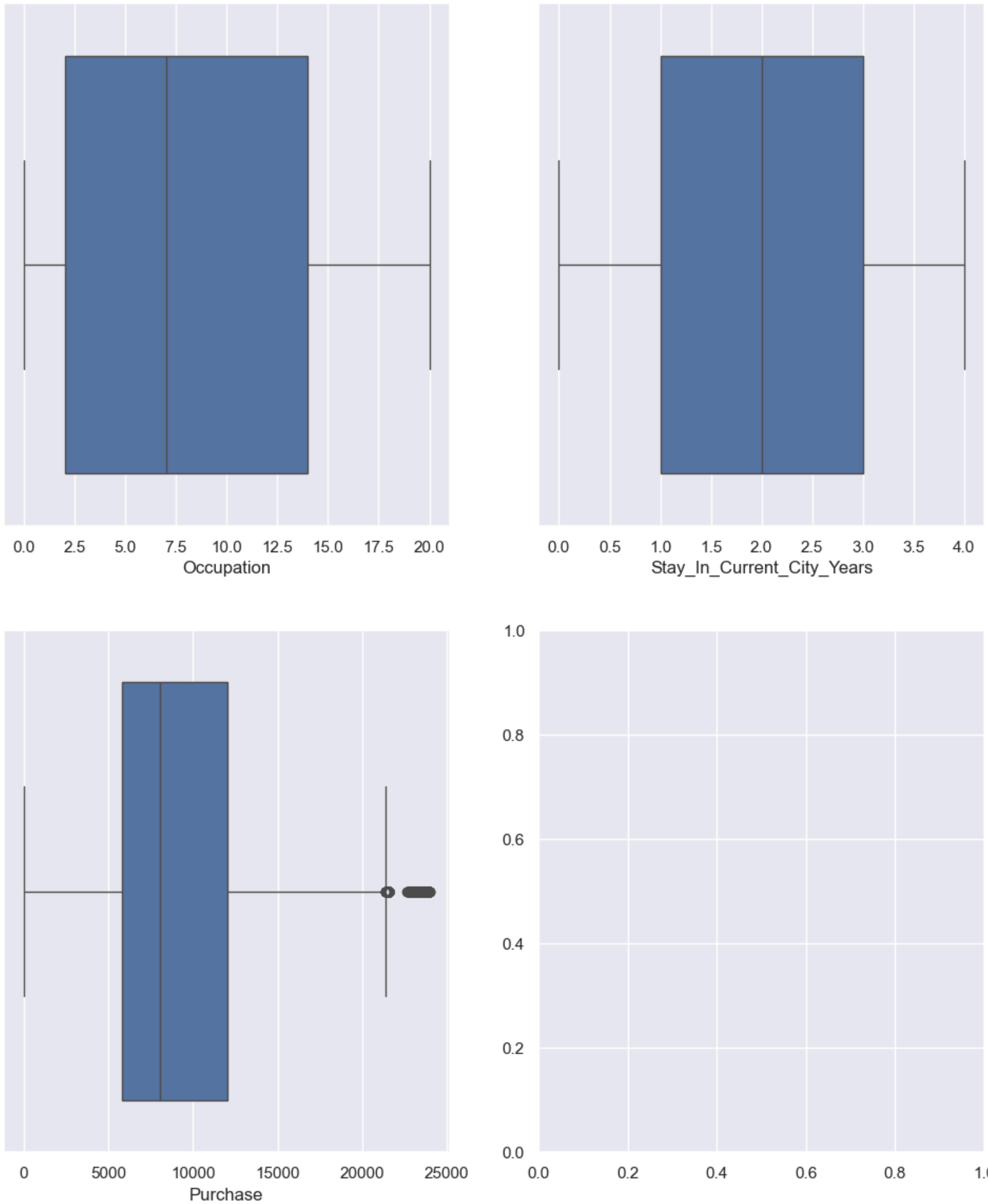
- Many buyers are male while the minority are female. Difference is due to the categories on sale during Black Friday, evaluating a particular category may change the count between genders.
- There are 7 categories defined to classify the age of the buyers
- Majority of the buyers are single
- Display of the occupation of the buyers. Occupation 8 has extremely low count compared with the others; it can be ignored for the calculation since it won't affect much the result.
- Majority of the products are in category 1, 5 and 8. The low number categories can be combined into a single category to greatly reduce the complexity of the problem.
- Higher count might represent the urban area indicates more population in City_Category.
- Most buyers have one year living in the city. Remaining categories are in uniform distribution

Data Visualization with categorical features

Here, we'll focus on the categorical data, like gender, age, and city category. We'll use different types of charts to show how these categories relate to purchases. This will help us understand which categories have the most impact on purchasing behavior.

