```
#✅ Step 1 — Import all required libraries

import pandas as pd
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
```

```
#✅ Step 2 — Load the dataset (sales_data_sample.csv)

df = pd.read_csv("sales_data_sample.csv", encoding ='latin1')
df.head()
```

	ORDERNUMBER	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	ORDERDATE	STATUS	QTR_ID	MONTH_ID	YEAR_ID	...	ADDRESSLINE1	ADDRE
0	10107	30	95.70	2	2871.00	2/24/2003 0:00	Shipped	1	2	2003	...	897 Long Airport Avenue	
1	10121	34	81.35	5	2765.90	5/7/2003 0:00	Shipped	2	5	2003	...	59 rue de l'Abbaye	
2	10134	41	94.74	2	3884.34	7/1/2003 0:00	Shipped	3	7	2003	...	27 rue du Colonel Pierre Avia	
3	10145	45	83.26	6	3746.70	8/25/2003 0:00	Shipped	3	8	2003	...	78934 Hillside Dr.	
4	10159	49	100.00	14	5205.27	10/10/2003 0:00	Shipped	4	10	2003	...	7734 Strong St.	

5 rows × 25 columns

```
#✅ Step 3 — Select only numeric columns for clustering

X = df.select_dtypes(include=['float64', 'int64']).dropna()
X.head()
```

	ORDERNUMBER	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	QTR_ID	MONTH_ID	YEAR_ID	MSRP
0	10107	30	95.70	2	2871.00	1	2	2003	95
1	10121	34	81.35	5	2765.90	2	5	2003	95
2	10134	41	94.74	2	3884.34	3	7	2003	95
3	10145	45	83.26	6	3746.70	3	8	2003	95
4	10159	49	100.00	14	5205.27	4	10	2003	95

Next steps: Generate code with X | New interactive sheet

What this does (simple words):

Code	Meaning
`select_dtypes(include=['float64', 'int64'])`	Keeps only numeric columns (like SALES, QUANTITYORDERED, etc.).
`.dropna()`	Removes rows that have missing (NaN) values — keeps data clean.
`X.head()`	Shows first 5 rows of the numeric-only data.

```
#✅ Step 4 — Scale (Normalize) the data

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

What this does in simple words:

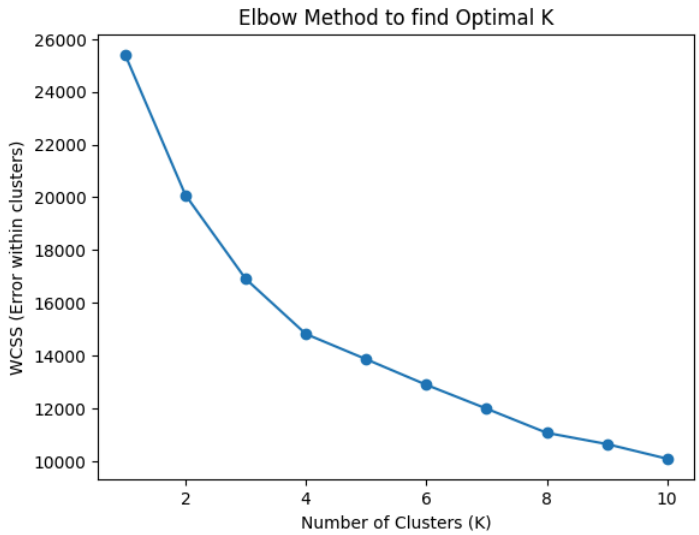
Code	Meaning
`StandardScaler()`	Selects method to scale/normalize data.
`fit_transform(X)`	Learns the scaling from the data and applies it.
`X_scaled`	Now contains the same data but standardized → perfect for K-Means.

```
#✅ Step 5 — Use the Elbow Method to find the best number of clusters (K)

wcss = []  # WCSS = Within-Cluster Sum of Squares (measures how tight the clusters are)

for i in range(1, 11):   # Try K = 1 to 10 clusters
    kmeans = KMeans(n_clusters=i, random_state=42)
    kmeans.fit(X_scaled)
    wcss.append(kmeans.inertia_)  # inertia_ = WCSS for that K

# Plot the Elbow Graph
plt.plot(range(1, 11), wcss, marker='o')
plt.title('Elbow Method to find Optimal K')
plt.xlabel('Number of Clusters (K)')
plt.ylabel('WCSS (Error within clusters)')
plt.show()
```



What this does:

Tries different values of K (1 to 10).

Calculates WCSS (how spread out the points are inside each cluster).

Plots a graph:

X-axis → Number of clusters (K)

Y-axis → WCSS

We look for a point that looks like an elbow/bend in the graph → that's the best K.

Eg. If the graph sharply drops until K=3 and then slows → K = 3 is best.

```
#✅ Step 6 — Apply K-Means clustering using the best K value

kmeans = KMeans(n_clusters = 3, random_state = 42)
df['Cluster'] = kmeans.fit_predict(X_scaled)
```

What this means (super simple):

Code	Meaning
`KMeans(n_clusters=3)`	We are telling the model to form **3 groups/clusters**.
`fit_predict(X_scaled)`	Groups the data and returns which cluster each row belongs to.
`df['Cluster']`	Adds a new column named **Cluster** to the original dataset to store results.

```
#✅ Step 7 — View the clustering results

# Count how many rows are in each cluster
print(df['Cluster'].value_counts())

# Show first few rows with cluster labels
print("\nSample data with Cluster labels:\n")
print(df[['ORDERNUMBER', 'SALES', 'Cluster']].head())
```

```
Cluster
1    1183
2     907
0     733
Name: count, dtype: int64

Sample data with Cluster labels:

   ORDERNUMBER    SALES  Cluster
0        10107  2871.00        1
1        10121  2765.90        2
2        10134  3884.34        1
3        10145  3746.70        1
4        10159  5205.27        1
```

What this shows:

Output	Meaning
`value_counts()`	Tells how many records belong to Cluster 0, 1, 2, etc.
`df[['ORDERNUMBER', 'SALES', 'Cluster']]`	Shows ORDERNUMBER, its SALES value, and which cluster it belongs to.