dv8owa5zr

May 14, 2025

0.1 Walmart : Black Friday Purchases (Customer Purchase Behaviour)

0.1.1 Objective

This project aims to analyze the customer purchase behaviour (specifically, purchase amount) against the customer's gender and the various other factors to help the business make better decisions. The Management team at Walmart Inc. wants to understand if the spending habits differ between male and female customers:

Do women spend more on Black Friday than men?

Exploratory Data Analysis

[6]:
```
import pandas as pd

import matplotlib.pyplot as plt
%matplotlib inline

import numpy as np

import seaborn as sns
sns.set(color_codes=True)

import scipy.stats as stats
from scipy.stats import norm
import warnings
warnings.filterwarnings("ignore")
```

[8]:
```
walmart_df = pd.read_csv('/Users/adyashamohapatra/Desktop/Data Science Projects/
↪WALMART_DS_Customer Purchase Behaviour.csv')
```

Data Overview

[11]:
```
#a glimpse at the dataset

walmart_df.head()
```

[11]:
```
   User_ID Product_ID Gender   Age  Occupation City_Category  \
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

  Stay_In_Current_City_Years  Marital_Status  Product_Category  Purchase
0                          2               0                 3      8370
1                          2               0                 1     15200
2                          2               0                12      1422
3                          2               0                12      1057
4                         4+               0                 8      7969
```

[17]:
```python
walmart_df.shape
```

[17]:
```
(550068, 10)
```

[19]:
```python
walmart_df.columns
```

[19]:
```
Index(['User_ID', 'Product_ID', 'Gender', 'Age', 'Occupation', 'City_Category',
       'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Category',
       'Purchase'],
      dtype='object')
```

[21]:
```python
walmart_df.dtypes
```

[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
```

Finding Unique Values and Count Them

[26]:
```python
def print_nunique_values(df):
    for column in df.columns:
        unique_values = df[column].nunique()
        print(f"\nUnique Values in {column} are ", unique_values)

print_nunique_values(walmart_df)
```

```
Unique Values in User_ID are  5891
```

```
Unique Values in Product_ID are  3631

Unique Values in Gender are  2

Unique Values in Age are  7

Unique Values in Occupation are  21

Unique Values in City_Category are  3

Unique Values in Stay_In_Current_City_Years are  5

Unique Values in Marital_Status are  2

Unique Values in Product_Category are  20

Unique Values in Purchase are  18105
```

Data Cleaning

I will make some changes to the data for better analysis.For example, I'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.

[30]:
```
walmart_df.Stay_In_Current_City_Years.nunique()
```

[30]:
```
5
```

[32]:
```
walmart_df.Stay_In_Current_City_Years.unique()
```

[32]:
```
array(['2', '4+', '3', '1', '0'], dtype=object)
```

[34]:
```
#cleaning up this 4+ and other '+' in the data !
walmart_df.Stay_In_Current_City_Years = walmart_df.Stay_In_Current_City_Years.
  ↪str.replace("+","")
```

[36]:
```
walmart_df.Stay_In_Current_City_Years.unique()
```

[36]:
```
array(['2', '4', '3', '1', '0'], dtype=object)
```

[38]:
```
#now the '+' have been taken care of ! let's convert them to numeric for better␣
  ↪analysis.

walmart_df['Stay_In_Current_City_Years']= pd.
  ↪to_numeric(walmart_df['Stay_In_Current_City_Years'])
```

[40]:
```
walmart_df.Stay_In_Current_City_Years.unique()
```

[40]: array([2, 4, 3, 1, 0])

[42]:
```
walmart_df.Stay_In_Current_City_Years.dtypes
```

[42]: dtype('int64')

Statistical Summary

[45]:
```
walmart_df.select_dtypes(include=['int64']).skew()
```

[45]:
```
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
```

[47]:
```
walmart_df.describe()
```

[47]:

	User_ID	Occupation	Stay_In_Current_City_Years
count	5.500680e+05	550068.000000	550068.000000
mean	1.003029e+06	8.076707	1.858418
std	1.727592e+03	6.522660	1.289443
min	1.000001e+06	0.000000	0.000000
25%	1.001516e+06	2.000000	1.000000
50%	1.003077e+06	7.000000	2.000000
75%	1.004478e+06	14.000000	3.000000
max	1.006040e+06	20.000000	4.000000

	Marital_Status	Product_Category	Purchase
count	550068.000000	550068.000000	550068.000000
mean	0.409653	5.404270	9263.968713
std	0.491770	3.936211	5023.065394
min	0.000000	1.000000	12.000000
25%	0.000000	1.000000	5823.000000
50%	0.000000	5.000000	8047.000000
75%	1.000000	8.000000	12054.000000
max	1.000000	20.000000	23961.000000

[49]:
```
walmart_df.describe(include = 'all')
```

[49]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category
count	5.500680e+05	550068	550068	550068	550068.000000	550068
unique	NaN	3631	2	7	NaN	3
top	NaN	P00265242	M	26-35	NaN	B
freq	NaN	1880	414259	219587	NaN	231173