In [47]:
```
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(12, 10))
fig.subplots_adjust(top=1.2)

sns.boxplot(data=walmart_df, x="Occupation", ax=axis[0,0])
sns.boxplot(data=walmart_df, x="Stay_In_Current_City_Years", orient='h', ax=
sns.boxplot(data=walmart_df, x="Purchase", orient='h', ax=axis[1,0])

plt.show()
```

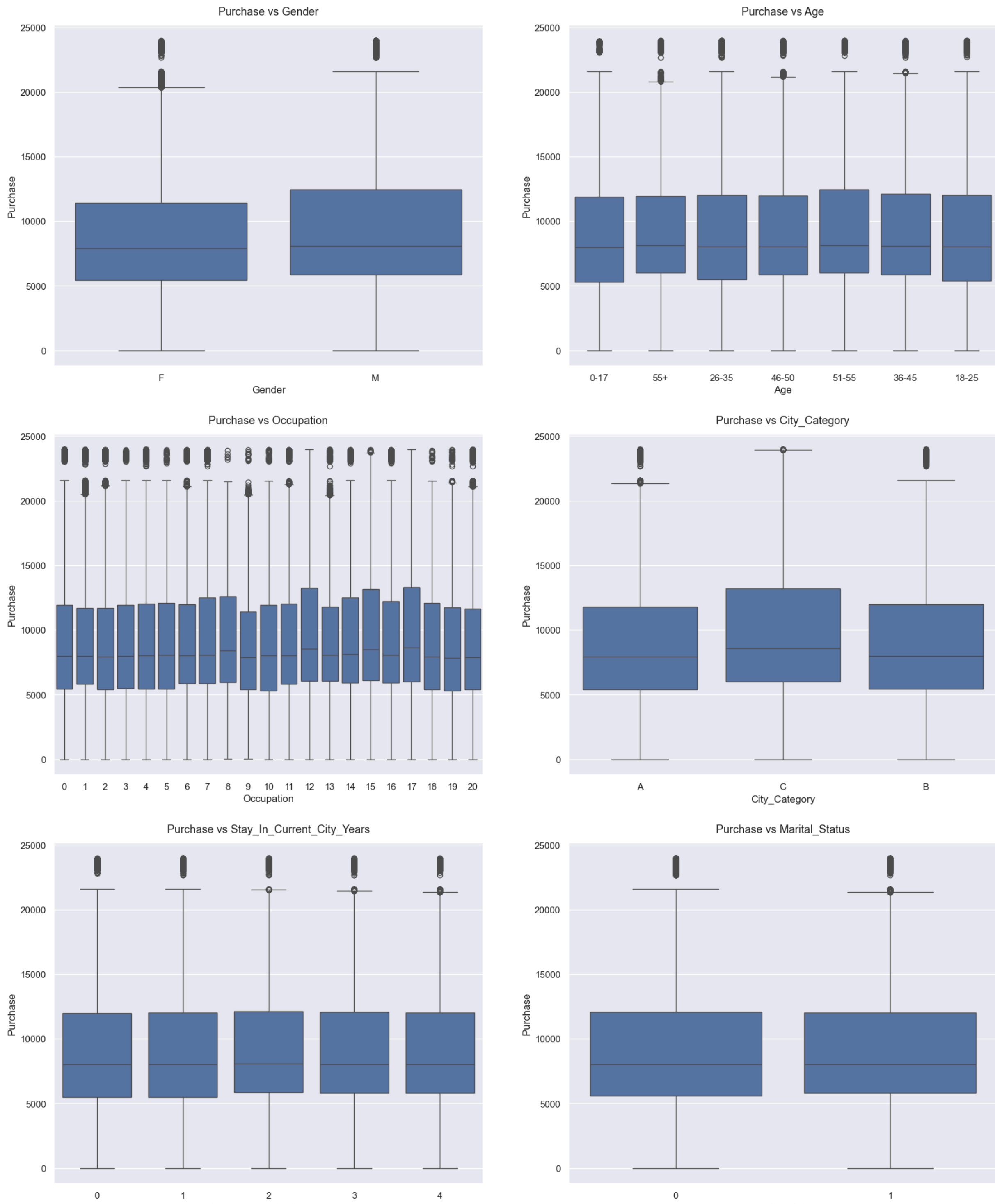

0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Occupation
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Stay_In_Current_City_Years
0
5000
10000
15000
20000
25000
Purchase
0.0
0.2
0.4
0.6
0.8
1.0

