


```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans, DBSCAN, AgglomerativeClustering
from scipy.cluster.hierarchy import dendrogram, linkage
from sklearn.metrics import silhouette_score

df = pd.read_csv('Wine_clust.csv')
df.head()
df.info()
df.describe()
```



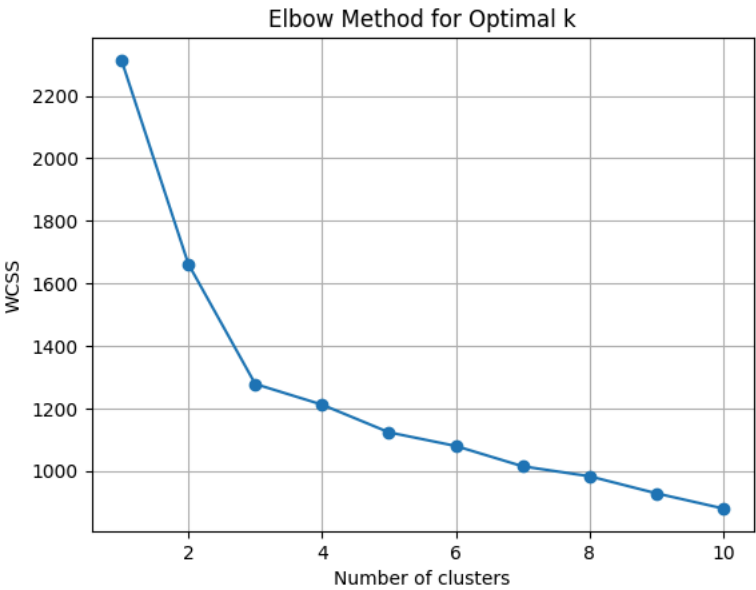
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 178 entries, 0 to 177
Data columns (total 13 columns):
Column Non-Null Count Dtype
--- -
0 Alcohol 178 non-null float64
1 Malic_Acid 178 non-null float64
2 Ash 178 non-null float64
3 Ash_Alcanity 178 non-null float64
4 Magnesium 178 non-null int64
5 Total_Phenols 178 non-null float64
6 Flavanoids 178 non-null float64
7 Nonflavanoid_Phenols 178 non-null float64
8 Proanthocyanins 178 non-null float64
9 Color_Intensity 178 non-null float64
10 Hue 178 non-null float64
11 OD280 178 non-null float64
12 Proline 178 non-null int64
dtypes: float64(11), int64(2)
memory usage: 18.2 KB

	Alcohol	Malic_Acid	Ash	Ash_Alcanity	Magnesium	Total_Phenols	Flavanoids	Nonflavanoid_Phenols	Proanthocyanins	Color_Intensity
count	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000
mean	13.000618	2.336348	2.366517	19.494944	99.741573	2.295112	2.029270	0.361854	1.590899	15.127432
std	0.811827	1.117146	0.274344	3.339564	14.282484	0.625851	0.998859	0.124453	0.572359	3.440871
min	11.030000	0.740000	1.360000	10.600000	70.000000	0.980000	0.340000	0.130000	0.410000	11.910000
25%	12.362500	1.602500	2.210000	17.200000	88.000000	1.742500	1.205000	0.270000	1.250000	13.675000
50%	13.050000	1.865000	2.360000	19.500000	98.000000	2.355000	2.135000	0.340000	1.555000	15.127432
75%	13.677500	3.082500	2.557500	21.500000	107.000000	2.800000	2.875000	0.437500	1.950000	16.782500
max	14.830000	5.800000	3.230000	30.000000	162.000000	3.880000	5.080000	0.660000	3.580000	18.000000

```
scaler = StandardScaler()
scaled_data = scaler.fit_transform(df)

wcss = []
#KMEAN
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, random_state=42)
    kmeans.fit(scaled_data)
    wcss.append(kmeans.inertia_)

# Plotting the Elbow Curve
plt.plot(range(1, 11), wcss, marker='o')
plt.title('Elbow Method for Optimal k')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.grid(True)
plt.show()
```



```
for i in range(2, 11):
    kmeans = KMeans(n_clusters=i, random_state=42)
    labels = kmeans.fit_predict(scaled_data)
    score = silhouette_score(scaled_data, labels)
    print(f"Silhouette Score for k={i}: {score}")
```



Silhouette Score for k=2: 0.2650328591008738
Silhouette Score for k=3: 0.2848589191898987
Silhouette Score for k=4: 0.25422758316007776
Silhouette Score for k=5: 0.18362105107698137
Silhouette Score for k=6: 0.16899191019013057
Silhouette Score for k=7: 0.1726015561094921
Silhouette Score for k=8: 0.16250411307671142
Silhouette Score for k=9: 0.1738739334545086
Silhouette Score for k=10: 0.13956723664297546

```
kmeans = KMeans(n_clusters=3, random_state=42)
df['KMeans_Cluster'] = kmeans.fit_predict(scaled_data)
df.head()
```