```
mean    1.003029e+06       NaN     NaN     NaN      8.076707          NaN
std     1.727592e+03       NaN     NaN     NaN      6.522660          NaN
min     1.000001e+06       NaN     NaN     NaN      0.000000          NaN
25%     1.001516e+06       NaN     NaN     NaN      2.000000          NaN
50%     1.003077e+06       NaN     NaN     NaN      7.000000          NaN
75%     1.004478e+06       NaN     NaN     NaN     14.000000          NaN
max     1.006040e+06       NaN     NaN     NaN     20.000000          NaN

        Stay_In_Current_City_Years  Marital_Status  Product_Category  \
count                550068.000000   550068.000000     550068.000000
unique                         NaN             NaN               NaN
top                            NaN             NaN               NaN
freq                           NaN             NaN               NaN
mean                      1.858418        0.409653          5.404270
std                       1.289443        0.491770          3.936211
min                       0.000000        0.000000          1.000000
25%                       1.000000        0.000000          1.000000
50%                       2.000000        0.000000          5.000000
75%                       3.000000        1.000000          8.000000
max                       4.000000        1.000000         20.000000

             Purchase
count   550068.000000
unique            NaN
top               NaN
freq              NaN
mean      9263.968713
std       5023.065394
min         12.000000
25%       5823.000000
50%       8047.000000
75%      12054.000000
max      23961.000000
```

Observations from Analysis

- There are no missing values in the data.

- Customers with age group of 26-35 have done more purchases (2,19,587) compared with others

- Customers in City_Category of B have done more purchases (2,31,173) compared with other City_Category

- Out of 5,50,000 data point. 4,14,259's 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 Value Detection

[57]:
```
walmart_df.isna().sum()
```

[57]:
```
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
```

Duplicate Value Detection

[60]:
```
walmart_df.duplicated(subset=None,keep='first').sum()
```

[60]:
```
0
```

Data Visualization

[63]:
```
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
```

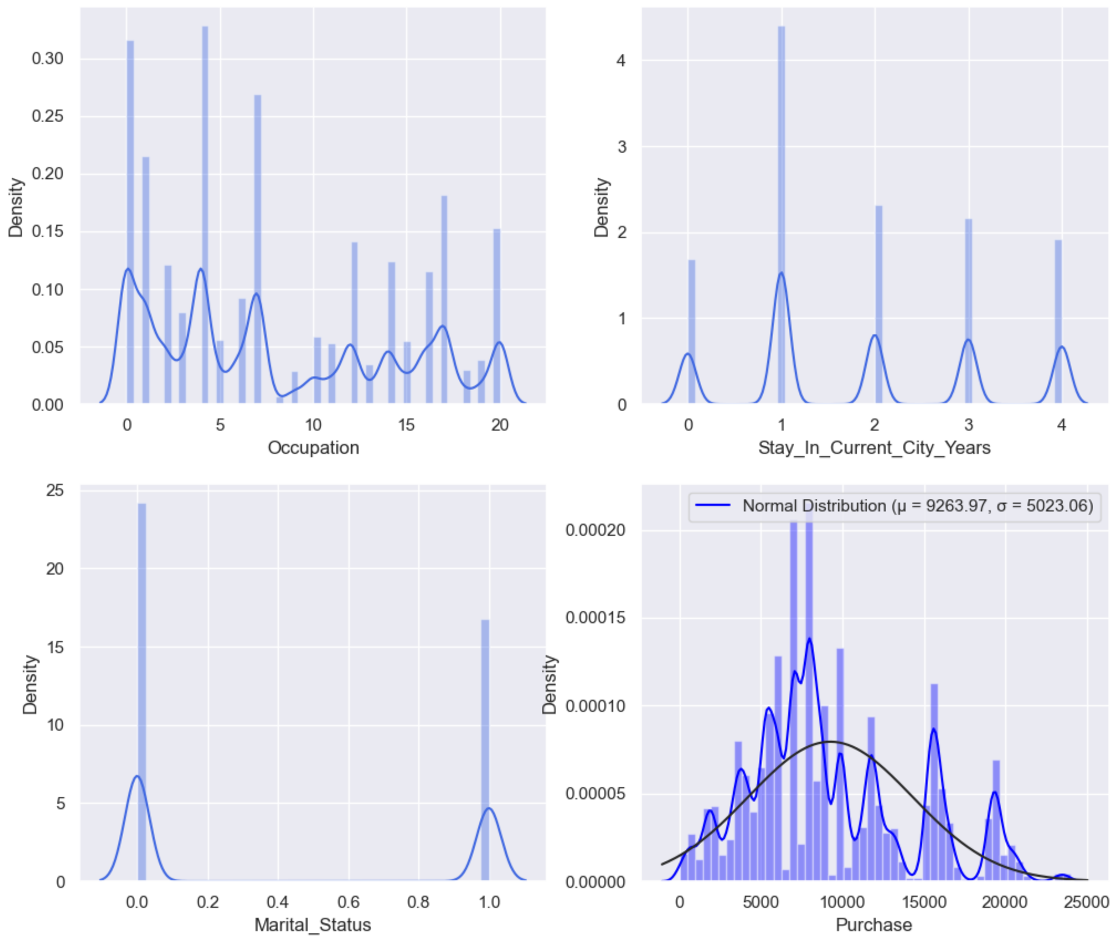
Data Visualization with Numerical Features

[79]:
```
[col for col in walmart_df.select_dtypes(include=['int64']).columns]
```

[79]:
```
['User_ID',
 'Occupation',
 'Stay_In_Current_City_Years',
 'Marital_Status',
 'Product_Category',
 'Purchase']
```

[83]:
```
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import norm

