"Customer Shopping Trends"

Link here

My EDA is shown below results and predictions by using three regression models. What will be the summary according to the below finding? What approaches are used to make business profitable by seeing them? What type of decisions we can make from these findings?

Demographic Insights

1- Males are more contributor than females in the purchases 2- Age range of customer is 18-70

Purchase Patterns

1- Minimum Purchase amount is 20$ 2- Reviews range from a minimum of 2.5 to a maximum of 5 3- Medium-sized products witness the highest sales compared to other sizes 4- Olive-colored items have a higher sales volume compared to other colors 5- Most sales occur during the spring season 6- The least sales are observed during the winter season

Product Attributes

1- Products with medium sizes receive the highest review ratings, while larger sizes have the lowest 2- Medium-sized products are significant contributors to overall sales

Business Strategy Implications

Targeted Marketing

The data indicates a significant male customer base. Consider diversifying marketing strategies to attract more female customers.

Age-Driven Marketing Strategies

Analyze age distribution to tailor marketing strategies for different age groups.

Pricing Strategies

Use purchase amounts to decide on promotions and discounts, formulating effective pricing strategies.

Customer Satisfaction

Prioritize addressing low ratings by identifying and resolving issues such as product quality and delivery. Utilize Customer Relations Officers (CROs) and customer reviews for confirmation.

Product Focus

Focus marketing efforts on medium-sized products, the main contributors to sales.

Inventory and Production

Leverage color insights for inventory and production decisions.

Seasonal Planning

Plan marketing campaigns, inventory management, and production based on seasonal trends.

Product Suitability

Evaluate product suitability for winter to address lower sales during this season.

City-Wise Analysis

Investigate customer characteristics in "Montana" for insights into higher sales. Explore opportunities for improvement in "Kansas" due to lower sales.

Payment Optimization

Optimize the checkout experience based on preferred payment methods.

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
colors = ["#89CFF0", "#FF69B4", "#FFD700", "#7B68EE", "#FF4500",
 "#9370DB", "#32CD32", "#8A2BE2", "#FF6347", "#20B2AA",
 "#FF69B4", "#00CED1", "#FF7F50", "#7FFF00", "#DA70D6"]

#Regression Models
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVR

#Import Metrics
from sklearn.metrics import mean_absolute_error,mean_absolute_error,r2_score

# #DecisionTreeClassifier
# from sklearn.tree import DecisionTreeClassifier
# from sklearn.metrics import f1_score,accuracy_score,precision_score
```

In [2]:
```
fpath= "D:\\Data analyst\\Data Sciences\\datasets\\Customer shoping trend\\s
smc=pd.read_csv(fpath)
cstrend=smc
marketrend=smc
```

In [3]:
```
smc.head()
```

Out[3]:

	Customer ID	Age	Gender	Item Purchased	Category	Purchase Amount (USD)	Location	Siz
0	1	55	Male	Blouse	Clothing	53	Kentucky	
1	2	19	Male	Sweater	Clothing	64	Maine	
2	3	50	Male	Jeans	Clothing	73	Massachusetts	
3	4	21	Male	Sandals	Footwear	90	Rhode Island	
4	5	45	Male	Blouse	Clothing	49	Oregon	

In [4]:
```
smc.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3900 entries, 0 to 3899
Data columns (total 18 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Customer ID             3900 non-null   int64  
 1   Age                     3900 non-null   int64  
 2   Gender                  3900 non-null   object 
 3   Item Purchased          3900 non-null   object 
 4   Category                3900 non-null   object 
 5   Purchase Amount (USD)   3900 non-null   int64  
 6   Location                3900 non-null   object 
 7   Size                    3900 non-null   object 
 8   Color                   3900 non-null   object 
 9   Season                  3900 non-null   object 
 10  Review Rating           3900 non-null   float64
 11  Subscription Status     3900 non-null   object 
 12  Shipping Type           3900 non-null   object 
 13  Discount Applied        3900 non-null   object 
 14  Promo Code Used         3900 non-null   object 
 15  Previous Purchases      3900 non-null   int64  
 16  Payment Method          3900 non-null   object 
 17  Frequency of Purchases  3900 non-null   object 
dtypes: float64(1), int64(4), object(13)
memory usage: 548.6+ KB
```

In [5]:
```
smc.describe()
```

Out[5]:

	Customer ID	Age	Purchase Amount (USD)	Review Rating	Previous Purchases
count	3900.000000	3900.000000	3900.000000	3900.000000	3900.000000
mean	1950.500000	44.068462	59.764359	3.749949	25.351538
std	1125.977353	15.207589	23.685392	0.716223	14.447125
min	1.000000	18.000000	20.000000	2.500000	1.000000
25%	975.750000	31.000000	39.000000	3.100000	13.000000
50%	1950.500000	44.000000	60.000000	3.700000	25.000000
75%	2925.250000	57.000000	81.000000	4.400000	38.000000
max	3900.000000	70.000000	100.000000	5.000000	50.000000

In [6]:
```
Min_review_rating=smc["Review Rating"].min()
print(Min_review_rating)
min_reviewed_item=smc[smc["Review Rating"]==Min_review_rating]["Item Purchas
print(min_reviewed_item)
```

```
2.5
['Sweater' 'Handbag' 'Belt' 'Backpack' 'Gloves' 'Hoodie' 'Shorts'
 'Sandals' 'Coat' 'Socks' 'Sneakers' 'Sunglasses' 'Jacket' 'Boots' 'Shirt'
 'Hat' 'Jewelry' 'Shoes' 'Scarf' 'Dress' 'Skirt' 'Pants' 'Jeans' 'T-shirt']
```

In [7]:
```
Max_review_rating=smc["Review Rating"].max()
print(Max_review_rating)
max_reviewed_item=smc[smc["Review Rating"]==Max_review_rating]["Item Purchas
print(max_reviewed_item)
```

```
5.0
['Shorts' 'Belt' 'Jewelry' 'Backpack' 'Coat' 'Hat' 'Shirt' 'Boots'
 'Handbag' 'Jacket' 'Blouse' 'Sandals' 'Sunglasses' 'Sneakers' 'T-shirt'
 'Jeans' 'Scarf' 'Hoodie' 'Gloves' 'Dress' 'Socks' 'Skirt' 'Sweater'
 'Pants']
```

In [8]:
```
smc.isnull().sum()
```

Out[8]:
```
Customer ID               0
Age                       0
Gender                    0
Item Purchased            0
Category                  0
Purchase Amount (USD)     0
Location                  0
Size                      0
Color                     0
Season                    0
Review Rating             0
Subscription Status       0
Shipping Type             0
Discount Applied          0
Promo Code Used           0
Previous Purchases        0
Payment Method            0
Frequency of Purchases    0
dtype: int64
```

In [9]:
```
smc.dtypes
```

Out[9]:
```
Customer ID                int64
Age                        int64
Gender                    object
Item Purchased            object
Category                  object
Purchase Amount (USD)      int64
Location                  object
Size                      object
Color                     object
Season                    object
Review Rating            float64
Subscription Status       object
Shipping Type             object
Discount Applied          object
Promo Code Used           object
Previous Purchases         int64
Payment Method            object
Frequency of Purchases    object
dtype: object
```

Check Normalization of data

Use Shapiro welk or kolmogroov, if value is less than 0.05, data is normal othewise need to normalize it

These tests will work on numerical data

In [10]:
```
smc.columns
```

Out[10]:
```
Index(['Customer ID', 'Age', 'Gender', 'Item Purchased', 'Category',
       'Purchase Amount (USD)', 'Location', 'Size', 'Color', 'Season',
       'Review Rating', 'Subscription Status', 'Shipping Type',
       'Discount Applied', 'Promo Code Used', 'Previous Purchases',
       'Payment Method', 'Frequency of Purchases'],
      dtype='object')
```

In [11]:
```
smc.head()
```

Out[11]:

	Customer ID	Age	Gender	Item Purchased	Category	Purchase Amount (USD)	Location	Siz
0	1	55	Male	Blouse	Clothing	53	Kentucky	
1	2	19	Male	Sweater	Clothing	64	Maine	
2	3	50	Male	Jeans	Clothing	73	Massachusetts	
3	4	21	Male	Sandals	Footwear	90	Rhode Island	
4	5	45	Male	Blouse	Clothing	49	Oregon	

In [12]:
```
from scipy.stats import shapiro
data=smc["Age"].dropna()
statistics,p_value=shapiro(data)
print(statistics,p_value)
```

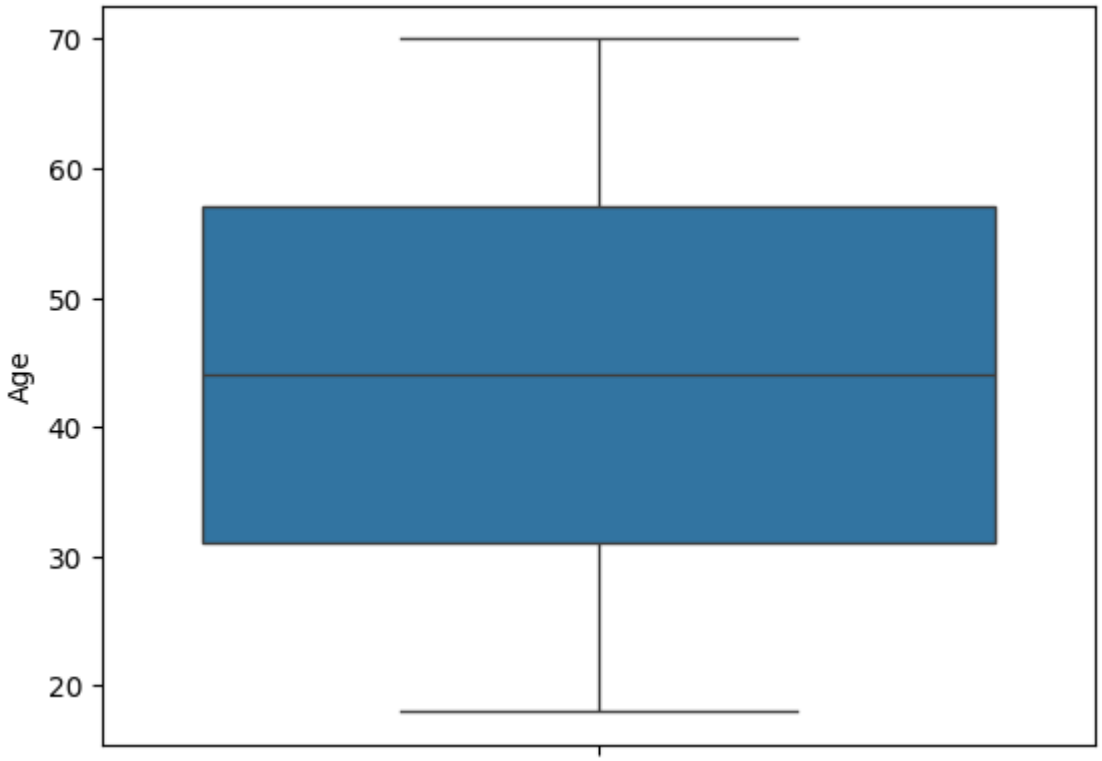
```
0.9550292491912842 4.4223607253491293e-33
```

In [13]:
```
if p_value>0.05:
 print("Data is normal")
else:
 print("Data is not normal")
```

```
Data is not normal
```

In [14]:
```
sns.boxplot(smc["Age"])
```

Out[14]: <Axes: ylabel='Age'>



In [15]:
```
smc.head()
```

Out[15]:

	Customer ID	Age	Gender	Item Purchased	Category	Purchase Amount (USD)	Location	Siz
0	1	55	Male	Blouse	Clothing	53	Kentucky	
1	2	19	Male	Sweater	Clothing	64	Maine	
2	3	50	Male	Jeans	Clothing	73	Massachusetts	
3	4	21	Male	Sandals	Footwear	90	Rhode Island	
4	5	45	Male	Blouse	Clothing	49	Oregon	

In [16]:
```
max_age=smc["Age"].max()
max_age
```

Out[16]: 70

In [17]:
```
max_pur=smc["Purchase Amount (USD)"].max()
max_pur
```

Out[17]: 100

In [18]:
```
max_rev=smc["Review Rating"].max()
max_rev
```

Out[18]: 5.0

In [19]:
```
max_prev_pur=smc["Previous Purchases"].max()
max_prev_pur
```

Out[19]: 50

In [20]:
```
new_age=(smc["Age"])/(smc["Age"].max())
new_age
```

Out[20]:
```
0       0.785714
1       0.271429
2       0.714286
3       0.300000
4       0.642857
          ...
3895    0.571429
3896    0.742857
3897    0.657143
3898    0.628571
3899    0.742857
Name: Age, Length: 3900, dtype: float64
```

In [21]:
```
new_pur=(smc["Purchase Amount (USD)"])/max_pur
new_pur
```

Out[21]:
```
0       0.53
1       0.64
2       0.73
3       0.90
4       0.49
        ...
3895    0.28
3896    0.49
3897    0.33
3898    0.77
3899    0.81
Name: Purchase Amount (USD), Length: 3900, dtype: float64
```

In [22]:
```
new_rev=smc["Review Rating"]/max_rev
new_rev
```

Out[22]:
```
0       0.62
1       0.62
2       0.62
3       0.70
4       0.54
        ...
3895    0.84
3896    0.90
3897    0.58
3898    0.76
3899    0.62
Name: Review Rating, Length: 3900, dtype: float64
```

In [23]:
```
new_prev_pur=(smc["Previous Purchases"])/max_prev_pur
new_prev_pur
```

Out[23]:
```
0       0.28
1       0.04
2       0.46
3       0.98
4       0.62
        ...
3895    0.64
3896    0.82
3897    0.48
3898    0.48
3899    0.66
Name: Previous Purchases, Length: 3900, dtype: float64
```

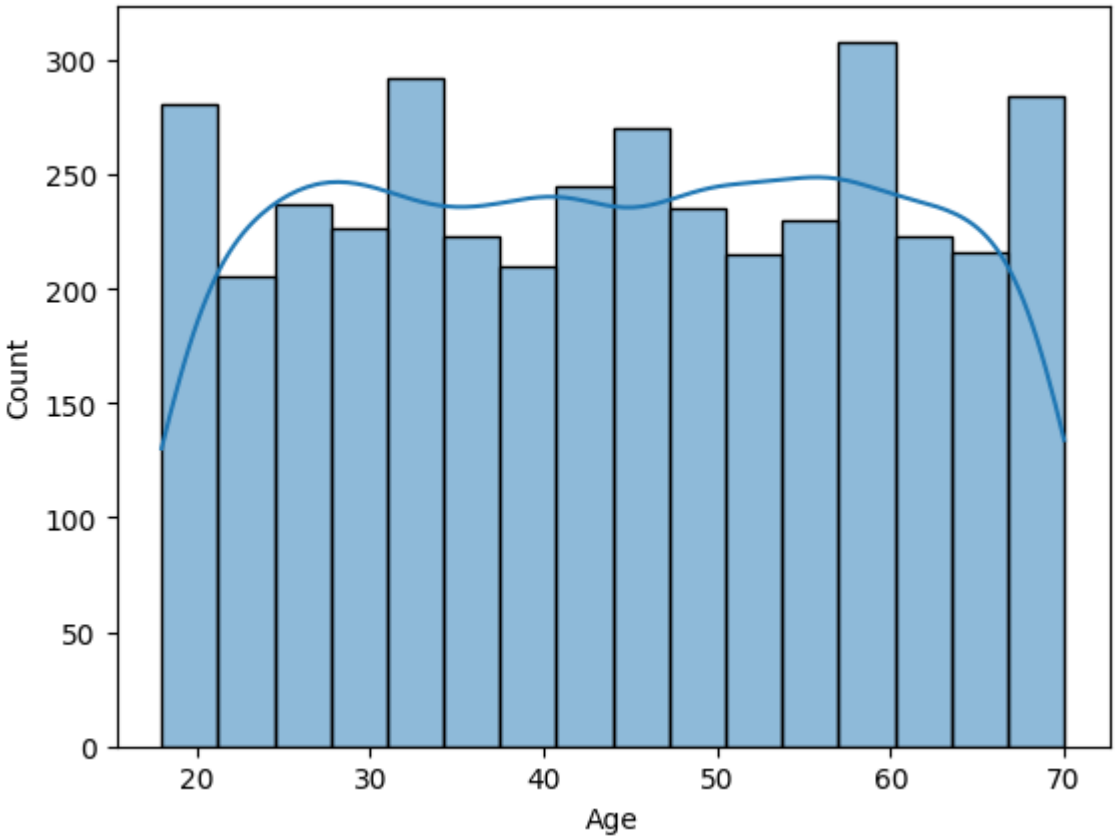
In [24]:
```
#below is showing normalized data
```

In [25]:
```
shapir_age=smc["Age"]
statistics,p_value=shapiro(shapir_age)
print(statistics,p_value)
if p_value>0.05:
 print("data is normal")
else:
 print("data is not normal")
```

```
0.9550292491912842 4.4223607253491293e-33
data is not normal
```

In [26]:
```
sns.histplot(smc,x=smc["Age"],kde=True)
```

Out[26]:
```
<Axes: xlabel='Age', ylabel='Count'>
```



In [27]:
```
#Do it Normal
#Apply Log_transform or Z_score,boccox etc