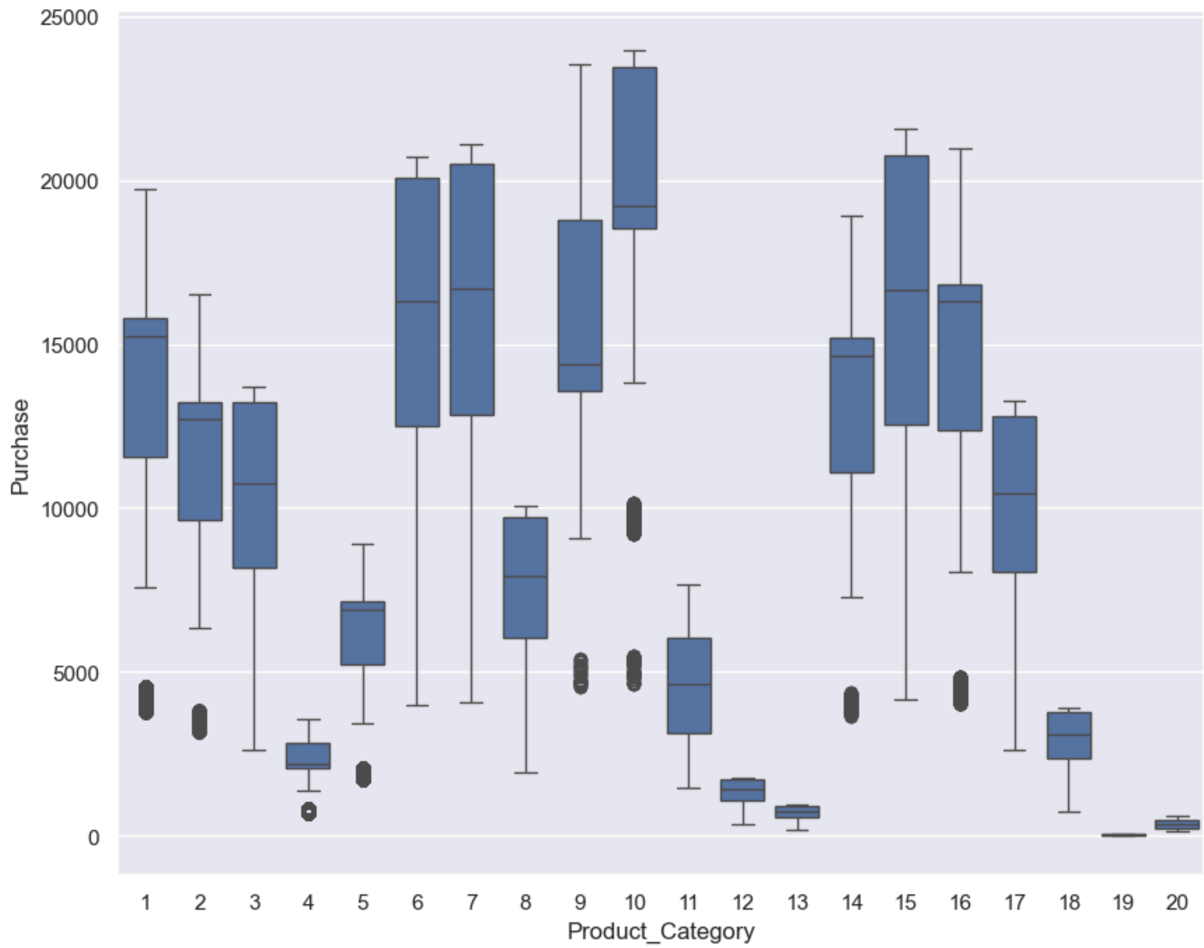


Purchase & Our Features

In [51]:
```
attrs = ['Gender', 'Age', 'Occupation', 'City_Category', 'Stay_In_Current_Ci
sns.set(color_codes = True)
fig, axs = plt.subplots(nrows=3, ncols=2, figsize=(20, 16))
fig.subplots_adjust(top=1.3)
count = 0
for row in range(3):
    for col in range(2):
        sns.boxplot(data=walmart_df, y='Purchase', x=attrs[count], ax=axs[rc
        axs[row,col].set_title(f"Purchase vs {attrs[count]}", pad=12, fontsi
```

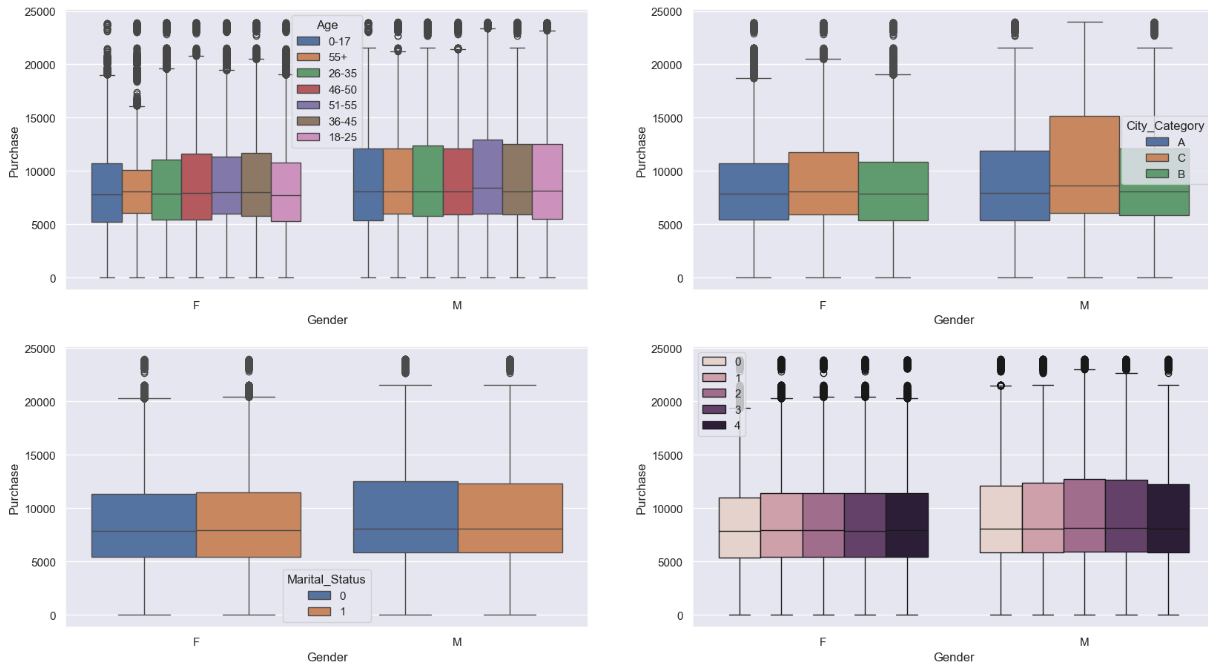
```
        count += 1
plt.show()

plt.figure(figsize=(10, 8))
sns.boxplot(data=walmart_df, y='Purchase', x=attrs[-1])
plt.show()
```