# 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="royalblue")
sns.distplot(walmart_df['Stay_In_Current_City_Years'].astype(int), kde=True,␣
 ↪ax=axis[0,1], color="royalblue")
sns.distplot(walmart_df['Marital_Status'], kde=True, ax=axis[1,0],␣
 ↪color="royalblue")

# Plotting a distribution plot for the 'Purchase' variable with normal curve fit
sns.distplot(walmart_df['Purchase'], ax=axis[1,1], color="blue", fit=norm)

# 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 curve".
 ↪format(mu, sigma))

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

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

```
The mu (mean) is 9263.968712959126 and sigma (standard deviation) is
5023.060827959928 for the curve
```



[76]:
```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␣
 ↪Category", "Purchase")
)

# 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=3,␣
 ↪col=1)
```

```
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()
```


Count Plots
Gender
400k
300k
200k
100k
0
F
M
Age
200k
150k
100k
50k
0
0-17
55+
26-35
46-50
51-55
36-45
18-25
Occupation
60k
40k
20k
0
0
5
10
15
20
City Category
200k
150k
100k
50k
0
A
C
B
Stay In Current City Years
200k
150k
100k
50k
0
0
2
4
Marital Status
300k
200k
100k
0
−0.5
0
0.5
1
1.5
Product Category
150k
100k
50k
0
5
10
15
20
Purchase
15k
10k
5k
0
0
5k
10k
15k
20k

Observations:

- 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.

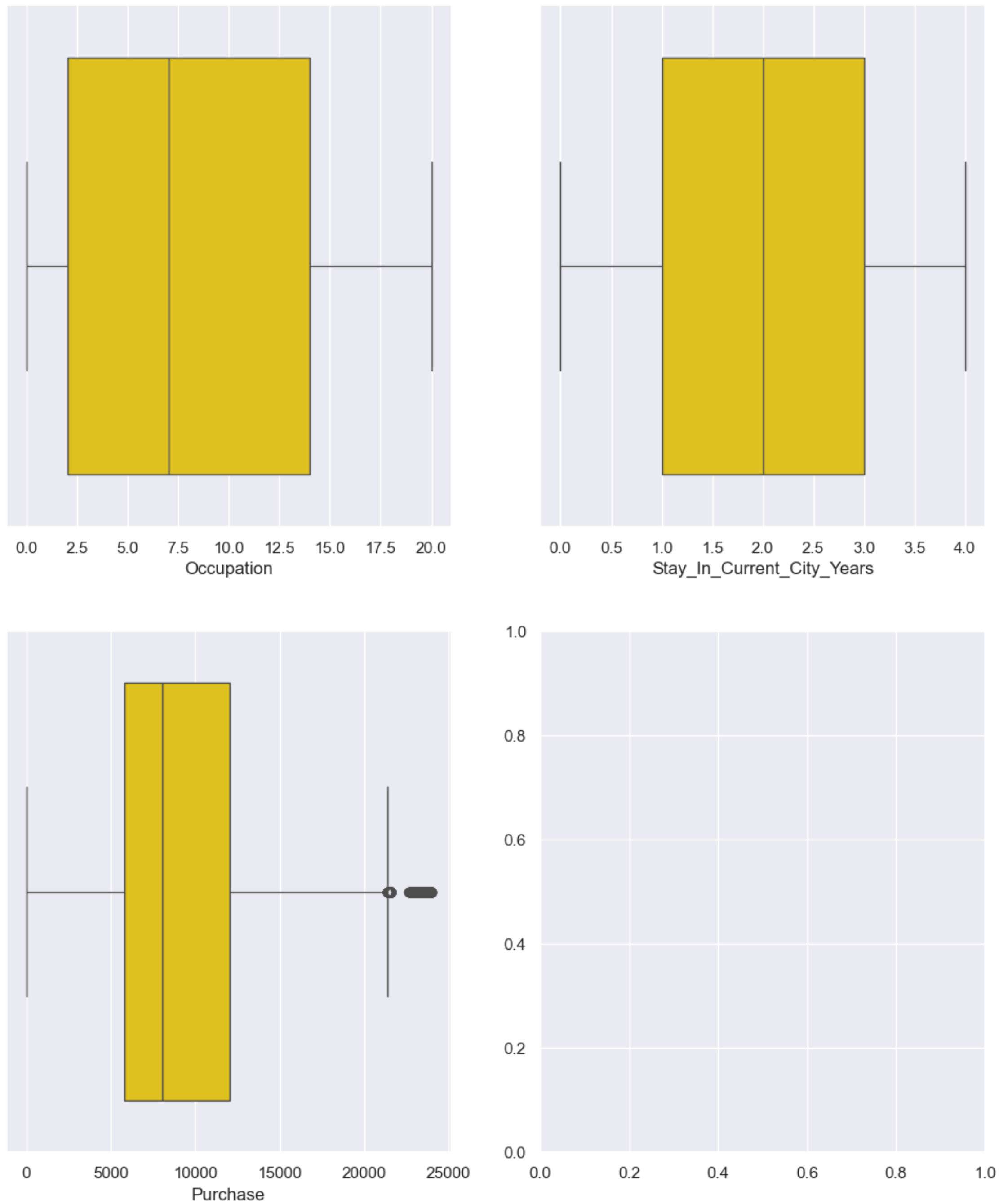
- Majority of the products are in category 1, 5 and 8. The low number categories can be combined into a single category to greatly reduce the complexity of the problem.