#Z_score
#smc["Age"]=(smc["Age"]-smc["Age"].mean())/smc["Age"].std()
#boxcox
```

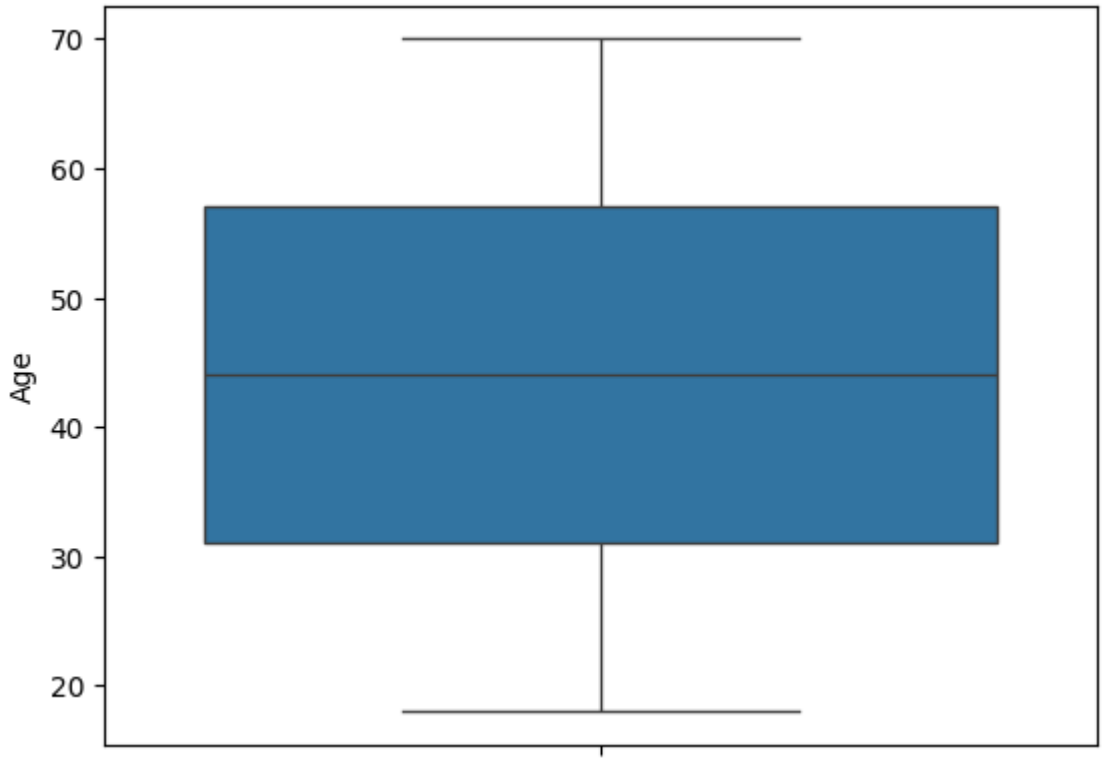
In [28]:
```
shapir_age=smc["Age"]
statistics,p_value=shapiro(shapir_age)
print(statistics,p_value)
if p_value>0.05:
 print("data is normal")
else:
 print("data is not normal")
```

```
0.9550292491912842 4.4223607253491293e-33
data is not normal
```

In [29]:
```
outlr=smc["Age"]
```

In [30]:
```
sns.boxplot(data=smc,y=smc["Age"])
```

Out[30]: <Axes: ylabel='Age'>



In [31]:
```
smc_lin=smc[(smc["Age"]>=20) & (smc["Age"]<=75)]
smc_lin
```

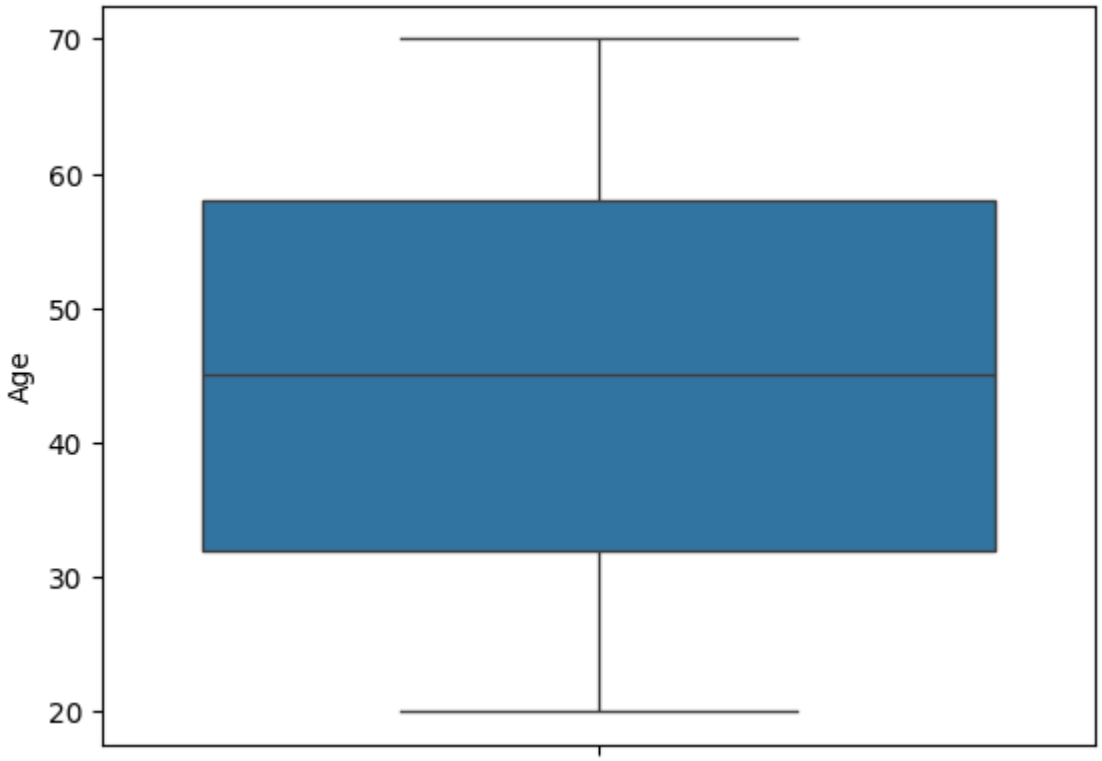
Out[31]:

	Customer ID	Age	Gender	Item Purchased	Category	Purchase Amount (USD)	Location
0	1	55	Male	Blouse	Clothing	53	Kentucky
2	3	50	Male	Jeans	Clothing	73	Massachusetts
3	4	21	Male	Sandals	Footwear	90	Rhode Island
4	5	45	Male	Blouse	Clothing	49	Oregon
5	6	46	Male	Sneakers	Footwear	20	Wyoming
...	...	...	...	...	...	...	...
3895	3896	40	Female	Hoodie	Clothing	28	Virginia
3896	3897	52	Female	Backpack	Accessories	49	Iowa
3897	3898	46	Female	Belt	Accessories	33	New Jersey
3898	3899	44	Female	Shoes	Footwear	77	Minnesota
3899	3900	52	Female	Handbag	Accessories	81	California

3750 rows × 18 columns

In [32]:
```
sns.boxplot(data=smc_lin,y=smc_lin["Age"])
```

Out[32]:
```
<Axes: ylabel='Age'>
```



In [33]:
```
smc_lin["Age"].isnull().sum()
```

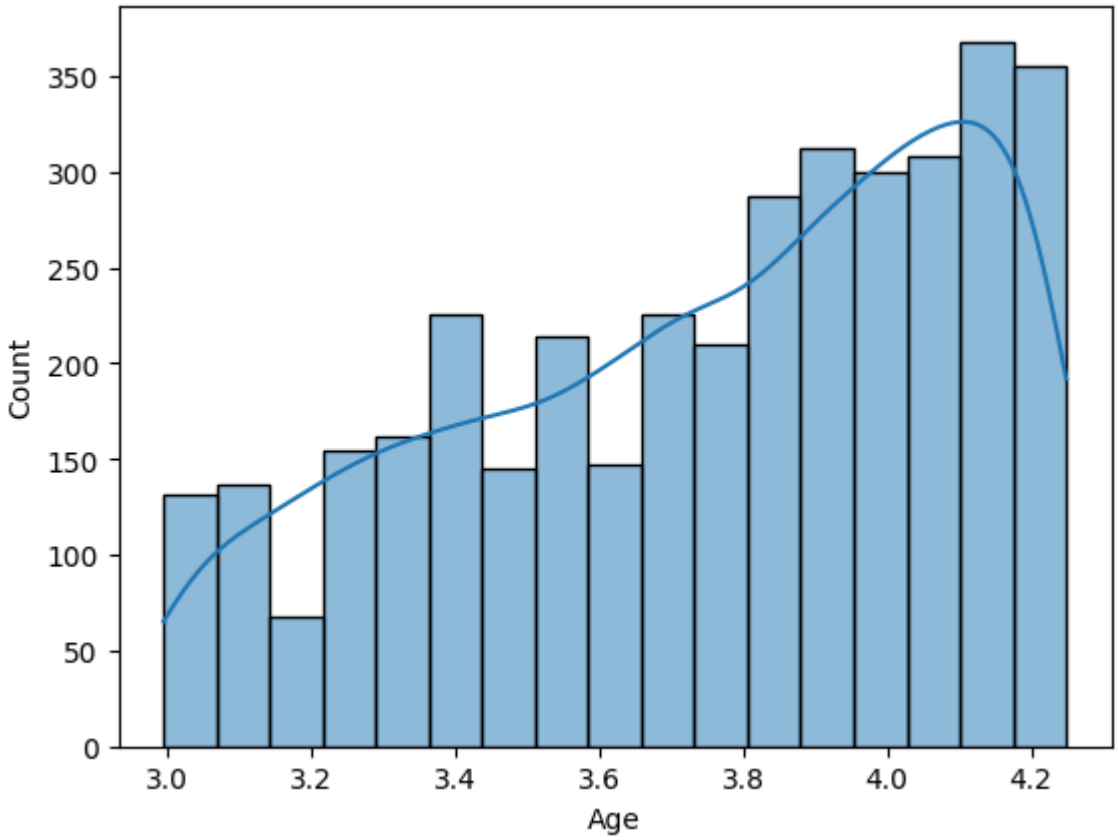
Out[33]:
```
0
```

In [34]:
```
smc_lin["Age"]=np.log(smc_lin["Age"])
```

```
C:\Users\Muhammad\AppData\Local\Temp\ipykernel_14092\2849705432.py:1: Settin
gWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  smc_lin["Age"]=np.log(smc_lin["Age"])
```

In [35]:
```
sns.histplot(smc_lin,x=smc_lin["Age"], kde=True)
```

Out[35]:
```
<Axes: xlabel='Age', ylabel='Count'>
```

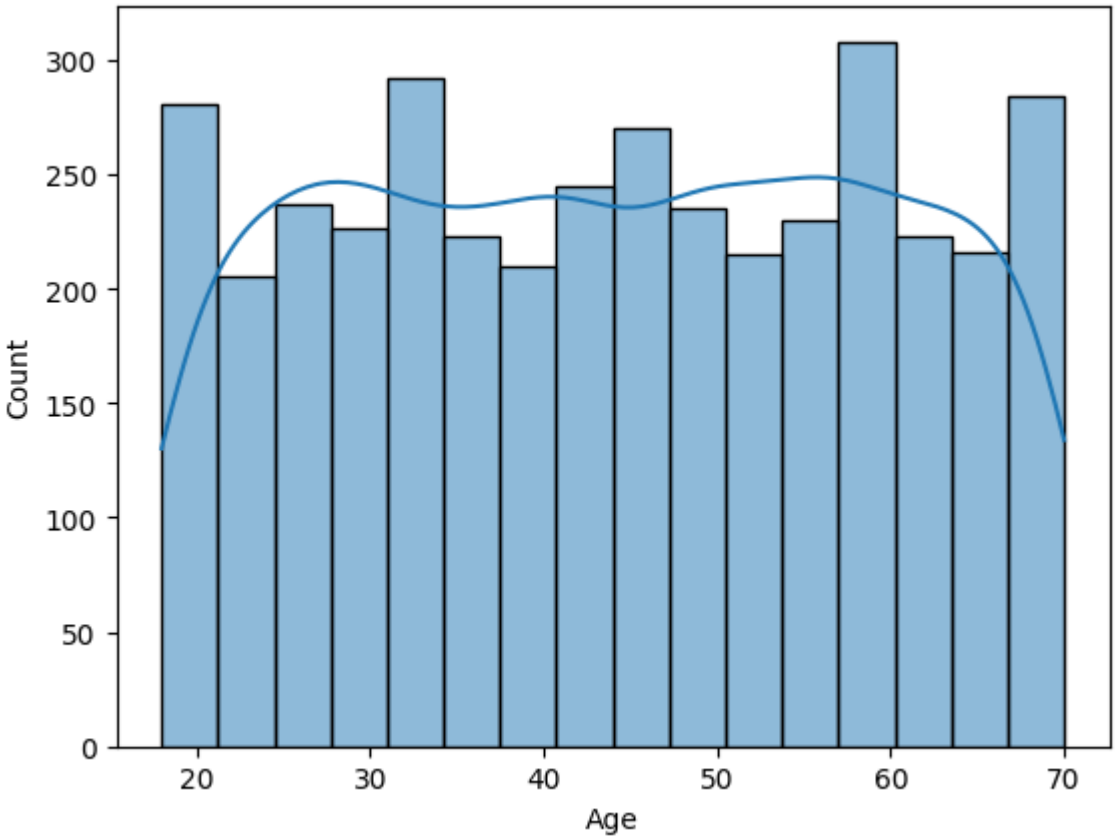


In [36]:
```
shapir_age=smc_lin["Age"]
statistics,p_value=shapiro(shapir_age)
print(statistics,p_value)
if p_value>0.05:
 print("data is normal")
else:
 print("data is not normal")
```

```
0.9419093132019043 4.623799567325405e-36
data is not normal
```

In [37]:
```
Q1 = smc["Age"].quantile(0.25)
Q3 = smc["Age"].quantile(0.75)
IQR = Q3 - Q1
smc_no_outliers = smc[(smc["Age"] >= Q1 - 1.5 * IQR) & (smc["Age"] <= Q3 + 1
```

In [38]:
```
sns.histplot(smc_no_outliers["Age"], kde=True)
plt.show()
```



In [39]:
```
smc_lin["Age"]=np.log(smc_lin["Age"])

shapir_age=smc_lin["Age"]
statistics,p_value=shapiro(shapir_age)
print(statistics,p_value)
if p_value>0.05:
 print("data is normal")
else:
 print("data is not normal, but close to normal distribution")
```

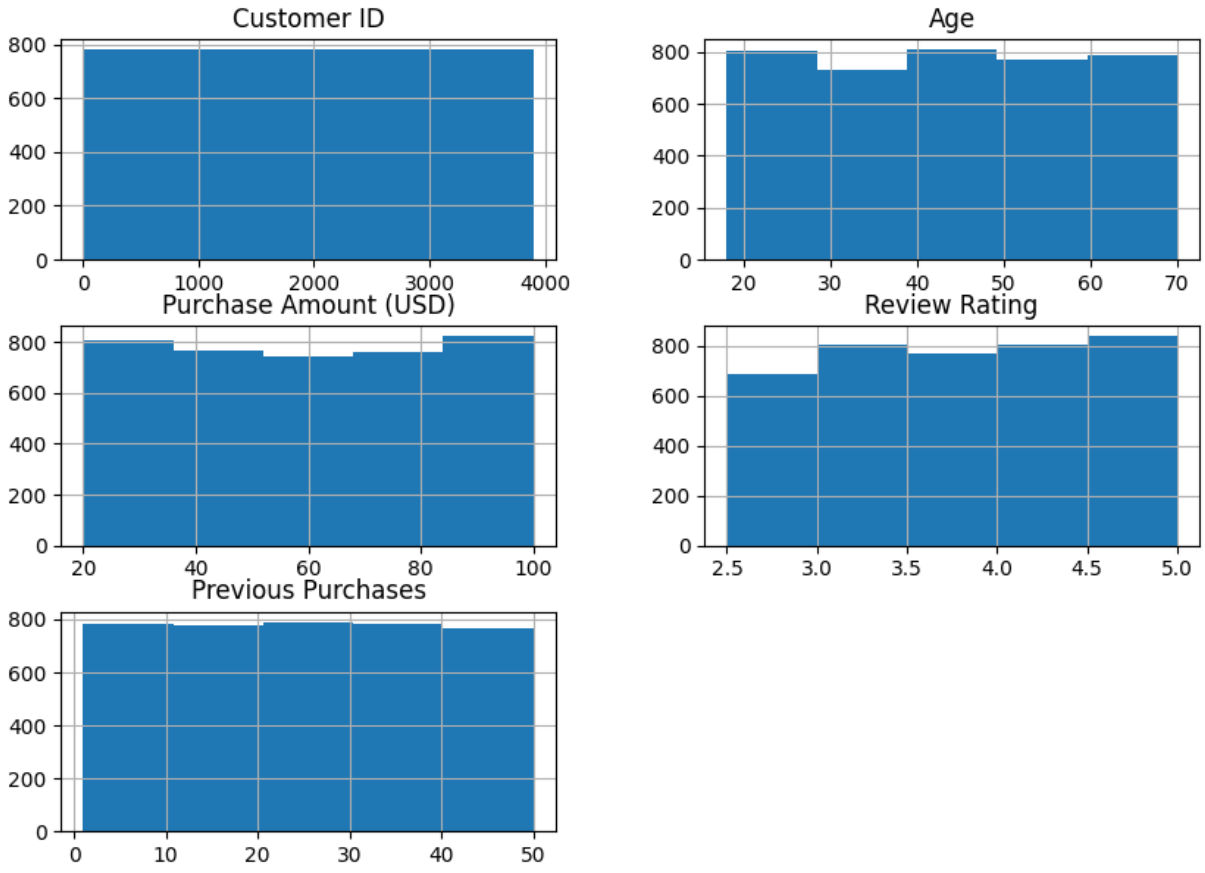
```
0.9321163892745972 2.629516389607633e-38
data is not normal, but close to normal distribution
C:\Users\Muhammad\AppData\Local\Temp\ipykernel_14092\2515282573.py:1: Settin
gWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/
stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  smc_lin["Age"]=np.log(smc_lin["Age"])
```

In [40]:
```
# from scipy.stats import yeojohnson


# # Add a small constant to handle zero values
# constant = 0.001
# transformed_age, lambda_value = yeojohnson(smc_no_outliers['Age'] + consta
# print("lambda_value:", lambda_value)

ic,p_value=shapiro(transformed_age)
```

```
# p_value
# if p_value>0.05:
#     print("data is notmal")
# else:
#     print("data is still not normal")

