Problem Statement:

To address the business problem and provide actionable insights to Walmart and conduct a thorough analysis of the provided dataset.

Dataset Overview

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

+ Code + Text

```
# Load the dataset
df = pd.read_csv('/kaggle/input/walmart-data/walmart_data.csv')

# Display the first few rows of the dataset
df.head()
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marita
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	

Non-Graphical Analysis

```
# Checking the structure and summary of the dataset
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)
memory usage: 42.0+ MB
```

```
cat_cols = df.select_dtypes(include='object').columns.to_list()
cat_cols.extend(['Marital_Status', 'Product_Category'])
df[cat_cols] = df[cat_cols].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  int64
 1   Product_ID                  550068 non-null  category
 2   Gender                      550068 non-null  category
 3   Age                         550068 non-null  category
 4   Occupation                  550068 non-null  int64
 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(7), int64(3)
memory usage: 16.9 MB
```

```
df.nunique()
```

```
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
```

```
df[['Occupation', 'Purchase']].describe()
```

	Occupation	Purchase
count	550068.000000	550068.000000
mean	8.076707	9263.968713
std	6.522660	5023.065394
min	0.000000	12.000000
25%	2.000000	5823.000000
50%	7.000000	8047.000000
75%	14.000000	12054.000000
max	20.000000	23961.000000

```
df.describe(include='category')
```

	Product_ID	Gender	Age	City_Category	Stay_In_Current_City_Years	Marital_Status	Pro
count	550068	550068	550068	550068	550068	550068	
unique	3631	2	7	3	5	2	
top	P00265242	M	26-35	B	1	0	
freq	1880	414259	219587	231173	193821	324731	

```
df.isnull().sum()
```

```
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
```

Visual Analysis

Univariate Analysis

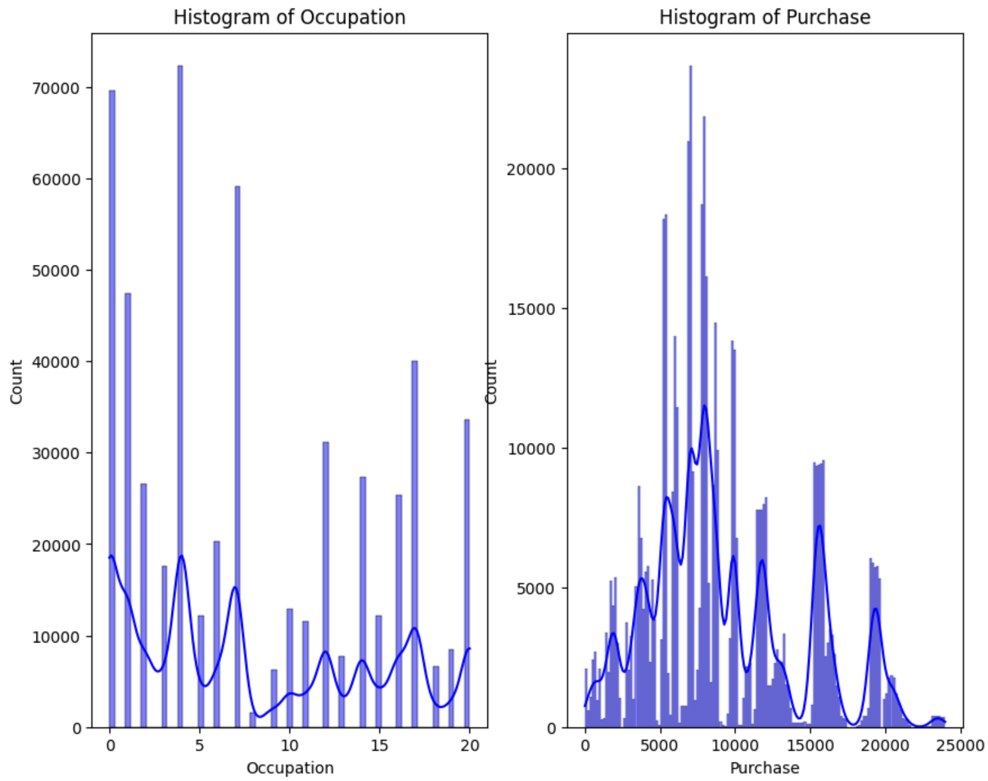
```
def plot_continuous_variable(data, variable, type='hist'):
    # Histogram
    if type=='hist':
        sns.histplot(data[variable].dropna(), color='blue', kde=True)
        plt.title(f'Histogram of {variable}')


def plot_categorical_variable(data, category, rotation=0):
    # Boxplot
    if len(data[category].value_counts()) > 5:
        top_5_categories = data[category].value_counts().nlargest(5).index
    # Filter the data to include only the top 5 categories
        filter_data = data[data[category].isin(top_5_categories)]
        sns.countplot(data=filter_data, x=category, palette='Set2', order=filter_data[category].value_counts().index)
        plt.xticks(rotation=rotation)
    else:
        sns.countplot(data=data, x=category, palette='Set2')
    plt.title(f'Barplot of {category}')
    plt.xlabel(category)
```