- 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

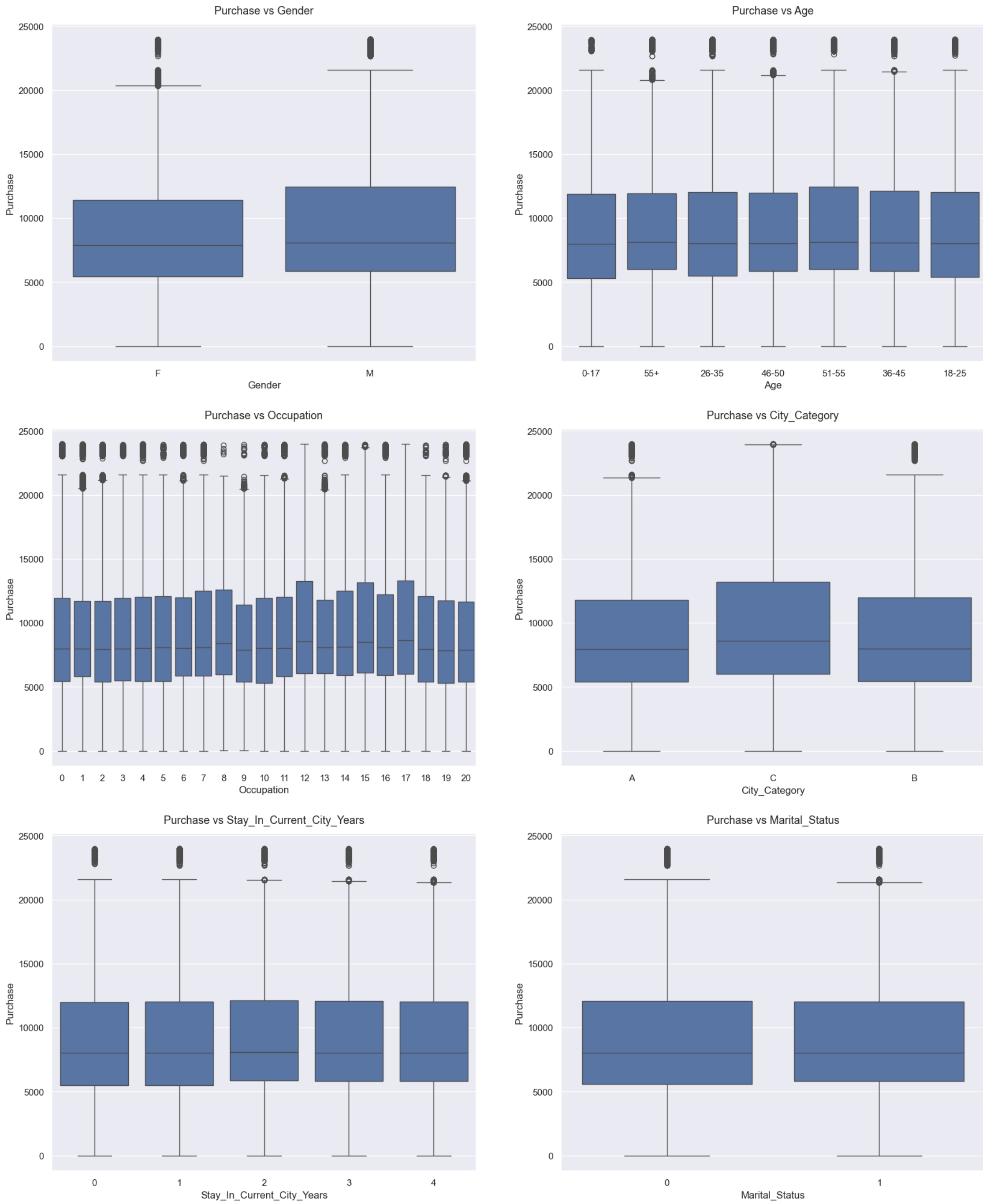
[92]:
```
#box plots to understand the overall summary + outliers, median, etc.

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],color = '#FFD700')
sns.boxplot(data=walmart_df, x="Stay_In_Current_City_Years", orient='h',␣
 ↪ax=axis[0,1],color = '#FFD700')
sns.boxplot(data=walmart_df, x="Purchase", orient='h', ax=axis[1,0],color =␣
 ↪'#FFD700')

plt.show()
```