# shapir_age=smc_no_outliers["Age"]
# statistics,p_value=shapiro(shapir_age)
# print(statistics,p_value)
# if p_value>0.05:
#  print("data is normal")
# else:
#  print("data is not normal")
```

In [41]:
```
smc.hist(bins=5,figsize=(10,7))
```

Out[41]:
```
array([[<Axes: title={'center': 'Customer ID'}>,
        <Axes: title={'center': 'Age'}>],
       [<Axes: title={'center': 'Purchase Amount (USD)'}>,
        <Axes: title={'center': 'Review Rating'}>],
       [<Axes: title={'center': 'Previous Purchases'}>, <Axes: >]],
      dtype=object)
```

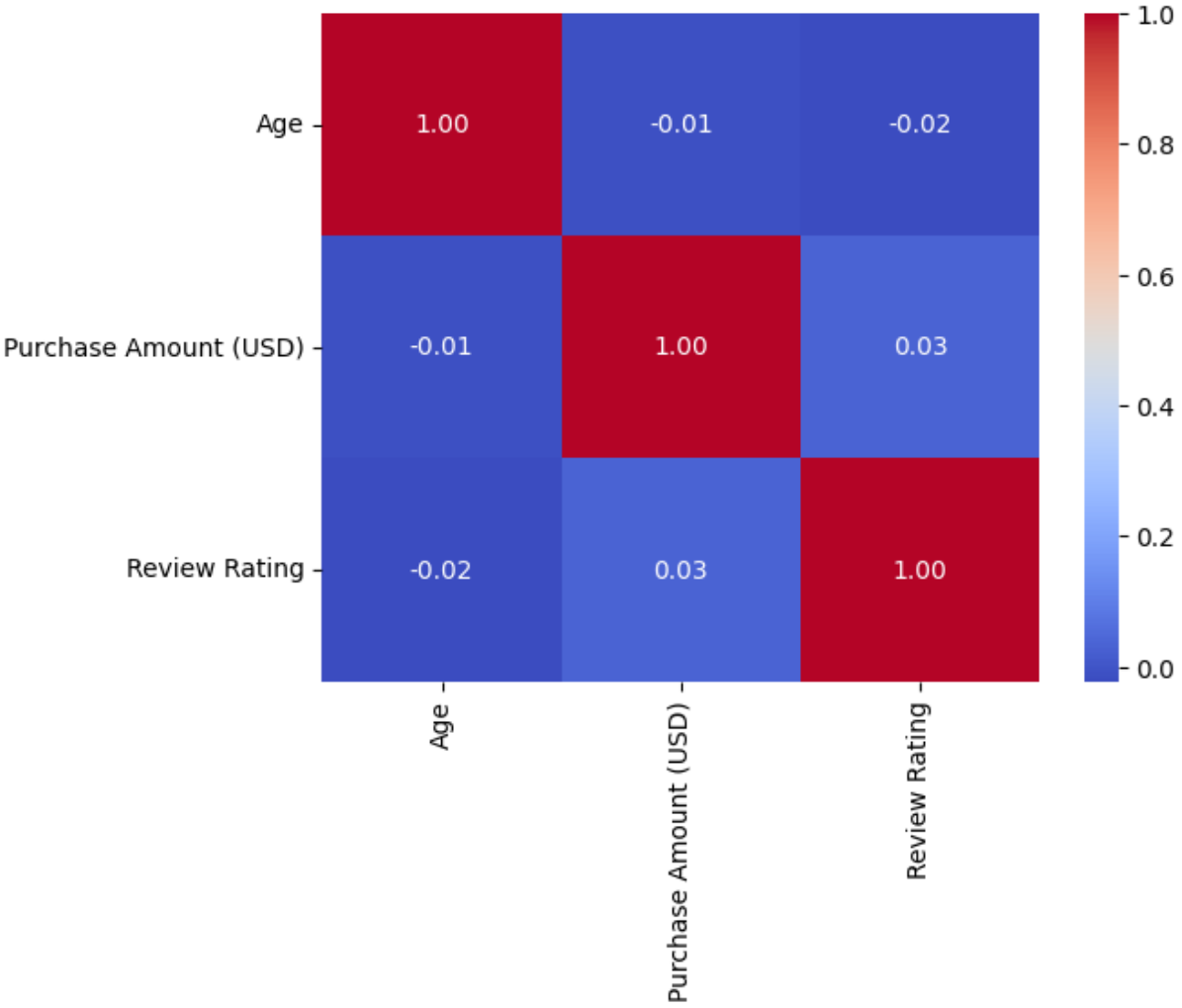


In [42]:
```
smc.describe()
```

Out[42]:

	Customer ID	Age	Purchase Amount (USD)	Review Rating	Previous Purchases
count	3900.000000	3900.000000	3900.000000	3900.000000	3900.000000
mean	1950.500000	44.068462	59.764359	3.749949	25.351538
std	1125.977353	15.207589	23.685392	0.716223	14.447125
min	1.000000	18.000000	20.000000	2.500000	1.000000
25%	975.750000	31.000000	39.000000	3.100000	13.000000
50%	1950.500000	44.000000	60.000000	3.700000	25.000000
75%	2925.250000	57.000000	81.000000	4.400000	38.000000
max	3900.000000	70.000000	100.000000	5.000000	50.000000

In [43]:
```
selected_columns = ['Age', 'Purchase Amount (USD)', 'Review Rating']
g = sns.heatmap(smc[selected_columns].corr(), fmt=".2f", cmap="coolwarm", ar

# Show the plot
plt.show()

# g=sns.heatmap(smc[smc["Age","Purchase Amount (USD)","Review Rating"]].corr
# g
```

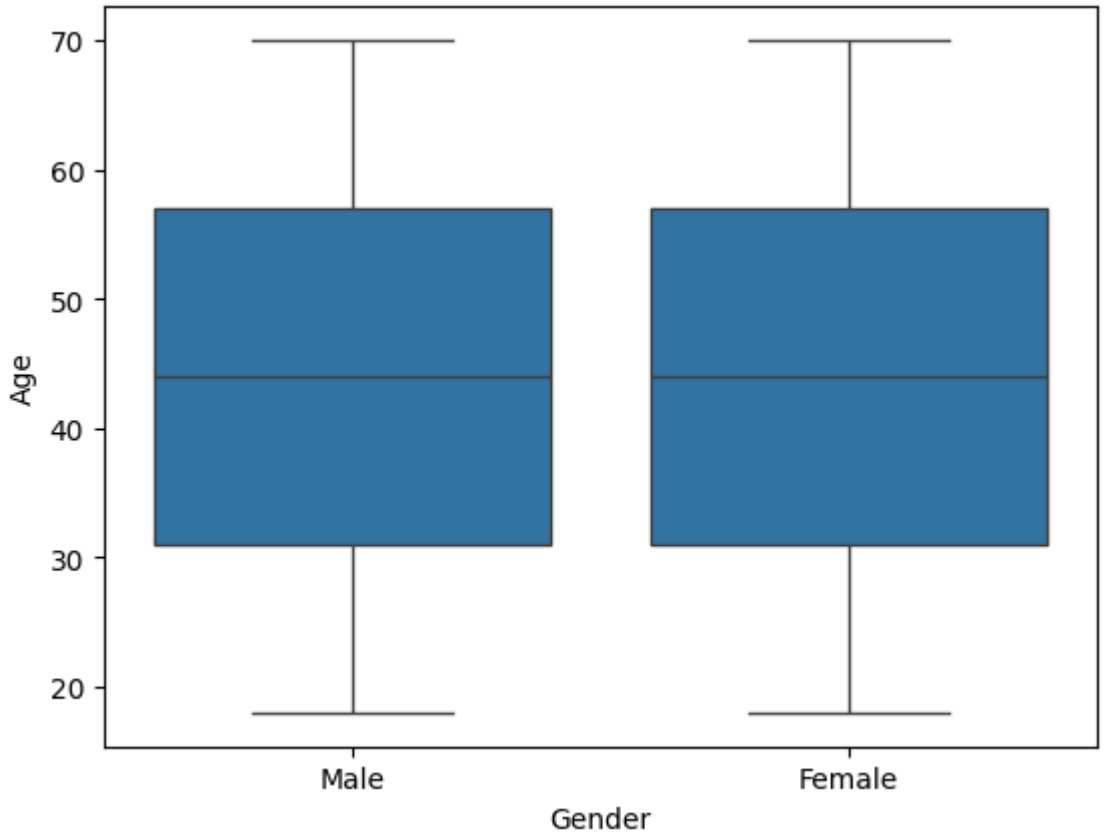


In [44]:
```
smc.columns
```

Out[44]:
```
Index(['Customer ID', 'Age', 'Gender', 'Item Purchased', 'Category',
       'Purchase Amount (USD)', 'Location', 'Size', 'Color', 'Season',
       'Review Rating', 'Subscription Status', 'Shipping Type',
       'Discount Applied', 'Promo Code Used', 'Previous Purchases',
       'Payment Method', 'Frequency of Purchases'],
      dtype='object')
```

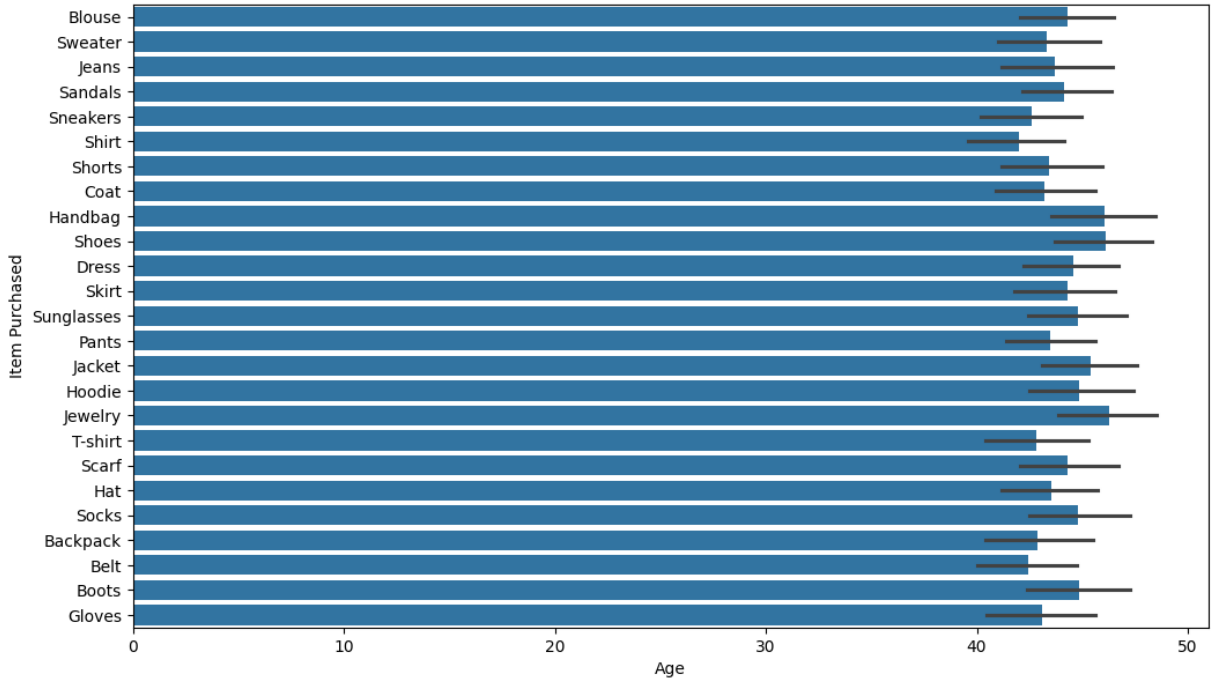
In [45]:
```
#plot boxplot to check data distribution and outliers
sns.boxplot(data=smc,x="Gender",y="Age")
```

Out[45]:
```
<Axes: xlabel='Gender', ylabel='Age'>
```



In [46]:
```
plt.figure(figsize=(12,7))
sns.barplot(data=smc,y="Item Purchased",x="Age")
```

Out[46]: <Axes: xlabel='Age', ylabel='Item Purchased'>



In [47]:
```
smc.dtypes
```

Out[47]:
```
Customer ID                int64
Age                        int64
Gender                    object
Item Purchased            object
Category                  object
Purchase Amount (USD)      int64
Location                  object
Size                      object
Color                     object
Season                    object
Review Rating            float64
Subscription Status       object
Shipping Type             object
Discount Applied          object
Promo Code Used           object
Previous Purchases         int64
Payment Method            object
Frequency of Purchases    object
dtype: object
```

In [48]:
```
smc['Age'] = pd.to_numeric(smc['Age'], errors='coerce').astype('Int64')
```

In [49]:
```
#will see it later
# maxitems=smc.groupby("Age")["Item Purchased"].max()
# sns.barplot(data=maxitems, x="Age",hue="Item Purchased")
```

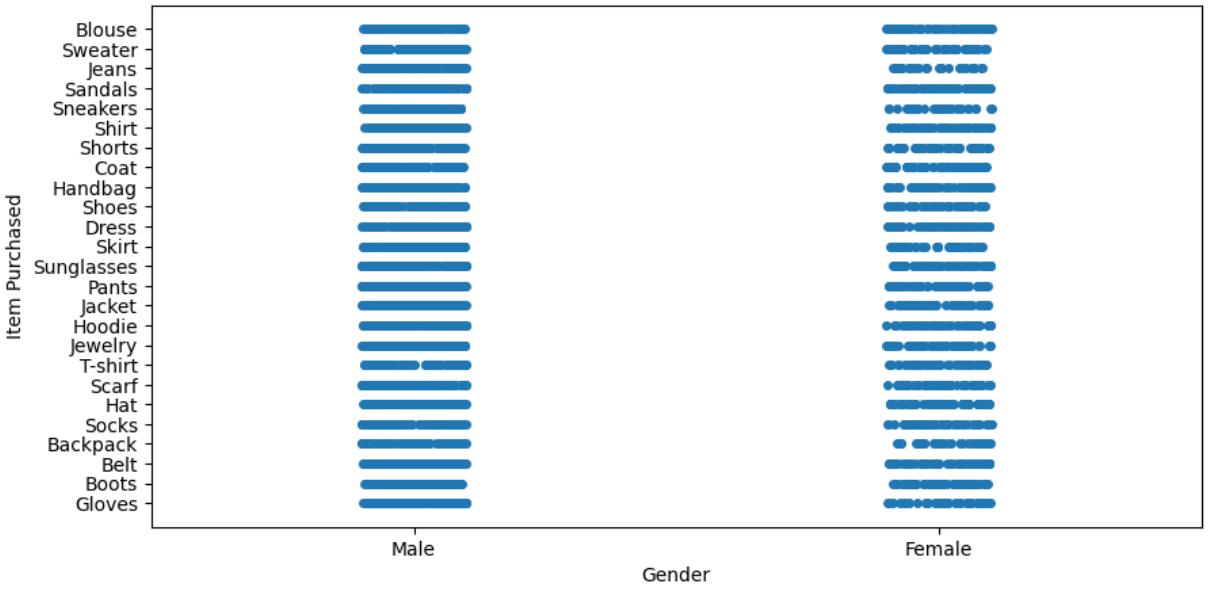
In [50]:
```
smc.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3900 entries, 0 to 3899
Data columns (total 18 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Customer ID             3900 non-null   int64
 1   Age                     3900 non-null   Int64
 2   Gender                  3900 non-null   object
 3   Item Purchased          3900 non-null   object
 4   Category                3900 non-null   object
 5   Purchase Amount (USD)   3900 non-null   int64
 6   Location                3900 non-null   object
 7   Size                    3900 non-null   object
 8   Color                   3900 non-null   object
 9   Season                  3900 non-null   object
 10  Review Rating           3900 non-null   float64
 11  Subscription Status     3900 non-null   object
 12  Shipping Type           3900 non-null   object
 13  Discount Applied        3900 non-null   object
 14  Promo Code Used         3900 non-null   object
 15  Previous Purchases      3900 non-null   int64
 16  Payment Method          3900 non-null   object
 17  Frequency of Purchases  3900 non-null   object
dtypes: Int64(1), float64(1), int64(3), object(13)
memory usage: 552.4+ KB
```

In [51]:
```
plt.figure(figsize=(10,5))
```

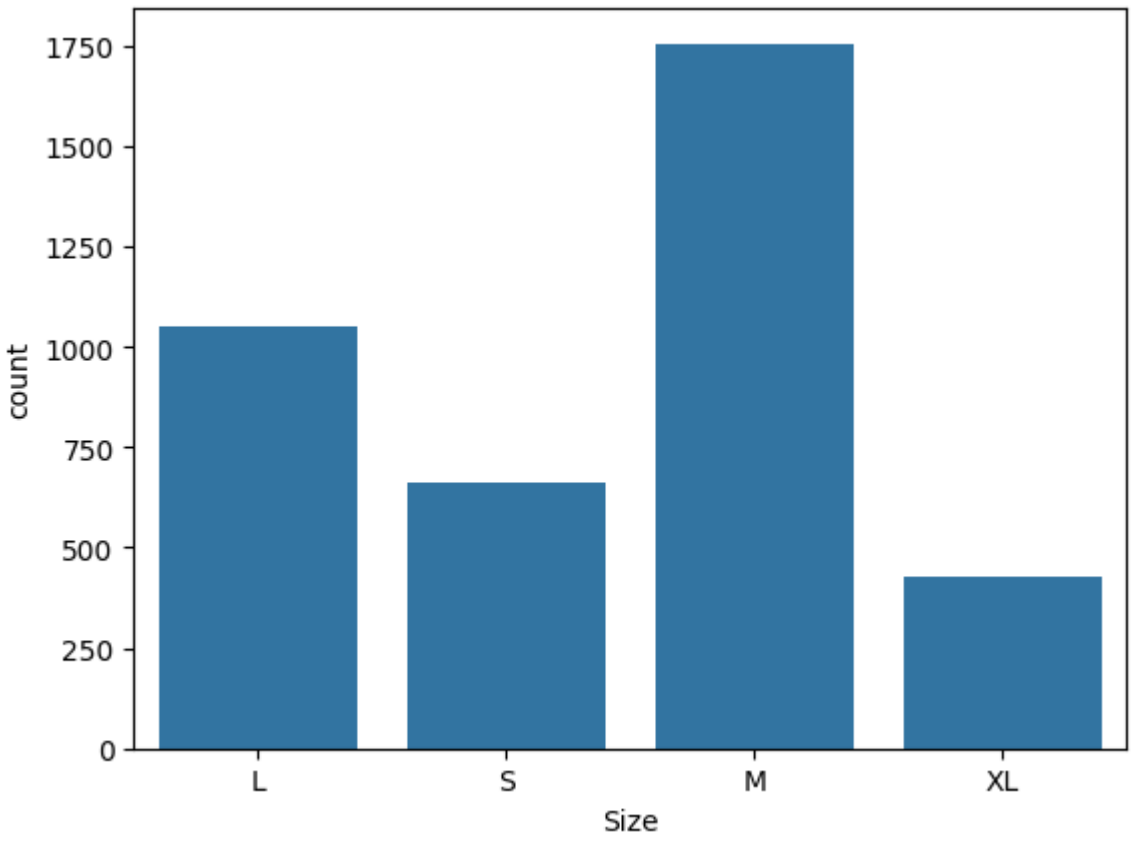
```
sns.stripplot(data=smc,x="Gender", y="Item Purchased")
```

Out[51]: <Axes: xlabel='Gender', ylabel='Item Purchased'>



In [52]:
```
sns.countplot(data=smc,x="Size")
```

Out[52]: <Axes: xlabel='Size', ylabel='count'>



In [53]:
```
# #Make groups of item purchased and check which item sell more
# find_item_sell=smc.groupby("Item Purchased")["Size"].value_counts().idxmax
# # find_item_sell=smc["Item Purchased"].value_counts().idxmax()
# st_sold_item=smc[smc["Item Purchased"]==find_item_sell]
```

