In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import norm
```

In [2]:

```
walmart = pd.read_csv("walmart_data.csv")
```

In [3]:

```
df = walmart.copy()
```

In [4]:

```
df.head()
```

Out[4]:

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

EDA

In [5]:

```
df.shape
```

Out[5]:

```
(550068, 10)
```

In [6]:

```
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  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)
```

```
dtypes: int64(5), object(5)
memory usage: 42.0+ MB
```

In [7]:

```
df.isna().sum()
```

Out[7]:

	0
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 [8]:

```
df.duplicated().sum()
```

Out[8]:

```
0
```

In [9]:

```
df.nunique()
```

Out[9]:

	0
User_ID	5891
Product_ID	3631
Gender	2
Age	7
Occupation	21
City_Category	3
Stay_In_Current_City_Years	5
Marital_Status	2
Product_Category	20
Purchase	18105

dtype: int64

In [10]:

```
for _ in df.columns[:-1]:
  df[_] = df[_].astype('category')

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  category
 1   Product_ID                  550068 non-null  category
 2   Gender                      550068 non-null  category
 3   Age                         550068 non-null  category
 4   Occupation                  550068 non-null  category
 5   City_Category               550068 non-null  category
 6   Stay_In_Current_City_Years  550068 non-null  category
 7   Marital_Status              550068 non-null  category
 8   Product_Category            550068 non-null  category
 9   Purchase                    550068 non-null  int64
dtypes: category(9), int64(1)
memory usage: 10.3 MB
```

In [11]:

```
df.describe()
```

Out[11]:

	Purchase
count	550068.000000
mean	9263.968713
std	5023.065394
min	12.000000
25%	5823.000000
50%	8047.000000
75%	12054.000000
max	23961.000000

In [12]:

```
df.describe(include='category').T
```

Out[12]:

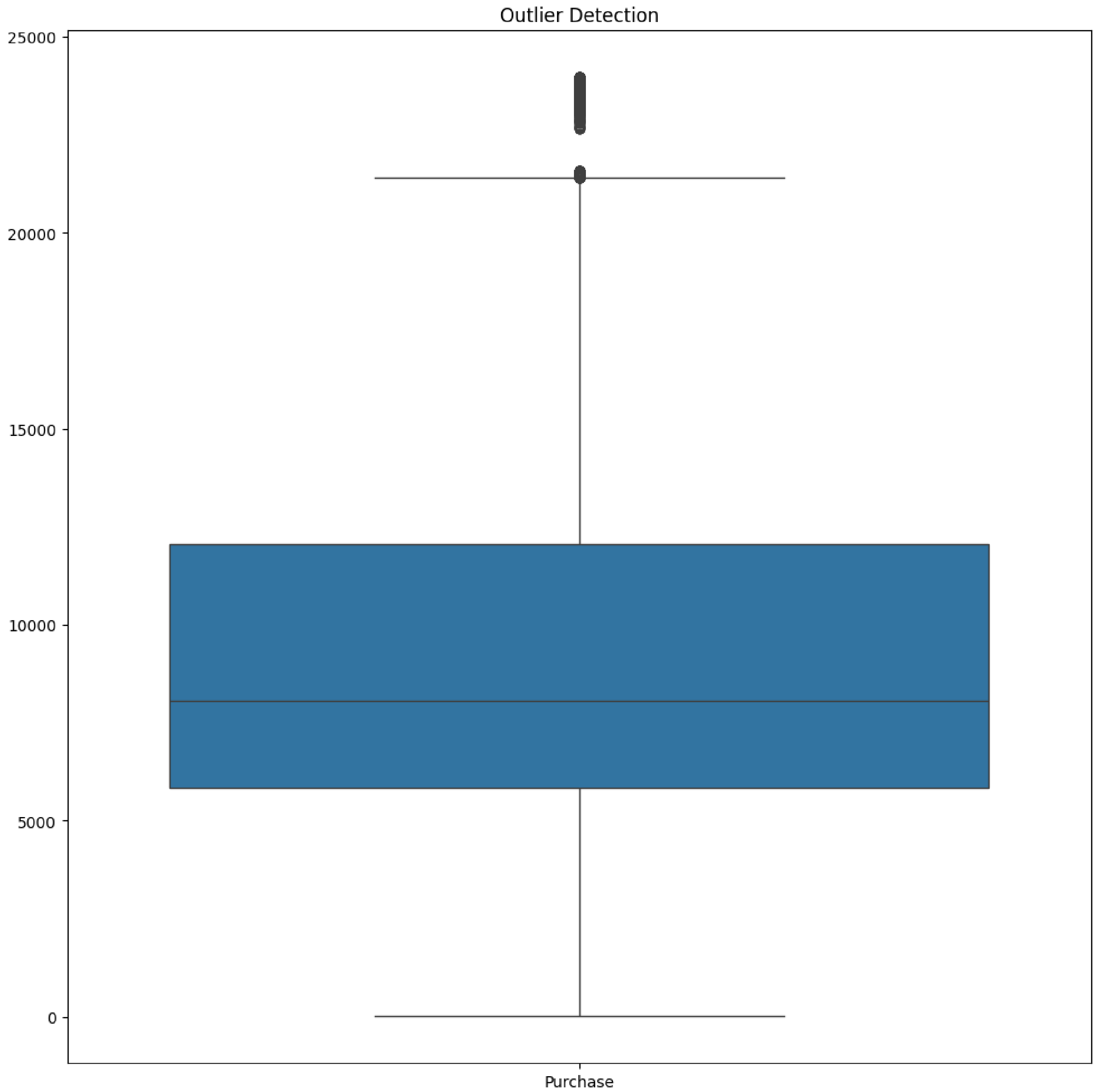
	count	unique	top	freq
User_ID	550068	5891	1001680	1026
Product_ID	550068	3631	P00265242	1880
Gender	550068	2	M	414259
Age	550068	7	26-35	219587
Occupation	550068	21	4	72308
City_Category	550068	3	B	231173
Stay_In_Current_City_Years	550068	5	1	193821
Marital_Status	550068	2	0	324731
Product_Category	550068	20	5	150933

Outlier detection

In [13]:

```
plt.figure(figsize=(10,10))
sns.boxplot(data=df)
```

```
plt.title('Outlier Detection')
plt.tight_layout()
plt.show()
```



In [14]:

```
# Calculate quartiles and IQR for the specified column
Q1 = np.percentile(df['Purchase'], 25)
Q3 = np.percentile(df['Purchase'], 75)
IQR = Q3 - Q1

# Upper and lower bounds for outliers
upper_bound = Q3 + (1.5 * IQR)
lower_bound = Q1 - (1.5 * IQR)

# Outliers in the specified column
upper_outliers_df = df[df['Purchase'] > upper_bound]
lower_outliers_df = df[df['Purchase'] < lower_bound]

# Count of outliers
upper_count = len(upper_outliers_df)
lower_count = len(lower_outliers_df)

total_count = upper_count + lower_count
```

```python
print(f"Upper Outliers Count: {upper_count}")
print(f"Lower Outliers Count: {lower_count}")
print(f"Overall Outliers Count: {total_count}")
```

```
Upper Outliers Count: 2677
Lower Outliers Count: 0
Overall Outliers Count: 2677
```

In [15]:

```python
outliers_df = df[df['Purchase'] > upper_bound]
outliers_df
```

Out[15]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_C
343	1000058	P00117642	M	26-35	2	B	3	0	
375	1000062	P00119342	F	36-45	3	A	1	0	
652	1000126	P00087042	M	18-25	9	B	1	0	
736	1000139	P00159542	F	26-35	20	C	2	0	
1041	1000175	P00052842	F	26-35	2	B	1	0	
...	...	...	...	...	...	...	...	...	
544488	1005815	P00116142	M	26-35	20	B	1	0	
544704	1005847	P00085342	F	18-25	4	B	2	0	
544743	1005852	P00202242	F	26-35	1	A	0	1	
545663	1006002	P00116142	M	51-55	0	C	1	1	
545787	1006018	P00052842	M	36-45	1	C	3	0	

2677 rows × 10 columns

In [16]:

```python
filtered_data = df[(df['Purchase'] >= lower_bound) & (df['Purchase'] <= upper_bound)]
filtered_data
```

Out[16]:

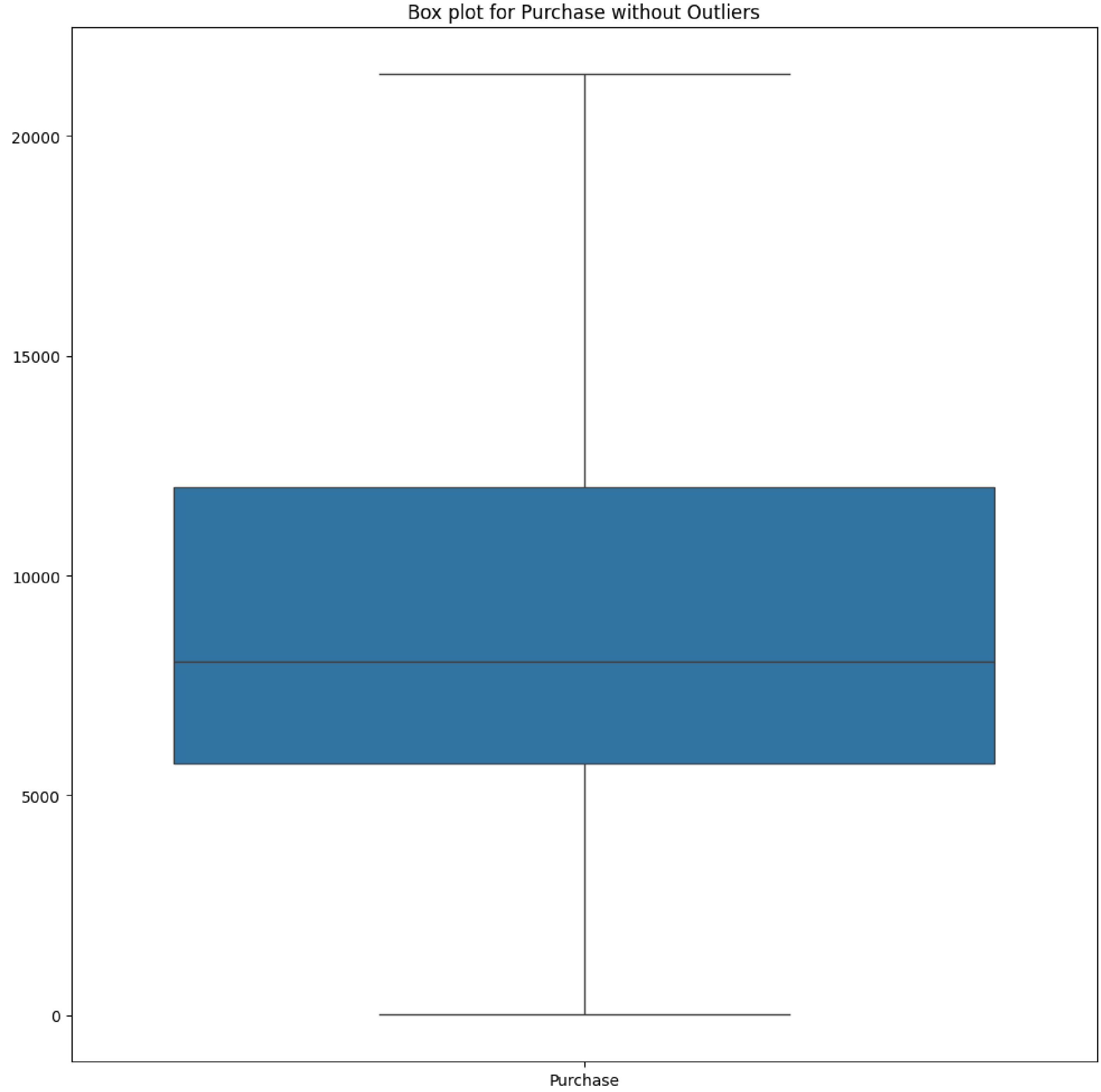
	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_C
0	1000001	P00069042	F	0-17	10	A	2	0	
1	1000001	P00248942	F	0-17	10	A	2	0	
2	1000001	P00087842	F	0-17	10	A	2	0	
3	1000001	P00085442	F	0-17	10	A	2	0	
4	1000002	P00285442	M	55+	16	C	4+	0	
...	...	...	...	...	...	...	...	...	
				51-					

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_C
550063	1006033	P00372445	M	51-55	13	B	1	1	
550064	1006035	P00375436	F	26-35	1	C	3	0	
550065	1006036	P00375436	F	26-35	15	B	4+	1	
550066	1006038	P00375436	F	55+	1	C	2	0	
550067	1006039	P00371644	F	46-50	0	B	4+	1	

547391 rows × 10 columns

In [17]:

```
plt.figure(figsize=(10,10))
sns.boxplot(data=filtered_data)
plt.title('Box plot for Purchase without Outliers')
plt.tight_layout()
plt.show()
```



In [18]:

```
## Map numerical values in Marital_status to categorical lables

df['Marital_Status'] = df['Marital_Status'].apply(lambda x: 'Married' if x == 1 else 'Si
ngle')
```

In [19]:

```
df.head()
```

Out[19]:

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

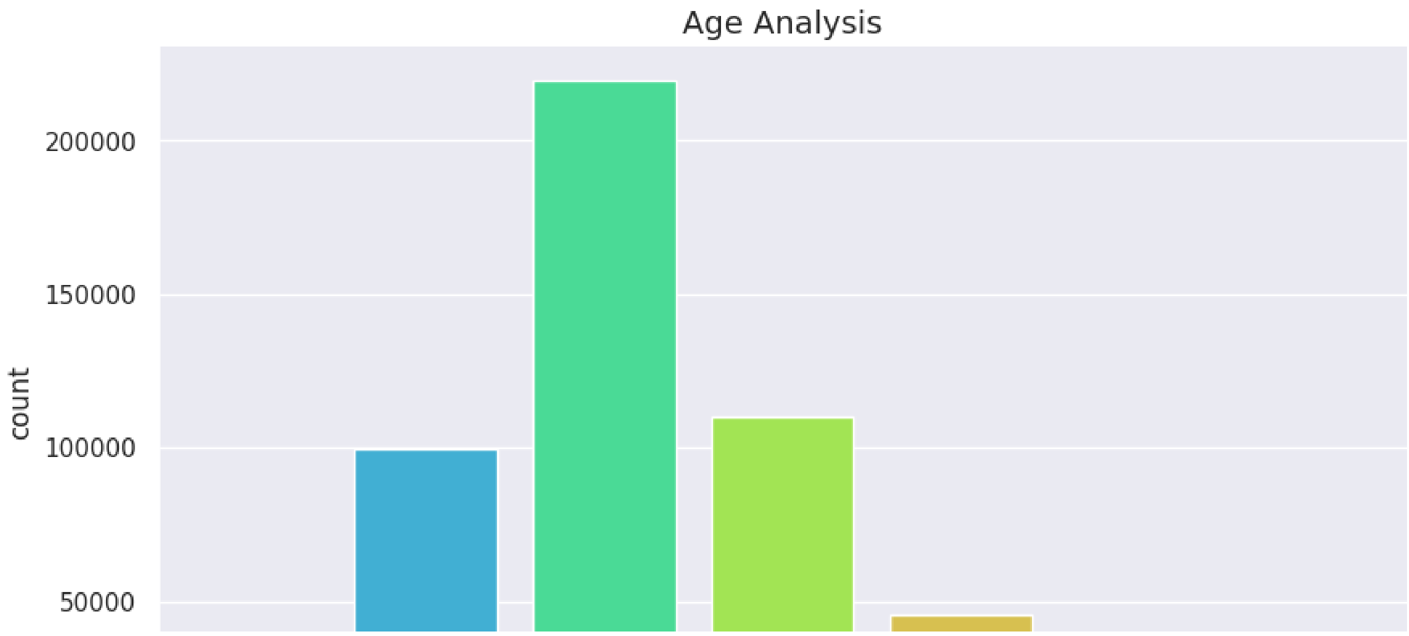
Univariate Analysis

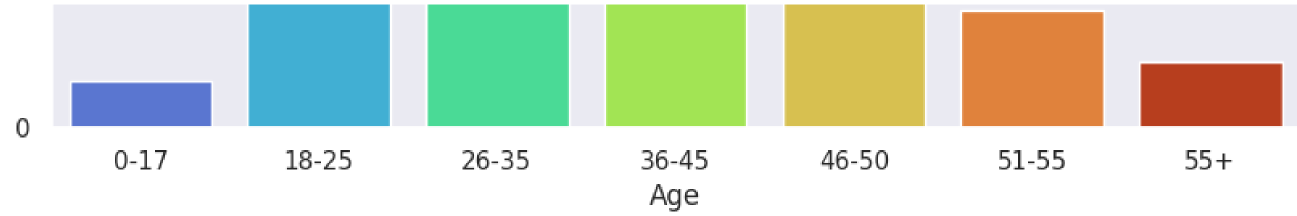
In [20]:

```
category = ['Age', 'Occupation', 'City_Category', 'Stay_In_Current_City_Years', 'Marital_
Status', 'Product_Category']
```

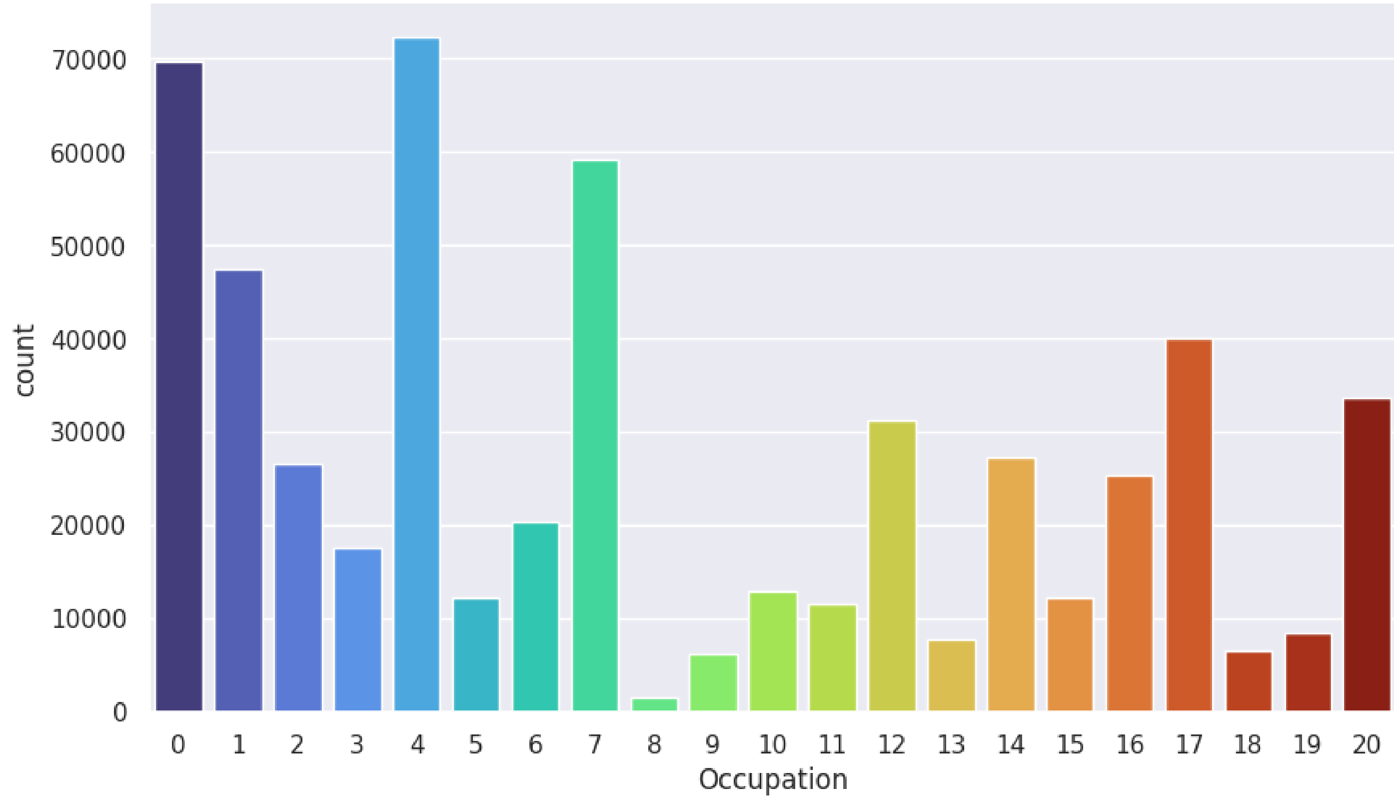
In [21]:

```
plt.figure(figsize=(10,40))
sns.set(style='darkgrid')

# Plot each categorical column
for i, col in enumerate(category, 1):
    plt.subplot(6, 1, i)
    sns.countplot(data=df, x=col, hue=col, palette='turbo', legend=False)
    sns.despine()
    plt.title(f'{col} Analysis', fontsize=14, fontfamily='sans-serif')

