walmart-analysis

October 8, 2024

[25]:
```
import pandas as pd
#import yfinance as yf
import datetime
from datetime import date, timedelta
import plotly.graph_objects as go
import plotly.express as px
```

[29]:
```
data = pd.read_excel("Downloads/DA01 Retail_Inventory_Optimization_Data.xlsx")
```

[33]:
```
data.head()
```

[33]:

	transaction_id	customer_id	product_id	product_name	category	quantity_sold	unit_price	transaction_date	store_id	store_location	…	customer_loyalty_level	payment_method	promotion_applied	promotion_type	weather_conditions	holiday_indicator	weekday
0	1	2824	843	Fridge	Electronics	3	188.46	2024-03-31 21:46:34	3	Miami, FL	…	Silver	Credit Card	True	NaN	Stormy	False	Friday
1	2	1409	135	TV	Electronics	4	1912.04	2024-07-28 12:45:58	5	Dallas, TX	…	Gold	Cash	True	Percentage Discount	Rainy	False	Monday
2	3	5506	391	Fridge	Electronics	4	1377.75	2024-06-10 04:55:47	1	Los Angeles, CA	…	Platinum	Cash	False	NaN	Sunny	False	Tuesday
3	4	5012	710	Smartphone	Electronics	5	182.31	2024-08-15 01:03:56	5	Miami, FL	…	Silver	Cash	True	Percentage Discount	Sunny	True	Sunday
4	5	4657	116	Laptop	Electronics	3	499.28	2024-09-13 00:45:01	6	Chicago, IL	…	Bronze	Digital Wallet	False				

```
4                  NaN               Sunny              False  Thursday

   stockout_indicator forecasted_demand actual_demand
0                True               172           179
1                True               109           484
2                True               289           416
3               False               174           446
4                True               287           469

[5 rows x 28 columns]
```

[35]:
```
data.tail()
```

[35]:
```
      transaction_id  customer_id  product_id     product_name     category  \
4995            4996         6898         852       Headphones   Appliances
4996            4997         8412         886           Laptop   Appliances
4997            4998         8331         934           Fridge  Electronics
4998            4999         7505         439           Laptop   Appliances
4999            5000         1003         926  Washing Machine   Appliances

      quantity_sold  unit_price    transaction_date  store_id  \
4995              1      682.15 2024-07-08 06:13:38        17
4996              3     1418.09 2024-02-07 11:30:11        16
4997              5      398.66 2024-08-20 00:38:16        16
4998              3     1000.95 2024-08-26 11:05:15        16
4999              1      710.03 2024-02-09 01:27:01        12

       store_location  …  customer_loyalty_level  payment_method  \
4995     New York, NY  …                    Gold            Cash
4996  Los Angeles, CA  …                  Bronze  Digital Wallet
4997     New York, NY  …                  Bronze  Digital Wallet
4998        Miami, FL  …                  Silver      Debit Card
4999     New York, NY  …                Platinum      Debit Card

      promotion_applied  promotion_type  weather_conditions  \
4995              False             NaN               Sunny
4996               True             NaN               Sunny
4997               True             NaN              Cloudy
4998               True             NaN              Stormy
4999               True            BOGO              Stormy

      holiday_indicator    weekday  stockout_indicator forecasted_demand  \
4995              False  Wednesday                True               257
4996               True     Sunday                True               388
4997              False   Thursday                True               314
4998              False    Tuesday               False               488
4999               True  Wednesday               False               142
```

```
      actual_demand
4995            294
4996            397
4997            204
4998            144
4999            148

[5 rows x 28 columns]
```

[69]:
```
data.columns
```

[69]:
```
Index(['transaction_id', 'customer_id', 'product_id', 'product_name',
       'category', 'quantity_sold', 'unit_price', 'transaction_date',
       'store_id', 'store_location', 'inventory_level', 'reorder_point',
       'reorder_quantity', 'supplier_id', 'supplier_lead_time', 'customer_age',
       'customer_gender', 'customer_income', 'customer_loyalty_level',
       'payment_method', 'promotion_applied', 'promotion_type',
       'weather_conditions', 'holiday_indicator', 'weekday',
       'stockout_indicator', 'forecasted_demand', 'actual_demand'],
      dtype='object')
```

