Machine Learning - Prescriptive Modeling

City Segmentation: Clustering Cities by Sales Performance Using KMeans

How can we group cities based on sales performance to uncover patterns for better sales strategy?

1. Overview

In a competitive business environment where sales performance can vary significantly across locations, understanding geographic sales patterns is critical for strategic planning. This project leverages KMeans Clustering, a machine learning technique, to segment cities based on their Total Sales and Units Purchased. By grouping similar-performing cities, the analysis provides actionable insights that can shape targeted marketing strategies, resource allocation, and performance improvement initiatives. The result is a visual and data-driven framework to support smarter, more localized business decisions.

2. Goal

- To group cities into distinct clusters based on their total sales revenue and units purchased.
- To identify underlying patterns in city-level sales performance.
- To visualize city clusters and explore performance similarities or differences.
- To provide data-driven recommendations for refining sales strategy, resource distribution, and market penetration.

3. Business Challenge

- Inconsistent sales performance across multiple cities with limited understanding of the root causes.
- Difficulty in prioritizing regions for sales efforts and investment.
- Inefficient marketing and sales allocation, leading to suboptimal ROI.
- Lack of segmentation intelligence for customized regional strategies.

4. Analysis Approach

- Data Preparation: Cleaned and grouped city-level sales and purchase data from the dataset.

- Feature Selection: Focused on Total Sales and Units Purchased as key performance indicators.
- Modeling: Applied KMeans Clustering to categorize cities into 3 distinct performance clusters.
- Visualization: Developed a scatter plot to represent cluster assignments with intuitive color mapping.
- Insight Reporting: Created a summary table to present each city's cluster, sales, and purchase volume.
- Strategic Interpretation: Used clustering output to recommend targeted actions for high, mid, and low-performing cities.

Importing libraries

In [9]:
```
import pandas as pd
import matplotlib.pyplot as plt
```

Loading the clean dataframe (post-ETL process)

In [11]:
```
df = pd.read_csv("C:\\Monthly_Sales\\cleaned_data.csv")
```

In [12]:
```
df.head(10)
```

Out[12]:

	Order ID	Product Name	Units Purchased	Unit Price	Order Date	Delivery Address	Month	Month Name	Year
0	160155	Alienware Monitor	1	400.99	2024-01-01 05:04:00	765 Ridge St, Portland, OR 97035	1	January	2024
1	151041	AAA Batteries (4-pack)	1	4.99	2024-01-01 05:04:00	964 Lakeview St, Atlanta, GA 30301	1	January	2024
2	146765	AAA Batteries (4-pack)	1	4.99	2024-01-01 05:20:00	546 10th St, San Francisco, CA 94016	1	January	2024
3	145617	Amana Washing Machine	1	600.00	2024-01-01 05:24:00	961 Meadow St, Portland, OR 97035	1	January	2024
4	156535	Lightning Charging Cable	2	14.95	2024-01-01 05:45:00	451 Elm St, Los Angeles, CA 90001	1	January	2024
5	156535	iPhone	1	700.00	2024-01-01 05:45:00	451 Elm St, Los Angeles, CA 90001	1	January	2024
6	145534	Samsung Galaxy Phone	1	650.00	2024-01-01 05:56:00	881 Madison St, Los Angeles, CA 90001	1	January	2024
7	157179	Apple Airpods Headphones	1	150.00	2024-01-01 06:25:00	279 Maple St, New York City, NY 10001	1	January	2024
8	153780	Lightning Charging Cable	1	14.95	2024-01-01 06:35:00	13 Madison St, Dallas, TX 75001	1	January	2024

	Order ID	Product Name	Units Purchased	Unit Price	Order Date	Delivery Address	Month	Month Name	Year
9	144264	LG UltraGear Monitor	1	399.99	2024-01-01 06:49:00	430 Forest St, Portland, OR 97035	1	January	2024

Replace 'Boston (\rA)' with 'Boston (MA)'

In [14]:

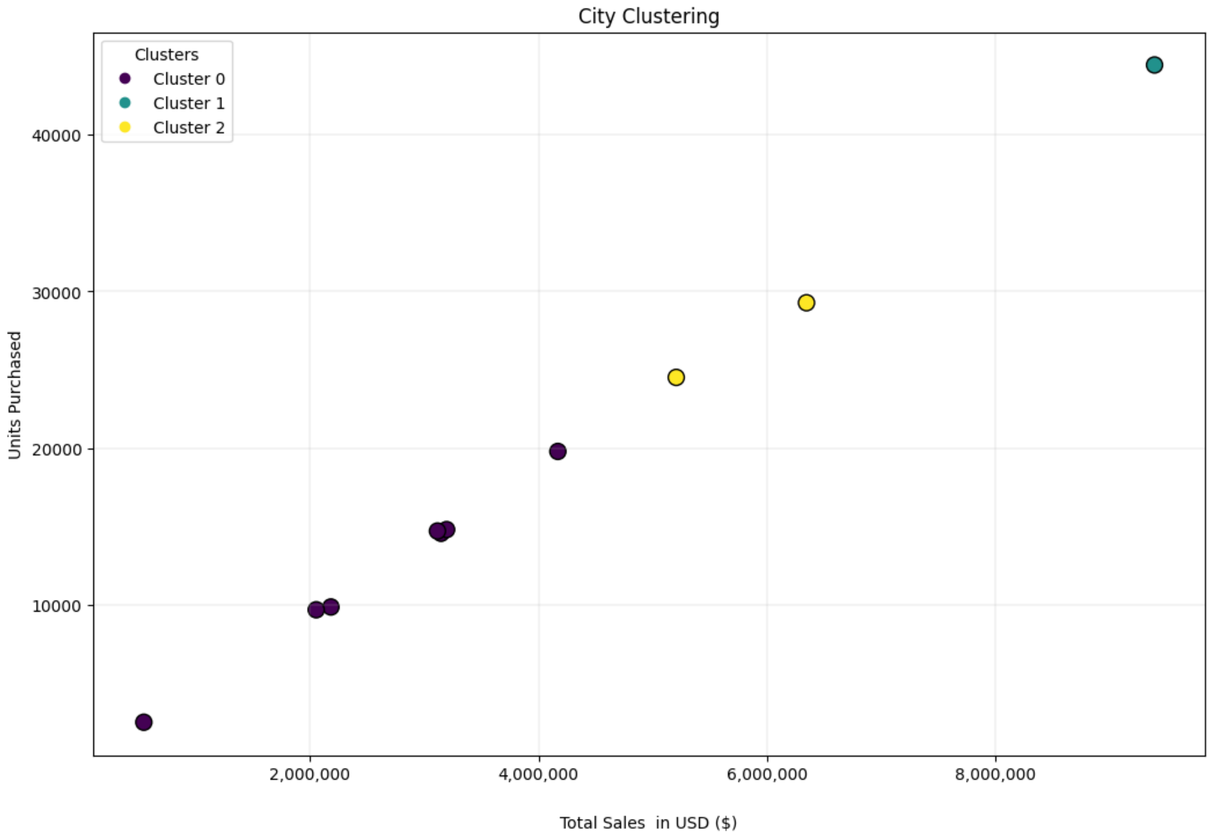
```
import re

df['City'] = df['City'].str.replace(r'Boston\s+\(\rA\)', 'Boston  (MA)', regex=True
```