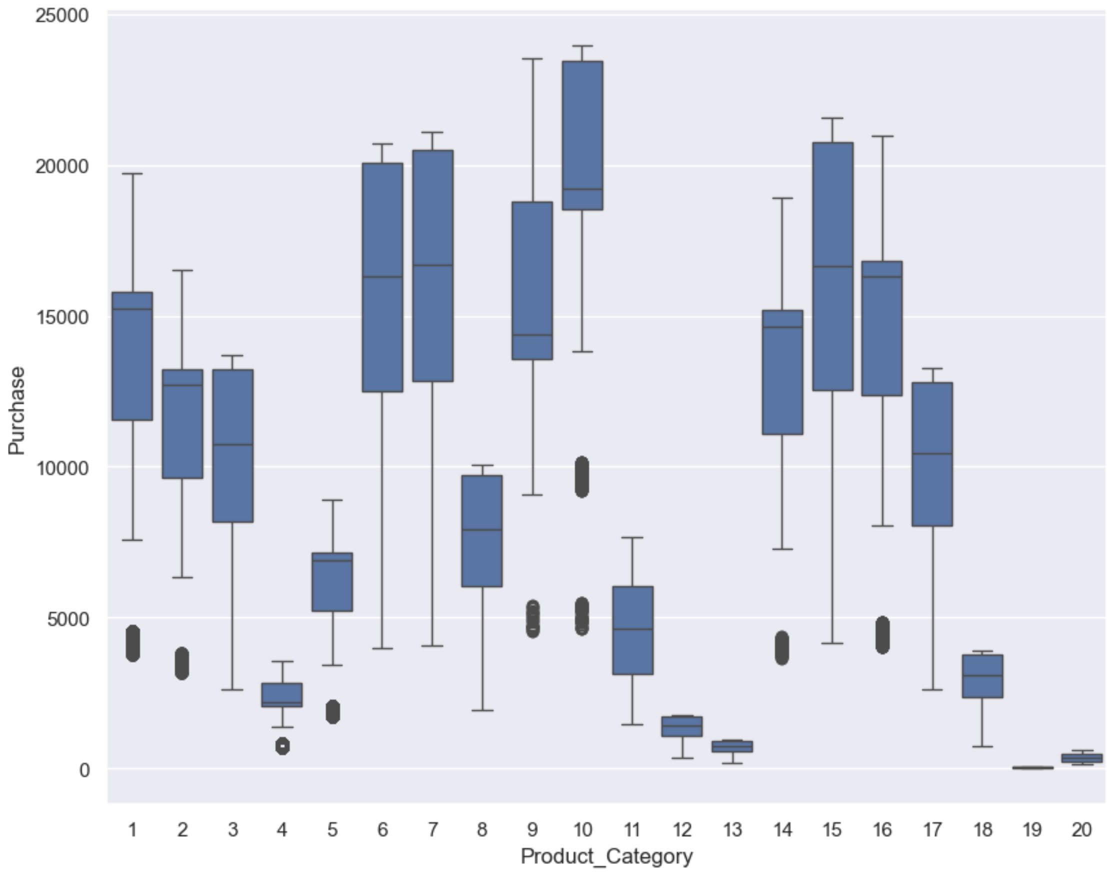


Purchase & Our Features

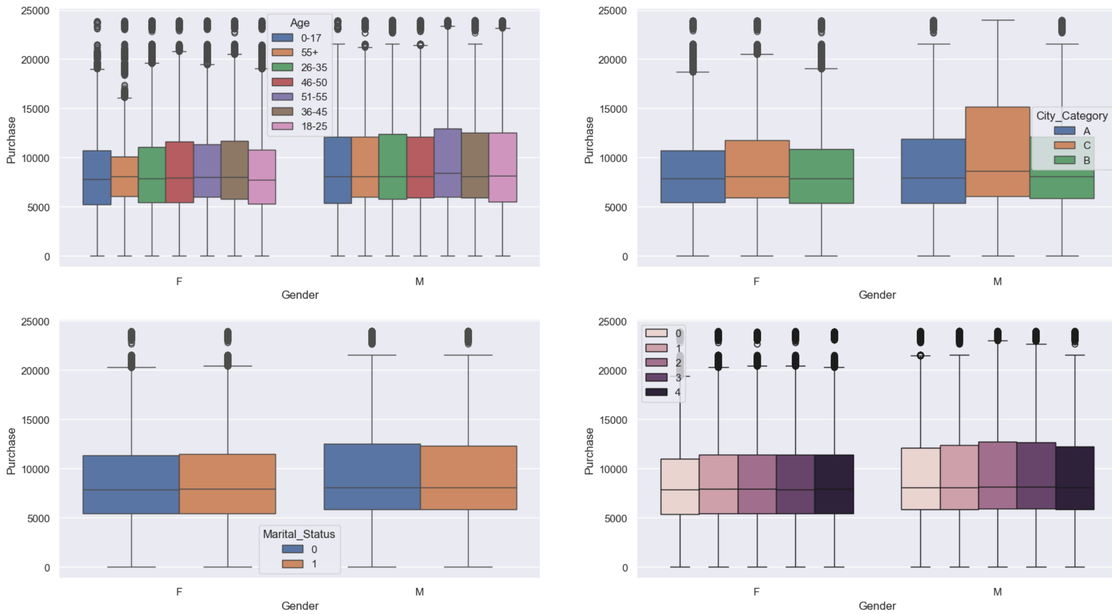
[95]:
```
attrs = ['Gender', 'Age', 'Occupation', 'City_Category',␣
↪'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Category']
sns.set(color_codes = True)
fig, axs = plt.subplots(nrows=3, ncols=2, figsize=(20, 16))
fig.subplots_adjust(top=1.3)
```

```python
count = 0
for row in range(3):
    for col in range(2):
        sns.boxplot(data=walmart_df, y='Purchase', x=attrs[count], ax=axs[row,␣
 ↪col])
        axs[row,col].set_title(f"Purchase vs {attrs[count]}", pad=12,␣
 ↪fontsize=13)
        count += 1
plt.show()

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


Purchase vs Gender
Purchase
Gender
F
M
Purchase vs Age
Age
0-17
55+
26-35
46-50
51-55
36-45
18-25
Purchase vs Occupation
Occupation
Purchase vs City_Category
City_Category