```
num_cols = ['Occupation', 'Purchase']
cat_cols = cat_cols[1:]
```

Numerical data

```
plt.figure(figsize=(10, 8))
i = 1
for col in num_cols:
    plt.subplot(1, 2, i)
    plot_continuous_variable(df, col, 'hist')
    i += 1
plt.show()
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf_as_na opt
  with pd.option_context('mode.use_inf_as_na', True):
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf_as_na opt
  with pd.option_context('mode.use_inf_as_na', True):
```



Most of the numerical data is not a normally distributed data.

Categorical Data

```
plt.figure(figsize=(15, 15))
i = 1
for col in cat_cols:
    plt.subplot(3, 3, i)
    plot_categorical_variable(df, col)
    i += 1
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/categorical.py:641: FutureWarning: The default of
  grouped_vals = vals.groupby(grouper)
/opt/conda/lib/python3.10/site-packages/seaborn/categorical.py:641: FutureWarning: The default of
  grouped_vals = vals.groupby(grouper)
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```

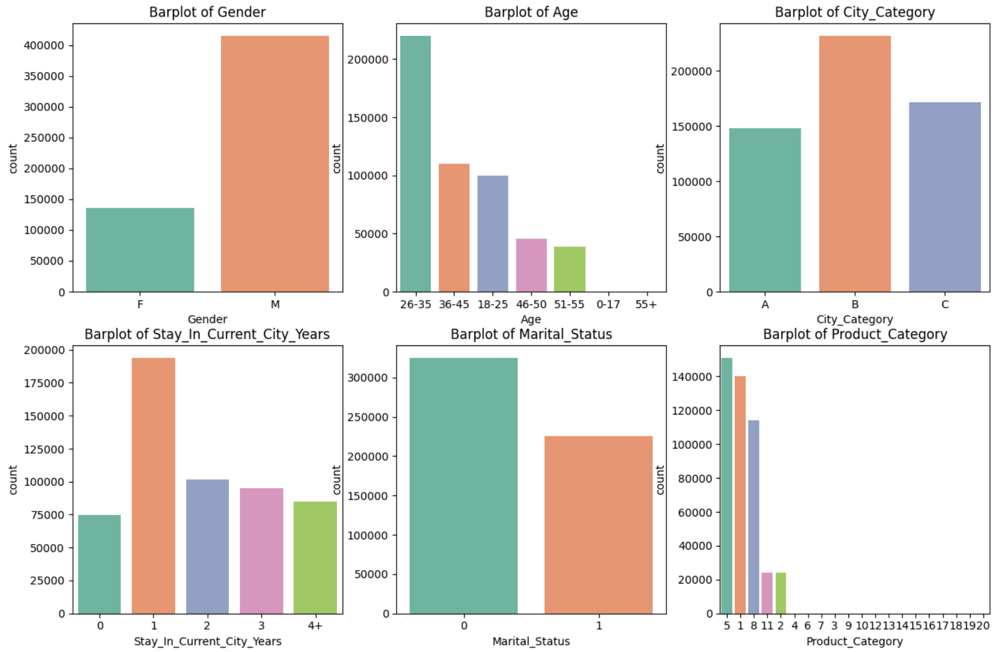

Most of the Categorical Data is orthogonal with largest groups being:

- Gender: Male
- Age: 26-35
- City_Category: B
- Stay_In_Current_City_Years: 1
- Marital_Status: Unmarried
- Product_Category: 5

Bi-variate Analysis

```
def plot_bivariate_plot_NC(data, category, variable):
    sns.violinplot(x=df[category].dropna(), y=df[variable].dropna())
    plt.title(f'violinplot of {variable} by {category}',fontdict={'fontsize':10})
    plt.xlabel(category)
    plt.ylabel(variable)


def plot_bivariate_plot_CC(data, category_1, category_2, rotation=0):
    sns.countplot(data=data, x=category_1, hue=category_2, palette='Set2')
    plt.xticks(rotation=rotation)
    plt.title(f'Grouped Barplot of {category_1} and {category_2}')
    plt.legend(bbox_to_anchor=(0.95, 1), loc='upper left')

# Define a function to create the required bivariate plots for continuous-continuous variables
def plot_bivariate_plot_NN(data, variable_1, variable_2):
    # Scatterplot
    sns.scatterplot(x=variable_1, y=variable_2, data=data)
    plt.title(f'scatterPlot of {variable_1} by {variable_2}')
    plt.xlabel(variable_1)
    plt.ylabel(variable_2)
```

