Business Case: Walmart - Confidence Interval and CLT

Business Problem:

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.

Dataset:

The company collected the transactional data of customers who purchased products from the Walmart Stores. The dataset has the following features:

Variable	Description
User_ID:	User ID
Product_ID:	Product ID
Gender:	Sex of User
Age:	Age in bins
Occupation:	Occupation(Masked)
City_Category:	Category of the City (A,B,C)
StayInCurrentCityYears:	Number of years stay in current city
Marital_Status:	Marital Status
ProductCategory:	Product Category (Masked)
Purchase:	Purchase Amount

In [2]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import missingno as msno
sns.set_theme(style="darkgrid")
from scipy.stats import t
from tabulate import tabulate
```

In [3]:

```
df = pd.read_csv(r"https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/2
```

In [4]:

```
df.head()
```

Out[4]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years
0	1000001	P00069042	F	0-17	10	A	2
1	1000001	P00248942	F	0-17	10	A	2
2	1000001	P00087842	F	0-17	10	A	2
3	1000001	P00085442	F	0-17	10	A	2
4	1000002	P00285442	M	55+	16	C	4+

1. Analyzing Basic Metrics.

In [5]:

```
print(f"Number of rows: {df.shape[0]:,} \nNumber of columns: {df.shape[1]}",'\n')
print(df.info())
```

```
Number of columns: 10

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067
Data columns (total 10 columns):
 #   Column                      Non-Null Count   Dtype 
---  ------                      --------------   ----- 
 0   User_ID                     550068 non-null  int64 
 1   Product_ID                  550068 non-null  object
 2   Gender                      550068 non-null  object
 3   Age                         550068 non-null  object
 4   Occupation                  550068 non-null  int64 
 5   City_Category               550068 non-null  object
 6   Stay_In_Current_City_Years  550068 non-null  object
 7   Marital_Status              550068 non-null  int64 
 8   Product_Category            550068 non-null  int64 
 9   Purchase                    550068 non-null  int64 
dtypes: int64(5), object(5)
memory usage: 42.0+ MB
None
```

Changing the data types of - Occupation, Marital_Status, Product_Category

In [6]:

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

In [7]:

```
df.dtypes
```

Out[7]:

```
User_ID                         int64
Product_ID                     object
Gender                         object
Age                            object
Occupation                     object
City_Category                  object
Stay_In_Current_City_Years     object
Marital_Status                 object
Product_Category               object
Purchase                        int64
dtype: object
```

In [8]:

```
df.memory_usage()
```

Out[8]:

```
Index                              128
User_ID                        4400544
Product_ID                     4400544
Gender                         4400544
Age                            4400544
Occupation                     4400544
City_Category                  4400544
Stay_In_Current_City_Years     4400544
Marital_Status                 4400544
Product_Category               4400544
Purchase                       4400544
dtype: int64
```

In [9]:

```
df.describe()
```

Out[9]:

	User_ID	Purchase
count	5.500680e+05	550068.000000
mean	1.003029e+06	9263.968713
std	1.727592e+03	5023.065394
min	1.000001e+06	12.000000
25%	1.001516e+06	5823.000000
50%	1.003077e+06	8047.000000
75%	1.004478e+06	12054.000000
max	1.006040e+06	23961.000000

Observations

- There are no missing values in the dataset.
- Purchase amount might have outliers.

---

2. Missing Value & Outlier Detection.

2.1 Missing Value

In [10]:

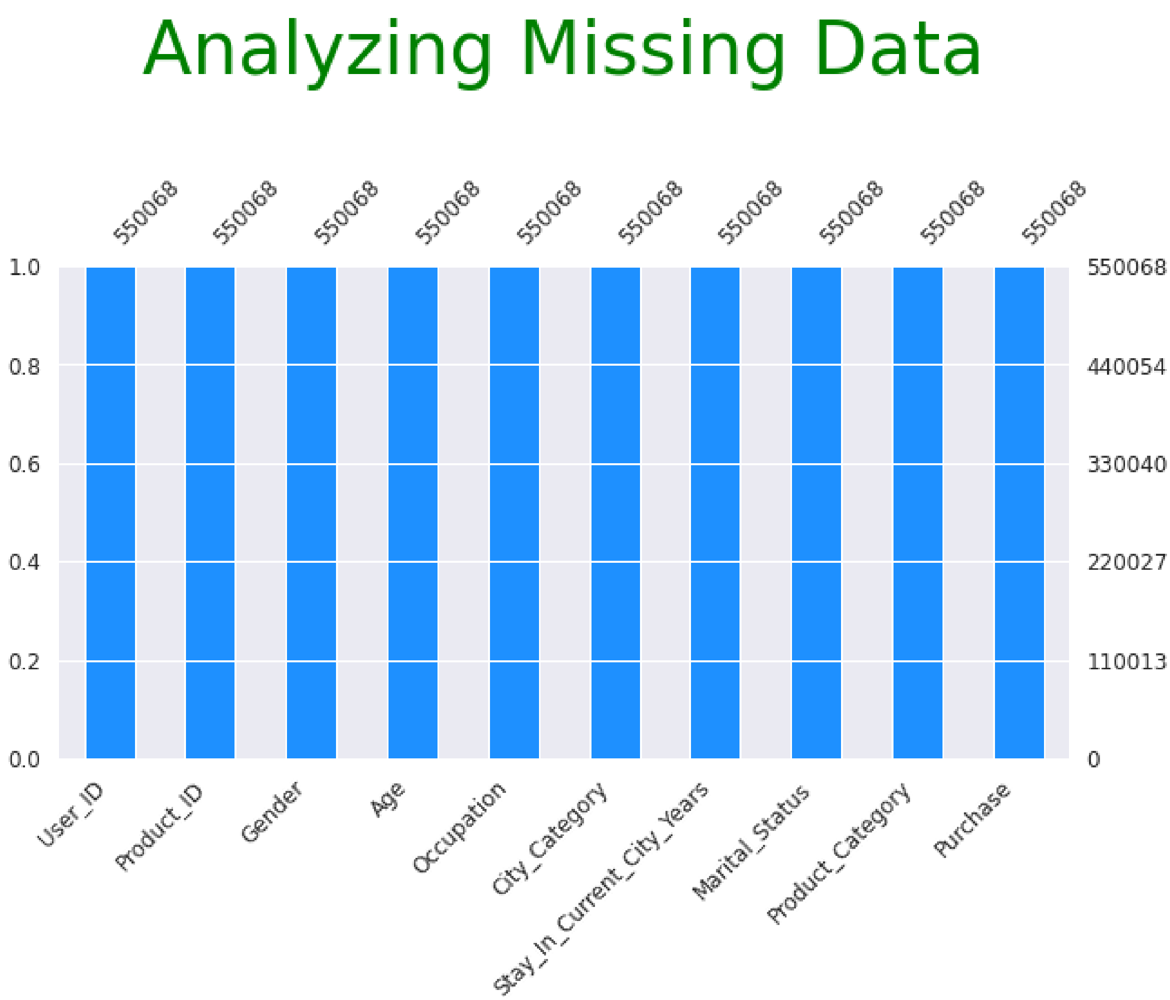
```
# checking null values
df.isnull().sum()/len(df)*100
```

Out[10]:

```
User_ID                       0.0
Product_ID                    0.0
Gender                        0.0
Age                           0.0
Occupation                    0.0
City_Category                 0.0
Stay_In_Current_City_Years    0.0
Marital_Status                0.0
Product_Category              0.0
Purchase                      0.0
dtype: float64
```

In [11]:

```
msno.bar(df, color="dodgerblue", sort="ascending", figsize=(10,5), fontsize=12);
plt.title("\nAnalyzing Missing Data\n", fontsize=40, color="green")
plt.show()
```



In [12]:

```
df.describe()
```

Out[12]:

	User_ID	Purchase
count	5.500680e+05	550068.000000
mean	1.003029e+06	9263.968713
std	1.727592e+03	5023.065394
min	1.000001e+06	12.000000
25%	1.001516e+06	5823.000000
50%	1.003077e+06	8047.000000
75%	1.004478e+06	12054.000000
max	1.006040e+06	23961.000000

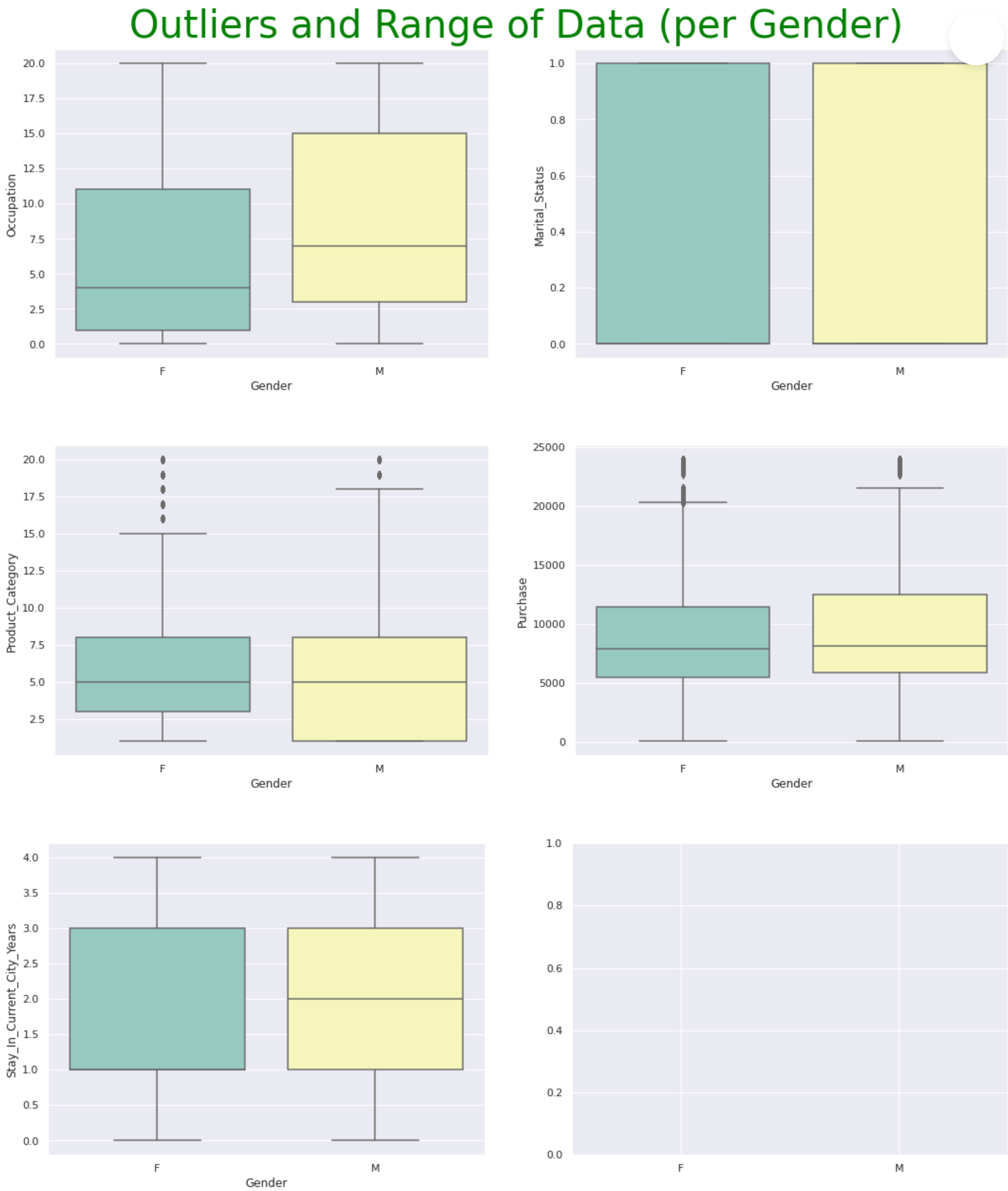
2.2 Outliers Detection

In [13]:

```
#df1.drop(['User_ID','Product_ID'], axis=1, inplace=True)
df['Age']=(df['Age'].str.strip('+'))
df['Stay_In_Current_City_Years']=(df['Stay_In_Current_City_Years'].str.strip('+').astyp
```

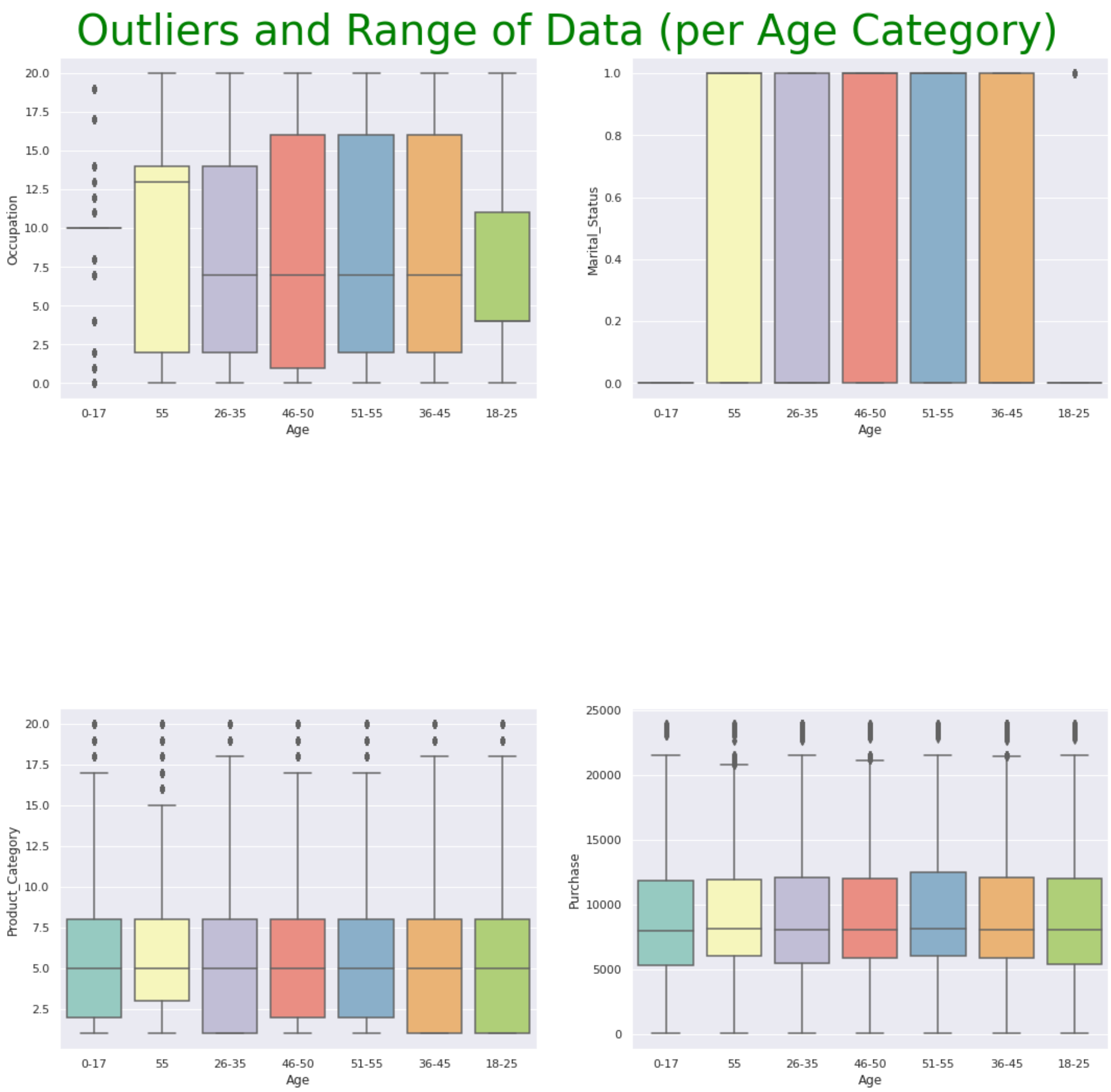
In [14]:

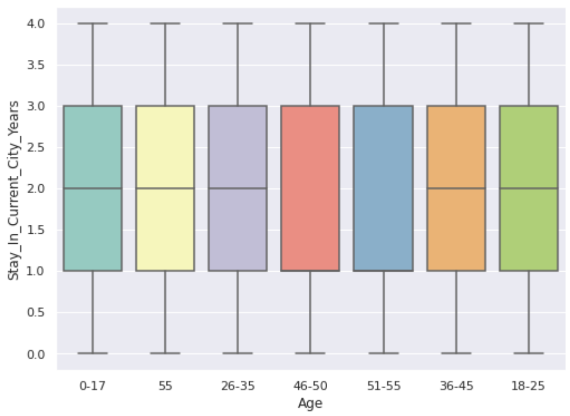
```
for col, r, c in [['Occupation', 0, 0], ['Marital_Status', 0, 1], ['Product_Category',
    if c == 0:
        fig, axes = plt.subplots(1, 2, sharex=True, figsize=(18,6))
    sns.boxplot(data=df, y=col, ax=axes[c], x='Gender',palette='Set3')
    if c == 1:
        if r == 0:
            fig.suptitle("Outliers and Range of Data (per Gender)", fontsize=40, color=
        plt.show()
```

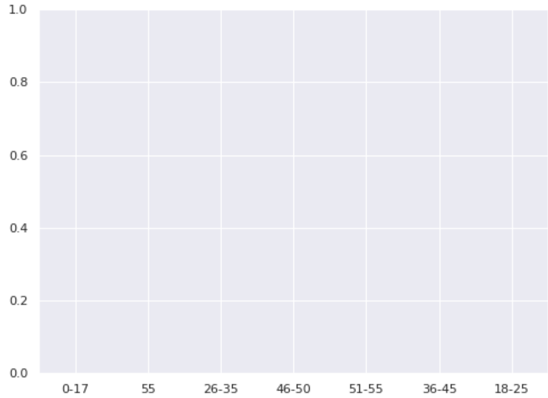


In [15]:

```
for col, r, c in [['Occupation', 0, 0], ['Marital_Status', 0, 1], ['Product_Category',
    if c == 0:
        fig, axes = plt.subplots(1, 2, sharex=True, figsize=(18,6))
    sns.boxplot(data=df, y=col, ax=axes[c], x='Age',palette='Set3')
    if c == 1:
        if r == 0:
            fig.suptitle("Outliers and Range of Data (per Age Category)", fontsize=40,
        plt.show()
```







3. Value Counts and Unique Attributes.

In [16]:

```
df.columns
# Finding Unique values from all columns in dataset
print("\nTotal unique values", end ='\n\n')
df_dict = {}
col = []
total_count = []
for i in df.columns:
    col.append(i)
    total_count.append(df[i].nunique())
df_dict = {'Column Names':col, 'Total count of Unique records':total_count}
print(tabulate(df_dict, headers='keys', tablefmt='fancy_grid',showindex =range(1,df.sha
```