[37]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 28 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   transaction_id          5000 non-null   int64
 1   customer_id             5000 non-null   int64
 2   product_id              5000 non-null   int64
 3   product_name            5000 non-null   object
 4   category                5000 non-null   object
 5   quantity_sold           5000 non-null   int64
 6   unit_price              5000 non-null   float64
 7   transaction_date        5000 non-null   datetime64[ns]
 8   store_id                5000 non-null   int64
 9   store_location          5000 non-null   object
 10  inventory_level         5000 non-null   int64
 11  reorder_point           5000 non-null   int64
 12  reorder_quantity        5000 non-null   int64
 13  supplier_id             5000 non-null   int64
 14  supplier_lead_time      5000 non-null   int64
 15  customer_age            5000 non-null   int64
 16  customer_gender         5000 non-null   object
 17  customer_income         5000 non-null   float64
```

```
 18  customer_loyalty_level  5000 non-null   object
 19  payment_method          5000 non-null   object
 20  promotion_applied       5000 non-null   bool
 21  promotion_type          1593 non-null   object
 22  weather_conditions      5000 non-null   object
 23  holiday_indicator       5000 non-null   bool
 24  weekday                 5000 non-null   object
 25  stockout_indicator      5000 non-null   bool
 26  forecasted_demand       5000 non-null   int64
 27  actual_demand           5000 non-null   int64
dtypes: bool(3), datetime64[ns](1), float64(2), int64(13), object(9)
memory usage: 991.3+ KB
```

[39]:
```
data.describe()
```

[39]:

	transaction_id	customer_id	product_id	quantity_sold	unit_price
count	5000.000000	5000.000000	5000.000000	5000.000000	5000.000000
mean	2500.500000	5542.497200	551.233400	2.982800	1023.467294
min	1.000000	1001.000000	100.000000	1.000000	50.100000
25%	1250.750000	3279.000000	322.000000	2.000000	537.775000
50%	2500.500000	5558.000000	559.000000	3.000000	1029.175000
75%	3750.250000	7767.250000	776.000000	4.000000	1506.307500
max	5000.000000	9998.000000	999.000000	5.000000	1999.850000
std	1443.520003	2582.126997	258.826606	1.419474	559.614242

	transaction_date	store_id	inventory_level
count	5000	5000.000000	5000.000000
mean	2024-05-11 05:10:52.154800128	10.525000	253.121800
min	2024-01-01 00:31:27	1.000000	0.000000
25%	2024-03-07 19:21:43.249999872	5.000000	130.000000
50%	2024-05-11 20:03:01	11.000000	253.000000
75%	2024-07-16 08:58:58	16.000000	377.250000
max	2024-09-16 20:22:03	20.000000	500.000000
std	NaN	5.786888	142.885456

	reorder_point	reorder_quantity	supplier_id	supplier_lead_time
count	5000.000000	5000.000000	5000.00000	5000.000000
mean	99.788000	200.517000	300.12560	5.523000
min	50.000000	100.000000	100.00000	1.000000
25%	75.000000	150.750000	199.00000	3.000000
50%	100.000000	200.500000	299.00000	6.000000
75%	125.000000	251.000000	405.00000	8.000000
max	150.000000	300.000000	500.00000	10.000000
std	29.132387	58.257381	116.39486	2.863549

	customer_age	customer_income	forecasted_demand	actual_demand
count	5000.000000	5000.000000	5000.000000	5000.00000

```
mean      44.124000     70041.627846         297.134000      299.08840
min       18.000000     20005.340000         100.000000       90.00000
25%       31.000000     44865.417500         195.000000      194.00000
50%       44.000000     70188.290000         297.500000      299.00000
75%       58.000000     95395.872500         395.000000      404.00000
max       70.000000    119999.780000         500.000000      510.00000
std       15.329358     29053.371736         115.568806      121.68078
```

[77]:
```
# data cleaning
# handling Missing value in Promotion type Attribut
data["promotion_type"].isnull().sum()
```

[77]:
```
0
```

[51]:
```
data['promotion_type'].value_counts(dropna=False)
```

[51]:
```
promotion_type
NaN                   3407
BOGO                   820
Percentage Discount    773
Name: count, dtype: int64
```

[61]:
```
# replace Null Value With None
data['promotion_type'].fillna(value="None", inplace=True)
```

[63]:
```
data['promotion_type'].value_counts(dropna=False)
```

[63]:
```
promotion_type
None                  3407
BOGO                   820
Percentage Discount    773
Name: count, dtype: int64
```

[65]:
```
# Recommended Analysis
```

[67]:
```
import seaborn as sns
import matplotlib
import matplotlib.pyplot as plt
%matplotlib inline