```
# age_wise=smc.groupby("Age")["Item Purchased"].value_counts().idxmax()
# age_wise
# sns.countplot(data=find_most_sold_item,x="Size")
```

In [54]:
```
smc.columns
```

Out[54]:
```
Index(['Customer ID', 'Age', 'Gender', 'Item Purchased', 'Category',
       'Purchase Amount (USD)', 'Location', 'Size', 'Color', 'Season',
       'Review Rating', 'Subscription Status', 'Shipping Type',
       'Discount Applied', 'Promo Code Used', 'Previous Purchases',
       'Payment Method', 'Frequency of Purchases'],
      dtype='object')
```

In [55]:
```
maxi_sold_item_count=smc["Item Purchased"].value_counts().max()
print("Maxi Sold Item Count", maxi_sold_item_count)
max_sold_item=smc["Item Purchased"].value_counts().idxmax()
print("Maxi Sold Item", max_sold_item)
```

```
Maxi Sold Item Count 171
Maxi Sold Item Blouse
```

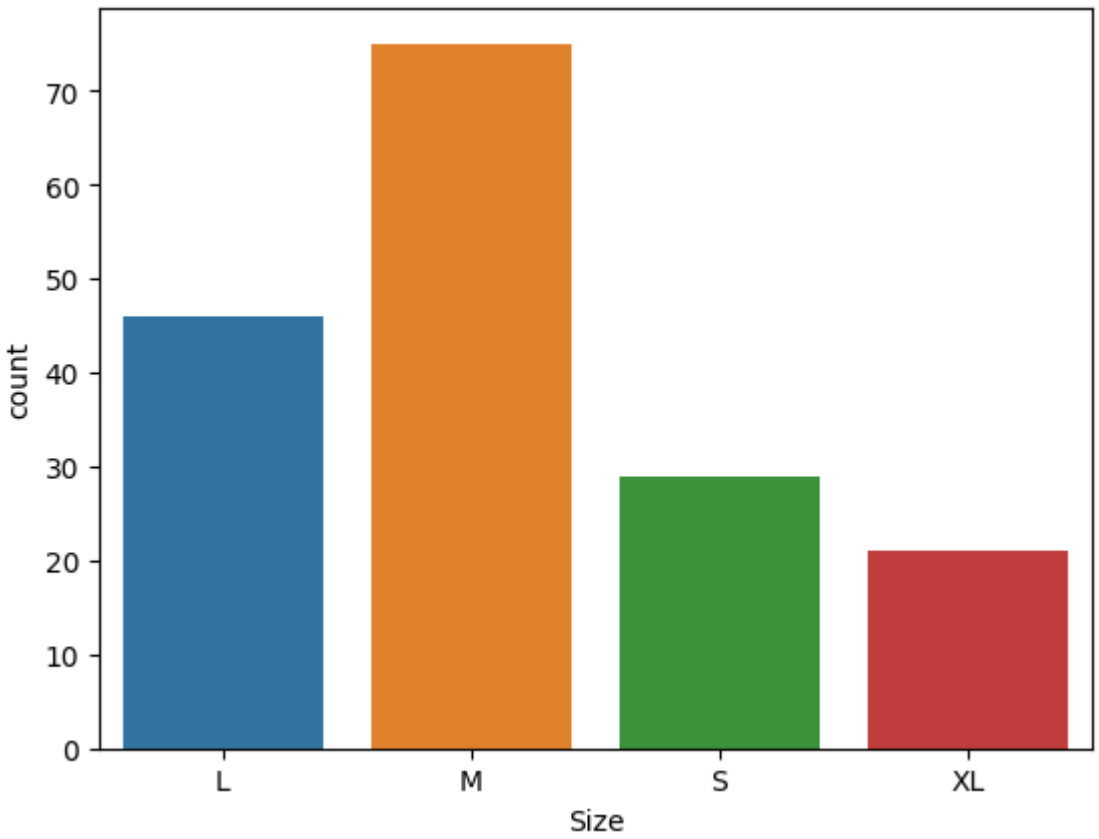
In [56]:
```
maxi=smc["Size"].value_counts().max()
m_size=smc["Size"].value_counts().idxmax()
print("count of maxi purchase item size",maxi)
print("maximum purchased size",m_size)
```

```
count of maxi purchase item size 1755
maximum purchased size M
```

In [57]:
```
maxi_pur_color=smc["Color"].value_counts().max()
print("Maxi purchased color",maxi_pur_color)
maxi_count=smc["Color"].value_counts().idxmax()
print("count of Maxi purchased color",maxi_count)
```

```
Maxi purchased color 177
count of Maxi purchased color Olive
```

In [64]:
```
# Most_purchased_item = smc["Item Purchased"].value_counts().idxmax()
# Subset_mpi = smc[smc["Item Purchased"] == Most_purchased_item]
# sns.countplot(data=Subset_mpi, x="Size", color="Green")
rating_purchasing = smc["Item Purchased"].value_counts().idxmax()
Subset_mpi = smc[smc["Item Purchased"] == rating_purchasing]
high_rating=Subset_mpi .groupby("Item Purchased")["Review Rating"].mean().id
final_subset=Subset_mpi[Subset_mpi["Item Purchased"]==high_rating]
final_subset
sns.countplot(data=final_subset,x="Size",hue="Size")
plt.show()
```



In [65]:
```
#check unique value of sizes in subset_mpi
print(Subset_mpi["Size"].unique())
```

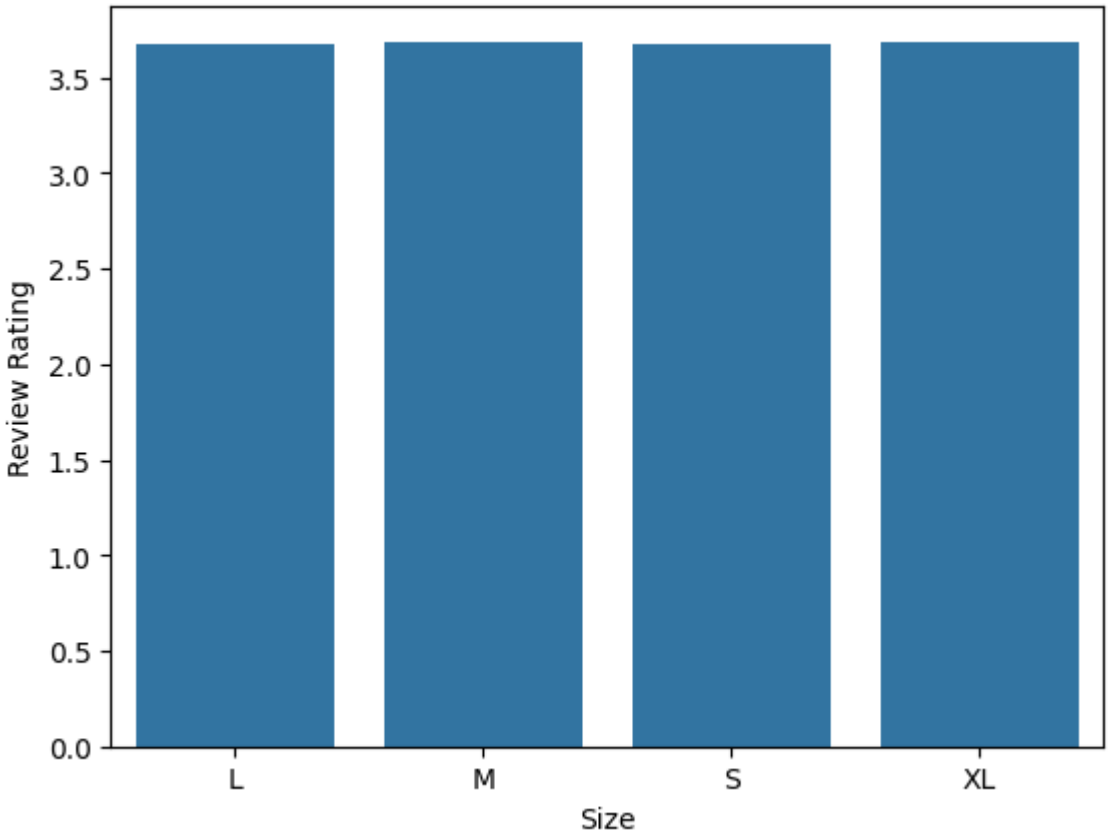
```
['L' 'M' 'S' 'XL']
```

In [66]:
```
#check mean of Review rating item by Size in subset_mpi
print(Subset_mpi.groupby("Size")["Review Rating"].mean())
```

```
Size
L     3.678261
M     3.688000
S     3.679310
XL    3.685714
Name: Review Rating, dtype: float64
```

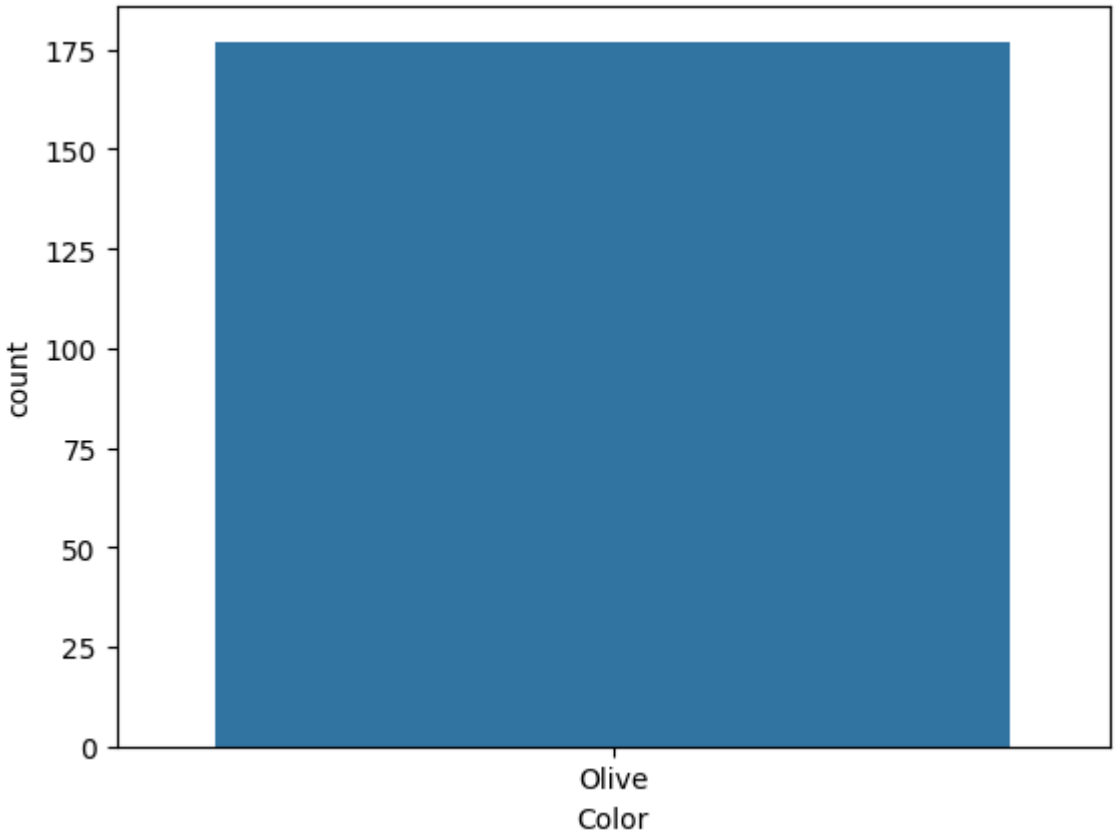
In [67]:
```
most_purchasing_item=smc["Item Purchased"].value_counts().idxmax()
subset_mpi=smc[smc["Item Purchased"]==most_purchasing_item]
average_rating=subset_mpi.groupby("Size")["Review Rating"].mean().reset_inde
sns.barplot(data=average_rating, x="Size",y="Review Rating")
print(Subset_mpi.groupby("Size")["Review Rating"].mean())
```