```
Total unique values
```

	Column Names	Total count of Unique records
1	User_ID	5891
2	Product_ID	3631
3	Gender	2
4	Age	7
5	Occupation	21
6	City_Category	3
7	Stay_In_Current_City_Years	5
8	Marital_Status	2
9	Product_Category	20
10	Purchase	18105

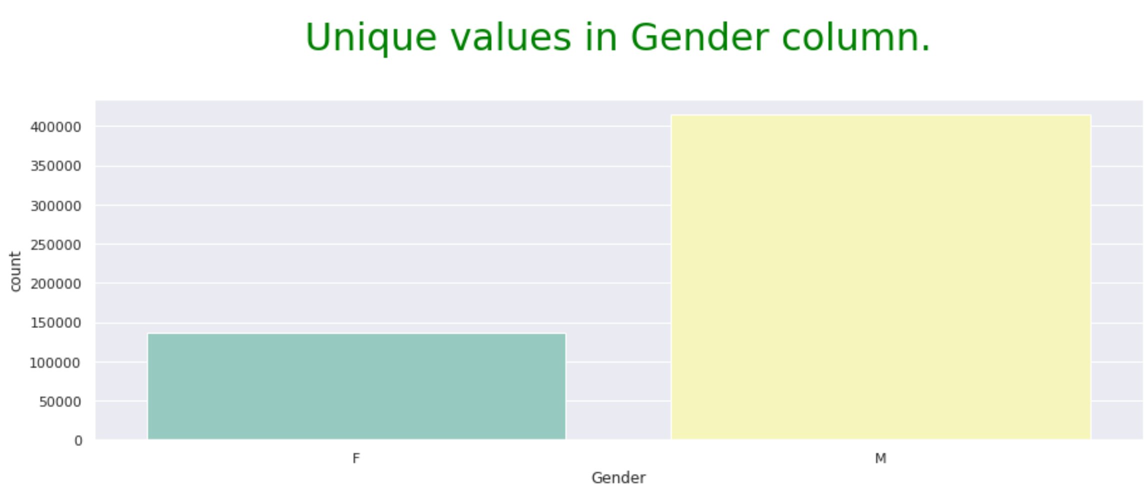
In [17]:

```
for i in df.columns:
    print("\nTotal unique values for",'\033[1m'+str(i)+'\033[0m', end ='\n\n')
    print(df[i].value_counts().reset_index())
    print()
```

```
Total unique values for User_ID

        index  User_ID
0     1001680     1026
1     1004277      979
2     1001941      898
3     1001181      862
4     1000889      823
...       ...      ...
5886  1002690        7
5887  1002111        7
5888  1005810        7
5889  1004991        7
5890  1000708        6

[5891 rows x 2 columns]
```

In [18]:

```
for column in df.columns[2:-1]:
    fig, axes = plt.subplots(figsize=(15,5))
    sns.countplot(data=df, x=column,palette='Set3')
    plt.title(f"\nUnique values in {column} column.\n", fontsize=30, color="green")
    plt.show()
```



Value_counts for the following:

- Age
- City_Category

- Gender
- Marital_Status
- Occupation
- Product_Category
- Stay_In_Current_City_Years

In [19]:

```
categorical_cols = ['Gender', 'Age', 'Occupation', 'City_Category', 'Stay_In_Current_Ci
df[categorical_cols].melt().groupby(['variable', 'value'])[['value']].count()/len(df)
```

Out[19]:

		value
variable	**value**	
Age	**0-17**	0.027455
	18-25	0.181178
	26-35	0.399200
	36-45	0.199999
	46-50	0.083082
	51-55	0.069993
	55	0.039093
City_Category	**A**	0.268549
	B	0.420263
	C	0.311189
Gender	**F**	0.246895
	M	0.753105
Marital_Status	**0**	0.590347
	1	0.409653
Occupation	**0**	0.126599
	1	0.086218
	2	0.048336
	3	0.032087
	4	0.131453
	5	0.022137
	6	0.037005
	7	0.107501
	8	0.002811
	9	0.011437
	10	0.023506
	11	0.021063
	12	0.056682
	13	0.014049
	14	0.049647
	15	0.022115
	16	0.046123
	17	0.072796

variable	value	value
	18	0.012039
	19	0.015382
	20	0.061014
Product_Category	1	0.255201
	2	0.043384
	3	0.036746
	4	0.021366
	5	0.274390
	6	0.037206
	7	0.006765
	8	0.207111
	9	0.000745
	10	0.009317
	11	0.044153
	12	0.007175
	13	0.010088
	14	0.002769
	15	0.011435
	16	0.017867
	17	0.001051
	18	0.005681
	19	0.002914
	20	0.004636
Stay_In_Current_City_Years	0	0.135252
	1	0.352358
	2	0.185137
	3	0.173224
	4	0.154028

Observations

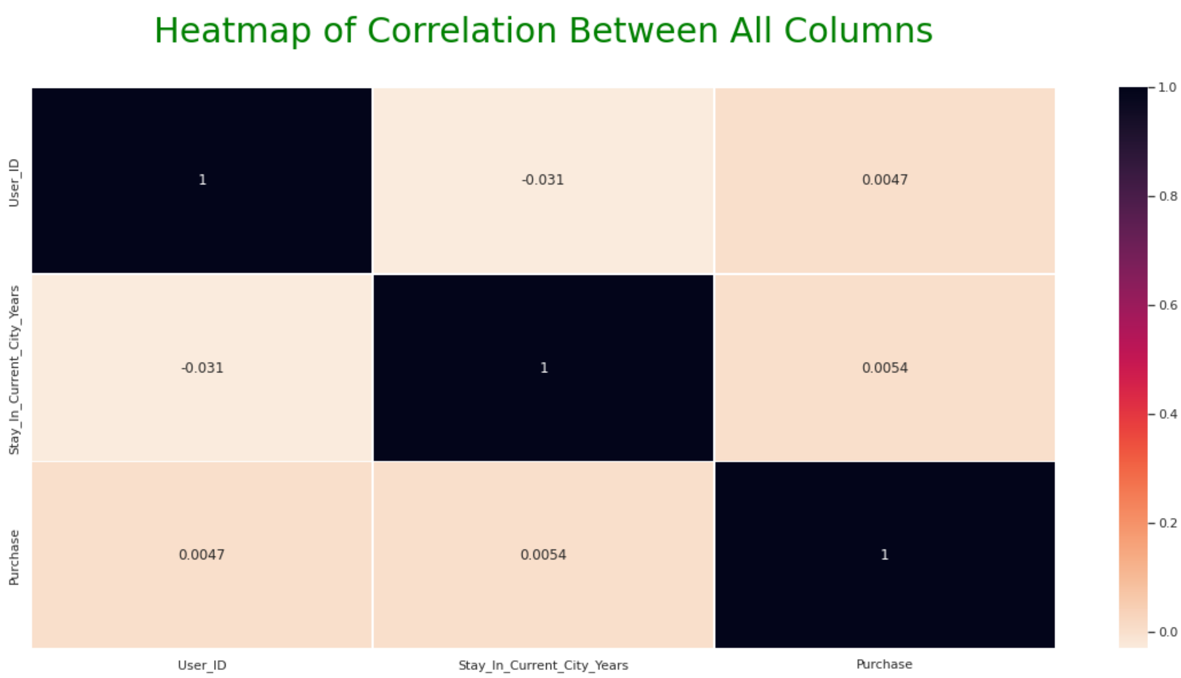
- ~ 80% of the users are between the age 18-50 (40%: 26-35, 18%: 18-25, 20%: 36-45)
- 75% of the users are `Male` and 25% are `Female`
- 60% Single, 40% Married
- 35% Staying in the city from 1 year, 18% from 2 years, 17% from 3 years
- Total of 20 product categories are there
- There are 20 differnent types of occupations in the city

4. Business Insights based on Non- Graphical and Visual Analysis.

Type *Markdown* and LaTeX: α^2

In [20]:

```
fig, ax = plt.subplots(figsize=(20,9))
sns.heatmap(df.corr(), linewidths=.5, cmap=sns.cm.rocket_r, annot=True, ax=ax)
plt.title("\nHeatmap of Correlation Between All Columns\n", fontsize=30, color="green")
plt.show()
```

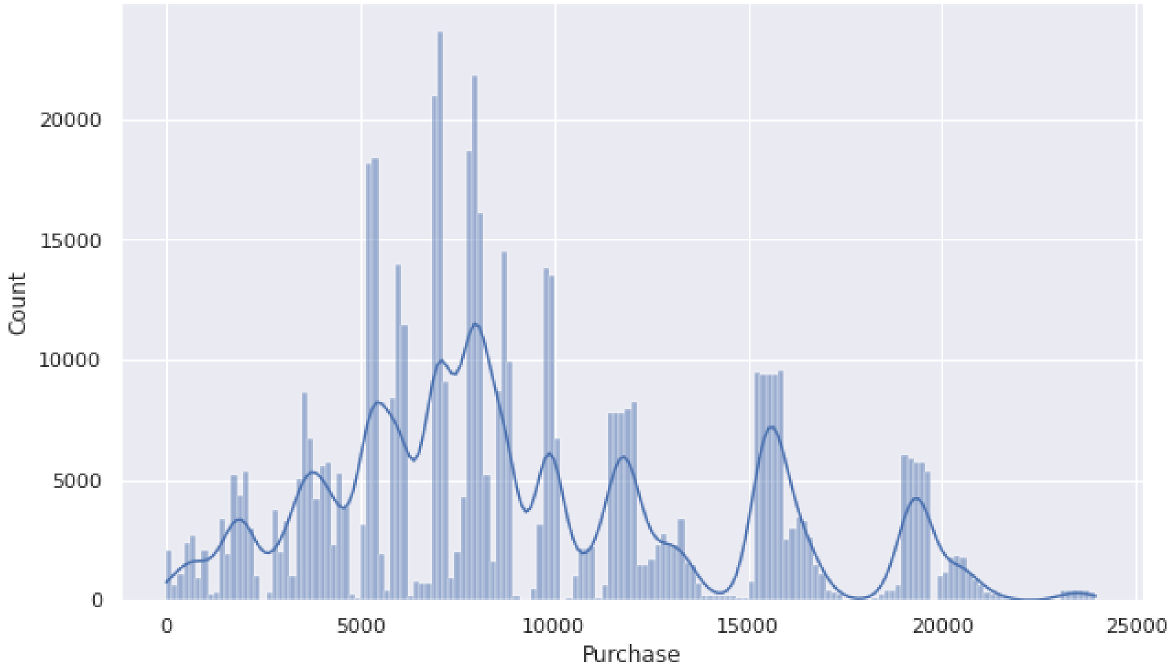


4.1 Univariate Analysis

Understanding the distribution of data and detecting outlies for continuous variables

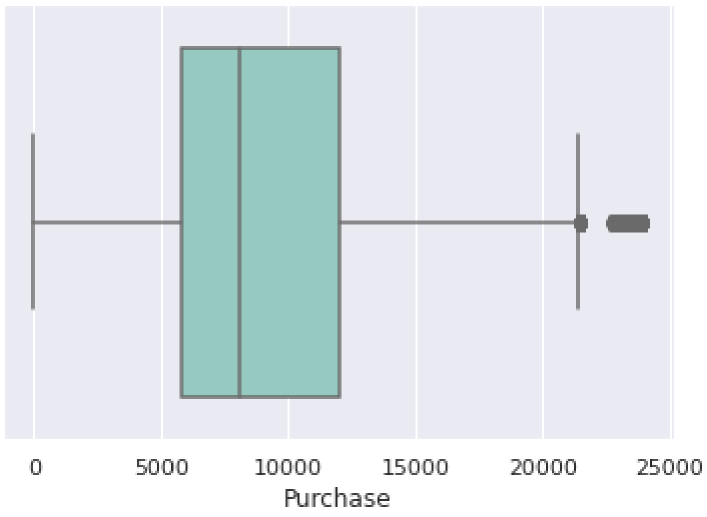
In [21]:

```
plt.figure(figsize=(10, 6))
sns.histplot(data=df, x='Purchase', kde=True, palette='Set3')
plt.show()
```



In [22]:

```
sns.boxplot(data=df, x='Purchase', orient='h',palette='Set3')
plt.show()
```



Observation

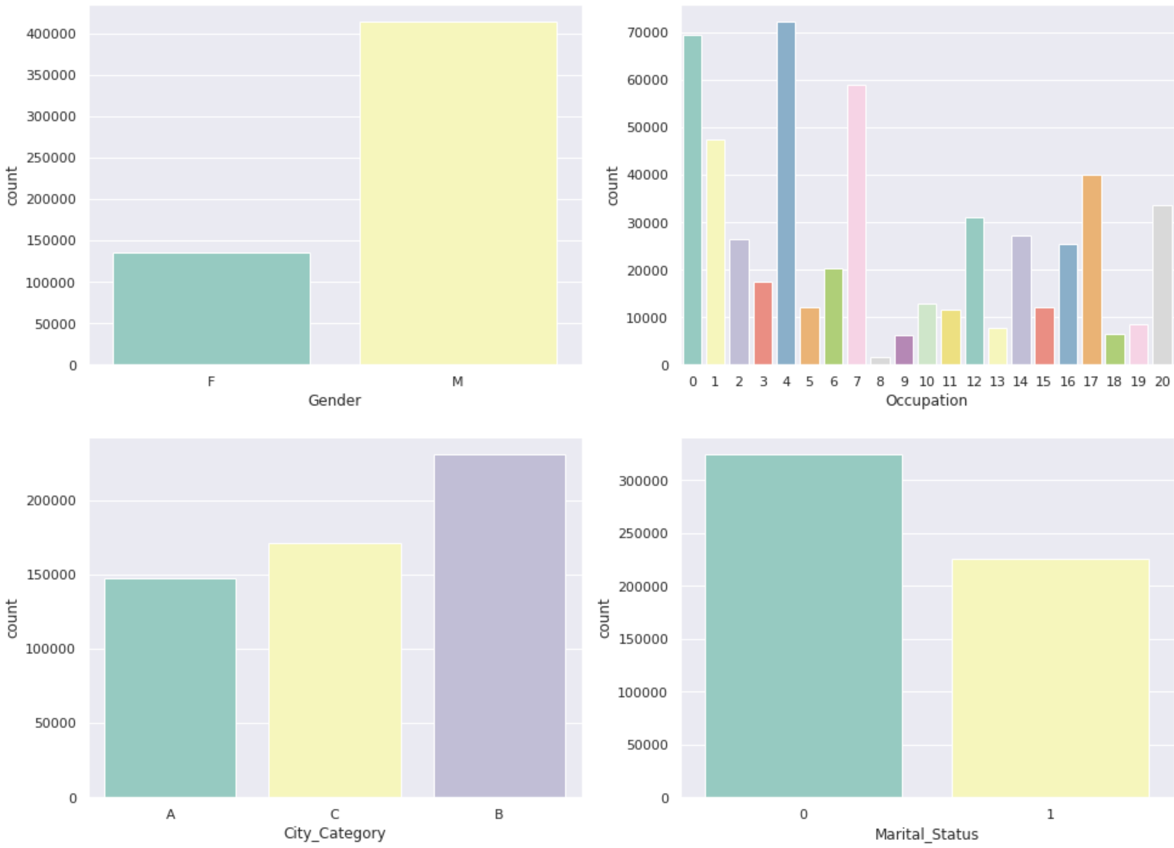
- Purchase is having outliers

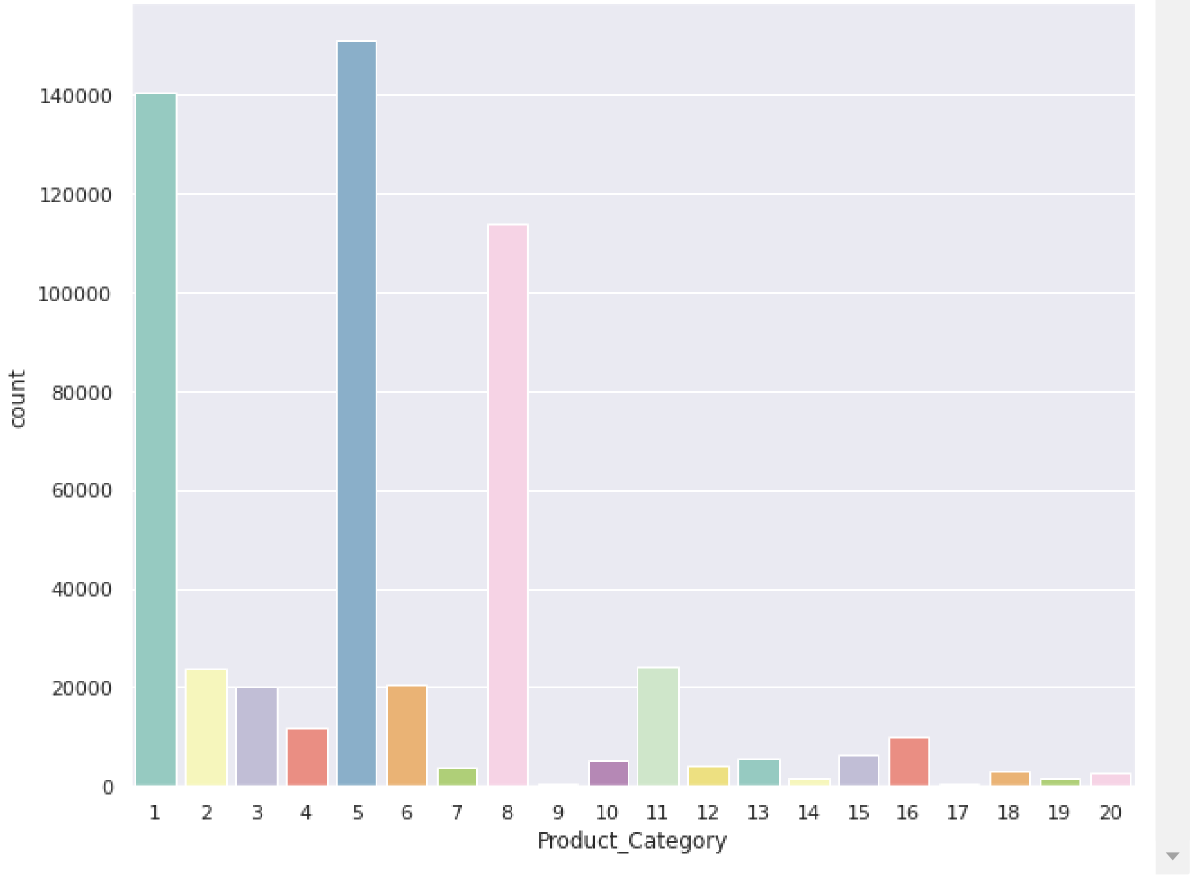
Understanding the distribution of data for the categorical variables

- Gender
- Age
- Occupation
- City_Category
- Stay_In_Current_City_Years
- Marital_Status
- Product_Category

In [23]:

```
categorical_cols = ['Gender', 'Occupation','City_Category','Marital_Status','Product_Ca

fig, axs = plt.subplots(nrows=2, ncols=2, figsize=(16, 12))
sns.countplot(data=df, x='Gender', ax=axs[0,0],palette='Set3')
sns.countplot(data=df, x='Occupation', ax=axs[0,1],palette='Set3')
sns.countplot(data=df, x='City_Category', ax=axs[1,0],palette='Set3')
sns.countplot(data=df, x='Marital_Status', ax=axs[1,1],palette='Set3',)
plt.show()

plt.figure(figsize=(10, 8))
sns.countplot(data=df, x='Product_Category',palette='Set3')
plt.show()
```



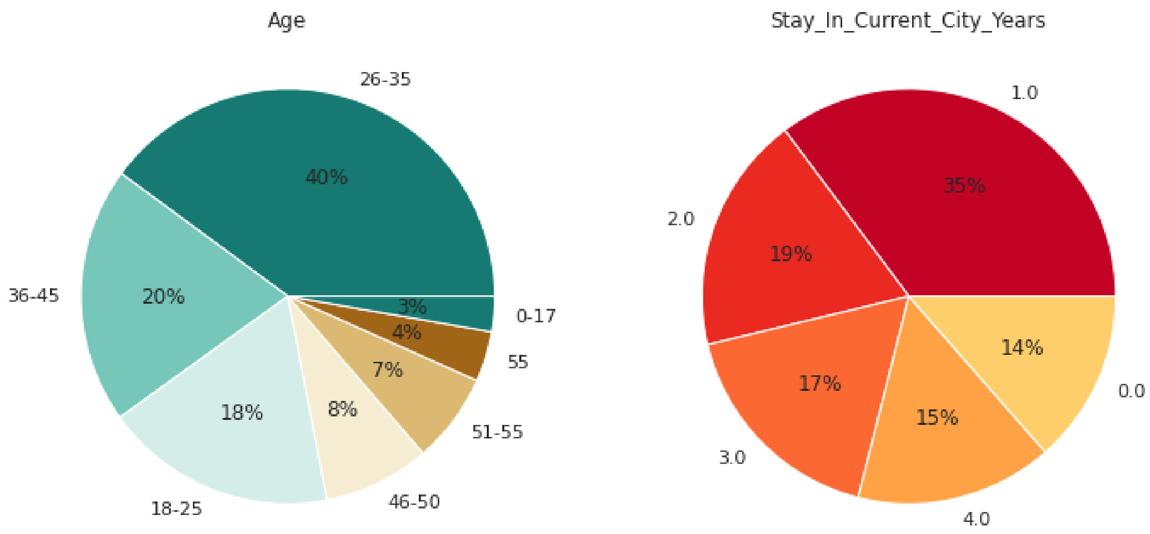


Observations

- Most of the users are **Male**
- There are 20 different types of **Occupation** and **Product_Category**
- More users belong to **B City_Category**
- More users are **Single** as compare to **Married**
- **Product_Category - 1, 5, 8, & 11** have highest purchasing frequency.

In [24]:

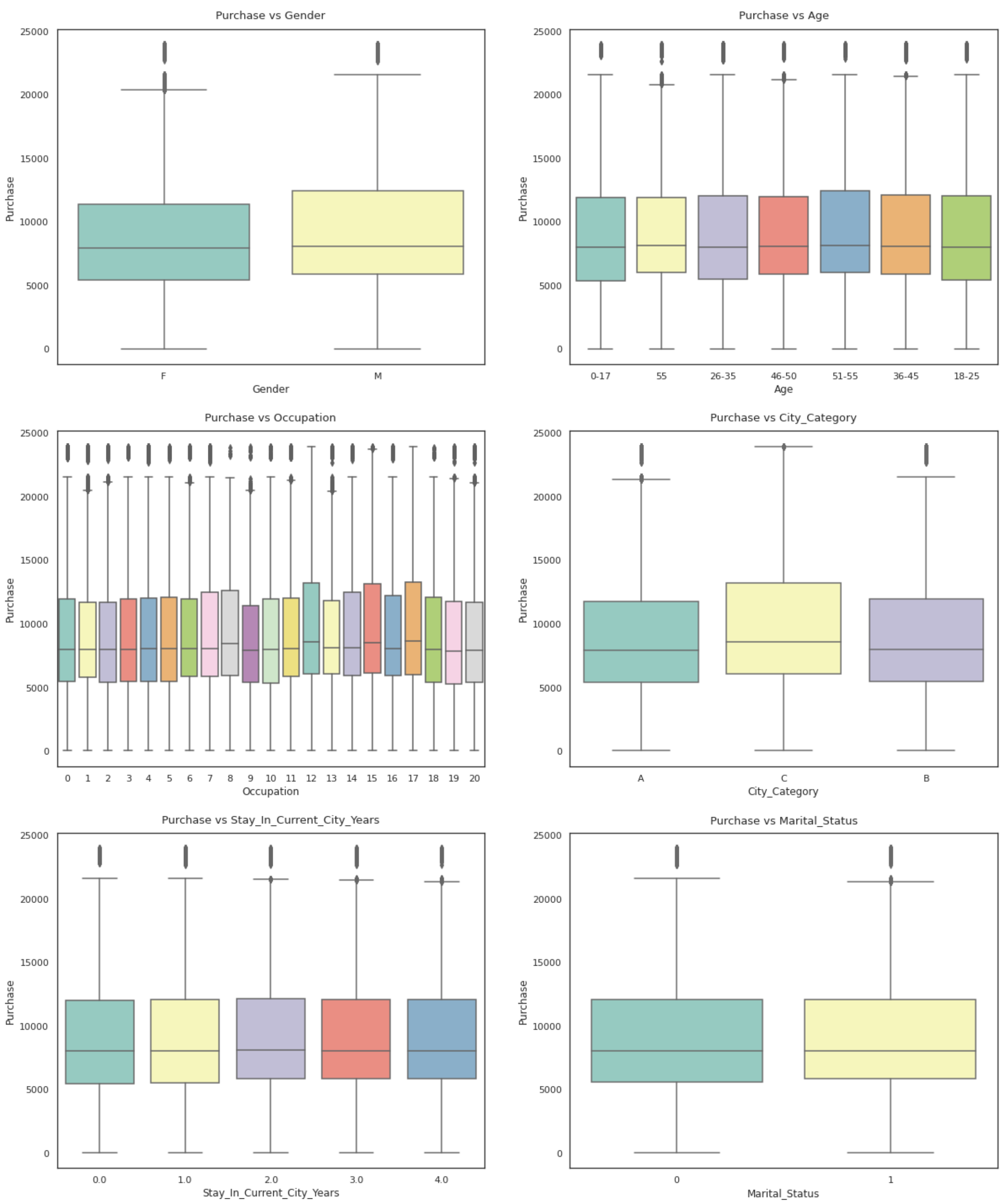
```
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(12, 8))

data = df['Age'].value_counts(normalize=True)*100
palette_color = sns.color_palette('BrBG_r')
axs[0].pie(x=data.values, labels=data.index, autopct='%.0f%%', colors=palette_color)
axs[0].set_title("Age")

data = df['Stay_In_Current_City_Years'].value_counts(normalize=True)*100
palette_color = sns.color_palette('YlOrRd_r')
axs[1].pie(x=data.values, labels=data.index, autopct='%.0f%%', colors=palette_color)
axs[1].set_title("Stay_In_Current_City_Years")


plt.show()
```

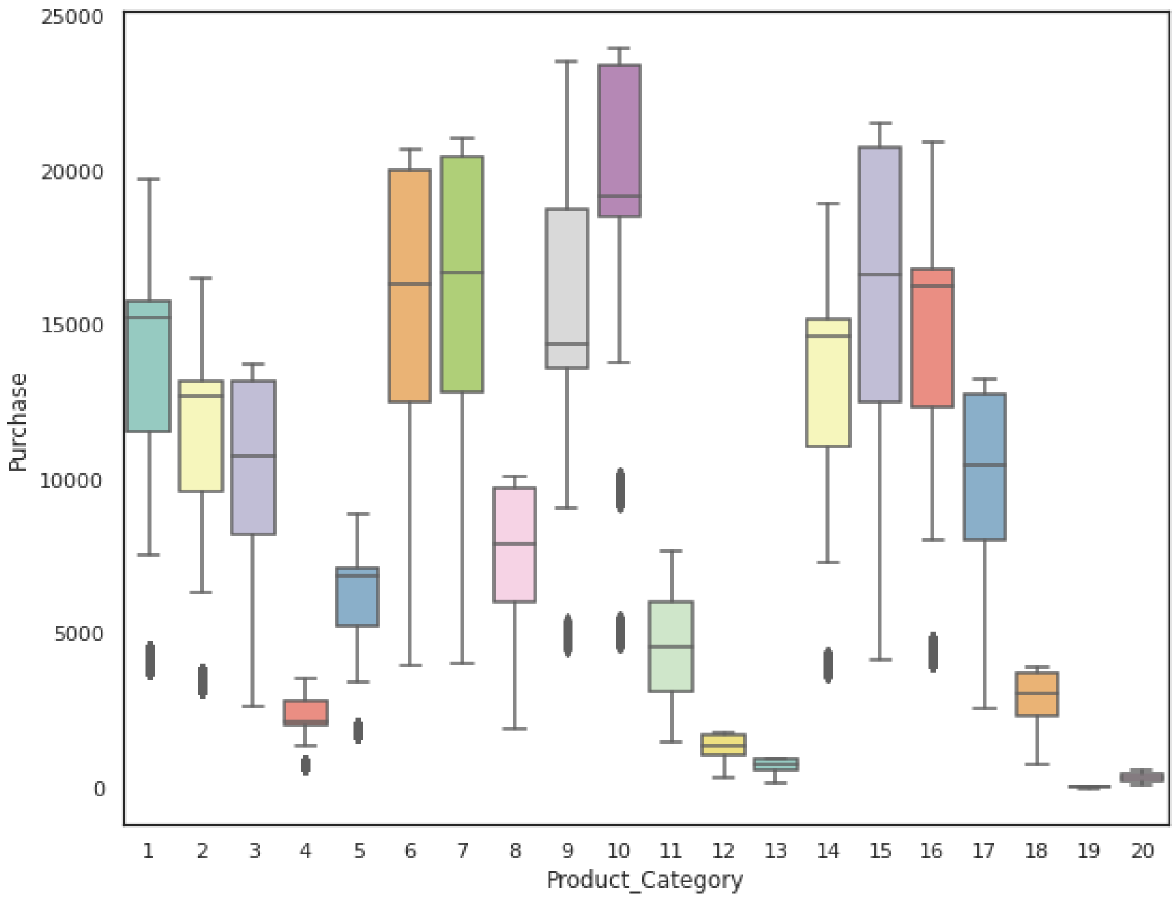


4.2 Bi-variate Analysis

In [25]:

```python
attrs = ['Gender', 'Age', 'Occupation', 'City_Category', 'Stay_In_Current_City_Years',
sns.set_style("white")

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=df, y='Purchase', x=attrs[count], ax=axs[row, col], palette='S
        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=df, y='Purchase', x=attrs[-1], palette='Set3')
plt.show()
```



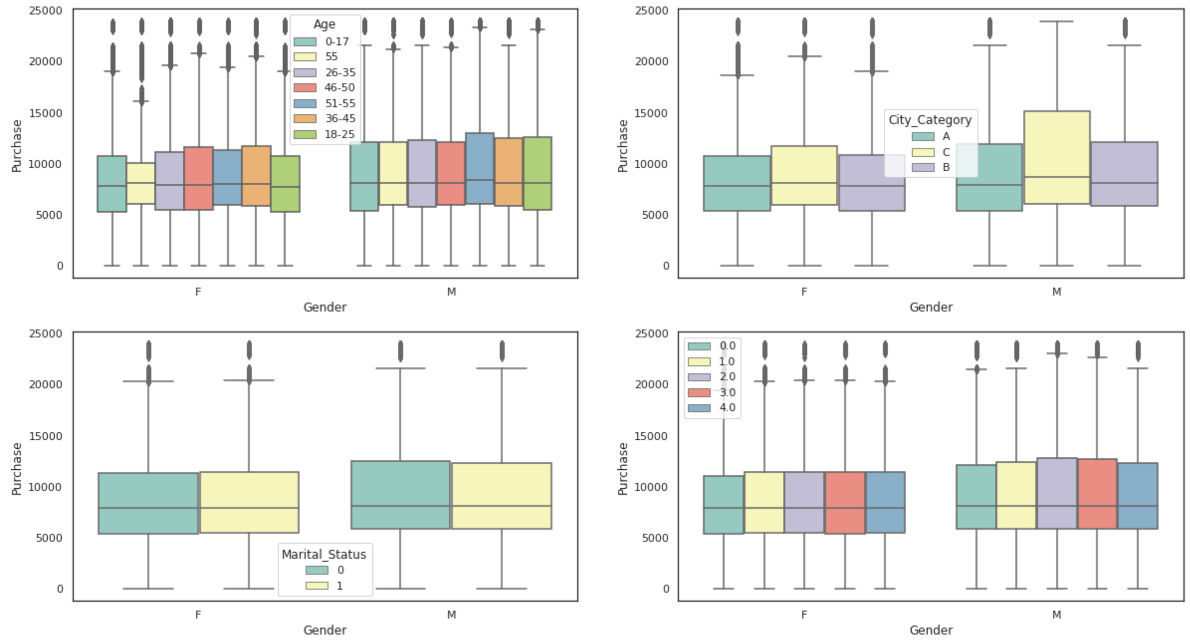


25000
20000
15000
10000
5000
0
Purchase
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Product_Category

4.3 Multivariate Analysis

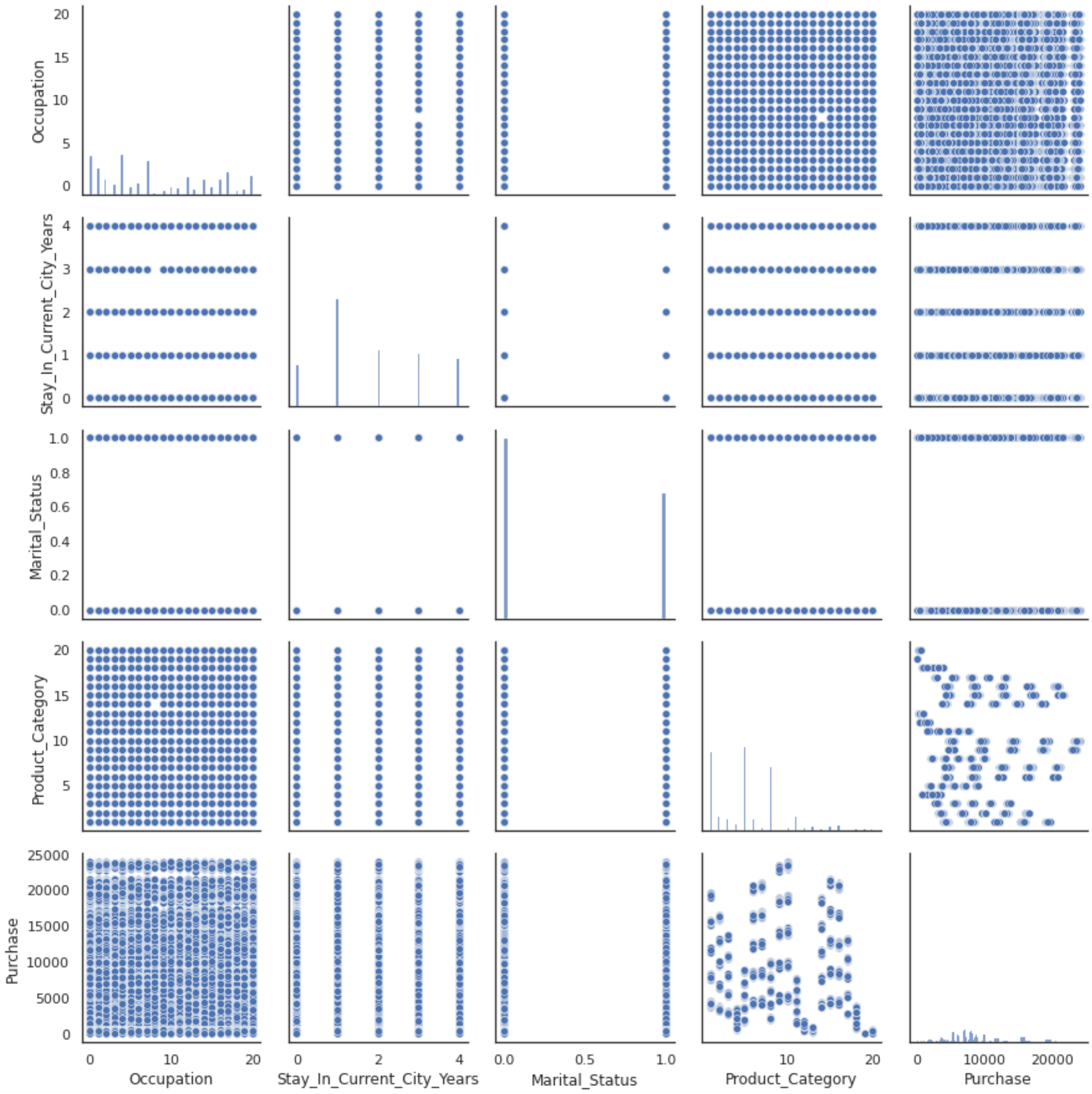
In [26]:

```
fig, axs = plt.subplots(nrows=2, ncols=2, figsize=(20, 6))
fig.subplots_adjust(top=1.5)
sns.boxplot(data=df, y='Purchase', x='Gender', hue='Age', palette='Set3', ax=axs[0,0])
sns.boxplot(data=df, y='Purchase', x='Gender', hue='City_Category', palette='Set3', ax=

sns.boxplot(data=df, y='Purchase', x='Gender', hue='Marital_Status', palette='Set3', ax
sns.boxplot(data=df, y='Purchase', x='Gender', hue='Stay_In_Current_City_Years', palett
axs[1,1].legend(loc='upper left')

plt.show()
```



In [27]:

```
sns.pairplot(df[['Occupation','Stay_In_Current_City_Years','Marital_Status','Product_Ca
plt.show()
```



5. Confidence intervals for Male and Female spendings.

Average amount spend per customer for Male and Female

In [28]:

```
amt_df = df.groupby(['User_ID', 'Gender'])[['Purchase']].sum()
amt_df = amt_df.reset_index()
amt_df
```

Out[28]:

	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 [29]:

```
# Gender wise value counts
amt_df['Gender'].value_counts()
```

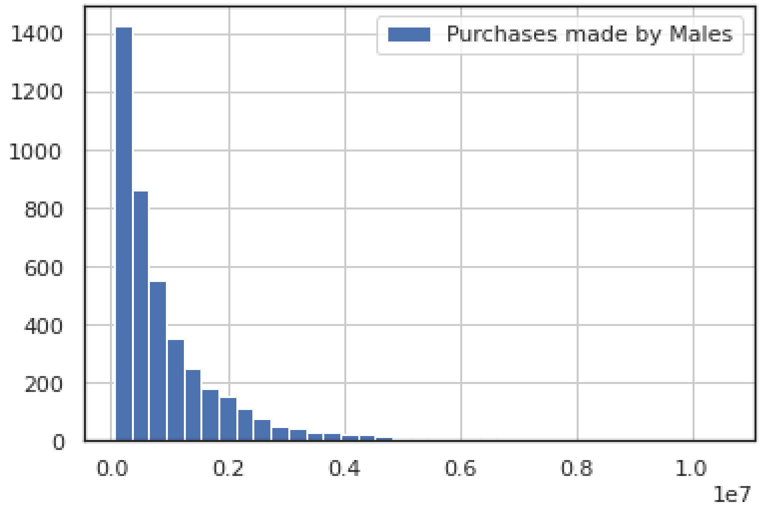
Out[29]:

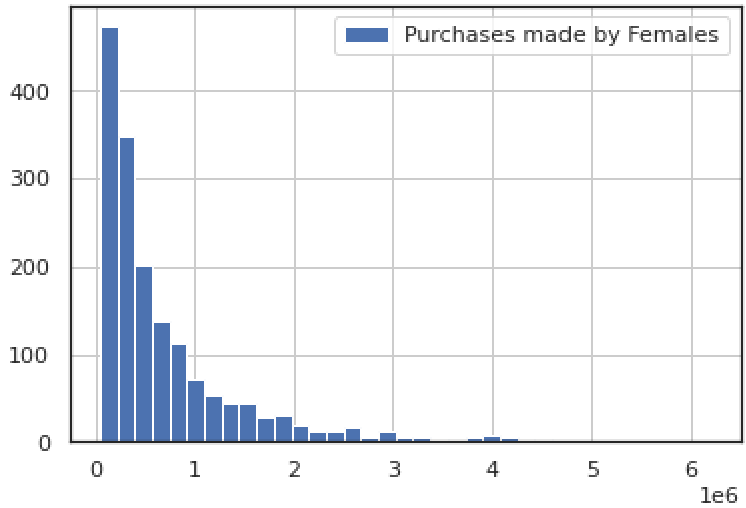
```
M    4225
F    1666
Name: Gender, dtype: int64
```

In [30]:

```
print('Histogram of average amount spend for each customer - Male & Female')
amt_df[amt_df['Gender']=='M']['Purchase'].hist(bins=35)
plt.legend(['Purchases made by Males'])
plt.show()
amt_df[amt_df['Gender']=='F']['Purchase'].hist(bins=35)
plt.legend(['Purchases made by Females'])
plt.show()
```

```
Histogram of average amount spend for each customer - Male & Female
```





In [31]:

```
male_avg = amt_df[amt_df['Gender']=='M']['Purchase'].mean()
female_avg = amt_df[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
```

Observation

1. Male customers spend more money than female customers

In [32]:

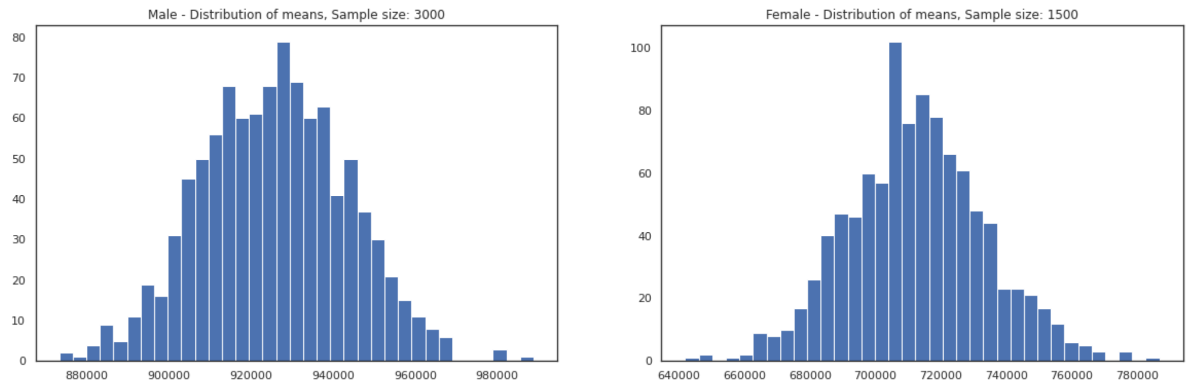
```
male_df = amt_df[amt_df['Gender']=='M']
female_df = amt_df[amt_df['Gender']=='F']
```

In [33]:

```
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)
```

In [34]:

```
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()
```



In [35]:

```
print("Population mean - Mean of sample means of amount spend for Male: {:.2f}".format(
print("Population mean - Mean of sample means of amount spend for Female: {:.2f}".forma

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

```
Population mean - Mean of sample means of amount spend for Male: 925614.84
Population mean - Mean of sample means of amount spend for Female: 712439.18

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

Observation

Now using the **Central Limit Theorem** for the **population** we can say that:

1. Average amount spend by male customers is **9,85,830.10**
2. Average amount spend by female customers is **8,07,370.73**

In [36]:

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

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

In [37]:

```python
gendermap = {'M':'Male', 'F':'Female'}
for gender in ['M', 'F']:
    data = df[df.Gender==gender]['Purchase']
    print("\nGender: ", gendermap[gender])
    m = data.mean()
    s = data.std()
    dof = len(data)-1
    for confidence in [0.90, 0.95, 0.99]:
        t_crit = np.abs(t.ppf((1-confidence)/2,dof))
        print(f"{confidence*100}% Confidence Interval:", (m-s*t_crit/np.sqrt(len(data))
```

```
Gender:  Male
90.0% Confidence Interval: (9424.512468203842, 9450.539612740688)
95.0% Confidence Interval: (9422.019402055814, 9453.032678888716)
99.0% Confidence Interval: (9417.14682877079, 9457.90525217374)

Gender:  Female
90.0% Confidence Interval: (8713.287689504074, 8755.843840806878)
95.0% Confidence Interval: (8709.21132117373, 8759.92020913722)
99.0% Confidence Interval: (8701.24420611832, 8767.887324192632)
```

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. Confidence intervals for spendings of Married and Unmarried individuals.

In [38]:

```
amt_df = df.groupby(['User_ID', 'Marital_Status'])[['Purchase']].sum()
amt_df = amt_df.reset_index()
amt_df
```

Out[38]:

	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 [39]:

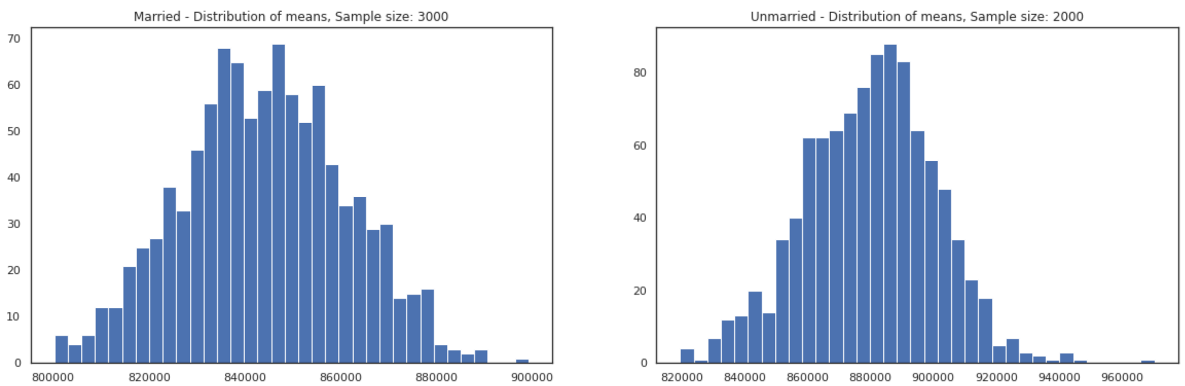
```
amt_df['Marital_Status'].value_counts()
```

Out[39]:

```
0    3417
1    2474
Name: Marital_Status, dtype: int64
```

In [40]:

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

for _ in range(num_repitions):
    marid_mean = amt_df[amt_df['Marital_Status']==1].sample(marid_samp_size, replace=Tr
    unmarid_mean = amt_df[amt_df['Marital_Status']==0].sample(unmarid_sample_size, rep]

    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}".forr
print("Population mean - Mean of sample means of amount spend for Unmarried: {:.2f}".fc

print("\nMarried - Sample mean: {:.2f} Sample std: {:.2f}".format(amt_df[amt_df['Marita
print("Unmarried - Sample mean: {:.2f} Sample std: {:.2f}".format(amt_df[amt_df['Marita
```




```
Population mean - Mean of sample means of amount spend for Married: 844070.9
6
Population mean - Mean of sample means of amount spend for Unmarried: 87990
7.83

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

Observation

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)**

In [41]:

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

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

    new_df = amt_df[amt_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, u
```

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

In [42]:

```python
statusmap = {0:'Unmarried', 1:'Married'}
for status in [0, 1]:
    data = df[df.Marital_Status==status]['Purchase']
    print("\nMarital Status: ", statusmap[status])
    m = data.mean()
    s = data.std()
    dof = len(data)-1
    for confidence in [0.90, 0.95, 0.99]:
        t_crit = np.abs(t.ppf((1-confidence)/2,dof))
        print(f"{confidence*100}% Confidence Interval:", (m-s*t_crit/np.sqrt(len(data))
```

```
Marital Status:  Unmarried
90.0% Confidence Interval: (9251.396344426079, 9280.418893416934)
95.0% Confidence Interval: (9248.616353737028, 9283.198884105985)
99.0% Confidence Interval: (9243.182995563593, 9288.63224227942)

Marital Status:  Married
90.0% Confidence Interval: (9243.79064243542, 9278.558505729326)
95.0% Confidence Interval: (9240.460315792989, 9281.888832371758)
99.0% Confidence Interval: (9233.951339733765, 9288.397808430982)
```

---

7. Confidence intervals for spendings of different Age groups.

Calculating the average amount spent by Age

In [43]:

```
amt_df = df.groupby(['User_ID', 'Age'])[['Purchase']].sum()
amt_df = amt_df.reset_index()
amt_df
```

Out[43]:

	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 [44]:

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

Out[44]:

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

In [45]:

```
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 = amt_df[amt_df['Age']==age_interval].sample(sample_size, replace=True)['P
        all_means[age_interval].append(mean)
```

In [46]:

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

    new_df = amt_df[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, l
```

```
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 [47]:

```python
ages = df['Age'].unique()
for age in ages:
    print("\nAge group: ", age)
    data = Unmarried = df[df.Age==age]['Purchase']
    m = Unmarried.mean()
    s = Unmarried.std()
    dof = len(data)-1
    for confidence in [0.90, 0.95, 0.99]:
        t_crit = np.abs(t.ppf((1-confidence)/2,dof))
        print(f"{confidence*100}% Confidence Interval:", (m-s*t_crit/np.sqrt(len(data))
```