Categorical - Continuous Data

```
plt.figure(figsize=(15,30))
i = 1
for col_n in num_cols:
    for col_c in cat_cols:
        plt.subplot(6, 2, i)
        plot_bivariate_plot_NC(df, col_c, col_n)
        i += 1
plt.show()
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/categorical.py:641: FutureWarning: The default of
  grouped_vals = vals.groupby(grouper)
/opt/conda/lib/python3.10/site-packages/seaborn/categorical.py:641: FutureWarning: The default of
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/opt/conda/lib/python3.10/site-packages/seaborn/categorical.py:641: FutureWarning: The default of
  grouped_vals = vals.groupby(grouper)
/opt/conda/lib/python3.10/site-packages/seaborn/categorical.py:641: FutureWarning: The default of
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  grouped_vals = vals.groupby(grouper)
```
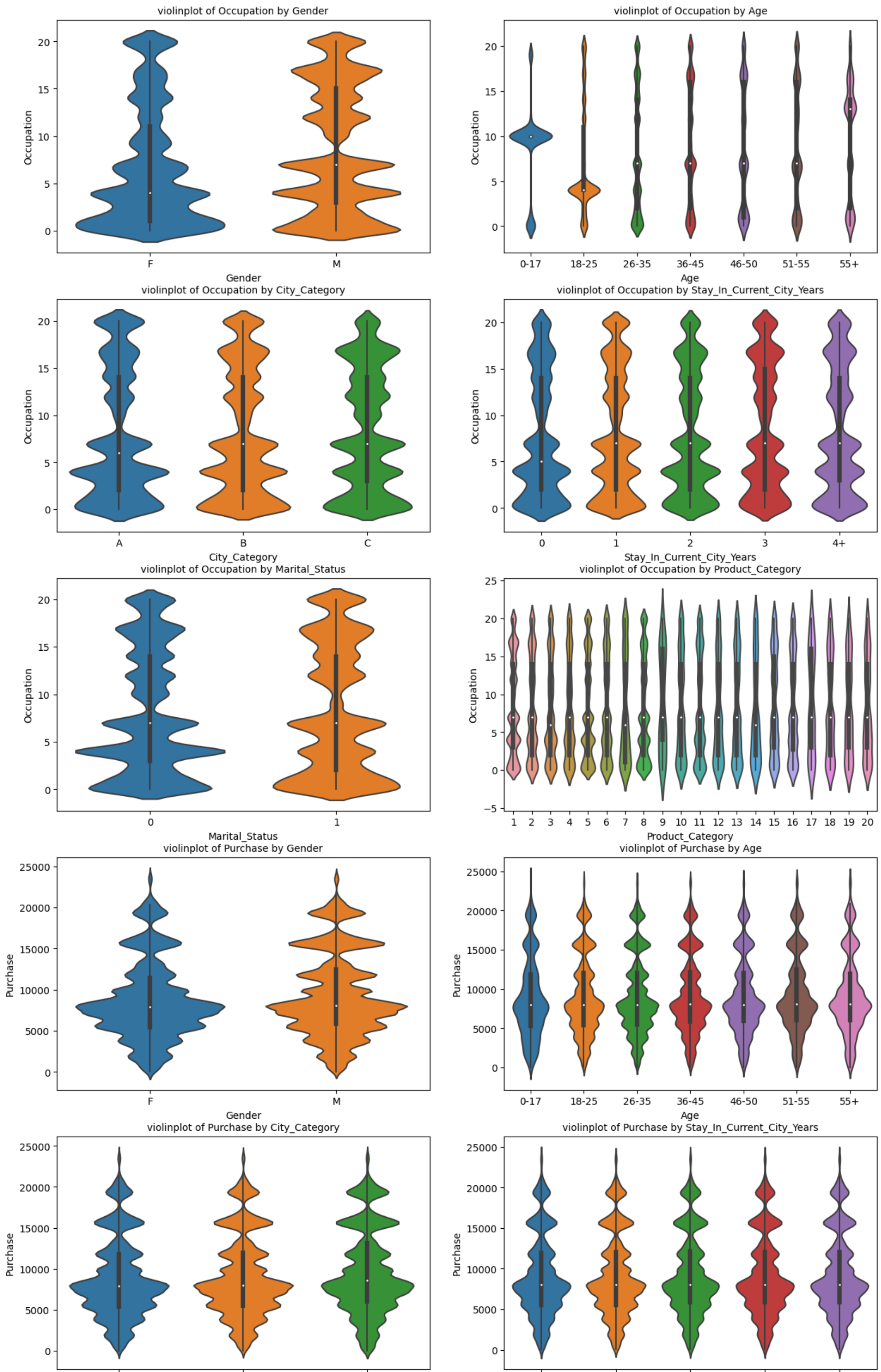
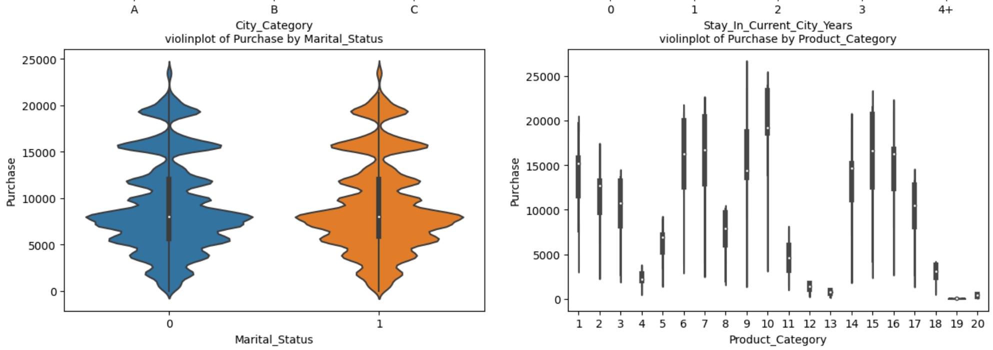
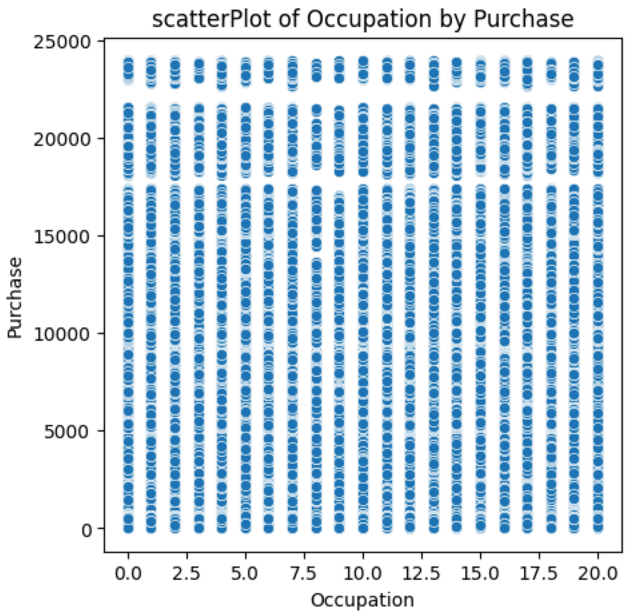