In [52]:

```
sns.set(color_codes = True)
fig, axs = plt.subplots(nrows=2, ncols=2, figsize=(20, 6))

fig.subplots_adjust(top=1.5)
sns.boxplot(data=walmart_df, y='Purchase', x='Gender', hue='Age', ax=axs[0,0
sns.boxplot(data=walmart_df, y='Purchase', x='Gender', hue='City_Category', 

sns.boxplot(data=walmart_df, y='Purchase', x='Gender', hue='Marital_Status',
sns.boxplot(data=walmart_df, y='Purchase', x='Gender', hue='Stay_In_Current_
axs[1,1].legend(loc='upper left')

plt.show()
```



Data Analysis

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

In [53]:
```
# Average amount spend per customer for Male and Female
amt_df = walmart_df.groupby(['User_ID', 'Gender'])[['Purchase']].sum()
avg_amt_df = amt_df.reset_index()
avg_amt_df
```

Out[53]:

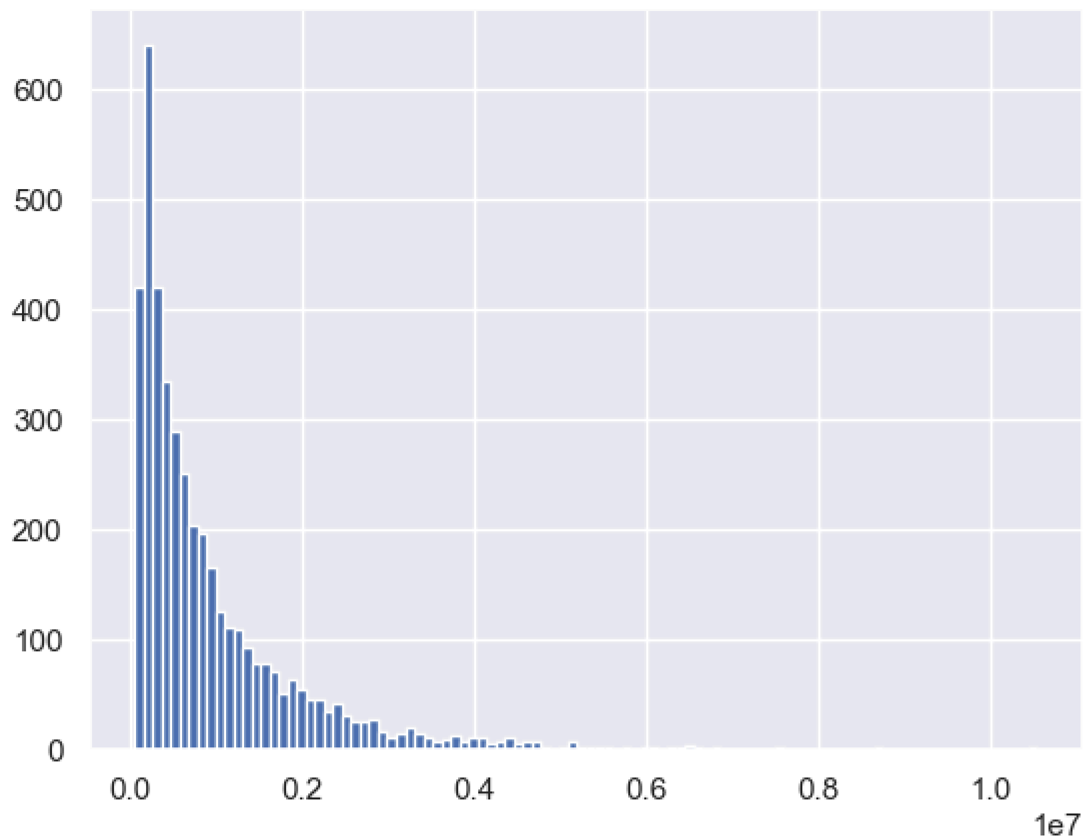
	User_ID	Gender	Purchase
0	1000001	F	334093
1	1000002	M	810472
2	1000003	M	341635
3	1000004	M	206468
4	1000005	M	821001
...	...	...	...
5886	1006036	F	4116058
5887	1006037	F	1119538
5888	1006038	F	90034
5889	1006039	F	590319
5890	1006040	M	1653299