sns.set_style('darkgrid')
matplotlib.rcParams['font.size'] = 14
matplotlib.rcParams['figure.figsize'] = (9, 5)
matplotlib.rcParams['figure.facecolor'] = '#00000000'
```

[73]:
```
# Q1  What is the total sales volume across all Walmart stores?
Total_sales = data['quantity_sold'].sum()
```

```
Total_sales
```

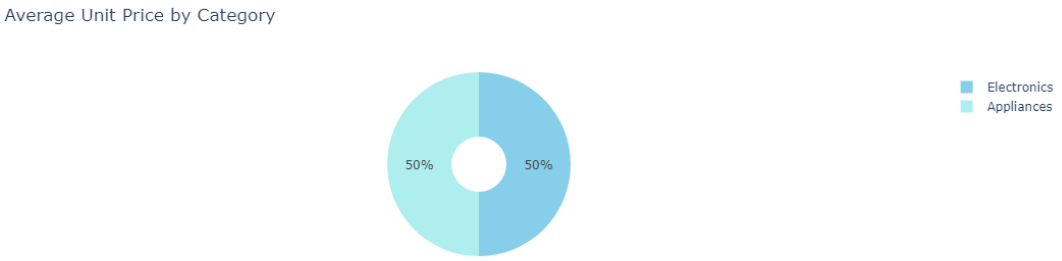
[73]:
```
14914
```

[87]:
```
# Q2 What is the average unit price of all products sold, by category?
average_unit_price = data.groupby('category')['unit_price'].mean().reset_index()
average_unit_price.columns = ['category', 'average_unit_price']
average_unit_price
```

[87]:

	category	average_unit_price
0	Appliances	1023.381503
1	Electronics	1023.547443

[198]:
```
custom_blue_colors = ['#AEEEEE', '#87CEEB', '#4682B4', '#1E90FF', '#00BFFF']
fig = px.pie(average_unit_price,
             names='category',
             values='average_unit_price',
             title='Average Unit Price by Category',
             color='category',
            color_discrete_sequence=custom_blue_colors,
             hole=0.3)
fig.show()
```



[108]:
```
# Q3  Which stores are underperforming in terms of sales volume?

# Calculate the total quantity sold by store_id
store_sales_volume = data.groupby('store_id')['quantity_sold'].sum().
 ↪reset_index()
# Rename the columns for clarity

store_sales_volume.columns = ['store_id', 'total_quantity_sold']

# Sort the result in ascending order
```

```
store_sales_volume_sorted = store_sales_volume.
 ↪sort_values(by='total_quantity_sold',ascending= True).head(1)

# Display the result
print(store_sales_volume_sorted)
```

```
   store_id  total_quantity_sold
5         6                  658
```

[112]:
```
#Q4  What percentage of transactions involved promotions?
# Count total transactions
total_transactions = len(data)

# Count transactions with promotions
transactions_with_promotions = data['promotion_applied'].sum()  # Assuming True␣
 ↪indicates a promotion applied

# Calculate percentage
percentage_promotions = (transactions_with_promotions / total_transactions) *␣
 ↪100

# Display result
print(f"Percentage of Transactions Involving Promotions: {percentage_promotions:
 ↪.2f}%")
```

```
Percentage of Transactions Involving Promotions: 52.14%
```

[122]:
```
# Q5 What is the total revenue generated from sales during promotional events?