Continuous - Continuous Data

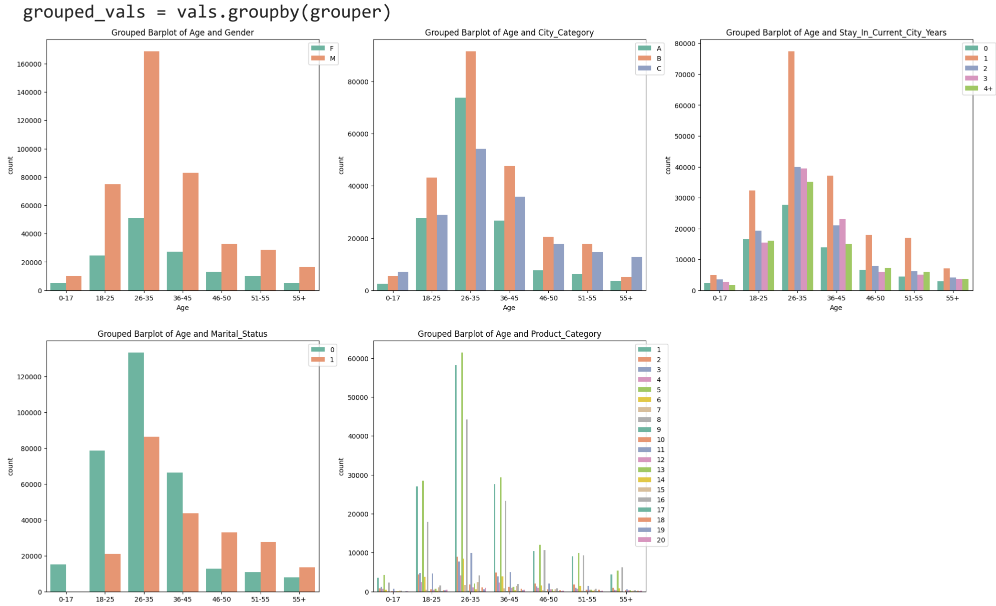
```
plt.figure(figsize=(5, 5))
plot_bivariate_plot_NN(df, num_cols[0], num_cols[1])
plt.show()
```