5891 rows × 3 columns

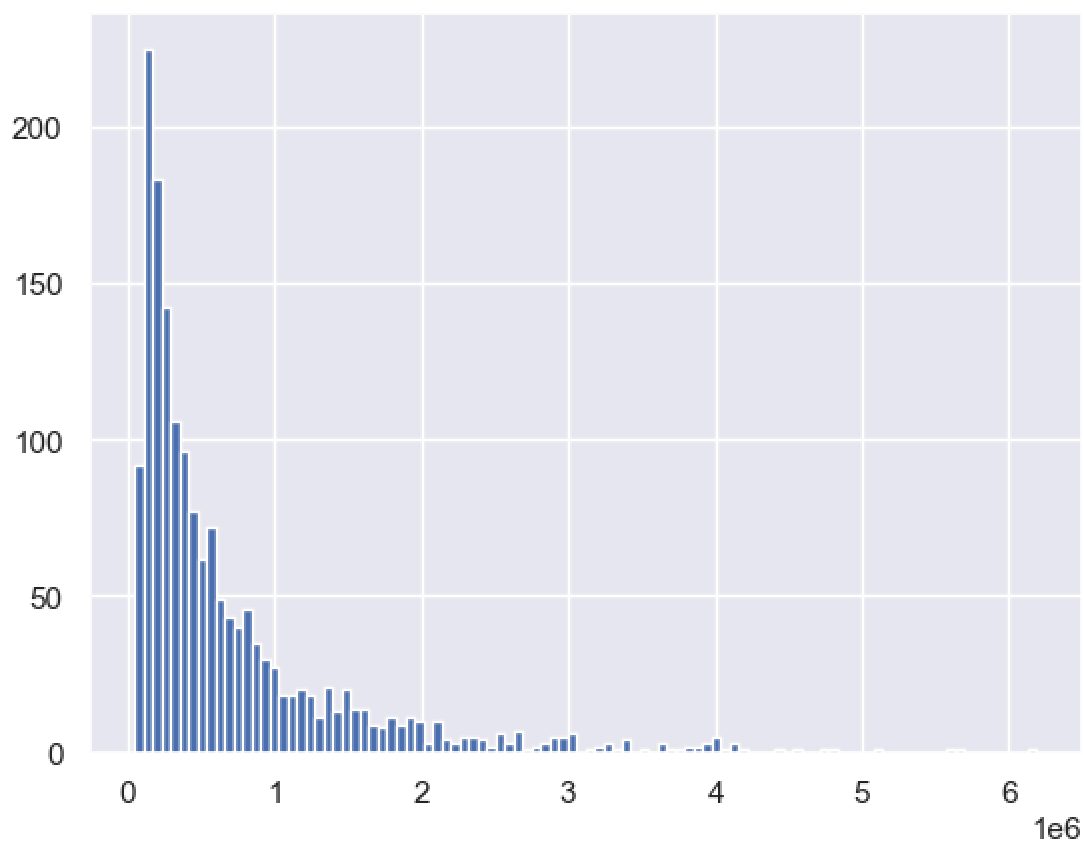
In [54]:
```
# Gender wise value counts in avg_amt_df
avg_amt_df['Gender'].value_counts()
```

Out[54]:
```
Gender
M    4225
F    1666
Name: count, dtype: int64
```

In [55]:
```
# Histogram of average amount spend for each customer - Male
avg_amt_df[avg_amt_df['Gender']=='M']['Purchase'].hist(bins=100)
plt.show()
```



In [56]:
```
# Histogram of average amount spend for each customer - Female
avg_amt_df[avg_amt_df['Gender']=='F']['Purchase'].hist(bins=100)
plt.show()
```



In [57]:
```python
male_avg = avg_amt_df[avg_amt_df['Gender']=='M']['Purchase'].mean()
female_avg = avg_amt_df[avg_amt_df['Gender']=='F']['Purchase'].mean()

print("Average amount spend by Male customers: {:.2f}".format(male_avg))
print("Average amount spend by Female customers: {:.2f}".format(female_avg))
```

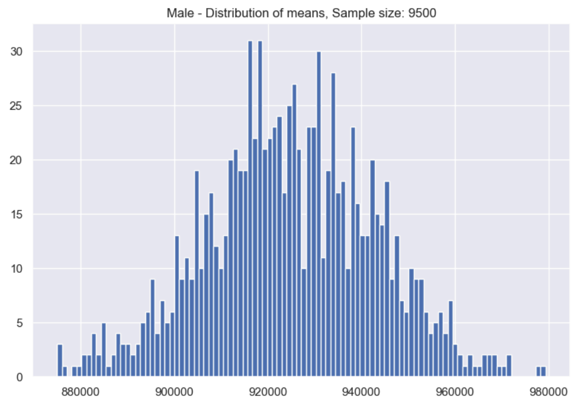
```
Average amount spend by Male customers: 925344.40
Average amount spend by Female customers: 712024.39
```