```
Size
L     3.678261
M     3.688000
S     3.679310
XL    3.685714
Name: Review Rating, dtype: float64
```



In [68]:
```
most_purchased_color=smc["Color"].value_counts().idxmax()
Subset_mpo=smc[smc["Color"]==most_purchased_color]
sns.countplot(data=Subset_mpo, x="Color")
```

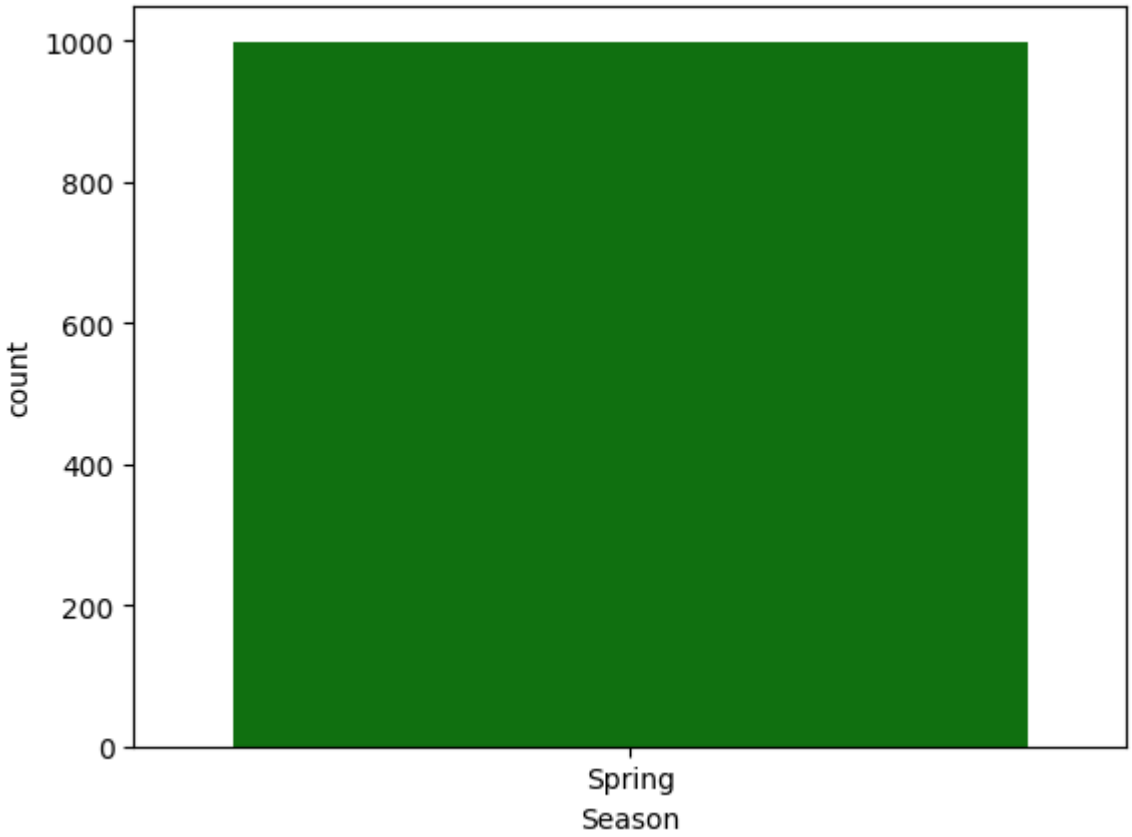
Out[68]: <Axes: xlabel='Color', ylabel='count'>



In [69]:
```
# Minim_purchased_item = smc["Item Purchased"].value_counts().idxmin()
# Subset_mpi = smc[smc["Item Purchased"] == Minim_purchased_item]
# sns.countplot(data=Subset_mpi, x="Size", color="Green")
```

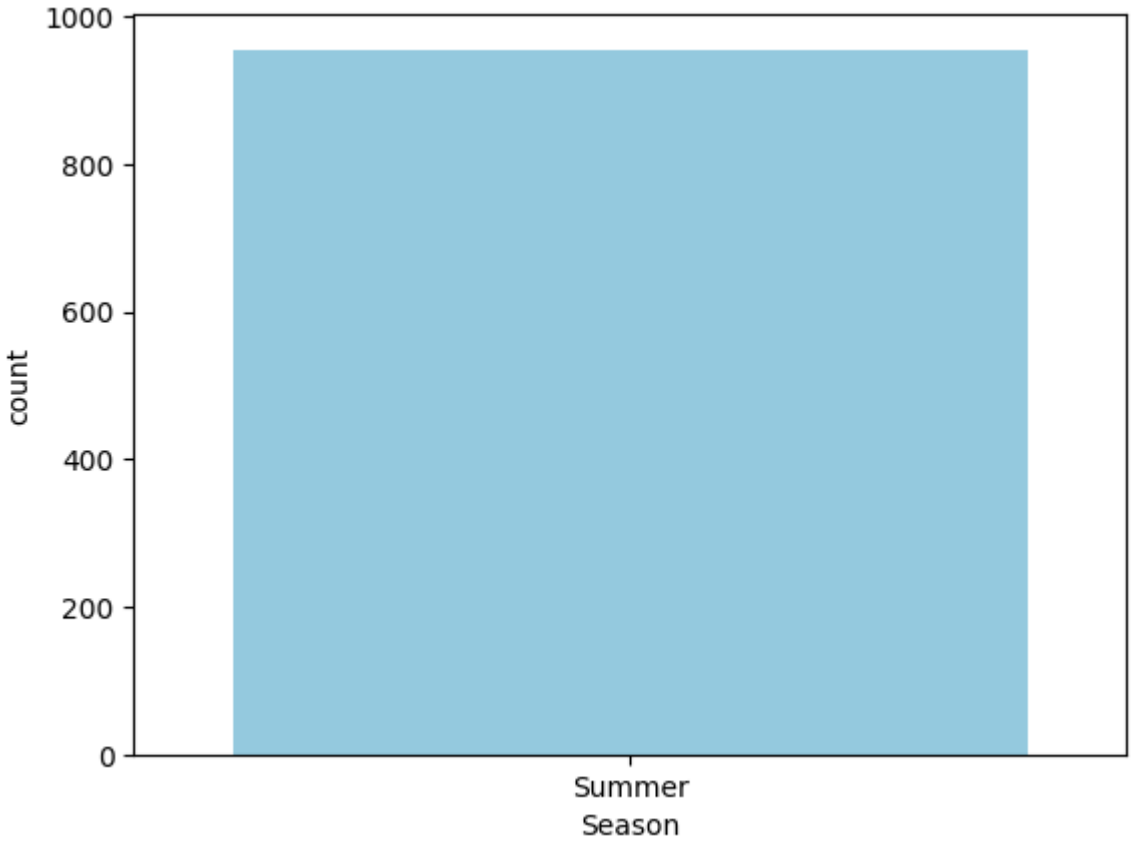
In [70]:
```
Most_purchasing_item = smc["Season"].value_counts().idxmax()
Subset_mpi = smc[smc["Season"] == Most_purchasing_item]
sns.countplot(data=Subset_mpi, x="Season", color="Green")
```

Out[70]: <Axes: xlabel='Season', ylabel='count'>



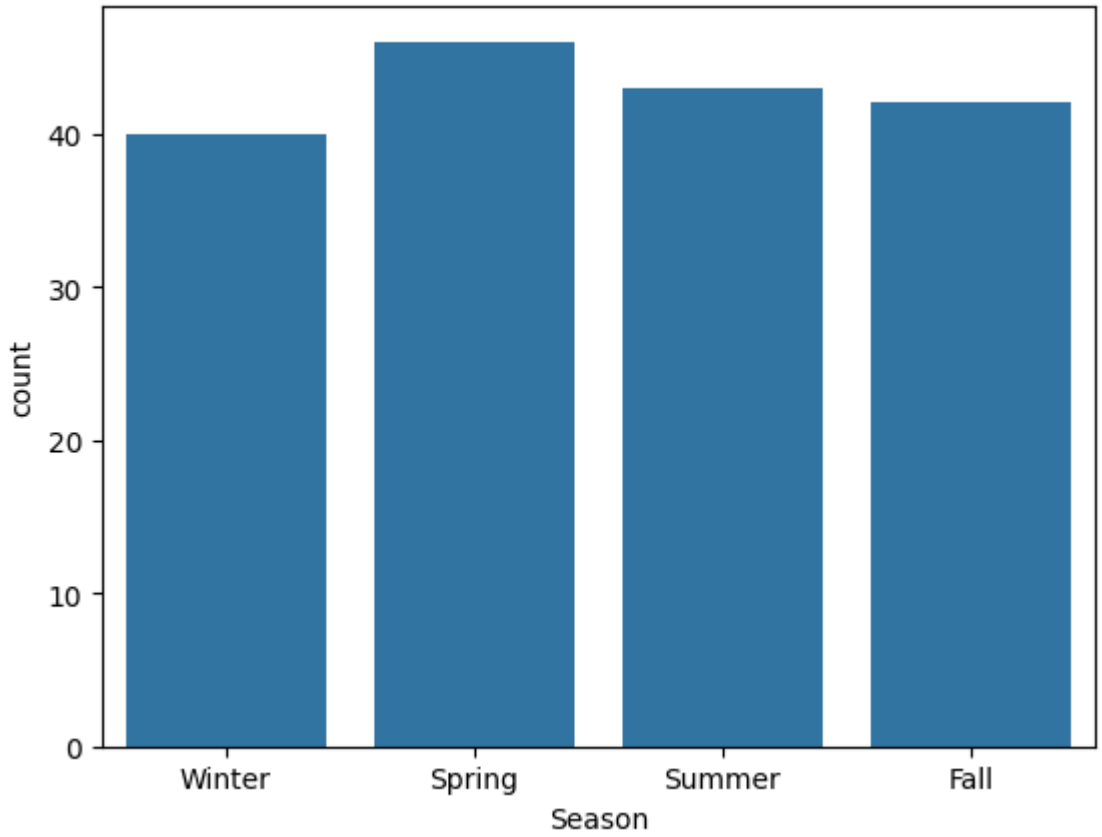
In [71]:
```
Minim_purchasing_item = smc["Season"].value_counts().idxmin()
Subset_mpi = smc[smc["Season"] == Minim_purchasing_item]
sns.countplot(data=Subset_mpi, x="Season", color="skyblue")
```

Out[71]: <Axes: xlabel='Season', ylabel='count'>



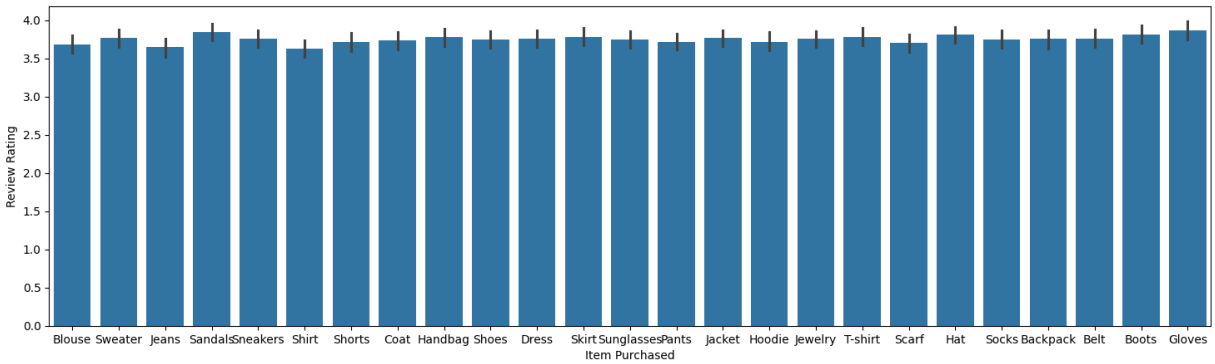
In [72]:
```
seasonal_purchasing = smc["Item Purchased"].value_counts().idxmax()
Subset_mpi = smc[smc["Item Purchased"] == seasonal_purchasing]
sns.countplot(data=Subset_mpi, x="Season")
```

Out[72]: <Axes: xlabel='Season', ylabel='count'>



In [73]:
```
# seasonal_purchasing = smc["Item Purchased"].value_counts().idxmax()
# Subset_mpi = smc[smc["Item Purchased"] == seasonal_purchasing]
plt.figure(figsize=(18,5))
sns.barplot(data=smc, x="Item Purchased",y="Review Rating")
```

Out[73]: <Axes: xlabel='Item Purchased', ylabel='Review Rating'>



In [74]:
```
# rating_purchasing = smc["Item Purchased"].value_counts().idxmax()
# Subset_mpi = smc[smc["Item Purchased"] == rating_purchasing]
# high_rating=Subset_mpi .groupby("Item Purchased")["Review Rating"].mean().
# final_subset=Subset_mpi[Subset_mpi["Item Purchased"]==high_rating]
# final_subset
# sns.countplot(data=final_subset,x="Size",hue="Size")
# plt.show()
```

In [75]:
```
print(Subset_mpi.groupby("Item Purchased")["Review Rating"].value_counts().r
```

	Item Purchased	Review Rating	count
0	Blouse	4.0	18
1	Blouse	3.0	14
2	Blouse	3.1	11
3	Blouse	3.3	11
4	Blouse	2.6	10
5	Blouse	2.7	8
6	Blouse	4.2	8
7	Blouse	4.9	7
8	Blouse	4.8	7
9	Blouse	3.9	7
10	Blouse	4.7	6
11	Blouse	3.8	6
12	Blouse	3.7	6
13	Blouse	3.5	6
14	Blouse	3.2	6
15	Blouse	3.4	5
16	Blouse	4.4	5
17	Blouse	4.6	5
18	Blouse	2.9	5
19	Blouse	2.8	5
20	Blouse	4.3	4
21	Blouse	5.0	4
22	Blouse	3.6	3
23	Blouse	4.1	2
24	Blouse	4.5	2

In [76]:
```
print(smc["Item Purchased"].unique())
```