Categorical - Categorical Data

```
plt.figure(figsize=(25, 15))
i = 1
for col in cat_cols:
    if col!='Age':
        plt.subplot(2, 3, i)
        plot_bivariate_plot_CC(df, 'Age', col)
        i += 1
plt.show()
```

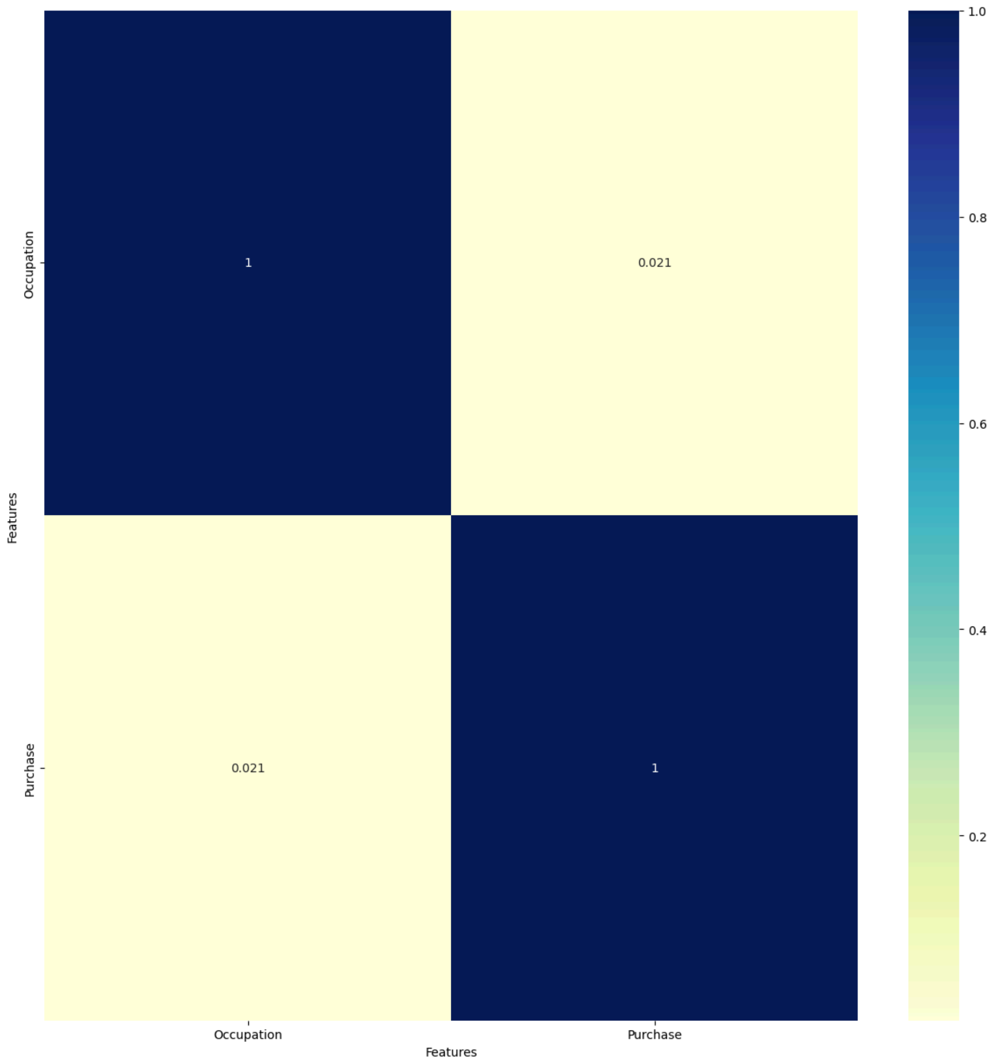
```
/opt/conda/lib/python3.10/site-packages/seaborn/categorical.py:641: FutureWarning: The default of
  grouped_vals = vals.groupby(grouper)
```



Correlation Analysis

Correlation Heatmap

```
correlation_matrix = df[num_cols].corr()

plt.figure(figsize=(15, 15))
sns.heatmap(correlation_matrix, annot=True, cmap="YlGnBu")
plt.xlabel('Features')
plt.ylabel('Features')
plt.show()
```