# Step 1: Filter data for promotional events
promotional_data = data[data['promotion_applied'] == True].copy()  # Use .
 ↪copy() to avoid warnings

# Step 2: Calculate revenue for promotional transactions using .loc
promotional_data.loc[:, 'revenue'] = promotional_data['quantity_sold'] *␣
 ↪promotional_data['unit_price']

# Step 3: Sum the revenue
total_revenue_promotions = promotional_data['revenue'].sum()

# Display the total revenue generated from sales during promotional events
print(f"Total Revenue Generated from Sales during Promotional Events:␣
 ↪${total_revenue_promotions:.2f}")
```

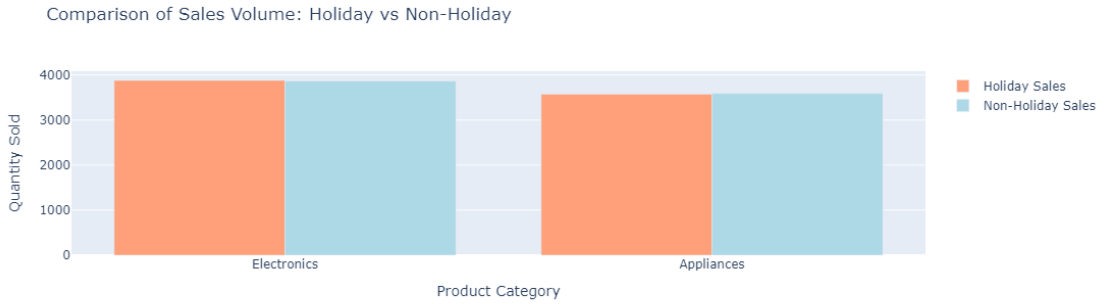
```
Total Revenue Generated from Sales during Promotional Events: $8062411.03
```

[126]:
```
# Q6: Which product categories see the largest increase in demand during␣
 ↪holidays?

# Step 1: Calculate total quantity sold during holidays
holiday_sales = data[data['holiday_indicator'] == True].
 ↪groupby('category')['quantity_sold'].sum().reset_index()
holiday_sales.rename(columns={'quantity_sold': 'holiday_quantity_sold'},␣
 ↪inplace=True)

# Step 2: Calculate total quantity sold during non-holidays
non_holiday_sales = data[data['holiday_indicator'] == False].
 ↪groupby('category')['quantity_sold'].sum().reset_index()
non_holiday_sales.rename(columns={'quantity_sold':␣
 ↪'non_holiday_quantity_sold'}, inplace=True)

# Step 3: Merge both DataFrames
merged_sales = pd.merge(holiday_sales, non_holiday_sales, on='category',␣
 ↪how='outer').fillna(0)

# Step 4: Calculate increase in demand during holidays
merged_sales['demand_increase'] = merged_sales['holiday_quantity_sold'] -␣
 ↪merged_sales['non_holiday_quantity_sold']

# Step 5: Sort the results by demand increase
sorted_results = merged_sales.sort_values(by='demand_increase', ascending=False)

# Display the results
print(sorted_results[['category', 'holiday_quantity_sold',␣
 ↪'non_holiday_quantity_sold', 'demand_increase']])
```

```
      category  holiday_quantity_sold  non_holiday_quantity_sold  \
1  Electronics                   3880                       3865
0   Appliances                   3576                       3593

   demand_increase
1               15
0              -17
```

[130]:
```
# Create a bar chart
fig = go.Figure()

# Add holiday sales to the bar chart
fig.add_trace(go.Bar(
    x=sorted_results['category'],
    y=sorted_results['holiday_quantity_sold'],
    name='Holiday Sales',
    marker_color='lightsalmon'
```

```
))

# Add non-holiday sales to the bar chart
fig.add_trace(go.Bar(
    x=sorted_results['category'],
    y=sorted_results['non_holiday_quantity_sold'],
    name='Non-Holiday Sales',
    marker_color='lightblue'
))

# Update layout
fig.update_layout(
    title='Comparison of Sales Volume: Holiday vs Non-Holiday',
    xaxis_title='Product Category',
    yaxis_title='Quantity Sold',
    barmode='group'
)