A
C
B
Purchase vs Stay_In_Current_City_Years
Stay_In_Current_City_Years
Purchase vs Marital_Status
Marital_Status
25000
20000
15000
10000
5000
0



[97]:
```
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',␣
    ↪ax=axs[0,1])

sns.boxplot(data=walmart_df, y='Purchase', x='Gender', hue='Marital_Status',␣
    ↪ax=axs[1,0])
sns.boxplot(data=walmart_df, y='Purchase', x='Gender',␣
    ↪hue='Stay_In_Current_City_Years', ax=axs[1,1])
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?

[101]:
```python
# 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
```

[101]:

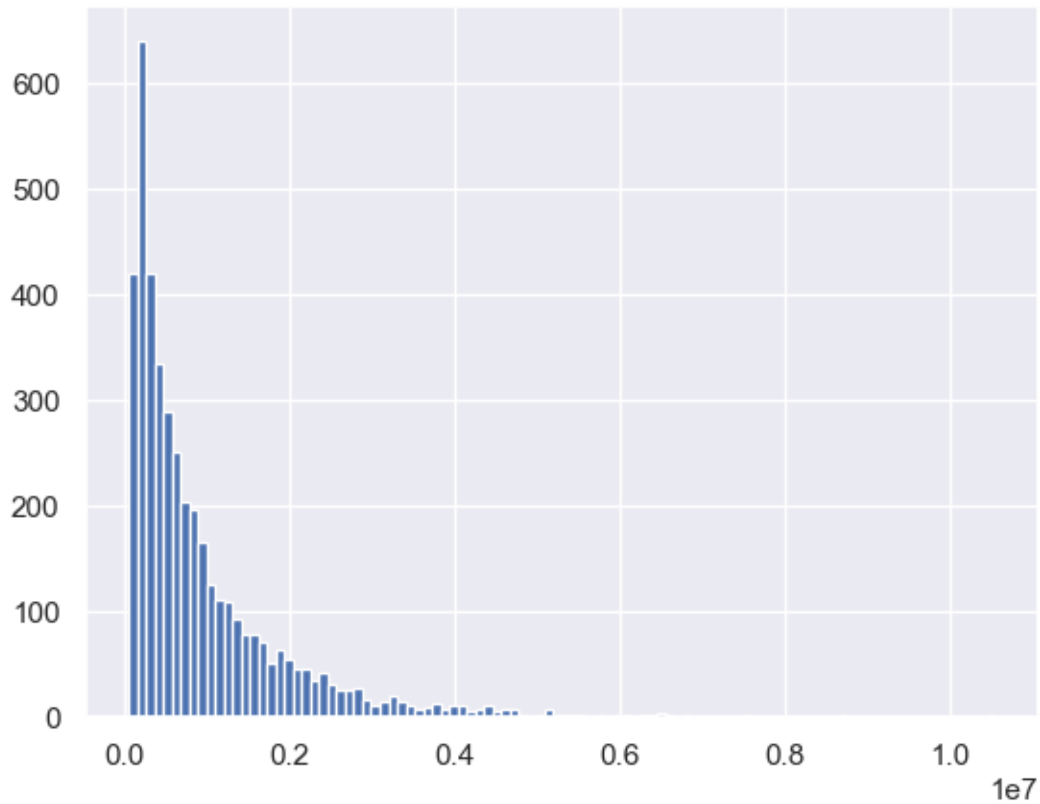
	User_ID	Gender	Purchase
0	1000001	F	334093
1	1000002	M	810472
2	1000003	M	341635
3	1000004	M	206468
4	1000005	M	821001
…	…	…	…
5886	1006036	F	4116058
5887	1006037	F	1119538
5888	1006038	F	90034
5889	1006039	F	590319
5890	1006040	M	1653299