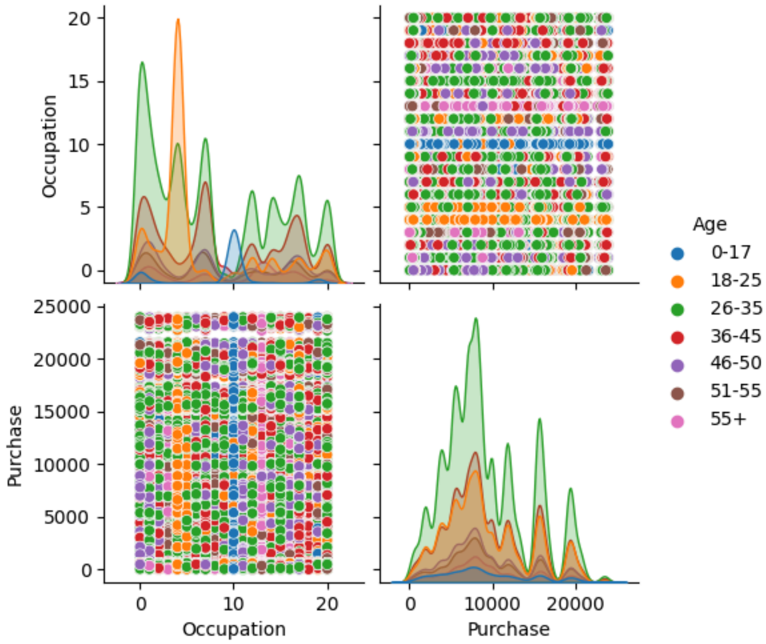


There is little to no correlation between the two numerical columns.

Pairplot

```
sns.pairplot(df.drop(['User_ID', 'Product_ID'],axis=1), hue='Age')
plt.show()
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf_as_na opt
  with pd.option_context('mode.use_inf_as_na', True):
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1057: FutureWarning: The default of ol
  grouped_data = data.groupby(
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1075: FutureWarning: When grouping wit
  data_subset = grouped_data.get_group(pd_key)
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf_as_na opt
  with pd.option_context('mode.use_inf_as_na', True):
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1057: FutureWarning: The default of ol
  grouped_data = data.groupby(
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1075: FutureWarning: When grouping wit
  data_subset = grouped_data.get_group(pd_key)
```



Outlier Detection

```
# Checking for outliers using IQR method
num_data = df[num_cols]
Q1 = num_data.quantile(0.25)
Q3 = num_data.quantile(0.75)
IQR = Q3 - Q1
outliers = num_data[(num_data < (Q1 - 1.5 * IQR)) | (num_data > (Q3 + 1.5 * IQR))].dropna(how='all')
outliers
```

	Occupation	Purchase
343	NaN	23603.0
375	NaN	23792.0
652	NaN	23233.0
736	NaN	23595.0
1041	NaN	23341.0
...	...	...
544488	NaN	23753.0
544704	NaN	23724.0
544743	NaN	23529.0
545663	NaN	23663.0
545787	NaN	23496.0