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

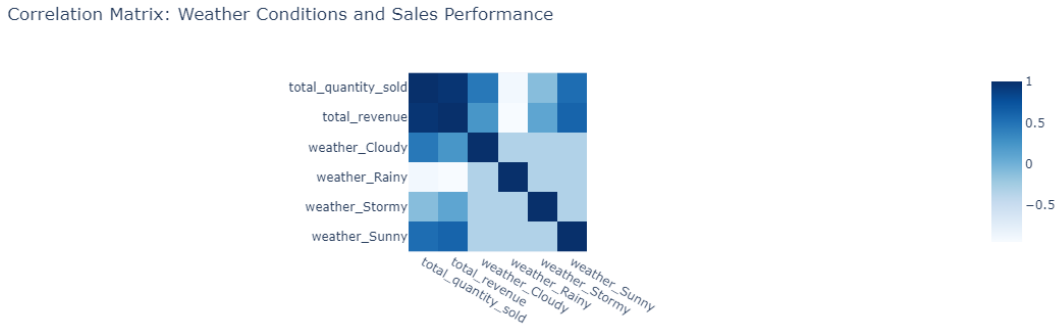


[142]:
```
# Q7: What is the correlation between weather conditions and sales performance?

# Group by weather conditions and calculate total revenue or quantity sold
weather_sales = data.groupby('weather_conditions').agg(
    total_quantity_sold=('quantity_sold', 'sum'),
    total_revenue=('unit_price', lambda x: (x * data.loc[x.index,␣
 ↪'quantity_sold']).sum())
).reset_index()

# Display the aggregated data
print(weather_sales)
```

```
  weather_conditions  total_quantity_sold  total_revenue
```

0	Cloudy	3823	3878416.82
1	Rainy	3545	3562222.42
2	Stormy	3707	3843358.52
3	Sunny	3839	3979603.69

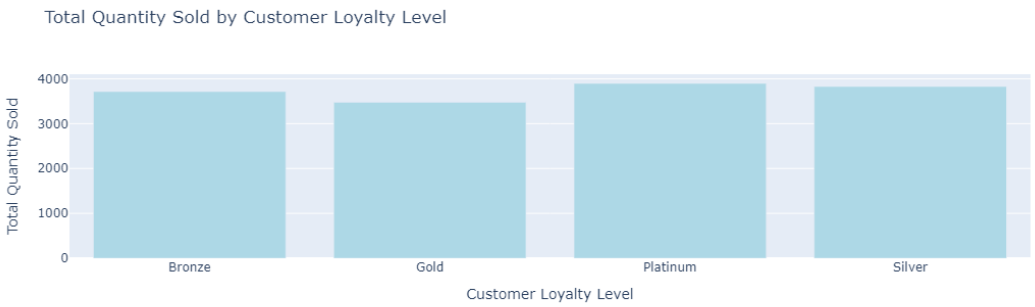
[194]:
```
# Visualization
# Plot correlation heatmap
fig = px.imshow(correlation_matrix,
                title='Correlation Matrix: Weather Conditions and Sales␣
 ↪Performance',
                color_continuous_scale='blues')

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



[154]:
```
# Q8: How does customer loyalty level affect purchasing patterns?

# Group by customer loyalty level and calculate total quantity sold
loyalty_quantity_sold = data.groupby('customer_loyalty_level')['quantity_sold'].
 ↪sum().reset_index()

# Rename the columns for better understanding
loyalty_quantity_sold.columns = ['Customer Loyalty Level', 'Total Quantity␣
 ↪Sold']

# Display the aggregated data
print(loyalty_quantity_sold)
```

	Customer Loyalty Level	Total Quantity Sold
0	Bronze	3714
1	Gold	3477
2	Platinum	3896
3	Silver	3827

[158]:
```
# visualization

# Create a bar chart for total quantity sold by loyalty level
fig_quantity = go.Figure()

fig_quantity.add_trace(go.Bar(
    x=loyalty_quantity_sold['Customer Loyalty Level'],
    y=loyalty_quantity_sold['Total Quantity Sold'],
    marker_color='lightblue'
))

# Update layout
fig_quantity.update_layout(
    title='Total Quantity Sold by Customer Loyalty Level',
    xaxis_title='Customer Loyalty Level',
    yaxis_title='Total Quantity Sold'
)