```
['Blouse' 'Sweater' 'Jeans' 'Sandals' 'Sneakers' 'Shirt' 'Shorts' 'Coat'
 'Handbag' 'Shoes' 'Dress' 'Skirt' 'Sunglasses' 'Pants' 'Jacket' 'Hoodie'
 'Jewelry' 'T-shirt' 'Scarf' 'Hat' 'Socks' 'Backpack' 'Belt' 'Boots'
 'Gloves']
```

In [77]:
```
smc.columns
```

Out[77]:
```
Index(['Customer ID', 'Age', 'Gender', 'Item Purchased', 'Category',
       'Purchase Amount (USD)', 'Location', 'Size', 'Color', 'Season',
       'Review Rating', 'Subscription Status', 'Shipping Type',
       'Discount Applied', 'Promo Code Used', 'Previous Purchases',
       'Payment Method', 'Frequency of Purchases'],
      dtype='object')
```

In [78]:
```
Mostly_Choosed_shipping=smc["Shipping Type"].value_counts().idxmax()
Mostly_Choosed_shipping
```

Out[78]:
```
'Free Shipping'
```

In [79]:
```
Pay=smc["Payment Method"].value_counts()
Pay
```

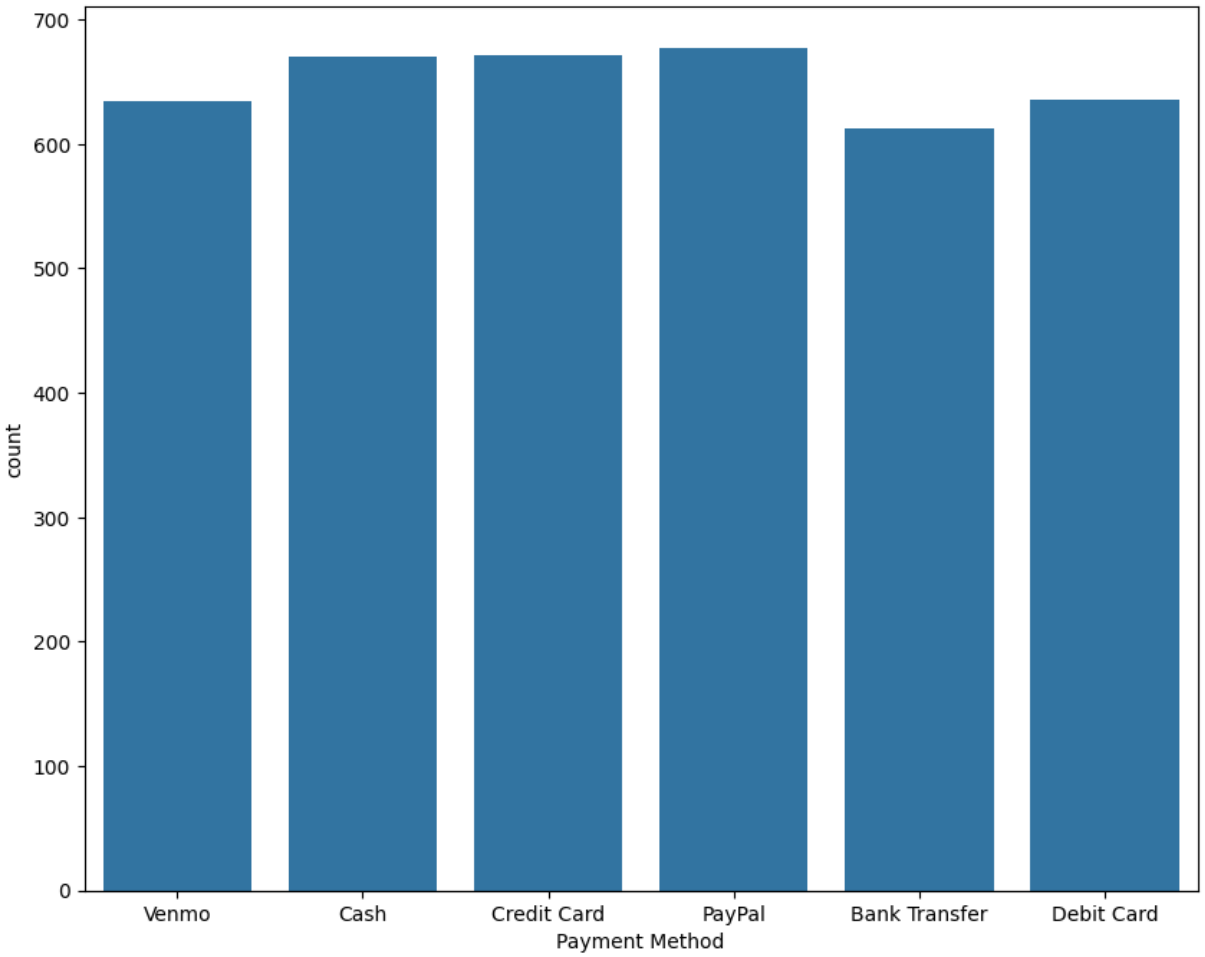
Out[79]:
```
Payment Method
PayPal           677
Credit Card      671
Cash             670
Debit Card       636
Venmo            634
Bank Transfer    612
Name: count, dtype: int64
```

In [80]:
```
Mostly_Choosed_Payment_Method=smc["Payment Method"].value_counts().idxmax()
Mostly_Choosed_Payment_Method
```

Out[80]:
```
'PayPal'
```

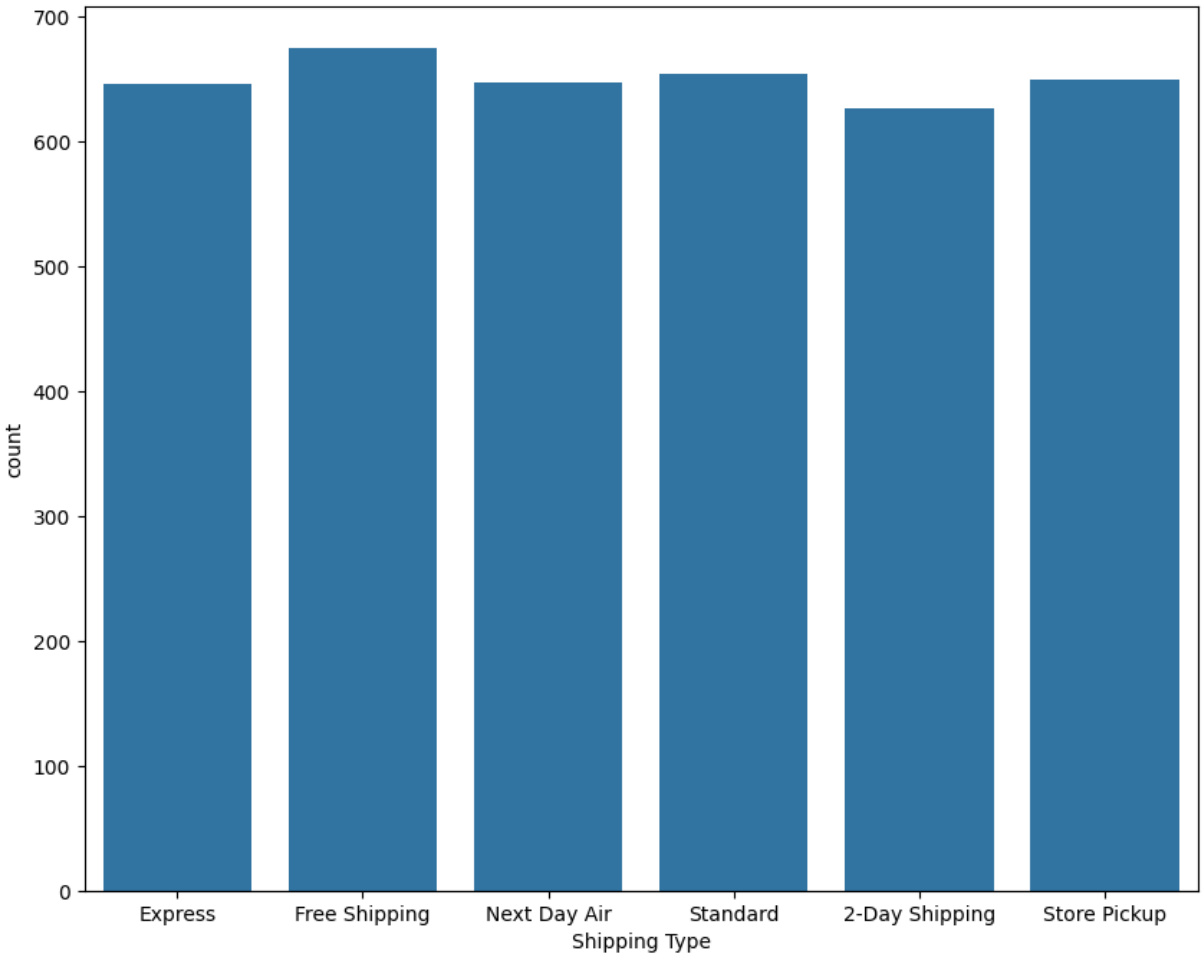
In [81]:
```
plt.figure(figsize=(10,8))
sns.countplot(data=smc,x="Payment Method")
```

Out[81]:
```
<Axes: xlabel='Payment Method', ylabel='count'>
```



In [82]:
```
plt.figure(figsize=(10,8))
sns.countplot(data=smc,x="Shipping Type")
```

Out[82]:
```
<Axes: xlabel='Shipping Type', ylabel='count'>
```

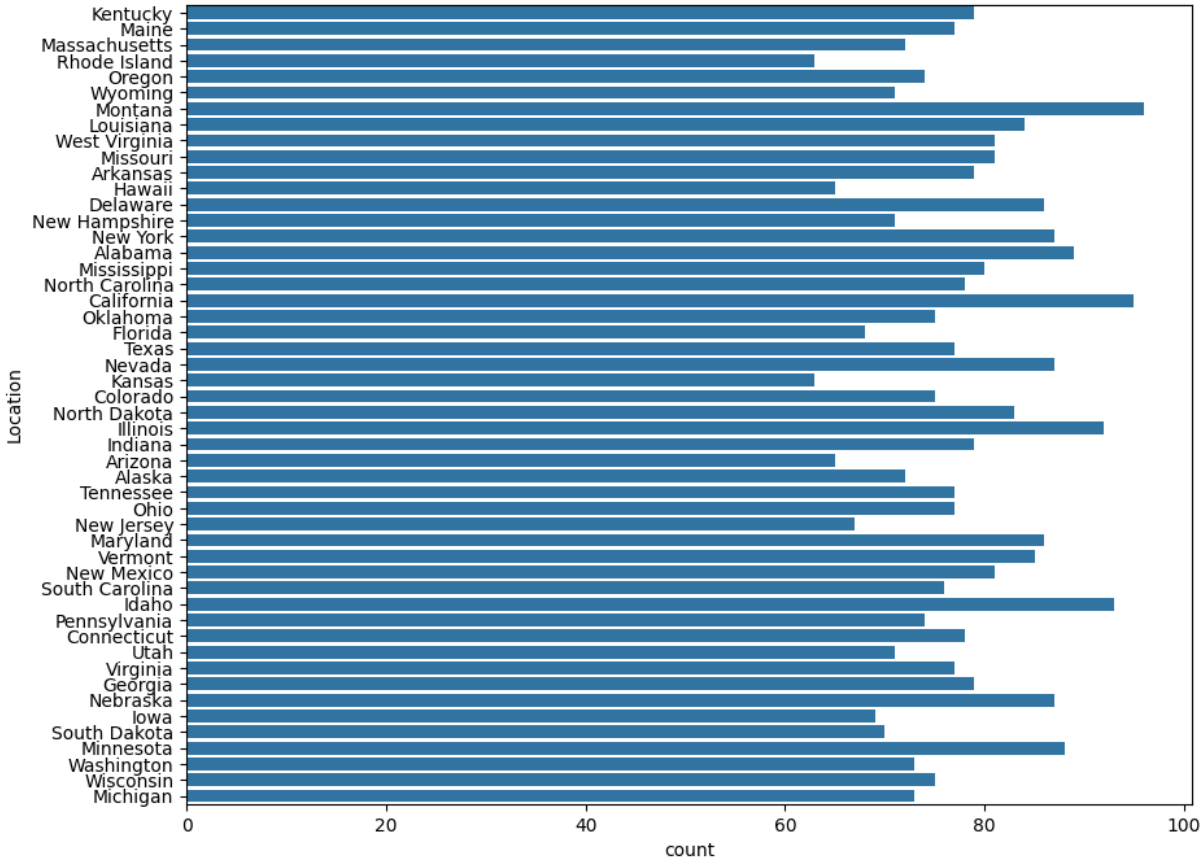


In [83]:
```
# Ages=smc.groupby("Age")['Item Purchased'].value_counts()
Ages=smc[smc["Age"]==70].groupby("Age")['Item Purchased'].value_counts()
Ages
# sns.countplot(data=Ages,x="Age")
```

Out[83]:
```
Age  Item Purchased
70   Socks             7
     Belt              6
     Jewelry           6
     Scarf             5
     Sweater           4
     Sneakers          4
     Handbag           3
     Hat               3
     Boots             3
     Pants             3
     Shoes             3
     Coat              2
     Skirt             2
     Shorts            2
     Sandals           2
     Blouse            2
     Jacket            2
     Hoodie            2
     Gloves            2
     Shirt             1
     Dress             1
     Jeans             1
     T-shirt           1
Name: count, dtype: int64
```

In [84]:
```
plt.figure(figsize=(10,8))
sns.countplot(data=smc,y="Location")
```

Out[84]:
```
<Axes: xlabel='count', ylabel='Location'>
```



In [85]:
```
most_purchases_Location=smc['Location'].value_counts().idxmax()
subset_of_location=smc[smc["Location"]==most_purchases_Location]
most_purchases_Location
```

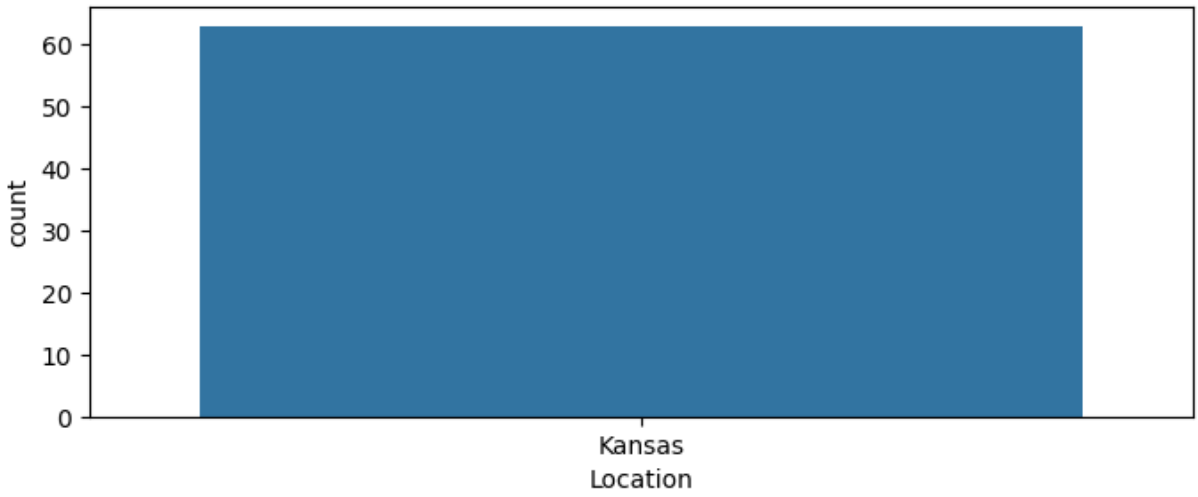
Out[85]: 'Montana'

In [86]:
```
min_purchases_Location=smc['Location'].value_counts().idxmin()
subset_of_location_min=smc[smc["Location"]==min_purchases_Location]
min_purchases_Location
```

Out[86]: 'Kansas'

In [87]:
```
plt.figure(figsize=(8,3))
sns.countplot(data=subset_of_location_min,x="Location")
```

Out[87]: <Axes: xlabel='Location', ylabel='count'>

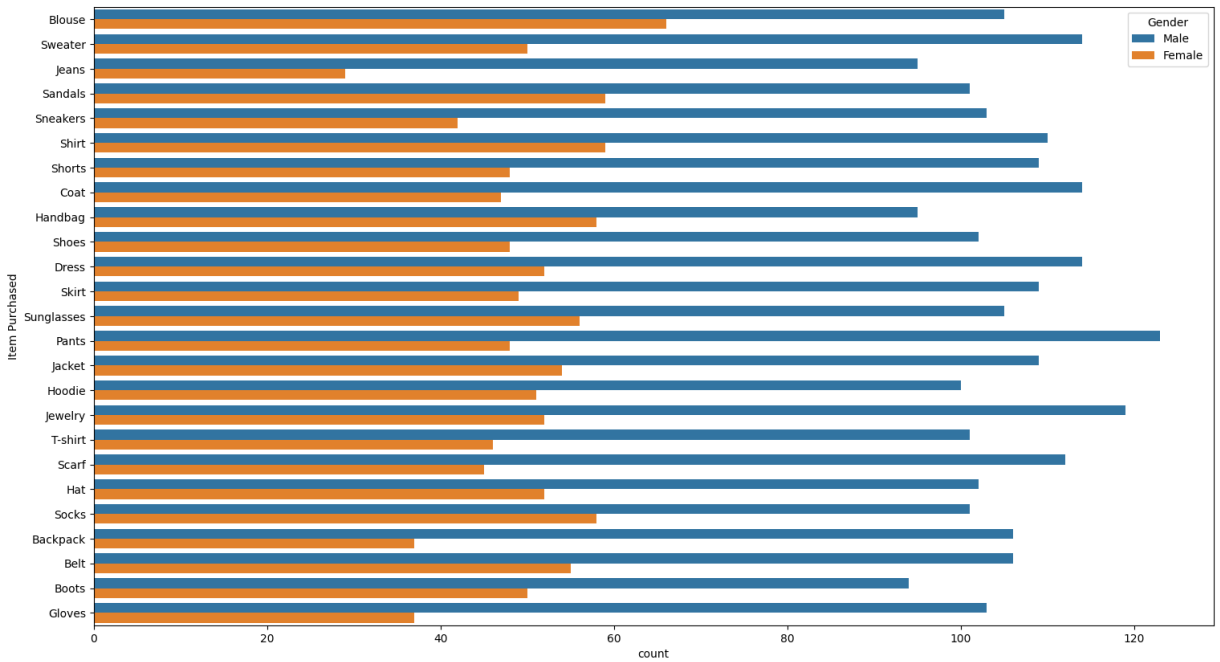


In [88]:
```
smc.columns
```

Out[88]:
```
Index(['Customer ID', 'Age', 'Gender', 'Item Purchased', 'Category',
       'Purchase Amount (USD)', 'Location', 'Size', 'Color', 'Season',
       'Review Rating', 'Subscription Status', 'Shipping Type',
       'Discount Applied', 'Promo Code Used', 'Previous Purchases',
       'Payment Method', 'Frequency of Purchases'],
      dtype='object')
```

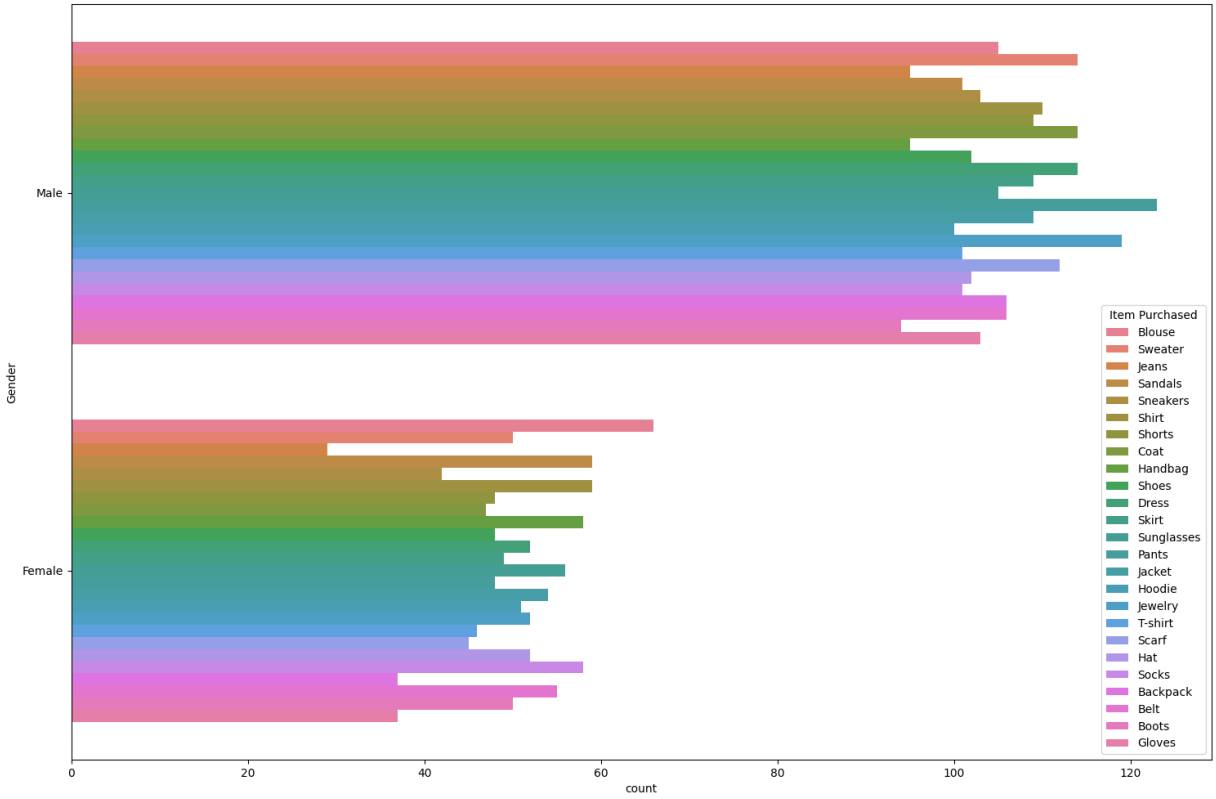
In [89]:
```
plt.figure(figsize=(18,10))
sns.countplot(data=smc,y="Item Purchased",hue="Gender")
```

Out[89]:
```
<Axes: xlabel='count', ylabel='Item Purchased'>
```



In [90]:
```
plt.figure(figsize=(18,12))
sns.countplot(data=smc,y="Gender", hue="Item Purchased")
```

Out[90]:
```
<Axes: xlabel='count', ylabel='Gender'>
```



In [91]:
```
# counts = smc.groupby('Item Purchased')['Gender'].value_counts().idxmax()
counts = smc.groupby('Gender')["Item Purchased"].size()
print(counts)
# count.sort(data=counts)
```

```
Gender
Female    1248
Male      2652
Name: Item Purchased, dtype: int64
```

In [92]:
```
# counts = smc.groupby('Age')["Item Purchased"].size().reset_index(name="Cou
# counts.sort_values("Counts",ascending=True,inplace=True)
print("Maximum", counts.max())
print("Minimum", counts.min())
# print(counts)
```

```
Maximum 2652
Minimum 1248
```

In [93]:
```
Product_sell_byarea=smc.groupby("Item Purchased")["Location"].value_counts()
Product_sell_byarea
```

Out[93]:

	Item Purchased	Location	Count of item
0	Backpack	Nevada	10
1	Backpack	Nebraska	8
2	Backpack	Alaska	5
3	Backpack	Virginia	5
4	Backpack	South Dakota	5
...	...	...	...
1194	T-shirt	Wyoming	2
1195	T-shirt	Georgia	2
1196	T-shirt	Nebraska	1
1197	T-shirt	Rhode Island	1
1198	T-shirt	South Carolina	1

1199 rows × 3 columns

In [94]:
```
uni=smc["Item Purchased"].unique()
uni
```

Out[94]:
```
array(['Blouse', 'Sweater', 'Jeans', 'Sandals', 'Sneakers', 'Shirt',
       'Shorts', 'Coat', 'Handbag', 'Shoes', 'Dress', 'Skirt',
       'Sunglasses', 'Pants', 'Jacket', 'Hoodie', 'Jewelry', 'T-shirt',
       'Scarf', 'Hat', 'Socks', 'Backpack', 'Belt', 'Boots', 'Gloves'],
      dtype=object)
```

In [95]:
```
Product_sell_byarea=smc[smc["Item Purchased"]=="T-shirt"].groupby("Item Purc
Product_sell_byarea
```

Out[95]:

	Item Purchased	Location	Count of item
0	T-shirt	Wisconsin	6
1	T-shirt	Louisiana	5
2	T-shirt	North Carolina	5
3	T-shirt	Missouri	5
4	T-shirt	Vermont	5
5	T-shirt	Ohio	5
6	T-shirt	Kansas	4
7	T-shirt	New York	4
8	T-shirt	Oregon	4
9	T-shirt	Alaska	4
10	T-shirt	Minnesota	4
11	T-shirt	Massachusetts	4
12	T-shirt	Maryland	4
13	T-shirt	Tennessee	4
14	T-shirt	Montana	4
15	T-shirt	Oklahoma	4
16	T-shirt	West Virginia	4
17	T-shirt	Idaho	4
18	T-shirt	Indiana	4
19	T-shirt	Connecticut	3
20	T-shirt	California	3
21	T-shirt	New Mexico	3
22	T-shirt	New Hampshire	3
23	T-shirt	Washington	3
24	T-shirt	Texas	3
25	T-shirt	Florida	3
26	T-shirt	Michigan	3
27	T-shirt	Delaware	3
28	T-shirt	Pennsylvania	2
29	T-shirt	South Dakota	2
30	T-shirt	Virginia	2
31	T-shirt	Utah	2
32	T-shirt	Alabama	2

	Item Purchased	Location	Count of item
33	T-shirt	North Dakota	2
34	T-shirt	Nevada	2
35	T-shirt	Mississippi	2
36	T-shirt	Maine	2
37	T-shirt	Iowa	2
38	T-shirt	Illinois	2
39	T-shirt	Hawaii	2
40	T-shirt	Georgia	2
41	T-shirt	Colorado	2
42	T-shirt	Arkansas	2
43	T-shirt	Arizona	2
44	T-shirt	Wyoming	2
45	T-shirt	Nebraska	1
46	T-shirt	Rhode Island	1
47	T-shirt	South Carolina	1

In [96]:
```
Product_name_byarea=smc[smc["Item Purchased"]=="Blouse"].groupby("Item Purch
Product_name_byarea
```

Out[96]:

	Item Purchased	Location	Count of item
0	Blouse	Georgia	7
1	Blouse	New Hampshire	7
2	Blouse	Wisconsin	7
3	Blouse	Mississippi	6
4	Blouse	Kansas	6
5	Blouse	Oregon	5
6	Blouse	Connecticut	5
7	Blouse	Delaware	5
8	Blouse	North Dakota	5
9	Blouse	Hawaii	5
10	Blouse	Idaho	5
11	Blouse	New York	5
12	Blouse	Alaska	4
13	Blouse	Alabama	4
14	Blouse	Maryland	4
15	Blouse	South Carolina	4
16	Blouse	West Virginia	4
17	Blouse	Minnesota	4
18	Blouse	Wyoming	4
19	Blouse	Maine	4
20	Blouse	Illinois	4
21	Blouse	Arizona	3
22	Blouse	Arkansas	3
23	Blouse	Washington	3
24	Blouse	Virginia	3
25	Blouse	Utah	3
26	Blouse	Texas	3
27	Blouse	South Dakota	3
28	Blouse	Pennsylvania	3
29	Blouse	Ohio	3
30	Blouse	Nevada	3
31	Blouse	Michigan	3
32	Blouse	Kentucky	3

	Item Purchased	Location	Count of item
33	Blouse	Indiana	3
34	Blouse	New Jersey	3
35	Blouse	California	2
36	Blouse	Louisiana	2
37	Blouse	Vermont	2
38	Blouse	Iowa	2
39	Blouse	New Mexico	2
40	Blouse	Rhode Island	2
41	Blouse	Colorado	2
42	Blouse	Massachusetts	2
43	Blouse	North Carolina	2
44	Blouse	Montana	2
45	Blouse	Tennessee	1
46	Blouse	Nebraska	1
47	Blouse	Oklahoma	1
48	Blouse	Missouri	1
49	Blouse	Florida	1

In [97]:
```
Product_sell_byarea=smc[smc["Item Purchased"]=="Blouse"].groupby("Item Purch
Product_sell_byarea
```

Out[97]: ('Blouse', 'Georgia')

In [98]:
```
Product_name_sell_inseason=smc[smc["Item Purchased"]=="Backpack"].groupby("I
print("Product Name", Product_name_sell_inseason)
Product_sell_inseason=smc[smc["Item Purchased"]=="Backpack"].groupby("Item P
print("Product sell in season", Product_sell_inseason)
```