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

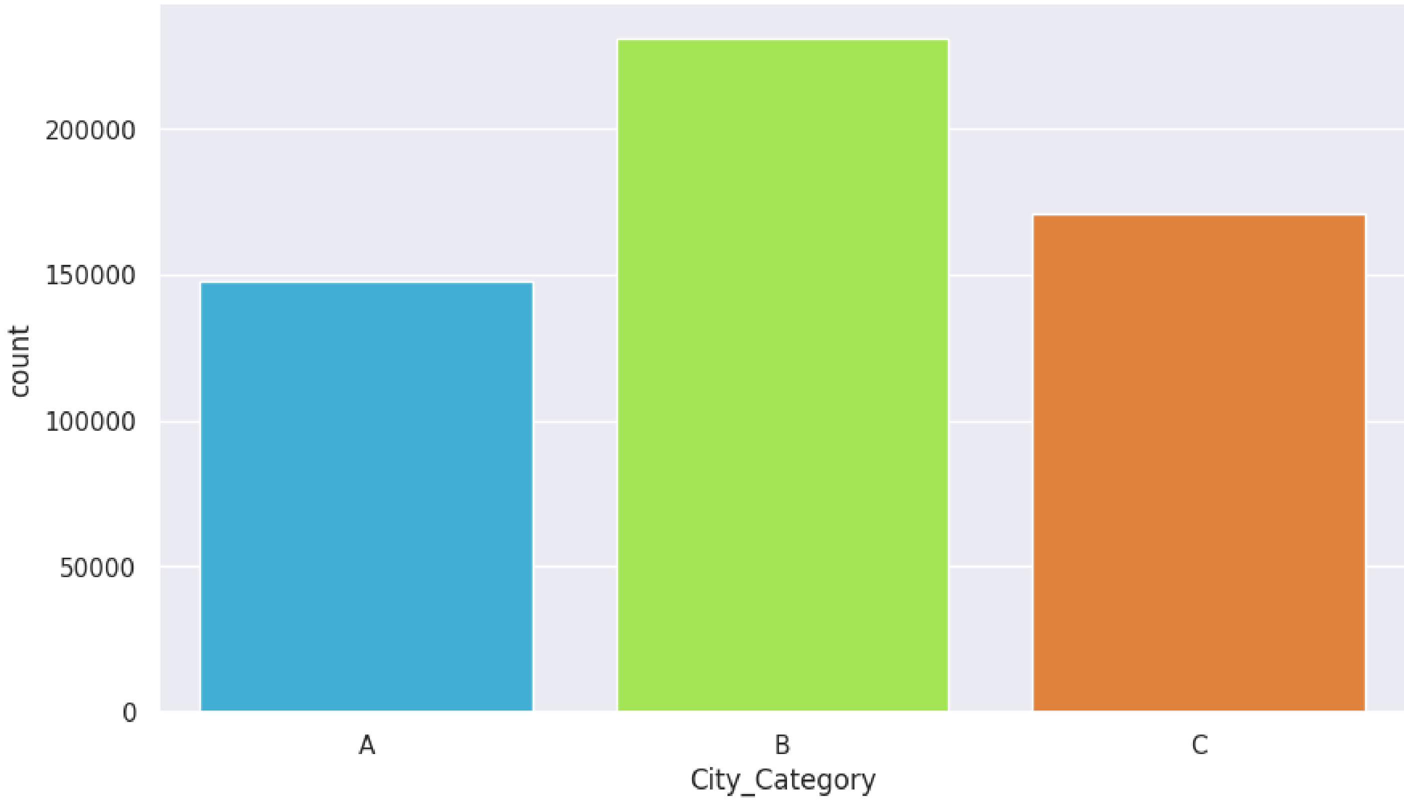




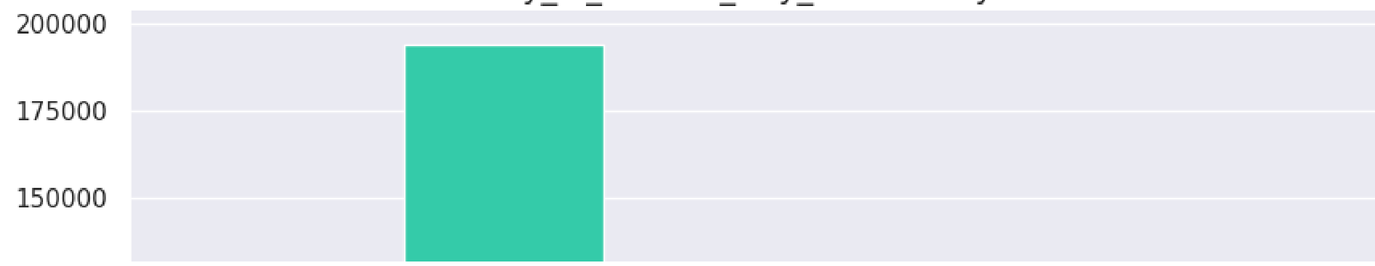
Occupation Analysis

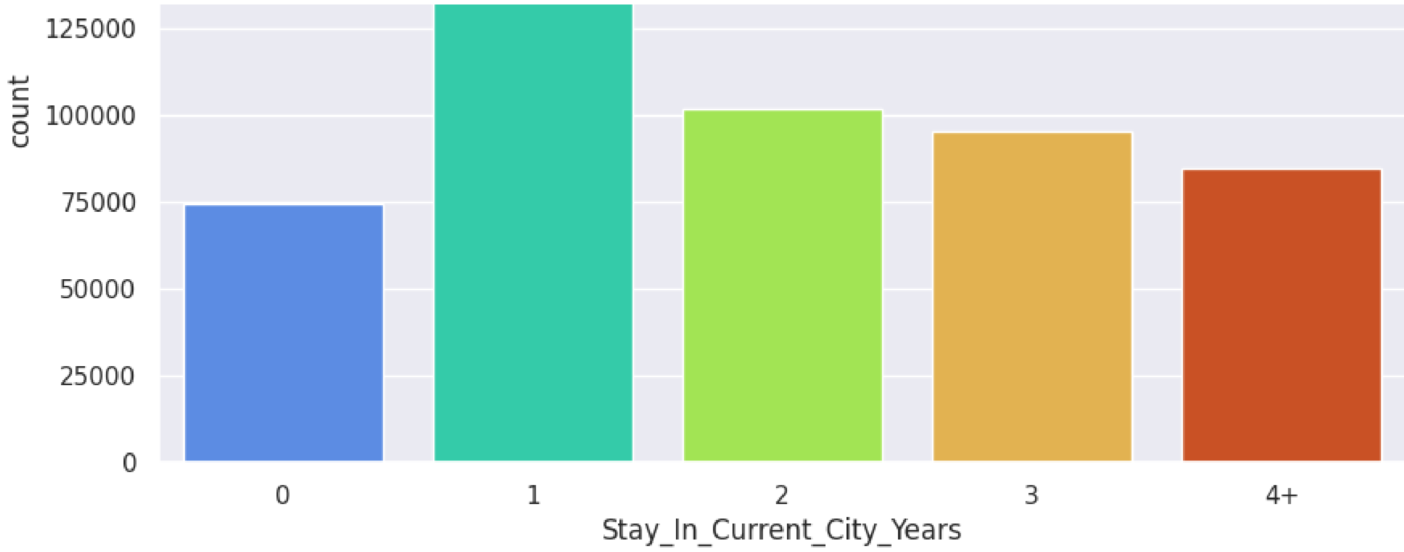


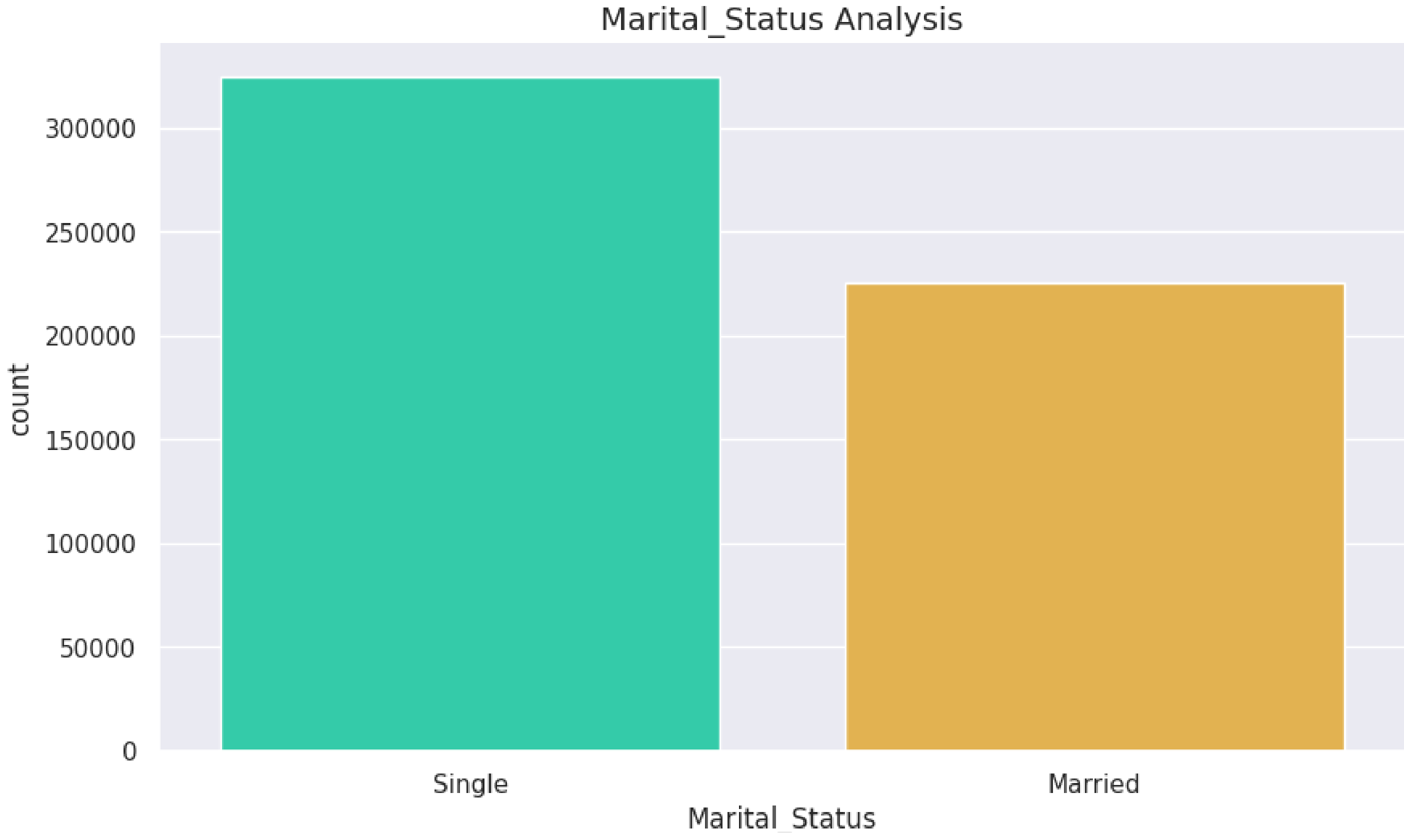
City_Category Analysis

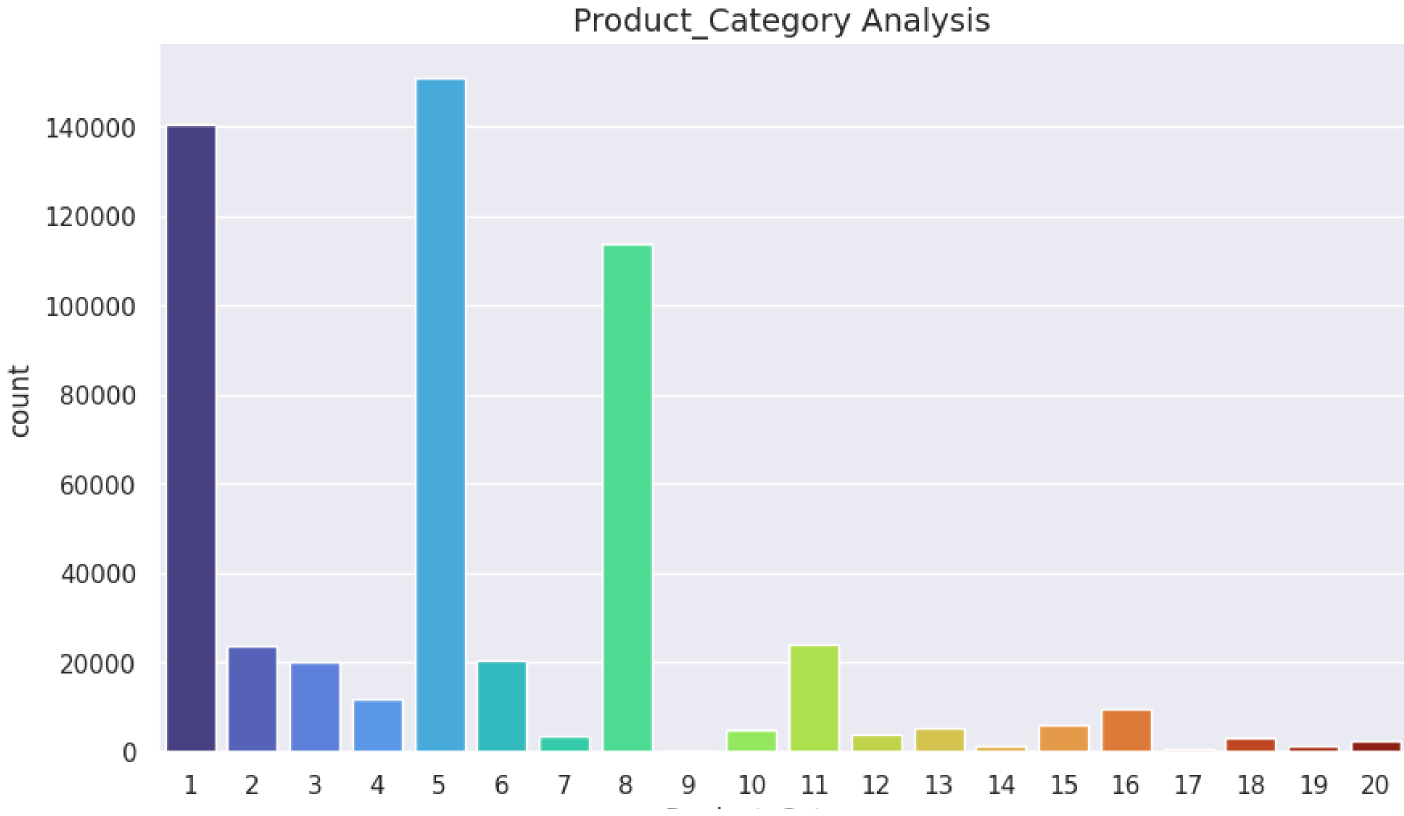


Stay_In_Current_City_Years Analysis




count
125000
100000
75000
50000
25000
0
0
1
2
3
4+
Stay_In_Current_City_Years


Marital_Status Analysis
count
300000
250000
200000
150000
100000
50000
0
Single
Married
Marital_Status


Product_Category Analysis
count
140000
120000
100000
80000
60000
40000
20000
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20

Product_Category

Insights:

Age Group Distribution:

The age group '26-35' has the highest count, indicating that customers in this age range make the most purchases. It is followed by the age groups '36-45' and '18-25'.

Occupation Analysis:

Occupation '4' has the highest count, suggesting that customers with occupation '4' have the highest representation in the dataset. Occupations '0', '7', and '1' also have significant counts.

City Category Distribution:

City_Category 'B' has the highest count, indicating that customers from City_Category 'B' have made the most purchases. City_Category 'C' and 'A' follow in terms of count.

City Residence Duration Impact:

Customers who have stayed in their current city for more than 1 year show a higher purchase tendency, suggesting a positive correlation between the duration of stay and purchasing behavior.

Marital Status Impact:

Customers with a marital status of 'Single' have a higher count compared to those who are 'Married', suggesting that single individuals make more purchases in the dataset.

Product Category Purchase Analysis:

Product categories '1' and '5' exhibit higher purchase amounts, indicating that these categories contribute significantly to the overall sales revenue.

