Machine Learning - Prescriptive Modeling

Clustering Cities Using the KMeans Model

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. Methodology

- 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.

Let's take a deep dive into the data

Import necessary libraries

In [11]:
```
import pandas as pd
import os
import glob
```

In [12]:
```
folder_path = r"C:\Monthly_Sales"

# Retrieve all CSV files from the folder using glob
all_files = glob.glob(os.path.join(folder_path, "*.csv"))

# All CSV files combined as one DataFrame
all_data = pd.concat([pd.read_csv(file) for file in all_files], ignore_index=True)

# Merged DataFrame saved into a new CSV
output_file = os.path.join(folder_path, "all_data.csv")
all_data.to_csv(output_file, index=False)

print("All files integrated into:", output_file)
```

```
All files integrated into: C:\Monthly_Sales\all_data.csv
```

Load the updated DataFrame

In [14]:
```
# Skip Blank Rows if present in the dataset

df = pd.read_csv(r'C:\Monthly_Sales\all_data.csv', skip_blank_lines=True)
df.head()
```

Out[14]:

	Order ID	Product Name	Units Purchased	Unit Price	Order Date	Delivery Address
0	175667	iPhone	1	700.0	04/24/24 19:12	135 Meadow St, Boston, MA 02215
1	175668	AA Batteries (4-pack)	1	5.84	04/20/24 13:45	592 4th St, San Francisco, CA 94016
2	175669	AA Batteries (4-pack)	1	5.84	04/28/24 09:17	632 Park St, Dallas, TX 75001
3	175670	AA Batteries (4-pack)	2	5.84	04/23/24 14:06	131 Pine St, San Francisco, CA 94016
4	175671	Samsung Odyssey Monitor	1	409.99	04/23/24 12:13	836 Forest St, Boston, MA 02215

Data Cleaning Process

Thoroughly clean and standardize the data to eliminate errors, ensure consistency, and build a solid foundation for meaningful insights.

Find and remove rows with NaN values

In [17]:
```
df.isna().sum()
```

Out[17]:
```
Order ID            24640
Product Name        24640
Units Purchased     24642
Unit Price          24642
Order Date          24643
Delivery Address    24644
dtype: int64
```

In [18]:
```
# If Nan value is present in Order ID and Unit Purchased, it will be impossible to
# Therefore, drop Nan values in Order ID and Units Purchased.

df.dropna(subset=['Order ID', 'Units Purchased'], inplace=True)

# Check if Nan value is present
df.isna().sum()
```

Out[18]:
```
Order ID            0
Product Name        0
Units Purchased     0
Unit Price          0
Order Date          1
Delivery Address    2
dtype: int64
```

In [19]:
```
# Further check if any NaN values or blank rows are present
```

```
blank_rows_na = df[df.isnull().any(axis=1)]
blank_rows_na
```

Out[19]:

	Order ID	Product Name	Units Purchased	Unit Price	Order Date	Delivery Address
2195228	Charging Cable	1	14.95	05/24/24 07:04	852 Hickory St, San Francisco, CA 94016	NaN
3001506	150766	iPhone	1	7	NaN	NaN

Find and remove rows with duplicate values

In [21]:
```
# Find duplicate values

df.duplicated()
```

Out[21]:
```
0          False
1          False
2          False
3          False
4          False
           ...
9489202     True
9489203     True
9489204     True
9489205     True
9489206     True
Length: 9464565, dtype: bool
```

In [22]:
```
# Check again for duplicated values

df.drop_duplicates(inplace = True)

# Check again for duplicated values
df.duplicated()
```

Out[22]:
```
0          False
1          False
2          False
3          False
4          False
           ...
172530     False
2195228    False
3001506    False
6370083    False
6403571    False
Length: 171546, dtype: bool
```

Verify and fix incorrect data types in the dataset

In [24]:
```
# check for data types

df.dtypes
```

Out[24]:
```
Order ID            object
Product Name        object
Units Purchased     object
Unit Price          object
Order Date          object
Delivery Address    object
dtype: object
```