```
Product Name ('Backpack', 'Summer')
Product sell in season ('Backpack', 'Nevada')
```

In [99]:
```
# Product_name_sell_inseason=smc[smc["Item Purchased"]=="T-shirt"].max()
# print("Product Name", Product_name_sell_inseason)
# Product_sell_inseason=smc[smc["Item Purchased"]=="T-shirt"].groupby("Item
# print("Product sell in season", Product_sell_inseason)
```

In [100…
```
Product_Name=smc[smc["Item Purchased"]=="Backpack"].groupby("Item Purchased"
Product_Name
```

Out[100… ('Backpack', 'Nevada')

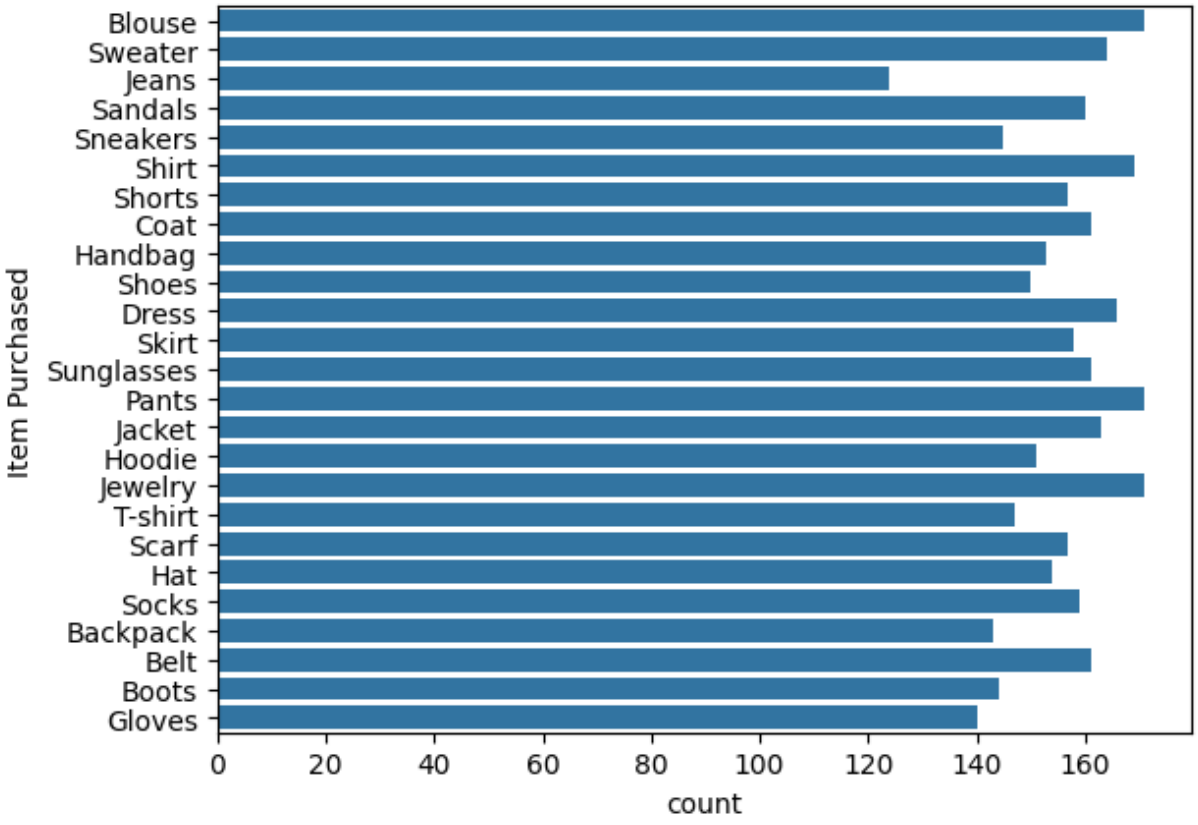
In [101…
```
item_max=smc[smc["Item Purchased"]=="Backpack"].groupby("Item Purchased")["S
item_max
```

Out[101…
```
('Backpack', 'Summer')
```

In [102…
```
counting=smc["Item Purchased"].value_counts().idxmax()
print(counting)
sns.countplot(data=smc,y="Item Purchased")
```

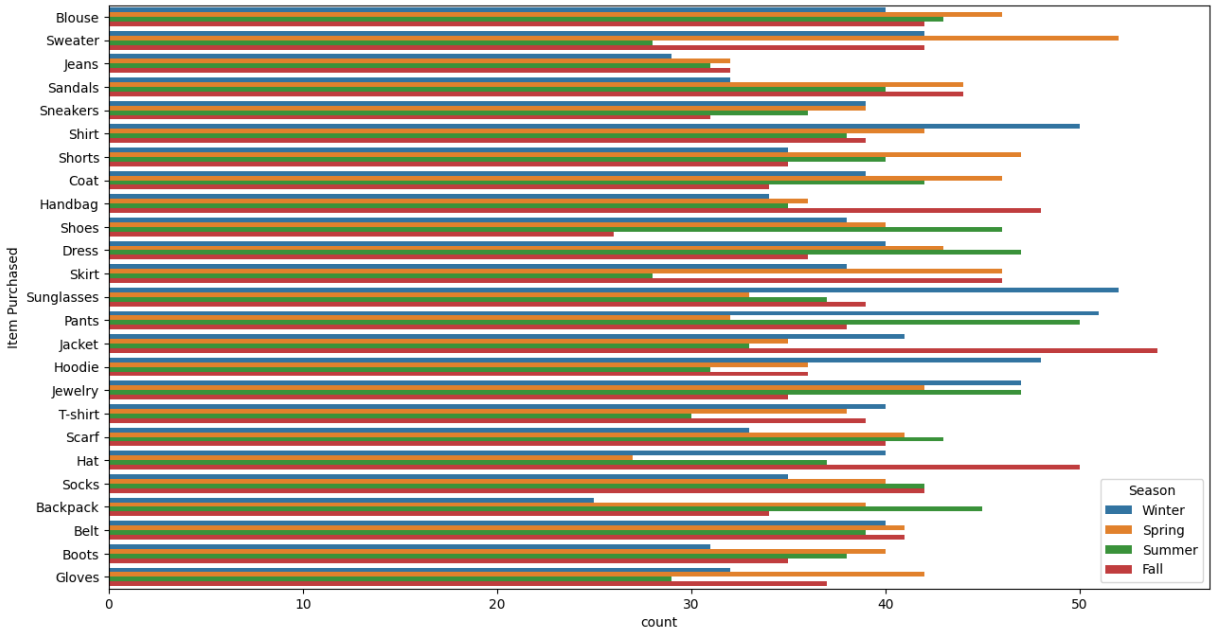
```
Blouse
```

Out[102…
```
<Axes: xlabel='count', ylabel='Item Purchased'>
```



In [103…
```
plt.figure(figsize=(15,8))
sns.countplot(data=smc,y="Item Purchased",hue="Season")
```

Out[103…
```
<Axes: xlabel='count', ylabel='Item Purchased'>
```



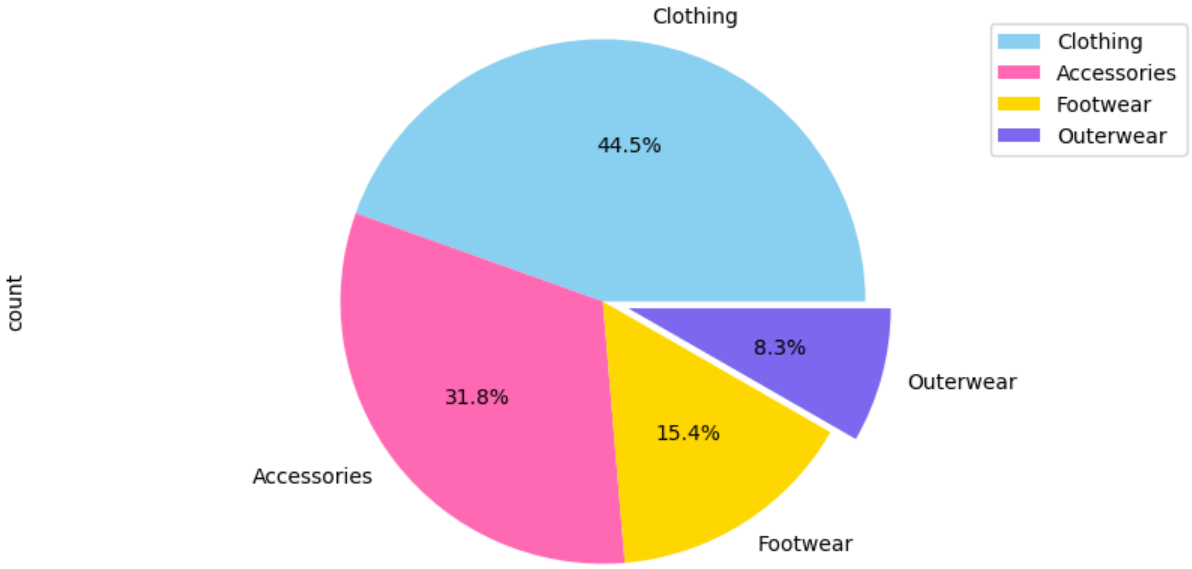
In [104…
```
Subscibers_status=smc["Subscription Status"].value_counts()
Subscibers_status
```

Out[104…
```
Subscription Status
No     2847
Yes    1053
Name: count, dtype: int64
```

In [105…
```
Categories_status=smc["Category"].value_counts()
Categories_status
```

Out[105…
```
Category
Clothing       1737
Accessories    1240
Footwear        599
Outerwear       324
Name: count, dtype: int64
```

In [106…
```
plt.figure(figsize = (10, 5))
counts = smc["Category"].value_counts()
explode = (0, 0.0, 0.0, 0.1)
counts.plot(kind = 'pie', fontsize = 10, colors = colors, explode = explode,
plt.axis('equal')
plt.legend(loc = "best")
plt.show()
```



Model preparation

In [107…
```
smc.head()
```

Out[107…

	Customer ID	Age	Gender	Item Purchased	Category	Purchase Amount (USD)	Location	Siz
0	1	55	Male	Blouse	Clothing	53	Kentucky	
1	2	19	Male	Sweater	Clothing	64	Maine	
2	3	50	Male	Jeans	Clothing	73	Massachusetts	
3	4	21	Male	Sandals	Footwear	90	Rhode Island	
4	5	45	Male	Blouse	Clothing	49	Oregon	

In [108…
```
smc.isnull().sum()
```

Out[108…
```
Customer ID               0
Age                       0
Gender                    0
Item Purchased            0
Category                  0
Purchase Amount (USD)     0
Location                  0
Size                      0
Color                     0
Season                    0
Review Rating             0
Subscription Status       0
Shipping Type             0
Discount Applied          0
Promo Code Used           0
Previous Purchases        0
Payment Method            0
Frequency of Purchases    0
dtype: int64
```

In [109…
```
smc.dtypes
```

Out[109…
```
Customer ID                int64
Age                        Int64
Gender                    object
Item Purchased            object
Category                  object
Purchase Amount (USD)      int64
Location                  object
Size                      object
Color                     object
Season                    object
Review Rating            float64
Subscription Status       object
Shipping Type             object
Discount Applied          object
Promo Code Used           object
Previous Purchases         int64
Payment Method            object
Frequency of Purchases    object
dtype: object
```

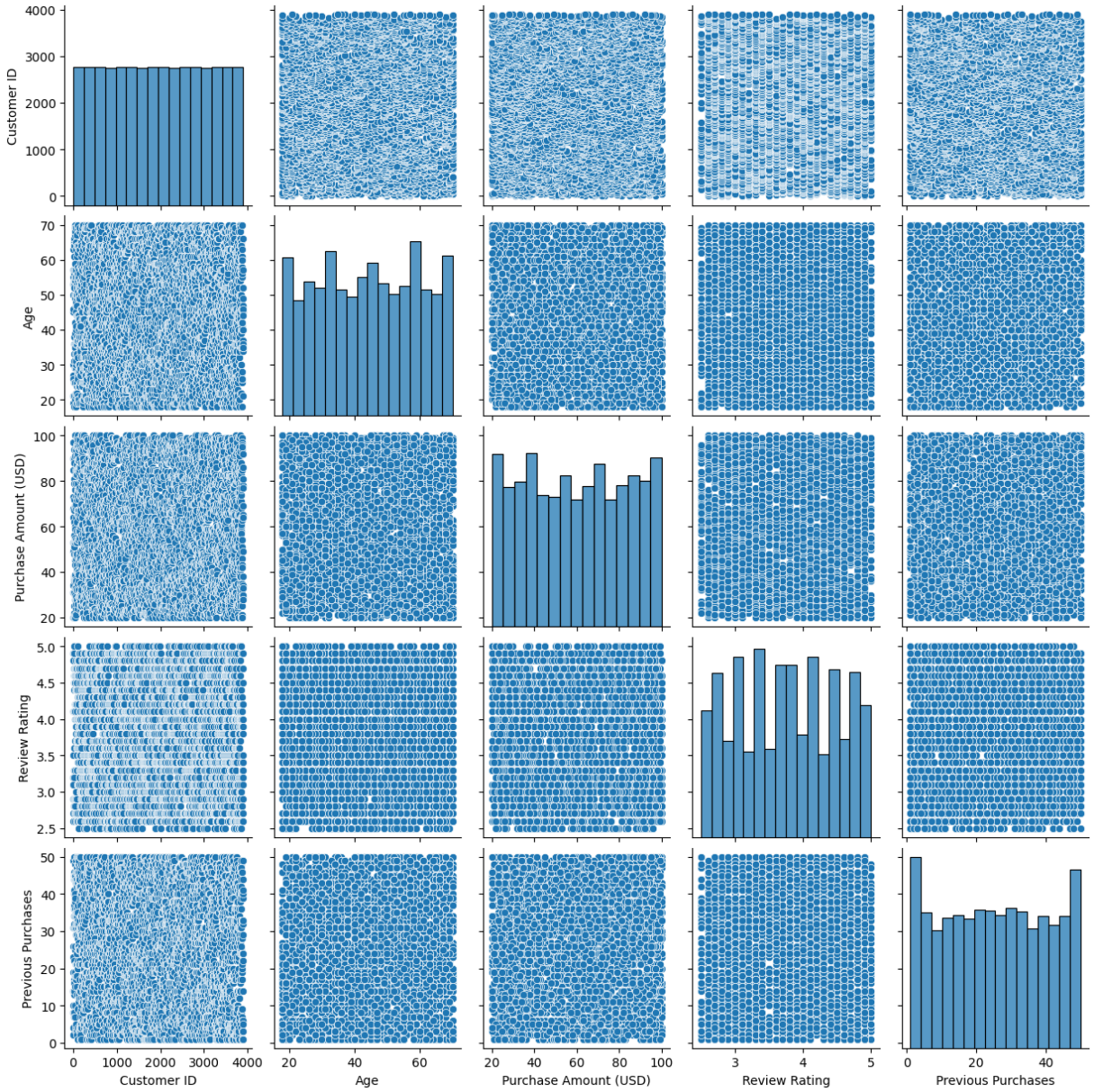
In [110…
```
smc.describe()
```

Out[110…

	Customer ID	Age	Purchase Amount (USD)	Review Rating	Previous Purchases
count	3900.000000	3900.0	3900.000000	3900.000000	3900.000000
mean	1950.500000	44.068462	59.764359	3.749949	25.351538
std	1125.977353	15.207589	23.685392	0.716223	14.447125
min	1.000000	18.0	20.000000	2.500000	1.000000
25%	975.750000	31.0	39.000000	3.100000	13.000000
50%	1950.500000	44.0	60.000000	3.700000	25.000000
75%	2925.250000	57.0	81.000000	4.400000	38.000000
max	3900.000000	70.0	100.000000	5.000000	50.000000

In [111…

```
smc_numeric=["Customer ID",     "Age",  "Purchase Amount (USD)",        "Rev
sns.pairplot(smc[smc_numeric])
plt.show()
```



In [112…

```
corr_matrix = smc[smc_numeric].corr()
sns.heatmap(corr_matrix, annot=True,linewidths=True, cmap="plasma",vmin=0,vm
plt.show()
```

In [113…