2677 rows × 2 columns

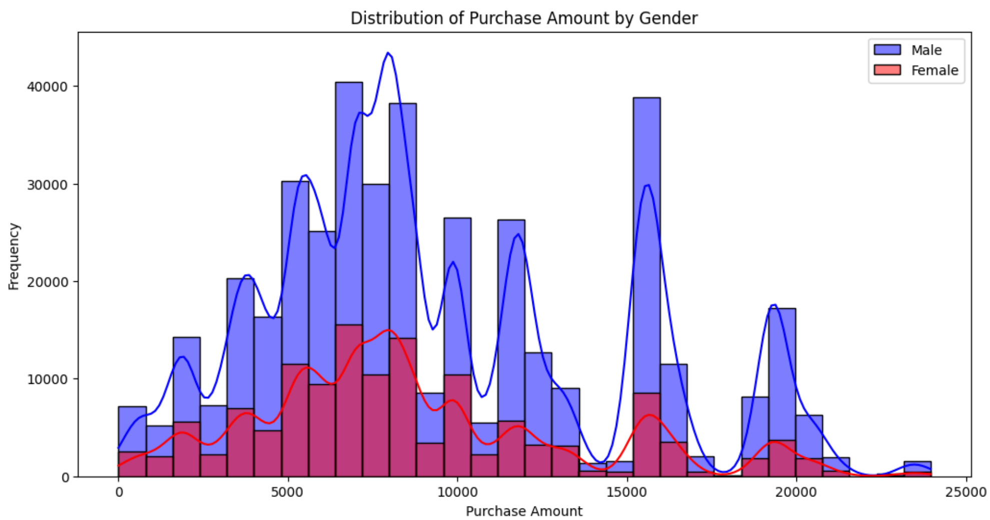
Business Insight Analyis

```
# Calculate Total and Average Spending per Gender
gender_spending = df.groupby('Gender')['Purchase'].agg(['sum', 'mean', 'count']).reset_index()
print(gender_spending)
```

```
  Gender         sum         mean   count
0      F  1186232642  8734.565765  135809
1      M  3909580100  9437.526040  414259
/tmp/ipykernel_33/326892395.py:2: FutureWarning: The default of observed=False is deprecated and will be changed to True in a future version of pandas
  gender_spending = df.groupby('Gender')['Purchase'].agg(['sum', 'mean', 'count']).reset_index()
```

```
# Plot Spending Distribution by Gender
plt.figure(figsize=(12, 6))
sns.histplot(df[df['Gender'] == 'M']['Purchase'], color='blue', label='Male', kde=True, bins=30)
sns.histplot(df[df['Gender'] == 'F']['Purchase'], color='red', label='Female', kde=True, bins=30)
plt.legend()
plt.title('Distribution of Purchase Amount by Gender')
plt.xlabel('Purchase Amount')
plt.ylabel('Frequency')
plt.show()
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf_as_na opt
  with pd.option_context('mode.use_inf_as_na', True):
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf_as_na opt
  with pd.option_context('mode.use_inf_as_na', True):
```



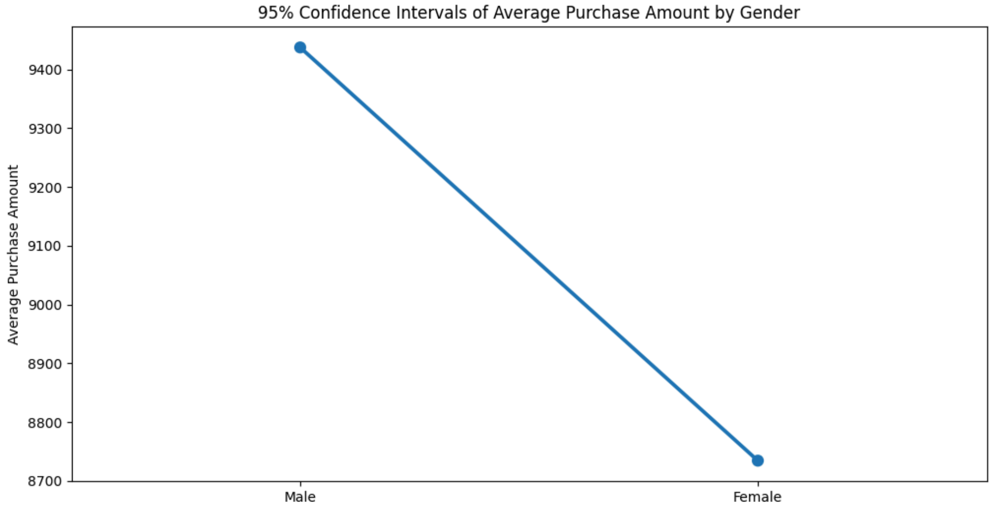

```
# Confidence Interval Calculation for Male and Female
import scipy.stats as stats

def calculate_confidence_interval(data, confidence=0.95):
    n = len(data)
    mean = np.mean(data)
    std_err = stats.sem(data)
    h = std_err * stats.t.ppf((1 + confidence) / 2., n-1)
    return mean, mean-h, mean+h
```

```
male_purchase = df[df['Gender'] == 'M']['Purchase']
female_purchase = df[df['Gender'] == 'F']['Purchase']

male_ci = calculate_confidence_interval(male_purchase)
female_ci = calculate_confidence_interval(female_purchase)

print(f'Male Purchase Confidence Interval (95%): {male_ci}')
print(f'Female Purchase Confidence Interval (95%): {female_ci}')
```