Fix incorrect data types

In [26]:
```
df['Order Date'] = pd.to_datetime(df['Order Date'], format='%m/%d/%y %H:%M', errors

df['Units Purchased'] = pd. to_numeric(df['Units Purchased'], errors='coerce')

df['Unit Price'] = pd. to_numeric(df['Unit Price'], errors='coerce')
```

In [27]:
```
# Verify the presence of NaN values remaining in the columns as a result of using e

df.isna().sum()
```

Out[27]:
```
Order ID            0
Product Name        0
Units Purchased     1
Unit Price          2
Order Date          3
Delivery Address    2
dtype: int64
```

In [28]:
```
df = df.dropna()
```

Change the data type to optimize memory usage (Optional)

In [30]:
```
df['Order ID'] = pd.to_numeric(df['Order ID'], downcast='integer')
df['Product Name'] = df['Product Name'].astype('category')
df['Units Purchased'] = df['Units Purchased']. astype('int8')
df['Unit Price'] = pd.to_numeric(df['Unit Price'], downcast='float')
df['Delivery Address'] = df['Delivery Address'].astype('category')
```

Expand the dataset with supplementary columns

In [32]:
```
# Add City column

def city(address):
    return address.split(",")[1].strip(" ")

def state_abbrev(address):
    return address.split(",")[2].split(" ")[1]
```

```
df['City'] = df['Delivery Address'].apply(lambda x: f"{city(x)}  ({state_abbrev(x)}
df.head()
```

Out[32]:

	Order ID	Product Name	Units Purchased	Unit Price	Order Date	Delivery Address	City
0	175667	iPhone	1	700.00000	2024-04-24 19:12:00	135 Meadow St, Boston, MA 02215	Boston (MA)
1	175668	AA Batteries (4-pack)	1	5.84000	2024-04-20 13:45:00	592 4th St, San Francisco, CA 94016	San Francisco (CA)
2	175669	AA Batteries (4-pack)	1	5.84000	2024-04-28 09:17:00	632 Park St, Dallas, TX 75001	Dallas (TX)
3	175670	AA Batteries (4-pack)	2	5.84000	2024-04-23 14:06:00	131 Pine St, San Francisco, CA 94016	San Francisco (CA)
4	175671	Samsung Odyssey Monitor	1	409.98999	2024-04-23 12:13:00	836 Forest St, Boston, MA 02215	Boston (MA)

In [33]:

```
# Add Total Sales column

df['Total Sales'] = df['Units Purchased'] * df['Unit Price']
df.head()
```

Out[33]:

	Order ID	Product Name	Units Purchased	Unit Price	Order Date	Delivery Address	City	Total Sales
0	175667	iPhone	1	700.00000	2024-04-24 19:12:00	135 Meadow St, Boston, MA 02215	Boston (MA)	700.00000
1	175668	AA Batteries (4-pack)	1	5.84000	2024-04-20 13:45:00	592 4th St, San Francisco, CA 94016	San Francisco (CA)	5.84000
2	175669	AA Batteries (4-pack)	1	5.84000	2024-04-28 09:17:00	632 Park St, Dallas, TX 75001	Dallas (TX)	5.84000
3	175670	AA Batteries (4-pack)	2	5.84000	2024-04-23 14:06:00	131 Pine St, San Francisco, CA 94016	San Francisco (CA)	11.68000
4	175671	Samsung Odyssey Monitor	1	409.98999	2024-04-23 12:13:00	836 Forest St, Boston, MA 02215	Boston (MA)	409.98999

Format Unit Price and Total Sales to 2 decimal places

In [35]:
```
df['Unit Price'] = df['Unit Price'].apply(lambda x: "%.2f" % x)

df['Total Sales'] = df['Total Sales'].apply(lambda x: "%.2f" % x)
df.head()
```

Out[35]:

	Order ID	Product Name	Units Purchased	Unit Price	Order Date	Delivery Address	City	Total Sales
0	175667	iPhone	1	700.00	2024-04-24 19:12:00	135 Meadow St, Boston, MA 02215	Boston (MA)	700.00
1	175668	AA Batteries (4-pack)	1	5.84	2024-04-20 13:45:00	592 4th St, San Francisco, CA 94016	San Francisco (CA)	5.84
2	175669	AA Batteries (4-pack)	1	5.84	2024-04-28 09:17:00	632 Park St, Dallas, TX 75001	Dallas (TX)	5.84
3	175670	AA Batteries (4-pack)	2	5.84	2024-04-23 14:06:00	131 Pine St, San Francisco, CA 94016	San Francisco (CA)	11.68
4	175671	Samsung Odyssey Monitor	1	409.99	2024-04-23 12:13:00	836 Forest St, Boston, MA 02215	Boston (MA)	409.99

In [36]:
```
# Convert from string to numeric

df['Unit Price'] = pd.to_numeric(df['Unit Price'])
df['Total Sales'] = pd.to_numeric(df['Total Sales'])
```

In [37]:
```
df.dtypes
```

Out[37]:
```
Order ID                    int32
Product Name             category
Units Purchased              int8
Unit Price                float64
Order Date          datetime64[ns]
Delivery Address         category
City                       object
Total Sales               float64
dtype: object
```

Organize Data by Order Date Chronologically and Reindex

In [39]:
```
df = df.sort_values(by = 'Order Date')

df = df.reset_index(drop=True)
df
```

Out[39]:

	Order ID	Product Name	Units Purchased	Unit Price	Order Date	Delivery Address	City	Total Sales
0	160155	Alienware Monitor	1	400.99	2024-01-01 05:04:00	765 Ridge St, Portland, OR 97035	Portland (OR)	400.99
1	151041	AAA Batteries (4-pack)	1	4.99	2024-01-01 05:04:00	964 Lakeview St, Atlanta, GA 30301	Atlanta (GA)	4.99
2	146765	AAA Batteries (4-pack)	1	4.99	2024-01-01 05:20:00	546 10th St, San Francisco, CA 94016	San Francisco (CA)	4.99
3	145617	Amana Washing Machine	1	600.00	2024-01-01 05:24:00	961 Meadow St, Portland, OR 97035	Portland (OR)	600.00
4	156535	iPhone	1	700.00	2024-01-01 05:45:00	451 Elm St, Los Angeles, CA 90001	Los Angeles (CA)	700.00
...	...	...	...	...	...	...	...	...
171538	297748	iPhone	1	700.00	2025-01-01 02:37:00	258 Forest St, Los Angeles, CA 90001	Los Angeles (CA)	700.00
171539	284606	Bose SoundSport Headphones	1	99.99	2025-01-01 02:50:00	211 Johnson St, Boston, MA 02215	Boston (MA)	99.99
171540	302330	AA Batteries (4-pack)	1	5.84	2025-01-01 03:03:00	665 6th St, San Francisco, CA 94016	San Francisco (CA)	5.84
171541	284711	AA Batteries (4-pack)	1	5.84	2025-01-01 03:19:00	250 8th St, San Francisco, CA 94016	San Francisco (CA)	5.84

	Order ID	Product Name	Units Purchased	Unit Price	Order Date	Delivery Address	City	Total Sales
171542	303626	USB-C Charging Cable	3	11.95	2025-01-01 04:43:00	651 Lakeview St, Dallas, TX 75001	Dallas (TX)	35.85