Bivariate Analysis

In [22]:

```
pivot = lambda index: df.pivot_table(index=df[index], columns='Gender', aggfunc='size', fill_value=0, observed=False)
```

In [23]:

```
pivot('Age')
```

Out[23]:

Gender	F	M
Age		
0-17	5083	10019
18-25	24628	75032
26-35	50752	168835
36-45	27170	82843
46-50	13199	32502
51-55	9894	28607
55+	5083	16421

In [24]:

```
pivot('Occupation')
```

Out[24]:

Out[24]:

Gender	F	M
Occupation		
0	18112	51526
1	17984	29442
2	8629	17959
3	7919	9731
4	17836	54472
5	2220	9957
6	8160	12195
7	10028	49105
8	361	1185
9	5843	448
10	4003	8927
11	1500	10086
12	3469	27710
13	1498	6230
14	6763	20546
15	2390	9775
16	4107	21264
17	3929	36114
18	230	6392
19	2017	6444
20	8811	24751

In [25]:

```
pivot('City_Category')
```

Out[25]:

Gender	F	M
City_Category		
A	35704	112016
B	57796	173377
C	42309	128866

In [26]:

```
pivot('Stay_In_Current_City_Years')
```

Out[26]:

Gender	F	M
Stay_In_Current_City_Years		
0	17063	57335
1	51298	142523
2	24332	77506
3	24520	70765
4+	18596	66130

Gender	F	M

In [27]:

```
pivot('Marital_Status')
```

Out[27]:

Gender	F	M
Marital_Status		
Single	78821	245910
Married	56988	168349

In [28]:

```
pivot('Product_Category')
```

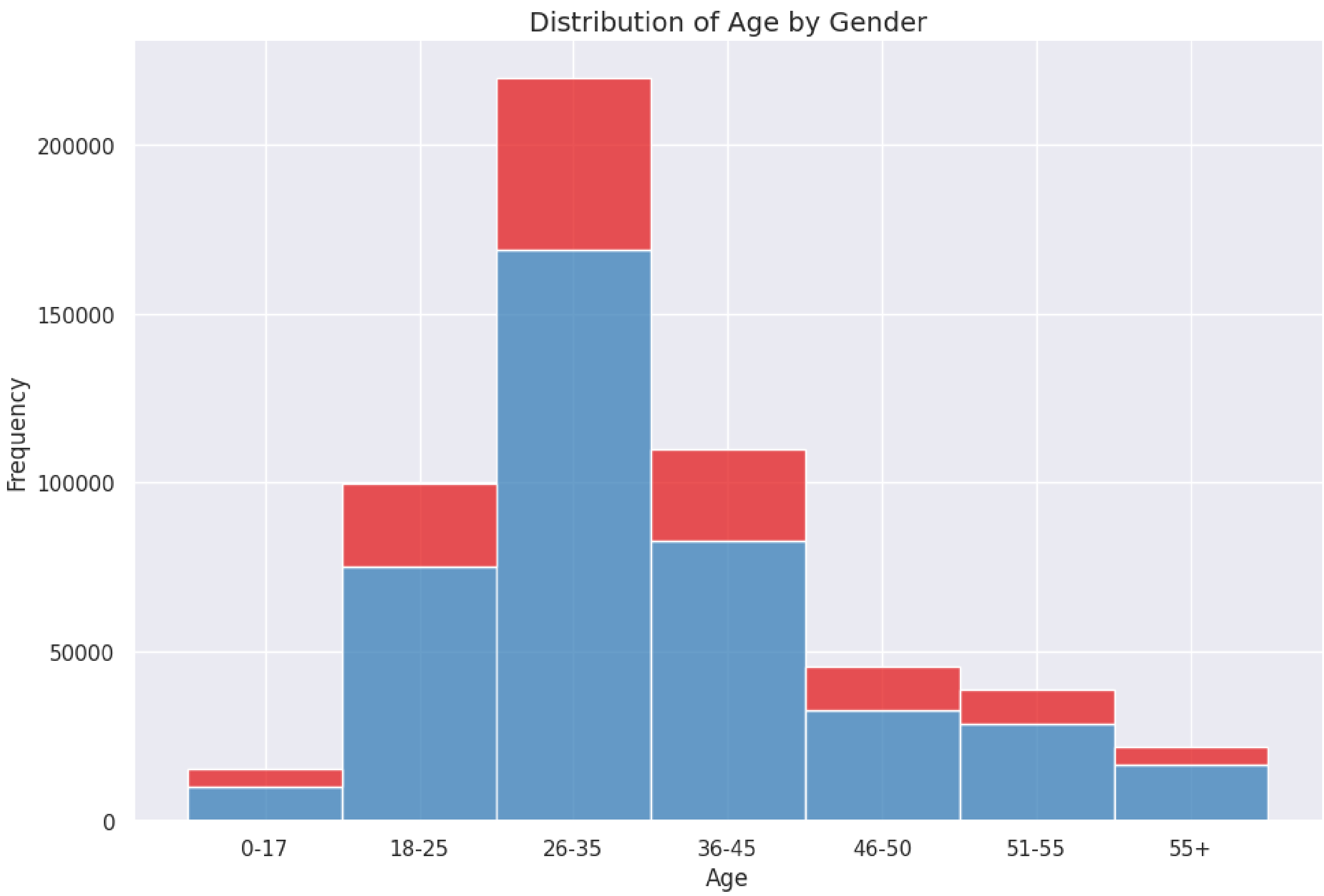
Out[28]:

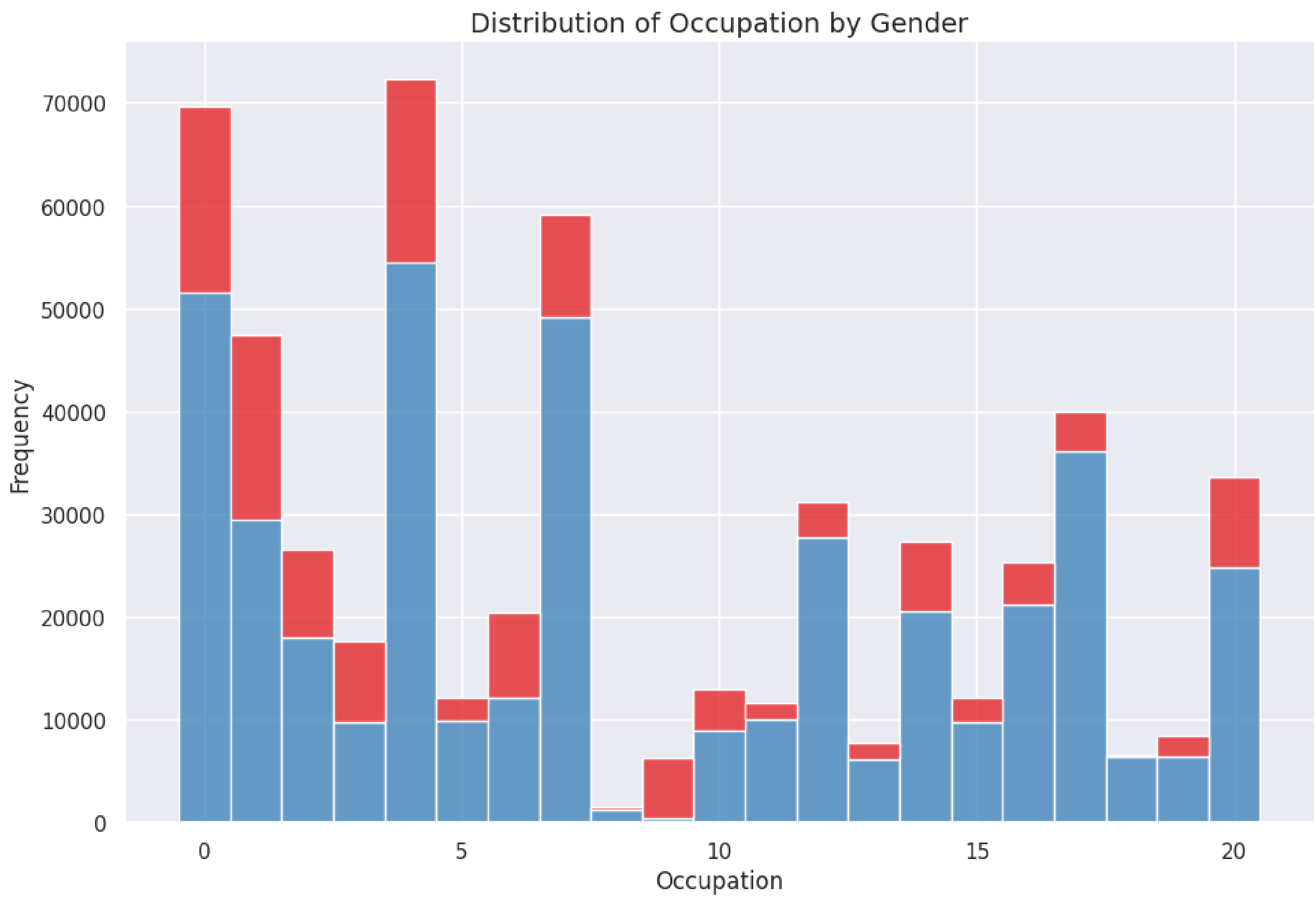
Gender	F	M
Product_Category		
1	24831	115547
2	5658	18206
3	6006	14207
4	3639	8114
5	41961	108972
6	4559	15907
7	943	2778
8	33558	80367
9	70	340
10	1162	3963
11	4739	19548
12	1532	2415
13	1462	4087
14	623	900
15	1046	5244
16	2402	7426
17	62	516
18	382	2743
19	451	1152
20	723	1827

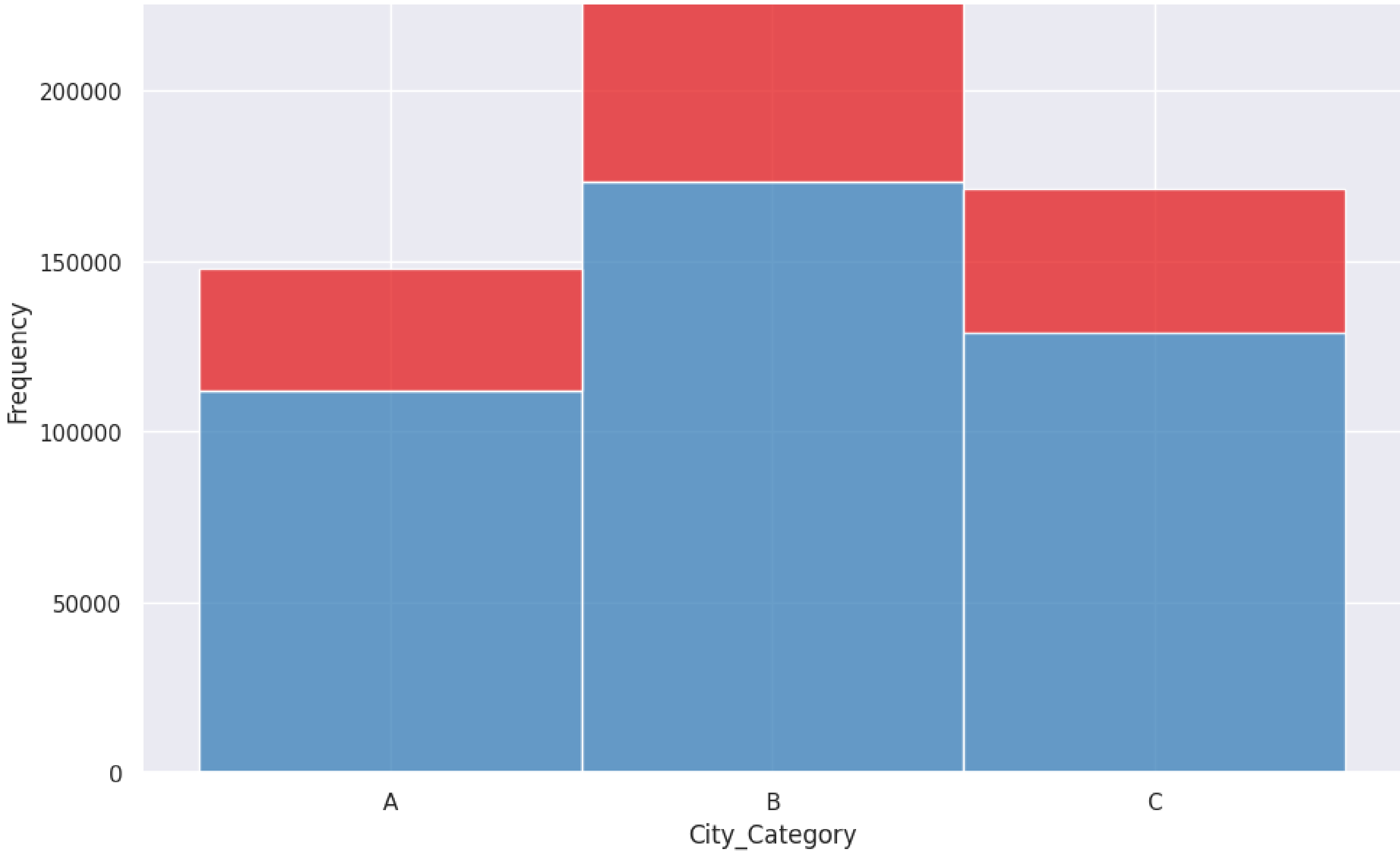
In [29]:

```
plt.figure(figsize=(10, 40))
sns.set(style = 'darkgrid')

for i, col in enumerate(category, 1):
  plt.subplot(6, 1, i)
  sns.histplot(data=df, x=col, hue='Gender', palette='Set1', legend=False, multiple='stack')
  sns.despine()

  plt.xlabel(f'{col}', fontsize=12)
  plt.ylabel('Frequency', fontsize=12)
```

