Retail Transaction Insights and Trends (EDA)

In [126…
```
# NB:  This whole notebook was created in Kaggle
```

Importing Libraries

In [127…
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

Loading Dataset

In [68]:
```
path = '/kaggle/input/transactions/transactions.xlsx'
df = pd.read_excel(path)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 38500 entries, 0 to 38499
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Transaction_ID     38500 non-null  int64
 1   Date               38500 non-null  object
 2   Customer_Name      38500 non-null  object
 3   Total_Items        38500 non-null  int64
 4   Amount($)          38500 non-null  float64
 5   Payment_Method     38500 non-null  object
 6   City               38500 non-null  object
 7   Store_Type         38500 non-null  object
 8   Discount_Applied   38500 non-null  bool
 9   Customer_Category  38500 non-null  object
 10  Season             38500 non-null  object
 11  Promotion          25529 non-null  object
dtypes: bool(1), float64(1), int64(2), object(8)
memory usage: 3.3+ MB
```

In [69]:
```
df.head(3)
```

Out[69]:

	Transaction_ID	Date	Customer_Name	Total_Items	Amount($)	Payment_Method	City	Store_Type	Disc
0	1000667075	2022-09-12 17:40:23	David King	5	30.98	Debit Card	Chicago	Warehouse Club	
1	1000156022	2022-01-20 23:03:20	Michael Williamson	3	23.29	Credit Card	Boston	Warehouse Club	
2	1000681674	2022-10-15 07:49:59	Chelsea Garza	7	25.62	Debit Card	Chicago	Pharmacy	

In [70]:
```
df.describe()
```

Out[70]:

	Transaction_ID	Total_Items	Amount($)
count	3.850000e+04	38500.000000	38500.000000
mean	1.000500e+09	5.490649	52.459843
std	2.890708e+05	2.868476	27.442214
min	1.000000e+09	1.000000	5.000000
25%	1.000248e+09	3.000000	28.760000
50%	1.000501e+09	5.000000	52.260000
75%	1.000751e+09	8.000000	76.350000
max	1.001000e+09	10.000000	100.000000

In [71]:

```
df.columns
```

Out[71]:

```
Index(['Transaction_ID', 'Date', 'Customer_Name', 'Total_Items', 'Amount($)',
       'Payment_Method', 'City', 'Store_Type', 'Discount_Applied',
       'Customer_Category', 'Season', 'Promotion'],
      dtype='object')
```

In [72]:

```
#Dropping Unnecessary Columns

df.drop(columns=['Date','Customer_Name'],axis=1, inplace=True)
df.head(3)
```

Out[72]:

	Transaction_ID	Total_Items	Amount($)	Payment_Method	City	Store_Type	Discount_Applied	Customer_Cat
0	1000667075	5	30.98	Debit Card	Chicago	Warehouse Club	True	Te
1	1000156022	3	23.29	Credit Card	Boston	Warehouse Club	True	Home
2	1000681674	7	25.62	Debit Card	Chicago	Pharmacy	False	Te

01. Finding out the average transaction amount($) across different store types, and how does it vary by season.

In [73]:

```
#Finding the unique values of the Store_Types

store_types = df['Store_Type'].unique()
store_types
```

Out[73]:

```
array(['Warehouse Club', 'Pharmacy', 'Convenience Store', 'Supermarket',
       'Department Store', 'Specialty Store'], dtype=object)
```

In [74]:

```
store_counts=df['Store_Type'].value_counts()
store_counts
```

Out[74]:
```
Store_Type
Convenience Store    6588
Warehouse Club       6495
Pharmacy             6447
Supermarket          6395
Department Store     6319
Specialty Store      6256
Name: count, dtype: int64
```

In [75]:
```
#Finding the unique values of the Sesaon

df['Season'].unique()
```

Out[75]:
```
array(['Fall', 'Winter', 'Summer', 'Spring'], dtype=object)
```

In [76]:
```
season_counts=df['Season'].value_counts()
season_counts
```

Out[76]:
```
Season
Fall      9749
Spring    9602
Winter    9582
Summer    9567
Name: count, dtype: int64
```

Dropping Unnecessary Columns Irrelevanrt for 01 Analysis

In [77]:
```
df_01 = df.drop(columns = ['Total_Items','City','Payment_Method',
                           'Discount_Applied','Customer_Category',
                           'Promotion'], axis=1)
df_01.head(5)
```

Out[77]:

	Transaction_ID	Amount($)	Store_Type	Season
0	1000667075	30.98	Warehouse Club	Fall
1	1000156022	23.29	Warehouse Club	Winter
2	1000681674	25.62	Pharmacy	Fall
3	1000692089	14.64	Pharmacy	Summer
4	1000328702	62.27	Convenience Store	Summer

In [78]:
```
#Grouping data by Season and Store_Type and finding the Average Amount of that

grouped_data_2 = df_01.groupby(['Season', 'Store_Type'])['Amount($)'].mean().reset_index()
grouped_data_2
```

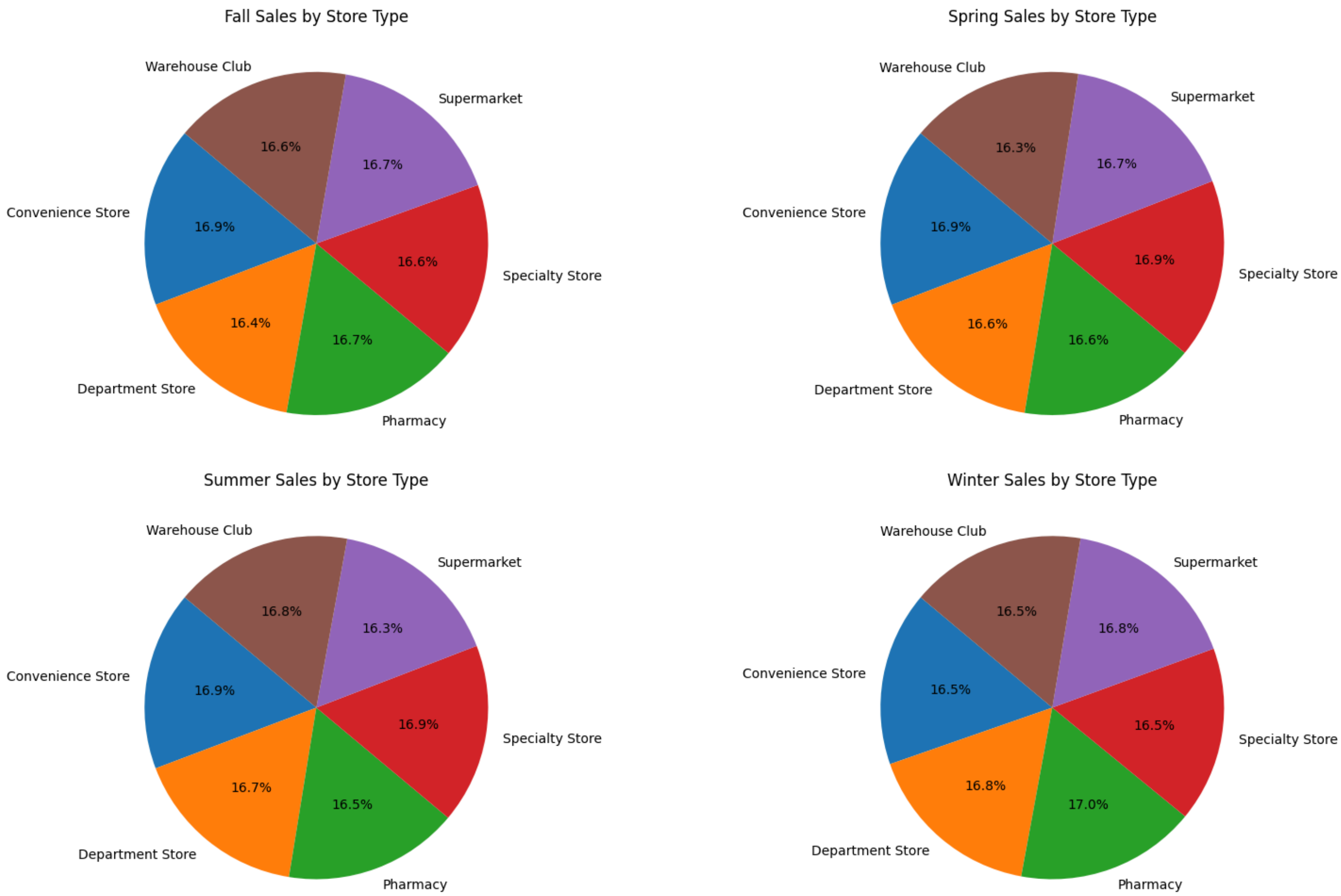
Out[78]:

	Season	Store_Type	Amount($)
0	Fall	Convenience Store	52.872504
1	Fall	Department Store	51.384757
2	Fall	Pharmacy	52.363508
3	Fall	Specialty Store	51.823011
4	Fall	Supermarket	52.285728
5	Fall	Warehouse Club	52.027853
6	Spring	Convenience Store	53.537230
7	Spring	Department Store	52.573781
8	Spring	Pharmacy	52.458672
9	Spring	Specialty Store	53.524048
10	Spring	Supermarket	52.691298
11	Spring	Warehouse Club	51.597471
12	Summer	Convenience Store	53.345305
13	Summer	Department Store	52.782716
14	Summer	Pharmacy	52.049365
15	Summer	Specialty Store	53.594788
16	Summer	Supermarket	51.443950
17	Summer	Warehouse Club	53.009120
18	Winter	Convenience Store	51.595034
19	Winter	Department Store	52.575652
20	Winter	Pharmacy	53.218725
21	Winter	Specialty Store	51.782338
22	Winter	Supermarket	52.640624
23	Winter	Warehouse Club	51.818594

In [79]:

```
# Groupping data by season and store type
grouped_data_pie = grouped_data_2.groupby(['Season', 'Store_Type']).sum().reset_index()

# Unique seasons for the subplot
seasons = grouped_data_2['Season'].unique()

# Create subplots
fig, axes = plt.subplots(2, 2, figsize=(16, 10))
axes = axes.flatten()

# Plotting each season's pie chart in a subplot
for i, season in enumerate(seasons):
    season_data = grouped_data_pie[grouped_data_pie['Season'] == season]
    axes[i].pie(season_data['Amount($)'], labels=season_data['Store_Type'],
                autopct='%1.1f%%', startangle=140)
    axes[i].set_title(f'{season} Sales by Store Type')


for j in range(len(seasons), len(axes)):
    fig.delaxes(axes[j])
```

```python
plt.tight_layout()
plt.savefig('/kaggle/working/00_average_transaction_plot_by_season_store_01.png',
            dpi=300, bbox_inches='tight')

plt.show()
```



The pie charts depict the distribution of sales amounts across different store types for each season.

> - **Fall**: Sales are evenly distributed, with "Pharmacy" and "Supermarket" contributing slightly more compared to others.
> - **Spring**: "Convenience Stores" and "Specialty Stores" dominate sales, reflecting a seasonal preference for these types.
> - **Summer**: "Specialty Stores" lead in sales, while "Supermarket" lags behind, indicating shifting consumer preferences during the summer.
> - **Winter**: "Pharmacy" sales peak, likely driven by seasonal health-related purchases, while other store types maintain a balanced contribution. ion.

This data highlights the seasonal variations in consumer spending patterns across store types.

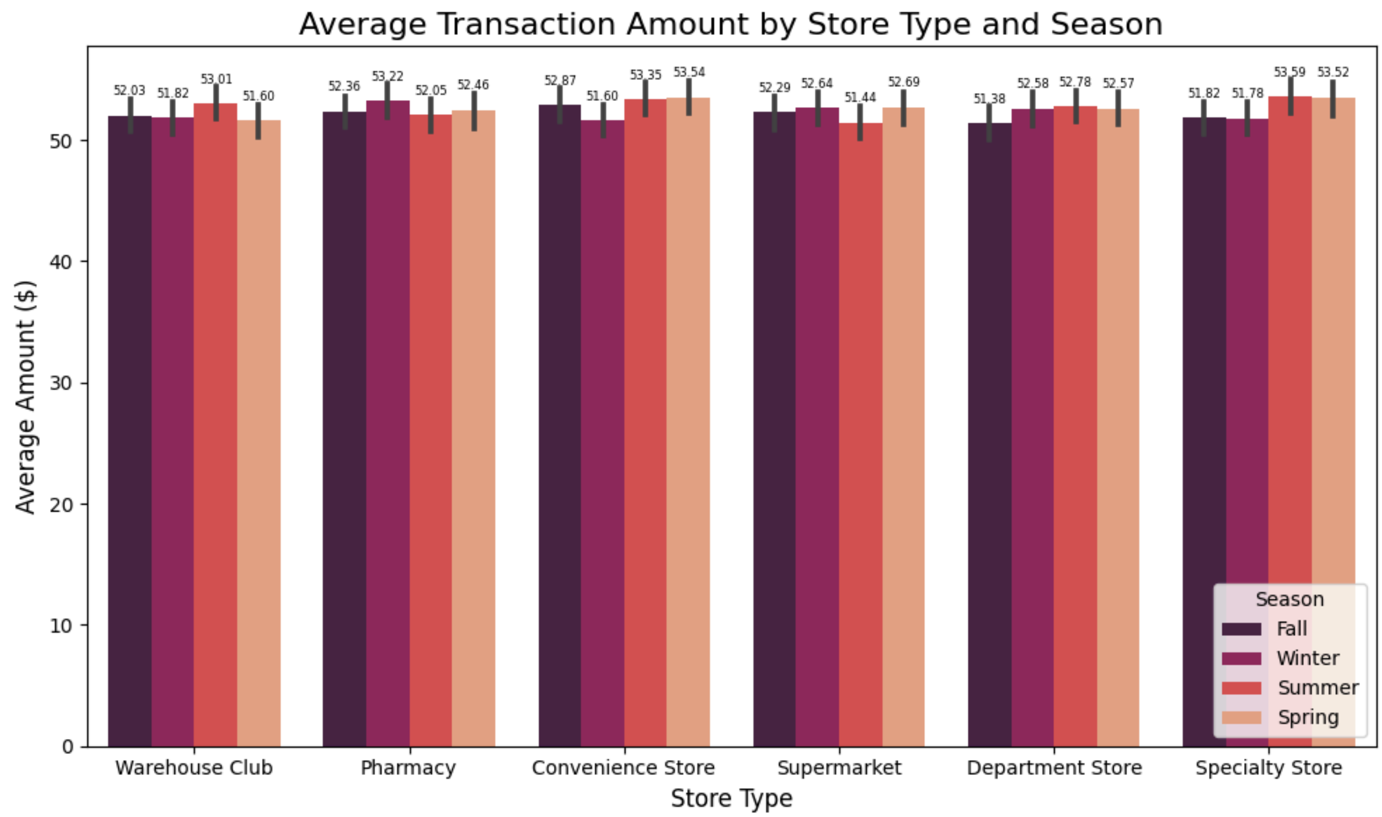
In [80]:
```python
#Groupping by 'Store_Type' and 'Season', then calculating the mean of 'Amount($)'

grouped_data = df_01.groupby(['Store_Type', 'Season'])['Amount($)'].mean().reset_index()
grouped_data
```