[5891 rows x 3 columns]

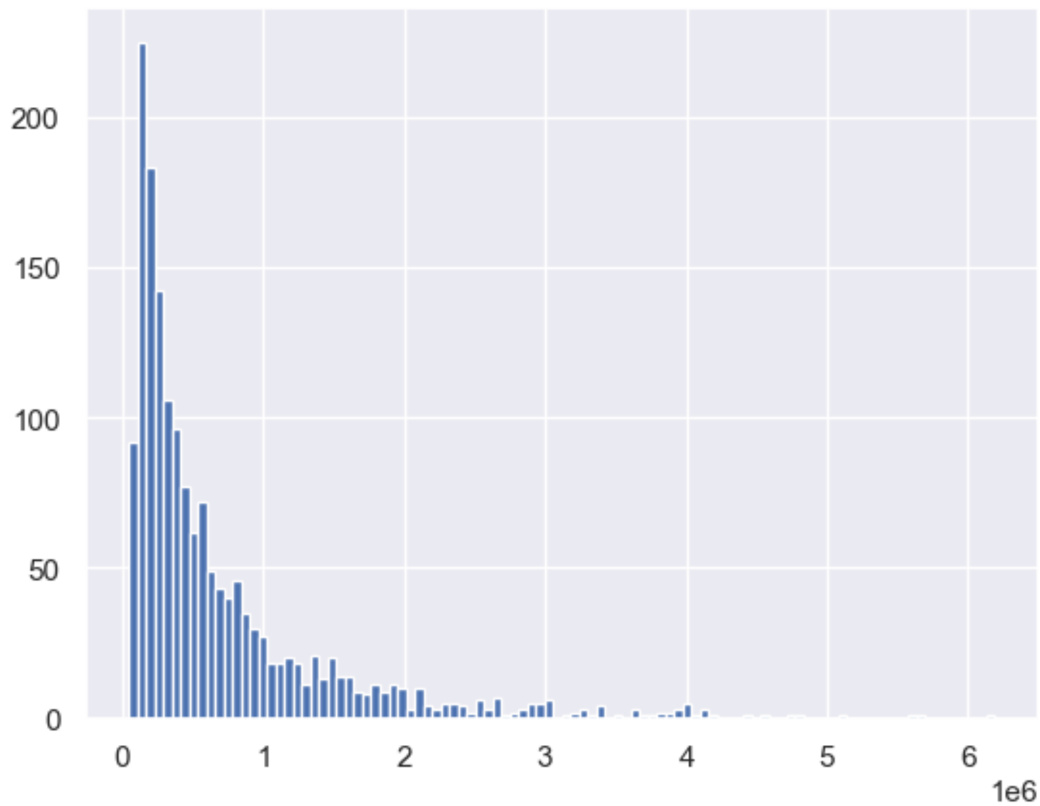
[103]:
```python
# Gender wise value counts in avg_amt_df
avg_amt_df['Gender'].value_counts()
```

[103]:
```
Gender
M    4225
F    1666
Name: count, dtype: int64
```

[105]:
```python
# histogram of average amount spend for each customer - Male
avg_amt_df[avg_amt_df['Gender']=='M']['Purchase'].hist(bins=100)
plt.show()
```



[107]:
```python
# histogram of average amount spend for each customer - Female
avg_amt_df[avg_amt_df['Gender']=='F']['Purchase'].hist(bins=100)
plt.show()
```



[109]:
```
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
```

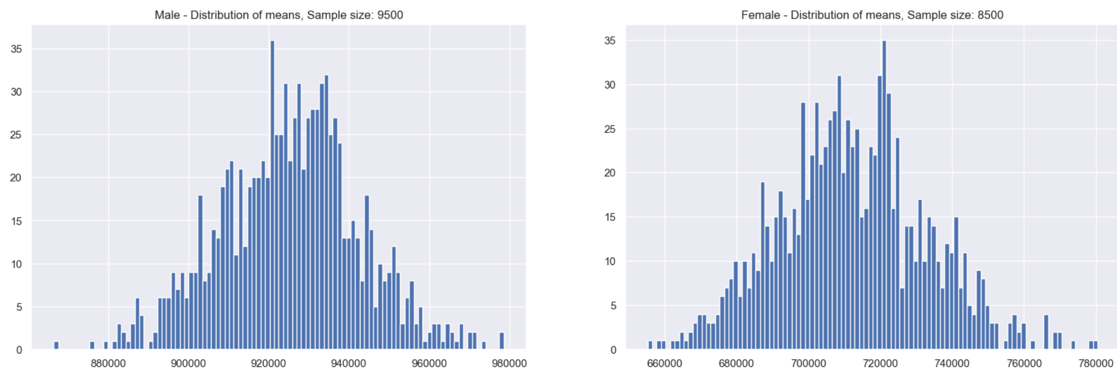
2. Confidence intervals and distribution of the mean of the expenses by female and male customers