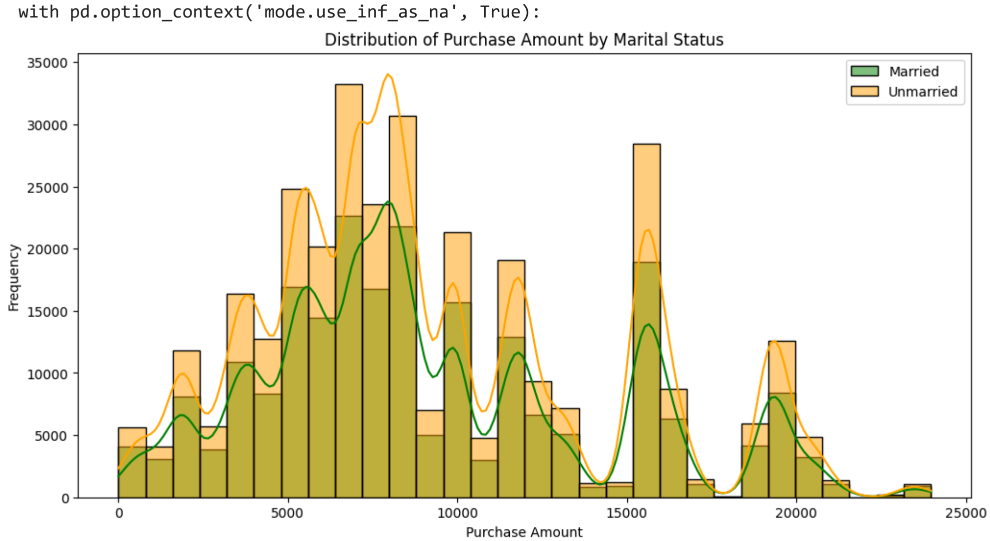
```
Male Purchase Confidence Interval (95%): (9437.526040472265, 9422.019402055814, 9453.032678888716)
Female Purchase Confidence Interval (95%): (8734.565765155476, 8709.21132117373, 8759.92020913722)
```

```
# Visualization of Confidence Intervals
plt.figure(figsize=(12, 6))
sns.pointplot(x=['Male', 'Female'], y=[male_ci[0], female_ci[0]], capsize=0.2, ci='sd')
plt.title('95% Confidence Intervals of Average Purchase Amount by Gender')
plt.ylabel('Average Purchase Amount')
plt.show()

# Repeat Analysis for Marital Status
marital_spending = df.groupby('Marital_Status')['Purchase'].agg(['sum', 'mean', 'count']).reset_index()
print(marital_spending)

# Plot Spending Distribution by Marital Status
plt.figure(figsize=(12, 6))
sns.histplot(df[df['Marital_Status'] == 1]['Purchase'], color='green', label='Married', kde=True, bins=30)
sns.histplot(df[df['Marital_Status'] == 0]['Purchase'], color='orange', label='Unmarried', kde=True, bins=30)
plt.legend()
plt.title('Distribution of Purchase Amount by Marital Status')
plt.xlabel('Purchase Amount')
plt.ylabel('Frequency')
plt.show()
```

```
/tmp/ipykernel_33/373699443.py:3: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar='sd'` for the same effect.

  sns.pointplot(x=['Male', 'Female'], y=[male_ci[0], female_ci[0]], capsize=0.2, ci='sd')
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1765: FutureWarning: unique with argu
  order = pd.unique(vector)
```




```
/tmp/ipykernel_33/373699443.py:9: FutureWarning: The default of observed=False is deprecated and w
  marital_spending = df.groupby('Marital_Status')['Purchase'].agg(['sum', 'mean', 'count']).reset_
  Marital_Status         sum         mean   count
0              0  3008927447  9265.907619  324731
1              1  2086885295  9261.174574  225337
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf_as_na opt
  with pd.option_context('mode.use_inf_as_na', True):
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf_as_na opt
  with pd.option_context('mode.use_inf_as_na', True):
```



```
# Repeat Analysis for Age Groups
age_spending = df.groupby('Age')['Purchase'].agg(['sum', 'mean', 'count']).reset_index()
print(age_spending)

# Plot Spending Distribution by Age Group
plt.figure(figsize=(12, 6))
sns.boxplot(x='Age', y='Purchase', data=df)
plt.title('Boxplot of Purchase Amount by Age Group')
plt.xlabel('Age Group')
plt.ylabel('Purchase Amount')
plt.show()
```

```
/tmp/ipykernel_33/4276004380.py:2: FutureWarning: The default of observed=False is deprecated and
  age_spending = df.groupby('Age')['Purchase'].agg(['sum', 'mean', 'count']).reset_index()
/opt/conda/lib/python3.10/site-packages/seaborn/categorical.py:641: FutureWarning: The default of
  grouped_vals = vals.groupby(grouper)
     Age         sum         mean   count
0   0-17   134913183  8933.464640   15102
1  18-25   913848675  9169.663606   99660
2  26-35  2031770578  9252.690633  219587
3  36-45  1026569884  9331.350695  110013
4  46-50   420843403  9208.625697   45701
5  51-55   367099644  9534.808031   38501
6    55+   200767375  9336.280459   21504
```