```
from matplotlib import colormaps
list(colormaps)
```

Out[113…

```
['magma',
 'inferno',
 'plasma',
 'viridis',
 'cividis',
 'twilight',
 'twilight_shifted',
 'turbo',
 'Blues',
 'BrBG',
 'BuGn',
 'BuPu',
 'CMRmap',
 'GnBu',
 'Greens',
 'Greys',
 'OrRd',
 'Oranges',
 'PRGn',
 'PiYG',
 'PuBu',
 'PuBuGn',
 'PuOr',
 'PuRd',
 'Purples',
 'RdBu',
 'RdGy',
 'RdPu',
 'RdYlBu',
 'RdYlGn',
 'Reds',
 'Spectral',
 'Wistia',
 'YlGn',
 'YlGnBu',
 'YlOrBr',
 'YlOrRd',
 'afmhot',
 'autumn',
 'binary',
 'bone',
 'brg',
 'bwr',
 'cool',
 'coolwarm',
 'copper',
 'cubehelix',
 'flag',
 'gist_earth',
 'gist_gray',
 'gist_heat',
 'gist_ncar',
 'gist_rainbow',
 'gist_stern',
 'gist_yarg',
 'gnuplot',
```

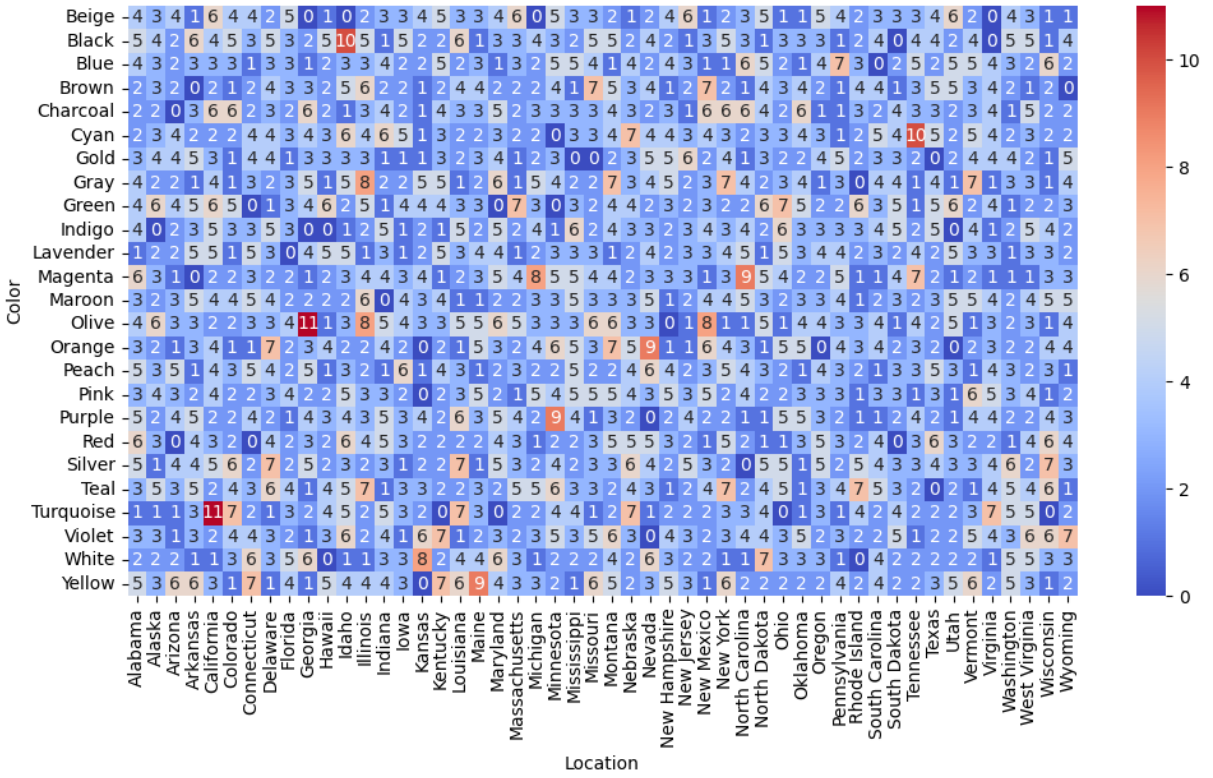
```
'gnuplot2',
'gray',
'hot',
'hsv',
'jet',
'nipy_spectral',
'ocean',
'pink',
'prism',
'rainbow',
'seismic',
'spring',
'summer',
'terrain',
'winter',
'Accent',
'Dark2',
'Paired',
'Pastel1',
'Pastel2',
'Set1',
'Set2',
'Set3',
'tab10',
'tab20',
'tab20b',
'tab20c',
'grey',
'gist_grey',
'gist_yerg',
'Grays',
'magma_r',
'inferno_r',
'plasma_r',
'viridis_r',
'cividis_r',
'twilight_r',
'twilight_shifted_r',
'turbo_r',
'Blues_r',
'BrBG_r',
'BuGn_r',
'BuPu_r',
'CMRmap_r',
'GnBu_r',
'Greens_r',
'Greys_r',
'OrRd_r',
'Oranges_r',
'PRGn_r',
'PiYG_r',
'PuBu_r',
'PuBuGn_r',
'PuOr_r',
'PuRd_r',
'Purples_r',
```

```
'RdBu_r',
'RdGy_r',
'RdPu_r',
'RdYlBu_r',
'RdYlGn_r',
'Reds_r',
'Spectral_r',
'Wistia_r',
'YlGn_r',
'YlGnBu_r',
'YlOrBr_r',
'YlOrRd_r',
'afmhot_r',
'autumn_r',
'binary_r',
'bone_r',
'brg_r',
'bwr_r',
'cool_r',
'coolwarm_r',
'copper_r',
'cubehelix_r',
'flag_r',
'gist_earth_r',
'gist_gray_r',
'gist_heat_r',
'gist_ncar_r',
'gist_rainbow_r',
'gist_stern_r',
'gist_yarg_r',
'gnuplot_r',
'gnuplot2_r',
'gray_r',
'hot_r',
'hsv_r',
'jet_r',
'nipy_spectral_r',
'ocean_r',
'pink_r',
'prism_r',
'rainbow_r',
'seismic_r',
'spring_r',
'summer_r',
'terrain_r',
'winter_r',
'Accent_r',
'Dark2_r',
'Paired_r',
'Pastel1_r',
'Pastel2_r',
'Set1_r',
'Set2_r',
'Set3_r',
'tab10_r',
'tab20_r',
```

```
'tab20b_r',
'tab20c_r',
'rocket',
'rocket_r',
'mako',
'mako_r',
'icefire',
'icefire_r',
'vlag',
'vlag_r',
'flare',
'flare_r',
'crest',
'crest_r']
```

In [114…

```
plt.figure(figsize=(12,6))
cross_tab = pd.crosstab(smc['Color'], smc['Location'])
sns.heatmap(cross_tab, annot=True, cmap="coolwarm")
plt.show()
```



In [115…

```
smc.columns
```

Out[115…

```
Index(['Customer ID', 'Age', 'Gender', 'Item Purchased', 'Category',
       'Purchase Amount (USD)', 'Location', 'Size', 'Color', 'Season',
       'Review Rating', 'Subscription Status', 'Shipping Type',
       'Discount Applied', 'Promo Code Used', 'Previous Purchases',
       'Payment Method', 'Frequency of Purchases'],
      dtype='object')
```

In [116…
```
#convert variables in label encoding or one-hot
# Check corr of Purchased amount usd with other variables
#
```

In [117…
```
data_num = smc[['Customer ID', 'Age', 'Gender', 'Purchase Amount (USD)','Ite
data_num_dum = pd.get_dummies(data_num, columns=['Gender', 'Item Purchased',
```

In [118…
```
data_num_dum.head()
```

Out[118…

	Customer ID	Age	Purchase Amount (USD)	Review Rating	Gender_Female	Gender_Male	Purchase
0	1	55	53	3.1	False	True	
1	2	19	64	3.1	False	True	
2	3	50	73	3.1	False	True	
3	4	21	90	3.5	False	True	
4	5	45	49	2.7	False	True	

5 rows × 114 columns

In [119…
```
#Check Corrlation with target value'Purchase Amount (USD)' and other featur
corr_mat=data_num_dum.corr()
val=corr_mat["Purchase Amount (USD)"]
val
```

Out[119…
```
Customer ID              0.011048
Age                     -0.010424
Purchase Amount (USD)    1.000000
Review Rating            0.030776
Gender_Female            0.014044
                           ...
Color_Yellow            -0.004772
Season_Fall              0.043701
Season_Spring           -0.025439
Season_Summer           -0.032681
Season_Winter            0.014417
Name: Purchase Amount (USD), Length: 114, dtype: float64
```

In [120…
```
data_num.head()
```

Out[120…

	Customer ID	Age	Gender	Purchase Amount (USD)	Item Purchased	Review Rating	Location	Size
0	1	55	Male	53	Blouse	3.1	Kentucky	L
1	2	19	Male	64	Sweater	3.1	Maine	L
2	3	50	Male	73	Jeans	3.1	Massachusetts	S
3	4	21	Male	90	Sandals	3.5	Rhode Island	M
4	5	45	Male	49	Blouse	2.7	Oregon	M

In [121…
```
data_num_dum.head()
```

Out[121…

	Customer ID	Age	Purchase Amount (USD)	Review Rating	Gender_Female	Gender_Male	Purchase
0	1	55	53	3.1	False	True	
1	2	19	64	3.1	False	True	
2	3	50	73	3.1	False	True	
3	4	21	90	3.5	False	True	
4	5	45	49	2.7	False	True	

5 rows × 114 columns

In [122…
```
corr_mat.head()
```

Out[122…

	Customer ID	Age	Purchase Amount (USD)	Review Rating	Gender_Female	Ge
Customer ID	1.000000	-0.004079	0.011048	0.001343	0.807960	
Age	-0.004079	1.000000	-0.010424	-0.021949	-0.002763	
Purchase Amount (USD)	0.011048	-0.010424	1.000000	0.030776	0.014044	
Review Rating	0.001343	-0.021949	0.030776	1.000000	-0.008164	
Gender_Female	0.807960	-0.002763	0.014044	-0.008164	1.000000	

5 rows × 114 columns

Check the missing value

In [123…
```
smc.isnull().sum()
```

Out[123…

```
Customer ID                0
Age                        0
Gender                     0
Item Purchased             0
Category                   0
Purchase Amount (USD)      0
Location                   0
Size                       0
Color                      0
Season                     0
Review Rating              0
Subscription Status        0
Shipping Type              0
Discount Applied           0
Promo Code Used            0
Previous Purchases         0
Payment Method             0
Frequency of Purchases     0
dtype: int64
```

Model Building

In [124…

```
data_num_dum.head()
```

Out[124…

	Customer ID	Age	Purchase Amount (USD)	Review Rating	Gender_Female	Gender_Male	Purchase
0	1	55	53	3.1	False	True	
1	2	19	64	3.1	False	True	
2	3	50	73	3.1	False	True	
3	4	21	90	3.5	False	True	
4	5	45	49	2.7	False	True	

5 rows × 114 columns

In [125…

```
#Linear Regression
# X = data_num_dum.drop(columns=["Purchase Amount (USD)"])
X_new=data_num_dum[["Age","Gender_Male","Review Rating"]]
y = data_num_dum["Purchase Amount (USD)"]
```

In [126…

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression


model= LinearRegression()
model.fit(X_new,y)
```

Out[126… ▾ LinearRegression

LinearRegression()

In [127…
```
# WE have to give below three X_new values for prediction of y
#X_new=data_num_dum[["Age","Gender_Male","Review Rating"]]
# model.predict([[42, 0 , 3.1]])
model.predict([[50,0,2.4]])
```

```
d:\Python\myenvs\myenv\Lib\site-packages\sklearn\base.py:465: UserWarning: X
does not have valid feature names, but LinearRegression was fitted with feat
ure names
  warnings.warn(
```

Out[127… array([58.79760565])

Model is predicting on the bases of X_new,

Now we have to evaluate this model that on different inputs,

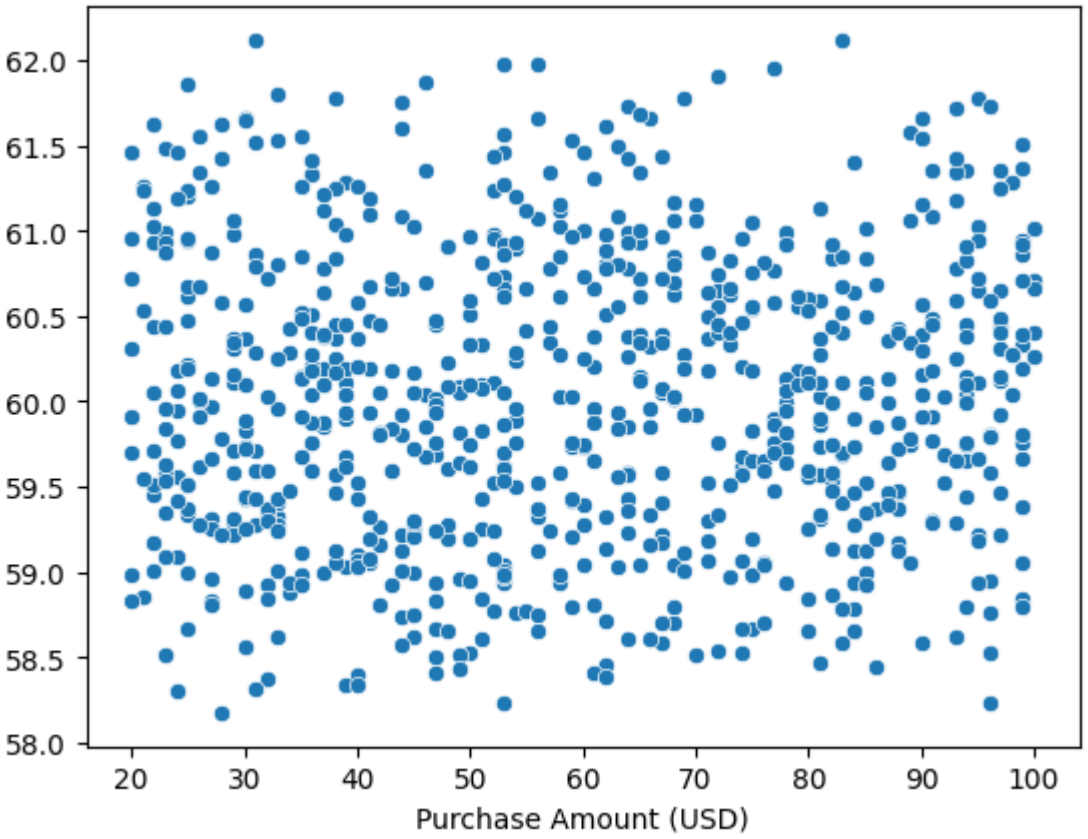
the response of the model is approperiate?

Do sampling of data in train and test

In [128…
```
X_new=data_num_dum[["Age","Gender_Male","Review Rating"]]
y=data_num_dum["Purchase Amount (USD)"]

X_new_train,X_new_test,y_train,y_test=train_test_split(X_new,y,test_size=0.2

model = LinearRegression()
model.fit(X_new_train,y_train)

y_pred = model.predict(X_new_test)
```

In [129…
```
sns.scatterplot(x=y_test,y=y_pred)

# sns.regplot(x=X_new,y=y,scatter=False,color="red")
```

Out[129… <Axes: xlabel='Purchase Amount (USD)'>



In [130…

```
#Use Evaluation Metrics for assessment of our model
from sklearn.metrics import mean_absolute_error,mean_squared_error,r2_score
mae = mean_absolute_error(y_test,y_pred)
mse = mean_squared_error(y_test,y_pred)
rmse = mean_squared_error(y_test,y_pred,squared=False)
r2 = r2_score(y_test,y_pred)
print("mean_absolute_error:", mae)
print("mean_squared_error:", mse)
print("root_mean_squared_error:", rmse)
print("r2_score:", r2)
```

```
mean_absolute_error: 20.397625061488363
mean_squared_error: 553.5226015214491
root_mean_squared_error: 23.527061047258943
r2_score: -0.001673140079833546
```

RandomForest Classifier

(I choose this model because i am working the continuous variables)

RandomForestClassifier

Most code will be same but few changes will be required

In [131…
```
#DecisionTreeClassifier
# X = data_num_dum.drop(columns=["Purchase Amount (USD)"])
X_new=data_num_dum[["Age","Gender_Male","Review Rating"]]
y = data_num_dum["Purchase Amount (USD)"]
```

In [132…
```
# from sklearn.metrics import confusion_matrix
# model = DecisionTreeClassifier()
# model.fit(X_new_train,y_train)



from sklearn.metrics import mean_absolute_error,mean_squared_error,r2_score

ran_model = RandomForestClassifier()
ran_model.fit(X_new_train,y_train)


ran_predic= ran_model.predict(X_new_test)
```

In [133…
```
# model.predict([[42, 0 , 3.1]])
ran_model.predict([[50,0,2.4]])
```

```
d:\Python\myenvs\myenv\Lib\site-packages\sklearn\base.py:465: UserWarning: X
does not have valid feature names, but RandomForestClassifier was fitted wit
h feature names
  warnings.warn(
```

Out[133…
```
array([49], dtype=int64)
```

In [134…
```
ran_mae  = mean_absolute_error(y_test,ran_predic)
ran_mse  = mean_squared_error(y_test,ran_predic)
ran_rmse = mean_squared_error(y_test,ran_predic,squared=False)
ran_r2   = r2_score(y_test,ran_predic)

print("mean_absolute_error",ran_mae)
print("mean_squared_error",ran_mse)
print("root_mean_absolute_error",ran_rmse)
print("r2_score", ran_r2)
```

```
mean_absolute_error 27.6
mean_squared_error 1139.4128205128204
root_mean_absolute_error 33.75518953454151
r2_score -1.061919810741586
```

In [135…
```
#Apply SVM(Support Vector Machine)
#It is good for both classification and regression

from sklearn.metrics import mean_absolute_error, mean_squared_error,r2_score


X_new=data_num_dum[["Age","Gender_Male","Review Rating"]]
y = data_num_dum["Purchase Amount (USD)"]
```

In [136…
```
sv_model = SVR()
sv_model.fit(X_new_train,y_train)
```

```
sv_predict=sv_model.predict(X_new_test)
```

In [137…
```
# sv_predict([[42, 0 , 3.1]])
sv_model.predict([[55,1,2.4]])
```

```
d:\Python\myenvs\myenv\Lib\site-packages\sklearn\base.py:465: UserWarning: X
does not have valid feature names, but SVR was fitted with feature names
  warnings.warn(
```

Out[137…
```
array([59.52365285])
```

In [138…
```
sv_mae  = mean_absolute_error(y_test,sv_predict)
sv_mse  = mean_squared_error(y_test,sv_predict)
sv_rmse = mean_squared_error(y_test,sv_predict,squared=False)
sv_r2   = r2_score(y_test,sv_predict)

print("mean_absolute_error",sv_mae)
print("mean_squared_error",sv_mse)
print("root_mean_absolute_error",sv_rmse)
print("r2_score", sv_r2)
```

```
mean_absolute_error 20.42435019888067
mean_squared_error 554.8454325089967
root_mean_absolute_error 23.555157238044426
r2_score -0.004066979582411534
```

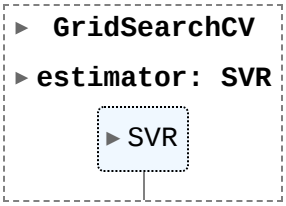
As check different metrics, it is found that

SVM is good model for this dataset.

Hyperparameters tunningTo optimize the working of model

In [139…
```
#Import GridCV for hyperparameters that envloves to search best values of hy
from sklearn.model_selection import GridSearchCV

#
grid_para={
    "C"      : [0.1,1,10],
    "kernel" : ["linear","rbf"],
    "gamma"  : [0.1,0,10]
    }

grid_Search= GridSearchCV(SVR(),grid_para, cv=5)

grid_Search.fit(X_new_train,y_train)
```

Out[139…



In [140…

```
best_params = grid_Search.best_params_
print("Best Hyperparameters:", best_params)

# Get the best model
best_model = grid_Search.best_estimator_

# Evaluate the best model on the test set
best_model_predictions = best_model.predict(X_new_test)
best_model_mse = mean_squared_error(y_test, best_model_predictions)
print("Best Model Mean Squared Error:", best_model_mse)
```

```
Best Hyperparameters: {'C': 0.1, 'gamma': 0, 'kernel': 'rbf'}
Best Model Mean Squared Error: 554.3689743589744
```

In [141…

```
#save model
import joblib
joblib.dump(sv_model,"SVM_model.sk1")
```

Out[141…

```
['SVM_model.sk1']
```

Concepts of statistic and ML used in above code

Data Exploration and Visualization,

Data Preprocessing,

Linear Regression Model,

RandomForest Classifier,

Support Vector Machine (SVM),

Hyperparameter Tuning