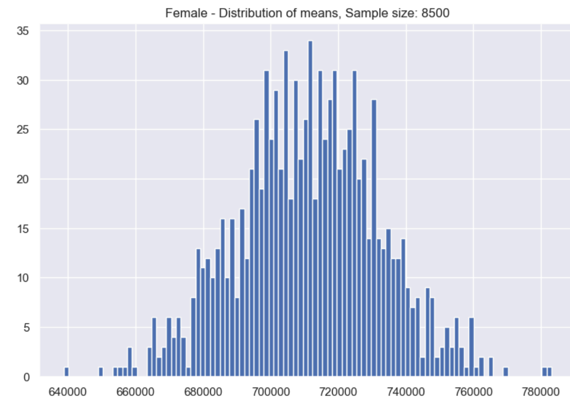
2. Confidence intervals and distribution of the mean of the expenses by female and male customers

In [58]:
```python
male_df = avg_amt_df[avg_amt_df['Gender']=='M']
female_df = avg_amt_df[avg_amt_df['Gender']=='F']
```

In [59]:
```python
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'].m
    female_mean = female_df.sample(female_sample_size, replace=True)['Purcha

    male_means.append(male_mean)
    female_means.append(female_mean)
```

In [60]:
```python
fig, axis = plt.subplots(nrows=1, ncols=2, figsize=(20, 6))

axis[0].hist(male_means, bins=100)
axis[1].hist(female_means, bins=100)
axis[0].set_title("Male - Distribution of means, Sample size: 9500")
axis[1].set_title("Female - Distribution of means, Sample size: 8500")

plt.show()

print("\n")
print("Population mean - Mean of sample means of amount spend for Male: {:.2
print("Population mean - Mean of sample means of amount spend for Female: {:

print("\nMale - Sample mean: {:.2f} Sample std: {:.2f}".format(male_df['Purc
print("Female - Sample mean: {:.2f} Sample std: {:.2f}".format(female_df['Pu
```






```
Population mean - Mean of sample means of amount spend for Male: 924723.05
Population mean - Mean of sample means of amount spend for Female: 711167.23

Male - Sample mean: 925344.40 Sample std: 985830.10
Female - Sample mean: 712024.39 Sample std: 807370.73
```

In [61]:
```
male_margin_of_error_clt = 1.64*male_df['Purchase'].std()/np.sqrt(len(male_c
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 = 1.64*female_df['Purchase'].std()/np.sqrt(len(fe
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_lowe
print("Female confidence interval of means: ({:.2f}, {:.2f})".format(female_
```

```
Male confidence interval of means: (900471.15, 950217.65)
Female confidence interval of means: (679584.51, 744464.28)
```

In [62]:
```
male_margin_of_error_clt = 1.96*male_df['Purchase'].std()/np.sqrt(len(male_c
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(fe
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_lowe
print("Female confidence interval of means: ({:.2f}, {:.2f})".format(female_
```

```
Male confidence interval of means: (895617.83, 955070.97)
Female confidence interval of means: (673254.77, 750794.02)
```

In [63]:
```
male_margin_of_error_clt = 2.58*male_df['Purchase'].std()/np.sqrt(len(male_c
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 = 2.58*female_df['Purchase'].std()/np.sqrt(len(fe
```

```
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_lowe
print("Female confidence interval of means: ({:.2f}, {:.2f})".format(female_
```

```
Male confidence interval of means: (886214.53, 964474.27)
Female confidence interval of means: (660990.91, 763057.88)
```

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

- The confidence intervals of average male and female spendings are not overlapping.
- Walmart can leverage this problem by taking sample dataset and apply this to whole population dataset by performing Central Limit Theorem and Confidence Intervals of 90%, 95%, or 99% by playing around with the width parameter by reporting those observations to Walmart.

4. Results when the same activity is performed for Married vs Unmarried customers

In [64]:
```
amt_df = walmart_df.groupby(['User_ID', 'Marital_Status'])[['Purchase']].sum
avg_amt_df = amt_df.reset_index()
avg_amt_df
```

Out[64]:

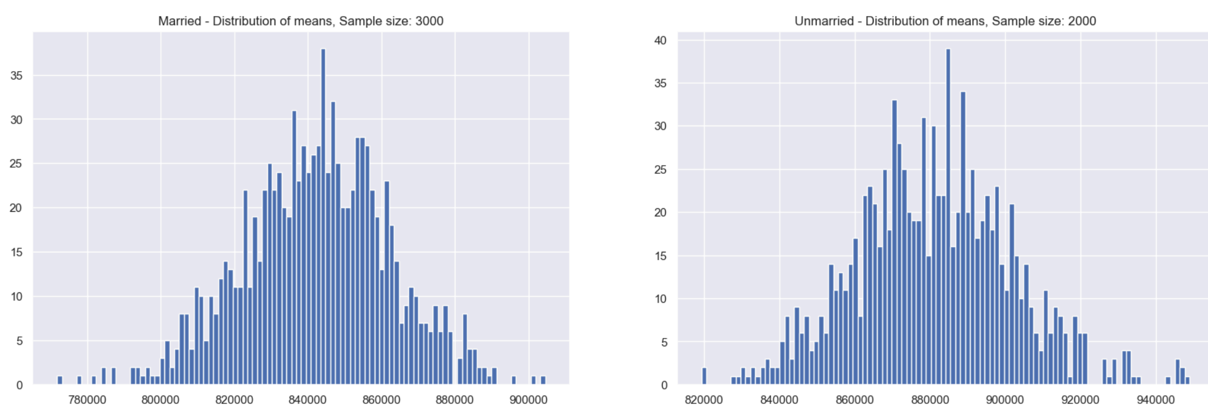
	User_ID	Marital_Status	Purchase
0	1000001	0	334093
1	1000002	0	810472
2	1000003	0	341635
3	1000004	1	206468
4	1000005	1	821001
...	...	...	...
5886	1006036	1	4116058
5887	1006037	0	1119538
5888	1006038	0	90034
5889	1006039	1	590319
5890	1006040	0	1653299