	Alcohol	Malic_Acid	Ash	Ash_Alcanity	Magnesium	Total_Phenols	Flavanoids	Nonflavanoid_Phenols	Proanthocyanins	Color_Intensity
0	14.23	1.71	2.43	15.6	127	2.80	3.06	0.28	2.29	5.64
1	13.20	1.78	2.14	11.2	100	2.65	2.76	0.26	1.28	4.38
2	13.16	2.36	2.67	18.6	101	2.80	3.24	0.30	2.81	5.68
3	14.37	1.95	2.50	16.8	113	3.85	3.49	0.24	2.18	7.80
4	13.24	2.59	2.87	21.0	118	2.80	2.69	0.39	1.82	4.32

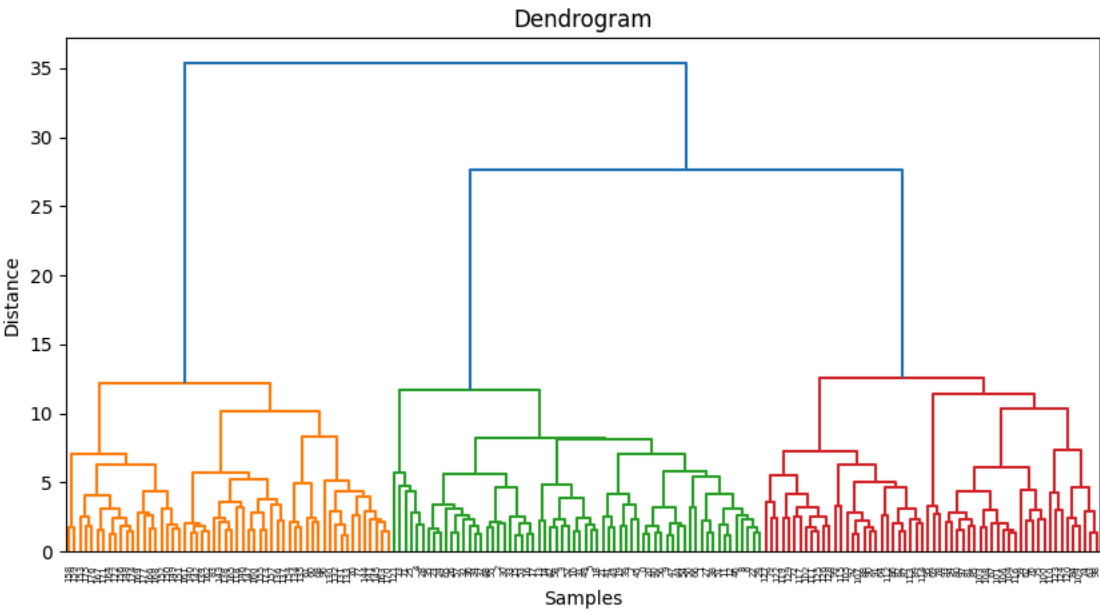
Next steps:

Generate code with df

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```
linked = linkage(scaled_data, method='ward') #HIERARCHICAL
plt.figure(figsize=(10, 5))
dendrogram(linked)
plt.title('Dendrogram')
plt.xlabel('Samples')
plt.ylabel('Distance')
plt.show()
```



```
hc = AgglomerativeClustering(n_clusters=3, metric='euclidean', linkage='ward')
df['Hierarchical_Cluster'] = hc.fit_predict(scaled_data)
df.head()
```



	Alcohol	Malic_Acid	Ash	Ash_Alcanity	Magnesium	Total_Phenols	Flavanoids	Nonflavanoid_Phenols	Proanthocyanins	Color_Intensity
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Next steps:

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```
db = DBSCAN(eps=2, min_samples=5) #DBSCAN
df['DBSCAN_Cluster'] = db.fit_predict(scaled_data)
df['DBSCAN_Cluster'].value_counts()
```





DBSCAN_Cluster	count
-1	85
0	66
4	9
1	8
2	5
3	5

dtype: int64

```
df[['KMeans_Cluster', 'Hierarchical_Cluster', 'DBSCAN_Cluster']].head(10)
```



	KMeans_Cluster	Hierarchical_Cluster	DBSCAN_Cluster	
0	2	2	0	
1	2	2	0	
2	2	2	0	
3	2	2	0	
4	2	2	-1	
5	2	2	0	
6	2	2	0	