171543 rows × 8 columns

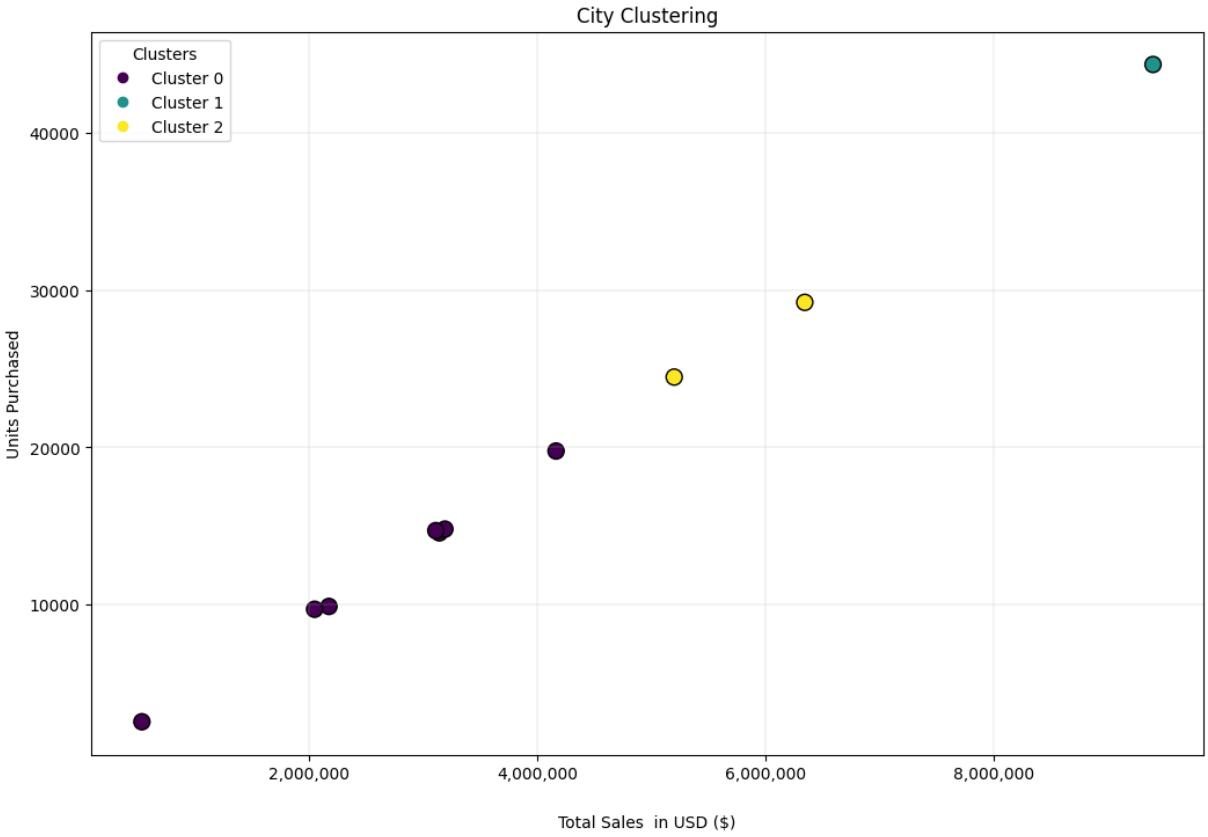
Replace 'Boston (\rA)' with 'Boston (MA)'

In [41]:
```
import re

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

Plot City Clustering using KMeans

In [43]:
```
import matplotlib.pyplot as plt
from matplotlib.ticker import FuncFormatter
from sklearn.cluster import KMeans

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

# Cluster 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))

# 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'
)

# Axis labels 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}'))

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

# Prepare table 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.show()
```



Cluster	City	Units Purchased	Total Sales
0	Atlanta (GA)	14,561	$3,145,310
0	Austin (TX)	9,878	$2,178,729
0	Boston (MA)	19,769	$4,166,658
0	Dallas (TX)	14,800	$3,193,629
2	Los Angeles (CA)	29,229	$6,343,771
2	New York City (NY)	24,476	$5,200,781
0	Portland (ME)	2,541	$541,532
0	Portland (OR)	9,700	$2,053,174
1	San Francisco (CA)	44,368	$9,391,882
0	Seattle (WA)	14,704	$3,114,139

Key Insights and Strategic Recommendations

1. Cluster 0 – High Sales & High Volume Cities

Interpretation:

- Cities in this cluster show 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, these cities are more likely to adopt.

- Consider using these cities as benchmarks or pilots for new product launches.

2. Cluster 1 – 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 2 – 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?