

```

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from scipy.cluster.hierarchy import dendrogram, linkage, fcluster

```

```

df = pd.read_csv("/content/sales_data_sample.csv" ,encoding='latin1')    # Change path if needed
print("Dataset Loaded Successfully")
print(df.head())
print("\nColumns:", df.columns)

```

Dataset Loaded Successfully

	ORDERNUMBER	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	\
0	10107	30	95.70		2	2871.00
1	10121	34	81.35		5	2765.90
2	10134	41	94.74		2	3884.34
3	10145	45	83.26		6	3746.70
4	10159	49	100.00		14	5205.27

	ORDERDATE	STATUS	QTR_ID	MONTH_ID	YEAR_ID	...	\
0	2/24/2003 0:00	Shipped	1	2	2003	...	
1	5/7/2003 0:00	Shipped	2	5	2003	...	
2	7/1/2003 0:00	Shipped	3	7	2003	...	
3	8/25/2003 0:00	Shipped	3	8	2003	...	
4	10/10/2003 0:00	Shipped	4	10	2003	...	

	ADDRESSLINE1	ADDRESSLINE2	CITY	STATE	\
0	897 Long Airport Avenue		NaN	NYC	NY
1	59 rue de l'Abbaye		NaN	Reims	NaN
2	27 rue du Colonel Pierre Avia		NaN	Paris	NaN
3	78934 Hillside Dr.		NaN	Pasadena	CA
4	7734 Strong St.		NaN	San Francisco	CA

	POSTALCODE	COUNTRY	TERRITORY	CONTACTLASTNAME	CONTACTFIRSTNAME	DEALSIZE	
0	10022	USA	NaN	Yu	Kwai	Small	
1	51100	France	EMEA	Henriot	Paul	Small	
2	75508	France	EMEA	Da Cunha	Daniel	Medium	
3	90003	USA	NaN	Young	Julie	Medium	
4	NaN	USA	NaN	Brown	Julie	Medium	

[5 rows x 25 columns]

Columns: Index(['ORDERNUMBER', 'QUANTITYORDERED', 'PRICEEACH', 'ORDERLINENUMBER', 'SALES', 'ORDERDATE', 'STATUS', 'QTR_ID', 'MONTH_ID', 'YEAR_ID', 'PRODUCTLINE', 'MSRP', 'PRODUCTCODE', 'CUSTOMERNAME', 'PHONE', 'ADDRESSLINE1', 'ADDRESSLINE2', 'CITY', 'STATE', 'POSTALCODE', 'COUNTRY', 'TERRITORY', 'CONTACTLASTNAME', 'CONTACTFIRSTNAME', 'DEALSIZE'], dtype='object')

```

df = df.dropna()

# Step 4: Select numeric features for clustering
X = df.select_dtypes(include=['float64', 'int64'])

print("\n Numerical Columns used for Clustering:")
print(X.columns)

# Step 5: Feature scaling
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

```

Numerical Columns used for Clustering:
Index(['ORDERNUMBER', 'QUANTITYORDERED', 'PRICEEACH', 'ORDERLINENUMBER', 'SALES', 'QTR_ID', 'MONTH_ID', 'YEAR_ID', 'MSRP'], dtype='object')

```

wcss = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=42, n_init='auto')
    kmeans.fit(X_scaled)
    wcss.append(kmeans.inertia_)

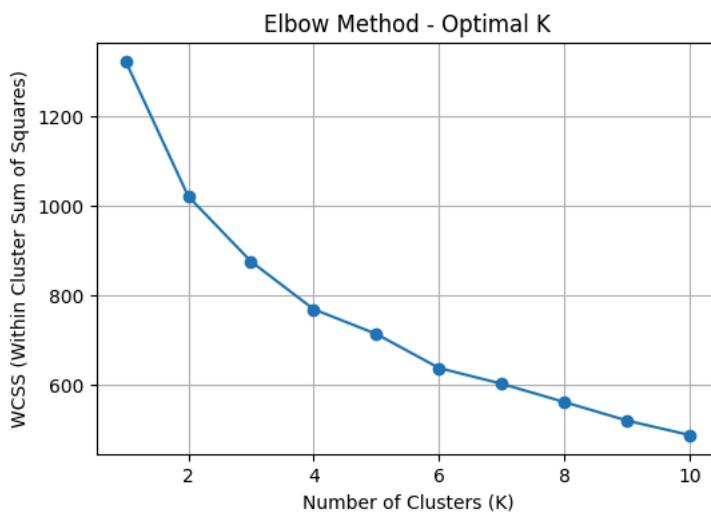
```

```

plt.figure(figsize=(6,4))
plt.plot(range(1, 11), wcss, marker='o')
plt.title("Elbow Method - Optimal K")
plt.xlabel("Number of Clusters (K)")
plt.ylabel("WCSS (Within Cluster Sum of Squares)")