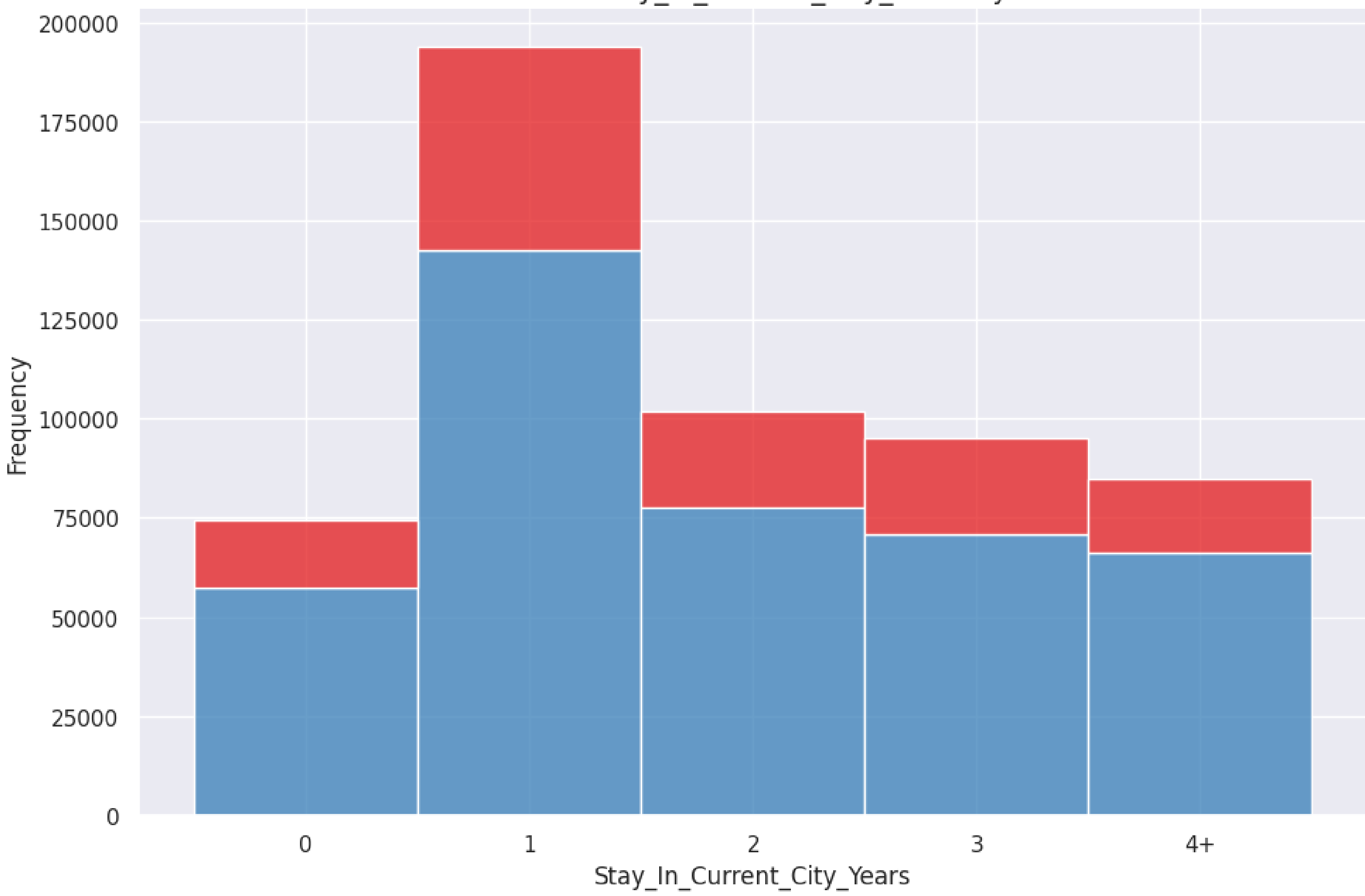
```
  plt.title(f'Distribution of {col} by Gender', fontsize=14, fontfamily='sans-serif')

  plt.tight_layout()

plt.show()
```



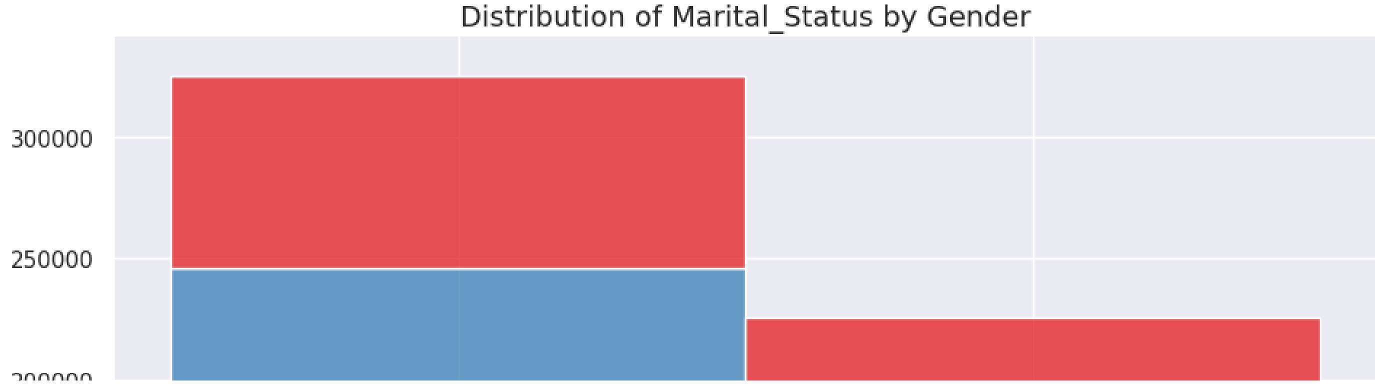


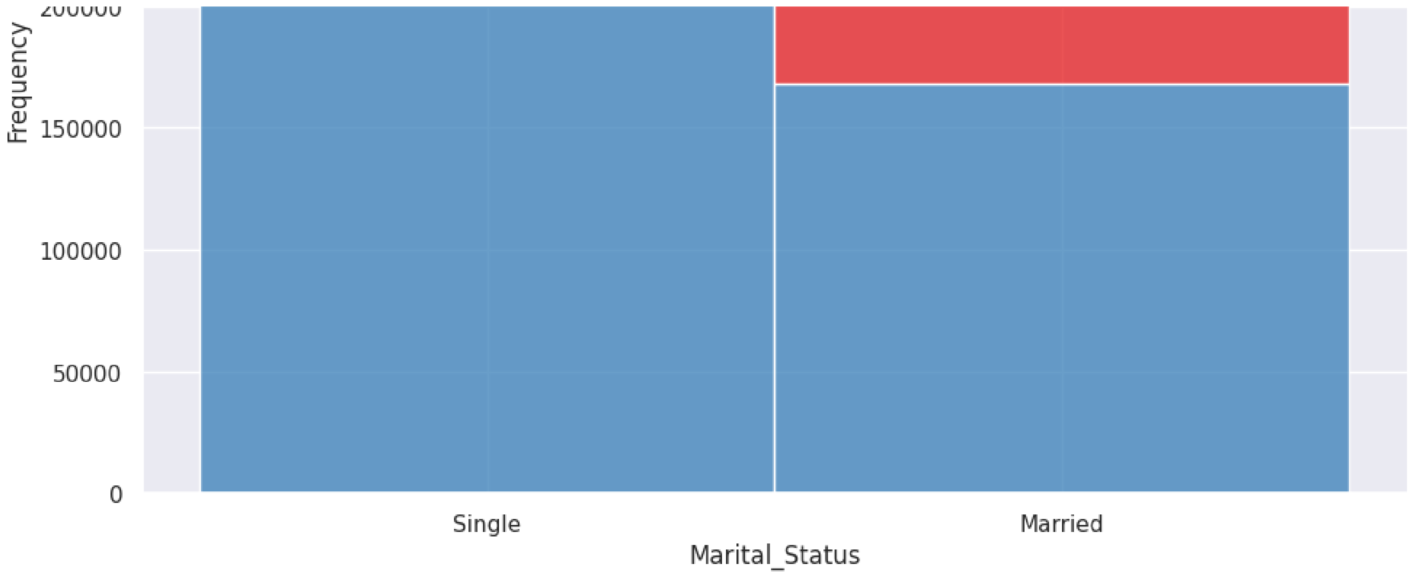


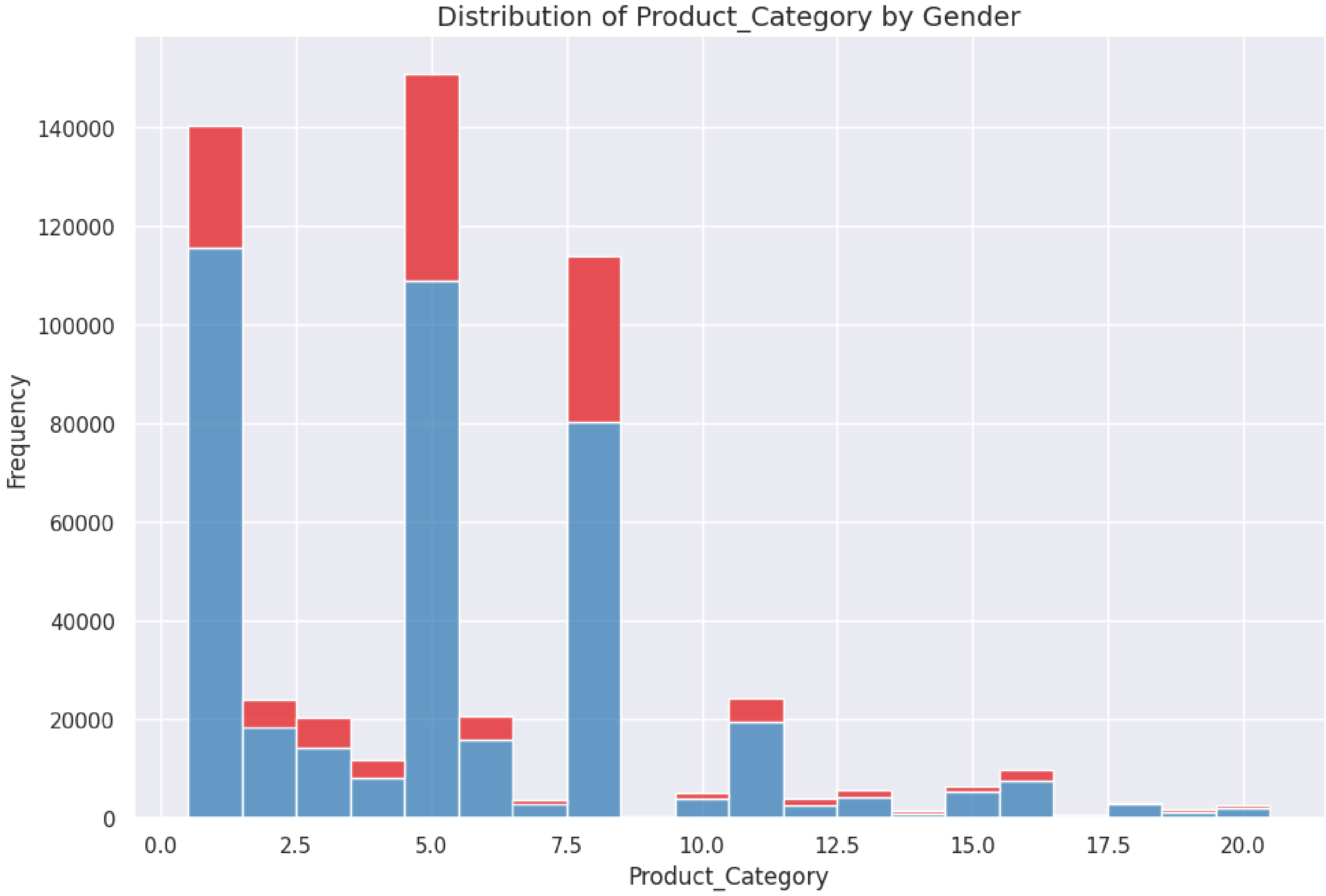
Distribution of Stay_In_Current_City_Years by Gender



Distribution of Marital_Status by Gender







Insights:

Gender-Related Purchase Analysis:

Across various age groups, males tend to have higher purchase counts compared to females, with the age group '26-35' showing the most significant difference.

Occupation-Related Purchase Analysis:

Occupations '0' and '4' show the highest purchase counts, suggesting that individuals in these occupations contribute significantly to overall sales, with '4' having notably higher purchases than others.

City Category-Related Purchase Analysis:

City_Category 'B' has the highest purchase counts for both genders, indicating that customers residing in City_Category 'B' contribute significantly to overall sales compared to 'A' and 'C'.

Stay in Current City Duration Impact:

Customers who have stayed in their current city for 1 year exhibit the highest purchase counts, suggesting that individuals with a 1-year residence duration have a higher tendency to make purchases compared to other durations.