Out[80]:

	Store_Type	Season	Amount($)
0	Convenience Store	Fall	52.872504
1	Convenience Store	Spring	53.537230
2	Convenience Store	Summer	53.345305
3	Convenience Store	Winter	51.595034
4	Department Store	Fall	51.384757
5	Department Store	Spring	52.573781
6	Department Store	Summer	52.782716
7	Department Store	Winter	52.575652
8	Pharmacy	Fall	52.363508
9	Pharmacy	Spring	52.458672
10	Pharmacy	Summer	52.049365
11	Pharmacy	Winter	53.218725
12	Specialty Store	Fall	51.823011
13	Specialty Store	Spring	53.524048
14	Specialty Store	Summer	53.594788
15	Specialty Store	Winter	51.782338
16	Supermarket	Fall	52.285728
17	Supermarket	Spring	52.691298
18	Supermarket	Summer	51.443950
19	Supermarket	Winter	52.640624
20	Warehouse Club	Fall	52.027853
21	Warehouse Club	Spring	51.597471
22	Warehouse Club	Summer	53.009120
23	Warehouse Club	Winter	51.818594

In [81]:

```
# Creating the grouped bar chart
plt.figure(figsize=(10, 6))
ax = sns.barplot(data=df_01, x='Store_Type', y='Amount($)', hue='Season', palette='rocket')

# Adding values on top of bars
for container in ax.containers:
    ax.bar_label(container, fmt='%.2f', label_type='edge', fontsize=6, padding=9)

#Showing the plot
plt.title('Average Transaction Amount by Store Type and Season', fontsize=16)
plt.xlabel('Store Type', fontsize=12)
plt.ylabel('Average Amount ($)', fontsize=12)
plt.xticks(rotation=0, ha='center', fontsize=10)
plt.legend(title='Season', fontsize=10, loc='lower right')
plt.tight_layout()

# Saving the plot
plt.savefig('/kaggle/working/01_average_transaction_plot_01.png', dpi=300, bbox_inches='tight')

plt.show()
```



The data outlines the average sales amount across various store types and seasons:

> **Convenience Stores** maintain consistently high sales in Spring (53.54 Dollar) and Summer (53.35Dollar), but drop slightly in Winter (51.60Dollar).
>
> **Department Stores** show stable sales across all seasons, peaking in Summer (52.78Dollar).
>
> **Pharmacies** see their highest sales in Winter (53.22Dollar), likely due to seasonal health demands.
>
> **Specialty Stores** perform best in Summer (53.59Dollar) and Spring (53.52Dollar), reflecting seasonal consumer preferences.
>
> **Supermarkets** experience steady sales across seasons, with a slight dip in Summer (51.44Dollar).
>
> **Warehouse Clubs** show their highest sales in Summer (53.01Dollar) but lower averages in other seasons.

Overall, Summer and Spring emerge as the peak seasons for most store types, with Winter favoring Pharmacies.

02. Which payment method is most commonly used in high-value transactions (Above the average transiction amount) and how does it varies accross cities?

In [82]:
```
df.sort_values(by='Amount($)', ascending=False).head(3)
```

Out[82]:

	Transaction_ID	Total_Items	Amount($)	Payment_Method	City	Store_Type	Discount_Applied	Custo
29771	1000531045	10	100.0	Cash	Dallas	Supermarket	False	
2645	1000408241	9	100.0	Debit Card	Atlanta	Warehouse Club	True	
12181	1000591212	1	100.0	Credit Card	San Francisco	Convenience Store	True	

In [83]:
```
#Finding the mean of the transaction amount
mean_amount = df['Amount($)'].mean()
mean_amount
```

Out[83]:
```
52.45984311688312
```

In [84]:
```
df_02 = df[df['Amount($)'] > mean_amount]

print("Filtered Dataset Shape with High-Vale Transactions Only is ",df_02.shape)
```

```
Filtered Dataset Shape with High-Vale Transactions Only is  (19190, 10)
```

Unique Payment Methods

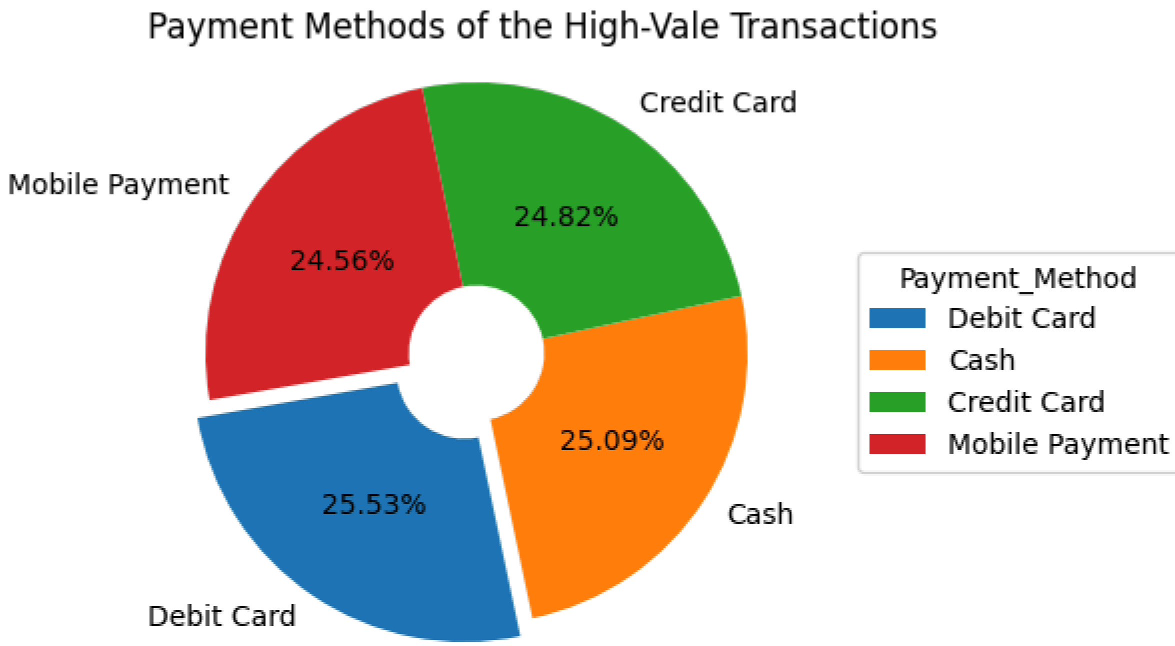
In [85]:
```
df_02['Payment_Method'].unique()
```

Out[85]:
```
array(['Credit Card', 'Cash', 'Mobile Payment', 'Debit Card'],
      dtype=object)
```

In [86]:
```
payment_method = df_02['Payment_Method'].value_counts()
payment_method
```

Out[86]:
```
Payment_Method
Debit Card        4900
Cash              4814
Credit Card       4763
Mobile Payment    4713
Name: count, dtype: int64
```

In [87]:
```
plt.figure(figsize=(6, 4))

plt.pie(payment_method, labels=payment_method.index, autopct="%1.2f%%",
        explode=(0.08,0,0,0), shadow=False, startangle=190,
        wedgeprops=dict(width=0.75))

plt.legend(payment_method.index, title="Payment_Method", loc='center left',
           bbox_to_anchor=(0.9, 0.5))

plt.title("Payment Methods of the High-Vale Transactions", loc='right')
plt.axis('equal')

# Saving the plot
plt.savefig('/kaggle/working/02_payment_methods_of_transaction_plot_02.png', dpi=300, bbox_inche


plt.show()
```



This pie chart illustrates the distribution of payment methods for high-value transactions. It divides the total percentage into four categories:

> **Debit Card (blue):** 25.53% of the transactions were completed using debit cards, making it the most utilized method.
>
> **Cash (orange):** 25.09% of the payments were made in cash, slightly less than debit card usage.
>
> **Credit Card (green):** 24.82% of transactions involved credit cards, ranking third.
>
> **Mobile Payment (red):** 24.56% of the transactions used mobile payment methods, which is the least used but very close to others.