5891 rows × 3 columns

In [65]:
```
avg_amt_df['Marital_Status'].value_counts()
```

```
Out[65]: Marital_Status
         0    3417
         1    2474
         Name: count, dtype: int64
```

```
In [66]: married_samp_size = 3000
married_samp_size = 2000
num_repitions = 1000
married_means = []
unmarried_means = []

for _ in range(num_repitions):
    married_mean = avg_amt_df[avg_amt_df['Marital_Status']==1].sample(marrie
    unmarried_mean = avg_amt_df[avg_amt_df['Marital_Status']==0].sample(marr

    married_means.append(married_mean)
    unmarried_means.append(unmarried_mean)


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

axis[0].hist(married_means, bins=100)
axis[1].hist(unmarried_means, bins=100)
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("\n")
print("Population mean - Mean of sample means of amount spend for Married: {
print("Population mean - Mean of sample means of amount spend for Unmarried:

print("\nMarried - Sample mean: {:.2f} Sample std: {:.2f}".format(avg_amt_df
print("Unmarried - Sample mean: {:.2f} Sample std: {:.2f}".format(avg_amt_df
```




```
Population mean - Mean of sample means of amount spend for Married: 842249.2
4
Population mean - Mean of sample means of amount spend for Unmarried: 88102
2.10

Married - Sample mean: 843526.80 Sample std: 935352.12
Unmarried - Sample mean: 880575.78 Sample std: 949436.25
```

In [67]:
```
for val in ["Married", "Unmarried"]:

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

    new_df = avg_amt_df[avg_amt_df['Marital_Status']==new_val]

    margin_of_error_clt = 1.64*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, lo
```

```
Married confidence interval of means: (812686.46, 874367.13)
Unmarried confidence interval of means: (853938.67, 907212.90)
```

In [68]:
```
for val in ["Married", "Unmarried"]:

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

    new_df = avg_amt_df[avg_amt_df['Marital_Status']==new_val]

    margin_of_error_clt = 2.58*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, lo
```

```
Married confidence interval of means: (795009.68, 892043.91)
Unmarried confidence interval of means: (838671.05, 922480.51)
```

5. Results when the same activity is performed for Age

We will analyze the spending patterns of customers in different age groups. By calculating confidence intervals for each age group, we can see which age range tends to spend more and how certain age groups differ in their spending habits.

In [69]:
```
amt_df = walmart_df.groupby(['User_ID', 'Age'])[['Purchase']].sum()
avg_amt_df = amt_df.reset_index()
avg_amt_df
```

Out[69]:

	User_ID	Age	Purchase
0	1000001	0-17	334093
1	1000002	55+	810472
2	1000003	26-35	341635
3	1000004	46-50	206468
4	1000005	26-35	821001
...	...	...	...
5886	1006036	26-35	4116058
5887	1006037	46-50	1119538
5888	1006038	55+	90034
5889	1006039	46-50	590319
5890	1006040	26-35	1653299

5891 rows × 3 columns

In [70]:
```
avg_amt_df['Age'].value_counts()
```

Out[70]:
```
Age
26-35    2053
36-45    1167
18-25    1069
46-50     531
51-55     481
55+       372
0-17      218
Name: count, dtype: int64
```

In [71]:
```
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 = avg_amt_df[avg_amt_df['Age']==age_interval].sample(sample_siz
        all_means[age_interval].append(mean)
```

Now we can infer about the population that, 90% of the times

In [72]:
```
for val in ['26-35', '36-45', '18-25', '46-50', '51-55', '55+', '0-17']:

    new_df = avg_amt_df[avg_amt_df['Age']==val]
```

```
    margin_of_error_clt = 1.64*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})".forma
```

```
For age 26-35, confidence interval of means: (952320.12, 1026998.51)
For age 36-45, confidence interval of means: (832542.56, 926788.86)
For age 18-25, confidence interval of means: (810323.44, 899402.80)
For age 46-50, confidence interval of means: (726410.64, 858686.93)
For age 51-55, confidence interval of means: (703953.00, 822448.85)
For age 55+, confidence interval of means: (487192.99, 592201.50)
For age 0-17, confidence interval of means: (542553.13, 695182.50)
```