Marital Status-Related Purchase Analysis:

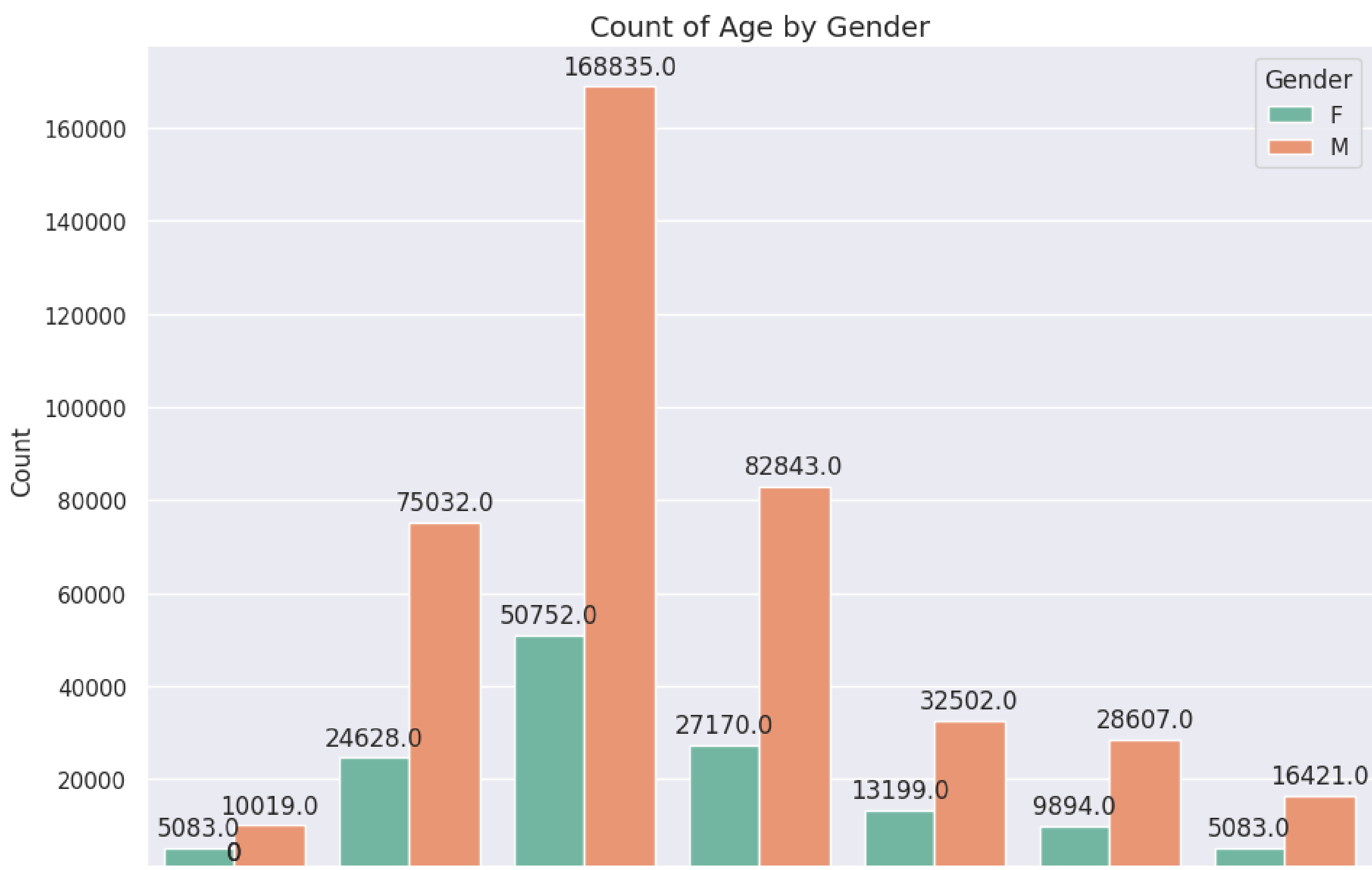
Individuals with a marital status of 'Single' have higher purchase counts compared to those who are 'Married', indicating that single individuals contribute more to overall sales.

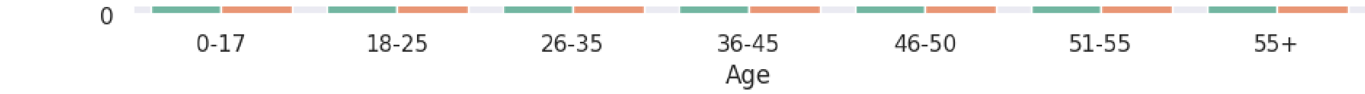
Product Category-Related Purchase Analysis:

Product Category '1' has the highest purchase counts, indicating that it significantly contributes to overall sales. Product Categories '5' and '8' also show notable purchase counts.

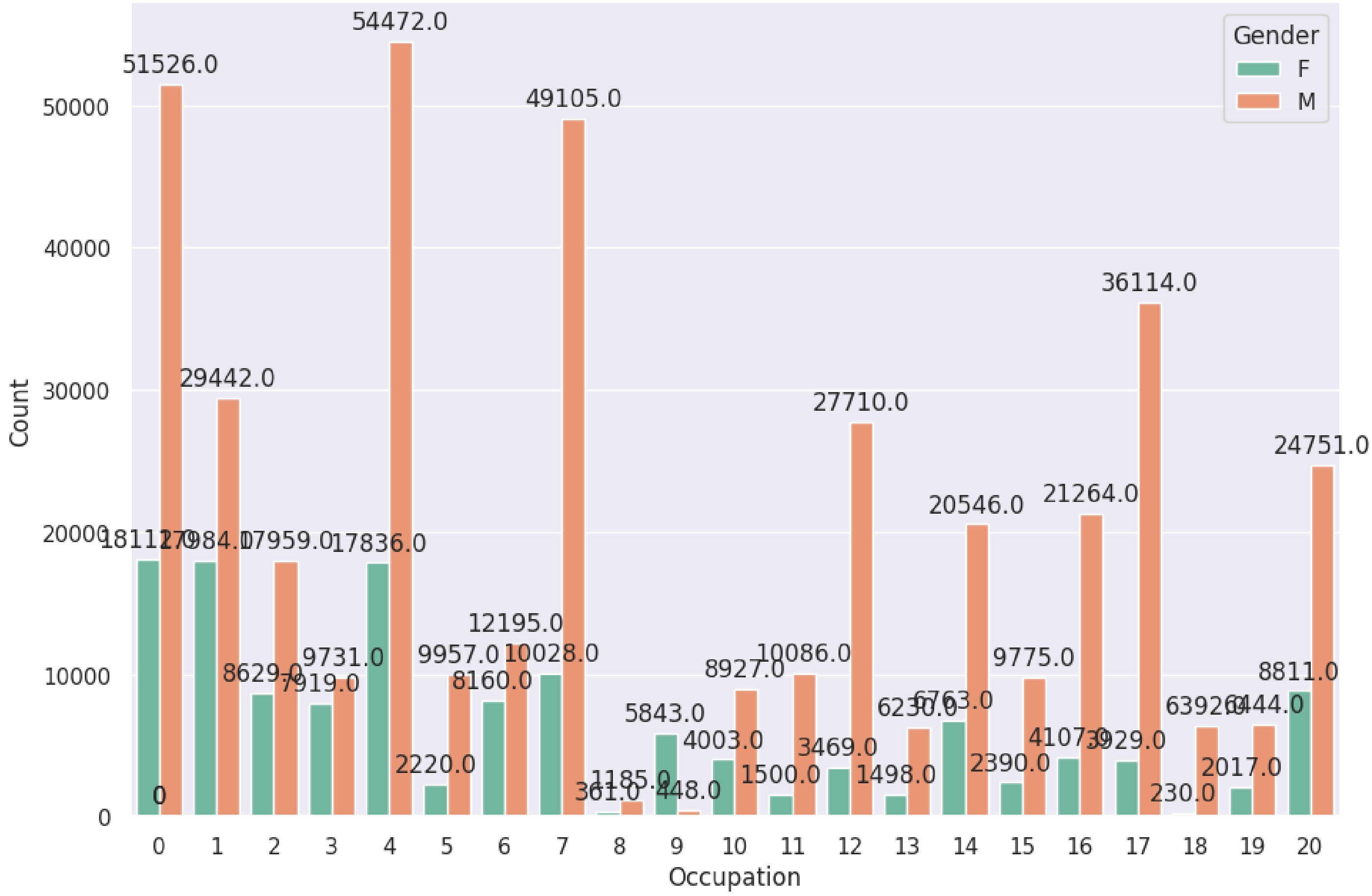
In [30]:

```
plt.figure(figsize=(10, 40))
sns.set(style='darkgrid')

# Plot each categorical column
for i, col in enumerate(category, 1):
    plt.subplot(6, 1, i)
    ax = sns.countplot(data=df, x=col, hue='Gender', palette='Set2')
    sns.despine()

    plt.title(f'Count of {col} by Gender', fontsize=14, fontfamily='sans-serif')
    plt.xlabel(col)
    plt.ylabel('Count')

    # Add bar counts as text labels
    for p in ax.patches:
        ax.annotate(f'{p.get_height()}',
                    (p.get_x() + p.get_width() / 2.,
                     p.get_height()),
                    ha='center',
                    va='center',
                    xytext=(0, 10),
                    textcoords='offset points')

    plt.tight_layout()

plt.show()
```