The chart shows a fairly balanced distribution among the four payment methods, with no significant dominance by any single category.

Unique Cities

In [88]:
```
df_02['City'].unique()
```

Out[88]:
```
array(['Miami', 'Seattle', 'New York', 'Dallas', 'Houston', 'Los Angeles',
       'Atlanta', 'Boston', 'Chicago', 'San Francisco'], dtype=object)
```

In [89]:
```
city_counts = df['City'].value_counts()
city_counts
```

Out[89]:
```
City
Houston          3898
Boston           3892
San Francisco    3891
New York         3880
Los Angeles      3869
Chicago          3855
Miami            3834
Seattle          3824
Dallas           3809
Atlanta          3748
Name: count, dtype: int64
```

In [90]:
```
columns_to_drop_02 = ['Transaction_ID','Total_Items',
                      'Store_Type','Discount_Applied',
                      'Customer_Category','Season',
                      'Promotion']
df_02 = df_02.drop(columns=columns_to_drop_02)
```

In [91]:
```
df_02.head(5)
```

Out[91]:

	Amount($)	Payment_Method	City
4	62.27	Credit Card	Miami
6	88.07	Cash	Seattle
7	62.51	Mobile Payment	New York
11	68.68	Mobile Payment	Dallas
12	59.65	Debit Card	Miami

In [92]:
```
high_value_df = df_02.groupby(['Payment_Method','City']).size().reset_index(name='Count')
high_value_df
```

Out[92]:

	Payment_Method	City	Count
0	Cash	Atlanta	467
1	Cash	Boston	485
2	Cash	Chicago	516
3	Cash	Dallas	454
4	Cash	Houston	492
5	Cash	Los Angeles	485
6	Cash	Miami	467
7	Cash	New York	482
8	Cash	San Francisco	489
9	Cash	Seattle	477
10	Credit Card	Atlanta	452
11	Credit Card	Boston	471
12	Credit Card	Chicago	507
13	Credit Card	Dallas	466
14	Credit Card	Houston	484
15	Credit Card	Los Angeles	453
16	Credit Card	Miami	489
17	Credit Card	New York	480
18	Credit Card	San Francisco	504
19	Credit Card	Seattle	457
20	Debit Card	Atlanta	451
21	Debit Card	Boston	484
22	Debit Card	Chicago	484
23	Debit Card	Dallas	538
24	Debit Card	Houston	492
25	Debit Card	Los Angeles	518
26	Debit Card	Miami	485
27	Debit Card	New York	453
28	Debit Card	San Francisco	483
29	Debit Card	Seattle	512
30	Mobile Payment	Atlanta	506
31	Mobile Payment	Boston	427
32	Mobile Payment	Chicago	455
33	Mobile Payment	Dallas	422
34	Mobile Payment	Houston	462
35	Mobile Payment	Los Angeles	492

	Payment_Method	City	Count
36	Mobile Payment	Miami	485
37	Mobile Payment	New York	510
38	Mobile Payment	San Francisco	490
39	Mobile Payment	Seattle	464

In [93]:

```
total_payments_by_method = high_value_df.groupby('Payment_Method')['Count'].sum().reset_index()

total_payments_by_method.sort_values(by='Count', ascending=False)
```

Out[93]:

	Payment_Method	Count
2	Debit Card	4900
0	Cash	4814
1	Credit Card	4763
3	Mobile Payment	4713

Most Common Payment Method for High-Valued Transaction by Cities

In [94]:

```
most_common_payment_method = high_value_df.loc[high_value_df.groupby('City')['Count'].idxmax()]
most_common_payment_method_sorted = most_common_payment_method.sort_values(by='Count',ascending
most_common_payment_method_sorted
```

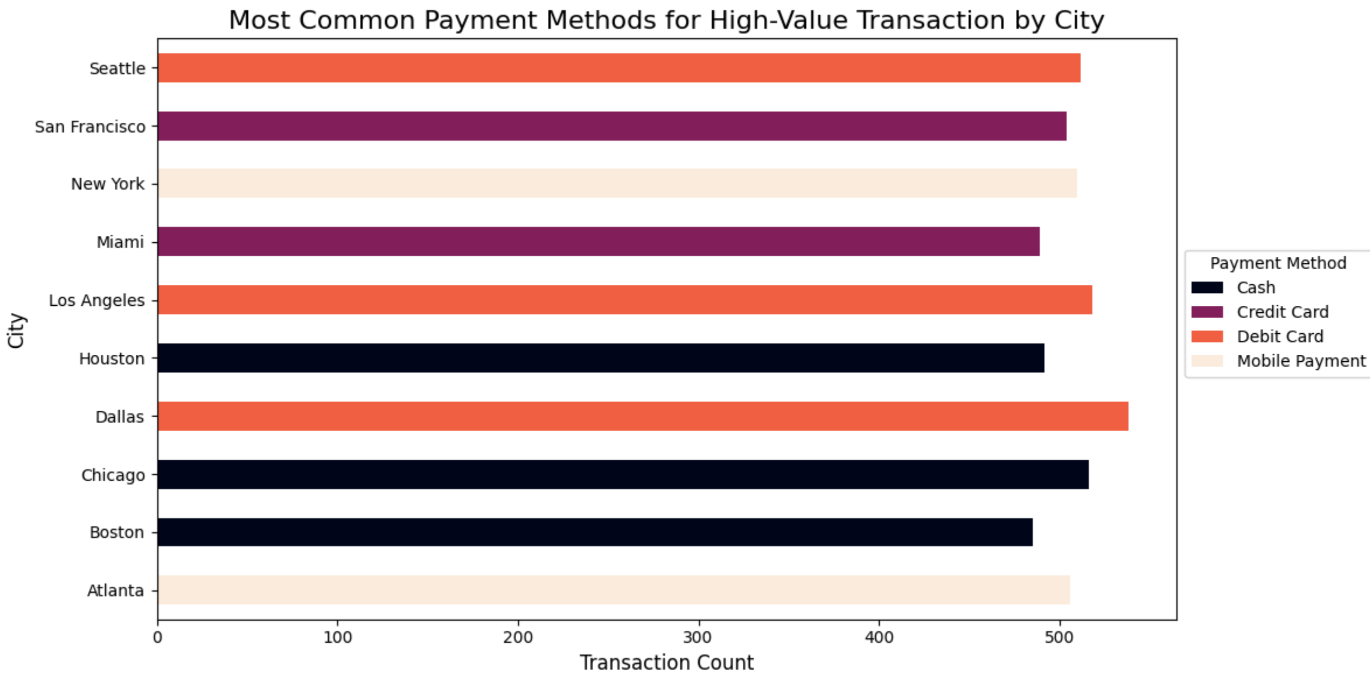
Out[94]:

	Payment_Method	City	Count
1	Cash	Boston	485
16	Credit Card	Miami	489
4	Cash	Houston	492
18	Credit Card	San Francisco	504
30	Mobile Payment	Atlanta	506
37	Mobile Payment	New York	510
29	Debit Card	Seattle	512
2	Cash	Chicago	516
25	Debit Card	Los Angeles	518
23	Debit Card	Dallas	538

In [95]:

```
#pivot method for stacked bar plot
pivot_df = most_common_payment_method_sorted.pivot_table(index='City',
                                                         columns='Payment_Method',
                                                         values='Count', aggfunc='sum',
                                                         fill_value=0)

# Plotting
ax = pivot_df.plot(kind='barh', stacked=True,
                   figsize=(12, 6), colormap='rocket')

# Customizing the plot
plt.title('Most Common Payment Methods for High-Value Transaction by City', fontsize=16)
plt.xlabel('Transaction Count', fontsize=12)
```

```python
plt.ylabel('City', fontsize=12)
plt.legend(title='Payment Method', fontsize=10, bbox_to_anchor=(1, 0.65))

# Adjusting layout
plt.tight_layout()

# Saving the plot
plt.savefig('/kaggle/working/03_most_common_payment_method_plot_02.png', dpi=300, bbox_inches='t

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



> This data represents payment methods used across various cities, along with the count of transactions.The counts range from 485 (lowest, Cash in Boston) to 538 (highest, Debit Card in Dallas). Debit Card transactions have the highest count (518 in Los Angeles, 538 in Dallas).Mobile Payments were relatively higher in New York (510) and Atlanta (506).Credit Card usage is notable in Miami (489) and San Francisco (504).Cash is common in Chicago (516) and Houston (492).
>
> This provides insights into payment preferences across cities, with varying transaction counts for each payment method.

Most Common Payment Method for High Valed Transaction

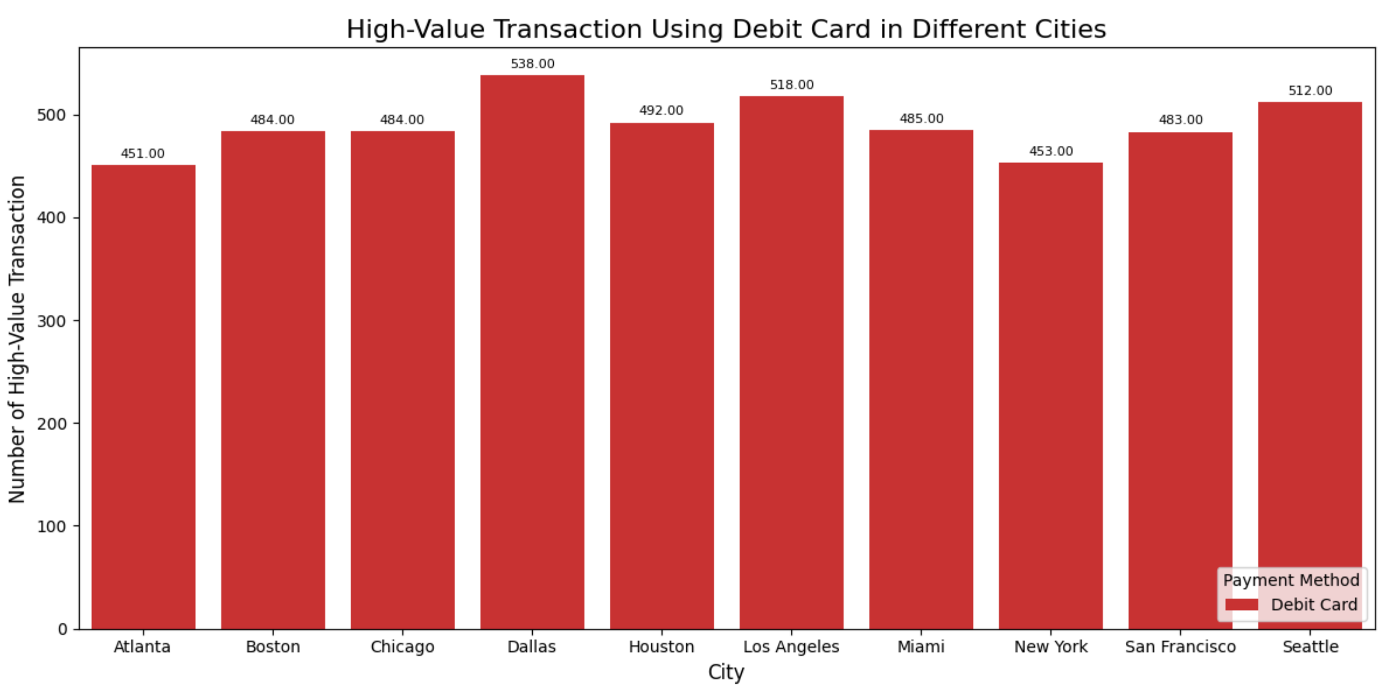
In [96]:
```python
# Filtering where 'Payment_Method' is 'Debit Card'
debit_card_payments = high_value_df[high_value_df['Payment_Method'] == 'Debit Card']
debit_card_payments
```

Out[96]:

	Payment_Method	City	Count
20	Debit Card	Atlanta	451
21	Debit Card	Boston	484
22	Debit Card	Chicago	484
23	Debit Card	Dallas	538
24	Debit Card	Houston	492
25	Debit Card	Los Angeles	518
26	Debit Card	Miami	485
27	Debit Card	New York	453
28	Debit Card	San Francisco	483
29	Debit Card	Seattle	512

In [97]:

```
# Creating the grouped bar chart
plt.figure(figsize=(12, 6))
ax = sns.barplot(data=debit_card_payments, x='City', y='Count',
                 hue='Payment_Method', palette='Set1')

# Adding values on top of bars
for container in ax.containers:
    ax.bar_label(container, fmt='%.2f', label_type='edge', fontsize=8, padding=3)

#Showing the plot
plt.title('High-Value Transaction Using Debit Card in Different Cities', fontsize=16)
plt.xlabel('City', fontsize=12)
plt.ylabel('Number of High-Value Transaction', fontsize=12)
plt.xticks(rotation=0, ha='center', fontsize=10)
plt.legend(title='Payment Method', fontsize=10, loc='lower right')
plt.tight_layout()