[112]:
```
male_df = avg_amt_df[avg_amt_df['Gender']=='M']
female_df = avg_amt_df[avg_amt_df['Gender']=='F']
```

[114]:
```
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)
```

[116]:
```
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: {:.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: 925236.87
Population mean - Mean of sample means of amount spend for Female: 712166.24
```

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

[118]:
```python
male_margin_of_error_clt = 1.64*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 = 1.64*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: (900471.15, 950217.65)
Female confidence interval of means: (679584.51, 744464.28)
```

[120]:
```python
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: (895617.83, 955070.97)
Female confidence interval of means: (673254.77, 750794.02)
```

[122]:
```python
male_margin_of_error_clt = 2.58*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 = 2.58*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: (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

[127]:
```
amt_df = walmart_df.groupby(['User_ID', 'Marital_Status'])[['Purchase']].sum()
avg_amt_df = amt_df.reset_index()
avg_amt_df
```

[127]:

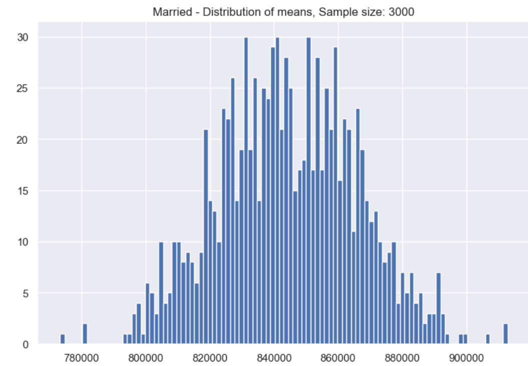
	User_ID	Marital_Status	Purchase
0	1000001	0	334093
1	1000002	0	810472
2	1000003	0	341635
3	1000004	1	206468
4	1000005	1	821001
…	…	…	…
5886	1006036	1	4116058
5887	1006037	0	1119538
5888	1006038	0	90034
5889	1006039	1	590319
5890	1006040	0	1653299

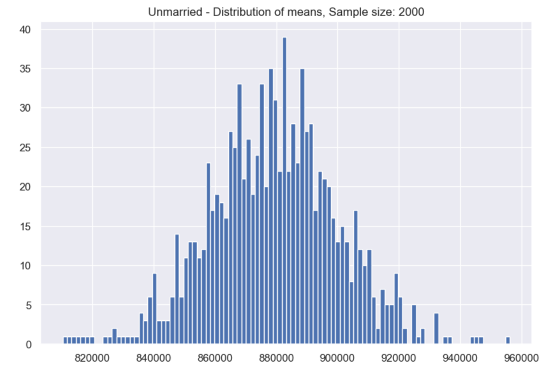
[5891 rows x 3 columns]

[129]:
```
avg_amt_df['Marital_Status'].value_counts()
```

[129]:
```
Marital_Status
0    3417
1    2474
Name: count, dtype: int64
```

[131]:
```
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(married_samp_size, replace=True)['Purchase'].mean()
    unmarried_mean = avg_amt_df[avg_amt_df['Marital_Status']==0].
↪sample(married_samp_size, replace=True)['Purchase'].mean()

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

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






```
Population mean - Mean of sample means of amount spend for Married: 844282.00
Population mean - Mean of sample means of amount spend for Unmarried: 879284.57

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

[133]:
```
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,␣
 ↪lower_lim, upper_lim))
```

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

[135]:
```
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,␣
 ↪lower_lim, upper_lim))
```

```
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

[141]:
```
amt_df = walmart_df.groupby(['User_ID', 'Age'])[['Purchase']].sum()
avg_amt_df = amt_df.reset_index()
avg_amt_df
```

[141]:

	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 x 3 columns]

[143]:
```
avg_amt_df['Age'].value_counts()
```

[143]:
```
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
```

[145]:
```
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_size,␣
↪replace=True)['Purchase'].mean()
        all_means[age_interval].append(mean)
```

[147]:
```
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})".
↪format(val, lower_lim, upper_lim))
```

```
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)
```

[149]:
```
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})".
↪format(val, lower_lim, upper_lim))
```

```
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)
```

```
[151]: 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})".
 ↪format(val, lower_lim, upper_lim))
```

```
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.

Actionable Insights

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)

- 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)

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

- 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)

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

- 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)

0.1.2 Recommendations

Men spent more money than women, So company should focus on retaining the female customers and getting more female customers.

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.

Unmarried customers spend more money than married customers, So company should focus on acquisition of married customers.

Customers in the age 25-40 spend more money than the others, So company should focus on acquisition of customers of other age groups.

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.

[ ]:

```

```