In [73]:
```
for val in ['26-35', '36-45', '18-25', '46-50', '51-55', '55+', '0-17']:

    new_df = avg_amt_df[avg_amt_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})".forma
```

```
For age 26-35, confidence interval of means: (945034.42, 1034284.21)
For age 36-45, confidence interval of means: (823347.80, 935983.62)
For age 18-25, confidence interval of means: (801632.78, 908093.46)
For age 46-50, confidence interval of means: (713505.63, 871591.93)
For age 51-55, confidence interval of means: (692392.43, 834009.42)
For age 55+, confidence interval of means: (476948.26, 602446.23)
For age 0-17, confidence interval of means: (527662.46, 710073.17)
```

In [74]:
```
for val in ['26-35', '36-45', '18-25', '46-50', '51-55', '55+', '0-17']:

    new_df = avg_amt_df[avg_amt_df['Age']==val]

    margin_of_error_clt = 2.58*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})".forma
```

```
For age 26-35, confidence interval of means: (930918.39, 1048400.25)
For age 36-45, confidence interval of means: (805532.95, 953798.47)
For age 18-25, confidence interval of means: (784794.60, 924931.63)
For age 46-50, confidence interval of means: (688502.19, 896595.37)
For age 51-55, confidence interval of means: (669993.82, 856408.03)
For age 55+, confidence interval of means: (457099.09, 622295.40)
For age 0-17, confidence interval of means: (498811.78, 738923.84)
```

Final Insights

After analyzing the data, we have gathered key insights about customer spending patterns based on age, gender, marital status, city category, and product categories.

- For Age feature, we observed that ~ 80% of the customer's who belong to the age group 25-40 (40%: 26-35, 18%: 18-25, 20%: 36-45) tend to spend the most.

- For Gender feature, ~75% of the number of purchases are made by Male customer's and rest of the 25% is done by female customer's. This tells us the Male consumers are the major contributors to the number of sales for the retail store.On average the male gender spends more money on purchase contrary to female, and it is possible to also observe this trend by adding the total value of purchase.

  - Average amount spend by Male customers: 9,25,408.28
  - Average amount spend by Female customers: 7,12,217.18
- When we combined Purchase and Marital_Status for analysis (60% are Single, 40% are Married). We came to know that Single Men spend the most during the Black Friday. It also tells that Men tend to spend less once they are married. It maybe because of the added responsibilities.

- There is an interesting column Stay_In_Current_City_Years, after analyzing this column we came to know the people who have spent 1 year in the city tend to spend the most. This is understandable as, people who have spent more than 4 years in the city are generally well settled and are less interested in buying new things as compared to the people new to the city, who tend to buy more (35% Staying in the city since 1 year, 18% since 2 years, 17% since 3 years).

- When examining the City_Category which city the product was purchased to our surprise, even though the city B is majorly responsible for the overall sales income, but when it comes to the above product, it majorly purchased in the city C.

- Total of 20 product_categories are there. Product_Category - 1, 5, 8, & 11 have highest purchasing frequency.

- There are 20 differnent types of Occupation's in the city

Confidence Intervals

Now using the Central Limit Theorem for the population:

- Average amount spend by male customers is 9,25,408.28
- Average amount spend by female customers is 7,12,217.18

Now we can infer about the population that, 90% of the times:

- Average amount spend by male customer will lie in between: (900471.15, 950217.65)

- Average amount spend by female customer will lie in between: (679584.51, 744464.28)

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

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

Now we can infer about the population that, 99% of the times:

- Average amount spend by male customer will lie in between: (886214.53, 964474.27)
- Average amount spend by female customer will lie in between: (660990.91, 763057.88)

Confidence Interval by Marital_Status

Now we can infer about the population that, 90% of the times:

- Married confidence interval of means: (812686.46, 874367.13)
- Unmarried confidence interval of means: (853938.67, 907212.90)

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

- Married confidence interval of means: (806668.83, 880384.76)
- Unmarried confidence interval of means: (848741.18, 912410.38)

Now we can infer about the population that, 99% of the times:

- Married confidence interval of means: (795009.68, 892043.91)
- Unmarried confidence interval of means: (838671.05, 922480.51)

Confidence Interval by Age

Now we can infer about the population that, 90% of the times:

- For age 26-35, confidence interval of means: (952320.12, 1026998.51)
- For age 36-45, confidence interval of means: (832542.56, 926788.86)
- For age 18-25, confidence interval of means: (810323.44, 899402.80)
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Now we can infer about the population that, 95% of the times:

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- For age 0-17, confidence interval of means: (527662.46, 710073.17)

Now we can infer about the population that, 99% of the times:

- For age 26-35, confidence interval of means: (930918.39, 1048400.25)
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- For age 18-25, confidence interval of means: (784794.60, 924931.63)
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- For age 51-55, confidence interval of means: (669993.82, 856408.03)
- For age 55+, confidence interval of means: (457099.09, 622295.40)
- For age 0-17, confidence interval of means: (498811.78, 738923.84)

Recommendations

1. Men spent more money than women, So company should focus on retaining the female customers and getting more female customers.
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 company should focus on acquisition of married customers.
4. Customers in the age 25-40 spend more money than the others, So company should focus on acquisition of customers of other age groups.
5. The tier-2 city called B has the highest number of population, management should open more outlets in the tier-1 and tier-2 cities like A and C in order to increase the buisness.