```

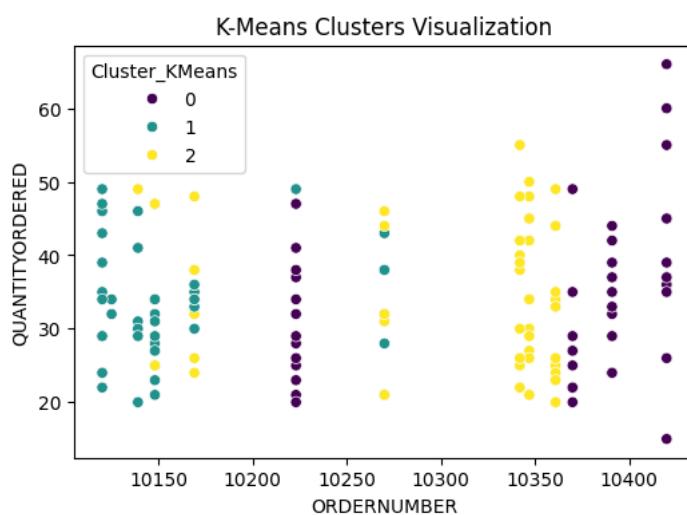
```
plt.grid()  
plt.show()
```



```
k = 3 # Change based on elbow result  
kmeans = KMeans(n_clusters=k, random_state=42, n_init='auto')  
df["Cluster_KMeans"] = kmeans.fit_predict(X_scaled)  
  
print("\n✓ KMeans Clustering Completed")  
print(df["Cluster_KMeans"].value_counts())
```

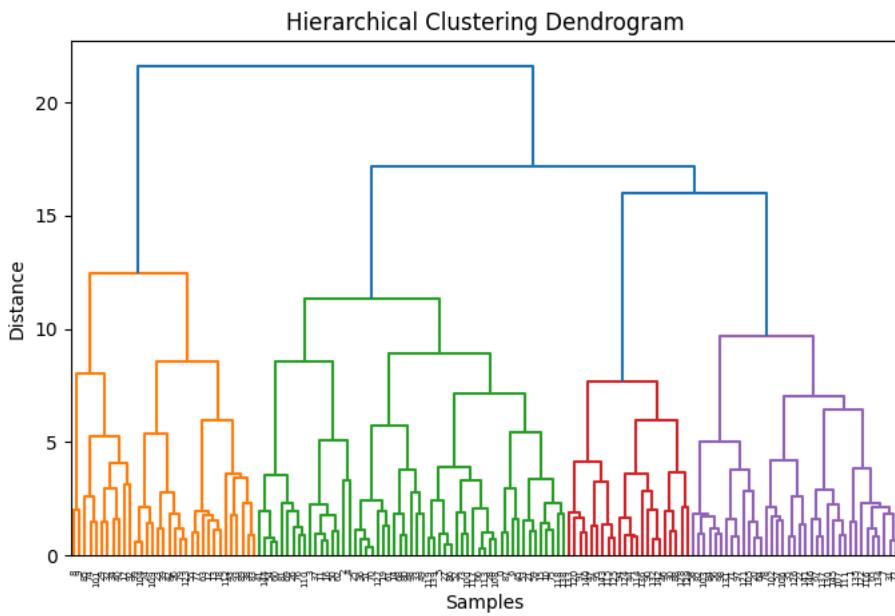
```
✓ KMeans Clustering Completed  
Cluster_KMeans  
2    53  
1    48  
0    46  
Name: count, dtype: int64
```

```
# Step 8: Visualize clusters (first 2 features)  
plt.figure(figsize=(6,4))  
sns.scatterplot(  
    x=X.iloc[:,0], y=X.iloc[:,1],  
    hue=df["Cluster_KMeans"], palette='viridis'  
)  
plt.title("K-Means Clusters Visualization")  
plt.xlabel(X.columns[0])  
plt.ylabel(X.columns[1])  
plt.show()
```



```
linked = linkage(X_scaled, method='ward')  
  
plt.figure(figsize=(8,5))  
dendrogram(linked)  
plt.title("Hierarchical Clustering Dendrogram")  
plt.xlabel("Samples")  
plt.ylabel("Distance")  
plt.show()
```

```
# Assign clusters (example: 3)
df["Cluster_Hier"] = fcluster(linked, k, criterion='maxclust')
print("\n✓ Hierarchical Clustering Completed")
print(df["Cluster_Hier"].value_counts())
```



✓ Hierarchical Clustering Completed
Cluster_Hier
3 59
2 55
1 33
Name: count, dtype: int64

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