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



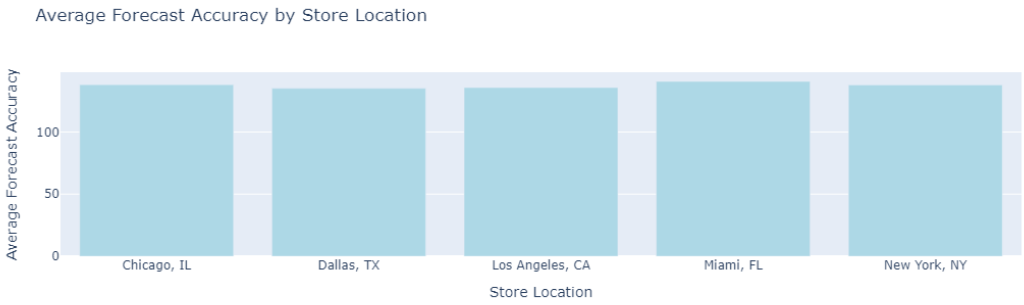
[168]:
```
# Q9: What is the forecast accuracy for each store location?

# Create a new column for the absolute difference
data['forecast_accuracy'] = abs(data['forecasted_demand'] -␣
 ↪data['actual_demand'])

# Create a new column for percentage error
data['percentage_error'] = (data['forecast_accuracy'] /␣
 ↪data['forecasted_demand']) * 100
```

[170]:
```
# Q9: What is the forecast accuracy for each store location?

# Group by store location and calculate the average absolute difference
```

```
forecast_accuracy_by_store = data.
 ↪groupby('store_location')['forecast_accuracy'].mean().reset_index()

# Alternatively, if using percentage error
# forecast_accuracy_by_store = data.
 ↪groupby('store_location')['percentage_error'].mean().reset_index()

# Rename the columns for better understanding
forecast_accuracy_by_store.columns = ['Store Location', 'Average Forecast␣
 ↪Accuracy']

# Display the aggregated data
print(forecast_accuracy_by_store)
```

```
    Store Location  Average Forecast Accuracy
0      Chicago, IL                 138.150049
1       Dallas, TX                 135.162325
2  Los Angeles, CA                 135.755299
3        Miami, FL                 140.740664
4     New York, NY                 137.945289
```

[176]:
```
# Visualization

# Create a bar chart for average forecast accuracy by store location
fig_forecast_accuracy = go.Figure()

fig_forecast_accuracy.add_trace(go.Bar(
    x=forecast_accuracy_by_store['Store Location'],
    y=forecast_accuracy_by_store['Average Forecast Accuracy'],
    marker_color='lightblue'
))

# Update layout
fig_forecast_accuracy.update_layout(
    title='Average Forecast Accuracy by Store Location',
    xaxis_title='Store Location',
    yaxis_title='Average Forecast Accuracy'
)

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



[182]:
```
# Q10: What is the stockout rate at each store?

# Create a new column for stockout occurrences
data['stockout'] = (data['inventory_level'] <= data['reorder_point']).
 ↪astype(int)

# Calculate the total number of transactions per store
total_transactions = data.groupby('store_id').size().
 ↪reset_index(name='total_transactions')

# Calculate the total stockouts per store
total_stockouts = data.groupby('store_id')['stockout'].sum().
 ↪reset_index(name='total_stockouts')

# Merge both DataFrames
stockout_data = pd.merge(total_transactions, total_stockouts, on='store_id')

# Calculate stockout rate
stockout_data['stockout_rate'] = (stockout_data['total_stockouts'] /␣
 ↪stockout_data['total_transactions']) * 100

# Display the stockout rate by store
print(stockout_data[['store_id', 'stockout_rate']])
```

```
   store_id  stockout_rate
0         1      18.250951
1         2      20.000000
2         3      15.139442
3         4      24.034335
4         5      21.722846
5         6      19.730942
6         7      16.115702
7         8      15.384615
8         9      18.218623
```

```
9          10       18.032787
10         11       17.928287
11         12       18.181818
12         13       20.075758
13         14       19.762846
14         15       21.484375
15         16       13.095238
16         17       22.448980
17         18       19.277108
18         19       20.717131
19         20       18.677043
```

[186]:
```python
# Visualization

# Create a bar chart for stockout rate by store
fig_stockout_rate = go.Figure()

fig_stockout_rate.add_trace(go.Bar(
    x=stockout_data['store_id'],
    y=stockout_data['stockout_rate'],
    marker_color='Lightblue'
))

# Update layout
fig_stockout_rate.update_layout(
    title='Stockout Rate by Store',
    xaxis_title='Store ID',
    yaxis_title='Stockout Rate (%)'
)

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