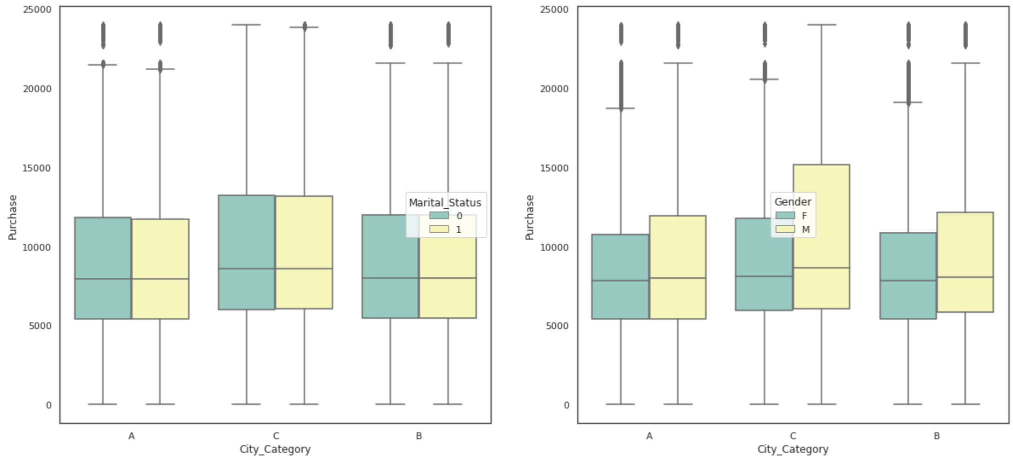
```
Age group:  0-17
90.0% Confidence Interval: (8865.049497531349, 9001.8797833586)
95.0% Confidence Interval: (8851.941436361221, 9014.987844528727)
99.0% Confidence Interval: (8826.320033768494, 9040.609247121454)

Age group:  55
90.0% Confidence Interval: (9280.065285868366, 9392.495633030443)
95.0% Confidence Interval: (9269.295063935433, 9403.265854963376)
99.0% Confidence Interval: (9248.243867862855, 9424.317051035954)

Age group:  26-35
90.0% Confidence Interval: (9235.102926382391, 9270.278339357385)
95.0% Confidence Interval: (9231.733560884022, 9273.647704855754)
99.0% Confidence Interval: (9225.148284007466, 9280.23298173231)

Age group:  46-50
90.0% Confidence Interval: (9170.406084331049, 9246.845310605606)
95.0% Confidence Interval: (9163.08393647555, 9254.167458461105)
99.0% Confidence Interval: (9148.772763375606, 9268.478631561049)

Age group:  51-55
90.0% Confidence Interval: (9492.160404787175, 9577.455657133296)
95.0% Confidence Interval: (9483.989875153999, 9585.626186766473)
99.0% Confidence Interval: (9468.020441793446, 9601.595620127026)

Age group:  36-45
90.0% Confidence Interval: (9306.441166444858, 9356.26022339089)
95.0% Confidence Interval: (9301.669084404875, 9361.032305430872)
99.0% Confidence Interval: (9292.34219880095, 9370.359191034797)

Age group:  18-25
90.0% Confidence Interval: (9143.432787777778, 9195.8944247448)
95.0% Confidence Interval: (9138.40756914702, 9200.919643375557)
99.0% Confidence Interval: (9128.585922624949, 9210.741289897629)
```

8. Purchase behaviour in different Cities per Gender and Marital status

In [48]:

```
fig, ax = plt.subplots(1, 2, figsize=(20,9))
fig.suptitle("Purchase behaviour in different Cities per Gender and Marital status.", f
sns.boxplot(data=df, y='Purchase', x='City_Category', hue='Marital_Status', ax=ax[0], p
sns.boxplot(data=df, y='Purchase', x='City_Category', hue='Gender', ax=ax[1], palette='
plt.show()
```

Purchase behaviour in different Cities per Gender and Marital status.

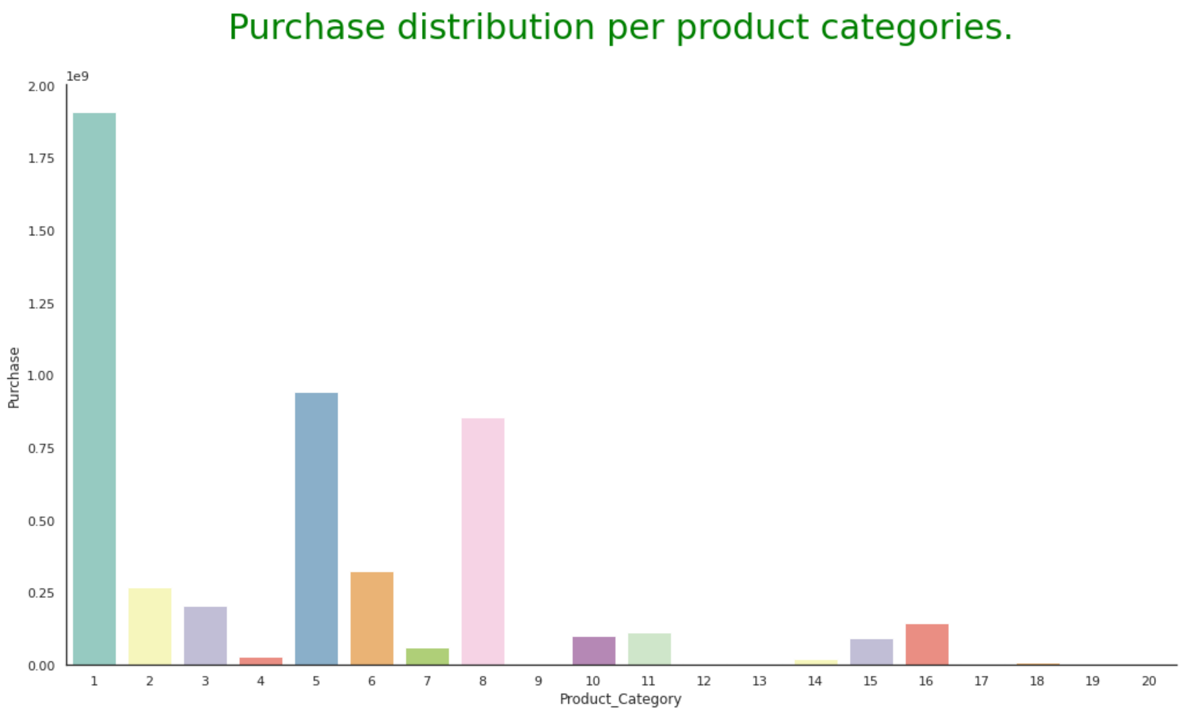


9. Purchase distribution per product categories

In [49]:

```
category_purchases = df[['Product_Category', 'Purchase']].groupby('Product_Category')[
plt.figure(figsize = (15,8))
sns.catplot(x="Product_Category", y="Purchase", kind="bar", data=category_purchases, he
plt.title("\nPurchase distribution per product categories.\n", fontsize=30, color="gree
plt.show()
```

<Figure size 1080x576 with 0 Axes>



10. Business Insights.

- **A.** Male customers are significantly more than Females ie 75% of the users are Male and 25% are Female.
- **B.** Buyers with age between 26 and 35 are significantly more than any other age category ie ~ 80% of the users are between the age 18-50 (40%: 26-35, 18%: 18-25, 20%: 36-45).
- **C.** There are more buyers in City Category B than the other two City Categories.
- **D.** Buyers who have spent 1 year in the city are significantly more than the buyers who have spent 2 years, 3 years, more than 4 years and less than 1 year in the city ie 35% Staying in the city from 1 year, 18% from 2 years, 17% from 3 years.
- **E.** Unmarried buyers are more in numbers than the married buyers ie 60% are single and 40% are married.
- **F.** Males in City Category C tend to spend more amount of money than all the other individual buyers.
- **G.** There are 20 product categories in total wherein 1, 5, 8, & 11 have highest purchasing frequency.
- **H.** There are 20 different types of occupation in the city.
- **I.** With 90%, 95% and even 99% of confidence level, we can see that Male buyers spend significantly more money than the Female Buyers, since there is no overlap between confidence interval.
- **J.** With 90%, 95% and even 99% of confidence level, we can see that Marital Status has no impact on spendings.
- **K.** With 90%, 95% and even 99% of confidence level, we can see that buyers aged between 0-17, significantly spend less money than the other Buyers, since there is no overlap between confidence

interval.

- **L.** With 90%, 95% and even 99% of confidence level, we can see that buyers aged between 51-55, significantly spend more money than the other Buyers, since there is no overlap between confidence interval.
- **M.** Products under categories 1, 5 and 8 generate a huge amount of revenue for Walmart.

Confidence Interval

Confidence Interval by Gender

Now using the **Central Limit Theorem** for the **population**:

1. Average amount spend by **male** customers is **9,85,830.10**
2. Average amount spend by **female** customers is **8,07,370.73**

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)**

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)**

11. Recommendations.

- **A.** Men spent more money than women, So company should focus on retaining the male customers and getting more male customers.
- **B.** Could probably create an additional offer for female buyers, so that the no.of potential female buyers would increase and hence the average spend would also increase for female buyers.
- **C. 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.
- **D.** The Average spending of married and unmarried are too close to each other. So, the differentiation between them is very low. Hence, an equal approach to target married and unmarried customers would be advised. Both couple-type products and other products will get sold based on the data given.
- **E. Unmarried** customers spend more money than married customers, So company should focus on acquisition of Unmarried customers.

- **F.** 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**
- **G.** 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.
- **H.** Walmart should invest in advertisements for expensive products to target male buyers in city category C.
- **I.** Walmart should collaborate with celebrities to promote male products.
- **J.** Walmart should invest in targeted advertisements for individual buyers aged between 51-55.
- **K.** Walmart should engage in different marketing campaigns to target individual buyers in city category B.
- **L.** Walmart should invest in ad campaigns to boost sells of products categorized under 1, 5 and 8 product categories.