# Saving the plot
plt.savefig('/kaggle/working/04_Transactions_Using_Dabit_Card.png', dpi=300, bbox_inches='tight'

plt.show()
```



This data focuses on **Debit Card transactions** across 10 cities, summarizing the transaction counts as follows:

> **Highest Transactions:** - **Dallas** recorded the highest number of Debit Card transactions with **538**.
>
> **Lowest Transactions:** - **Atlanta** had the lowest number of transactions, with **451**.
> **Other Cities:** Cities like **Seattle (512)**, **Los Angeles (518)**, and **Houston (492)** also show high transaction counts. - **Boston (484)**, **Chicago (484)**, **Miami (485)**, and **San Francisco (483)** have nearly identical transaction counts, indicating similar patterns of Debit Card usage. **New York (453)** has slightly lower transaction counts compared to other major Cities. other major cities.

The data highlights **Dallas** as the city with the highest usage of Debit Cards and **Atlanta** as the lowest. Overall, transaction counts vary but show a moderate-to-high adoption of Debit Cards across cities.

03. How do the sales amounts in transactions with discounts compare to those without discounts, and what trends can be observed over the month??

In [98]:
```
df.head(2)
```

Out[98]:

	Transaction_ID	Total_Items	Amount($)	Payment_Method	City	Store_Type	Discount_Applied	Customer_Cat
0	1000667075	5	30.98	Debit Card	Chicago	Warehouse Club	True	Te
1	1000156022	3	23.29	Credit Card	Boston	Warehouse Club	True	Home

In [99]:
```
columns_to_drop_03 = ['Total_Items', 'Amount($)',
                      'Payment_Method','City',
                      'Store_Type','Customer_Category',
                      'Promotion']
df_03 = df.drop(columns=columns_to_drop_03)
df_03.head()
```

Out[99]:

	Transaction_ID	Discount_Applied	Season
0	1000667075	True	Fall
1	1000156022	True	Winter
2	1000681674	False	Fall
3	1000692089	False	Summer
4	1000328702	False	Summer

In [100…
```
df_03.shape
```

Out[100]:
```
(38500, 3)
```

In [101…

```
df_03["Transaction_ID"] = range(1, len(df_03) + 1)
df_03.head()
```

Out[101]:

	Transaction_ID	Discount_Applied	Season
0	1	True	Fall
1	2	True	Winter
2	3	False	Fall
3	4	False	Summer
4	5	False	Summer

In [102…

```
discount_counts = df_03['Discount_Applied'].value_counts()
discount_counts
```

Out[102]:

```
Discount_Applied
True     19433
False    19067
Name: count, dtype: int64
```

In [103…

```
df_03['Season'].unique()
```

Out[103]:

```
array(['Fall', 'Winter', 'Summer', 'Spring'], dtype=object)
```

In [104…

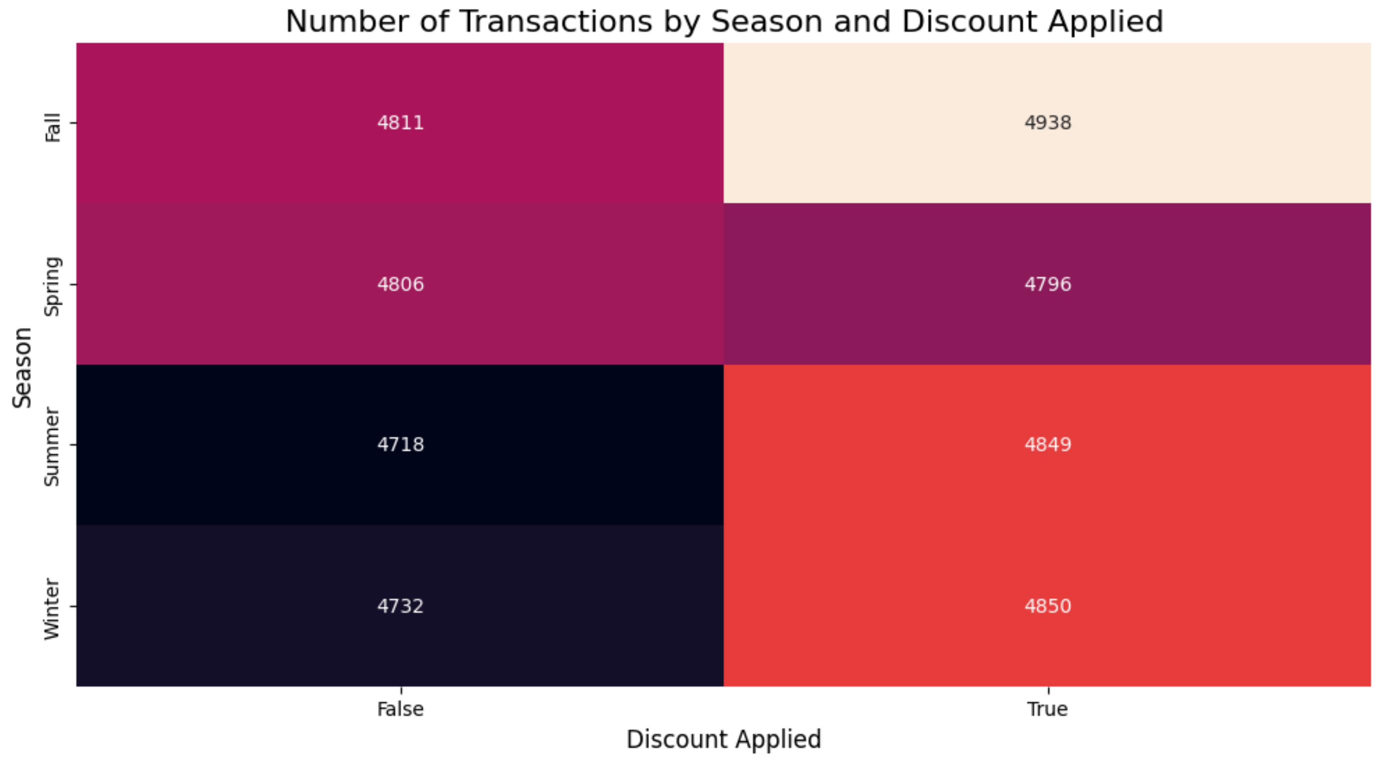
```
discount_by_season = df_03.groupby(['Season', 'Discount_Applied']).size().unstack(fill_value=0)
discount_by_season
```

Out[104]:

Discount_Applied	**False**	**True**
Season		
Fall	4811	4938
Spring	4806	4796
Summer	4718	4849
Winter	4732	4850

In [105…

```
# Plotting the heatmap
plt.figure(figsize=(12, 6))
sns.heatmap(discount_by_season, annot=True, cmap='rocket', fmt='g', cbar=False)

# Customizing the plot
plt.title('Number of Transactions by Season and Discount Applied', fontsize=16)
plt.xlabel('Discount Applied', fontsize=12)
plt.ylabel('Season', fontsize=12)


plt.savefig('/kaggle/working/05_no_of_transaction_season_discount_03.png', dpi=300, bbox_inches=

plt.show()
```



> Across all seasons, there are more transactions with discounts than without. Here’s a quick summary:
>
> Fall has the largest difference, with slightly more transactions getting discounts. The summer follows, with discounts applied in more transactions than not. Moreover winter also shows more discounted transactions, but the gap is smaller than Fall and Summer. Whereas Spring is the closest, with nearly the same number of discounted and non-discounted transactions.
>
> In short, discounts are most popular in Fall and Summer, and less emphasized in Spring.

04. What are the top three cities with the highest average number of items per transaction, and how do their sales amounts vary across seasons??

In [106…

```
df.head(2)
```

Out[106]:

	Transaction_ID	Total_Items	Amount($)	Payment_Method	City	Store_Type	Discount_Applied	Customer_Ca
0	1000667075	5	30.98	Debit Card	Chicago	Warehouse Club	True	Te
1	1000156022	3	23.29	Credit Card	Boston	Warehouse Club	True	Home

In [107…

```
columns_to_drop_04 = ['Amount($)',
                      'Payment_Method',
                      'Store_Type','Discount_Applied','Customer_Category',
                      'Promotion']
```

```
df_04 = df.drop(columns=columns_to_drop_04)
df_04.head()
```

Out[107]:

	Transaction_ID	Total_Items	City	Season
0	1000667075	5	Chicago	Fall
1	1000156022	3	Boston	Winter
2	1000681674	7	Chicago	Fall
3	1000692089	5	Atlanta	Summer
4	1000328702	4	Miami	Summer

In [108…