Plot City Clustering using KMeans

In [16]:

```
from matplotlib.ticker import FuncFormatter
from sklearn.cluster import KMeans

# Deep copy to avoid modifying the original DataFrame
df_cluster = df.copy(deep=True)

# Clustering Cities Based on Total Sales
city_sales_data = df_cluster.groupby('City').agg({'Total Sales': 'sum','Units Purch

city_sales_data.columns = city_sales_data.columns.str.strip()
city_sales_data['City'] = city_sales_data['City'].astype(str).str.replace(r'[\r\n\t

# KMeans clustering
kmeans = KMeans(n_clusters=3, random_state=42)
city_sales_data['Cluster'] = kmeans.fit_predict(city_sales_data[['Total Sales', 'Un

fig, ax = plt.subplots(figsize=(12, 8))

# Creating a Scatter Plot
df_scatter = ax.scatter(
    city_sales_data['Total Sales'],
    city_sales_data['Units Purchased'],
    c=city_sales_data['Cluster'],
    cmap='viridis',
    s=100,
    edgecolor='black'
)

# Labeling Axes and Formatting
ax.set_xlabel('Total Sales  in USD ($)', labelpad=20)
ax.set_ylabel('Units Purchased')
ax.set_title('City Clustering')
ax.grid(linewidth=0.2)
ax.xaxis.set_major_formatter(FuncFormatter(lambda x, _: f'{x:,.0f}'))
```

```
# Adding Legend
handles, _ = df_scatter.legend_elements()
ax.legend(handles, [f'Cluster {i}' for i in range(len(handles))], title='Clusters')

# Preparing Tabular Data
table_data = city_sales_data[['Cluster', 'City', 'Units Purchased', 'Total Sales']]
table_data['Units Purchased'] = table_data['Units Purchased'].apply(lambda x: f'{x:
table_data['Total Sales'] = table_data['Total Sales'].apply(lambda x: f'${x:,.0f}')

cell_text = table_data.values.tolist()
columns = table_data.columns.tolist()

table = plt.table(
    cellText=cell_text,
    colLabels=columns,
    loc='bottom',
    cellLoc='center',
    bbox=[0.0, -0.6, 1, 0.4]  # Lowered the table further
)
table.auto_set_font_size(False)
table.set_fontsize(10)

plt.subplots_adjust(left=0.1, bottom=0.10)

plt.savefig(r"C:/Users/DELL/OneDrive - COVENANT UNIVERSITY/Desktop/1. Retail Sales /

plt.show()
```



Cluster	City	Units Purchased	Total Sales
0	Atlanta (GA)	14,581	$3,146,660
0	Austin (TX)	9,888	$2,182,211
0	Boston (MA)	19,797	$4,169,732
0	Dallas (TX)	14,818	$3,195,317
2	Los Angeles (CA)	29,269	$6,347,341
2	New York City (NY)	24,514	$5,206,534
0	Portland (ME)	2,544	$543,656
0	Portland (OR)	9,709	$2,053,496
1	San Francisco (CA)	44,418	$9,395,525
0	Seattle (WA)	14,726	$3,115,290

Key Insights and Strategic Recommendations

1. Cluster 1 – High Sales & High Volume City

Interpretation:

- The Only City in this cluster, San Francisco (CA) shows strong performance in both revenue and unit sales.
- Indicates high demand, strong customer base, and effective local execution.

Strategic Recommendations:

- Double down on success: Increase inventory levels, staffing, and marketing budget.
- Introduce loyalty programs to retain high-value customers.
- Launch premium products or upsell/cross-sell strategies, this city is more likely to adopt.

- Consider using this city as benchmark or pilots for new product launches.

2. Cluster 2 – Moderate Sales & Moderate Volume Cities

Interpretation:

- These cities perform reasonably well but have room for growth.
- Represents stable markets with potential to be moved into the high-performing cluster.

Strategic Recommendations:

- Localized promotions to drive awareness and increase repeat purchases.
- Sales training or incentive programs to boost performance.
- Monitor customer behavior and competitor activity.

3. Cluster 0 – Low Sales & Low Volume Cities

Interpretation:

- Underperforming regions with low revenue and low units sold.
- Maybe an indication of market saturation, low demand, or ineffective sales presence.

Strategic Recommendations:

- Cost-efficiency measures: Evaluate whether continued investment is justified.
- Reassess market potential: Are these markets viable with a different strategy?