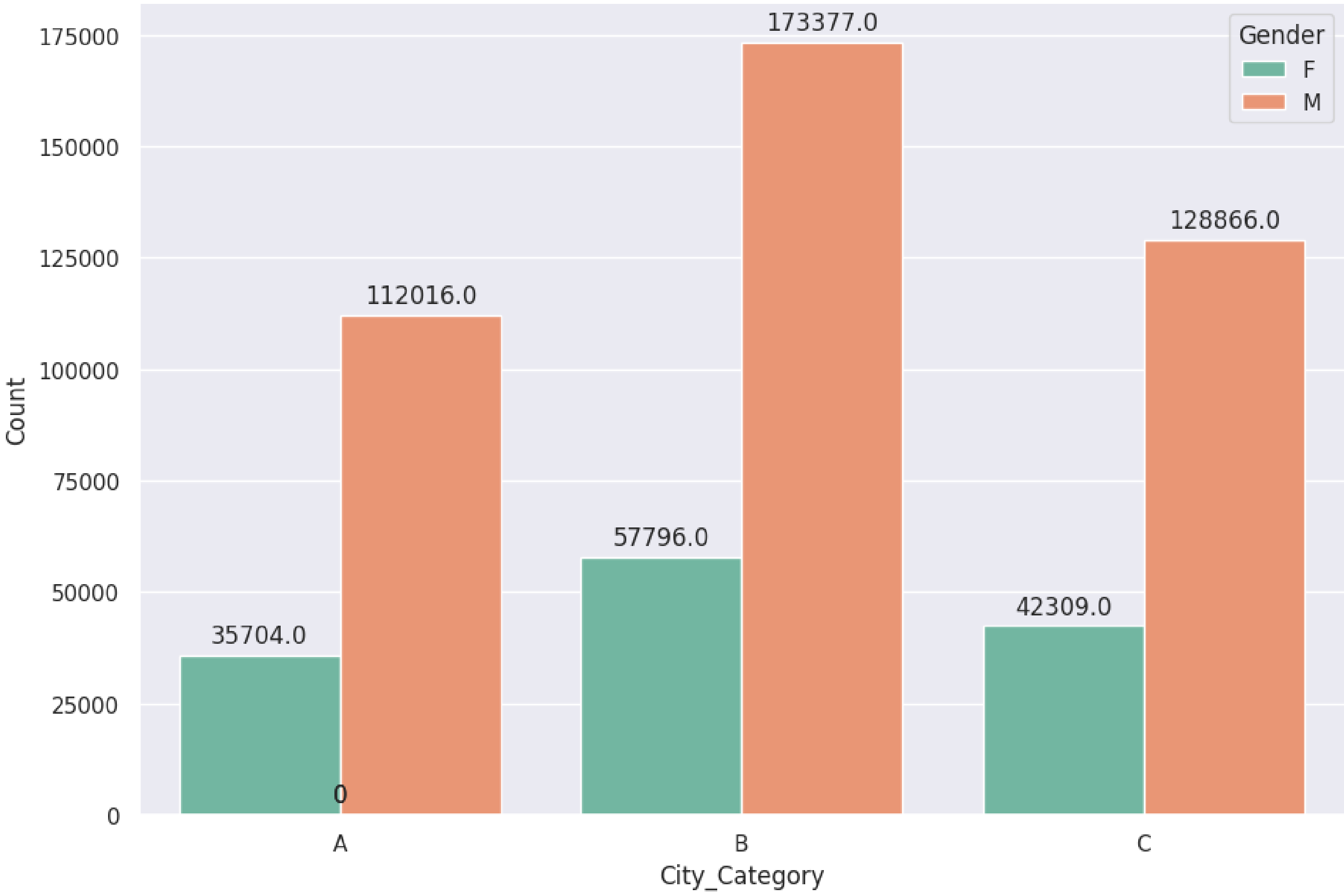




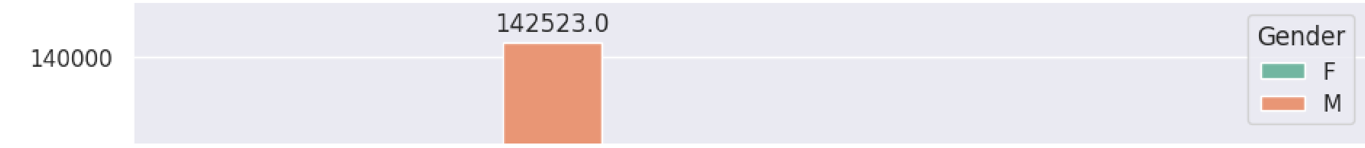
Count of Occupation by Gender



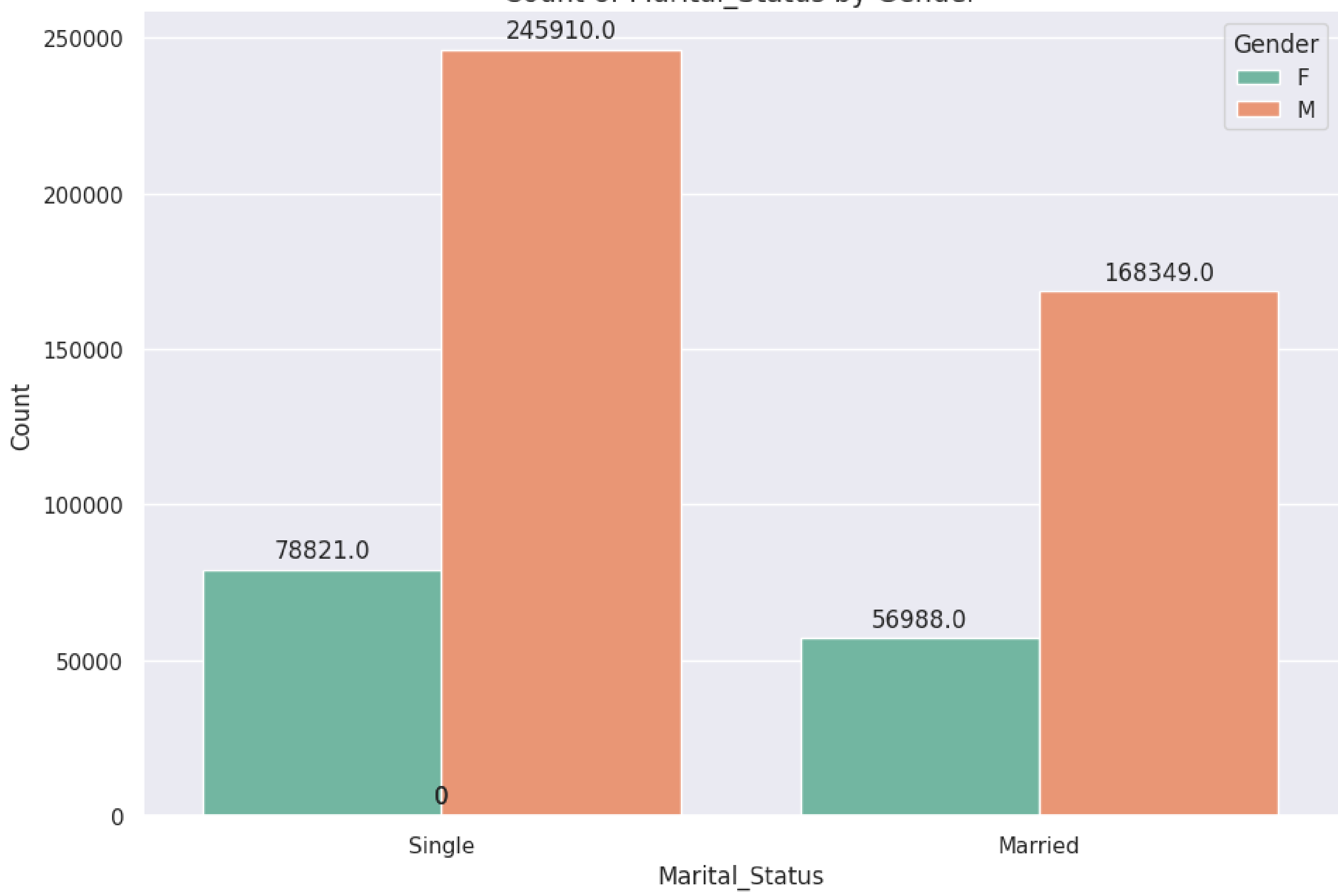
Count of City_Category by Gender



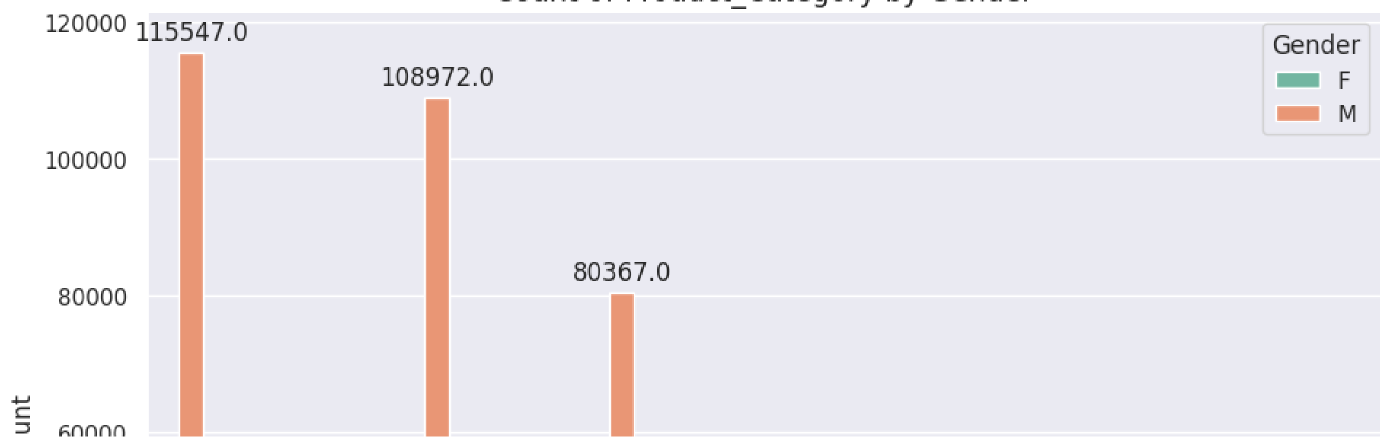
Count of Stay_In_Current_City_Years by Gender

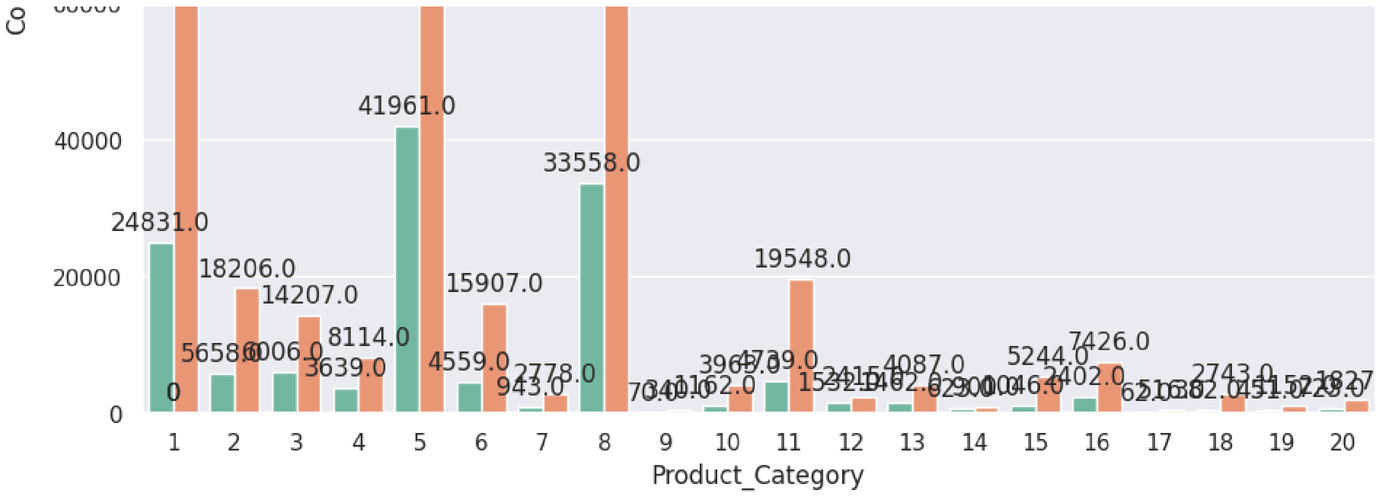


Count of Marital_Status by Gender



Count of Product_Category by Gender





Black Friday Sales Analysis on Gender

In [31]:

```
import warnings

warnings.simplefilter(action='ignore', category=FutureWarning)
```

In [32]:

```
avg_purchase = df.groupby('Gender')[['Purchase']].mean().reset_index().round(2)
avg_purchase
```

Out[32]:

	Gender	Purchase
0	F	8734.57
1	M	9437.53

In [33]:

```
df_male = df[df['Gender']=='M']
df_female = df[df['Gender']=='F']

print(f'Male customers - {len(df_male)}')
print(f'Female customers - {len(df_female)}')
```

```
Male customers - 414259
Female customers - 135809
```

In [34]:

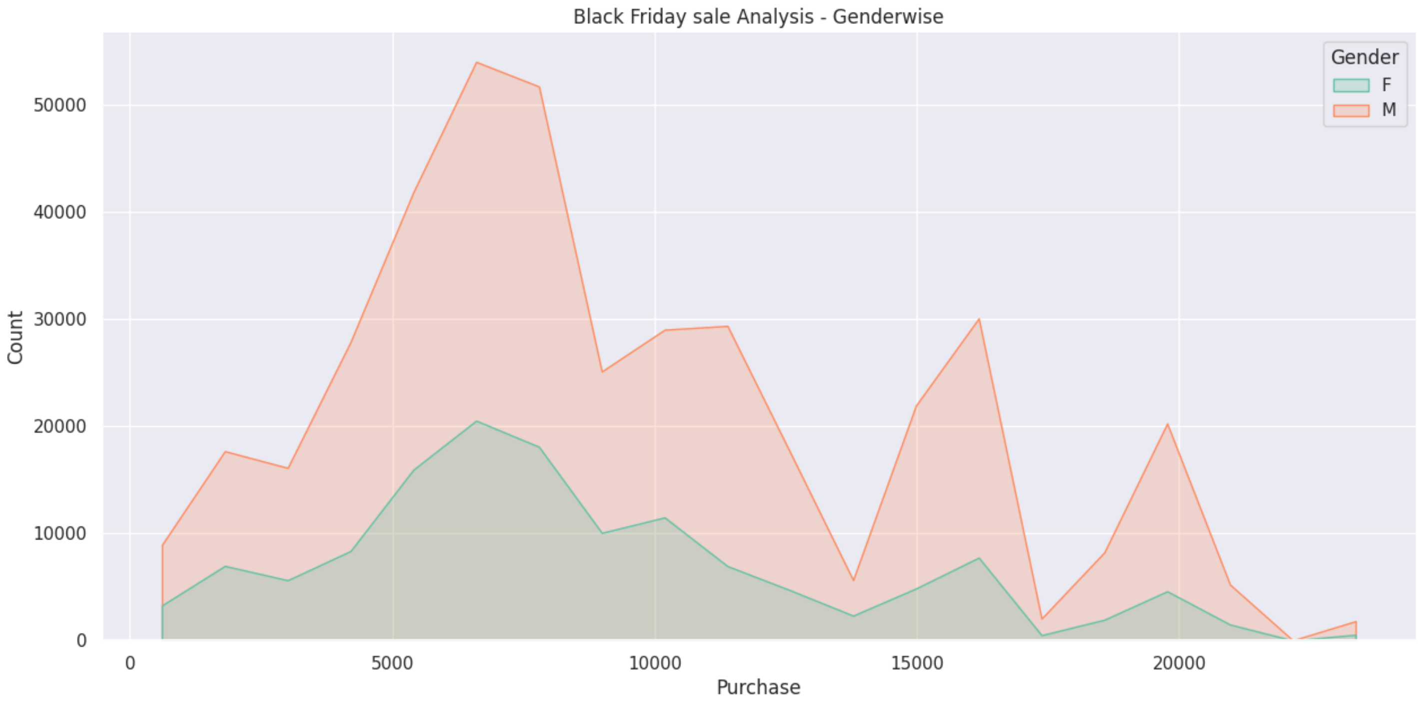
```
df.groupby('Gender')['Purchase'].describe().T
```

Out[34]:

Gender	F	M
count	135809.000000	414259.00000
mean	8734.565765	9437.52604
std	4767.233289	5092.18621
min	12.000000	12.00000
25%	5433.000000	5863.00000
50%	7914.000000	8098.00000
75%	11400.000000	12454.00000
max	23959.000000	23961.00000

In [35]:

```
plt.figure(figsize=(15,7))
sns.set(style='darkgrid')
sns.histplot(data=df, x = "Purchase", bins=20, hue = "Gender",element='poly',palette= 'S
et2')
sns.despine()
plt.title('Black Friday sale Analysis - Genderwise')
plt.show()
```



Insights:

Men spent more money than women during the Black Friday sale.