```
df_04["Transaction_ID"] = range(1, len(df_04) + 1)
df_04.head()
```

Out[108]:

	Transaction_ID	Total_Items	City	Season
0	1	5	Chicago	Fall
1	2	3	Boston	Winter
2	3	7	Chicago	Fall
3	4	5	Atlanta	Summer
4	5	4	Miami	Summer

In [109…

```
# Average items per transaction by city
avg_items_per_city = df_04.groupby("City")["Total_Items"].mean().sort_values(ascending=False)

# top 3 cities
top_cities = avg_items_per_city.head(3)
top_cities
```

Out[109]:

```
City
Chicago    5.547601
Houston    5.530272
Miami      5.521909
Name: Total_Items, dtype: float64
```

These are the top three cities having average items per transaction.

In [110…

```
sales_by_season = df_04.groupby(["City", "Season"])["Total_Items"].sum().unstack(fill_value=0)
sales_by_season
```

Out[110]:

Season	Fall	Spring	Summer	Winter
City				
Atlanta	5296	5095	4921	5158
Boston	5707	5108	5262	5264
Chicago	5287	5482	5323	5294
Dallas	5062	5278	5130	5441
Houston	5348	5294	5385	5530
Los Angeles	5345	5209	5163	5510
Miami	5587	5186	5288	5110
New York	5277	5353	5385	5208
San Francisco	5335	5413	5262	5223
Seattle	4985	5281	5385	5220

In [111…

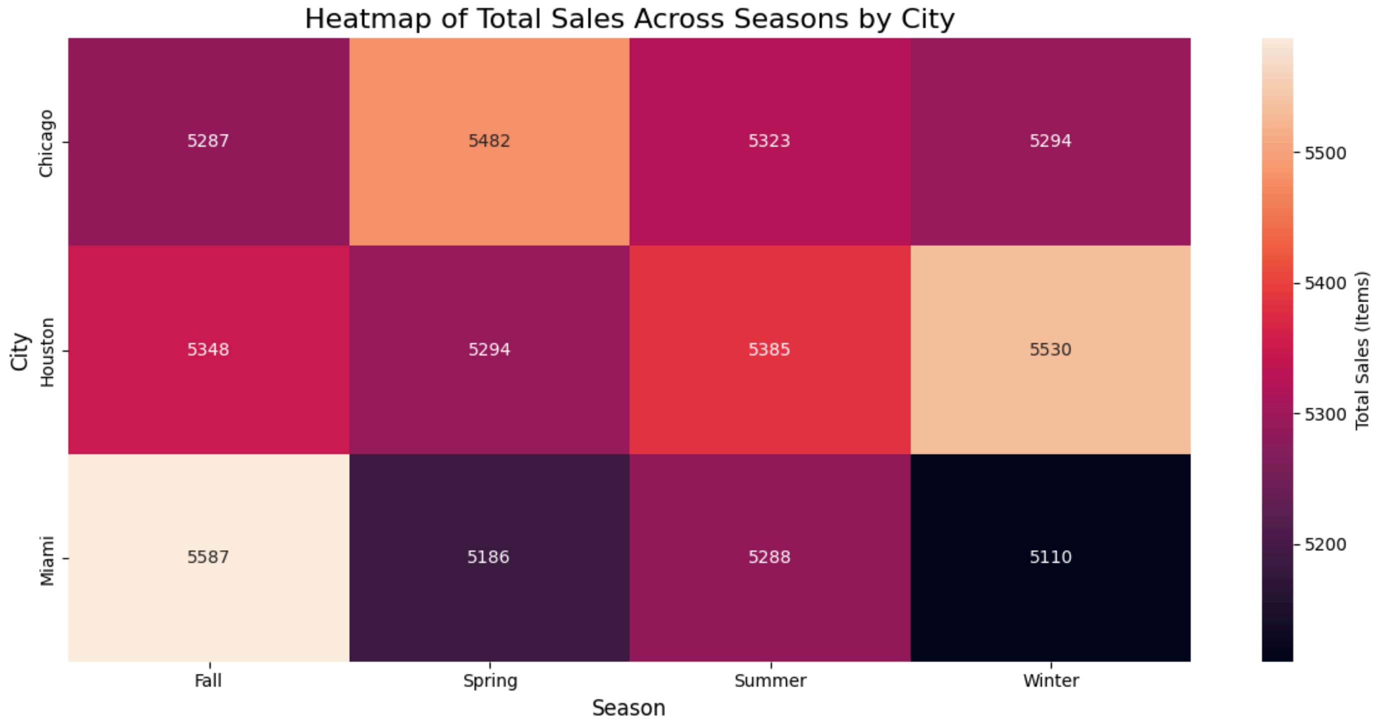
```
selected_cities = ["Chicago", "Houston", "Miami"]
filtered_table = sales_by_season.loc[selected_cities]
filtered_table
```

Out[111]:

Season	Fall	Spring	Summer	Winter
City				
Chicago	5287	5482	5323	5294
Houston	5348	5294	5385	5530
Miami	5587	5186	5288	5110

In [112…

```
plt.figure(figsize=(12, 6))
sns.heatmap(filtered_table, annot=True, fmt=".0f",
            cmap="rocket", cbar_kws={'label': 'Total Sales (Items)'})


plt.title("Heatmap of Total Sales Across Seasons by City", fontsize=16)
plt.xlabel("Season", fontsize=12)
plt.ylabel("City", fontsize=12)
plt.xticks(rotation=0, ha='center', fontsize=10)
plt.yticks(fontsize=10)
plt.tight_layout()


plt.savefig('/kaggle/working/06_Total_Sales_Across_Seasons_by_City.png', dpi=300, bbox_inches='t
plt.show()
```



This data represents seasonal transaction counts across top three cities:

> **Chicago:** - Transactions are relatively stable across seasons, ranging from **5287 (Fall)** to **5482 (Spring)**, with **Spring** having the highest activity.
>
> **Houston:** - Transaction counts peak in **Winter (5530)** and are lowest in **Spring (5294)**, showing a notable seasonal variation.
>
> **Miami:** - **Fall (5587)** has the highest transactions, while **Winter (5110)** shows the lowest, indicating a decrease in activity during colder months. months.

Overall, **Miami** shows the highest fall transactions, **Houston** peaks in winter, and **Chicago** maintains a consistent distribution across seasons.

05. How effective are different promotions in driving higher transaction amounts, and which promotion type performs best in each season? ?

In [113…

```
df.head(2)
```

Out[113]:

	Transaction_ID	Total_Items	Amount($)	Payment_Method	City	Store_Type	Discount_Applied	Customer_Ca
0	1000667075	5	30.98	Debit Card	Chicago	Warehouse Club	True	Te
1	1000156022	3	23.29	Credit Card	Boston	Warehouse Club	True	Home

In [114…

```
columns_to_drop_05 = ['Total_Items','Payment_Method','City',
                      'Store_Type','Discount_Applied','Customer_Category']
```

```
df_05 = df.drop(columns=columns_to_drop_05)
df_05.head()
```

Out[114]:

	Transaction_ID	Amount($)	Season	Promotion
0	1000667075	30.98	Fall	BOGO (Buy One Get One)
1	1000156022	23.29	Winter	Discount on Selected Items
2	1000681674	25.62	Fall	Discount on Selected Items
3	1000692089	14.64	Summer	Discount on Selected Items
4	1000328702	62.27	Summer	NaN

In [115…

```
df_05['Promotion'] = df_05['Promotion'].fillna('No Promotion')
```

In [116…

```
df_05["Promotion"].unique()
```

Out[116]:

```
array(['BOGO (Buy One Get One)', 'Discount on Selected Items',
       'No Promotion'], dtype=object)
```

In [117…

```
mean_amonunt=df_05["Amount($)"].mean()
mean_amount
```

Out[117]:

```
52.45984311688312
```

In [118…

```
high_value_transaction = df_05[df_05["Amount($)"]>mean_amount]

print(high_value_transaction.shape)
print("These is the filtered dataframe for high value transaction")
```

```
(19190, 4)
These is the filtered dataframe for high value transaction
```

In [119…

```
high_value_transaction.sort_values(by="Amount($)",ascending = False)
```

Out[119]:

	Transaction_ID	Amount($)	Season	Promotion
2645	1000408241	100.00	Summer	Discount on Selected Items
29771	1000531045	100.00	Summer	BOGO (Buy One Get One)
12181	1000591212	100.00	Fall	No Promotion
16789	1000341701	99.99	Fall	No Promotion
35217	1000966260	99.99	Fall	BOGO (Buy One Get One)
...	...	...	...	...
15011	1000658998	52.47	Fall	Discount on Selected Items
28990	1000140374	52.47	Summer	Discount on Selected Items
21520	1000099845	52.47	Winter	Discount on Selected Items
487	1000518133	52.47	Summer	Discount on Selected Items
36119	1000553050	52.46	Fall	BOGO (Buy One Get One)

19190 rows × 4 columns

In [120…

```
# Group by 'Promotion' and counting the number of transactions
transactions_per_promotion = high_value_transaction.groupby('Promotion')['Transaction_ID'].count
```

```
print(transactions_per_promotion)
```

```
Promotion
BOGO (Buy One Get One)         6372
Discount on Selected Items     6388
No Promotion                   6430
Name: Transaction_ID, dtype: int64
```

> The data shows that most transactions happen without any promotion (6,430), followed by those with a "Discount on Selected Items" (6,388) and "BOGO" (6,372). This suggests that while promotions can encourage people to buy, many purchases still happen without any special offers, meaning other factors like need or product appeal also play a big role.

In [121…

```
total_amount = high_value_transaction.groupby(['Season', 'Promotion'])['Amount($)'].sum().unstac
total_amount
```

Out[121]:

Promotion	BOGO (Buy One Get One)	Discount on Selected Items	No Promotion
Season			
Fall	121315.28	122068.94	123084.42
Spring	121080.44	125415.04	122392.07
Summer	124757.79	120471.53	122663.40
Winter	121204.90	117847.91	122369.21

In [122…

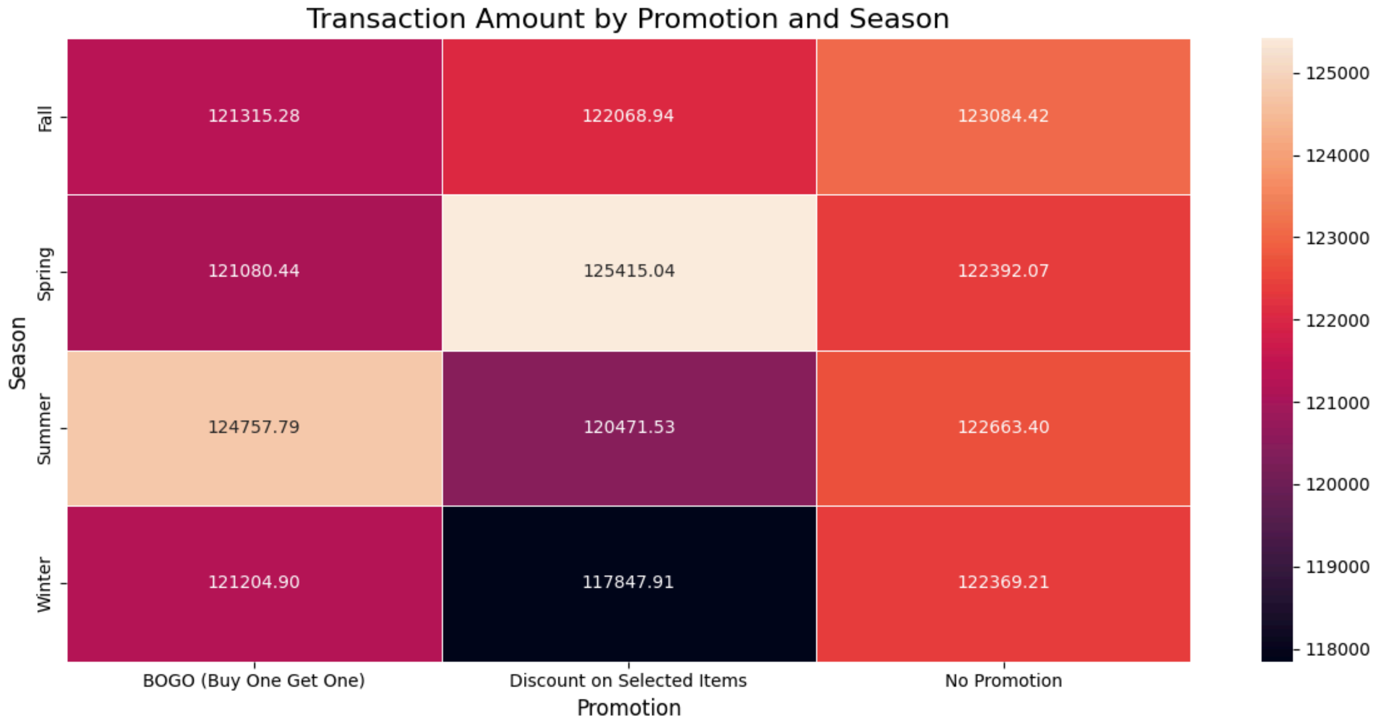
```
best_promotions = total_amount.idxmax(axis=1)
best_promotions
```

Out[122]:

```
Season
Fall                      No Promotion
Spring    Discount on Selected Items
Summer        BOGO (Buy One Get One)
Winter                    No Promotion
dtype: object
```

In [123…

```
plt.figure(figsize=(12, 6))
sns.heatmap(total_amount, annot=True, cmap="rocket", fmt='.2f', linewidths=0.5)

# Customizing the plot
plt.title('Transaction Amount by Promotion and Season', fontsize=16)
plt.xlabel('Promotion', fontsize=12)
plt.ylabel('Season', fontsize=12)

# Show the plot
plt.tight_layout()

plt.savefig('/kaggle/working/07_Transaction_Amount_by_Promo_Season.png', dpi=300, bbox_inches='t
plt.show()
```



This data shows sales revenue across four seasons for three types of promotions: **No Promotion:**

- Revenue remains consistent across all seasons, ranging from **122,369.21 (Winter)** to **123,084.42 (Fall)**.
- **Fall** generated the highest revenue without promotions.
    1. **BOGO (Buy One Get One):**
- **Summer (124,757.79)** saw the highest revenue, while **Spring (121,080.44)** had the lowest.
- BOGO performs better in warmer seasons like **Summer*

1. **Discount on Selected Items:**
    - **Spring (125,415.04)** generated the highest revenue, while **Winter (117,847.91)** was the lowest.
    - Discounts on selected ite best during Spring. perform best during **Spring**.

Overall, **Spring** and **Summer** tend to drive higher revenues with promotions, while **Fall** performs well even without promotions.