- **The total number of male customers exceeds the total number of female customers.**
- **The average amount spent by male customers (9437) is higher than the average amount spent by female customers (8734).**
- **With a larger male customer base, it is likely that men will make more purchases compared to females.**
- **The higher sales among male customers could be attributed to a product range better suited to their preferences, leading to increased sales of products targeted towards men.**

In [36]:

```
# Calculates the 95% confidence interval and width for a specified category within a give
n variable in the dataset.

def data_ci(data, variable, category, confidence_level=0.95):

    category_data = data[data[variable] == category]['Purchase']
    category_mean = category_data.mean()
    category_std = category_data.std()

    # standard error of the mean
    category_sem = category_std / np.sqrt(len(category_data))

    # margin of error
    category_moe = category_sem * norm.ppf((1 + confidence_level) / 2)

    # confidence interval
    category_ci = (category_mean - category_moe, category_mean + category_moe)

    # width
    category_width = category_ci[1] - category_ci[0]
```

```
    print(f'{category} 95% confidence interval: {category_ci}')
    print(f'{category} Width: {category_width}')
```

In [37]:

```
# Calculates the 95% confidence interval and width for a specified category within a give
n variable in a sampled dataset.

def sample_ci(data, variable, category, sample_size):

    category_data = data[data[variable] == category]['Purchase']
    sample_data = category_data.sample(n=sample_size, random_state=42)
    mean_val = sample_data.mean()
    std_dev = sample_data.std()

    # standard error of the mean
    sem = std_dev / np.sqrt(sample_size)

    # margin of error
    moe = sem * norm.ppf((1 + 0.95) / 2)  # 1.96 corresponds to the Z-score for a 95% co
nfidence interval

    # confidence interval
    ci = (mean_val - moe, mean_val + moe)

    category_width = ci[1] - ci[0]

    print(f"\nSample Size: {sample_size}")
    print(f'{category} 95% confidence interval: {ci}')
    print(f'{category} Width: {category_width}')
```

Confidence intervals for the Average amount spent per gender.

95% confidence interval of Entire *Dataset*

In [38]:

```
data_ci(df, 'Gender', 'M')
data_ci(df, 'Gender', 'F')
```

```
M 95% confidence interval: (9422.01944736257, 9453.032633581959)
M Width: 31.013186219388444
F 95% confidence interval: (8709.21154714068, 8759.919983170272)
F Width: 50.70843602959212
```

In [38]:

```
```

95% confidence interval of 300 samples

In [39]:

```
sample_ci(df, 'Gender', 'M', 300)
sample_ci(df, 'Gender', 'F', 300)
```

```
Sample Size: 300
M 95% confidence interval: (9283.731565877591, 10491.715100789075)
M Width: 1207.9835349114837

Sample Size: 300
F 95% confidence interval: (8308.865304074718, 9426.034695925284)
F Width: 1117.1693918505662
```

In [39]:

```
```

95% confidence interval of 3000 samples

In [40]:

```
sample_ci(df, 'Gender', 'M', 3000)
sample_ci(df, 'Gender', 'F', 3000)
```

```
Sample Size: 3000
M 95% confidence interval: (9460.10182838994, 9831.170171610062)
M Width: 371.0683432201222

Sample Size: 3000
F 95% confidence interval: (8630.481387808419, 8982.545945524913)
F Width: 352.06455771649416
```

In [40]:

```

```

95% confidence interval of 30000 samples

In [41]:

```
sample_ci(df, 'Gender', 'M', 30000)
sample_ci(df, 'Gender', 'M', 30000)
```

```
Sample Size: 30000
M 95% confidence interval: (9428.950211018666, 9544.881322314668)
M Width: 115.9311112960022

Sample Size: 30000
M 95% confidence interval: (9428.950211018666, 9544.881322314668)
M Width: 115.9311112960022
```

In [41]:

```

```

Insights:

- **The confidence interval computed using the entire dataset is wider for males compared to females, indicating higher variability in the amount spent by males.**
- **The width of the confidence interval is inversely affected by the sample size; as the sample size increases, the interval becomes narrower, providing more precise estimates.**
- **The confidence intervals for different sample sizes overlap, suggesting that observed differences may not be statistically significant.**
- **Larger sample sizes result in more normally shaped distributions of means due to the Central Limit Theorem.**

Confidence intervals for the average amount spent per Marital_Status.

95% confidence interval of Entire Dataset

In [42]:

```
data_ci(df, 'Marital_Status', 'Married')
data_ci(df, 'Marital_Status', 'Single')
```

```
Married 95% confidence interval: (9240.460427057078, 9281.888721107669)
Married Width: 41.42829405059092
Single 95% confidence interval: (9248.61641818668, 9283.198819656332)
Single Width: 34.58240146965181
```

In [42]:

```

```

95% confidence interval of 300 samples

In [43]:

```
sample_ci(df, 'Marital_Status', 'Married', 300)
sample_ci(df, 'Marital_Status', 'Single', 300)
```

```
Sample Size: 300
Married 95% confidence interval: (8887.305881933493, 10041.72745139984)
Married Width: 1154.4215694663471

Sample Size: 300
Single 95% confidence interval: (9051.928693931213, 10213.504639402121)
Single Width: 1161.5759454709078
```

In [43]:

```

```

95% confidence interval of 3000 samples

In [44]:

```
sample_ci(df, 'Marital_Status', 'Married', 3000)
sample_ci(df, 'Marital_Status', 'Single', 3000)
```

```
Sample Size: 3000
Married 95% confidence interval: (9118.562018709765, 9482.974647956902)
Married Width: 364.4126292471374

Sample Size: 3000
Single 95% confidence interval: (9246.175079645862, 9612.375587020804)
Single Width: 366.2005073749424
```

In [44]:

```

```

95% confidence interval of 30000 samples

In [45]:

```
sample_ci(df, 'Marital_Status', 'Married', 30000)
sample_ci(df, 'Marital_Status', 'Single', 30000)
```

```
Sample Size: 30000
Married 95% confidence interval: (9198.15616601518, 9312.029900651485)
Married Width: 113.87373463630502

Sample Size: 30000
Single 95% confidence interval: (9229.816006946752, 9343.573126386582)
Single Width: 113.7571194398297
```

In [45]:

```

```

Insights:

- **The confidence interval for the 'Married' group is wider than that for the 'Single' group, indicating higher variability in the amount spent for married individuals.**

- The width of the confidence interval decreases as the sample size increases, showcasing the impact of larger sample sizes on precision.
- Yes, the confidence intervals for 'Married' and 'Single' groups overlap, suggesting that observed differences may not be statistically significant across sample sizes.
- As the sample size increases, the width of the confidence interval decreases, leading to a more precise estimate of the mean and resulting in a more normal distribution of sample means.

Confidence intervals for the average amount spent per Marital_Status

95% confidence interval of Entire Dataset

In [46]:

```
data_ci(df, 'Age', '0-17')
data_ci(df, 'Age', '18-25')
data_ci(df, 'Age', '26-35')
data_ci(df, 'Age', '36-45')
data_ci(df, 'Age', '46-50')
data_ci(df, 'Age', '55+')
```

```
0-17 95% confidence interval: (8851.947970542686, 9014.981310347262)
0-17 Width: 163.03333980457683
18-25 95% confidence interval: (9138.407948753442, 9200.919263769136)
18-25 Width: 62.51131501569398
26-35 95% confidence interval: (9231.73367640003, 9273.647589339746)
26-35 Width: 41.913912939715374
36-45 95% confidence interval: (9301.669410965314, 9361.031978870433)
36-45 Width: 59.36256790511834
46-50 95% confidence interval: (9163.085142648752, 9254.166252287903)
46-50 Width: 91.08110963915169
55+ 95% confidence interval: (9269.29883441773, 9403.262084481079)
55+ Width: 133.96325006334882
```

95% confidence interval of 300 samples

In [47]:

```
sample_ci(df, 'Age', '0-17',300)
sample_ci(df, 'Age', '18-25',300)
sample_ci(df, 'Age', '26-35',300)
sample_ci(df, 'Age', '36-45',300)
sample_ci(df, 'Age', '46-50',300)
sample_ci(df, 'Age', '55+',300)
```

```
Sample Size: 300
0-17 95% confidence interval: (8042.115409806883, 9195.43792352645)
0-17 Width: 1153.3225137195668

Sample Size: 300
18-25 95% confidence interval: (8841.832523352577, 9998.79414331409)
18-25 Width: 1156.961619961512

Sample Size: 300
26-35 95% confidence interval: (8371.065497628038, 9519.247835705293)
26-35 Width: 1148.1823380772548

Sample Size: 300
36-45 95% confidence interval: (9058.511768661903, 10168.321564671429)
36-45 Width: 1109.8097960095256

Sample Size: 300
46-50 95% confidence interval: (8791.503247273875, 9927.150086059457)
46-50 Width: 1135.646838785582

Sample Size: 300
55+ 95% confidence interval: (8666.663992004576, 9849.616007995422)
55+ Width: 1182.9520159908461
```

95% confidence interval of 3000 samples

In [48]:

```
sample_ci(df, 'Age', '0-17',3000)
sample_ci(df, 'Age', '18-25',3000)
sample_ci(df, 'Age', '26-35',3000)
sample_ci(df, 'Age', '36-45',3000)
sample_ci(df, 'Age', '46-50',3000)
sample_ci(df, 'Age', '55+',3000)
```

```
Sample Size: 3000
0-17 95% confidence interval: (8687.664588770689, 9055.084744562644)
0-17 Width: 367.42015579195504

Sample Size: 3000
18-25 95% confidence interval: (9001.345443138514, 9364.180556861487)
18-25 Width: 362.8351137229729

Sample Size: 3000
26-35 95% confidence interval: (9110.626934190286, 9470.271065809715)
26-35 Width: 359.64413161942866

Sample Size: 3000
36-45 95% confidence interval: (9253.797851839656, 9615.063481493678)
36-45 Width: 361.26562965402263

Sample Size: 3000
46-50 95% confidence interval: (9029.905975457834, 9385.392691208832)
46-50 Width: 355.486715750998

Sample Size: 3000
55+ 95% confidence interval: (9184.95957145098, 9549.377761882353)
55+ Width: 364.41819043137366
```

Insights

- **The 26-35 group shows the narrowest confidence interval, indicating consistent spending.**
- **Wider confidence intervals among both younger (0-17) and older (55+) groups suggest these age groups might exhibit less predictable spending patterns, possibly due to varying income levels or spending priorities.**
- **The decreasing width of the confidence interval with middle age groups highlights the impact of sample size and spending consistency on precision, as larger sample sizes lead to narrower intervals and, therefore, more reliable mean estimates.**
- **This pattern underscores that a larger and more stable sample size contributes to more accurate confidence intervals, reflecting a narrower range of likely spending behaviors around the mean.**

Recommendations:

1. **Target Male Shoppers:**

   Since male customers account for a significant portion of Black Friday sales and tend to spend more per transaction on average, Walmart should tailor its marketing strategies and product offerings to incentivize higher spending among male customers while ensuring competitive pricing for female-oriented products.
2. **Focus on 26 - 45 Age Group:**

   With the age group between 26 and 45 contributing to the majority of sales, Walmart should specifically cater to the preferences and needs of this demographic.This could include offering exclusive deals on products that are popular among this age group.
3. **Engage Younger Shoppers:**

   Knowing that customers in the 0 - 17 age group have the lowest spending per transaction, Walmart can try to increase their spending per transaction by offering them more attractive discounts, coupons, or rewards

programs. It's essential to start building brand loyalty among younger consumers.

4. **Customer Segmentation:**

   Since customers in the 18 - 25, 26 - 35, and 46 - 50 age groups exhibit similar buying characteristics, and so do the customers in 36 - 45 and 55+, Walmart can optimize its product selection to cater to the preferences of these age groups. Also, Walmart can use this information to adjust their pricing strategies for different age groups.

5. **Enhance the 51 - 55 Age Group Shopping Experience:**

   Considering that customers aged 51 - 55 have the highest spending per transaction, Walmart offer them exclusive pre-sale access, special discount or provide personalized product recommendations for this age group. Walmart can also introduce loyalty programs specifically designed to reward and retain customers in the 51 - 55 age group.

In [48]:

```

```